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Review

Utilizing UAVs in Wireless Networks: Advantages, Challenges, Objectives, and Solution Methods

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Abstract: Unmanned aerial vehicles (UAVs) have emerged as a promising technology to enhance the performance and functionality of mobile networks. UAVs can act as flying base stations, relays, or users to provide wireless services to ground users or devices. However, the optimal placement and trajectory design of UAVs in mobile networks is a challenging problem, as it involves multiple objectives, constraints, and uncertainties. In this paper, we provide a comprehensive survey of the state-of-the-art research on UAV placement and trajectory optimization in cellular networks. We first introduce the main objectives and challenges of UAV placement and trajectory optimization, such as maximizing coverage, throughput, energy efficiency, or reliability, while minimizing interference, delay, or cost. We also examine the primary models and assumptions employed for UAV placement and trajectory optimization, including channel models, mobility models, network architectures, and constraints. Additionally, we discuss the main methods and algorithms employed for UAV placement and trajectory optimization. These include optimization techniques, heuristic algorithms, machine learning approaches, and distributed solutions. Analytical results, numerical simulations, or experimental tests are further discussed as the main performance metrics and evaluation methods used for UAV placement and trajectory optimization. We also highlight the main applications and scenarios of UAV placement and trajectory optimization, such as cellular offloading, emergency communications, or aerial base stations. Finally, we identify some open problems and future research directions on UAV placement and trajectory optimization in cellular networks.

Keywords: flying base station; UAV-assisted 5G; UAV positioning; UAV trajectory planning

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1. Introduction

In the realm of wireless communications, unmanned aerial vehicles (UAVs) are emerging as a pivotal technology for enhancing cellular network services. These aerial platforms, operating as high-altitude base stations, are instrumental in augmenting network coverage and capacity. Their deployment is particularly advantageous in regions bereft of robust ground infrastructure, as they can be maneuvered to optimize signal propagation, ensuring superior service delivery. UAVs are adept at providing on-demand cellular connectivity, catering to areas with high user density, such as during special events, or in response to emergency situations where terrestrial networks may be compromised [1,2].

The drone industry has advanced significantly in recent years, leading to new applications of UAVs in various fields [3–6]. In the context of wireless networks, UAVs have been deployed as flying base stations (FBSs) to extend the coverage of cellular networks and enhance the quality of service (QoS) [7]. The primary application of UAVs is to provide wider network coverage, especially during emergencies like earthquakes and floods, or when ground-based infrastructure is compromised. UAVs offer immediate and reliable services in these situations, ensuring continued connectivity [8]. Additionally, UAVs are deployed in areas where installing terrestrial base stations is impractical or uneconomical, such as mountainous or rugged terrains, and during events with high traffic loads like sports or cultural events [9,10]. As mentioned by "Fortune Business Insights", the global UAV market was valued at USD 27.43 billion in 2022 and is expected to grow to USD 91.23 billion by 2030 with an annual growth rate of 16.3%. Given that the price of UAVs ranges from a few dollars to millions of dollars, the number of active UAVs in use is likely in the millions.

UAVs offer unique advantages, including easy and low-cost deployment and a high likelihood of Line of Sight (LoS) communication [11]. Their mobility allows UAVs to enhance QoS and reduce impairments by changing positions as needed. This mobility can also increase the number of covered network users and provide higher data rates by expanding the coverage area and the number of UAVs [12].

The benefits of using UAVs in wireless networks are numerous. Firstly, UAVs provide cost-effective and swift deployment compared to traditional infrastructure, which can be both time consuming and expensive to install. Secondly, their ability to operate in hard-to-reach or hazardous areas makes them invaluable for emergency response and disaster recovery, ensuring connectivity when it is most needed. UAVs also offer flexibility in network management, as they can be repositioned as needed to address fluctuating demand or coverage gaps. Additionally, they can support high-capacity data transmission and enhance network resilience by providing alternative communication links. Overall, UAVs significantly enhance the efficiency, flexibility, and reliability of wireless networks [13–15].

The deployment environment for UAVs in wireless networks presents a complex and multifaceted landscape. The spatial configuration of this environment can be conceptualized in both two-dimensional (2D) and three-dimensional (3D) planes, which significantly influence the strategic positioning and maneuverability of UAVs to optimize network efficacy. The air-to-ground (A2G) channel model is paramount in this context, delineating the signal transmission pathways between UAVs and terrestrial receivers. This model causes a comprehensive consideration of various factors, including path loss, shadowing, multipath fading, and Doppler shifts, which arise from the relative motion between UAVs and ground entities [10,16].

The phenomenon of path loss in A2G communications is predominantly affected by the UAV's elevation and its proximity to the terrestrial receiver. Elevated altitudes diminish path loss, which is primarily because of the establishment of a clearer line-of-sight (LoS) trajectory, albeit potentially escalating free-space path loss because of increased transmission distances [12]. Shadowing emerges when physical obstructions, such as edifices or foliage, impede the signal trajectory, engendering fluctuations in the power of the received signal. Conversely, multipath fading is the consequence of signal reflections from assorted surfaces prior to reception, engendering interference patterns that can damage signal integrity [11].

The attenuation criterion is indispensable for gauging signal deterioration over distances and through impediments, which informs the strategic placement and navigation of UAVs to sustain robust communication links. The complexity escalates when the deployment encompasses not just a solitary UAV but a fleet, causing concurrent operation. This scenario demands advanced algorithms capable of managing resources, mitigating interference, and executing real-time modifications in response to environmental dynamics and user requirements [17]. A profound comprehension of these elements is imperative for the formulation of efficacious UAV-assisted wireless network solutions, ensuring the provision of communication services that are reliable, efficient, and versatile, catering to a spectrum of operational scenarios [18].

The use of UAVs assumes that base stations are equipped with multiple antennas and analog beamforming capabilities. Analog beamforming enhances spectral efficiency by directing beams toward multiple users at different frequencies or time slots, improving coverage and capacity, particularly in mmWave bands that require high path loss and LoS communication. This method reduces hardware complexity and power usage by using one radio frequency chain per antenna array, extending the UAV's battery life and flight time while lowering equipment costs and weight [19].

However, analog beamforming presents limitations, such as the lack of spatial multiplexing, which restricts the transmission of multiple data streams simultaneously. This can limit high-demand applications like video streaming or virtual reality due to data rate and throughput constraints. Another challenge is fast and accurate beam tracking, as the UAV must constantly adjust its beam direction and width to maintain a reliable link with user equipment (UE). The UE must relay channel state information (CSI) back to the drone base station, which can slow response times and increase system load, potentially decreasing performance [20].

UAVs are typically battery-powered and have limited energy resources, necessitating optimal positioning and effective path planning to maximize coverage and QoS while extending the UAV lifetime. In addition to 3D positioning and trajectory planning, UAV deployment must consider the impact of interference with neighboring base stations due to strong LoS signals and channel modeling challenges in UAV-assisted 5G networks [21].

Extensive research has been conducted on 2D and 3D deployment strategies for drones and stations in various wireless networks [22–24]. Studies have also explored drone movements in wireless networks, the Internet of Things, and sensor networks [25,26]. According to the issues raised, the main goal of this paper is to review positioning and trajectory methods and classify them based on their assumptions of the problem environments and solutions. The motivation and goal of this paper which are separated by "*" are as follows: * Comprehensive survey: The paper provides an exhaustive review of the state-of-the-art research on UAV placement and trajectory optimization in cellular networks, encompassing a wide range of objectives, challenges, models, and methods. * Detailed Analysis of Objectives and Challenges: It systematically introduces and categorizes the main objectives (e.g., maximizing coverage, throughput, energy efficiency) and challenges (e.g., minimizing interference, delay, and cost) involved in UAV placement and trajectory design. * Evaluation of Models and Assumptions: The paper critically examines the primary models and assumptions used in the research, including channel models, mobility models, network architectures, and constraints, offering insights into how these factors influence UAV optimization. * Diverse Methods and Algorithms: A key contribution is the discussion of various methods and algorithms for UAV placement and trajectory optimization, including optimization techniques, heuristic algorithms, machine learning approaches, and distributed solutions. * Performance Metrics and Evaluation Methods: The paper discusses different performance metrics and evaluation methods, such as analytical results, numerical simulations, and experimental tests, providing a comprehensive view of how UAV optimization is assessed. * Applications and Scenarios: It highlights the practical applications and scenarios where UAV placement and trajectory optimization are most impactful, such as cellular offloading, emergency communications, and aerial base stations. * Identification of Open Problems and Future Directions: The paper concludes by identifying unresolved challenges and proposing future research directions, guiding ongoing and future work in this rapidly evolving field.

As presented in Figure 1, in this paper, we have compared different literature works from the point of view of UAV positioning (Section 2) and trajectory planning (Section 3). In each section, we have compared the works of each perspective based on the considered environmental conditions in solving the problem. Therefore, in each section (UAV deployment and trajectory planning), the related works have been compared based on the dimension of the problem, the number of UAVs considered to solve the problem, path loss, interference, considering the NLoS links, energy limitation, etc.

The rest of paper is as follows: in Section 2, the UAV deployment methods are reviewed. Then, in Section 3, the trajectory planning papers are investigated. Finally, Section 4 concludes the paper.

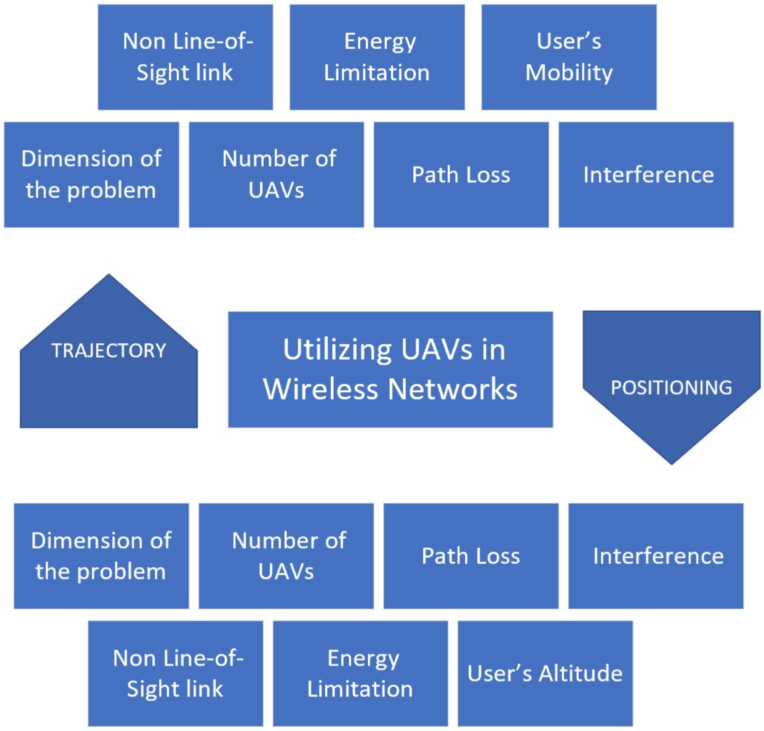

Figure 1. The topics addressed for each category.

2. Optimizing the Deployment of UAVs

Recently, the issue of deploying UAVs in wireless networks has been extensively studied in the literature. Generally, these studies can be categorized in terms of problem dimensions, considering the path loss, the LoS or NLoS links, the number of UAVs which are used in the target area, energy constraints, and interference among cells. Additionally, in real-world scenarios, wireless network users, especially mobile network users in urban areas, are positioned at different heights. Considering the altitude of antennas at base stations and UAVs, the altitude of users is also non-negligible. Therefore, another category under the title of users' altitudes is considered in this review. Subsequently, a comprehensive review of the articles and previous works is conducted to investigate the outstanding studies in each of these categories.

2.1. Dimension of the Problem

The dimension of the problem is the most fundamental category in solving optimization problems for UAV deployment. Some articles solely address the solution of the 2D deployment problem and finding the x and y coordinates of UAVs. Another approach involves the initial identification of the optimal two-dimensional positions for UAVs, which is followed by the application of heuristic algorithms to determine the optimal altitude for the UAV. Another category of papers focuses on determining the position of the UAVs in all three dimensions concurrently. In the subsequent section, a review is presented on the works that tackle the issue of deploying UAVs in three dimensions.

Zhang in [22] investigates a communication system utilizing multiple base stations mounted on UAVs to minimize the required number of UAVs and improve the coverage rate through optimization of the UAV's three-dimensional locations, user clustering, and frequency band allocation. The Quality of Service (QoS) requirements and the service capability of each UAV are considered, which makes the problem challenging. The authors propose a three-stage method for solving the formulated Mixed-Integer Programming (MIP) problem. Firstly, to ensure that each UAV can serve more users, the maximum service radius of UAVs is determined based on the minimum required signal power for users. Secondly, an algorithm based on the Artificial Bee Colony (ABC) algorithm is suggested to minimize the required number of UAVs. Lastly, the three-dimensional positions and frequency bands of each UAV are designed to enhance the power of target signals and reduce interference.

In [27], an approach for deploying a three-dimensional multi-UAVs system is proposed to meet QoS requirements for various user distributions. The system maximizes the achievable power for all ground users in the presence of channel interference. The proposed method is divided into two separate algorithms. In the first algorithm, it is demonstrated that the x and y coordinates of the UAV can be found using the ean-shift technique and prior knowledge about the user locations provided by the Global Positioning System (GPS). This is accomplished by ensuring that the UAVs communicate with the maximum number of users. Once the x and y coordinates of the UAVs are determined, their altitude and transmission power are optimized separately. Since these problems fall into the category of non-convex optimization problems, a successive convex optimization method is used to approximate their non-convex constraints. In the second algorithm, a block coordinate descent method is employed to jointly optimize the altitudes of UAV and power transmission by tightening the obtained bounds to approximated ones. It is then demonstrated that the proposed algorithm converges.

Wang et al. in [28] address the challenge of deploying UAVs equipped with Visible Light Communication (VLC) to enhance the energy efficiency of UAV-based networks. In their model, communication and illumination services are provided to ground users by UAVs. Due to the interference caused by ambient lighting in VLC links, it is crucial to consider the illumination distribution in the target area for optimal UAV deployment. This challenge is formulated as an optimization problem that jointly optimizes UAV deployment, user allocation, and energy efficiency, while accounting for users' communication and illumination requirements. To tackle this, they propose an algorithm that integrates Gated Recurrent Units with Convolutional Neural Networks, allowing UAVs to model and predict long-term and future illumination distributions. Based on these predictions, the primary non-convex optimization problem is divided into two subproblems, which are solved using a low-complexity iterative algorithm. The proposed approach is then employed to deploy drones and allocate users with the goal of minimizing total transmission power.

In [29], a method for the joint optimization of three-dimensional UAV placement and path loss exponent is proposed. Additionally, they optimize the path loss exponent for different deployment heights of UAV in non-urban environments. The authors of [30] solve a three-dimensional coverage problem and a task offloading problem for UAV clouds concurrently. The aim is to provide Internet of Things (IoT) services with specified delays. It proposes an effective heuristic solution based on the optimization algorithm of ion movement for solving the main mixed-integer problem.

In [23], a UAV deployment and user allocation problem with balanced load distribution is proposed. Initially, a clustering method for UAV deployment is introduced, which is followed by a user allocation strategy aiming at minimizing the maximum traffic of the subareas. The minimization is subject to capacity constraints and subarea shapes. A UAV deployment algorithm is proposed using a backtracking search for system load reassignment. Finally, the height of each UAV is adjusted to reduce system energy consumption. Based on user allocation and placement algorithms, results are close to optimal.

In [31], an algorithm to maximize the coverage range of users with different QoS requirements is proposed. Also, ref. [32] aims to maximize the summation of the data rate provided for users considering constraints on direct communication and fairness in data rate provisioning. IT also provides an algorithm for convexifying the proposed non-convex mathematical model.

Mozaffari et al. in [33] propose a framework for UAV-BS network planning along with low-latency UAV-UE allocation. In the network planning section, a method based on shortened hexagonal structures is proposed to ensure complete coverage of the desired area with the minimum number of UAVs. Additionally, a three-dimensional cell allocation scheme is suggested by considering UAV-UE latency. Firstly, a spatial distribution for UAV-UEs is estimated. Then, based on this distribution and DBS locations, three-dimensional UAV allocation is derived considering minimal latency achieved by optimal transport theory.

In [9], an optimal three-dimensional deployment method is presented by considering the backhaul in both user-centric and network-centric scenarios. It examines UAV robustness after selecting the UAV location and its coverage area. The authors propose an optimal UAV-BS deployment algorithm with backhaul, maximizing the number of served users plus the overall user delivered data rate. This article also provides an analytical expression for the probability of a backhaul connection for UAVs that can use either LTE with millimeter-wave backhaul or millimeter-wave access.

In [34], the three-dimensional deployment of UAVs with the objective of maximizing the number of ground users covered by the UAV is investigated. The authors propose an optimal three-dimensional placement method that maximizes the number of covered users using minimal required transmission power. UAV-BSs are separated into both horizontal and vertical dimensions, solving the deployment problem without losing efficiency.

Mozaffari et al. in [35] examine the optimal three-dimensional deployment of multiple UAV equipped with directional antennas to maximize the coverage area. They study the efficient deployment of FBSs to maximize the coverage area. Additionally, the authors determine the minimum number of UAVs needed to serve all ground users within a specified area. Furthermore, they present a method to find the optimal three-dimensional locations of UAVs equipped with directional antennas using circle packing theory, ensuring maximum overall coverage of the area. They consider various UAV-BSs sets to provide a wireless downlink service for a circular geographical area with a radius of 5 km. It is assumed that the UAVs are homogeneous and have the same transmission power and altitude. In the proposed model, each UAV utilizes a directional antenna with a specific bandwidth, and the UAVs operate using the same frequency band. The objective is to optimize the deployment of UAVs in three-dimensional space while their coverage area is maximized. Avoiding mutual interference using circle packing theory is also considered. The results provide detailed guidelines on how to adjust the location and especially the altitude of UAVs optimally based on antenna bandwidth, coverage size, and the number of UAVs.

In [36], the optimal three-dimensional location of FBSs with the aim of maximizing the number of covered users is determined. They also discuss finding the optimal three-dimensional location of a drone cell while the number of users whose signal-to-noise ratio (SNR) requirements are met is maximized.

In [37], the authors divide the problem of optimizing three-dimensional UAV deployment into three subproblems. First, they dynamically solve the two-dimensional UAV deployment problem using the k-means clustering algorithm. Then, they compute the optimal heights for the UAVs using game theory. Finally, they solve the problem of allocating users to UAVs. In [38], a three-dimensional deployment scheme to minimize the number of UAVs needed to cover all users with different QoS requirements is proposed. They first establish the relation between the altitude of UAV and their coverage range, and then they propose an algorithm that considers both the altitude and horizontal position of UAVs.

A framework for the dynamic deployment and mobility of UAVs is proposed in [39] to enable reliable and energy-efficient IoT communications. Here, four UAVs are deployed to collect data from IoT devices which are distributed uniformly in a geographical area of 1 km by 1 km. Then, using tools from optimization theory, the optimal three-dimensional positions of the UAV and tool-UAV dependencies are extracted. It tries to minimize the uplink transmission power of all devices while ensuring reliable communications. The result demonstrates that UAVs can be optimally utilized to enable efficient energy-wise telecommunications. In this system, sensors are activated at different time intervals, and it is necessary to find the new optimal positions of the UAVs. The system also determines the time intervals for device activation, the time required to compute the new point, and the UAV's ability to move between points. In the first phase, the optimal positions of the UAVs are found in two steps. As the first step, a fixed UAV position is considered, and the devices are classified to optimize energy consumption (assigned to UAVs). In the next step, by keeping the classification fixed, the UAV's positions are optimized in all three dimensions. These two phases are repeated consecutively. In the second phase, based on the positions found at different times, the process of routing between the available positions is accomplished.

2.2. The Number of UAVs

Some of the studies in the literature have solved the problem with a single UAV. In these articles, throughout the problem, there is only one UAV that must be deployed. The optimal position of that one UAV must be determined to maximize the number of covered users. Generally, problem solving for deploying one drone is much less challenging than finding multiple UAVs' positions. However, other studies, such as [22], have solved the problem with multiple UAVs and obtained the positions of several UAVs simultaneously. The articles that solve the problem with multiple UAVs fall into two categories: articles with a fixed number of UAVs and articles that minimize the required number of UAVs. First, studies that have solved the problem with multiple drones are discussed.

In [40], the deployment of UAVs with low efficiency and mobility for emergency scenarios in a wireless communication system equipped with multiple UAVs is investigated. The positions of the UAVs, the user allocation, and the transmission power of ground users are jointly optimized to maximize the energy efficiency of all ground users. When a UAV is removed from the field due to failure or battery depletion, the movement of other UAVs with minimal energy cost is also examined. The authors also present an alternate algorithm based on the Successive Convex Approximation (SCA) technique to solve the optimization problems.

Ref. [41] considers the problem of designing an efficient network to collect data from sensors in the target area using FBSs. In this regard, a joint optimization problem for deploying UAVs and allocating sensors in smart environments with a large number of sensors is formulated. Given the complexity of the optimal solution, a probabilistic learning method is used to find an approximate solution close to the global answer. Additionally, a penalty method is employed to deal with difficult and conflicting constraints.

In [16], the study examines the optimal deployment and movement of multiple UAVs for collecting data from IoT network nodes with energy being the key consideration. The authors present an analytical model to determine the ideal altitude for a UAV to maximize the covered area. They identify the optimal altitude by comparing the average path loss against a predefined threshold. At lower altitudes, shadowing effects reduce the likelihood of LoS communication between the transmitter and receiver, leading to a smaller coverage radius. At higher altitudes, although LoS communication is more likely, the increased distance causes higher path loss, reducing coverage efficiency. Thus, determining the optimal UAV altitude requires considering both the distance and LoS probability together.

In [42], evolutionary algorithms to find the optimal deployment of Low-Altitude Platforms (LAPs) and portable base stations for disaster relief scenarios are utilized. In this work, by deploying UAVs in optimal locations, the number of base stations required for full coverage of the desired area was minimized. A framework for the joint deployment and task assignment of UAVs was provided, serving ground users. Additionally, the problem of joint deployment and task assignment was examined using concepts from game theory and queuing theory.

A proactive drone-cell deployment framework to reduce the overload caused by flash crowd traffic in 5G networks is proposed in [43]. This approach assumed the cell placement problem as a clustering problem and considered users under the coverage of each drone as a cluster. Placing the drone at the center of each cluster ensures that the drone cell has the minimum sum of squared distances with all cluster members. Finally, a constraint bisecting k-means method was proposed to solve the drone placement problem. Traffic models for three social activity scenarios: stadium, parade, and gathering, were also investigated.

In [44], the problem of deploying multiple drones/UAVs and developing drone mapping to areas with high traffic demand using a neural network-based objective function is addressed. They investigate the problem of deploying multiple drones in such a way that the mapping method allocates drones to areas with high traffic demand using a neural network-based cost function.

Ref. [45] presents a study on optimizing the placement of drone base stations (DBSs) to enhance the coverage and service quality of 5G cellular networks. The paper addresses the reduced antenna coverage in 5G networks due to higher data transmission rates and the impact of environmental events on network coverage. The authors propose a fuzzy clustering algorithm to select specific candidate points for DBS placement, modeled as a P-median optimization problem, where P is the number of antennas needed to cover users.

In [46], an active deployment method for cache-enabled drones considering the content of messages to improve the Quality of Experience (QoE) for users is proposed. In this approach, drones cache the desired content based on a caching prediction model, which can reduce data packet transmission delay.

An adversarial search to find optimal locations for UAVs to address disasters and improve public communication security is used in [47]. The authors of [48] obtained optimal paths and positions for multiple drones, considered as aerial base stations for collecting data in the IoT, using the optimal transportation theory framework. Lyu et al. proposed a polynomial-time solvable algorithm for the deployment of mobile base stations, where drones are placed in a spiral path to cover ground users until all users are covered [49].

The authors of [50] provided an overview of optimization methods for solving the aerial base station placement problem. Additionally, they presented a general form of mathematical relationships for the drone base station deployment problem.

In [51], a macro-base station and multiple drone base stations are considered. The authors initially proposed an algorithm to find the three-dimensional locations of the drone base stations, allocate users to base stations, and allocate bandwidth for the access and backhaul of DBSs. Then, they optimized the locations of the DBSs using a particle swarm optimization algorithm to enhance efficiency.

In [52], a framework for using drones as an aerial backhaul network for ground base stations is proposed. Previous studies on drone network planning analyzed issues related to user association, three-dimensional deployment, backhaul connectivity, and optimizing the number of drones to be deployed in the network. However, there has been no real work focusing on signal transmission challenges. Additionally, articles such as [23,27,28,30,33], which were reviewed before, also address the problem in a multi-drone/UAV scenario.

2.3. Path Loss

After the problem dimension, the most important factor to categorize related works is path loss. Many studies in the literature consider path loss as the primary factor affecting service quality and incorporate it into problem solving. However, many other studies have disregarded path loss due to the complexity and non-linearity of the problem. Articles such as [22,23,29–33], which were discussed in the last section, have considered path loss in their respective problems. Moreover, in [53], a mathematical model to optimize UAV positions and user allocation in an IoT network is proposed. The objective of this model is to maximize user connectivity by minimizing the number of FBSs, considering network constraints such as path loss. Since the proposed optimization model is NP-hard and obtaining the optimal solution is exponentially complex, the authors proposed a linear scheme and an algorithm with low time complexity. Therefore, the solution obtained from the proposed method is close to the optimal solution but not exactly. The goal of [54] is to maximize the coverage of a UAV by three-dimensional deployment and allocate the desired bandwidth to users. It proposed a search algorithm to solve the problem and reduce its time complexity. Lai et al. in [55] presented an algorithm for deploying UAVs to provide on-demand services to a group of users. Their goal is to maximize the number of covered users while meeting their data rate requirements.

2.4. Interference

In order to make the assumed problem more realistic, it is crucial to consider the frequency interference among users within a cell and the interference between adjacent cells, as has been explored in some previous works. However, some prior studies have solely focused on intra-cell interference, neglecting inter-cell interference. Articles such as [22,27–29] have taken intra-cell interference into account in their problem formulations.

Additionally, Kalantari et al. in [56] calculated the minimum required number of UAVs and their optimal three-dimensional locations to cover users using an exploratory algorithm. In their proposed method, UAVs adjust their altitude to reduce interference with other antennas and users and obtain their coverage range. They achieve this by lowering their altitude in densely populated areas and increasing it in less populated areas.

Mozaffari et al. in [57] investigated finding optimal cell boundaries and deployment locations for non-interfering multiple UAVs. They optimized the deployment and communication of drone cells to meet user rate requirements while using the minimum transmit power of the drones. Furthermore, Mozaffari et al. in [58] first obtained the optimal altitude of drones to maximize coverage and minimize transmission energy. Then, they examined the maximum coverage problem using two drones in two scenarios: without interference and with interference. They determined the optimal altitude and positions of the drones in both interference scenarios and also obtained the optimal distance between the two drones to minimize interference.

Sobouti et al. in [59] explore the use of UAVs as flying small cell base stations (BSs) to provide network coverage for IoT applications. They address the challenge of deploying fixed infrastructure for IoT networks, which may not always be the best or most economical solution. The advancements in UAV technology offer an alternative by using them as flying BSs.

2.5. Non-Line-of-Sight Link

Consideration of line-of-sight (LoS) or non-line-of-sight (NLoS) links is an important aspect to consider in previous works. Some articles such as [24,27,28,32] have aimed to simplify the problem by disregarding obstacles in the scenario and thus considering an empty environment, relying solely on LoS links. However, articles like [22,23,29–31,33,53–55] have taken obstacles into account in the problem and solved it assuming the existence of NLoS links.

2.6. Energy Limitation

Energy serves as a significant limitation in problems associated with the utilization of drones/UAVs. Given the limited energy source and high energy consumption of UAV flights, it is essential to consider energy constraints in drone/UAV deployment problems. Moreover, it makes the problem more realistic. However, many previous works have disregarded energy constraints due to the complexity of the problem and the difficulty and time-consuming nature of solving it, assuming UAV energy to be infinite in the problem. Nevertheless, there are also articles in previous works that have addressed this issue.

In [60], the problem of minimizing the total energy loss of drones and the loss of data transmission from IoT devices is considered. The key to solving this problem is to calculate the deployment location of connection points and the number of these points when drones are collecting data. They propose a particle swarm optimization-based encoding scheme that confines the drone connection positions in one dimension. Therefore, the number of connection points to calculate is equal to the number of dimensions of the objective problem. This problem is considered as a dynamic dimensional optimization problem. During dimension tuning, the best individual for dynamic search is added or removed. A joint search among multiple individuals can significantly improve the local search optimization.

The swarm intelligence algorithms used in [60] include the Flower Pollination Algorithm (FPA), the Salp Swarm Algorithm (SSA), and the Sine Cosine Algorithm (SCA).

De Freitas et al. in [61] studied the use of drone relays to enhance the connectivity of ground wireless networks. In this work, aerial drones were optimally employed to ensure the transmission of sensor messages to destinations. Additionally, the deployment of multiple drones as wireless relays to provide service for ground sensors was investigated. Specifically, this work addressed the balance between connections among drones and maximizing the coverage area covered by drones. However, the use of drones as aerial base stations and their potential interference in LoS communications was not considered. Alzenad et al. in [10] proposed an algorithm to find the optimal location of drone base stations (DBSs) in two dimensions with the objective of maximizing the number of covered users while minimizing their energy consumption for transmission.

In [62], the three-dimensional placement of drone base stations with the objective of maximizing the number of covered users with different QoS requirements while minimizing energy consumption is considered. They modeled the problem as a multi-centralized circular placement problem. To achieve this, they divided the drone placement problem into vertical and horizontal parts and formulated it as a Mixed-Integer Second-Order Cone Problem (MISOCP). They proposed an improved genetic algorithm to solve it.

Khodashahi et al. in [63] considered a wireless sensor network with a mobile base station. In this work, after clustering the nodes and selecting cluster heads, the optimal location of the base station is determined based on the most efficient energy consumption for delivering data to the cluster heads. In other words, the base station location for the next round is determined in a way that minimizes the energy cost for data communications, where sending data through a step from all cluster heads to the base station prevents data overflow.

Liu et al. in [64] aim to maximize fair coverage while minimizing energy consumption and meeting backhaul requirements at different times. The authors devised a fairness index to ensure equal communication opportunities and area coverage ratios to prevent excessive QoS in covered locations to ensure fair QoS allocation. Then, they proposed an alternating proximal stochastic gradient-based approach for optimizing drone sites that repeatedly executes two optimization phases. This approach smoothens the way for fast single-point first-order methods to address challenging problems with constraints. Additionally, papers such as [27–30,32,40], as previously mentioned, have also considered energy constraints in their problem formulations.

2.7. User's Altitude

Given the prevalence of high raised buildings in urban areas, the significance of users' altitude relative to ground antennas and drones cannot be overlooked. It is essential to consider this parameter when engaging in problem-solving activities. Among the previous studies, only three articles [33,65,66] have considered the height of users. In [33], users themselves are drones, and the objective is to provide services to other drones. As far as the study has shown, this aspect has not been considered in any of the previous works. He et al. in [65] assumed that users are located on surfaces at different heights for the three-dimensional placement of drones. They formulated an optimal coverage model and an optimal connectivity model, both of which are NP-hard. To tackle this problem, they designed a meta-heuristic PSO algorithm and obtained an efficient solution. However, their results are not optimal due to the use of the PSO algorithm. Additionally, the required data rate parameter for users is not considered in their proposed method, but the required number of drones and the path loss under different conditions are compared in the numerical results. Ref. [66] discusses a method for deploying UAVs to ensure optimal network coverage for the IoT. It aims to determine the minimum number of UAVs required for effective IoT network coverage and to find their optimal positions. The authors propose an iterative algorithm that updates the number of required UAVs with each iteration. They also introduce a mathematical model to solve for the optimal positions of the UAVs after linearizing the problem.

2.8. Insight for Future Studies

Previous works in the field of drone/UAV placement, despite being numerous, have not provided a complete and comprehensive solution to this problem. Most relevant articles in this area either overlook some of the real-world constraints or deal with the problem approximately using heuristic or metaheuristic methods due to the NP hardness of the problem or the consideration of only part of the real-world constraints. In this paper, a method is proposed that can accurately solve the problem without losing its generality by considering important real-world constraints such as user heights, intra- and inter-cell interference, energy constraints, the presence of NLoS links, and also the data rate constraints in backhauls. Table 1 provides a general comparison of articles in the field of drone placement. Current hot research topics in the positioning of UAVs within wireless networks include the development of dynamic deployment strategies tailored for 5G and upcoming 6G networks. These strategies aim to optimize UAV positions to enhance network coverage, capacity, and reliability, particularly in challenging environments such as high-density urban areas or remote regions. One new research hot topic is using tethered UAVs. In these applications, UAVs are connected to the base with a line that can provide energy and other requirements. On one hand, this connection limits their mobility, but on the other hand, it increases the UAV's performance. Another key area of focus is the design of energy-efficient positioning algorithms, which seek to maximize UAV flight duration while maintaining optimal communication performance by leveraging advanced optimization techniques and machine learning models such as "Large Language Models". Another significant research interest is the application of artificial intelligence, particularly deep reinforcement learning, to enable UAVs to autonomously adjust their positions in response to real-time changes in network conditions, user demands, and environmental factors. Additionally, there is a growing interest in optimizing UAV positioning to support edge computing tasks, where UAVs can act as mobile edge nodes to process data closer to the source, reducing latency and improving the overall network quality of service. Research is also exploring the integration of UAVs in hybrid terrestrial and non-terrestrial networks, where their optimal positioning can ensure seamless connectivity and robustness in diverse operational scenarios, such as disaster recovery, emergency response, and rural connectivity. Finally, addressing the challenges of interference management, spectrum allocation, and secure communication for UAV-assisted networks represents another critical area of research with the aim of developing scalable and resilient solutions for future wireless communication networks.

Table 1. Comparison of the literature in the field of deployment of UAVs.

Paper	2D/3D	Users Altitude	Interference	Energy Limitations	Single/Multi UAV	LOS/NLOS	Attenuation
[16]	3D	-	-	-	Multi	Both	Path loss
[22]	3D	-	+	-	Multi	Both	Path loss
[23]	3D	-	-	-	Multi	Both	Path loss
[27]	3D	-	+	+	Multi	LoS	-
[28]	3D	-	+	+	Multi	LoS	-
[29]	3D	-	+	+	Single	Both	Path loss
[30]	3D	-	-	+	Multi	Both	Path loss
[31]	3D	-	-	-	Single	Both	Path loss
[32]	3D	-	-	+	Single	LoS	Path loss
[33]	3D	+	+	-	Multi	Both	Path loss
[34]	3D	-	-	-	Single	LoS	-
[35]	3D	-	+	+	Multi	Both	Path loss

Table 1. *Cont.*

Paper	2D/3D	Users Altitude	Interference	Energy Limitations	Single/Multi UAV	LOS/NLOS	Attenuation
[36]	3D	-	-	-	Single	Both	Path loss
[37]	3D	-	+	-	Single	LoS	-
[38]	3D	-	-	-	Multi	Both	Path loss
[39]	3D	-	-	+	Multi	Both	Path loss
[40]	2D	-	+	Energy efficiency	Multi	LoS	Path loss
[41]	2D	-	-	-	Multi	Both	Path loss
[42]	2D	-	-	-	Multi	-	-
[43]	2D	-	-	-	Multi	Both	Path loss
[44]	2D	-	+	-	Multi	LoS	Path loss
[45]	2D	-	-	-	Multi	LoS	Path loss
[46]	2D	-	+	-	Multi	Both	Path loss
[47]	2D	-	+	-	Multi	Both	Path loss
[48]	2D	-	-	+	Multi	LoS	Path loss
[49]	2D	-	-	-	Multi	LoS	Path loss
[51]	3D	-	+	-	Multi	LoS	Path loss
[52]	2D	-	+	-	Multi	Both	Path loss
[53]	2D	-	-	-	Multi	Both	Path loss
[54]	2D	-	-	-	Single	Both	Path loss
[55]	3D	-	-	-	Single	Both	Path loss
[56]	3D	-	+	-	Multi	Both	Path loss
[57]	3D	-	+	+	Multi	Both	Path loss
[58]	3D	-	+	+	Multi	Both	Path loss
[59]	2D	-	+	-	Multi	LoS	Path loss
[60]	2D	-	-	+	Single	-	-
[62]	3D	-	-	+	Single	Both	Path loss
[63]	2D	-	-	+	Multi	-	-
[64]	2D	-	-	+	Single	LoS	-
[65]	3D	+	-	-	Multi	Both	Path loss
[66]	3D	-	+	-	Multi	Both	Path loss

3. Optimizing the Trajectory of UAVs

Achieving the solution to the drone/UAV placement dilemma is a necessary step toward optimizing their paths. Previous research on path optimization can also be categorized based on multiple factors, including problem dimension, network path loss, NLoS links, number of UAVs, energy constraints, and interference investigation. Furthermore, the consideration of user mobility, particularly in cellular networks, as a significant factor necessitating drone mobility, can also be considered as another subject for classifying prior research. In the following section, the literature is reviewed based on the consideration of these categories.

3.1. Dimension of the Problem

The majority of the analyzed literature on optimizing drone trajectory approaches the problem from a two-dimensional perspective. To clarify, drones remain at a fixed altitude and do not vary their height during their journey. However, it is worth noting that some articles have approached the issue from a three-dimensional perspective, which is a matter that we will examine further.

Zhou et al. in [67] presented flight path planning for drones based on the optimization of the bat algorithm (BA) in a static environment. Their main goal is for drones to find a collision-free, shorter, and safer flight path between the starting and ending points in a complex three-dimensional battlefield environment. Based on the standard features of the bat algorithm and the artificial bee colony algorithm, they proposed a new modification of the bat algorithm called the improved bat algorithm (IBA). The IBA mainly utilizes the ABC algorithm to improve the bat algorithm and solve the problem of the BA's inability to perform local search.

Hua et al. in [68] investigated simultaneous uplink and downlink transmission networks with the help of drones, where one drone acting as a transmitter is connected to multiple access points and another drone acting as a base station collects data from multiple sensor nodes. Their goal is to maximize the system power by jointly optimizing the three-dimensional drone path, communication scheduling, and transmission power between drones and sensors. They initially considered a specific case where the path between the UAV-BS and UAV-AP is predetermined. Although the resulting problem is a non-convex optimization problem, they obtained a global solution using the polyblock outer approximation (POA) method based on the hidden uniform structure of the problem. Subsequently, for the general case considering the optimization of the three-dimensional drone path, an efficient iterative algorithm was proposed to optimally solve the subdivided problems based on the successive convex approximation technique.

In [69], Feng et al. focused on maximizing the energy received by all energy receivers by jointly optimizing the UAV's three-dimensional coverage, radiation pattern, and charging time. The optimization problem is non-convex, which is primarily due to the consideration of drone altitude and wireless coverage. To solve this, the authors proposed a low-complexity iterative approach, breaking the main problem into four subproblems and optimizing them sequentially. First, they applied a convex optimization algorithm without constraints to determine the global optimal two-dimensional position. Then, they calculated the optimal drone altitude. Next, they introduced a multi-objective evolutionary algorithm based on decomposition to adjust the antenna element phases for improved performance. Finally, with these variables optimized, the problem was reformulated into a single-variable optimization for charging time, which was solved using standard convex techniques. To minimize the UAV's flight distance, the branch and bound method, framed as a traveling salesman problem, was used.

You et al. in [70] used drones in a wireless sensor network to collect data from multiple sensor nodes. Their goal was to maximize the collected data from sensor nodes considering the scheduling program with three-dimensional drone movement. In this system, communication is not specifically considered as LoS, the effect of communication interruption is also considered, and the data collection rate is proportional to the communication channel model. To solve the problem of three-dimensional space movement, the path is optimized iteratively, once horizontally and once vertically.

Ding et al. in [71] addressed the issue of three-dimensional drone paths and spectrum allocation, considering drone energy consumption and fairness for ground users. To do this, they first defined drone energy consumption as a function of three-dimensional mobility. Then, considering energy constraints, they maximized operational fairness. They proposed a new algorithm based on deep reinforcement learning (DRL). The proposed method allows the drone to control its speed and direction to save energy and reach the desired destination while having enough energy and allocating spectrum bands to achieve fairness.

Wang et al. in [72] examined two types of drones in a secure network with the help of drones. One drone flies to transfer confidential data to a mobile phone user, while the second drone helps by creating artificial noise to distract attackers. Considering the mobility of drones and users, the authors aimed to increase stealthiness in the worst-case scenario for mobile phone users. This challenge was addressed by optimizing the three-dimensional drone path and considering constraints such as time allocation, maximum speed, collision avoidance, positioning error, and energy uptake.

Amrallah et al. examined a wireless communication network for post-disaster areas using UAV technology in [73,74]. Their optimization goal was to maximize the number of ground users visited by optimizing the UAV's flight trajectory. Next, a cost-aware multi-armed bandit algorithm is used to address this issue considering the limited energy for both the UAV and ground users.

3.2. Number of UAVs

In the majority of articles investigating the optimal path finding of drones/UAVs, unlike articles on drone/UAV deployment, the problem assumption revolves around the presence of a single drone/UAV and determining its optimal path. Ghafoor et al. proposed a new approach for the trajectory of a mobile sink in wireless sensor networks in [75]. Their proposed approach is based on the Hilbert space-filling curve; however, their proposed approach is different from previous work. This means that the order of the curve changes based on node density. They also first investigate the trajectory of the sink based on the order of the Hilbert curve, which depends on the network size. Second, they calculate the order of the Hilbert curve based on node density to modify the trajectory of the mobile sink.

Zhan et al. in [76] designed a path for drone movement to collect data from the maximum number of sensors. Their goal is to maximize the collected data, and they used the traveling salesman approach and convex optimization method. The drone's movement path was compared in four passing path modes: zigzag, rectangular, based on density, and the proposed method. Zhang and colleagues in [77] considered a cellular network consisting of a drone and several ground base stations. The drone is tasked with flying from a starting point to an end point and must be in communication with one of the ground base stations during the flight. The goal is to minimize the drone's mission completion time by optimizing its path while considering the constraints of maximum drone speed and minimum signal-to-noise ratio that must be maintained over time. It is noteworthy that the drone is serviced by ground base stations. The drone's path must be properly adjusted to fly between two consecutive points in less time than the expected delay and also comply with the communication constraints with ground stations. The desired problem is non-convex. The authors have reached an approximate solution close to the optimal solution using convex optimization techniques and the shortest path algorithms in the graph.

Zhang et al. in [78] considered the drone as a relay that performs reinforcement and transmission tasks. Meaning, it establishes communication between the user and the ground base station, which cannot establish direct communication due to the long distance. The goal is to minimize the probability of communication interruption by optimizing the drone's path and transmission power. In each of the consecutive time intervals, in the first interval, the mobile device sends a signal to the drone, and in the next interval, the drone amplifies the received signal and sends it to the base station. The probability of interruption in time interval t depends only on the location and energy parameters in time intervals t and $t+1$.

Wu et al. in [79] aim to maximize user throughput. Users can freely move on the ground, and the drone's path along with multi-objective communication planning is optimized. If the path is circular, users outside the circle cannot establish communication, leading to increased delay. However, if the path is such that the drone can fly close to the users and even hover above all of them to serve them all, the objective function increases. To address this issue, binary variables have been expanded into continuous variables, and the new problem has been solved with a suitable algorithm using the block coordinate descent method. However, even if user scheduling is fixed, optimizing the drone's path is still difficult due to its non-convexity. Finally, an iterative algorithm has been presented for the problem using block coordinate descent and convex optimization techniques. With the drone's path, the problem becomes a linear programming problem. It should be noted that any convex function with the first-order Taylor expansion at any point globally has a lower bound; thus, the problem can be solved.

Bulut et al. in [80] consider a drone with a mission to fly from a starting point to an endpoint and must find a path where its communication with one of the ground stations does not drop for more than a specified time interval. The maximum flight time is predetermined, and the goal is to minimize the length of the flight path so that the flight time does not exceed the maximum predetermined time. Since the speed is constant, the minimum path is equivalent to the minimum time. The path is dynamically determined, meaning that at each point, it is decided where to go next to comply with the threshold constraint of minimum communication interruption time and minimize the length of the path. It is necessary to note that the drone may need to pass through redundant locations. In this system, it is assumed that the drone flies at a constant speed and altitude. Communications are of LTE and 5G types, and all ground stations have the same altitude. Dynamic programming is used to solve the problem, which leads to an approximate solution. Initially, a network coverage over the area with the drone and ground stations is considered. If the drone can go to point (i, j) from a neighboring point, the constraint of communication interruption time is met, and its cost is less than the costs of paths previously calculated, the optimal new path from that neighboring point will be utilized.

Bayerlein et al. in [81] examine the optimal path of a drone that serves a number of users as a base station. User locations, drone altitude, and speed are assumed to be constant. The initial and final drone locations are specified, and the maximum flight time is given. The objective is to maximize the total data transmission during the flight time. The authors assume that the drone can adapt to the network topology, meaning it operates autonomously in the environment and learns the best path on its own. Movement decisions are made by a Q-learning-based system. That is, at time t, the drone observes a position, performs an action, and subsequently receives a reward. The goal is for the drone to learn a behavior that maximizes its received reward. Drone decisions are made based on a greedy algorithm and stop when the flight time ends.

Deruyck et al. in [82] consider a terrestrial network with several base stations that cannot satisfy their users. A drone flies as an FBS over the network and provides traffic that is not feasible with the terrestrial network. Users are clustered, users close to each other are placed in a cluster, and the problem is solved based on a clustering algorithm. That is, the drone is located at the center of a cluster at each step. Since the target area is square-shaped, the initial drone location is at the center of this square. In the next step, it is calculated which cluster has the lowest cost to go to, and that cluster is selected as the next destination. This process continues until all clusters are met.

The system proposed by Zeng et al. in [83] consists of a fixed source and destination and a drone (relay) whose objective is to maximize throughput by optimizing the drone's path and power allocation between the source and relay at a specified time. The maximum relay speed and its source and destination points are defined. Data transmission is performed by storing transmitted data from the source in a buffer and then transmitting it to the destination. The drone can improve communication quality and system performance by changing its location at any time.

He et al. in [84] propose an energy-efficient path planning algorithm based on multi-objective particle swarm optimization (MOPSO) to shorten the length of the mobile sink path and balance the load of proposed node sensors. The goal of their proposed algorithm is to reduce data delivery delay and increase network lifetime. To shorten the length of the mobile sink path, they design a mechanism to select potential visit points within the communication ranges of sensor nodes instead of sensor node locations. Additionally, considering the characteristics of the mobile sink path, an effective path encoding method is designed to create a path containing an unlimited number of visit points.

Qian et al. in [85] present a method in which a drone acts as a mobile server and offloads computational tasks to a group of ground mobile phone users moving according to a random waypoint model. The goal of their solution is to maximize the average throughput while considering energy consumption and customer requirements. Their proposed Monte Carlo tree search (MCTS) algorithm has helped them achieve this goal.

Fontanesi et al. in [86] propose a transfer learning (TL) method in which they use a teacher policy trained in one domain to assist the agent in learning the path in another domain. The agent designs a path in the new domain based on future relations with the environment while continuing exploratory and learning activities. They use a Deep Q-Network based on the Lyapunov model to solve the path design problem under 6 GHz, ensuring connectivity constraints. Additionally, Zhou et al. in [87] study a cognitive safe communication network of drones considering the high flexibility and mobility of a drone and the possibility of establishing LoS links.

In [88], Zhang et al. focus on emergency networks equipped with drones, where drones act as FBSs to collect data from ground users in disaster-stricken areas. They formulate an optimization problem for the drone path with energy constraints of user devices and the location of ground obstacles to maximize the connectivity efficiency of long-distance drone networks during flight duration. In [89], Li et al. propose a drone-assisted data collection method to collect data from multiple ground users. Their goal is to optimize the path, altitude, speed, and data links of the drone with ground users to minimize the total mission time. They target emergency applications in their proposed method, as mission time is the main concern there.

Gong et al. in [90] considered a scenario where a drone collects data from a set of sensors in a straight line. They considered that the drone could move or remain stationary while communicating with the sensors. Their goal was to minimize the total flight time of the drone from the starting point to the destination while allowing each sensor to successfully upload a certain amount of data using a specified amount of energy.

Huang et al. in [91] integrated deep reinforcement learning with drone navigation using the multiple-input multiple-output (MIMO) technique to design a deep Q-network for optimizing the drone's path by selecting an optimal policy.

Samir and colleagues in [92] considered a single-hop vehicular network assisted by drones, where sensors on vehicles generate time-sensitive data streams, and drones are used to collect and process these data while maintaining the minimum data age threshold.

However, there are also works that have addressed the problem with multiple drones. Tashtarian et al. in [93] studied the motion control problem of mobile sinks in deadline-based and event-driven applications to maximize network lifetime. In these applications, when an event-driven sensor node records an event, it must determine the visit time and deadline based on the amount of received data and the type of event. Then, the mobile sink needs to determine its trajectory for collecting data from active sensor nodes in single-hop transmission to increase the network lifetime. They showed that this problem is *NP-hard* when there is no predefined structure such as a virtual network or meeting points in the network. They proposed a decision tree-based algorithm and dynamic programming to determine an approximately optimal deadline-based trajectory (ODT) by considering the geographical locations of active sensor nodes and the characteristics of recorded events.

Pan et al. in [94] proposed a deep learning trained with genetic algorithm (DL-GA), which is a combination of the advantages of deep learning and genetic algorithms. The GA collects states and paths from various collection scenarios and then uses them to train the deep neural network to quickly provide an optimized path while encountering familiar scenarios that can meet the needs in a timely manner.

Xia et al. in [95] proposed a multi-drone path-planning method. The proposed method for creating an optimization model is based on the unit time distance rather than traditional station division, which simplifies the calculation of cost functions. Meanwhile, virtual parts are introduced to adapt to the different lengths of drone paths to reduce the total arrival time of drones at the destination. In the proposed model, non-linear constraints are transformed into cost functions, and to minimize the cost function, a sequential gradient-based optimization algorithm is presented, which separates the conflicting constraints with the goal of saving planning time in each iteration.

Samir et al. jointly optimize the trajectory and radio resources for multiple drones to deliver sensitive and critical data in vehicular networks on highways during accidents and disaster conditions [96]. Their aim is to minimize the number of deployed drones for full service to all vehicles. The formulated problem is the NP-hard type. To solve this problem, the authors have used a sequence of convex approximations. Then, they presented an efficient algorithm to solve this sequential problem.

Jiang et al. investigated the optimal path of drones equipped with multiple antennas to maximize the sum rate in relay communications [97]. The output of the relay-based drone system is maximized by jointly optimizing the drone path and the transmission power of the source/relay.

Dogancay studied path planning for multiple drones for passive emitter localization [98]. In this work, a set of path points leading to minimum localization is determined using the angle of arrival and time difference of arrival information. However, Dogancay's work is limited to localization and does not directly address any wireless communication problem. Ultimately, controlling the independent motion of UAVs requires low complexity, and therefore, implementable algorithms for UAV movement can achieve the maximum efficiency spectrum under realistic traffic scenarios. Finding a movement path that minimizes such interference becomes more challenging when BSs do not reside in the same location. The author also proposed an optimal movement pattern for multiple mobile phone BSs to maximize the lifetime of a wireless sensor network (WSN) and, accordingly, examined three movement patterns: random, grid, and spiral movement patterns.

Fadlullah et al. proposed a dynamic motion control algorithm for drones in [99]. This algorithm considers drones experiencing overcrowding and communication delays due to queuing above a threshold. To alleviate congestion in drones, their coordinates' center and, if necessary, their path radius are adjusted by this algorithm.

In [100], He et al. aim to optimize a three-dimensional path for multiple drones using ground devices (GDs) to select the target drone for offloading processing. Initially, they developed a three-dimensional mobile edge computing system with the assistance of multiple drones, allowing GDs to update tasks and enable real-time mobility. Then, they developed objective functions fairly distributing tasks among drones for computation, communication, and system energy consumption during flight.

Hu et al. investigated how to construct a path for a group of energy-limited drones dynamically operating in different positions in a wireless network in [101]. In their model, a group of drone base stations (DBSs) cooperatively dispatched to clusters of ground users with dynamic and unexpected requests. Their goal was to maximize the coverage range of users using a Value Decomposition-based Reinforcement Learning (VD-RL) approach.

3.3. Path Loss

Since the path loss is the most important factor for the attenuation, in previous works, various articles have considered path loss as the main factor in service quality in the problem of finding the optimal path.

Ji et al. in [102] have investigated the problem of secure transmission in a drone relay network with caching and device-to-device communications, assuming the presence of eavesdropping. Specifically, drone users and device-to-device (D2D) users are equipped with cache memory, which can retrieve some popular content for shared service to other users. The authors have formulated an optimization problem to maximize the minimum concealment among users by jointly optimizing the user allocation, drone scheduling, transmission power, and drone path in a limited period. The joint design problem is a non-convex mixed-integer optimization problem. To efficiently solve this problem, the authors have proposed an alternating iterative algorithm based on alternating block coordinate descent and successive convex approximation methods. In particular, the user–drone communication and scheduling, drone path, and transmission power are alternately optimized in each iteration, and the convergence of the algorithm has been proven.

Ji et al. in [103] have introduced a drone-based data transmission system using caching. Their goal is to minimize power consumption among receiver users from the drone by placing the cache memory and jointly optimizing the drone path and transmission power in a limited period. The optimization variables related to the cache memory, drone path, and transmission power are optimized alternately in three different blocks and periodically. Also, a comparison in the case of one, two, or three drones has been studied.

Wu et al. in [104] jointly optimize the user scheduling and drone path to maximize the average data rate among ground users. They consider a wireless communication system where drones serve a number of ground users. Drones operate periodically. The selection of the duration of the period has a significant impact on the system's performance. A larger T provides more time for drones to be close to users and create a stronger channel. However, it increases the delay time for other users. So, the T value must be chosen properly. Each drone must return to the initial point at the end of each period. Also, drone paths are planned considering speed constraints and avoiding collisions.

Tang et al. in [105] aim to maximize the average power by jointly designing the transmission power and movement path for an active network of UAVs. The common method to deal with this problem is based on alternative optimization, with repeated updates of power and path until convergence, resulting in a subproblem of finding a non-convex path. To develop more efficient methods, the authors have proposed a new alternating optimization method by combining power and path in an intermediate variable and then updating the power and path variables again. This new variable decomposes the main problem by turning it into two convex subproblems, namely a subproblem of maximizing operational power and an easier feasibility subproblem. Therefore, both of these subproblems can be solved globally. Tang et al. also propose an algorithm with low complexity to ensure the solvability of the subproblem by utilizing the Alternating Directional Method of Multipliers (ADMM), whose update step is performed in closed-form solutions.

Zhao et al. in [106] provide a NOMA-based network that utilizes UAVs and BSs simultaneously to cover users located on the ground. Their goal is to maximize the data rate by jointly optimizing NOMA precoding and the UAV's flight path. To achieve this, they decompose the problem into two stages. First, they maximize the sum rate of the users served by the UAV. Afterwards, they obtain the optimal NOMA encoding vectors through two different schemes with distinct constraints. The first scheme focuses on eliminating BS interference for the users served by the drone, while the second scheme limits the interference to a specific threshold. In both cases, the initially non-convex optimization problems are transformed into solvable forms using an iterative algorithm.

Zeng et al. in [107] consider a drone that delivers a shared file to a set of ground terminals. Their goal is to optimize the trajectory to minimize the drone mission time. The height is a constant and the minimum safe flight altitude. The obtained trajectory is formed by a number of waypoints, and it is an extension of the traveling salesman problem with the difference that it is not necessary to return to the starting point. Since the drone can communicate with more than one user simultaneously, it does not need to be above all users, so the number of line segments forming the trajectory is reduced. Therefore, these waypoints and the instantaneous speed of the drone along the paths connecting these waypoints must be optimally determined. The problem is reconstructed so that the paths are designed to meet the minimum connection time constraint, during which the horizontal distance between the drone and the terminal is less than a specified value. The optimal speed of the drone for the given waypoints is also obtained by solving a linear programming problem.

In their work [108], Xu et al. consider a drone as an energy transmitter, which is tasked with charging a number of energy receivers on the ground. Their goal is to optimize the drone's path and maximize the amount of energy transferred to the energy receivers (ERs). To ensure fair energy transfer, the problem is transformed into maximizing the minimum received energy of ERs. The solution to this problem suggests finding points where the drone hovers for a certain period at each of these points and flies between these points at its maximum speed. Then, the path must be specified in such a way that it meets all these points and minimizes the time or, in other words, the minimum flight distance. Ground users have fixed points; therefore, initially, specific points for the drone that have the highest transmitted energy to users are created, and then the drone moves between these points using an optimal routing algorithm. The optimal routing algorithm is also designed based on the selected points. Initially, a number of points are selected as optimal points for the drone to hover, and then a smooth movement according to the drone's maximum speed is created on these points.

In [109], Nguyen et al. developed a drone-assisted IoT system that maximizes the amount of data collected from IoT devices while depending on the shortest flight paths of drones. Then, a deep reinforcement learning-based method was developed to determine the best path and operational power in a covered area. After training, the drone was able to independently collect all the data from user nodes and improve the total data rate while using fewer resources.

3.4. Interference

Some of the reviewed articles have overlooked the presence of interference within or between cells in order to simplify the problem of finding drone paths. However, articles such as [68,69,102,104,106] have considered this issue.

The first feature Huang et al. pointed out in [110] is the different perspectives on users based on their QoS requirements, categorizing them into delay-sensitive and delay-tolerant groups and jointly optimizing various parameters. Their objective is to maximize the minimum rate of delay-sensitive users while minimizing the power allocation to different users and the drone trajectory. They solved the problem by breaking it down into two optimization subproblems: bandwidth/power allocation and routing, which were optimized sequentially in two separate blocks while keeping the other fixed.

In [111], Chowdhury et al. address the problem of finding an optimal path for a drone to improve the coverage of a ground mobile phone network. They assume that a drone travels from one point to another within a specified time range and can simultaneously assist the mobile phone network with coverage during its mission. Considering the downlink link with cellular network interference constraints, the authors model an optimization problem to maximize the fair data rate of the mobile phone network and explore dynamic programming techniques to find the optimal drone path. They also investigate optimal drone paths and compare the capacity and performance of three different coverage methods.

Ref. [112] examines the challenge of optimizing the flight paths of multiple UAVs to minimize interference in next-generation wireless networks. The paper tackles the issue of co-channel interference among UAVs when they are used as FBSs in beyond 5G networks. The unit disk graph (UDG) model is employed to create interference-aware UAV trajectories.

3.5. Non-Line-of-Sight Link

In previous works, the existence of obstacles has been disregarded in order to simplify the problem of finding the optimal path. In this case, the assumption is that the communication link between the drone/UAV and users is LoS. However, some articles have acknowledged the inclusion of the NLoS link in their investigation.

Hu et al. in [113] considered scenarios where drones are tasked with real-time sensing and solved the distributed drone path design problem using reinforcement learning. The authors first extracted a sensing and transmission protocol for coordinating multiple drones. To evaluate the performance of this protocol, they examined the successful data transmission probability using Markov chain Monte Carlo methods. Then, after formulating the drone path problem under the reinforcement learning framework, they proposed an improved multi-agent Q-learning algorithm for effective problem solving.

Zhang et al. in [114] studied a cellular drone system where a drone collectively performs sensing and data transmission tasks to a base station. By optimizing data sensing and transmission on the drone, the drone's energy efficiency is maximized. Zhang et al. divided this non-convex problem into two subproblems: data sensing optimization and data transmission optimization to the base station. In the data sensing optimization section, they designed the drone's path and speed using convex optimization and differential methods. In the data transmission optimization section, transmission power is optimized using extremum principles.

3.6. Energy Limitation

In the problem of finding an optimal drone path, energy is one of the most challenging and important constraints. Since the flight and movement of drones constitute a significant portion of their energy consumption, many previous works have considered this crucial factor in their problem-solving approaches.

Tang et al. in [115] proposed a combination of enhanced optimization algorithms, including improved particle swarm optimization (PSO), artificial potential, the path exploration state change strategy, and the energy-based scheduling mechanism to optimize global or local path planning. In their proposed model, the PSO algorithm improves based on adaptive inertia weight updating and the mutation mechanism related to the number of iterations, resulting in smoother global paths. Then, the artificial potential algorithm is used for optimization to solve the problem of inaccessible target points and local minima. Finally, the model comprehensively considers site information to achieve drone task scheduling.

Zhou et al. in [67] studied a secure cognitive drone communication network with a high flexibility of drones and the ability to establish LoS links. The secondary network's average concealment with optimized drone movement path and transmission power is maximized. The problem formulation encompasses two practical location estimation cases: worst-case and outage-constrained scenarios. To solve the non-convex problems in this formulation, an iterative algorithm based on the S-procedure for the worst-case and a Bernstein-type inequality-based iterative algorithm for the outage-constrained case are presented, which have found suboptimal solutions to the respective main problems.

Di Franco et al. in [116] proposed a drone path-planning algorithm for the visual sensing of a specific geographical area. The proposed algorithm covers the entire area under examination while minimizing the overall energy consumption for the drone. To achieve this, the authors computed the optimal set of path points and the optimal speed for the drone along the path between these points. Considering an avoidance of collisions, no-fly zones, and altitude constraints, the optimal drone paths minimizing fuel consumption were calculated using mixed-integer linear programming (MILP).

Another example of path optimization in the work of Mozaffari et al. in [39] is observable. Specifically, they considered a scenario of an IoT network aided by UAVs, where five UAVs are utilized for data collection from ground IoT devices. A set of 500 IoT devices is uniformly distributed within a 1 km by 1 km geographical area. The IoT network varies over time, where the total active IoT devices change over time based on a beta distribution. Thus, to effectively serve the IoT devices, UAVs need to update their locations according to the active device locations. In this model, predefined time slots are assumed during which UAVs collect data from active IoT devices. At the end of each time slot (i.e., update time), UAVs update their locations according to the IoT device activation pattern. With such a time-variable network, the objective is to find the optimal paths for UAVs so that they can update their locations with minimal energy consumption while serving the IoT devices along optimal routes.

Alsharoa et al. in [117] considered a wireless relay system composed of several mobile users. In this system, users seek to transfer data to a common destination, but their distances from each other are such that direct communication is not possible. The authors' goal is to optimize the energy consumption of the relay and the trajectories of the drones to maximize the total data transmission from ground users to the destination. Each drone is assigned a predetermined path, which can be adjusted if necessary based on the drone's energy constraints and path constraints.

Zeng et al. in [118] proposed another wireless relay system, where the transmission of signals from mobile devices to the base station is performed by a relay drone responsible for the encryption and transmission of the signal. The drone performs decryption and transmission operations and can improve communication quality by changing its location and transferred energy. In the first stage of each time interval, the mobile device sends the signal to the drone. Then, in the second stage, the drone decrypts, encrypts, and transmits the signal to the base station. The probability of communication link failure is defined as the probability that the received signal falls below a predetermined threshold. The objective function minimizes the probability of link failure by optimizing the drone's path and transmission energy. Since the problem is non-convex, the authors decomposed it into two subproblems. Since the first subproblem is still non-convex, it is solved separately for each time interval. In the first phase of each time interval, the mobile device sends the signal to the drone, and in the second phase, the drone decrypts, encrypts, and transmits the signal. The probability of communication failure means that the signal-to-noise ratio received falls below a lower threshold, which depends only on the transmission power in that time interval.

Lyu et al. in [119] considered a single-cell communication system consisting of a drone, a ground base station, and several mobile terminals. In this system, the ground base station is located at the center of the cell. The optimal solution is obtained such that if the distance of a mobile terminal from the ground base station is less than this value, it is served by the ground base station, and if it is greater than this value, it is served by the drone. The drone's path is circular with constant speed and altitude, and it is centered at the location of the ground base station. In each time interval, mobile terminals that are close to the drone and can establish communication with it are scheduled. Thus, the objective is to maximize the minimum power of all mobile terminals by optimizing the radius of the drone's path and the threshold distance from the ground base station to the user.

Zeng et al. in [120] considered a drone flying horizontally at a constant speed and communicating with a ground terminal, which was responsible for transmitting information to it. The objective is to maximize the energy efficiency of the transmission by calculating the total number of information bits sent to the ground terminal. This is achieved by optimizing the drone's path and considering its energy consumption. In general, the authors presented a mathematical model for calculating the optimal circular path around a ground station considering the speed, acceleration, energy consumption, and other constraints of the drone.

Koyuncu et al. in [121] investigate the problem in two static and dynamic modes. In the static mode, terminals have a constant density function, but in the dynamic mode, their density changes over time. In the static mode, the goal is to find the optimal locations for drones to minimize the average energy consumption. However, in the dynamic mode, the objective is to find the optimal drone path while considering the constraint that the total distance traveled does not exceed a certain value, aiming to minimize the average energy consumption.

Wang et al. in [122] proposed an architecture for data offloading from smartphones to satellites in low Earth orbit using drones as relays. By doing so, they improved the connection time of smartphones, energy management, and drone path for network capacity enhancement. Their approach involves using non-linear integer programming (NLIP) for simulating the problem. Li et al. in [123] proposed an internal deep Q network for minimizing the packet loss of sensor devices. They performed this by optimizing device charging decisions, data collection strategies, and the instantaneous patrol speed of drones.

Wang et al. in [124] proposed an IoT network using drones, where a low-altitude drone platform serves as both a mobile data aggregator and an aerial anchor node to assist ground base stations in data collection and device localization. They introduced this method with the goal of minimizing the maximum energy consumption of all devices.

Zhan et al. in [125] considered a scenario where multiple drones collect data from a group of ground sensor nodes. They examined the trade-off between aerial costs, which include the energy consumption of propulsion and operational costs of all drones, and ground costs, which are defined as the energy consumption of all sensor nodes. Their goal was to minimize the weighted sum of these two costs by jointly optimizing the drone paths, time allocation, and transmission power of all sensor nodes.

Kouroshnezhad et al. in [126] determined drone paths for servicing IoT devices based on a connected graph. Their proposed method, known as Semi-dynamic Mobile Anchor Guidance, uses a weighted search algorithm to determine the shortest energy path for conservative planning with the goal of dynamically meeting nodes.

Building on prior work, [127] used fuzzy logic to optimize the positioning and trajectory of FBSs in advanced cellular networks, particularly for enhancing emergency response capabilities. While a detailed analysis awaits a full review of the paper, it is likely to introduce the role of FBSs in next-generation (5G and beyond) networks, highlighting the critical role of efficient deployment and movement strategies in emergency situations. The paper is expected to discuss how fuzzy logic can be applied to address uncertainties inherent in 3D positioning, which is a key factor for guaranteeing reliable communication during emergencies. Furthermore, it is anticipated that the authors formulate an optimization problem aimed at minimizing the number of deployed FBSs while maximizing network coverage and connectivity for emergency services. The solution likely involves a fuzzy logic-based algorithm that takes into account various constraints like energy consumption, coverage area, and quality of service.

3.7. User Mobility

The movement of users and their change in positions result in exiting the coverage range of base stations. In order to adequately cover and attend to them, the UAVs need to relocate to more advantageous positions. Although the mobility of users is a prevalent constraint in cellular networks, particularly in urban areas, only a few previous studies have incorporated this assumption into their problem formulation. One reason for this is that most previous works have been in the field of wireless sensors and IoT networks, where drones have mainly been used for data collection from fixed points. However, articles like [96,115] have taken user mobility into account in their problems and addressed the problem of finding optimal drone paths.

In [128], Hou and colleagues proposed a neural network (NN)-based method for optimizing discrete variables. They used a deep reinforcement learning-based pointer network called Advantage Pointer-Critic (APC) and a deep unfolding NN for optimizing continuous variables. To do this, they first created a Markov decision process to describe user interactions; then, they trained the APC network using the Advantage Actor–Critic method. The APC networks consisted of a pointer network and a multi-layer perceptron. From the perspective of deep unfolding NN, they first developed a coordinate descent method for optimizing FBS paths and transmission power; then, they incorporated the algorithm into a trainable-parameter-layer NN.

Sobouti et al. in [18] investigate methods to improve energy efficiency in cellular networks using FBSs. These UAV-based stations are crucial for expanding network coverage and quality of service, but their energy consumption poses a challenge. The authors propose a two-stage approach to optimize the 3D trajectories of multiple FBSs. In the first stage, they determine the minimum number of FBSs required and their optimal positioning for each network state. The second stage focuses on trajectory planning, where energy consumption and flight distances are considered to find the most efficient path for each FBS. This stage utilizes a binary linear problem (BLP) model to optimize travel between the starting and ending points while factoring in obstacles and avoiding collisions. Finally, the authors introduce a FBS set management (FSM) technique to manage the set of active FBSs and their power consumption efficiently, as the number of stations required can fluctuate.

3.8. Insight for Future Studies

Previous studies on optimizing drone paths have focused on three aspects: control and navigation, localization, and wireless communications. Specifically, in works related to drone/UAV communications, path optimization has been performed considering energy consumption, data rate, and reliability. For the effective use of drones in wireless networks, drone paths need to be optimized considering wireless metrics such as operational power, coverage, and the additional energy constraints of the drones. While optimizing both path and communications is a challenging task, it can significantly improve the performance of wireless networks managed by drones. Table 2 presents a comparison of previous works in the field of optimizing drone movement paths. Generally, path planning and the security of communications are studied well in vehicle applications, including UAVs [129,130].

Table 2. Comparison of the literature in the field of optimizing the trajectory of UAVs.

Paper	2D/3D	Users Mobility	Interference	Energy Limitations	Single/Multi UAV	LoS/NLoS	Attenuation
[18]	3D	+	+	+	Multi	Both	Path loss
[25]	3D	-	+	-	Multi	LoS	Path loss
[26]	3D	+	+	+	Multi	LoS	-
[67]	3D	-	-	-	Single	LoS	-
[68]	3D	-	+	+	Single	LoS	Path loss
[69]	3D	-	+	+	Single	LoS	Path loss
[70]	3D	-	-	-	Single	LoS	Rician fading
[71]	3D	-	+	+	Single	LoS	-
[72]	3D	+	+	+	Dual	LoS	Path loss
[76]	2D	-	-	-	Single	LoS	-
[77]	2D	-	-	-	Single	LoS	-
[78]	2D	-	-	+	Single	-	Path loss, channel fading coefficients
[80]	2D	-	-	+	Single	-	-
[81]	2D	-	-	-	Single	Both	Path loss, small-scale fading, obstacle shadowing
[84]	2D	-	-	Energy efficient	Single	-	-
[85]	3D	Random waypoint	-	+	Single	LoS	Free-space path loss
[86]	2D	-	-	-	Single	LoS	-
[87]	2D	-	+	+	Multi	LoS	-
[88]	2D	+	-	+	Single	Both	Fading
[89]	3D	+	-	-	Single	LoS	-
[90]	2D	-	-	+	Single	LoS	-
[91]	2D	-	-	-	Single	LoS	-
[92]	2D	-	-	-	Multi	LoS	-
[93]	2D	-	-	+	Multi	-	-
[94]	2D	-	-	+	Multi	LoS	-
[95]	2D	-	-	+	Multi	-	-

Table 2. *Cont.*

Paper	2D/3D	Users Mobility	Interference	Energy Limitations	Single/Multi UAV	LoS/NLoS	Attenuation
[96]	2D	+	-	-	Multi	LoS	-
[97]	2D	+	-	-	Multi	LoS	Path loss
[100]	3D	+	-	+	Multi	LoS	-
[101]	2D	-	-	-	Multi	LoS	-
[102]	2D	-	+	+	Single	LoS	Path loss
[103]	2D	-	+	+	Multi	LoS	Path loss
[104]	2D	-	+	+	Multi	LoS	Path loss
[105]	2D	-	-	+	Single	LoS	Path loss
[106]	2D	-	+	-	Single	LoS	Path loss
[107]	2D	-	-	+	Single	LoS	Path loss and Rician fading
[108]	2D	-	-	+	Single	LoS	Path loss
[110]	2D	-	+	+	Single	LoS	-
[111]	2D	-	+	-	Single	-	Path loss
[112]	3D	-	+	+	Multi	Both	-
[113]	2D	-	-	-	Multi	Both	Path loss
[114]	2D	-	-	+	Single	Both	Path loss
[115]	2D	+	-	+	Single	LoS	-
[117]	2D	+	-	+	Multi	Both	Path loss
[118]	3D	-	-	+	Single	-	Path loss
[121]	2D	-	-	+	Multi	LoS	Path loss
[122]	3D	+	+	+	Single	LoS	-
[123]	2D	-	-	-	Single	LoS	-
[124]	3D	-	-	+	Single	LoS	-
[125]	2D	-	-	+	Multi	LoS	-
[126]	2D	-	-	+	Single	LoS	-
[127]	3D	+	-	+	Multi	Both	Path loss

Hot research topics in the trajectory planning of UAVs within wireless networks include the development of adaptive path optimization algorithms that enable UAVs to dynamically adjust their flight paths in real time to maximize network coverage, minimize energy consumption, and reduce latency. Nowadays, the usage of machine learning and artificial intelligence techniques, such as reinforcement learning and deep learning, helps create intelligent UAV trajectory models that can autonomously navigate complex environments while maintaining optimal communication links with ground users and other network nodes. Another significant research interest involves the integration of UAV trajectory planning with non-terrestrial networks (NTNs), such as satellite and high-altitude platform systems (HAPSs), to provide seamless connectivity in remote or underserved areas. Additionally, research is exploring the impact of UAV trajectories on network performance metrics, such as throughput, spectral efficiency, and interference management, and developing algorithms that consider these factors to optimize the overall quality of service. Multi-UAV coordination for collaborative trajectory planning is another emerging area, where the focus is on designing decentralized algorithms that enable a fleet of UAVs to work together to enhance coverage, capacity, and network resilience. Furthermore, addressing challenges related to UAV trajectory security, such as preventing eavesdropping and jamming attacks, is becoming increasingly critical in ensuring secure and reliable communication in UAV-assisted networks. Finally, research is also focusing on the impact of environmental factors, such as wind, weather, and obstacles, on UAV trajectories and developing robust path-planning strategies that account for these uncertainties to ensure safe and efficient flight paths in diverse operating conditions. Moreover, trajectory planning for tethered UAVs is also drawing attention these days. Managing connected tethered UAVs presents a formidable challenge to tackle.

This survey has examined various research articles, categorizing them based on their approaches to the problem environment. Recognizing the importance of solution methods, the paper compares a selection of these works in Table 3. This comparison reveals that most prior studies lack real-world applicability, often neglecting crucial considerations in their problem formulations. Furthermore, as the application of UAVs in wireless networks is increasingly prevalent, and positioning and trajectory optimization are critical to the performance of any method, this article provides researchers with a comprehensive understanding of the key challenges in this field.

Table 3. Comparison of different works in the field of optimizing the trajectory of UAVs from the point of view of problem solving.

	[89]	[90]	[123]	[124]	[91]	[68]	[125]	[92]	[109]	[128]	[18]	[127]
Trajectory design	*			*	*	*	*	*	*	*	*	*
3D trajectory	*					*			*		*	*
Uplink		*	*	*		*	*	*	*			
Downlink						*				*	*	*
Obstacle consideration					*						*	
Dynamic environment				*			*	*	*	*	*	*
Sum-rate maximization			*			*		*	*	*	*	*
Energy optimization				*		*	*				*	
Time minimization	*	*	*						*			
Mathematical solution	*	*		*		*					*	*

4. Conclusions

The integration of UAVs into mobile networks offers significant potential to enhance network performance, providing critical services such as coverage extension, improved throughput, and increased energy efficiency. However, the challenges of optimal UAV placement and trajectory design remain complex, involving a balance of multiple objectives and constraints. This survey has reviewed the current state of research in this domain, highlighting the objectives, models, and methods used in UAV placement and trajectory optimization. The analysis reveals that while significant progress has been made through various optimization techniques, heuristic algorithms, machine learning approaches, and distributed solutions, there remain several open challenges that require further investigation. Future research should focus on addressing these challenges, particularly in the areas of dynamic and adaptive optimization, real-time decision making, and the integration of UAVs in more complex and heterogeneous network environments. Advances in these areas will be crucial for realizing the full potential of UAVs in enhancing mobile network performance. In our future research, we explore the development of hybrid optimization frameworks that combine up-to-date machine learning methods with traditional optimization techniques to better adapt to the dynamic nature of UAV-assisted wireless networks.

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Abbreviations

Full Name	Abbreviation
Unmanned aerial vehicles	UAV
flying base stations	FBS
quality of service	QoS
line of sight	LoS
non-line of sight	NLoS
air-to-ground	A2G
user equipment	UE
channel state information	CSI
Mixed-Integer Programming	MIP
Artificial Bee Colony	ABC
Global Positioning System	GPS
Visible Light Communication	VLC
Gated Recurrent Units	GRU
Convolutional Neural Network	CNN
Internet of Things	IoT
signal-to-noise ratio	SNR
Successive Convex Approximation	SCA
Low-Altitude Platform	LAP
drone base stations	DBSs
Quality of Experience	QoE
base stations	BSs
Flower Pollination Algorithm	FPA
Salp Swarm Algorithm	SSA
Sine Cosine Algorithm	SCA
Mixed-Integer Second-Order Cone Problem	MISOCP
bat algorithm	BA
improved bat algorithm	IBA
polyblock Outer Approximation	POA
deep reinforcement learning	DRL
multi-objective particle swarm optimization	MOPSO
Monte Carlo tree search	MCTS
transfer learning	TL
multiple-input multiple-output	MIMO
optimal deadline-based trajectory	ODT
deep learning trained with genetic algorithm	DL-GA
wireless sensor networkv	WSN
non-linear integer programming	NLIP
Value Decomposition-based Reinforcement Learning	VD-RL
device-to-device	D2D

Alternating Directional Method of Multipliers	ADMM
particle swarm optimization	PSO
Advantage Pointer–Critic	APC
binary linear problem	BLP
FBS set management	FSM

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