T.R.
ONDOKUZ MAYIS UNIVERSITY
INSTITUTE OF GRADUATE STUDIES
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3D PLACEMENT OF UNMANNED AERIAL VEHICLE BASE STATIONS USING METAHEURISTIC ALGORITHMS

Master's Thesis

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SAMSUN
2023

ACCEPTANCE AND APPROVAL OF THE THESIS

The study entitled **"3D PLACEMENT OF UNMANNED AERIAL VEHICLE BASE STATIONS USING METAHEURISTIC ALGORITHMS"** prepared by **Sadat DURAKI**, and supervised by **Asst. Prof. Dr. Sercan DEMİRCİ**, was found successful and unanimously accepted by committee members as Master thesis, following the examination on the date 19.10.2023.

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This thesis has been approved by the committee members that already stated above and determined by the Institute Executive Board.

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DECLARATION OF COMPLIANCE WITH SCIENTIFIC ETHIC

I hereby declare and undertake that I complied with scientific ethics and academic rules in all stages of my M.S. thesis, that I have referred to each quotation that I used directly or indirectly in the study, and that the works I have used consist of those shown in the references, that it was written in accordance with the institute writing guide and that the stated cases in article 3, section 9 of the Regulation for TÜBİTAK Research and Publication Ethics Board were not violated.

Is an Ethics Committee Necessary?

☐ Yes

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DECLARATION OF THE THESIS STUDY ORIGINALITY REPORT

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ÖZET

İNSANSIZ HAVA ARACI BAZ İSTASYONLARININ METASEZGİSEL ALGORİTMALAR KULLANILARAK 3 BOYUTLU YERLEŞTİRİLMESİ

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İnsansız hava araçları (İHA'lar), son on yılda çeşitli sektörlerde ve alanlarda önemli gelişmelerle birlikte uygulama ve kullanım açısından dikkate değer bir büyüme gözlemlemiştir. İHA'ların artan kullanımında, geliştirilmiş pil ömrü, yük kapasitesi ve uçuş kontrol sistemleri gibi temel faktörler etkili olmuştur. İHA'ların önemli bir uygulama alanı, özellikle felaket bölgelerinde kablosuz baz istasyonu olarak görev almalarıdır. Ancak, enerji tüketimi sorunu, İHA baz istasyonları için yaygın bir zorluk oluşturmaktadır. Bu çalışmada, Animal Migration Optimization (AMO), Immune Plasma Algorithm (IPA) ve Firefly Algorithm (FA) olmak üzere üç meta-sezgisel algoritma kullanarak bu sorunu ele almaktayız. Bu algoritmalar, tek İHA yerleştirme, çoklu İHA yerleştirme ve geri besleme bilinci olan yerleştirme olmak üzere üç ayrı 3D İHA yerleştirme sorununu çözmek için kullanılmaktadır.

Bu araştırmada gerçekleştirilen deneysel çalışmalar, meta-sezgisel algoritmaların İHA 3D yerleştirmesini optimize etme ve enerji tüketimini azaltma konusunda umut verici bir yaklaşım olduğunu göstermektedir. Deneysel sonuçlar, tek İHA yerleştirmede, her üç algoritmanın makul bir performans sergilediğini ortaya koymaktadır. Bununla birlikte, çoklu İHA yerleştirme ve geri besleme bilinci olan yerleştirme durumlarında, Firefly Algorithm (FA), Immune Plasma Algorithm (IPA) ve Animal Migration Optimization (AMO) yöntemlerine kıyasla daha düşük bir performans sergilemektedir.

Bu bulgular, meta-sezgisel algoritmaların İHA enerji tüketimi sorunlarına ve 3D yerleştirmenin optimize edilmesine yönelik önemini vurgulamaktadır. Bu çalışmadan elde edilen sonuçlar, meta-sezgisel yaklaşımların kablosuz baz istasyonu senaryolarında İHA performansını artırmak için pratik uygulamasına değerli bir perspektif katmaktadır. Ayrıca, İHA teknolojisi bağlamında meta-sezgisel algoritmaların daha fazla keşfedilmesi ve geliştirilmesi potansiyelini ortaya koymaktadır.

Anahtar Sözcükler: İnsansız Hava Araçları (İHA'lar), Kablosuz Baz İstasyonu, Enerji Tüketimi, Meta-sezgisel Algoritmalar, 3D Yerleştirme

ABSTRACT

3D PLACEMENT OF UNMANNED AERIAL VEHICLE BASE STATIONS USING METAHEURISTIC ALGORITHMS

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Unmanned aerial vehicles (UAVs) have witnessed a remarkable growth in application and utilization over the past decade, owing to significant advancements in various industries and domains. Key factors contributing to the increased use of UAVs include improved battery life, payload capacity, and flight control systems. One noteworthy application of UAVs lies in their role as wireless base stations, particularly in disaster-stricken areas. However, the issue of energy consumption poses a common challenge for UAV base stations. In this study, we address this problem by employing three meta-heuristic algorithms: Animal Migration Optimization (AMO), Immune Plasma Algorithm (IPA), and Firefly Algorithm (FA). These algorithms are utilized to solve three distinct 3D UAV placement problems, namely single UAV placement, multi UAV placement, and backhaul-aware placement.

Experimental studies conducted in this research demonstrate the effectiveness of meta-heuristic algorithms as a promising approach for optimizing UAV 3D placement and reducing energy consumption. Specifically, the experimental results reveal that all three algorithms perform reasonably well for single UAV placement. However, in the cases of multi UAV placement and backhaul-aware placement, the Firefly Algorithm (FA) exhibits lower performance compared to the Immune Plasma Algorithm (IPA) and Animal Migration Optimization (AMO).

These findings underscore the significance of meta-heuristic algorithms in addressing UAV energy consumption challanges and optimizing 3D placement. The results obtained from this study contribute valuable insights into the practical application of meta-heuristic approaches for enhancing UAV performance in wireless base station scenarios. Furthermore, they highlight the potential for further exploration and refinement of meta-heuristic algorithms in the context of UAV technology.

Keywords: Unmanned Aerial Vehicles (UAVs), Wireless Base Station, Energy Consumption, Meta-heuristic Algorithms, 3D Placement

ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious, the Most Merciful.

First and foremost, I would like to praise Allah, the Almighty, the Most Gracious, and the Most Merciful for His blessing given to me during my study and in completing this thesis. May Allah's blessing go to His final Prophet and Messenger Muhammad (peace be upon him), his family, and his companions. I am indebted to my esteemed supervisor, Asst. Prof. Dr. Sercan DEMİRCİ, and also express my sincere gratitude to Assoc. Prof. Dr. Selçuk ASLAN, whose expertise, wisdom, and dedication have been instrumental in shaping this thesis. Their invaluable guidance and constructive feedback have enriched my understanding and honed my research skills.

I would like to extend my heartfelt appreciation to my loving family, especially my parents and my brothers, for their unconditional love, prayers, and unwavering belief in my abilities. Their unwavering support has been the cornerstone of my achievements. I am grateful to my dear friends and classmates for their encouragement, motivation, and intellectual exchanges, which have fostered a stimulating academic environment. Their presence has been a source of inspiration and a reminder of the importance of collaboration and camaraderie.

Lastly, I acknowledge the contributions of all those individuals who, directly or indirectly, have supported me on this path. Your encouragement, advice, and assistance have been greatly appreciated. The efforts of all of them have shaped my growth, and I pray that Allah blesses them abundantly.

Sadat DURAKI

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SYMBOLS AND ABBREVIATIONS

ABC	:	Artificial Bee Colony
ACO	:	Ant Colony Optimization
AIS	:	Artificial Immune Systems
AMO	:	Animal Migration Optimization
BC	:	Bee Colony
BS	:	Base Stations
CA	:	Cultural Algorithms
CEA	:	Coevolutionary Algorithms
CMA-ES	:	Covariance Matrix Adaptation Evolution Strategy
DBS	:	Drone Base Stations
DE	:	Differential Evolution
DP	:	Dynamic Programming
D	:	Dimensions
EP	:	Evolutionary Programming
ES	:	Evolution Strategies
FA	:	Firefly Algorithm
GA	:	Genetic Algorithms
GLS	:	Guided Local Search
GP	:	Genetic Programming
GRASP	:	Greedy Adaptive Search Procedure
HRPSO	:	Hybrid Reduced Particle Swarm Optimization
ILS	:	Iterated Local Search
IPA	:	Immune Plasma Algorithm
LoS	:	Line-of-Sight
MIP	:	Mixed Integer Programming
NLoS	:	Non Line-of-Sight
NP	:	Number of Population
Pa	:	Probability Value
PSO	:	Particle Swarm Optimization
QoS	:	Quality of Service
SA	:	Simulated Annealing
TS	:	Tabu Search
UAVs	:	Unmanned Aerial Vehicles
VNS	:	Variable Neighborhood Search

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1. INTRODUCTION

The concept of flight has always fascinated humanity, and the idea of remotely controlled or autonomous aircraft operating without human assistance has particularly captured our imagination. This technology eliminates the risk of human injury in case of mishaps, making it even more appealing. However, the initial development of Unmanned Aerial Vehicles (UAVs) faced several challenges such as limited flight duration, low payload capacity, short battery life, and unreliable communication and data transmission. These limitations restricted their practical applications in real-life scenarios. Over time, extensive research and development efforts have addressed these challenges, leading to significant advancements in UAV design, propulsion systems, and communication technologies. Consequently, UAVs have experienced widespread adoption and have found diverse applications across various industries (Shakhatreh et al., 2019).

UAVs have demonstrated notable utility in autonomous vehicle missions and disaster scenarios, as supported by scholarly research (Restas et al., 2015). During disasters, when conventional cellular networks may experience disruption or failure, UAVs offer a viable solution by acting as wireless base stations. They can complement ground-based infrastructure, expanding network coverage in disaster-stricken areas. This capability holds tremendous potential for enhancing communication and connectivity during critical situations, facilitating effective response and aid distribution. However, the application of UAVs in these scenarios presents several challenges that need to be addressed, including ensuring reliable and stable connectivity, overcoming power and endurance limitations, managing the high cost of development and maintenance, among others.

Among the key issues faced by UAVs, power consumption stands out as a significant problem. In recent years, researchers have proposed various approaches to improve the energy efficiency of UAVs, with one of the promising strategies being the reduction of energy consumption required for transmission. Multiple approaches have been explored to tackle these challenges. Some studies have focused on solving these problems using Mixed Linear Integer Programming (Gholami et al., 2021), while others have employed distributed learning-based algorithms (Wang et al., 2022), and machine learning such as q-learning (Al-Ahmed et al., 2020). However, it appears that the most suitable approach is to leverage heuristic and meta-heuristic algorithms. Heuristic and meta-heuristic algorithms are inspired by natural phenomena and offer fast solutions close to optimal on complex optimization problems that conventional approaches and algorithms struggle to solve.

The appropriateness of employing meta-heuristic algorithms can be supported by a substantial body of research that has utilized such methods. For example, in (Aslan & Demirci, 2019) and (Shakhatreh et al., 2017), the authors proposed reducing transmission power by optimally locating UAVs using the Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) algorithms. Additionally, Perabathini et al. (2019) employed PSO for the 3D placement of UAVs with Quality of Service (QoS) assurance in Ad Hoc Wireless Networks.

1.1. Research Objectives

This research aims to address three distinct problems related to UAVs. The first problem involves the 3D placement of UAVs functioning as wireless base stations, with the goal of reducing power consumption. Due to the complexity of this problem, conventional methods are inadequate, and therefore, two meta-heuristic approaches, namely AMO and IPA, are employed. Various scenarios are considered, and the results obtained with AMO and IPA are analyzed and compared with other studies implementing meta-heuristic approaches. The second problem focuses on the 3D placement of multiple UAVs to further reduce power consumption, by ensuring an equal number of users are distributed among the UAVs. This strategy aims to achieve a well-balanced user allocation across the system. In addition to AMO and IPA, the FA is utilized to solve this problem. Extensive analysis and comparisons will be conducted on the obtained results. Lastly, the third problem involves the backhaul-aware 3D placement of UAVs serving as wireless base stations. These base stations face limitations and obstacles that may hinder the efficiency of the provided service. The main challenges include limitations on total data rates, total bandwidth, and energy consumption. Similar to the previous problems, AMO, IPA, and FA algorithms will be employed to solve this problem, and a comprehensive analysis and comparison will be provided.

Through the pursuit of these research objectives, the thesis makes substantial contributions to the understanding and optimization of UAV-based wireless communication systems. The proposed meta-heuristic algorithms not only provide efficient solutions to power consumption, user allocation, and backhaul-aware placement challenges, but also advance the realms of efficiency, performance, and reliability in critical applications, such as disaster scenarios. Furthermore, the thesis significantly enriches the existing knowledge on the suitability of meta-heuristic algorithms for addressing intricate optimization problems within the realm of UAV technology. The findings of this research offer valuable insights and pave the way for further exploration and refinement of meta-heuristic algorithms within the context of UAV-based wireless communication systems.

1.2. Thesis Structure

In this first chapter, an overview of the concept of UAVs and their applications is provided. The research objectives of the thesis are outlined, focusing on addressing power consumption challenges and optimizing the 3D placement of UAVs. Furthermore, the objective of the research and contributions of the thesis to the field of UAVs are highlighted.

Subsequently, the second chapter, Literature Review, offers a comprehensive review of the relevant literature. It covers various topics, including optimization methods such as exact methods and approximate methods, heuristic algorithms, and metaheuristic algorithms. This chapter also explores the history of UAVs, their applications in different industries, and related works in the field.

In the third chapter, Materials and Methods, the materials and methods employed in the research are described in detail. This chapter provides thorough explanations of the AMO algorithm, FA, and IPA, including their respective processes and principles. The aim is to establish a solid foundation for the subsequent experimental results.

Moving on to the fourth chapter, Experimental Results, the findings obtained from applying the AMO, FA, and IPA algorithms to specific problems are presented. This chapter encompasses the results of the 3D placement of single UAVs, 3D placement of multiple UAVs, and the backhaul-aware UAV-based station placement. It analyzes and discusses the experimental setup, scenarios, and the performance and effectiveness of the proposed algorithms.

Finally, in the fifth chapter, Conclusion, the key findings and contributions of the research are summarized. The conclusions drawn from the experimental results are discussed, along with their implications in the context of UAVs and power consumption reduction. The chapter also acknowledges the limitations of the study and provides suggestions for future research.

The thesis concludes with a References section, listing all the references cited throughout the thesis in the appropriate citation style. Additionally, the Curriculum Vitae of the author is included at the end of the document.

2. LITERATURE REVIEW

In this thesis, metaheuristic algorithms were employed to tackle UAV (Unmanned Aerial Vehicle) problems. Metaheuristic algorithms are a prominent approach utilized for solving optimization problems. To gain a comprehensive understanding of metaheuristic and heuristic algorithms, as well as the rationale behind their selection for addressing optimization problems, a concise overview of optimization techniques and the contemporary challenges optimization encounters will be presented.

2.1. Introduction to Optimization

Everyday, engineers are commonly faced with problems that require designing systems which will work under multiple constraints and produce optimal solutions. And in this case, this process of finding optimal solution is called optimization. It represent a set of actions which are necessary to implement in order to obtain optimized systems. In its simplest case, the process of optimization seeks for maximum or minimum value of an objective function, which corresponds to a variables defined within feasible range or space. In a broader context, it can be said that optimization is an exploration of a set of variables that yield optimal values for one or more objective functions. Mathematical expression for a single objective optimization model can be given as follows:

$$f(X), \qquad X = (x_1, x_2, ..., x_i, ..., x_N) \tag{2.1}$$

subject to

$$g_j(X) < b_j, \quad j = 1, 2, ..., m \tag{2.2}$$

$$x_i^{(L)} \leq x_i \leq x_i^{(U)}, \quad i = 1, 2, ..., N \tag{2.3}$$

In this case, expression show in Eq. 2.1 $f(X)$ represents the objective function while X represents a set of decision variables and x_i is the i-th decision variable. N is the number of the decision parameters which represents the number of dimensions of the optimization problem. In Eq. 2.2 $g_j(X)$ is constraint and b_j is its constant, while m represents number of constraints. In the Eq. 2.3 we have x_i decision variable together with its lower and upper bounds represent with $x_i^{(L)}$ and $x_i^{(U)}$ respectively.

In the following subsections will be provided a brief explanation of the main terms commonly used in optimization (Bozorg-Haddad et al., 2017).

2.1.1. Objective Function

Objective function represents goal of the optimization problem. That goal can be maximized or minimized by selecting appropriate decision variables that satisfy problem constraints. The value of the objective function associated with a particular set of variables measures the desirability of that solution. In brief, the objective function plays a crucial role in optimization as it defines the target to be optimized, and the selection of decision variables is guided by maximizing or minimizing its value.

2.1.2. Decision Variables

In optimization, decision variables determine the value of the objective function. We search for the decision variables that yield the best value or optimum. Decision variables can be either continuous, with a range between upper and lower bounds, or discrete, taking specific values within a bound. Optimization problems can involve continuous variables, discrete variables, or a mix of both. Optimization problems that contains only continuous decision variables are called continuous problems while those problems with discrete decision variables are known as discrete problems. There are also optimization problems that have both continuous and discrete decision variable, and this type of optimization problems are referred to as a mixed type problems.

2.1.3. Solutions of an Optimization Problem

Solution can be defined as a configuration of the decision variables that produces the best possible outcome according to the defined optimization criteria. Optimization problems that are considered to be N-dimensional problems also have solution represented with the vector of N-decision variables.

2.1.4. Decision Space

Decision space refers to all possible choices or values that the decision can take within the constraints imposed on the optimization problem. Therefore, process of finding best solution involves exploring this space to identify optimal value of decision variable.

2.1.5. Constraints

In optimization constraints are limitations that must be satisfied when finding the optimal solution. In practical terms, constraints reflect real-world considerations or requirements imposed by the problem being solved. They can be physical, logical or operational limitations of the problem and they can be represented as inequalities or as equations.

2.1.6. Global and Local Optimum

Each optimization problem has a well defined decision space and within this space each point of the objective function represents solution for optimization problem. In order to get optimal solution, extreme points of the objective functions must be examined. Since the optimization problem can be maximization or minimization, extreme points are examined according to optimization type. In the context of maximization, the objective is to ascertain the highest possible value of the objective function. Conversely, in the case of minimization, the objective is to determine the lowest attainable value of the objective function. In some cases there is only one extreme point of objective function, which is global optimum of the function, and that point yields optimal solution for optimization problem. This kind of problems with single extreme point are called single-modal problems. But when we deal with real-world problems, there are usually more than one extreme points. Problems that have multiple extremes are called multi-modal problems. Figure 2.1 bellow illustrates two types of problems: single-modal, depicted as (a), and multi-modal, denoted as (b). Extreme points that do not produce optimal solution are named local optimums,

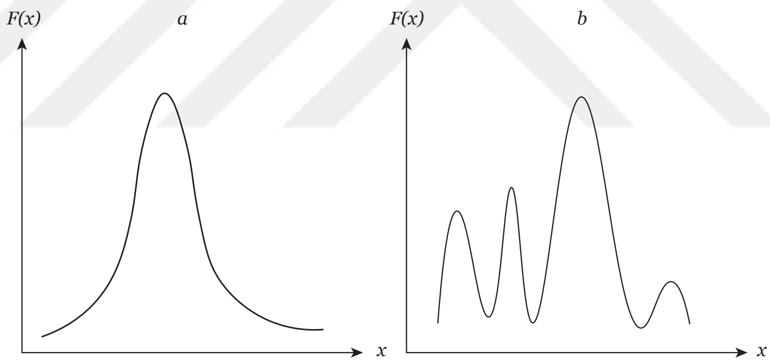

Figure 2.1. Optimization problem types

and they are considered to be optimum for a certain region of the decision space. Local optimum for maximization can be mathematically expressed like following:

$$f(X^*) \geq f(X), \quad X^* - \epsilon \leq X \leq X^* + \epsilon \tag{2.4}$$

And the mathematical expression for local optimum of minimization problem is like following:

$$f(X^*) \leq f(X), \quad X^* - \epsilon \leq X \leq X^* + \epsilon \tag{2.5}$$

Here X^* is local optimum and ϵ is some limited length around local optimum points. In the Figure 2.2 bellow it is illustrated one dimensional problem with local and global optimums.

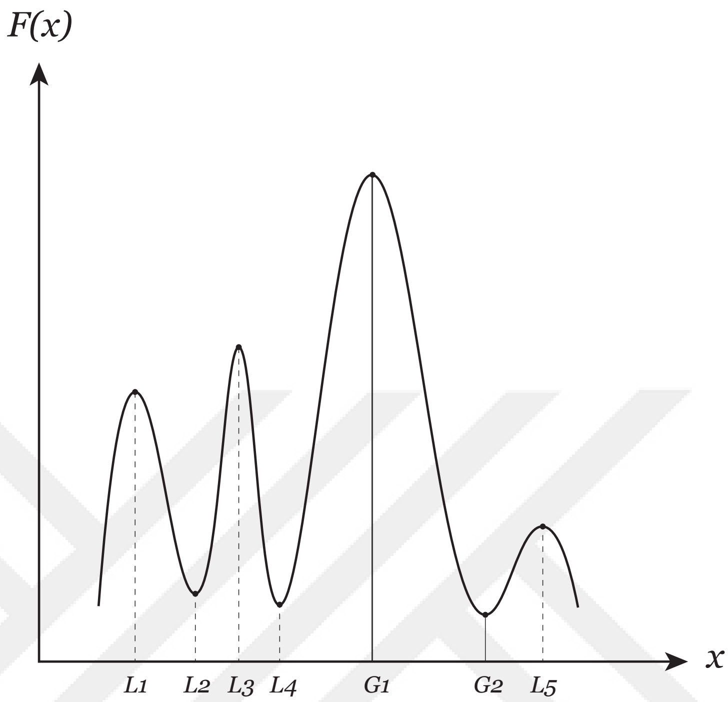

Figure 2.2. Global and Local Optimums

In the case of a maximization problem, points $L1$, $L3$, and $L5$ on the graph would be classified as local optima, whereas point $G1$ would represent the global optimum. Conversely, if the problem is a minimization one, points $L2$ and $L4$ would be regarded as local optima, while point $G2$ would represent the global optimum for the problem.

2.1.7. Near-optimal Solution

Near optimal solution refers to a solution which performance and quality are inferior to the global optimal solution but still provides satisfactory optimal solution by some acceptable margin error. In some real-world optimization problems finding optimal solution can be extremely complex or computationally expensive or even intractable. As a result, sometimes optimization algorithms aim to find near optimal solutions that provide a good balance between computational efficiency and solution quality. On the Figure 2.3 is depicted concept of a near-optimal solution for maximization problem.

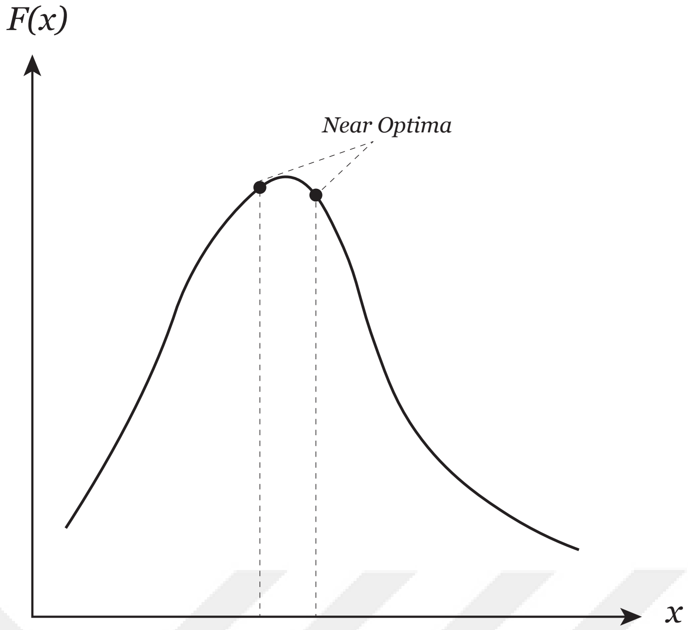

Figure 2.3. Near-Optimal Solution

2.2. Optimization Methods

For solving optimization problems two models or methods are used, exact method and approximate methods. Exact optimization methods are aiming to finding global optimal solution, likewise they also guarantee that the produced solution is best possible solution within the given problem constraints. On the other hand, approximate methods yield near-optimal solution within reasonable amount of time. Approximate methods doesn't provide any guarantee that the found solution is global optimal solution. Depending on the specific problem at hand, one of two methods can be employed, keeping in mind that each method has its own advantages and disadvantages(Festa, 2014). The Figure 2.4 below provides a comprehensive visual representation, illustrating a high-level overview of various optimization methods.

2.2.1. Exact Methods

Exact optimization methods are deterministic models that guarantee the attainment of a global optimal solution for a given optimization problem, while adhering to the specified problem constraints. During this process they are performing an comprehensive investigation of the whole solution space associated with the given problem. Exact methods are not always best approach for solving optimization problems, especially if the problem to be solved is NP-hard problem. Solving NP-hard problem using exact approach is often considered to be intractable even if the problem is medium-sized problem. Reason for this is that exact methods are mostly suitable for

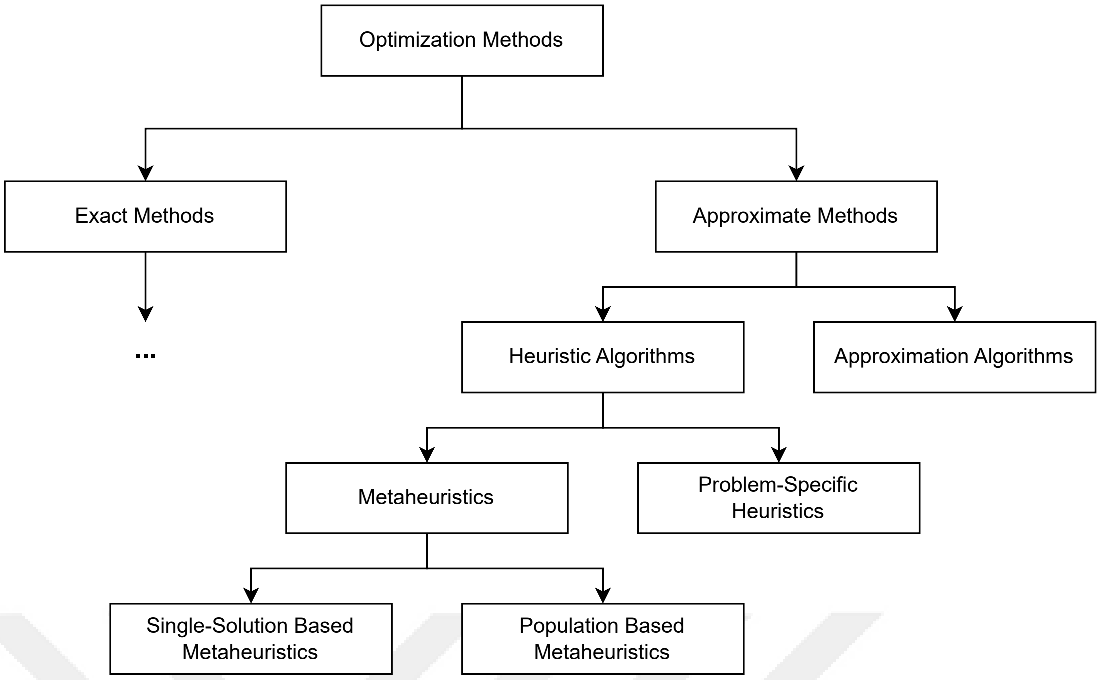

Figure 2.4. Visual representation of various optimization methods

problems that which requires polynomial effort grow in comparison with problem size. Since NP-hard problems require exponential effort, in most cases solving them with exact methods is not suitable. In cases like this, approach methods known as heuristic and metaheuristic algorithms are commonly used. These methods and algorithms will be discussed in more details in the subsequent chapters (Filip et al., 2013).

There are several categories of exact algorithms, and some of the most popular among them are, dynamic programming, linear programming, mixed integer programming, Branch and Bound algorithm, Constraint programming, A* family algorithms. Since these methods fall outside the scope of interest in this work, only a concise overview will be provided for a select few of them.

2.2.2. Dynamic Programming

Dynamic programming (DP) is an algorithmic strategy employed to explore an optimization problem by dividing it into multiple, more manageable subproblems (Hubert et al., 2001). It is crucial to recognize that the ultimate resolution of the entire problem relies on finding the optimal solutions to these subproblems. Consequently, a fundamental aspect of DP lies in effectively organizing the optimization problems into distinct levels, which are tackled in a sequential manner, one level at a time. By employing well-established optimization techniques, each level is systematically addressed, and the solution obtained at each level plays a pivotal role in shaping the characteristics of the subsequent level in the sequence. Typically, these levels correspond to different temporal periods within the broader context of the problem at hand. The branch and bound algorithm The branch and bound algorithm is a widely used method for solving optimization problems with exactness. It involves systematically exploring the search space by constructing a tree, where each node represents a subproblem and the leaf nodes represent potential solutions. The size of the subproblems decreases as the algorithm progresses towards the leaf nodes. Two key operators, branching and pruning, are employed to construct and navigate the tree. Branching determines the order in which branches are explored, while pruning eliminates partial solutions that cannot lead to optimal solutions. The algorithm iteratively improves the best-found solution by evaluating and eliminating nodes based on bounds and the branching strategy. The effectiveness of a branch and bound algorithm relies on the quality of bounds and the choice of branching strategy.

2.2.3. Constraint Programming

In constraint programming, optimization problems are represented through variables and constraints. The variables are assigned values from a finite domain, and the constraints can take various forms, either mathematical or symbolic. Global constraints pertain to a group of variables within the problem. Solving a feasibility problem in constraint programming involves an iterative process of propagation and search. Propagation algorithms associated with constraints help filter out infeasible values from variable domains. The propagation phase concludes when no further value elimination is possible. However, inconsistent values may still remain in variable domains, prompting the initiation of a search algorithm. The search algorithm employs a tree search approach, utilizing branching steps to divide the current problem into subproblems. Branching occurs by either assigning a feasible value to a variable or introducing a new constraint. Designing a search algorithm in constraint programming raises similar questions to those encountered in branch and bound algorithms. These include determining the branching order, deciding how to split the problem into subproblems when propagation is inconclusive, selecting the next subproblem for search, and determining the initial value for the branching variable (Rossi et al., 2008).

2.2.4. Integer Programming

Integer Programming is an optimization technique specifically tailored for addressing problems in which the decision variables are constrained to integer values. Unlike the continuous nature of variables in Linear Programming, Integer Programming imposes strict adherence to integers (Williams, 2009). Consequently, finding optimal solutions to such problems becomes inherently intricate, as the solution space entails a combination of continuous regions and isolated points.

Moreover, the inclusion of integer constraints often gives rise to a combinatorial explosion, resulting in an exponentially larger search space compared to linear programming. The computational complexity associated with solving Integer Programming problems surpasses that of linear programming due to the discrete nature of the variables involved. To tackle this challenge, a range of techniques, including branch and bound, cutting plane methods, and heuristics, are frequently employed to identify optimal or near-optimal solutions. Furthermore, in situations where only a subset of decision variables is subject to integer constraints while others retain the flexibility to assume any value, the problem is referred to as Mixed Integer Programming (MIP) (Wolsey, 2007).

2.2.5. Approximate methods

Approximate methods are usually divided into two groups, approximate algorithms and heuristic algorithm. Approximate algorithms Approximation algorithms, within the realm of optimization problems, are specifically crafted to efficiently seek solutions that are close to optimal. These algorithms offer explicit guarantees concerning the quality of the obtained solution as well as the computational runtime required. Given that many of these problems are classified as NP-hard, determining the exact optimal solution is computationally unfeasible (Vazirani, 2013).

In the realm of approximation algorithms, an integral aspect lies in the presence of a guaranteed bound on the solution's quality in relation to the global optimum. Specifically, an ϵ-approximation algorithm generates an approximate solution that is at most ϵ times the value of the optimal solution. The approximability of NP-hard problems varies considerably, as certain problems can be effectively approximated within any factor greater than 1, while others are fundamentally resistant to approximation within any constant factor. The objective behind designing approximation algorithms is to establish tight worst-case bounds, thereby gaining insight into the inherent complexity of the problem at hand and facilitating the development of efficient heuristics. It is worth noting, however, that the practical utility of approximation algorithms is somewhat constrained by their problem-specific nature, often resulting in solutions that may deviate significantly from the globally optimal solution.

2.3. Heuristic Algorithms

Heuristic algorithms encompass problem-solving methodologies that aim to find satisfactory solutions within a feasible timeframe for complex optimization problems. While they do not ensure optimal solutions, heuristic algorithms offer efficient approximations that are often effective in practice. These algorithms rely on intuitive guidelines, experiential knowledge, and informed judgments to guide the search process, rather than following an exhaustive or systematic approach (Kokash, 2005).

Heuristic algorithms can be categorized into two main groups: metaheuristic algorithms and problem-specific heuristics. Both metaheuristics and problem-specific heuristics play a crucial role in solving optimization problems. Metaheuristics offer a general framework applicable to a wide array of problems, while problem-specific heuristics provide tailored algorithms that exploit the unique properties of specific problems. The choice between these two approaches depends on the nature of the problem, the availability of problem-specific knowledge, and the trade-off between solution quality and computational efficiency.

Problem-specific heuristics are tailored algorithms designed to exploit the unique properties and constraints of specific optimization problems. They use domain-specific knowledge and insights to improve efficiency compared to general-purpose metaheuristics. Problem-specific heuristics are tailored to take advantage of problem-specific structures, objectives, and solution techniques. Examples of problem-specific heuristics encompass local search algorithms, greedy algorithms, dynamic programming, and branch-and-bound methods. These algorithms are often crafted based on the problem's constraints, objectives, and specific problem-solving techniques. However, due to the focus of this thesis, the discussion will not delve further into these specific algorithms(Rothlauf, 2011).

2.4. Metaheuristic Algorithms

Metaheuristics are high-level strategies that provide versatile frameworks for tackling optimization problems across diverse domains. They offer a flexible approach to explore the solution space and overcome local optima. Metaheuristics are generally independent of specific problem characteristics, making them applicable to a wide range of optimization problems. Although computationally demanding in searching for an exact solution, metaheuristic algorithms can be effective when a near-optimal solution is satisfactory. These techniques are particularly useful in situations where an optimal solution is not required. However, due to their stochastic nature, metaheuristic algorithms do not guarantee finding the optimal solution for any given problem. Nonetheless, they often succeed in finding a solution that is close to optimal if such a solution exists(Talbi, 2009).

Having on mind that main methods used for solving our problems in this thesis are metaheuristic algorithms, we find it necessary to provide definition of terms used in metaheuristic algorithms.

- *Initial state*: Every metaheuristic algorithm has its initial states, which can be defined as the starting configuration of variables or parameters from which the algorithm begins its search. The initial state is typically predetermined, randomly generated, or calculated deterministically using specific formulas or heuristics.

- *Iterations*: Algorithms engage in iterative operations as they strive to find a viable solution. Within the domain of metaheuristic algorithms, these iterative processes beg by initializing one or more preliminary solutions tailored to the specific optimization problem at hand. Sequential operations are subsequently executed to generate novel solutions, marking the progression of each iteration. The culmination of an iteration is marked by the emergence of a newfound potential solution, which subsequently assumes the role of the initial solution for the ensuing iteration of the algorithm.
- *Final State*: Upon satisfying the prescribed termination criteria, the algorithm finalizes its execution and presents the most optimal or conclusive solution attained for the given optimization problem. Termination criteria encompass a range of manifestations, including: (1) the completion of a designated number of iterations, (2) a specified threshold for enhancing the solution value between successive iterations, and (3) the passage of a specified runtime for the optimization algorithm. The initial criterion establishes an upper bound on the permissible number of iterations for the algorithm. The subsequent criterion sets a threshold that governs the level of progress required between consecutive steps. Lastly, the third criterion terminates the algorithm's execution upon the expiration of a predefined runtime, culminating in the reporting of the most favorable available solution.
- *Initial Data*: The initial information can be categorized into two main groups: (1) data pertaining to the optimization problem, which is necessary for simulation purposes, and (2) algorithm parameters, which are essential for the algorithm's execution and may require calibration. The latter type of initial information is crucial for fine-tuning the solution algorithm to address the optimization problem at hand. Virtually all metaheuristic algorithms involve parameters that necessitate adjustment. Selecting appropriate algorithm parameters is imperative to ensure the algorithm's effective application. An example of such a parameter is the stopping criterion, which is determined by the user. If the stopping criterion is not appropriately chosen, the algorithm may fail to converge towards the global solution. Conversely, the algorithm could continue running for an unnecessarily prolonged duration.
- *Decision Variables*: The decision variables are computed during the execution of the algorithm, and their values are ultimately presented as the solution to the optimization problem once the stopping criterion is satisfied. In the context of metaheuristic algorithms, the decision variables are initially initialized, and their values are subsequently recalculated throughout the algorithm's execution.
- *State Variables*: The state variables are closely associated with the decision variables, as their values dynamically evolve alongside changes in the decision variables. These

variables hold information about the current solution, such as its quality, feasibility, or any other relevant characteristics. As the algorithm advances, the state variables are subject to continual updates and modifications, mirroring the evolving nature of the search space exploration and the ongoing optimization process. The state variables play a crucial role in shaping the optimization process by capturing important insights from the algorithm's progress.

- *Objective Function*: The objective function serves as a critical component in optimization problems as it provides a mechanism to assess the quality or fitness of different solutions. It takes into consideration the problem's objectives and constraints and assigns a numerical value to each solution. This value represents the optimality or effectiveness of the solution in achieving the desired objectives.
- *Simulation Model*: A simulation model is a mathematical representation of a real-world problem or system used in optimization. It computes the values of state variables based on the given decision variables using mathematical operations. By capturing the relationship between decision and state variables, it evaluates how changes in the former affect the latter. The simulation model acts as a computational tool, emulating the behavior of the problem or system and providing insights into its performance. It is a crucial component of the optimization process, helping to evaluate and refine candidate solutions iteratively. By simulating the problem or system, it generates output values that guide the algorithm in finding optimal or near-optimal solutions.
- *Constraints*: Constraints play a vital role in meta-heuristic algorithms by defining the allowable solution space in an optimization problem. They directly impact the desirability of potential solutions. Once the objective function and state variables associated with each solution have been evaluated, the constraints are assessed to determine if the solution meets the required conditions for feasibility. If the constraints are satisfied, the solution is deemed feasible and accepted. However, if the constraints are not met, the solution is either eliminated or modified to align with the constraints.

In the domain of optimization and machine learning, a plethora of metaheuristic algorithms has been devised and applied to a diverse range of problems. The references associated with these metaheuristics signify their origins and relevance within the context of optimization and/or machine learning. Noteworthy examples encompass Ant Colonies Optimization (ACO) (Dorigo & Stützle, 2004), Artificial Bee Colony (ABC) (Karaboga, 2010), Artificial Immune Systems (AIS) (de Castro & Timmis, 2002), Bee Colony (BC) (Pham et al., 2005), Cultural Algorithms (CA) (Reynolds, 1994), Coevolutionary Algorithms (CEA) (Nolfi & Parisi, 1994), Covariance Matrix Adaptation Evolution Strategy (CMA-ES) (N. Hansen &

Ostermeier, 2001), Differential Evolution (DE) (Storn & Price, 1997), Evolutionary Programming (EP) (Fogel et al., 1966), Evolution Strategies (ES) (Beyer & Schwefel, 2002), Genetic Algorithms (GA) (Goldberg, 1989), Guided Local Search (GLS) (Boyer, 2001), Genetic Programming (GP) (Dowsland & Thompson, 1993), Greedy Adaptive Search Procedure (GRASP) (Lourenço et al., 2010), Iterated Local Search (ILS) (Lourenço et al., 2010), Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), Simulated Annealing (SA) (Kirkpatrick et al., 1983), Tabu Search (TS) (Glover & Laguna, 1997), and Variable Neighborhood Search (VNS) (P. Hansen & Mladenović, 2001).

In this thesis, the AMO (Li et al., 2014; Ma et al., 2015), IPA (Aslan & Demirci, 2020; Duraki et al., 2021), and FA (Yang, 2009, 2010b) were employed as solution methodologies for the addressed problems. A comprehensive explanation of these three algorithms will be presented in the subsequent chapter. Due to the extensive number of referenced metaheuristic algorithms, a detailed explanation of each algorithm is beyond the scope of this thesis. Nevertheless, to offer a comprehensive overview of the approach, a general algorithmic flow chart will be provided.

The algorithm begins by acquiring the input data required for the optimization problem, providing the necessary context and parameters. Subsequently, a set of initial solutions is generated, either through randomization or predefined rules, serving as a starting point for optimization. Fitness values of these solutions are then evaluated using a fitness function, quantitatively measuring their optimality. Renaming the current solutions as old solutions allows for tracking progress throughout the optimization process. Old solutions are ranked based on fitness values to identify the superior ones. A subset of old solutions with higher fitness values is selected, representing the most promising candidates for generating new solutions. This diversifies exploration within the solution space. The newly generated solutions undergo fitness evaluation, reflecting their updated quality. The algorithm checks if termination criteria have been met, such as reaching a maximum iteration count or meeting a desired fitness threshold. If termination criteria are not met, the algorithm iteratively proceeds by renaming the current solutions as old solutions and repeating the process. This iterative approach ensures continuous improvement. Once the termination criteria are satisfied, the algorithm concludes. It reports the most recently calculated solutions or the best solution achieved throughout the optimization process. These reported solutions are considered optimal or near-optimal, adhering to the problem's requirements.

In summary, the algorithm systematically generates, evaluates, and updates solutions to find the optimal or near-optimal solution for the given optimization problem. It starts by reading input data and generating initial solutions. Fitness values

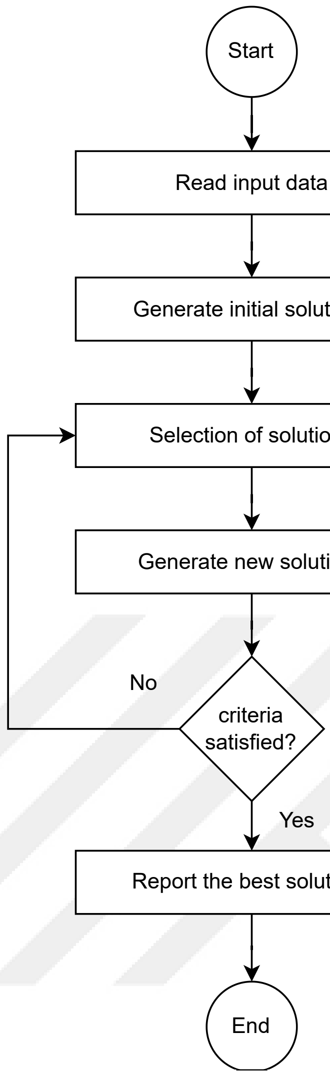

Figure 2.5. Flowchart of General Metaheuristic Algorithm

are evaluated, and the best solutions are identified. From this subset, new solutions are generated and their fitness evaluated. The algorithm iterates until termination criteria are met. The final output consists of the most recently computed or best solutions obtained, representing the optimal or near-optimal solution. This iterative process ensures continuous refinement and improvement towards achieving the best possible solution.

2.5. Unmanned Aerial Vehicles

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are autonomous or remotely controlled aircraft that operate without a human pilot on board. These sophisticated aerial systems have witnessed a significant surge in their global applications across diverse domains such as aerial photography and videography, agriculture, mapping and surveying, infrastructure inspection, search and rescue, environmental monitoring, disaster response, delivery and logistics, film and entertainment industry, wildlife conservation, military operations and many more. The multifaceted utility of UAVs holds tremendous potential for even broader applications in the foreseeable future as advancements in design technology continue to unfold. However, it is imperative to acknowledge that the local adoption of UAVs has been relatively limited, primarily constrained to research endeavors, experimental pursuits, and military deployments. This constrained utilization stems from various factors, notably the restricted exposure to civilian sectors and the presence of prohibitive policies governing their deployment (Mohsan et al., 2022). Nevertheless, the relentless progress in UAV technology, encompassing improved flight capabilities, enhanced sensing mechanisms, and more efficient energy systems, are driving efforts to overcome these challenges. With the evolution of regulatory frameworks and growing public acceptance, there is a palpable expectation for an increased integration of UAVs into everyday life, enabling innovative solutions and transformative applications across industries.

2.5.1. History

During the First World War, unmanned aerial vehicles (UAVs) were in the experimental phase and not widely used due to limitations in automation and technological development. However, they found some application in terror bombing missions, although their lack of accuracy hindered their effectiveness. In the interwar period, UAVs showed promise as target aircraft for training pilots and air defense units, as well as for aerial torpedoes to replace lost aircraft and reduce costs. In the arms race of the Cold War, UAVs continued to serve a purpose, particularly as supersonic target aircraft for training air defense personnel. The importance of strategic air reconnaissance led to the development of the first reconnaissance UAV, known as the Lightning Bug, after the U-2 incident over the Soviet Union highlighted the risks of manned aircraft in enemy territory. The Vietnam War saw advancements in live data networks, allowing instant analysis of images captured by UAVs, and the integration of electronic warfare capabilities. The advent of digital technology in the late 1970s and early 1980s enabled the creation of cheaper and lighter UAVs. In the conflicts of the 1990s, UAVs played a crucial role in gathering large quantities of information for rapid processing, contributing to the rise of information warfare. Currently, UAVs are an integral part of military forces worldwide, and their roles and numbers are expected to increase in the future. The development of UAVs has been motivated by military conflicts and the recognition of their advantages over manned aircraft, such as extended maneuverability, improved stealth capabilities, and longer flight durations. UAVs have proven effective in various theaters of operation, and their continued evolution is driven by emerging needs, capability limitations, and changing applications in conventional aviation. The development of unmanned aircraft systems and vehicles (UAS/V) technology in the 20th century has primarily been driven by military applications. The United States military initially utilized drones during the Korean War for mapping and surveying enemy territories without endangering pilots. This showcased the broader potential of the technology beyond immediate military needs. Although there was public interest in remote-controlled model airplanes in the 1960s and 1970s, commercial drone usage didn't gain traction until the early 2000s when government agencies employed them for disaster relief and wildfire management. Concurrently, civilian companies started using drones for tasks like crop spraying, land surveying, and infrastructure inspections. In 2006, the Federal Aviation Administration (FAA) issued its first commercial drone permit, cementing drones as a viable commercial tool. However, the adoption process was slow and the turning point came when prominent technology companies, such as Amazon under Jeff Bezos (Jung & Kim, 2017), expressed interest in drone-based delivery systems in 2013. The future of drone technology appears bright and promising. What began as a hobby has evolved into a fully viable avenue of exploration. In a last couple of years, numerous firms and government agencies not only use drones to enhance their operations but have established dedicated departments that both utilize drones for their own projects and license them out to other organizations (Keane & Carr, 2013).

2.5.2. Applications of UAVs

As mentioned before nowadays UAV have found application in many domains, starting from military uses to film and entertainment industries (Muchiri & Kimathi, 2022; Jumani et al., 2022).

2.5.2.1. Aerial Photography and Videography

Drones have gained significant popularity as a versatile tool for capturing footage that was previously reserved for expensive helicopters and cranes. Equipped with fast, high-resolution cameras, including action cameras, drones have made cinematography more accessible, enabling the capture of even sci-fi scenes. Their application extends to real estate and sports photography as well. Journalists have also recognized the immense potential of drones in capturing live footage and videos. However, along with the increased usage and popularity of drones in this field, certain challenges have emerged. These challenges are addressed in a comprehensive study conducted by Holton et al. (2015). The research examines the impact of unmanned aerial vehicles (UAVs) on journalism and the legal challanges they present. Moreover, the study highlights the key benefits that UAVs offer journalism. It concludes by delving into the evolving rules and regulations established by the FAA and their influence on the use of UAVs in journalism by private citizens, journalists, and news organizations.

2.5.2.2. Agriculture

UAV technologies have brought about a significant transformation in the agriculture industry, empowering farmers with modern tools. Farmers are now utilizing drones and UAV devices to efficiently monitor their extensive crop fields in a cost-effective manner. These devices are equipped with sensors that can quickly detect any signs of crop health issues and promptly alert farmers. In work done by Rahman et al. (2021), the paper concludes that there is a tremendous potential for a gradual increase in the field of agricultural UAVs. Firstly, the paper explores UAV charging methods, essential hardware and software components, and highlights the benefits of crop monitoring systems, UAV sprinkling, and livestock farming techniques. The study underscores the need for advancements in battery capacity, nozzle types, and image processing systems to reduce operational costs. Additionally, it discusses the use of UAVs for wildlife conservation through thermal imaging and species data gathering. Overall, the research concludes that UAVs are revolutionizing precision agriculture and offer significant potential for future agrarian purposes.

2.5.2.3. Disaster Management

Natural disasters pose a significant challenge worldwide, often hindering timely human response due to their extensive scope. With the anticipated increase in natural disasters due to climate change, research focuses on developing systems to predict, prevent, and respond effectively. Leveraging advancements in wireless communication, energy storage, computing power, Unmanned Aerial Vehicles, emerges as an ideal solution for disaster management. Aerial assessment facilitated by UAV systems offers rapid situational awareness, enabling swift and efficient search and rescue operations. Consequently, the disaster management community has shown growing interest in UAV technology in recent years. In work done by Luo et al. (2019), the authors address the importance of utilizing UAVs in disaster management scenarios. They highlight the significant impact of recent calamities worldwide, resulting in both human casualties and extensive economic damage. The paper emphasizes the role of UAVs as communication relays in areas where traditional communication infrastructure is destroyed. By acting as on-the-fly communication facilitators, UAVs can coordinate rescue teams and provide assistance to survivors in a timely manner. The authors investigate algorithms that enable communication between multiple UAVs, extending the coverage area and connecting disjointed segments. Real-time deployment scenarios are explored, focusing on the use of UAVs for communication in disaster management. The paper includes experimental results from the authors' own work, demonstrating successful communication bridging between ground stations and UAVs during rescue operations. Additionally, the paper explores various applications of UAVs in disaster prediction, management, and recovery, such as early warning systems, emergency communication, and search and rescue. The conclusion discusses the design challenges and considerations for UAV-based ad hoc networks in the context of disaster management.

2.5.2.4. Delivery and Shipping

Unmanned aerial vehicles (UAVs) provide a range of benefits when it comes to delivering goods to customers, including speed and flexibility. They are particularly valuable for tasks that are monotonous, hazardous, or dirty, offering an efficient solution. UAVs excel in time-sensitive deliveries, unaffected by traffic conditions, ensuring prompt and reliable service. Moreover, they are well-suited for short distances, efficiently delivering small parcels, meals, and other time-critical orders. Despite these advantages, the environmental and cost benefits of drone delivery remain a topic of ongoing debate, prompting further investigation and analysis (Kirschstein, 2020). Several major companies, including Amazon, Deutsche Post DHL, and Alphabet, have shown significant interest in utilizing drones for package delivery. Amazon's Prime Air project aims to deliver packages quickly using automated drones, while Deutsche Post DHL's Parcelcopter project focuses on transporting medicine to remote locations. Alphabet's Project Wing also envisions drones playing a crucial role in shipping larger packages. Other players in the e-commerce industry, such as Siroop, Domino's Pizza, and McDonald's, are exploring drone delivery options to enhance their home delivery services. Furthermore, drones have been used for transporting medicines between hospitals, particularly in African countries where accessibility is a challenge. Rwanda, Tanzania, and Ghana have implemented drone-based logistics systems to deliver vaccines, blood products, and drugs to remote areas efficiently. The interest and implementation of drone delivery by these prominent companies and organizations highlight the potential and versatility of this technology in various industries (Benarbia & Kyamakya, 2022).

2.5.2.5. Military

As previously mentioned, the initial development and improvement of UAVs were primarily driven by military applications. However, in recent times, the development of UAVs is not limited to military purposes alone. The applications of UAVs have expanded into numerous civil domains. Nevertheless, it remains noteworthy that military applications continue to be a significant domain where UAVs find extensive use. UAVs can be classified based on their characteristics and roles. In the military domain, UAVs serve various purposes such as information gathering, surveillance, combat, communication relay, aerial delivery, and research. ISTAR UAVs collect enemy information and patrol hostile airspace without endangering human lives. Radar and communication relay UAVs function as low-level surveillance systems, while multi-purpose UAVs can be weaponized for interdiction and reconnaissance missions. Aerial/supply delivery UAVs are designed for precise cargo delivery to special forces. UAVs are considered essential in modern military operations due to their ability to operate autonomously, carry payloads, and provide critical information, surveillance, target acquisition, and reconnaissance (ISTAR). They reduce risks by collecting battlefield imagery and have been successfully deployed in combat situations. Multi-purpose UAVs combine ISTAR capabilities with combat functionality, equipped with high-sensitivity imagery sensors and a significant ammunition capacity. With their versatility and capabilities, UAVs have revolutionized various domains, both military and civilian, enhancing efficiency and safety (Udeanu et al., 2016).

2.6. Related Works

Advancements in the field of unmanned aerial vehicles (UAVs) have led to the development of affordable and reliable drones, opening up numerous applications for UAVs in the realm of networking. These applications vary based on specific contexts and requirements, offering a wide range of roles that UAVs can fulfill.

This subsection provides a comprehensive review of existing academic literature focused on the applications of UAVs in networking and their optimization. It offers an overview of studies that delve into the challenges, methodologies, and strategies associated with integrating UAVs into wireless network systems.

In recent years, there has been a surge of research where UAVs are utilized as flying base stations or aerial relays. These UAVs establish wireless connections between remote areas and existing network infrastructure, serving as communication relays. Additionally, they can act as signal repeaters, extending network coverage to areas with limited or no connectivity. Notably, Erdelj et al. (2017) have presented in their work utilization of UAV in disaster management. UAVs can be deployed as temporary communication nodes in disaster-stricken regions to restore connectivity. Due to the limited capacity of battery of UAVs and limited flight time, it is of paramount importance to optimize paths how the UAVs move, and to optimize their placement that will minimize energy consumption and maximize signal quality provided to users in disaster-stricken areas.

Several studies have employed heuristic or metaheuristic algorithms to address the optimization of 3D UAV placement in disaster-stricken regions. For instance, Masroor et al. (2021) utilized heuristic algorithms to optimize the placement of UAVs in such areas. Similarly, Shakhatreh et al. (2017) applied the Particle Swarm Optimization algorithm, while Duraki et al. (2020) used the Animal Migration

Optimization algorithm to solve similar problems. Other noteworthy works include those by Aslan and Demirci (2019), Aliwi et al. (2020), and İleri et al. (2020), who leveraged the ABC algorithm, FA algorithm, and HSA algorithm, respectively. Furthermore, Zhang and Zhang (2022) proposed HRPSO, a hybrid reduced particle swarm optimization, for enhancing PSO performance in UAV localization for communication applications. HPSO was introduced to simplify the algorithm by collectively eliminating particles within the search space, reducing computational complexity and improving particle efficiency. RPSO was also introduced to handle scenarios with insufficient and sufficient particles. Experimental evaluations confirmed that HRPSO achieves superior accuracy and efficiency compared to conventional PSO in UAV localization. In their study, Pliatsios et al. (2021) investigated the effectiveness of swarm intelligence approaches in optimizing the deployment of drone base stations (DBS). They evaluated and compared the performance of five swarm intelligence algorithms (CS, EHO, GWO, MBO, SSA, and PSO) using three evaluation scenarios to assess overall network performance. The study took into account various parameters to determine the optimal positions for the DBSs. The results indicated that among the evaluated algorithms, GWO demonstrated the highest performance in determining the optimal DBS positions in the 3D space, thereby optimizing network performance.

In addition to single-drone optimization, some studies have explored the utilization of multiple drones. Kalantari et al. (2016) presented a new deployment plan for DBS that minimizes their number while efficiently serving users based on their traffic requirements. Since solving this optimization problem directly is computationally complex, the authors proposed a heuristic algorithm based on PSO. The algorithm estimated the number of DBSs and their 3D placement while satisfying coverage and capacity constraints of the system. Mohammed et al. (2021) addressed the problem of determining optimal flying locations for multiple UAV base stations to maximize the number of connected users. The study focused on non-uniformly distributed users and proposed an ad-hoc approach utilizing a gravity-inspired clustering algorithm and a two-tier connectivity model. In their study, Adam et al. (2021) focus on optimizing the placement of multiple UAVs to maximize user coverage with similar and different QoS requirements. They formulate the optimization problem as non-convex and propose two heuristic algorithms, SES and SMWA, to determine the UAV-BS locations. Through simulations, the authors demonstrate that the SES and SMWA algorithms outperform the state-of-the-art LA algorithm in terms of average user coverage for both similar and different QoS requirements. In their paper, Kang et al. (2020) focus on the joint optimization of 3D placement and bandwidth-and-power allocation for UAVs in a multi-UAV relaying system. They consider the elevation-angle dependent Rician fading UAV-ground channel model and formulate an optimization problem to maximize the minimum achievable expected rate among multiple pairs of ground nodes. To efficiently solve this problem, the authors propose a new IGS-BCD algorithm that combines the advantages of the GS (Gauss-Seidel) and BCD (Block Coordinate Descent) methods.

One of the challenges faced in deploying drone base stations as flying base stations is ensuring a reliable wireless backhaul. In their 2017 study, Kalantari et al. (2017) investigate the impact of different types of wireless backhaul, offering various data rates, on the number of served users. They propose two approaches: first approach aims to maximize the total number of served users, while the second approach maximizes the sum-rates of users with different rate requirements. Overall, the research focuses on optimizing the 3D placement of drone-BSs in urban areas considering rate requirements and wireless backhaul limitations, contributing to the advancement of drone-BS deployment strategies in heterogeneous networks. For finding backhaul-aware drone-BS placement, authors transform problem to binary integer linear programming (BILP), and use branch-and-bound method for solving it. In their 2022 article, Sabzehali et al. (2022) focus on the joint optimization of the number, placement, and backhaul connectivity of multi-UAV networks to provide wireless coverage to ground users. They formulate this optimization problem, called the BoaRD problem, as an ILP problem and prove its NP-Hardness. To address this challenge, the authors propose a computationally efficient algorithm based on graph-theoretic concepts, which offers performance guarantees. The proposed algorithm even outperforms the baseline greedy algorithm (without backhaul) in scenarios with higher ground-user density and lower backhaul SNR thresholds, highlighting its effectiveness.

In their 2021 paper, Shehzad et al. (2021) focus on the optimal placement of UAVs as fronthaul-hubs for the backhaul connectivity of TSBSs (Traditional Small Base Stations) in UAV communication systems. Their objective is to maximize the overall network's sum-rate by jointly optimizing the placement of UAV-hubs and the association of TSBSs. The authors consider multiple communication constraints, including backhaul data rate limit, available bandwidth, power, minimum and maximum altitude, and link capacity of UAV-hubs. To address this optimization problem, they propose a Genetic Algorithm (GA) approach. Simulation results demonstrate that the proposed GA-based approach outperforms the k-means algorithm in all evaluation parameters, highlighting its effectiveness in achieving optimal UAV-hub placement and TSBS association while satisfying stringent communication constraints. This research contributes to the field of UAV communication by providing insights into optimizing the placement and association of UAV-hubs for efficient backhaul connectivity in TSBS networks. These academic works contribute to the field of UAV networking by exploring various heuristic and metaheuristic algorithms, addressing optimization challenges, and providing insights into the deployment and optimization of UAVs for efficient communication and networking in diverse scenarios.

3. MATERIALS AND METHODS

This chapter is crucial part of this thesis as it provides a comprehensive overview of materials and methodologies used to find optimal 3D placement of UAV in different problems and and different scenarios, taking in account different parameters such as QoS, maximum rate, transmission power and maximum pathloss. For finding optimal solution three metaheuristic algorithms are used, AMO, IPA and FA. In subsequent subsections for each one of them will be provided comprehensive overview, ensuring transparency, reproducibility and validity of the results obtains in this study.

3.1. Animal Migration Optimization Algorithm

Animal migration, a fascinating phenomenon, has captivated the attention of researchers in the field of animal behavior ecology. It encompasses the long-distance movement of animals to new habitats, often occurring on a seasonal basis. Animal migrations are driven by a variety of factors, including limited food resources, local climate fluctuations, seasonal changes, or the need for mating opportunities. These migratory events are complex processes that have been studied extensively to unravel the underlying mechanisms and patterns.

Recent studies have shed light on the intricate dynamics of animal migration, particularly focusing on starling flocks. These studies have revealed remarkable behaviors exhibited by individual birds within these flocks. For instance, it has been observed that each bird adjusts its position in relation to its six or seven closest neighbors. This adaptive behavior ensures cohesion and synchronization within the group during their migratory journey. Understanding the principles governing animal migration has inspired the development of novel optimization algorithms. One such algorithm, the AMO algorithm, has gained attention for its effectiveness in problem-solving and optimization tasks. The AMO algorithm mimics the collective intelligence and adaptive behaviors observed in animal migration, offering valuable insights into the development of intelligent computational methods (Krause et al., 2010).

The AMO algorithm is based on several fundamental rules that guide the movement of animals during migration. These rules include moving in the same direction as neighboring individuals, maintaining proximity to neighbors, and avoiding collisions. By adhering to these rules, animals are able to navigate their surroundings effectively and optimize their migration experience (Tilles & Petrovskii, 2016).

Li et al. (2014) proposed the AMO algorithm, which simulates the intricate process of animal migration within a computational framework. To facilitate the description of the AMO algorithm, certain assumptions are made. Firstly, the animal with the highest fitness, often referred to as the group leader, is retained in the subsequent generation. This ensures the preservation of the most successful individuals in the population. Secondly, the population size remains fixed throughout the algorithm's execution. However, some animals have a probability of leaving the group, creating vacancies that are subsequently filled by new animals. This dynamic population update mechanism allows for exploration and diversification within the population. The AMO algorithm consists of distinct processes: initialization, migration, population update, and fitness comparison. Each process plays a crucial role in shaping the behavior of the algorithm and its convergence towards optimal solutions.

3.1.1. Initialization Process

The initialization process marks the beginning of the AMO algorithm. During this phase, the algorithm randomly generates a set of NP(number of population) animals, where each animal is characterized by D parameters. In the context of the AMO algorithm, animals can be seen as representations of unmanned aerial vehicles (UAVs), while the parameters correspond to the coordinates of the UAVs in three-dimensional space (x, y, and z). Random initialization is achieved by setting predefined minimum and maximum bounds, denoted as (X_{min}) and (X_{max}) respectively. The random generation of initial parameters within these bounds ensures diversity and exploration within the initial population. Equation for generation initial population is given below in Eq. 3.1.

$$X_{j,i} = X_{j,min} + rand[0, 1] \times (X_{j,max} - X_{j,min}) \tag{3.1}$$

in this equation $rand[0, 1]$ is some random number between 0 and 1. Parameter i takes values from 1 to NP and parameter takes values from 1 to D.

3.1.2. Migration Process

Following the initialization process, the migration process takes place. This process determines how animals migrate from their current habitats to new ones while adhering to the fundamental rules of migration. Avoiding collisions, moving in the same direction as neighbors, and maintaining close proximity to neighbors are crucial considerations during the migration process. To achieve these objectives, the AMO algorithm employs a mechanism based on the concept of local neighbors and a ring topology scheme. Local neighbors are determined by the selection of a fixed number of neighboring individuals. For simplicity, the AMO algorithm typically considers five neighbors for each animal. These neighbors play a significant role in shaping an individual's movement strategy. By interacting with their local neighbors, animals can adapt their trajectories and align their movements with those of their neighbors. This collective behavior ensures coordination and cooperation within the population. The migration process is mathematically described by an equation Eq. 3.2 that governs the movement of animals. The equation takes into account the current positions of animals and their neighbors. A random number, controlled by a Gaussian distribution, is introduced to add stochasticity to the movement. The equation calculates the next generation (G+1) of animals based on the current generation (G) and the randomly chosen neighbor among the five neighbors.

$$X_{i,G+1} = X_{i,G} + \delta \times (X_{neighborhood,G} - X_{i,G}) \tag{3.2}$$

3.1.3. Population Update Process

After the migration process, the population update process comes into play. In this phase, some animals leave the group, creating vacancies within the population. The departure of animals is determined by a probability value (Pa), which is calculated based on the fitness of each individual. Fitness represents the quality of a solution or an individual in the context of the optimization problem. The AMO algorithm utilizes fitness values to determine the likelihood of an animal leaving the population. The population update process follows a probabilistic approach. The probability values (Pa) are calculated for each individual based on their fitness values. The calculation involves sorting the individuals in descending order of their fitness values and assigning sequence numbers accordingly. Animals with higher fitness values have higher probabilities of remaining in the population. Conversely, animals with lower fitness values have a greater chance of leaving the group. This is shown in Eq. 3.3 below (Ma et al., 2015).

$$Pa_i = \frac{sn_i}{NP} \tag{3.3}$$

An animal is replaced with a new one if a randomly generated number, ranging from 0 to 1, exceeds the probability value (Pa) of the respective animal. The position of the new animal is then determined using Eq. 3.4 that considers random selection of two individuals (X_{r1} and X_{r2}) from the current population, excluding the selected animal (X_i). Additionally, an individual with the best fitness value (X_b) is incorporated into the equation, and a random number is generated to add stochasticity to the update process.

$$X_{i,G+1} = X_{r1,G} + rand \times (X_{b,G} - X_{i,G}) + rand \times (X_{r2,G} - X_{i,G}) \tag{3.4}$$

3.1.4. Fitness Comparison Process

Following both the migration and population update processes, the AMO algorithm performs a fitness comparison. This process involves evaluating the fitness values of the old and new populations. Fitness values indicate the quality of each individual's solution or performance. The AMO algorithm selects individuals with superior fitness values to be transferred to the population of the new generation. This selection mechanism ensures the retention of individuals with better performance, promoting the convergence of the algorithm towards optimal solutions.

In summary, the AMO algorithm simulates the collective intelligence and adaptive behaviors observed in animal migration. Through a series of processes including initialization, migration, population update, and fitness comparison, the algorithm seeks to optimize solutions in problem-solving contexts. The AMO algorithm's ability to mimic the intricate dynamics of animal migration offers valuable insights into the development of intelligent computational methods. By harnessing the power of animal-inspired algorithms, researchers can tackle complex optimization problems and enhance the efficiency and effectiveness of various applications. The Figure 3.1 below provides a visual representation of the comprehensive AMO algorithm process, illustrating the interplay between the different phases and their impact on the optimization process.

3.2. Firefly Algorithm

The Firefly algorithm (FA) is a swarm-based metaheuristic algorithm that has garnered significant attention for its remarkable performance in solving optimization problems. Introduced by Xin-She Yang in 2008 (Yang, 2008, 2009, 2010a, 2017), the algorithm draws inspiration from the fascinating behavior of fireflies in nature. By emulating the interactions and characteristics of these luminescent insects, the FA presents a powerful approach for addressing complex optimization challenges.

3.2.1. Behavior of Fireflies

Fireflies, scientifically known as Lampyridae, are nocturnal insects that exhibit bioluminescence. Their ability to produce and control light stems from the presence of certain chemicals, such as luciferin, within their bodies. Fireflies predominantly inhabit warm tropical regions, where they thrive in diverse ecosystems. These luminous creatures are most active during the nighttime hours when temperatures are more favorable compared to the scorching heat of the daytime (Branham et al., 2010). The primary function of light production in fireflies is to facilitate communication and mating rituals. Male fireflies emit specific patterns of flashes to attract potential female partners. The flashing signals serve as a unique identifier, allowing fireflies of the

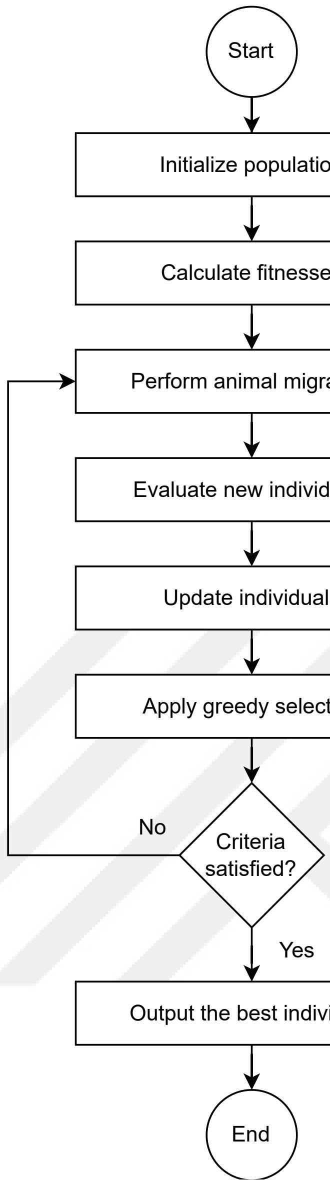

Figure 3.1. Flowchart of AMO Algorithm

opposite sex to recognize and locate each other in the darkness. Additionally, fireflies employ light as a means to indicate food sources or deceive unsuspecting prey. The visibility of firefly light is subject to the limitation of distance. As light travels through the surrounding medium, it gradually loses intensity, resulting in reduced visibility over greater distances. Consequently, the effectiveness of light signaling diminishes as fireflies move farther apart.

3.2.2. Core Principles of The FA

The FA adopts a swarm-based approach, harnessing the collective behavior of fireflies to solve optimization problems. It revolves around the concept of iterative improvement through the progressive update of firefly positions. The algorithm operates based on three fundamental rules:

- *Unisex Fireflies*: In the FA, fireflies are considered unisex, implying that any firefly is capable of attracting and being attracted to any other firefly within its proximity. This gender-neutral characteristic fosters an inclusive environment for interaction and attraction between fireflies.
- *Attraction Proportional to Brightness*: Fireflies are naturally drawn towards brighter individuals in their vicinity. This attraction is directly proportional to the perceived brightness, with less luminous fireflies exhibiting a stronger inclination towards brighter counterparts. When a firefly fails to locate a brighter neighbor within its proximity, it updates its position randomly, introducing an element of exploration into the algorithm.
- *Objective Function*: To evaluate the performance of fireflies and guide the optimization process, an objective function must be defined. The objective function quantifies the "fitness" or quality of a given solution within the context of the optimization problem at hand. By employing this fitness measure, the algorithm determines the brightness of each firefly, which in turn influences its attractiveness to other fireflies.

3.2.3. Light Intensity and Attractiveness

Light intensity and attractiveness serve as the key components that underpin the FA. These concepts play a vital role in determining the movement and interaction patterns of fireflies within the optimization landscape.

Light intensity represents the position of the light source in the algorithm. Analogous to a firefly's luminous emission, it signifies the location towards which other fireflies are naturally drawn. Attractiveness, on the other hand, characterizes the change in a firefly's position as it responds to the presence of a brighter individual. The level of attractiveness is influenced by the brightness of neighboring fireflies and serves as a guiding force for adjusting firefly positions.

Both light intensity and attractiveness can be expressed mathematically, allowing for precise calculations and optimization procedures. As mentioned earlier, the intensity of light diminishes as the distance between fireflies increases. This attenuation can be captured by an equation that relates light intensity (I) to the initial light intensity (I_0), the light absorption coefficient (γ), and the distance between fireflies (r):

$$I = I_0 e^{-\gamma r_{ij}^2} \tag{3.5}$$

In Eq. 3.5, the initial light intensity (I_0) is typically calculated using the objective function, while the light absorption coefficient (γ) ranges between 0.001 and 1000. The distance (r) between two fireflies can be measured using the Cartesian distance formula:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{d=1}^{D} (x_{id} - x_{jd})^2} \tag{3.6}$$

Here, (x_i) and (x_j) represent the locations of two fireflies, and the dimension size is denoted by D. Eq. 3.6 emphasizes that light intensity is inversely proportional to the square of the distance between fireflies.

Similarly, attractiveness can be mathematically defined as in Eq. 3.7 :

$$\beta = \beta_0 e^{-\gamma r_{ij}^2} \tag{3.7}$$

In Eq. 3.7, β_0 represents the global initial value of attractiveness, indicating the starting point for evaluating the attractiveness of fireflies.

3.2.4. Updating Firefly Locations

The process of updating firefly locations constitutes a crucial step within the FA. It involves modifying the positions of fireflies based on the attractiveness values of brighter individuals. By doing so, fireflies gradually converge towards better solutions within the optimization landscape.

The formula for updating the location of a firefly can be expressed as:

$$x_i = x_i + \beta(x_j - x_i) + \alpha(\phi - 1/2) \tag{3.8}$$

In Eq. 3.8, (x_i) represents the current location of firefly (i), while (x_j) denotes the location of a brighter firefly (j). The parameters β, γ, and α are constants that control the movement dynamics of fireflies. The term $\beta * e^{-\gamma r^2}$ quantifies the influence of attractiveness, guiding the firefly towards a brighter neighbor. Additionally, the α is constant, and term ϕ introduces a randomness and foster exploration and diversify of the search process.

The iterative nature of the FA allows fireflies to progressively update their positions based on the attractiveness and brightness of neighboring individuals. Over time, this iterative update mechanism drives the exploration of the optimization landscape and facilitates the discovery of optimal or near-optimal solutions.

In conclusion, the FA, inspired by the captivating behavior of fireflies, has proven to be a powerful metaheuristic algorithm for solving optimization problems. By capturing the principles of attraction and brightness observed in nature, the algorithm offers an effective means of navigating complex search spaces. Through the interplay of light intensity, attractiveness, and iterative location updates, fireflies collectively converge towards improved solutions. With its ability to tackle a wide range of optimization challenges, the FA continues to captivate researchers and find applications in various domains.

3.3. Immune Plasma Algorithm

The Immune Plasma Algorithm (IPA) has gained significant attention in the realm of medical research, particularly in response to the recent global health crisis caused by COVID-19. Esteemed medical experts and scientists have devoted substantial efforts to explore effective treatment modalities. Among these approaches, the utilization of immune plasma, also known as convalescent plasma, has emerged as a promising therapeutic option. When a pathogenic organism such as a virus or bacterium infiltrates the human body, the immune system mounts a defense mechanism by producing antibodies specifically tailored to neutralize and eliminate the invading entities (Parkin & Cohen, 2001; Delves & Roitt, 2000). However, it is imperative to acknowledge the inherent variability in immune responses among individuals following an infection. While some individuals demonstrate a robust immune response, resulting in complete recovery without the need for medical intervention, others experience a prolonged convalescence period or even progress to critical conditions, necessitating immediate medical attention. These divergent outcomes are influenced by the strength or weakness of an individual's immune system. Individuals with compromised immune systems, unable to generate antibodies in a timely manner, may benefit from treatment with immune plasma obtained from individuals who have successfully recovered from the infection and possess a substantial reservoir of antibodies (Shen et al., 2020). Aslan and Demirci (2020) has introduced a novel meta-heuristic algorithm known as the IPA, designed to address optimization problems. Within the framework of IPA, each person within the population represents a potential solution for the objective function being optimized, with the quality of the solution evaluated based on the individual's immune response. The IPA consists of three fundamental components: generating initial individuals, infection spreading and immune system response, and plasma extraction and transfer.

3.3.1. Generating Initial Individuals

The initial stage of the IPA involves generating initial individuals, a process accomplished through the application of Eq. 3.9. This equation enables the calculation of the initial population. Within Eq. 3.9, the parameter (x_{kj}) denotes the j-th decision parameter of the k-th person. Each individual is characterized by D decision parameters, and the total population size is represented by PS. Furthermore, the lower and upper bounds of the j-th parameter are respectively denoted as (xj-low) and (xj-high). Additionally, the term rand[0,1] signifies a randomly generated number between 0 and 1.

$$\begin{gathered} x_{kj} = x_j^{low} + rand(0,1) \times (x_j^{high} - x_j^{low}) \\ k = \{1, 2, ..., PS\} \quad and \quad j = \{1, 2, ..., D\} \end{gathered} \tag{3.9}$$

3.3.2. Infection Spreading and Immune System Response

Moving forward, the IPA progresses to the stage of infection spreading and immune system response. Here, each individual undergoes infection, as determined by Eq. 3.10. A critical criterion for evaluating the efficacy of this process lies in comparing the immune response (i.e., the value of the objective function) of the infected individual before and after infection. Should the immune response exhibit improvement following infection, the algorithm replaces the previous immune system with the newly generated immune system. Conversely, if the immune response fails to demonstrate enhancement, the original immune system is retained.

$$\begin{gathered} x_{kj}^{inf} = x_{kj} + rand(-1,1) \times (x_{kj} - x_{mj}) \\ k = \{1, 2, ..., PS\} \quad and \quad j = \{1, 2, ..., D\} - \{k\} \end{gathered} \tag{3.10}$$

Eq. 3.10 delineates the mechanics of infection spreading and immune system response. Specifically, (x_{kj}^{inf}) represents the infection of the j-th parameter of the k-th person. Additionally, (x_{kj}) signifies a randomly selected j-th parameter of the k-th person, while (x_{mj}) denotes the j-th parameter of a previously infected individual, randomly chosen. Lastly, $rand(-1,+1)$ refers to a randomly generated number ranging between -1 and +1.

3.3.3. Plasma Extraction and Transfer

Following the infection spreading and immune system response stage, the IPA proceeds to plasma extraction and transfer. Subsequent to the infection process, immune responses among individuals exhibit variation. Accordingly, the IPA identifies NoD (number of donors) individuals with the most favorable immune responses as plasma donors, while NoR (number of receivers) individuals with the least favorable immune responses are designated as plasma receivers. Plasma transfer is then executed using Eq. 3.11.

$$\begin{aligned} x_{kj}^{rcv-p} &= x_{kj}^{rcv} + rand(-1,1) \times (x_{kj}^{rcv} - x_{mj}^{dnr}) \\ j &= \{1, 2, ..., D\} \end{aligned} \tag{3.11}$$

In Eq. 3.11, (x_{kj}^{rcv}) denotes the j-th parameter of the k-th receiver, while (x_{mj}^{dnr}) represents the j-th parameter of the randomly selected m-th donor. Consequently, the outcome of this process is represented by (x_{kj}^{rcv-p}), signifying the j-th parameter of the k-th receiver following the plasma transfer.

3.3.4. Donor Update

Subsequent to the plasma treatment, the IPA implements a donor update process. The primary objective of this process lies in replacing the donors that have already been utilized. The donor update process utilizes two distinct equations, and the choice between them for generating new donors is determined based on a specific criterion. If the current evaluation divided by the maximum evaluation exceeds a randomly generated number between 0 and 1, Eq. 3.12 is employed. Otherwise, Eq. 3.9 is utilized to generate new donors.

$$x_{mj}^{dnr} = x_{mj}^{dnr} + rand(-1,1) x_{mj}^{dnr} \tag{3.12}$$

In conclusion, the IPA is an optimization heuristic algorithm specifically designed to address a wide array of optimization problems. Inspired by the concept of immune plasma transfer, IPA leverages the principles of the immune system's response to pathogens to enhance its problem-solving capabilities. By simulating the dynamic processes of immune responses and the exchange of plasma, IPA offers innovative solutions to complex optimization challenges. Through its metaphorical framework rooted in immune plasma transfer, IPA aims to optimize various objective functions and improve overall problem-solving outcomes. For a comprehensive understanding of IPA's intricacies, including its pseudo code and detailed explanations, an analysis of the relevant literature, such as (Aslan & Demirci, 2020), is highly recommended.

4. EXPERIMENTAL RESULTS

UAVs offer a broad range of applications in the field of networking, as mentioned previously. However, the diverse applications of UAVs also give rise to significant challenges that must be effectively addressed in order to achieve optimal and practical utilization of UAVs in networking scenarios. This chapter aims to tackle three distinct UAV-based problems in networking, employing heuristic approaches such as the AMO(Li et al., 2014) algorithm, FA(Yang, 2009), and IPA(Aslan & Demirci, 2020).

The first problem addressed in this chapter is the 3D Placement of a single UAV. This entails determining the optimal position for a single UAV to maximize its effectiveness in a given networking context. The second problem focuses on the 3D Placement of multiple UAVs, which involves optimizing multiple UAVs to achieve efficient network coverage and communication. Lastly, the chapter delves into the backhaul-aware 3D placement of UAVs, where the objective is to consider the availability of backhaul resources and optimize the positioning of UAVs accordingly. Each problem is introduced in subsequent subsections, providing a concise definition and highlighting the unique challenges it presents. Furthermore, experimental results obtained through the utilization of the aforementioned meta-heuristic algorithms are presented, showcasing their effectiveness in addressing the respective problems.

To provide comprehensive insights, each of the problems is individually solved using all three algorithms, enabling a detailed performance analysis and facilitating meaningful comparisons. The resulting solutions and their performance metrics are thoroughly evaluated and discussed, shedding light on the strengths and weaknesses of each algorithm in the context of UAV-based networking problems.

4.1. 3D Placement of Single UAV

In this section, the precise definition of the optimal localization problem for an unmanned aerial vehicle (UAV) equipped with a base station is presented. The influence of various factors, such as high altitude, on the total transmission power is specifically addressed. The paramount objective of this problem is to minimize the overall transmission power by leveraging the outdoor-indoor path loss channel model introduced by the esteemed International Telecommunication Union (ITU) (Series, 2009).

4.1.1. Problem Definition

Consideration is given to a scenario where a UAV and a user are positioned at coordinates $(X_{uav}, Y_{uav}, Z_{uav})$ and (x_u, y_u, z_u), respectively. The fundamental Euclidean distance between the UAV and the user, denoted as d_{3D}, assumes a pivotal role as a parameter in the pursuit of the optimal solution. To this end, the objective function denoted as L_i is formulated, encapsulating the minimization of the total path loss. The expression for L_i is derived as follows, as presented in Eq. 4.1:

$$\begin{pmatrix} L_i = L_F + L_B + L_I \\ L_F = \quad w\log(d_{3D}) + w\log(f_{\text{GHz}}) + g_1 \\ L_B = g_2 + g_3(1-\cos\theta)^2) \\ L_I = g_4 d_{2D} \end{pmatrix} \tag{4.1}$$

4.1.2. Objective Function Formulation

Within Eq. 4.1, L_F represents the free space path loss, elucidating the signal attenuation resulting from propagation through open space. Subsequently, L_B accounts for the building penetration loss, which characterizes the attenuation encountered when the signal traverses building structures. Lastly, L_I signifies the indoor loss, denoting the additional attenuation within indoor environments. The coefficient w, which is set at 20 (Series, 2009; Shakhatreh et al., 2017), reflects the relative importance assigned to the log-distance and frequency terms within the free space path loss equation. At the same time, the constants g_1, g_2, g_3, and g_4 assume the values 32.4, 14, 15, and 0.5, respectively, embodying the specific characteristics of the propagation environment (Series, 2009; Shakhatreh et al., 2017). Furthermore, the carrier frequency, denoted as $fGHz$ and quantified as 2 GHz, assumes the role of an indispensable parameter for accurate power calculations (Series, 2009; Shakhatreh et al., 2017). Furthermore, θ represents the incident angle, while d_{3D} represents the three-dimensional distance between the UAV and the user. The 2D indoor distance of the user within the building is represented by d_{2D}. For a visual depiction of these variables, refer to Figure 4.1.

In this experiment, we employed two meta-heuristic algorithms, namely AMO (Animal Migration Optimization) and IPA (Immune Plasma Algorithm), to solve the 3D UAV placement problem. The results obtained from these algorithms were compared with other well-known meta-heuristic algorithms such as FA, ABC, and PSO that also address the same 3D UAV placement problem.

In the AMO algorithm, animals were matched with the 3D locations of UAVs, while in the IPA algorithm, the immune system response was utilized to determine the

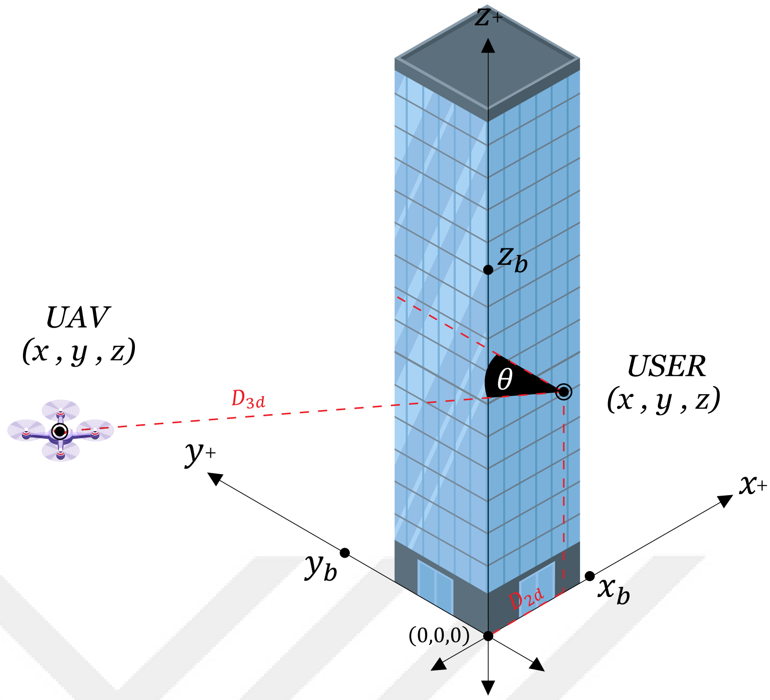

Figure 4.1. Visual depiction of Single UAV problem

3D localization of the UAVs. The objective function for each algorithm was aligned with the total path loss, calculated using Eq. 4.1. To ensure fair comparisons and enable meaningful evaluations, we adopted the same parameter values as reported in previous studies (Series, 2009; Shakhatreh et al., 2017).

4.1.3. Experimental Results

For the AMO algorithm, the population size, also referred to as NP, was set to 25, and the maximum evaluation number was limited to 50. In the case of IPA, the population size was set to 50. The experiments were conducted using six different building settings, each with a varying number of floors. Each floor had a height of 5 meters and contained 20 users randomly distributed within it. The dimensions of the buildings are presented in Table 4.1. The UAVs were positioned around the buildings within a range of +1000 to -1000 for the x, y, and z coordinates, following the approach outlined in (Series, 2009; Shakhatreh et al., 2017). For each building scenario, we performed 30 independent runs for each meta-heuristic algorithm.

The obtained results from the tests are shown in Table 4.2 and are compared with the results obtained by ABC (Aslan & Demirci, 2019) and FA (Aliwi et al., 2020). In Table 4.2, the overall best result is recorded as $best$, while the mean value of these best results across all tests is denoted as $mean$. The standard deviation of these

Table 4.1. x_b, y_b, z_b Values of the buildings

Buildings	x_b	y_b	z_b	Number of users
b1	20	50	200	800
b2	20	50	250	1000
b3	20	50	300	1200
b4	10	50	250	1000
b5	30	50	250	1000
b6	50	50	250	1000

best values is represented as Std. It is important to note that the standard deviation employs the sample variance s², incorporating Bessel's correction, which adjusts for the degrees of freedom (N-1). This variance calculation assumes that the data points are representative, possessing qualities such as independence and an identical distribution. Consequently, the obtained value is expected to provide an unbiased estimation of the actual variance within the population.

Table 4.2. Mean, Best, and Std Deviation Values from AMO, ABC, IPA, FA

	AMO			ABC		
	Mean	Best	Std.	Mean	Best	Std.
b1	6.92202e+4	6.921254e+4	9.66135e+0	7.31984e+4	7.318576e+4	1.24624e+1
b2	8.79384e+4	8.793087e+4	9.17274e+0	9.27853e+4	9.275358e+4	2.88788e+1
b3	1.07082e+5	1.070758e+5	6.52653e+0	1.12793e+5	1.127693e+5	1.93909e+1
b4	8.75306e+4	8.752069e+4	1.17767e+1	8.99616e+4	8.994869e+4	1.21535e+1
b5	8.83876e+4	8.837481e+4	1.35778e+1	9.57199e+4	9.569267e+4	4.52143e+1
b6	8.93258e+4	8.931520e+4	1.37403e+1	1.01385e+5	1.013525e+5	2.63622e+1

	IPA			FA		
	Mean	Best	Std.	Mean	Best	Std.
b1	6.92123e+4	6.921232e+4	7.81653e+0	7.41848e+4	6.926158e+4	5.00824e+3
b2	8.79446e+4	8.792938e+4	1.24948e+1	9.16237e+4	8.939184e+4	1.75310e+3
b3	1.07086e+5	1.070768e+5	1.36110e+1	1.15257e+5	1.076455e+5	5.30931e+3
b4	8.75357e+4	8.752229e+4	1.33701e+1	9.03051e+4	8.825465e+4	1.60515e+3
b5	8.83841e+4	8.837391e+4	9.07801e+0	9.52892e+4	8.903234e+4	4.85126e+3
b6	8.93215e+4	8.931645e+4	3.70679e+0	9.45602e+4	9.018717e+4	3.47724e+3

As observed from Table 4.2, Table 4.3 and Figure 4.2, IPA demonstrates superior performance in finding the best values for scenarios $b1$, $b2$, and $b5$, while AMO outperforms in scenarios $b3$, $b4$, and $b6$. However, the obtained best values for both

Table 4.3. Best Values and Locations from AMO, ABC, IPA, FA Algorithms

	AMO		ABC	
	Best	(Xuav, Yuav, Zuav)	Best	(Xuav, Yuav, Zuav)
b1	6.921254e+4	(-20.019, 29.397, 87.229)	7.318576e+4	(-20.002, 26.578, 91.27)
b2	8.793087e+4	(-20.001, 24.919, 130.070)	9.275358e+4	(-20.008, 25.362, 119.62)
b3	1.070758e+5	(-20.001, 26.335, 134.535)	1.127693e+5	(-20.046, 28.555, 144.93)
b4	8.752069e+4	(-20.001, 26.708, 124.624)	8.994869e+4	(0.011, 27.542, 124.858)
b5	8.837481e+4	(-20.001, 29.123, 119.311)	9.569267e+4	(-30.005, 28.981, 114.72)
b6	8.931520e+4	(-20.001, 28.171, 119.748)	1.013525e+5	(-26.553, 50.050, 120.75)

	IPA		FA	
	Best	(Xuav, Yuav, Zuav)	Best	(Xuav, Yuav, Zuav)
b1	6.921232e+4	(-6.9829, 2.9183, 9.1106)	6.926158e+4	(-20.079, 31.594, 90.256)
b2	8.792938e+4	(-2.6496, 2.4315, 1.2975)	8.939184e+4	(-21.564, 11.949, 96.585)
b3	1.070768e+5	(-4.0366, 2.6976, 1.3484)	1.076455e+5	(20.079, 15.137, 182.136)
b4	8.752229e+4	(-3.0006, 2.6805, 1.2461)	8.825465e+4	(-20.305, 39.972, 144.712)
b5	8.837391e+4	(-1.3063, 2.9424, 1.2004)	8.903234e+4	(-20.247, 12.362, 119.414)
b6	8.931645e+4	(-2.3660, 2.8282, 1.1971)	9.018717e+4	(-20.662, 44.375, 97.768)

algorithms are extremely close, suggesting that their performance is equally good. Moreover, upon examining Table 4.2, it can be concluded that both AMO and IPA exhibit superior performance in finding the overall best values when compared to ABC and FA. Furthermore, when analyzing the mean values and standard deviations in Table 4.3 as well as Figure 4.4 and Figure 4.3, it becomes apparent that AMO and IPA consistently yield similar or closely clustered solutions. This indicates that the algorithms are stable, robust, and reliable, consistently converging towards similar optimal or near-optimal solutions. Additionally, it implies that these algorithms are less sensitive to initial conditions or random variations, allowing them to reliably explore and exploit the solution space.

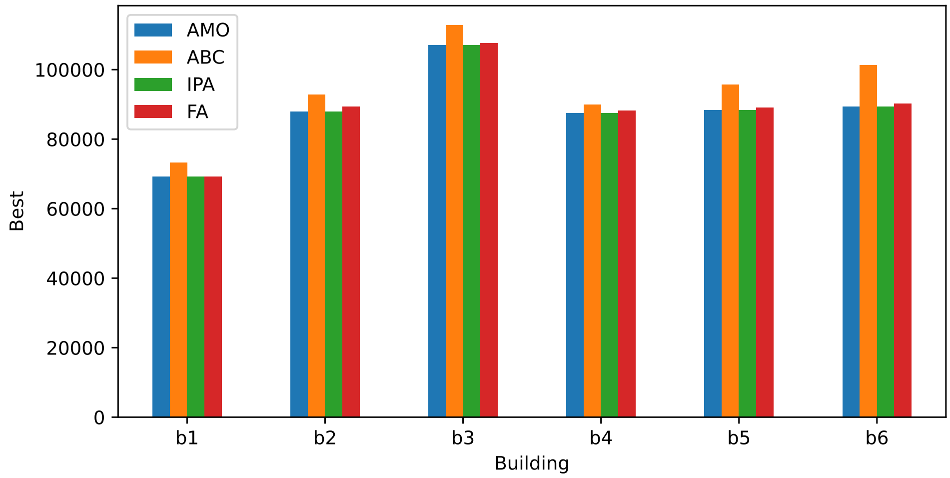

Figure 4.2. Comparing overall best values for different building configurations.

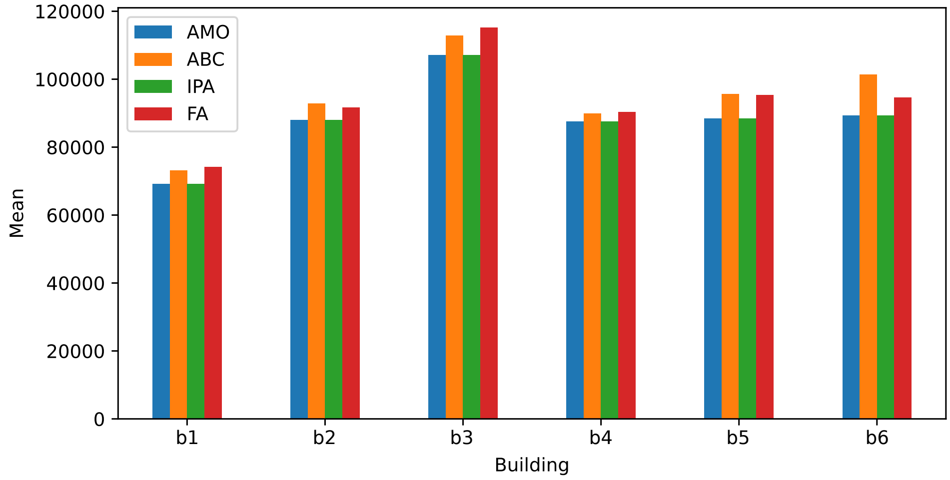

Figure 4.3. Comparing mean values for different building configurations.

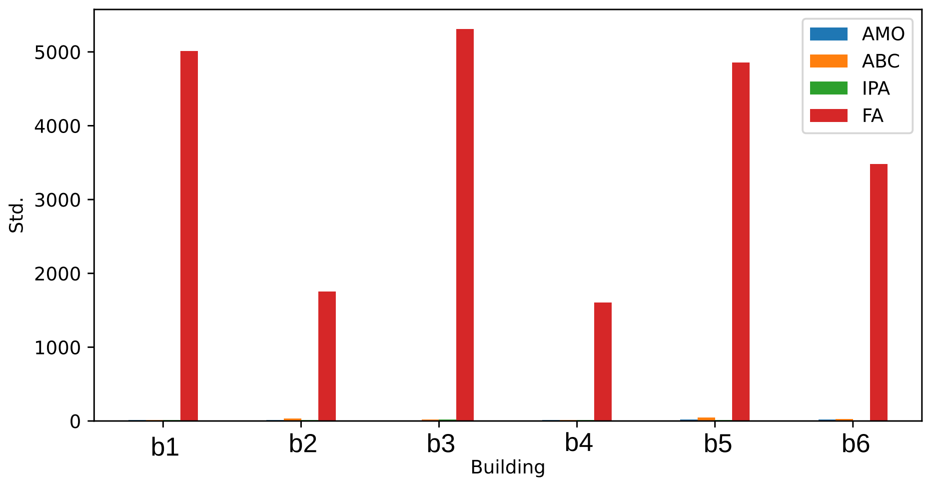

Figure 4.4. Comparing standard deviation values for different building configurations.

4.2. 3D Placement of Multiple UAVs

In this section, we present the experimental results of the 3D placement of multiple UAVs for the optimization problem. The problem involves finding the optimal placement of UAVs in a 3D space considering factors such as transmission power. The problem definition has been already provided in the previous section, so we will focus on discussing the different approaches taken in this section and analyzing the performance of the employed meta-heuristic algorithms.

4.2.1. Approach Description

In this proposed approach, a multi-UAV strategy is adopted to enhance the overall system performance. Four UAVs, specifically denoted as $UAV1$, $UAV2$, $UAV3$, and $UAV4$, are employed as wireless base stations. The allocation of users per UAV, represented by N, is calculated using Eq. 4.2:

$$N = \frac{U}{UAV}, \quad \frac{NumberOfTotalUsers}{NumberOfUAVS} \tag{4.2}$$

The initial step involves the determination of the optimal locations for $UAV1$ by considering all users present within the buildings. Subsequently, the users are ranked based on their fitness values, which quantify the quality of service (QoS) that the UAVs can deliver. The top N users are then assigned to $UAV1$ and designated as $U1$, establishing an exclusive service provision from $UAV1$ to these users. Consequently, the fitness value of $UAV1$ is recalculated exclusively based on the $U1$ users. To illustrate this approach, let us consider the $b1$ building scenario with a total of 800 users. $UAV1$ initiates its search for an optimal position, taking into account all 800 users. Once the optimal position is determined, $UAV1$ selects the 200 users with the highest fitness values for exclusive service provision. Subsequently, $UAV2$ proceeds with the search for its optimal position, considering the remaining 600 users, and the top 200 users, determined by their fitness values, are allocated to $UAV2$. This iterative process continues, with $UAV3$ and $UAV4$ finding their optimal positions and being assigned the best 200 users in each step, resulting in the distribution of the remaining 400 users between $UAV3$ and $UAV4$. The table presented as Table 4.1 provides a comprehensive overview of the number of users in each building scenario. The step-by-step process described above is visually depicted in Figure 4.5, Figure 4.6, Figure 4.7 and Figure 4.8, each corresponding to a specific stage of the approach. The matching colors in the figures represent the association between UAVs and the users within the buildings.

By adhering to this procedure, an equitable distribution of users is achieved among the four UAVs, thereby promoting a balanced allocation of resources across the system. This approach ensures that each UAV serves a equal number of users based on

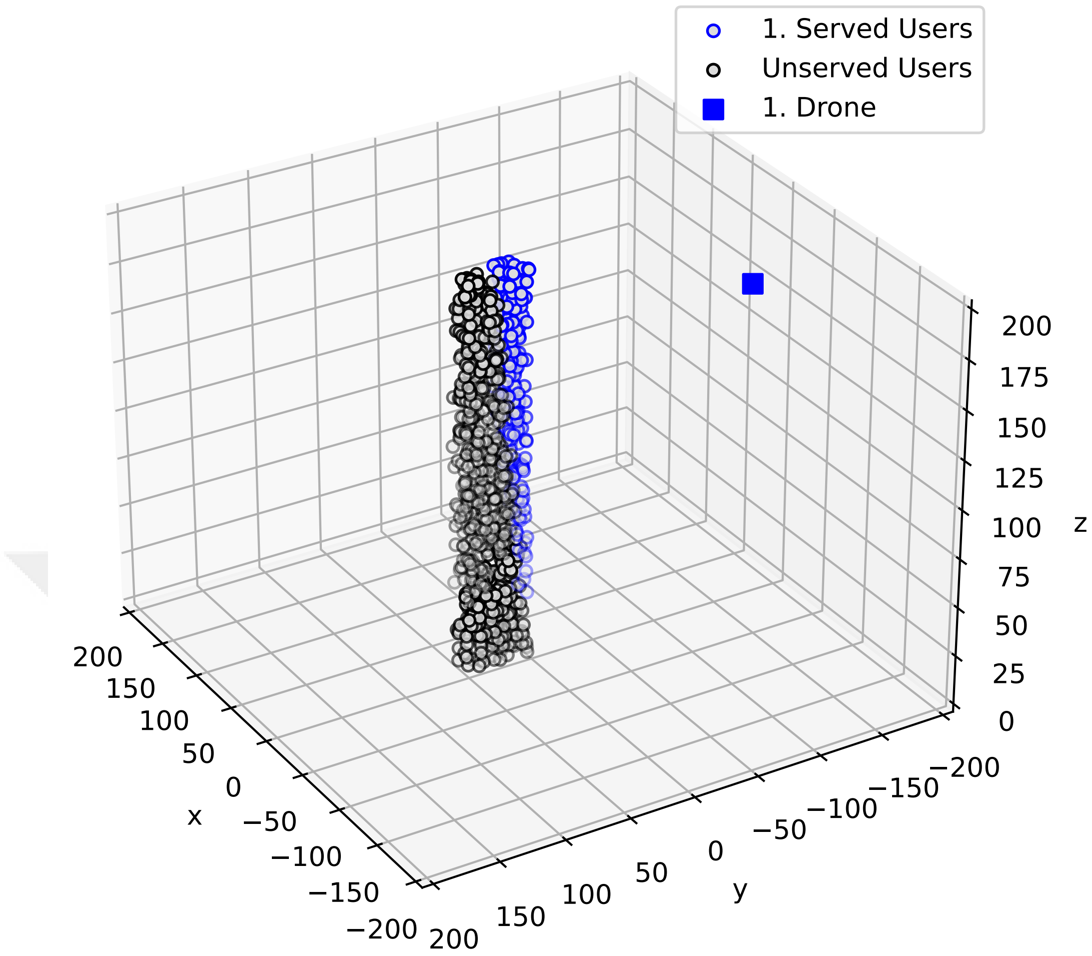

Figure 4.5. Step 1 in assigning users to the UAVs

their fitness values, thereby optimizing the overall system performance and resource utilization.

4.2.2. Experimental Setup

For the experimental evaluation, three meta-heuristic algorithms, namely Immune Plasma Algorithm (IPA), Animal Migration Optimization (AMO), and Firefly Algorithm (FA), are employed. Each algorithm corresponds to a different matching approach: AMO matches the UAVs with animals, IPA matches with immune system response, and FA matches with fireflies. The objective function for all three algorithms is the total path loss, which is calculated using Eq. 4.1. To ensure fair and comparable results, the same parameter settings are used for IPA, AMO, and FA. The population size (PS) is set to 25, and the evaluation number is set to 2500 (Aslan & Demirci, 2019; Aliwi et al., 2020; Duraki et al., 2020).

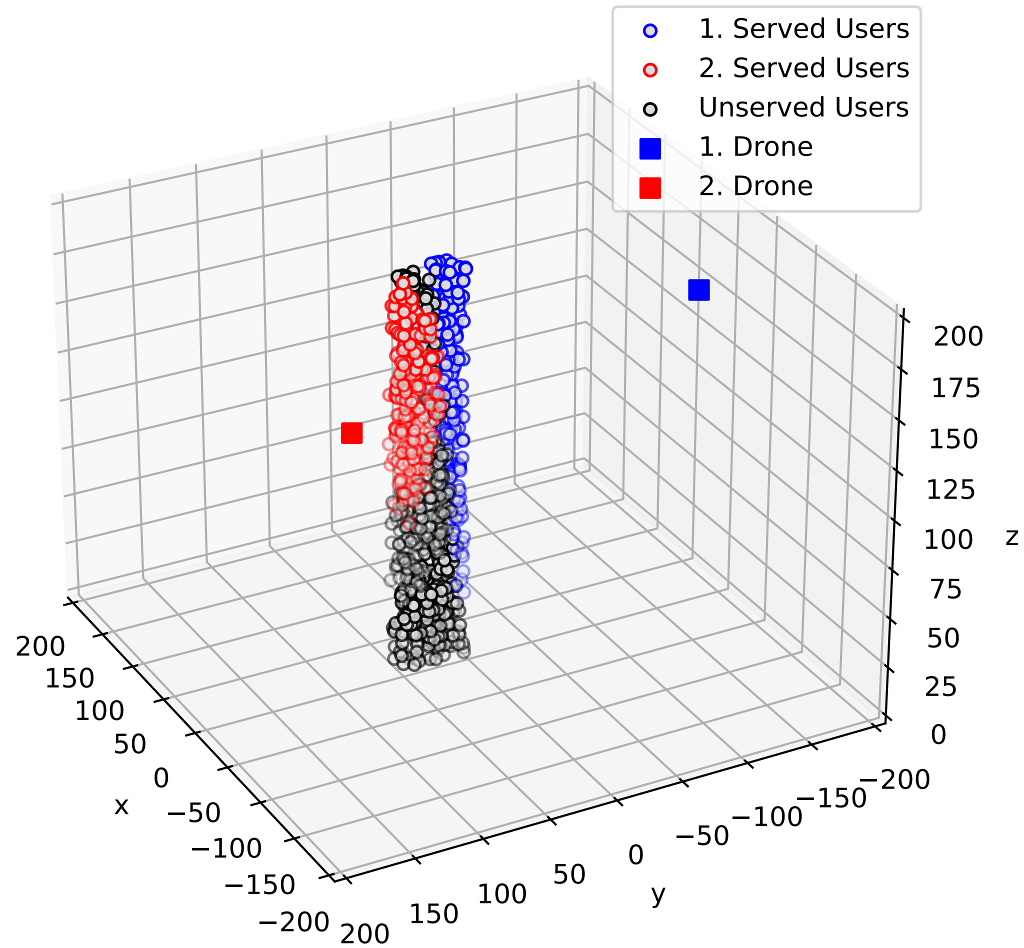

Figure 4.6. Step 2 in assigning users to the UAVs

4.2.3. Building Scenarios

Similar to the single drone problem discussed earlier, the experiment considers six different building scenarios (b1 to b6), each with varying building dimensions and number of users based on the building height. The height of each floor is 5 meters, and there are 20 randomly distributed users per floor. The total number of users varies across scenarios, with scenario b3 having 1200 users, scenario b1 having 800 users, and scenarios b2, b4, b5, and b6 having 1000 users. Table 4.1 provides the dimensions of each building and the number of users distributed inside.

4.2.4. Experimental Procedure

For each building scenario, the experiments are conducted by performing 30 independent runs of IPA, AMO, and FA. The obtained values are recorded and compared. The results, including the ”Best,” ”Mean,” and standard deviation (”Std.”) values, are shown in Table 3. The ”Mean” column represents the mean value of the 30

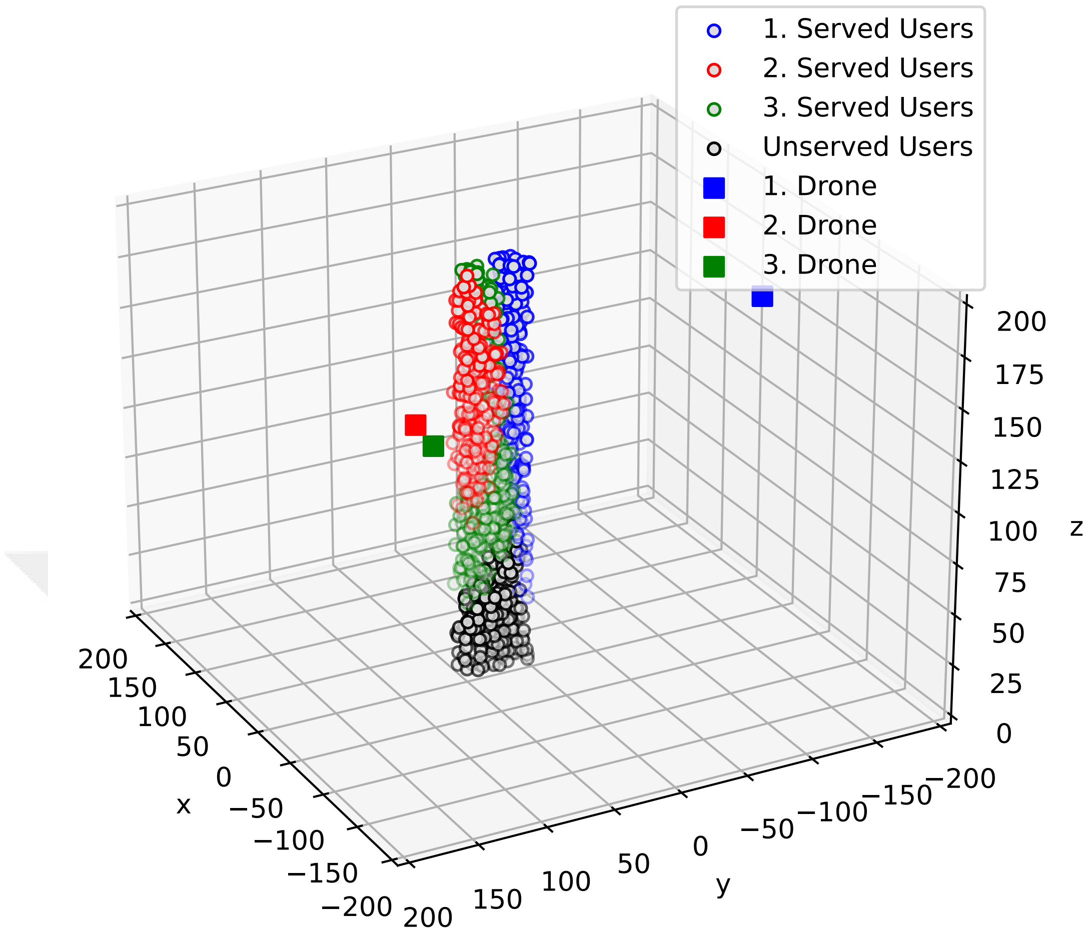

Figure 4.7. Step 3 in assigning users to the UAVs

independent runs for each scenario, while the "Std." value indicates the standard deviation. The standard deviation is calculated using the sample variance formula, taking into account Bessel's correction to compensate for the degrees of freedom (N-1).

4.2.5. Analysis of Results

Table 3 presents the results of IPA, AMO, and FA, including their "Best," "Mean," and standard deviation values. The "Best" value represents the sum of the best values obtained by the four UAVs. Upon examining Table 3, it can be observed that IPA performs the best overall for scenarios $b2$, $b3$, $b4$, $b5$, and $b6$, followed closely by AMO, which achieves similar results to IPA. However, for scenario b1, AMO demonstrates the best performance while IPA performs second best. In all six building scenarios, FA shows the weakest results in terms of finding the overall best value.

Additionally, when analyzing the mean and standard deviation values, it

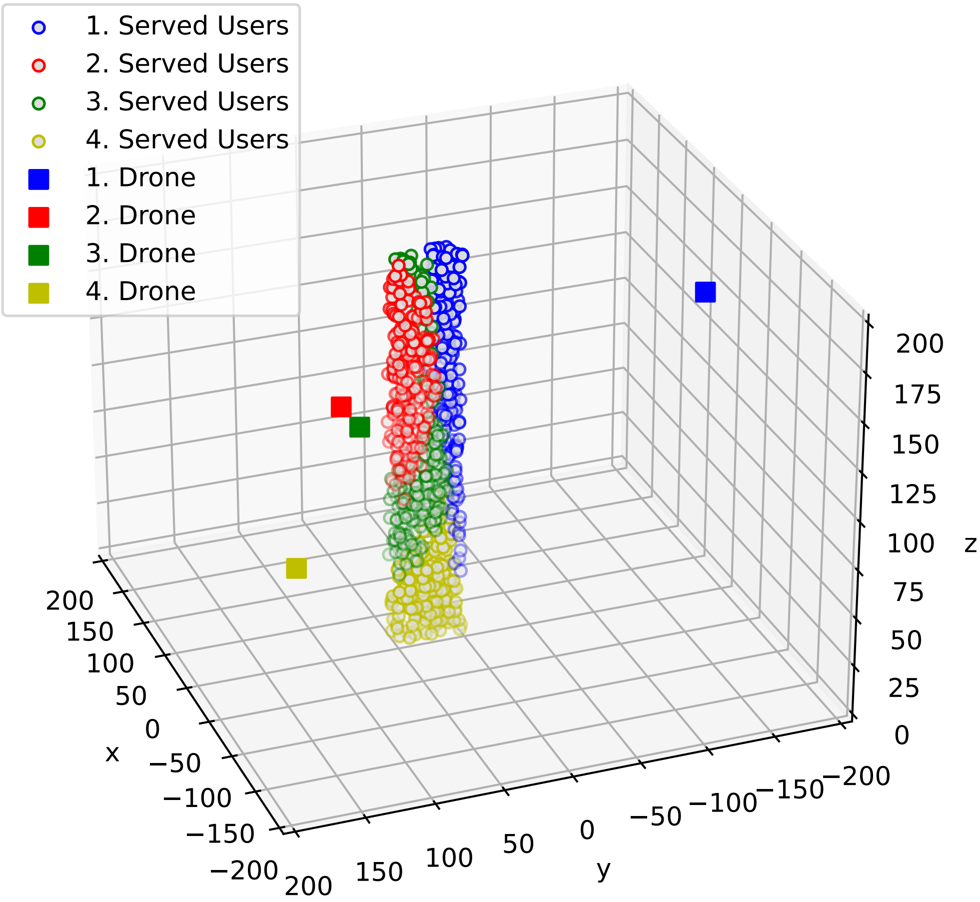

Figure 4.8. Step 4 in assigning users to the UAVs

becomes evident that AMO and IPA exhibit similar performance in terms of mean values. However, AMO demonstrates superiority in terms of standard deviation, as it consistently exhibits lower standard deviation values across all six building scenarios. Nevertheless, it is worth mentioning that IPA also shows a close performance to AMO in terms of standard deviation.

The low standard deviation values of both AMO and IPA, coupled with their mean values being very close to the overall best value, suggest that these algorithms are consistent in finding optimal solutions. They display a high level of precision, reliability, and effectiveness. Furthermore, the fact that they have low standard deviation while achieving extremely good overall best solutions indicates a good balance between exploration and exploitation. This balance allows for convergence to a good solution while avoiding getting trapped in local optima.

On the other hand, FA exhibits significantly higher differences between mean values and the overall best value, indicating greater variability and less consistent

Table 4.4. Mean, Best and Std. Deviations Values from IPA, AMO, and FA Algorithms

	IPA			AMO		
	Mean	Best	Std.	Mean	Best	Std.
b1	6.50609e+4	6.480441e+4	1.34360e+2	6.48981e+4	6.476590e+4	1.11372e+2
b2	8.19503e+4	8.158357e+4	2.01480e+2	8.18641e+4	8.170226e+4	7.93883e+1
b3	1.00733e+5	1.002076e+5	2.25122e+2	1.00782e+5	1.005910e+5	1.23180e+2
b4	8.12298e+4	8.093666e+4	1.19334e+2	8.12472e+4	8.107791e+4	1.62656e+2
b5	8.33291e+4	8.299491e+4	1.20956e+2	8.33925e+4	8.313309e+4	1.13168e+2
b6	8.54299e+4	8.525371e+4	8.65441e+1	8.54188e+4	8.529605e+4	5.67520e+1

	FA		
	Mean	Best	Std.
b1	7.75687e+4	7.257417e+4	3.02340e+3
b2	9.72093e+4	9.017545e+4	3.19901e+3
b3	1.18009e+5	1.108567e+5	3.85754e+3
b4	9.64689e+4	9.120771e+4	2.96080e+3
b5	9.76867e+4	9.393828e+4	2.52560e+3
b6	9.85824e+4	9.177843e+4	3.20615e+3

results. Similarly, FA displays significantly higher standard deviation compared to AMO and IPA, implying a wider exploration range. In some cases, this can lead to finding better solutions in initial iterations and increase the chance of finding the global optimum. However, the wide exploration space without balanced exploitation abilities can result in getting trapped in local optima, which is the case with the FA algorithm.

The findings discussed above are further illustrated in the accompanying chart.

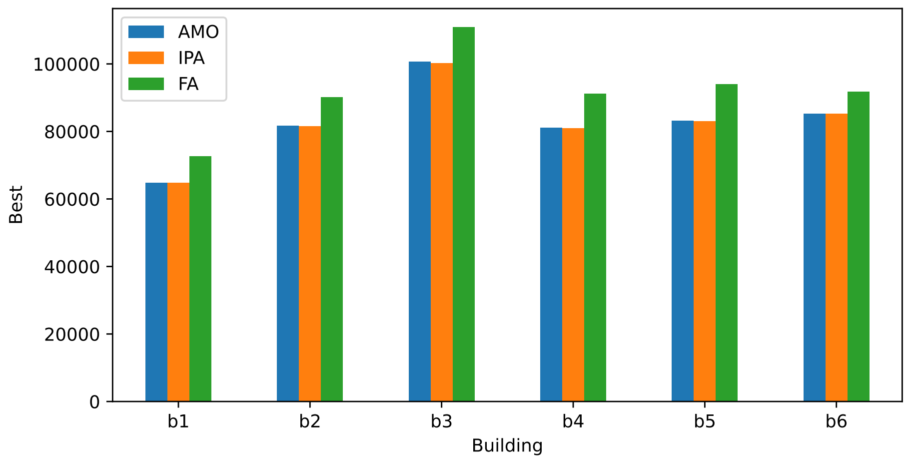

Figure 4.9. Comparing overall best values for different building configurations.

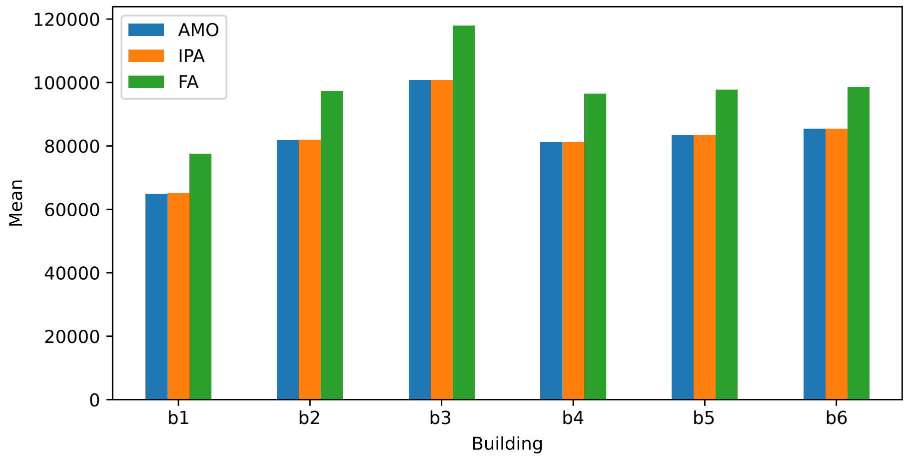

Figure 4.10. Comparing mean values for different building configurations.

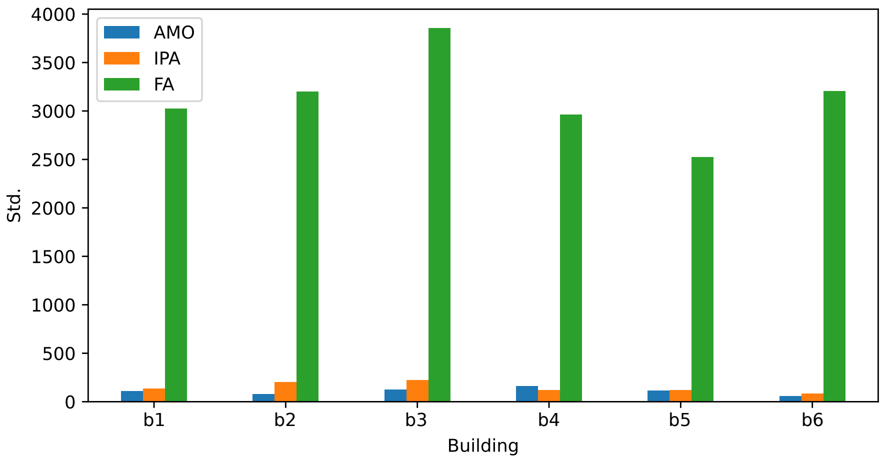

Figure 4.11. Comparing standard deviation values for different building configurations.

Overall, based on the analysis of mean and standard deviation values, it can be concluded that AMO and IPA demonstrate consistent performance and high precision in finding optimal solutions. They strike a good balance between exploration and exploitation. Conversely, FA shows greater variability and less consistent results, indicating a higher risk of getting trapped in local optima.

4.3. Backhaul Aware UAV-Based Stations

4.3.1. System Model

In this experimental test, we are going to use AMO, IPA, and FA to solve a backhaul-aware 3D placement problem. In this problem, an unmanned aerial vehicle (UAV) will be used to construct a network base station that can provide users with the network coverage in case of emergency or temporary events. However, this base station will may face some limitations and obstacles that may reduce the efficiency of the provided service. The primary challenges encompass various constraints such as limitations in the total data rates, available bandwidth, energy consumption, and other relevant factors. In this problem, we will use the same system model and limitations that were used in (Kalantari et al., 2017).

In this problem, pathloss model will be used as presented in (Al-Hourani et al., 2014), which states the existence of two primary connection types, the first one is line-of-sight (LoS) connections, and the second is non LoS ($NLoS$) connections that can still receive signals if the reflections are good enough to be caught. The probability of constructing an LoS connection between the signal transmitter and the receiver can be calculated using Eq. 4.3:

$$P(LoS) = \frac{1}{1 + a.exp(-b\frac{180}{\pi}\theta - a)} \tag{4.3}$$

where a and b are environmental constant variables, θ is the angle of the UAV which can also be calculated using Eq. 4.4:

$$\theta = \frac{r}{h} \tag{4.4}$$

where h is the height of the UAV (z_{uav}) and r is the horizontal distance between UAV and the receiving user. The average pathloss can be calculated using Eq. 4.5 which takes into consideration the probability of LoS that was calculated previously in Eq. 4.3.

$$PL(dB) = 20log(\frac{4\pi f_c d}{c}) + P(LoS)\eta_{LoS} + P(NLoS)\eta_{NLoS} \tag{4.5}$$

where f_c refers to carrier frequency, c is light-speed constant d is the distance between UAV and user which can calculated using Eq. 4.6, the probability of $NloS$ equals $1 - P(LoS)$, η_{LoS} and η_{NLoS} are additional environmental loss values.

$$d = \sqrt{h^2 + r^2} \tag{4.6}$$

After determining the connection model, the user location generating model must be determined too. Users location are generated using a Matérn cluster process which ensures that users locations are distributed heterogeneously (Haenggi, 2012; Ganti & Haenggi, 2009).

While constructing the UAV-based station, the model must take into consideration the limitations that will be faced, such as the total bandwidth and the total rates since every user in the targeted area will have different network rates requirements. In this model, I_i will be used as an indicator that shows the status of the user as in Eq. 4.7, where i refers to the i^{th} user.

$$I_i = \begin{cases} 1 & \text{if user is served} \\ 0 & \text{otherwise} \end{cases} \tag{4.7}$$

Since bandwidth and data rates are limited, the following conditions shown in Eq. 4.8 and Eq. 4.9 must be satisfied.

$$\sum_{i=1}^{N_u} r_i I_i \leq R \tag{4.8}$$

$$\sum_{i=1}^{N_u} b_i I_i \leq B \tag{4.9}$$

where r_i and b_i is the i^{th} user data rate and bandwidth usage respectively, R is the maximum data rate, B is the maximum bandwidth, and N_u is the total number of users. User's bandwidth (b_i) can be calculated using Eq. 4.10 where γ_i is the value of i^{th} user's signal-to-rate ratio.

$$b_i = \frac{r_i}{log_2(1+\gamma_i)} \tag{4.10}$$

In order to make sure that the provided service is efficient and satisfies the quality of service criterion (QoS), the pathloss (PL_i) of the received signal must not exceed the maximum PL_{max} value as in Eq. 4.11.

$$PL_i.I_i \leq PL_{max} \tag{4.11}$$

The last limitation is the bounds of the covered area, the UAV-based station's coordination must satisfy Eq. 4.12, Eq. 4.13 and Eq. 4.14, where x, y, h represents the location of the UAV-based station, $x_{min}, y_{min}, h_{min}$ are the lower bounds, and

$x_{max}, y_{max}, h_{max}$ are the upper ones.

$$x_{min} \leq x \leq x_{max} \tag{4.12}$$

$$y_{min} \leq y \leq y_{max} \tag{4.13}$$

$$h_{min} \leq h \leq h_{max} \tag{4.14}$$

According to all of the previous relations, the objective function that will be used in the optimization process is (Eq. 4.14):

$$max \sum_{i=1}^{N_u} \alpha_i I_i \tag{4.15}$$

subject to Eq. 4.8, Eq. 4.9, Eq. 4.11, Eq. 4.12, Eq. 4.13 and Eq. 4.14.

4.3.2. Experimental Results

In order to perform experiments, problem-related parameters and constants must be determined. In this test we used the same values listed in (Shehzad et al., 2021). While Table 4.5 shows the parameters of the optimization process, Table 4.6 shows the parameters used in generating users location using Matérn clustering method.

Table 4.5. Optimization process parameters

Parameter	Value	Parameter	Value
a	9.61	PL_{max}	120 dB
b	0.16	B	15 MHz
η_{LoS}	1 dB	P_t	5 watts
η_{NLoS}	20 dB	R	80 Mbps
f_c	2 GHz	c	3e9 m/s
x_{min}	0 m	x_{max}	4000 m
y_{min}	0 m	y_{max}	4000 m
h_{min}	0 m	h_{max}	200 m
Rates	[0.1, 0.5, 1, 1.5, 2] Mbps		

In order to investigate the performance of the AMO, IPA, and FA algorithms, we simulated the optimization process using four different drone number (population size) values: 5, 10, 20, and 25 as shown in Table 4.7 which contains the shared parameters of AMO, IPA, and FA. Algorithm-related control parameter values are listed in Table 4.8.

After running the first case where drone numbers equals 5. The results in Table 4.9 shows that IPA has the best performance in most cases, whereas FA was the worst one.

Table 4.6. User locations generating process parameters

Parameter	Value
Density of parent Poisson point process	10e-7 per m^2
Mean number of points in each cluster	90 users
Radius of cluster disk (for daughter points)	700 m

Table 4.7. Shared parameters of AMO, IPA, and FA

Parameter	Value
Population size	5, 10, 20, 25
Maximum evaluations	200
Number of runs	30

It also shows that AMO has served a number of users (241) close the served by IPA (243). On the other side, FA served just about 230 users. The graphs in Figure 4.12 shows the change in served users number to evaluation number.

When drones number equals 10, the obtained results are listed in Table 4.10. The analysis clearly indicates that IPA exhibits the highest level of performance across various scenarios, emerging as the superior algorithm. In contrast, FA lags behind as the least effective option. Furthermore, it is noteworthy that AMO has provided services to a comparable number of users (243) as IPA (244), showcasing their similar capabilities. Conversely, FA has managed to serve only around 238 users. To visualize the dynamic relationship between the number of served users and the evaluation count, Figure 4.13 presents a set of informative graphs.

In Table 4.11, we can see that the three algorithms results were close. In this case, FA algorithm performed well in compare with the previous cases where the mean of served users number has raised up to 241 users. But in general, IPA still have the superiority over the other methods. The evaluation graphs are shown in Figure 4.14.

In Table 4.12, when drones number was 25, AMO algorithm showed the best performance among all other algorithms and outperformed them. But the results of IPA were not far from the results of AMO in contrast with FA which again showed poor performance compared to the others. The graph of evaluations are shown in Figure 4.15.

Figure 4.16 shows a 3D simulation of users and UAV-based station (drone) where served users are colored in blue. The network-centric approach showed that the priority is to serve the maximum number of users regardless the rate usage of each one whenever

Table 4.8. AMO, IPA, and FA control parameter values

AMO		IPA		FA	
Parameter	Value	Parameter	Value	Parameter	Value
-	-	NoD	1	α	0.5
-	-	NoR	1	β	0.2
-	-	-	-	γ	1.0

Table 4.9. AMO, IPA, and FA results (number of drones = 5)

-	AMO	IPA	FA
Served users (Mean)	241.366667	243.466667	230.800000
Served users (Std.)	7.383501	3.794127	10.613589
Served users (Best)	248	248	245
Served users (Worst)	221	230	211
Total rates (Mean)	7.834000e+07	7.824000e+07	7.824333e+07
Total rates (Std.)	2.647054e+05	3.146974e+05	2.207875e+05
Total rates (Best.)	7.860000e+07	7.860000e+07	7.840000e+07
Total bandwidth (Mean)	1.493000e+07	1.490667e+07	1.490333e+07
Total bandwidth (Std.)	6.512587e+04	7.849152e+04	5.560534e+04
Total bandwidth (Best)	1.500000e+07	1.500000e+07	1.490000e+07
Best drone x	1123.356973	1290.119339	1201.847548
Best drone y	2993.131777	3093.414835	3026.142817
Best drone h	200.000000	200.000000	133.257825

maximum rate and bandwidth are not exceeded.

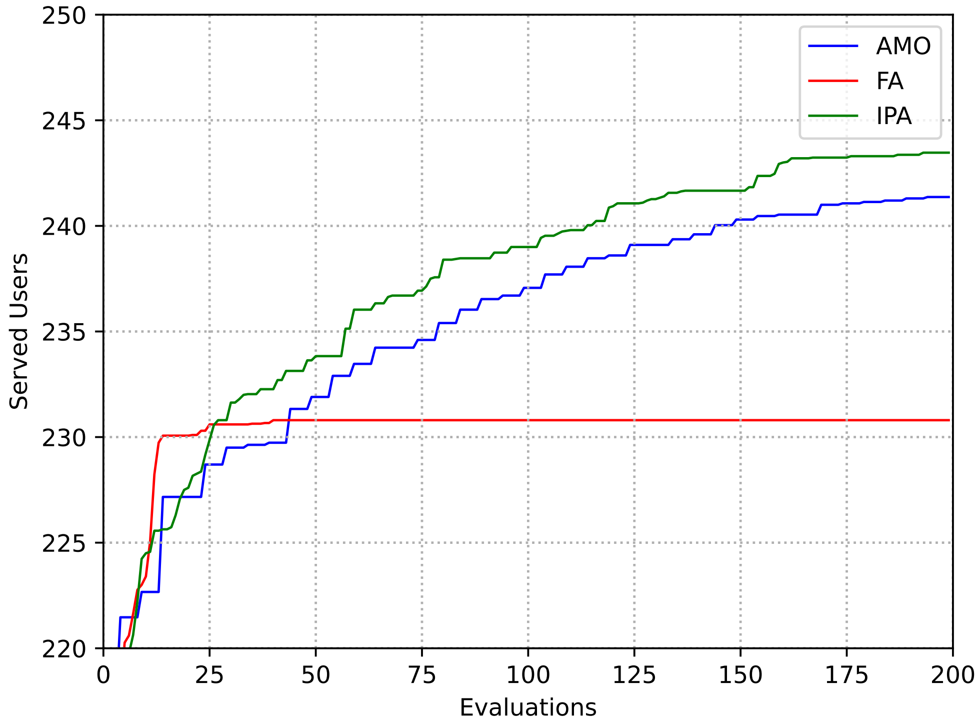

Figure 4.12. Evaluation graph of AMO, IPA, and FA (number of drones = 5)

Table 4.10. AMO, IPA, and FA results (number of drones = 10)

-	AMO	IPA	FA
Served users (Mean)	243.000000	243.833333	237.766667
Served users (Std.)	5.369133	2.889736	7.435624
Served users (Best)	248	248	247
Served users (Worst)	227	236	222
Total rates (Mean)	7.836333e+07	7.824333e+07	7.829000e+07
Total rates (Std.)	2.870580e+05	2.990598e+05	2.411895e+05
Total rates (Best.)	7.850000e+07	7.810000e+07	7.860000e+07
Total bandwidth (Mean)	1.493333e+07	1.490667e+07	1.491667e+07
Total bandwidth (Std.)	7.580980e+04	7.396792e+04	6.477192e+04
Total bandwidth (Best)	15000000.0	14900000.0	15000000.0
Best drone x	1147.509685	1172.431247	1085.699731
Best drone y	3014.261944	2987.366417	2931.952551
Best drone h	200.000000	200.000000	178.531111

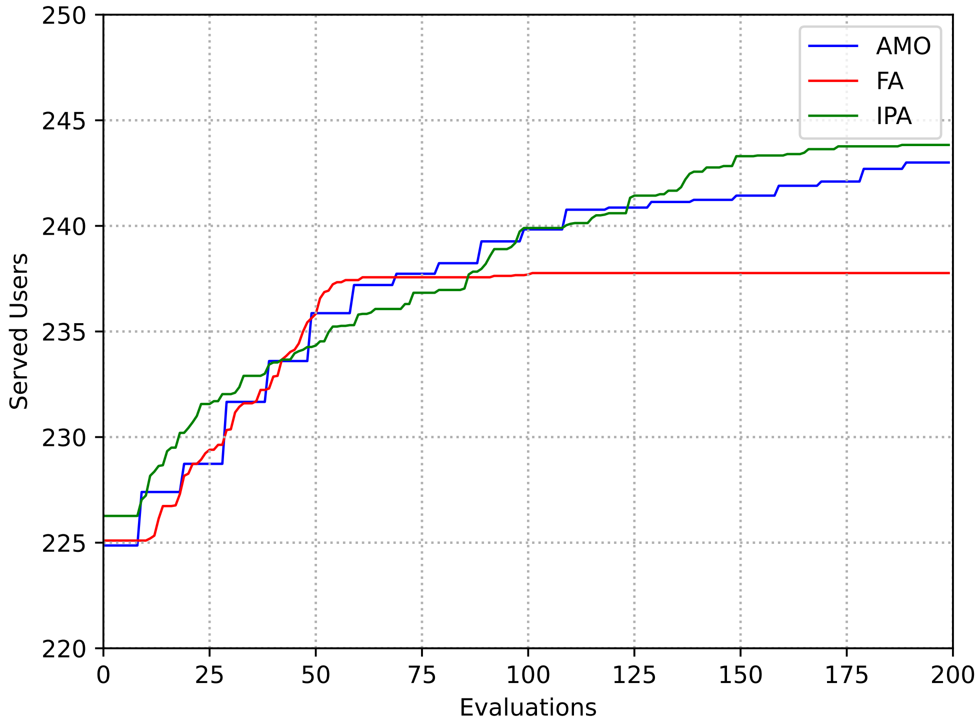

Figure 4.13. Evaluation graph of AMO, IPA, and FA (number of drones = 10)

Table 4.11. AMO, IPA, and FA results (number of drones = 20)

-	AMO	IPA	FA
Served users (Mean)	241.933333	242.633333	240.800000
Served users (Std.)	5.159079	3.056743	5.013086
Served users (Best)	249	248	247
Served users (Worst)	231	234	225
Total rates (Mean)	7.826333e+07	7.831000e+07	7.832667e+07
Total rates (Std.)	3.178411e+05	2.783572e+05	2.531638e+05
Total rates (Best.)	7.860000e+07	7.860000e+07	7.800000e+07
Total bandwidth (Mean)	1.491667e+07	1.491667e+07	1.492000e+07
Total bandwidth (Std.)	7.466399e+04	6.477192e+04	6.102571e+04
Total bandwidth (Best)	1.500000e+07	1.500000e+07	1.490000e+07
Best drone x	1153.985172	1297.947926	1143.385810
Best drone y	2994.387308	3056.043378	3010.515945
Best drone h	200.000000	199.778895	196.047409

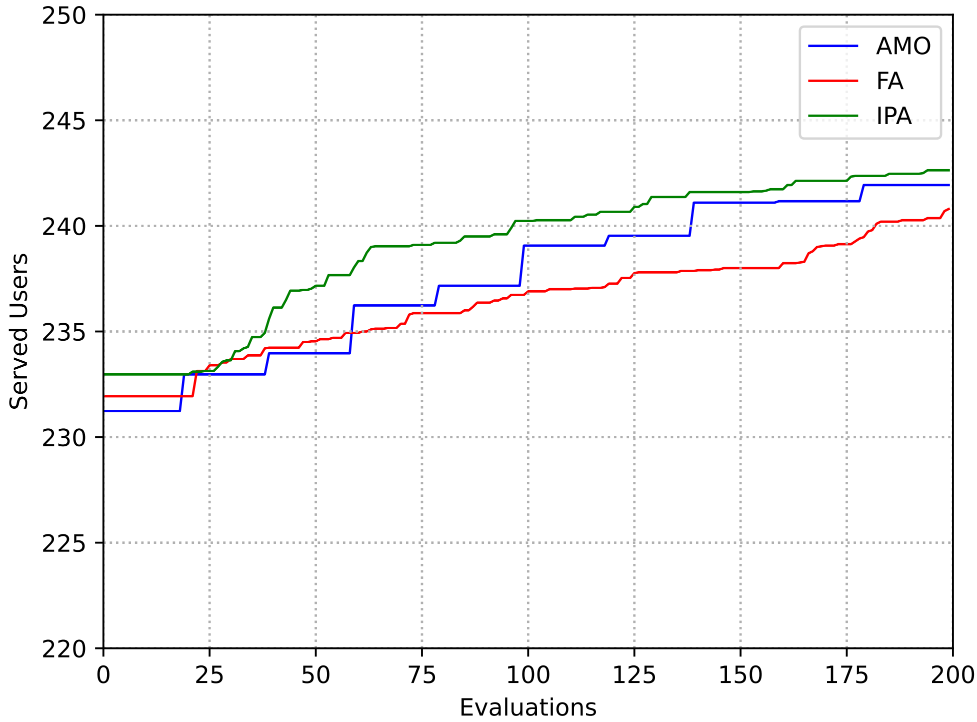

Figure 4.14. Evaluation graph of AMO, IPA, and FA (number of drones = 20)

Table 4.12. AMO, IPA, and FA results (number of drones = 25)

-	AMO	IPA	FA
Served users (Mean)	242.666667	241.133333	238.500000
Served users (Std.)	3.356243	4.673722	5.679667
Served users (Best)	247	248	246
Served users (Worst)	236	232	228
Total rates (Mean)	7.830333e+07	7.823333e+07	7.828667e+07
Total rates (Std.)	2.772815e+05	3.304472e+05	2.921186e+05
Total rates (Best.)	7.820000e+07	7.870000e+07	7.840000e+07
Total bandwidth (Mean)	1.492333e+07	1.491000e+07	1.491000e+07
Total bandwidth (Std.)	6.789105e+04	8.4486.27e+04	7.119666e+04
Total bandwidth (Best)	1.490000e+07	1.500000e+07	1.490000e+07
Best drone x	1378.347089	1355.003457	1197.142696
Best drone y	3195.319721	3240.188389	3064.684436
Best drone h	200.000000	200.000000	147.257902

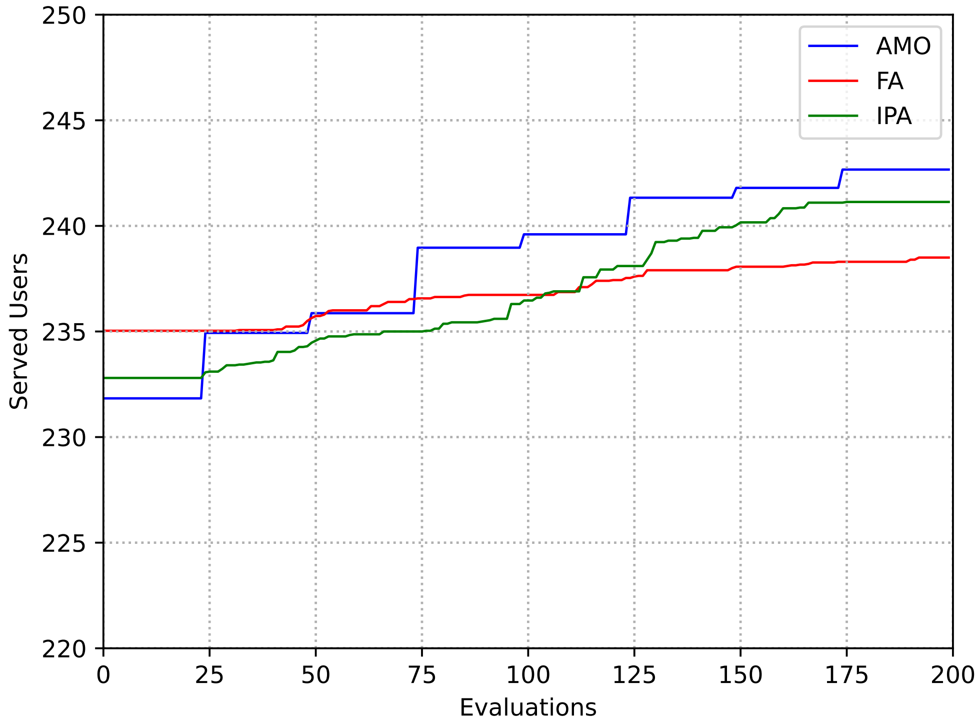

Figure 4.15. Evaluation graph of AMO, IPA, and FA (number of drones = 25)

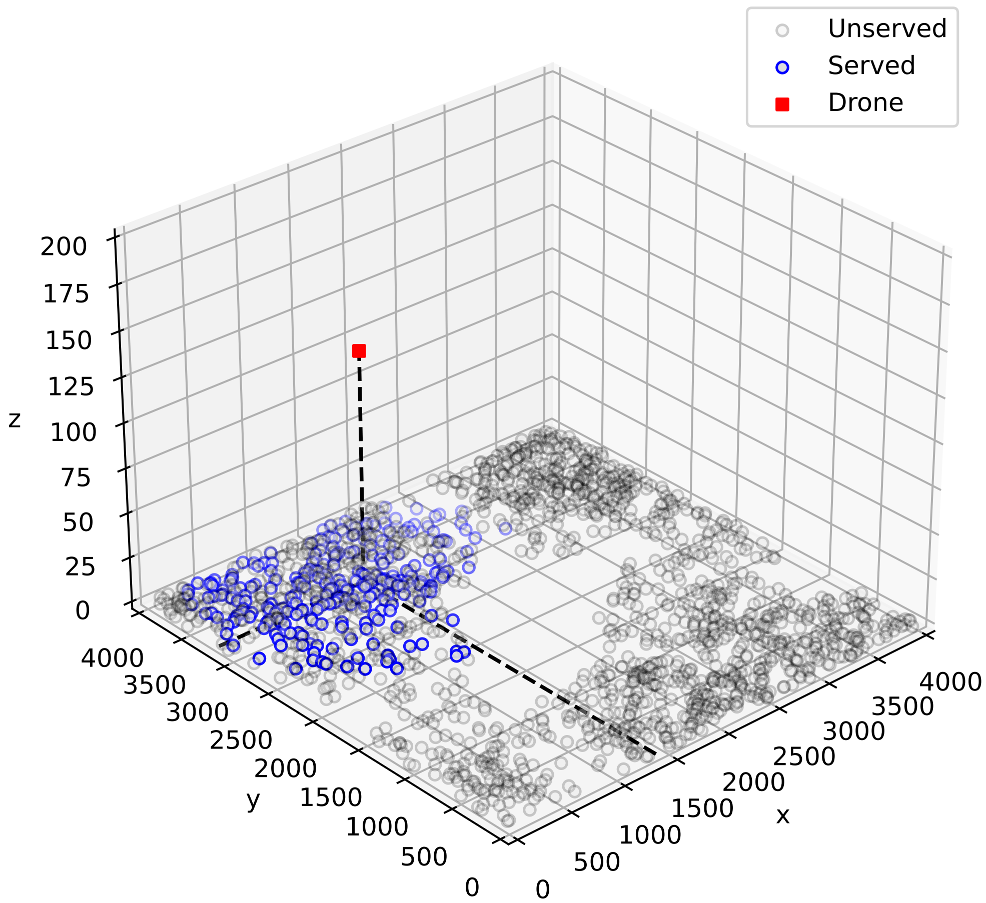

Figure 4.16. 3D simulation of users and UAV-based station (drone)

5. CONCLUSION

This thesis has focused on addressing the issue of power consumption in Unmanned Aerial Vehicles (UAVs) and has explored the suitability of employing meta-heuristic algorithms to optimize UAV placement and reduce energy consumption. The integration of these algorithms, inspired by natural phenomena, has provided fast and near-optimal solutions to complex optimization problems that conventional methods struggle to solve.

Extensive research in the field has supported the appropriateness of employing meta-heuristic algorithms. Studies utilizing algorithms such as ABC, PSO, and others have demonstrated promising results in reducing transmission power and optimizing the 3D placement of UAVs with Quality of Service (QoS) assurance in wireless networks. The research objectives of this study have centered around three distinct problems related to UAVs. Firstly, the 3D placement of UAVs as wireless base stations aimed to reduce power consumption. The application of Animal Migration Optimization (AMO) and Immune Plasma Algorithm (IPA) as meta-heuristic approaches facilitated the identification of optimal 3D placements for the UAVs, effectively reducing power consumption.

Secondly, the research explored the 3D placement of multiple UAVs to achieve a balanced user allocation and further reduce power consumption. In addition to AMO and IPA, the FA was employed to solve this problem. Extensive analysis and comparisons were conducted to evaluate the results obtained. The experimental results indicated that AMO and IPA yielded the best optimal solutions for the given problem, displaying robustness, reliability, and effectiveness. These findings highlight the practical applicability of these algorithms in real-life scenarios and applications. However, the FA algorithm lagged behind AMO and IPA, exhibiting less optimal solutions due to being trapped in local optima.

Lastly, the study addressed the backhaul-aware 3D placement of UAVs as wireless base stations, considering limitations on total data rates, bandwidth, and energy consumption. The AMO, IPA, and FA algorithms were utilized, and a comprehensive analysis and comparison were provided. The experimental results demonstrated that meta-heuristic algorithms are appropriate for achieving close-to-optimal solutions. Once again, AMO and IPA outperformed the FA algorithm in terms of performance.

In conclusion, this thesis has shed light on the potential of UAVs as wireless base stations and the significance of addressing power consumption challenges. The integration meta-heuristic algorithms has proven to be a promising approach for optimizing UAV 3D placement and reducing energy consumption. With future research UAV base station systems can be further improved, contributing to the development of efficient and reliable communication infrastructure in various critical applications.

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