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Advancing UAV Communications: A Comprehensive Survey of Cutting-Edge Machine Learning Techniques

CHENRUI SUN [1] (Student Member, IEEE), GIANLUCA FONTANESI [2] (Member, IEEE), BERK CANBERK [3,4] (Senior Member, IEEE), AMIRHOSSEIN MOHAJERZADEH [5] (Member, IEEE), SYMEON CHATZINOTAS [2] (Fellow, IEEE), DAVID GRACE [1] (Senior Member, IEEE), AND HAMED AHMADI [1] (Senior Member, IEEE)

[1]School of Physics, Engineering and Technology, University of York, YO10 5DD York, U.K.
[2]Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg, 1855 Luxembourg-Kirchberg, Luxembourg
[3]School of Computing, Engineering and The Built Environment, Edinbrough Napier University, EH10 5DT Edinburgh, U.K.
[4]Department of Artificial Intelligence and Data Engineering, Istanbul Technical University, 34469 Maslak-Istanbul, Türkiye
[5]Department of Computing and Information Technology, Sohar University, Sohar 311, Oman

CORRESPONDING AUTHOR: HAMED AHMADI (e-mail hamed.ahmadi@york.ac.uk)

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ABSTRACT This paper provides a comprehensive overview of the evolution of Machine Learning (ML), from traditional to advanced, in its application and integration into unmanned aerial vehicle (UAV) communication frameworks and practical applications. The manuscript starts with an overview of the existing research on UAV communication and introduces the most traditional ML techniques. It then discusses UAVs as versatile actors in mobile networks, assuming different roles from airborne user equipment (UE) to base stations (BS). UAV have demonstrated considerable potential in addressing the evolving challenges of next-generation mobile networks, such as enhancing coverage and facilitating temporary hotspots but pose new hurdles including optimal positioning, trajectory optimization, and energy efficiency. We therefore conduct a comprehensive review of advanced ML strategies, ranging from federated learning, transfer and meta-learning to explainable AI, to address those challenges. Finally, the use of state-of-the-art ML algorithms in these capabilities is explored and their potential extension to cloud and/or edge computing based network architectures is highlighted.

INDEX TERMS Unmanned aerial vehicle, 6G, federated learning, transfer learning, meta learning, and explainable AI.

I. INTRODUCTION

UAV are aircraft that operate without a pilot and have been recognised as a promising solution in a wide range of applications and scenarios due to their mobility, flexibility, and adaptive altitude [1]. The recent evolution of communication technology, exemplified by the advent of cutting-edge wireless networks, has ushered in a new era of capabilities for Unmanned Aerial Vehicle (UAV) systems. These advancements, exemplified in the survey conducted by Bithas et al. [2], bring higher reliability, reduced latency, and enhanced network throughput to UAVs. Consequently, UAVs now possess greater degrees of freedom, empowering them to undertake increasingly complex tasks.

One of the features of UAVs is their ability to operate effectively at low altitudes. In this role, UAVs can function as a cellular-connected User Equipments (UEs), enabling a wide variety of applications, including the deployment of probe sensors, facilitating short-distance air deliveries, real-time video streaming, and conducting surveillance operations, among others. Simultaneously, they can serve as Base Station (BS) to provide on-demand wireless communications for the specified ranges. Compared with traditional BS, UAV BSs can adjust their altitude, avoid obstacles, and establish Line of Sight (LoS) communication links with ground users [3]. In addition, UAVs can be rapidly deployed in a variety of real-world scenarios, including specific areas during temporary events and disaster situations. However, the integration of UAVs into communication networks is not without its challenges. Dynamic path planning, optimization of UAV spacing and hovering altitudes for maximum coverage, and addressing constraints related to size, weight, and power (SWAP), as outlined in Moza et al.'s survey [4], are among the hurdles that must be surmounted during implementation. In response to these challenges, an integrated framework of Machine Learning (ML) and Artificial Intelligent (AI) can provide suitable solutions for many UAV related problems, especially on UAV navigation, control, and autonomy [5].

This survey explores the relationship and applications between UAVs and ML techniques in communication, focusing on the integration of *recently developed and cutting-edge ML and AI*, offering insights into how these technologies can provide solutions to the challenges faced by UAVs in communication networks, with a particular focus on UAV navigation, control, and autonomy. Additionally, the survey highlights the pivotal role of UAVs in modern communication systems, addressing the opportunities and challenges presented by their rapid deployment and adaptability.

A. UAV CLASSIFICATION

With the rapid advancement of UAV technology and enhanced hardware capabilities, various types of UAVs have emerged to cater to diverse requirements. These classifications are typically based on their wireless system-carrying capabilities, range, altitude, flying mechanism, and size [6]. Within the realm of UAV communication, altitude and wing type serve as common categorization criteria. Based on altitudes, UAVs can be categorized into High Altitude Platform (HAP) and Low Altitude Platform (LAP). Regarding low-altitude UAV designs, they can be broadly categorized into fixed-wing and rotor-wing designs. The former emulates airplane designs, utilizing wings for lift generation, while the latter employs multiple rotors and propellers for thrust generation [7]. Both designs offer unique advantages and drawbacks. Fixed-wing designs are efficient due to reduced thrust requirements, resulting in prolonged flight time. However, they necessitate continuous forward movement, preventing them from hovering above specific locations. Additionally, fixed-wing UAVs require sizable open spaces for takeoff and landing, posing challenges in urban environments [8]. In contrast, rotor-wing UAVs are better suited for urban settings due to their hovering capabilities, but they grapple with battery life and resource limitations [9]. In addressing these issues, the level of intelligence and the type of ML applied become increasingly crucial. This underscores the need for advancing the intelligence of rotor-wing UAVs to overcome challenges related to their limited resources and operational duration.

In addition to traditional low-altitude and high-altitude UAVs, Tethered, as a special aircraft, has also begun to receive more and more attention, and found that it has its own unique advantages. To a certain extent, Tethered alleviates the problems of limited UAVs load, insufficient battery energy, and short air time, although part of the flexibility as a UAVis sacrificed. Tethered UAVs are a combination of UAVs and tethered integrated cables that transmit power and signals via cables that can remain in the air for longer time and complete their tasks. This significantly enhances the payload capacity and mission market for UAVs. Tethered carriers can be in different forms, mainly including Tethered Helikite and Tethered UAV. The tethered helikite is a new type of aircraft that combines a helium balloon and a kite. It maintains altitude through buoyancy and is controlled by connecting cables. The tethered UAV is a low-altitude UAV linked by cables. Tethered Helikite also remains stable in strong winds and is more capable of flying through the air than traditional balloons. At the same time, it can also reach a higher altitude to complete the task, but there is no UAV-level position adjustment ability or flexibility [6]. The tethered UAV can also achieve a larger size LAP with the support of the cable, which has a longer standby time. At the same time, in addition to cables, other pipes can also be embedded in the link, such as water pipes to serve as fire extinguishing UAV. This method significantly enhances the aircraft's payload capacity and utility. However, these two types of Tethered require vehicles or vessels to transport them, and they cannot stray too far from the carrier. Nevertheless, tethered aircraft are still greatly improved in many scenarios.

B. MOTIVATION

As the use of UAVs became more prevalent, it could be observed that they are increasingly desired in a growing variety of industries, particularly for enabling communication. As a flexible embedded flight platform, UAVs are able to combined with different kinds of devices to realize different complex functions. This has significant benefits for Internet of Things (IoT) and smart city related applications and enhances the overall potential of UAV systems.

During the implementation of these applications, several limitations that cannot be disregarded have been found. First, the UAV needs better quality communication circumstances in order to achieve their requirements, such as the chance of LoS between the controller and the UAVs. This necessitates good position awareness, stability, and comprehensive trajectory planning. However, as a small mass aircraft, the performance of UAVs will be significantly impacted by the weather and environment. It is challenging for UAVs to maintain steady performance under extreme weather conditions or complex environments. In addition, UAVs are restricted by the amount of weight they can carry, which will have an impact on the endurance time and processing power. Most commercially available low-altitude UAVs have a flight duration of less than three hours [2]. This significantly increases the dependence of UAV performance on good resource management, for which AI provides many suitable solutions for management and planning. In the beginning, UAVs were initially meant to be manually controlled by people, but with the advancement of UAV hardware and software technology, UAVs now need to operate in more complicated situations with faster speed and longer range. It is difficult to always maintain UAVs within people's sight, and manual control makes the UAV's flight in complicated terrain more reliant on the controller's knowledge and technology. In this instance, AI may utilise the data acquired by UAV sensors to do various tasks and make more sensible judgements on its own. The role of AI is becoming more and more important for UAVs, and at the same time, UAVs have higher and higher requirements for the intelligence and adaptability of AI.

Many current studies and markets have also proved that the combination of AI and UAV has greatly improved the performance of UAVs and their ability to deal with different scenarios, making UAVs an expected mainstream solution in many aspects in the future. ML is the most important technology and tool to realize the intelligence of UAVs. ML allows the integration of AI algorithms, which are able to enhance the overall system level of intelligence and effectively reduce the limitations of the constrained battery and low computational capabilities of UAVs. At the same time, ML-related technologies are updated and iterated fast enough that they can better adapt to the rapid upgrade of UAV hardware and the improved requirements of automation. UAVs benefit from these and have a chance to perform different functions in a wider variety of roles.

The driving impetus behind this paper is to outline the various types of ML methodologies and elucidate the integral role they play in the domain of UAV communication. To attain this objective, an exhaustive survey and classification of the associated ML technologies and their corresponding applications was completed, with an emphasis on the advancements made in recent years. The evolution of ML employed as a road map to compare the strengths of these emerging paradigms of conventional methodologies when applied to UAVs. Of special note is our focus on the groundbreaking applications of these nascent ML methodologies as they integrate with UAVs within the ambit of the forthcoming Sixth Generation (6G) communication networks [10]. In an endeavor to provide a comprehensive understanding, this paper presents a detailed exposition of the principles governing these novel ML techniques as well as delineates potential trajectories for their future application. This focus on the cutting edge and new types of ML underscores commitment to stay at the forefront of technological evolution and its implications for UAV communications.

C. EXISTING SURVEYS ON UAV COMMUNICATIONS

UAV communication has garnered the interest of a great number of people due to its status as an emerging technology that is integrated deeper and deeper with the Fifth Generation (5G) and 6G. As a result, a lot of recent research has been conducted in related areas. [11] surveys all the issues in UAV communication, identifies which problems merit more urgent attention and resolution, and then provides a summary of effective solutions. Then the tutorial in [18] provides an overview of Artificial Neural Networks (ANNs) in wireless communications, which started the discussion on the importance of ML in UAV-related problems.

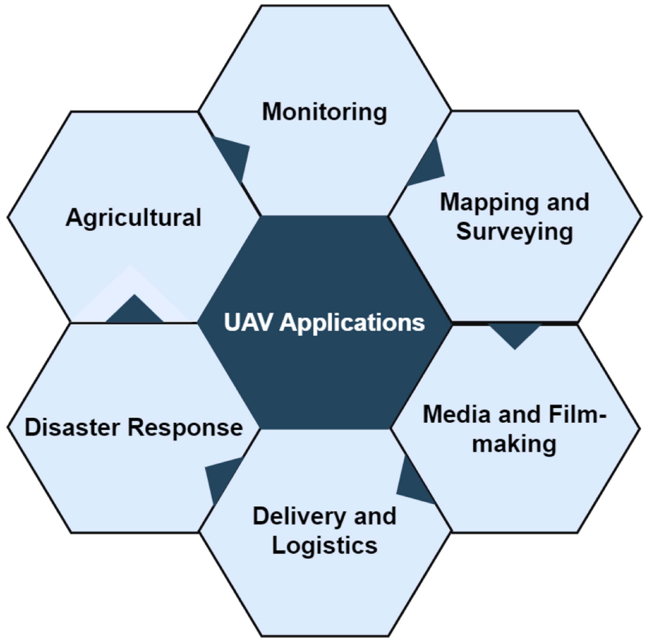

FIGURE 1. Researches on the applications of UAVs in different practical scenarios and regions.

In the context of UAV communication, [4], [19] provide an overview of the applications and challenges of UAV communication with a focus on cellular networks. The authors of [20] present a tutorial on wireless communication with UAVs, taking into account a wide range of potential applications, and have discussed in more detail the role of UAVs in communications. Then [12] provides an exhaustive review of various 5G techniques based on UAV platforms, which are categorized by different domains, including the physical layer, network layer, caching, and so on. [13] presents a comprehensive survey of the literature on the location optimization of UAV-BSs in Next Generation (6G and beyond) Wireless Networks. [7] focuses on the complementary activities from academia, industry, and standardization on the important issue of integrating UAVs into cellular systems. [14] surveys the UAV communication challenges and state of the art from the millimeter Wave (mmWave) point of view. In addition to ML technology, Fig. 1 shows the specific application of UAVs in different situations in actual scenarios. There are also many works summarizing these relevant UAV communication applications based on the types and characteristics of UAVs and then combining them with the specific requirements for communication, such as [21] and [8]. In particular, the authors of [8] have summarized the ML required for UAVs in the process of accomplishing their tasks. This paper builds on these articles by updating emerging ML techniques and the

TABLE 1. List of Related Works and Contribution of This Survey

Paper and year	Description	Application covered	ML Techniques covered	Unique Contributions
[12] 2015	Main issues in UAV communication	Features, Categorization, Control of UAV Network, Ad Hoc Network	None	Early overview of UAV communication challenges
[13] 2018	UAV Communications for 5G and Beyond	Space–Air–Ground Integrated Networks	Unsupervised learning	Early integration of UAVs in 5G networks
[14] 2019	Location optimization in UAV communication	Location optimization	Reinforcement Learning (RL)	Focus on UAV location optimization
[2] 2019	ML for UAV communications technologies and application	Safety, location, resource management of UAV	Unsupervised learning, RL	Application-specific ML techniques
[15] 2019	Key Technical Advantages and Challenges of 5G MmWave	Antenna technology, Radio propagation channel, Multi-access, security	Deep RL	Specialized in 5G MmWave challenges
[16] 2021	Artificial Intelligence for UAV-Enabled network	Channel estimation, UAV detection, IRS-enabled UAV network, resource management	RL, Federated Learning (FL)	Broad AI applications in UAV networks
[17] 2022	A review of Security of UAV-Aided Mobile Edge Computing in IoT System	Mobile Edge Computing (MEC), IoT	RL,FL	MEC security in IoT systems
[8] 2022	Challenges, Applications of UAV Operations and Communications	Performance Metrics, UAV Feature Extraction and Perception, Applications of ML	RL, Transfer Learning (TL)	Comprehensive ML applications in UAV.
[18] 2022	Future of UAV cellular communications	Key technologieS of UAV communication from 5G to 6G	AI	Evolutionary perspective from 5G to 6G
This Survey	Advanced Machine Learning (ML) in UAV communication systems, with UAV roles in networks and 6G implications	Positioning and trajectory, Physical Layer management, Resource and Network Management, Security and safety, 6G, O-RAN, Intelligent Edge Computing	RL, TL, FL, Explainable AI, Meta Learning	Comprehensive ML techniques coverage and forward-looking focus on 6G and intelligent networks

broader application areas of UAVs while investigating the role of different MLs in more detail from the perspective of the role that UAVs play in communications.

In addition, the real-life applications of ML in UAVs communication and networking have been expanded at a rapid rate [22] [23] [24][25], and more ML types, such as TL and meta learning, suitable for UAV-related applications have emerged. Existing aforementioned surveys do not fully cover these emerging ML-related approaches and their use cases in UAV communications. Table 1 shows a comparison of related surveys and the contributions of this survey, which also shows the ML areas covered.

D. METHODOLOGIES

This survey employs a meticulous methodology to explore the role of cutting-edge ML technologies in enhancing UAV communications, focusing on ML solutions that address key challenges in localization, trajectory optimization, and energy efficiency. Special attention is given to their application within emerging 6G networks and their contributions to the development of smart UAV functionalities. The approach for selecting articles is rooted in relevance, novelty, and recency (with a preference for studies published in the last decade), employing strategic keyword searches and citation tracking to pinpoint foundational and innovative research from esteemed sources such as IEEE Xplore and ACM Digital Library. Keywords such as “Unmanned Aerial Vehicles,” “Machine Learning,” “UAV communication systems,” “localization,” “trajectory optimization,” “energy management,” and “6G networks” were strategically chosen to aid this search. Through critical analysis and synthesis, the survey highlights current trends, advancements, and gaps in ML-driven UAV communications, underscoring the key roles of ML technologies in advancing this field. The examination focuses on the relationship and applications between UAV operations and ML innovations, offering a comprehensive overview of the state-of-the-art developments and guiding future research directions in this rapidly evolving area.

E. CONTRIBUTIONS AND THE STRUCTURE OF THE PAPER

This survey makes contributions to the field of UAV communication by focusing on the integration of ML techniques, especially modern and cutting-edge ones, and addressing the challenges and opportunities that arise in this domain. It provide a detailed survey and classification of various ML methodologies which go beyond traditional ML approaches and delve into the realm of cutting-Edge ML techniques, including meta learning, Explainable AI (XAI), FL, and more. this survey reviews the different roles of UAVs within the network architecture and explores the practical use cases of UAVs in various domains, highlighting the requirements and challenges they may encounter. To address these challenges, the proposed techniques are critically reviewed based on the unique characteristics of different use cases. By showcasing practical use cases, the versatility and wide-ranging applicability of UAV communication solutions are demonstrated. Additionally, the survey incorporates the latest advancements in 6G technology to anticipate future research directions. The potential application of UAVs in cloud radio access network (C-RA) and Open Radio Access Network (O-RA) architectures is examined, revealing UAVs' potential as mobile Radio Units (RUs). Moreover, this survey highlights the applications and advantages of UAVs as wireless infrastructure UE. By identifying the strengths and challenges associated with this role, the potential of UAVs to bridge connectivity gaps and expand the scope of communication applications is unveiled.

The rest of this paper is organised as follows: In Section II, a comprehensive overview of ML is provided, encompassing both traditional ML technologies and emerging ones, along with an analysis of their characteristics, differences, and application scopes. Following this, in Section III, the multifaceted roles that UAVs play in the field of communication are examined. This exploration is conducted within the context of application scenarios, focusing specifically on the roles of UAVs as BS and UE. In Section IV, The various challenges and problems that UAVs encounter are addressed. These issues have been categorized and addressed individually to provide a comprehensive understanding of the barriers faced in the deployment and use of UAV. Finally, the challenges and opportunities that emerge from integrating UAVs with 6G, the forthcoming era of communication technology, are explored. This leads to forecasting potential directions for future research, offering insights into the evolving landscape of UAV and ML interactions in the communication domain.

II. MACHINE LEARNING FOR UAV COMMUNICATION

ML is a subset of AI that consists of methods for teaching machines how to learn on their own, which can enhance system performance and make predictions based on past data or experiences. ML techniques are becoming popular in a myriad of domains, including transportation, finance, manufacturing, wireless communications, and so on. In general, ML is built on a framework for pattern recognition, and its primary goal is to automatically adapt to environmental changes by exploiting correlations between a collection of data and prior excellent action sequences [26] ML presents a number of opportunities for issue solving and performance enhancement within the realm of UAV communication. Specifically, in the context of wireless networks, ML delivers powerful predictive and intelligent data analytic functions for UAVs, which improve overall network operations, such as the prediction of environmental features. At the same time, ML is also an ideal tool for resource management of communication with UAVs, especially in the fields of frequency allocation, spectrum management, and intelligent beam-forming [27].

In particular, UAVs need to face complex and unstable environments most of the time, and traditional methods will be subject to many restrictions. On the other hand, ML has the ability to better integrate multiple sensors of UAVs and enhance the potential of their cooperative ability. All in all, the performance improvement of UAV communication by ML is multifaceted and significant. ML is a highly diversified method that involves various sorts of ML for different types of applications and problems. This section briefly introduces the main types of ML can be applied in the field of UAV communication and describes their advantages and limitations. The categories of ML include supervised learning, unsupervised learning, and RL. In addition, this survey also includes several emerging ML methods in recent years: TL, FL, Meta learning and Explainable AI. Because of their unique characteristics, each of them is suited for usage in a variety of contexts; nevertheless, in most cases, it is more typical for them to be combined in a variety of ways according to specific requirements in order to resolve a variety of issues. Fig. 2 shows the classification and relationship between different kinds of ML that can be used in the field of UAV.

A. SUPERVISED LEARNING

Supervised learning, a fundamental ML approach, involves training models with labeled data (Fig. 3). In this process, the model learns from a dataset that includes both the features (input) and the corresponding labels (desired output). This training aims to teach the model to achieve a specific goal by understanding the relationship between the input and output. Typically, datasets are divided into a training set, used to teach the model, and a test set, used to evaluate the model's accuracy by checking its predictions against known outcomes. For instance, supervised learning can classify UAV types, such as distinguishing between fixed-wing and rotary-wing UAVs, by training on data labeled with these categories. The process works with datasets where both the characteristics of UAVs (input) and their types (output) are clearly defined, making it suitable for tasks with ample historical data where the desired outcomes are known.

Most of the time, the supervised issues are separated into two categories: regression problems and classification problems. The example of classifying UAVs just mentioned is a classic classification problem. In classification problems, it is possible to anticipate the result of discrete outputs. In other words, input variables are capable of being translated into discrete categories. In regression problems, the model tries to predict the outcome as a continuous output by mapping the input variables to a continuous function.

In addition to these two most common usages, it can also be combined with neural networks to generate more flexible algorithms [28], such as Convolutions Neural Networks

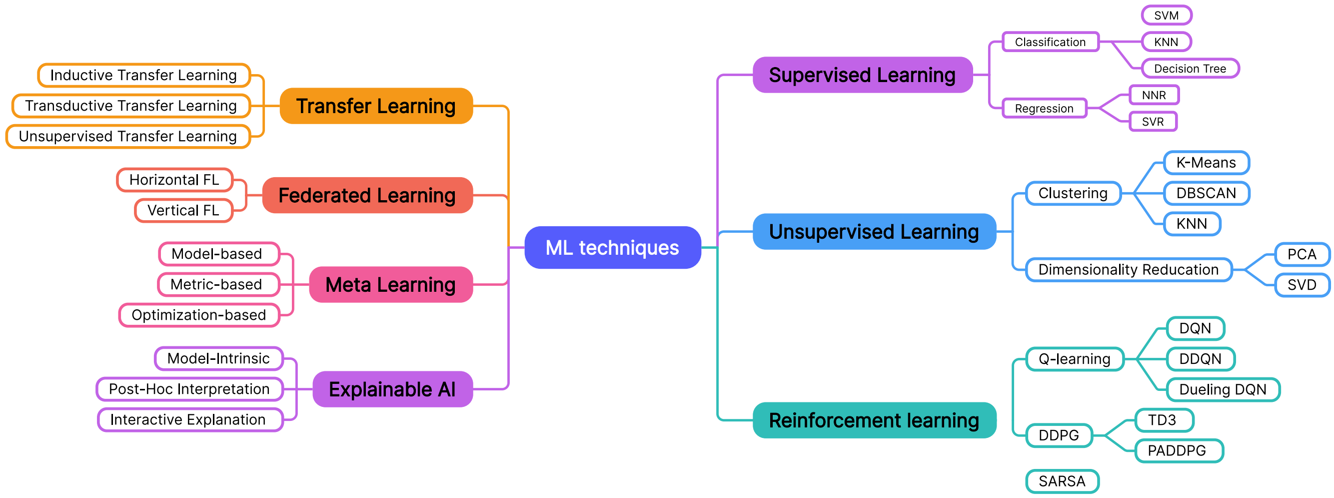

FIGURE 2. **The classification and summary of major types of machine learning with their example.**

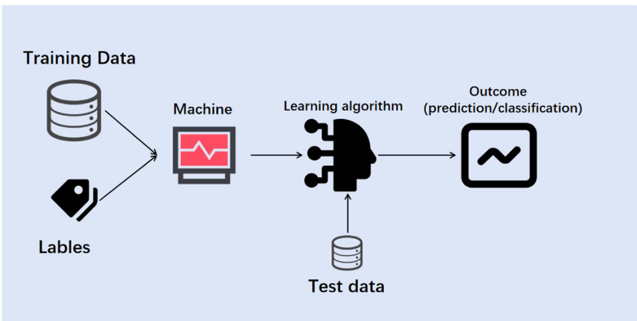

FIGURE 3. **Supervised learning.**

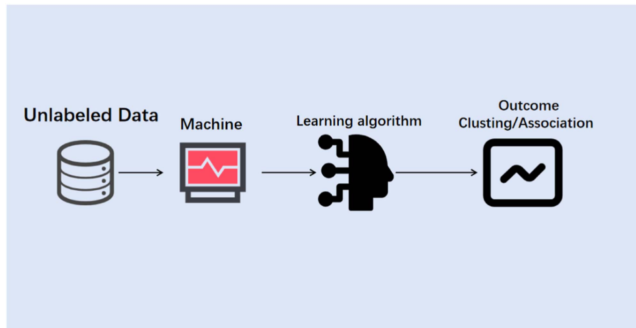

FIGURE 4. **Unsupervised learning.**

(CNNs), Recurrent Neural Networks (RNNs), and Multi-layer Perceptrons (MLP). The combination of supervised learning and deep learning has allowed for the development of these sophisticated applications. It finds extensive use in a variety of domains, including language processing, environment identification, and others. These, along with their many uses, will be discussed in further depth in the following paragraphs.

B. UNSUPERVISED LEARNING

Often referred to alongside Supervised learning is Unsupervised learning, but it does not use labeled data. Unsupervised learning (Fig. 4) allows us to approach problems with little or no knowledge of the intended solution. Even if effect of a variable is known, structure in the data still can not be found. Unsupervised learning is the method of grouping data variables according to the relationship between variables in the data to find some underlying structures or hidden patterns in the data. Once these have been discovered, they can be used to make decisions and provide outcomes. For instance, unsupervised learning can be used to discriminate UAV attributes in order to pick the UAV that is best suited for various settings, or UAVs can be trained to behave correctly in a variety of different sorts of environments according to the features of the environment.

This can be used to solve problems related to clustering the data, reducing data dimensions, and data generation. There are several applications that are used more frequently in the field of UAV communication. These applications include Hard clustering, in which each data-point belongs to only one group, such as K-means; Soft clustering, in which data-points can also belong to another group, such as Gaussian mixture models (GMMs) [29], and methods that are based on density, such as density-based spatial clustering of applications with noise (DBSCAN). Utilizing K-means as an example, the K-Means Clustering method is perhaps the most well-known example of the partitioning clustering technique. The data set is partitioned into a set of k groups when using this method, where K is used to specify the total number of groups that have been pre-defined. The center of the cluster is determined in such a manner that the distance between the data points of one cluster is as little as possible in comparison to the center of another cluster. In the same way that supervised learning will

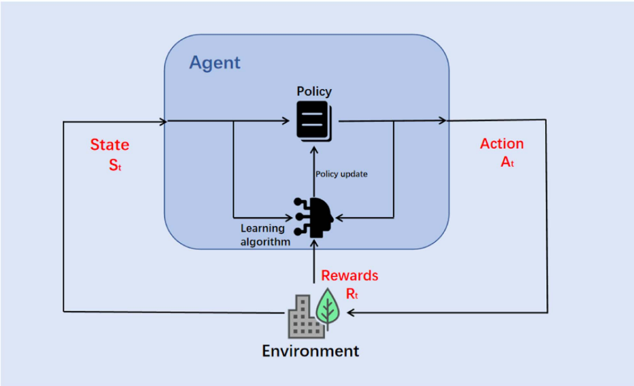

FIGURE 5. Reinforcement learning: Actions that maximize rewards are obtained by interacting with information from the environment.

be integrated with Deep Learning in the application process, unsupervised learning will also be mixed with Deep Learning in order to cater to a variety of requirements and intelligence levels.

C. REINFORCEMENT LEARNING

RL is a ML method that consists of an agent interacting with the environment iteratively. An agent refers to an object that has the actual capacity of behaving or taking actions. RL is an *agent*-based view of ML. The agent can be taught to reach its goal of completing a task as successfully as possible. Each attempt at the task is referred to as an *episode*. The task involves a series of actions, observations, and rewards.

In RL, the learning process can be succinctly described as follows: At any given time t, the agent observes the current state of its environment. Based on these observations, it selects an action and receives an immediate reward as feedback on the action's effectiveness. Observations are defined as the information received about the environment, effectively delineating the state of the agent. The reward serves as feedback from the environment, indicating the success or failure of the implemented action. Decision-making in RL regarding the action to take at time t is informed by both the current observation of the environment and a history of past observations. Therefore, the state s at time t encompasses all relevant information about the environment at that moment, critical data from previous moments, and details about the agent's internal structure. This iterative process of observation, action selection, and reward collection is depicted in Fig. 5. Mathematically, it can be described with the 4-tuple $< \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R} >$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, $\mathcal{P}$ is the state transition probability, and $\mathcal{R}$ the immediate reward received by the agent. The central concept of RL revolves around learning by reward, as previously mentioned, where the agent aims to maximize its rewards through interactions with the environment.

RL can also include a consideration of the underlying model, leading to a distinction between two main types of RL problems: model-based and model-free. Model-based RL relies on a model to simulate the environment's response to the agent's actions. Here, the goal is to predict the future state and action based on the current state and action, exemplified by Hidden Markov Models [30]. However, in many cases, supervised learning might offer a better approach to these issues [15], making model-free RL increasingly popular. In model-free RL, even without predicting future states, the agent can still identify the optimal action by evaluating and selecting the best rewards, as previously discussed. A classic model-free RL method is Q-learning, where the agent calculates and follows the action with the highest Q-value, reflecting the best expected reward [31].

D. DEEP REINFORCEMENT LEARNING

As mentioned in previous section, traditional ML methods face many limitations in solving complex problems, especially when using large action and state spaces. As a result, the Q-learning algorithm may not be able to find the optimal policy. In this case, the help of deep learning cannot be ignored. Thus, the Deep Q Learning (DQL) method has been developed to compensate for this problem. Intuitively, the DQL method uses a Deep Q-Network (DQN), which is a type of Deep Neural Network, in place of the Q-table in order to get an estimated value for Q [32]. This is what enables the agent to cope effectively even with unforeseen situations, contrary to the standard RL method. The combination of Deep Learning (DL) and Q table does provide solutions to many problems, but sometimes it is difficult to achieve the expected performance due to certain factors. Therefore, on the basis of DQN, there are many upgrade algorithms with specific solutions. For example, it is possible that the Q-learning algorithm has poor performance as a result of the significant overestimation of action values. In order to solve the issue of the Q learning algorithm producing too many estimates, the second Q-value function can be considered and used to simultaneously select and evaluate action values through the loss function. This algorithm is called double deep Q network (DDQN) [32].

In addition, there are many other improved algorithms, such as dueling DQN, distributional DQN and Deep Deterministic Policy Gradient (DDPG). The DDPG algorithm is yet another one that should be highlighted separately due to the fact that it DQN is incapable of handling continuous space action and cannot use stochastic policies. The Actor-Critic algorithm is the foundation of the DDPG, which is a model-free and off-policy technique. DDPG is able to help the agent find an optimal strategy by maximizing the reward return signal. The main advantage of such deep algorithms is that they perform well on high-dimensional or infinite continuous action spaces, which greatly improves the potential and application range of RL.

[33] explores the use of autonomous UAV in wireless sensor networks for tasks like smart farming in remote areas. It addresses the challenge of data loss due to drone maneuvers causing buffer overflows at ground sensors. A new maneuver control scheme, based on deep deterministic policy gradients

(DDPG-MC), is proposed to minimize data packet loss by optimizing drone movements and sensor selection. This method significantly reduces packet loss, outperforms other control and scheduling policies, and demonstrates the potential for efficient aerial data collection in sensor networks.

E. CUTTING-EDGE MACHINE LEARNING

The above-mentioned traditional ML approaches have shown their use and played a part in a variety of areas, which are becoming one of the top choices for UAV function optimization and intelligence. Nonetheless, as the complexity of challenges confronted by UAVs has risen, so has the amount and complexity of data handled by intelligent systems. At the same time, for the diversified development of UAV functions also increases the requirements for the diversification of problems that ML need to solve. This makes many traditional ML unable to meet the corresponding requirements and is limited in many application scenarios. Such as supervised learning, rely heavily on labeled data for training. While this is effective for some applications, it can be time-consuming and costly to label data, and it may not always be feasible to obtain labeled data for certain tasks. This dependence on labeled data also limits the scalability of traditional ML algorithms, as the amount of labeled data required increases with the complexity of the problem. Although the integration of deep learning has significantly enhanced the capabilities of these algorithms, RL in particular, more researchers are beginning to notice the development and use of new types of ML. Many of them are based on the deeper use of neural networks and more reasonable developments such as TLs and FL. These modern ML are more in line with people's requirements for reducing resource usage and improving security. They also offer significant advantages in terms of adaptability, scalability, and the ability to learn from unstructured data. On the other hand, XAI is another avenue that has garnered interest. It is anticipated that this would reduce the issue that ML is a black box that is difficult to explain and estimate risk. In the following subsections, these ML techniques will be reviewed.

1) FEDERATED LEARNING

FL is a approach to distributed ML allows multiple clients to train a shared model collaboratively while keeping their data decentralised and secure (Fig. 6). Google proposed the concept of FL in 2016 [34]; it is built on decentralised execution of ML algorithms without the requirement to download the training data to a central node or server. The training process in FL is typically carried out in several rounds. In each round, the central server distributes the current version of the model to participating devices. The devices then train the model on their local data, producing a set of updated model weights. These updated weights are then sent back to the central server, where they are averaged with the other participating devices' model weights to produce a new version of the model. This new version of the model is then distributed back to the participating devices, and the process repeats with each round of training.

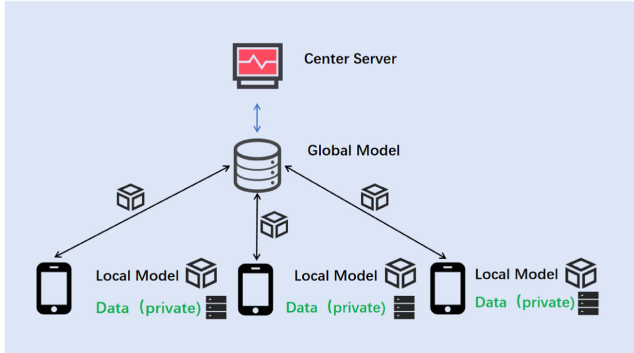

FIGURE 6. **Federated learning: Distributed ML structural framework.**

The characteristics and structure of FL are very suitable for UAV communication, which requires a central server and several clients. To a certain extent, it meets its needs for data protection and reduced on-board computing, because FL can be applied to restricted networks that cannot be exhaustively calculated on-board [35]. It enables the decoupling of model training and raw data access since UAVs are not obliged to exchange any data with the server; instead, they simply send their local update. This means that FL can reduce privacy and security concerns by minimizing raw data on the network.

In addition, FL also provides a basis for UAVs to work alternately and cooperate. For FL, even if one of the nodes is idle, its learning process can continue without being affected for a short time, and UAVs can resume updates while connected to the network. When one of the UAVs in the UAV communication system needs to be exchanged for charging, or an emergency failure occurs, this system can ensure that the overall function will not be affected [36]. This has great significance for the work of UAV system. A combined power allocation and scheduling optimization issue for a UAV swarm network has been proposed by the authors in [37]. The network under consideration consists of one leading UAV and a group of following UAV. Each following UAV applies a FL algorithm on its local data and then transmits the result to the leader UAV. The leader collects all local model changes to make a global model update. Several natural factors, including fading, wind, transmission delay, antenna gain and deviation, and interference, will influence the wireless communications between the UAV as they exchange updates. The influence of various wireless transmission parameters on the performance of the FL algorithm is evaluated.

Another author in [38] investigate forecasting the air quality index by integrating vision-based and sensor-based air quality sensing. The proposed approach involves two sensing components: aerial sensing through a network of UAVs trained on haze images and ground sensing via a wireless sensor network. To infer results from both terrestrial and aerial networks, deep learning models are employed. The research

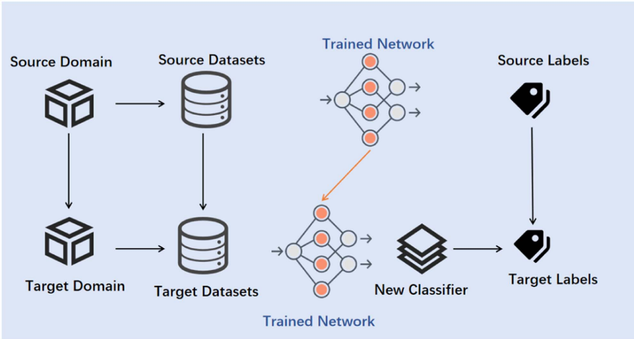

FIGURE 7. Transfer learning structure and process of transferring policy.

introduces a visual model based on Dense-Mobile-Net CNN and a Spatio-temporal inference model, with learning facilitated through FL techniques. The accuracy of this framework is assessed using real-world data and is demonstrated to outperform traditional methods.

In conclusion, FL emerges as a crucial and promising technique for UAV communication. By harnessing FL's power, UAVs can efficiently learn from diverse data sources, adapt to changing environments, and optimize communication performance. The collaborative learning approach fosters collective intelligence that enhances UAVs' decision-making and efficiency. Looking ahead, FL will continue to play a pivotal role in the advancement of UAV communication systems. As more UAVs are integrated into communication networks, FL's scalability and adaptability will prove indispensable in achieving reliable, secure, and efficient communication across diverse UAV applications.

2) TRANSFER LEARNING

An interesting and advantageous characteristic of neural networks is their ability to exploit a learned function on a certain input data to perform another function on the same input data, which is referred to as TL. TL focuses on the storage and application of knowledge acquired while solving one problem to a different but related problem (Fig. 7). Initially, TL was believed to help animals and humans realise their psychological similarities. Then, concepts from TL were applied to ML, such as regression, classification, medical image analysis, and similar applications.

The work in [39] demonstrated that layers proximate to the input tend to grasp generic features, implying they learn mappings independent of tasks and final neural network outputs. On the contrary, as layers proceed deeper into the network, their features become more task-specific, adapting to the current task. This observation implies that repurposing a pre-trained network for a distinct task could offer a beneficial performance boost while mitigating the computational complexity linked with training. In addition, leveraging knowledge from prior tasks to enhance the efficiency of a RL agent holds promise for practical improvements. This notion underlines the potential advantage of TL in various UAV wireless communication scenarios. In recent years, TL has been applied to UAV techniques. TL allows UAVs to leverage knowledge from pre-trained models to enhance their performance in new and diverse tasks. This approach significantly reduces the need for large data sets and training time, making UAVs more adaptable and efficient in various scenarios. TL plays a crucial role in empowering UAVs to overcome challenges, optimize communication, and unlock their full potential in real-world applications.

The work [25] utilizes knowledge distillation to tranfer knowledge from a teacher policy to a student agent operating in a different band. In this study, a pre-trained model involves initially training a DDQN, but targeting different domains that facilitate the transfer of knowledge across various environments. In [40], the authors investigate the use of continuous learning to dynamically transfer knowledge from a pre-trained environment to different environemts to reduce the overhead of retraining DRL models, enabling them to adapt to constantly changing environment.

3) META-LEARNING

Another very important type of ML is meta-learning, also known as "learning to learn". Meta-learning is a sub-field of ML that focuses on developing algorithms and techniques that enable machines to learn how to learn new tasks more efficiently and effectively. "Meta" typically denotes a more comprehensive or abstract level; for example, meta data are data that provide information about other data, whereas meta-learning refers to learning about learning. It is comparable to TL in that its objective is to increase the learner's generalization ability in multi tasking. Meta-learning focuses more on learning from the output of other ML models, as opposed to the application of trained content to new tasks in transfer learning. This indicates that meta-learning algorithms necessitate the presence of previously trained models.

Meta-learning has a significant advantage over traditional ML in that, if the task alters, the model does not need to be retrained from beginning. Meta-learning models are able to continuously revise their knowledge and adapt to changing conditions. By integrating feedback from new tasks or experiences, the model refines its task-independent representation and modifies its strategies accordingly. It is particularly useful when data is limited or when the model must adjust dynamically to new duties. It can lead to more robust and adaptable models in real-world applications that are better adapted to swiftly evolving and diverse tasks. Meta learning can lead to more powerful and flexible models better suited to diverse tasks in UAV applications. Augmentation and adaptation enable UAV communication systems to progress over time, refine their performance, and effectively manage varying network dynamics.

For example, a meta-learning algorithm could be used to help a UAV learn how to fly through a forest without crashing by using data from previous flights to inform its decision-making process. This could be especially useful in situations where the environment is constantly changing, such as in search and rescue missions or in monitoring wildlife populations. In the context of optimizing the UAV's trajectory, meta-learning can be utilized for trajectory design in wireless UAV networks [41]. Moreover, [42] uses continual meta-RL as a means to transfer information from previously experienced traffic configurations to new conditions, with the goal of reducing the time needed to optimize the UAV's policy. In addition to improving a UAV's ability to navigate and perform tasks, meta-learning can also be used to optimize its performance in other ways. For example, a meta-learning algorithm could be used to optimize a UAVs's energy consumption, allowing it to fly for longer periods of time and cover greater distances. The author of [43] proposed the structure of meta twin delayed deep deterministic policy gradient (Meta-TD3) based on deep reinforcement learning and meta learning, which is used to quickly track targets in environments with uncertain target movements.The results show that the combination of meta learning significantly improves the convergence performance and convergence speed.

In summary, Meta Learning proves to be of crucial significance for UAV applications. Meta Learning enables UAVs to quickly adapt and learn from multiple tasks, leading to enhanced decision-making, improved efficiency, and effective problem-solving in dynamic environments. By leveraging Meta Learning, UAV can efficiently optimize their performance, making them valuable and adaptable assets in a wide range of applications, including communication, surveillance, and disaster response.

4) EXPLAINABLE AI

During the majority of UAVs related missions, UAVs depend on advanced AI systems to function autonomously, make decisions, and communicate with other UAVs and ground control systems. These AI systems can make errors or act unexpectedly, which may be dangerous or costly. Typically, these expenditures are unacceptable. However, for the majority of AI and ML processes, we do not fully understand the foundation for their judgments or when they will make errors. This means that there is no guarantee of trust in UAVs, and the possible dangers associated with their use make it difficult to comply with local legal requirements. XAI enhances AI systems' ability to produce understandable and interpretative explanations for their choices and behaviours [44]. XAI can assist ensuring UAV choices and actions are explainable and clear to human operators, especially in complex and dynamic environments where there may be multiple factors influencing the decision. This openness enhances confidence in the system and enables operators to rapidly discover and address problems [45]. XAI's impact on drone navigation and collision avoidance is evident, providing crucial transparency in autonomous decision-making processes. The authors in [46] present a neural network-based reactive controller for small UAVs designed to autonomously navigate unknown outdoor environments with minimal computational load. It uses deep reinforcement learning to solve a navigation problem modelled as a Markov Decision Process (MDP). The research includes model interpretation methods for understanding flight decisions and global analysis for network refinement. This leads to a more credible and controllable autonomous navigation process for UAVs. [47] created a novel UAV-assisted communication scheme that tackles overlooked collision avoidance issues by dividing the problem into two parts: flight and power management using Dueling Double DQN, and collision avoidance using Monte Carlo tree search (MCTS). The integration framework improves decision transparency and reliability.

In the context of UAV assisted communications, the integration of XAI within novel communication schemes, such as those proposed in [48], has demonstrated significant advancements. The authors present a mixed interference-based graph neural network (MIGNN) to optimize distributed beamforming in UAV assisted IIoT. They address co-channel interference's in a heterogeneous network, enhancing the MIGNN with hypergraph concepts for better scalability and performance. Numerical simulations show that this method surpasses traditional deep learning approaches, making it suitable for advanced B5G and 6G technologies. Another research [49] built on the strengths of XAI in recognition and identification by presenting a deep learning (DL) framework for drone recognition using RF signals, enhanced by XAI tools such as SHAP and LIME. These tools improve accuracy and transparency and enable interpretable accounts of drone detection decisions. The model identifies drone signals from RF noise with 84.59 per cent accuracy. XAI can also be used to identify and explain the cause of faults or failures in UAV communication systems. By analyzing the data and decision-making processes, XAI can provide insights into the root cause of the fault, which can be used to improve the performance and reliability of the system. Also, XAI can be used to optimize the performance of UAV communication systems by providing insights into the factors that affect the system's performance. By analyzing the data and decision-making processes, XAI can provide recommendations for improving the system's performance, such as adjusting the transmission power or selecting a different frequency band.

At the end, XAI can be used to enhance the security and privacy of UAV communication systems by providing insights into the system's vulnerabilities and risks. By analyzing the data and decision-making processes, XAI can identify potential security threats and recommend countermeasures to mitigate the risks. In summary, XAI can provide insights into the data and decision-making processes, which can be used to optimize the performance, manage the network, and enhance the security and privacy of the system. With the understanding of the importance of ML in UAV applications, next section will explore the pivotal roles that UAVs play in communications. These roles highlight the impact of UAVs in various sectors, from disaster response and surveillance to providing reliable wireless connectivity and optimizing network architecture.

TABLE 2. Roles of UAV in Communications

Roles of UAV	Paper	Year	Description
UAV as Aerial BS	[52]	2015	FANET UAV Base station
	[53]	2017	UAV Base Stations Placement Optimization
	[54]	2019	Uav base BS location optimization
	[55]	2020	UAV Base Stations for Disaster Management
	[56]	2020	UAV navigation in deployment of small cell Base stations
	[57]	2022	3D positioning for UAV iot network coverag
	[58]	2018	Power Optimization for UAV Relay Networks
	[59]	2018	UAV relay in VANETs
UAV as Relay	[25]	2020	Channel Prediction for UAV Relay
	[60]	2020	Performance evaluation of (5G) UAV relay
	[61]	2022	IRS-UAV Relaying Networks for Energy Efficiency
UAV as UE	[62]	2019	UAV cache-enabled base stations and UE
	[63]	2022	cache-enabled multi- uavs networks
	[64]	2022	UAV in O-RAN system

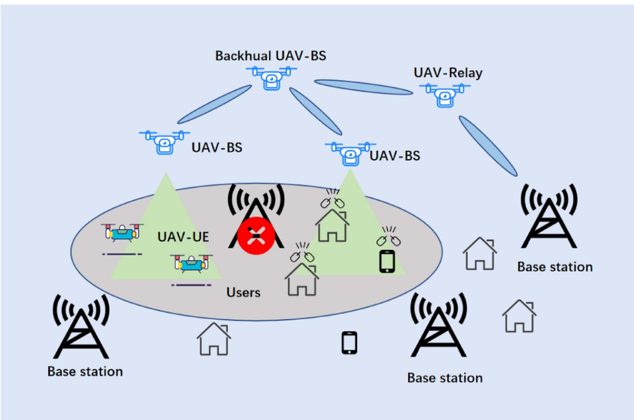

FIGURE 8. Reflect the position of each role of the UAV in the communication scene as a whole. UAV-BS is responsible for providing communication, UAV-Relay can extend the link, and UAV-UE provides services.

III. ROLES OF UAV IN COMMUNICATIONS

A. UAV AS FLYING INFRASTRUCTURE ARCHITECTURE

UAVs are becoming an indispensable element of both civilian and military missions. As a result, the usage of UAVs is spreading to include almost all sectors of life, including medical, commercial, entertainment, communications, and construction applications. Simultaneously, it plays an essential role in the area of communication and is a highly anticipated rising field. UAV can provide reliable and cost-effective wireless communication solutions for various real-world scenarios. In situations such as natural disasters or heavy traffic, UAVs could be deployed to supplement communications infrastructure or to augment existing communications systems to enhance performance. Table 2 presents the various roles of UAVs in communications for advanced applications. First, UAVs can be used as **aerial BS** that can provide reliable, economical, and on-demand wireless communications to desired areas. The rapid deployment, mobility, higher chance of propagation path clearing, and flexibility characteristics of UAV-BS bring many advantages, especially in terms of enhanced communication quality and greater freedom of arrangement.

UAVs can also be used as **wireless relays** to improve the connectivity and coverage of ground-based wireless devices. In regions or countries where building a full cellular infrastructure is expensive, deploying UAV becomes very beneficial as it eliminates the need for expensive tower and infrastructure deployments. Especially when the location is uncertain at sea or in the mountains, UAV wireless relay is the most efficient and economical solution. Finally, UAV can also co-exist with ground users as aerial UE, known as cellular-connected UAV. This application strategy significantly expands the UAV application range and versatility. This section will provide a quick overview of the three roles UAVs play in wireless communication networks. Fig. 8 is an example of a low-altitude UAV accessing the nearest local base station in an urban area to assist local communication. It simply shows the positioning of the three applications.

1) UAV AERIAL BS

Due to the ongoing decrease in the cost of UAV production and the shrinking of communication equipment devices, UAV have evolved into a new generation of more reliable flying platforms, which has also aroused strong interest in using UAV to provide reliable and cost-effective solutions for wireless communication in many real-world scenarios. In particular, by placing small base station or repeaters on a UAV, it can be rapidly deployed 3D space as a flying BS. This benefits from the light weight of commercially available LTE base stations that can currently be installed on moderately loaded UAVs. The authors in [63] showed the role of UAV as BS in the IoT and propose a model to optimize location. This kind of UAV base station can provide temporary reliable on-the-fly air-to-ground (A2G) communication

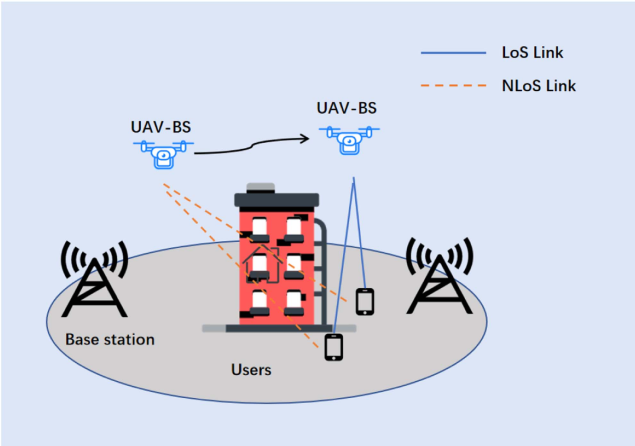

FIGURE 9. UAV base station improves communication quality by adjusting position to increase LoS.

links for designated areas, and can also be used as an embedded module to enhance wireless capacity and coverage of local communication. This can help meet the high demands of 5G and beyond cellular communications. UAV-assisted communications have the following principal benefits over traditional terrestrial communications with generally static BS installed in fixed locations. Initially, owing to the controlled high mobility of UAVs, Its position and height can be adjusted dynamically. This means UAV-BSs have an extra degree of freedom (DoF) for communication performance improvement (Fig. 9), by dynamically altering their 3D positions to have a higher chance of LoS connectivity with ground nodes [55] shows the advantages of UAVs after optimized 3D position deployment, and tries to reduce the number of UAVs to improve efficiency.

Besides, BS placed on low altitude, UAVs may be rapidly deployed on demand. This is particularly advantageous for situations involving temporary or unforeseen occurrences, emergency response, search and rescue, etc. At the same time, its mountable feature also allows it to better adapt to different situations and respond more quickly. In many real-life situations, the need for communication enhancement or local area coverage is short-term, or the location is not fixed. Under these circumstances, UAV base stations will have significant advantages such as low consumption and fast deployment compared with traditional ground base stations. Such as real-time live broadcast, disaster detection, etc.

The authors [52] also indicate that UAV base stations assist in distributing resources in localised locations, since the development of terrestrial wireless networks is often designed based on long-term traffic behaviour, resulting in a significant number of idle and unavailable resources at specific places. To accommodate shifting demand. UAV base stations are anticipated to assist shift extra network capacity to where demand exists, hence optimising network resource use and considerably enhancing Quality of Service (QoS).

As mentioned above, the rapid popularization of high-performance mobile devices such as smartphones, UAVs, and embedded devices, while the demand for high-speed wireless access has been growing, it has also promoted the rapid development of the Internet of Things. New communication technologies such as device-to-device (D2D) communication, millimeter wave (mmW) and massive Multiple Input Multiple Output (MIMO) make the use of UAVs more diversified [64]. UAV swarm systems with UAV BS as the core are also possible, such as Flying ad-hoc network (FANET) realized through multi-UAV cooperation and self-organizing swarm behavior [50].

Or assist other local wireless networks including Internet of Things (IoT), Internet of Vehicles, Wireless Sensor Networks (WSN) and so on through the mobility and line-of-sight communication of UAV base stations. UAVs can improve the reliability of wireless links in these local terrestrial network communications while exploiting transmit diversity.

2) WIRELESS RELAY COMMUNICATIONS

UAVs are able to used as relays in a communication system between ground-based terminals and a network base station. [65] And UAVs are well suited for this relay job since they can fast arrive at the mission area without relying on roads or existing infrastructure and can easily adjust their locations to respond to fluctuating communication settings. The deployment of the majority of relays in terrestrial systems at fixed locations is referred to static relaying. The initial phase corresponds to UAV information reception, where it continues to receive and decode data sent from the source. The UAV first flies at maximum speed toward the source, then transmits the data in its buffer to the destination, hovers above the nearest location to the destination if time permits, and then returns to its initial position at the end of the cycle [66]. To successfully design the UAV relay trajectory that enhances the communication performance of ground nodes, it is necessary to anticipate the air-to-ground communication channel quality between any arbitrary UAV location and ground nodes. At the same time, UAV relay is also an important part of the FANET mentioned above. In addition to the need for UAVs with relay functions in the self-organizing flight network to extend the range, FANET itself can be used as a relay system to ensure reliable communication links in environments with large areas such as deserts, agriculture, and mountains with obstacles. Moreover, considering the challenges posed by signal blockages in maritime environments due to mountains and high-rise buildings, Zhang's work introduces an aerial re-configurable intelligent surface (ARIS)-assisted maritime wireless communications system to overcome such obstacles. By employing ARIS, the system aims to enhance the capacity of maritime wireless systems, particularly for maritime users in blocked offshore areas, through optimized reflection elements that maximize achievable rates [67]

In addition to the traditional UAV communication relay, the author of [59] proposed another integrated intelligent reflecting surface (IRS)-UAV communication scheme. The author said that the IRS is installed on the UAV as a Mobile relay between base station (BS) and terrestrial users. IRS is a type of planer surface that is made up of several different reflecting components and has the ability to intelligently adjust the amplitude and phase shift of the incoming signal. It then maximizes the spectral efficiency of the system by optimizing the beam-forming and UAV trajectory and energy efficiency. These different relay methods provide important conditions for a more complete UAV integrated communication.

3) RU/DU IN C-RAN/O-RAN ARCHITECTURE

In C-RAN and O-RAN architectures, the RU is responsible for transmitting and receiving radio frequency signals, while theDistributed Unit (DU) carries out base-band processing tasks, such as error correction and signal decoding. These components are typically connected through a high-speed, low-latency interface, often referred to as fronthaul. UAVs can be integrated into this system in several ways. One of the most significant roles of a UAVs in a C-RAN or O-RAN architecture could be to function as a mobile RU. In this role, a UAV could be equipped with radio equipment to transmit and receive signals, effectively serving as an aerial base station. UAVs can also be deployed to optimize the positioning and connectivity of RU and DU. Through the use of ML algorithms, UAVs can help to determine the best locations and configurations for these units to maximize coverage and minimize interference. This could be especially beneficial in dynamic environments where network conditions are constantly changing. Furthermore, UAVs can be used for the monitoring and maintenance of C-RAN or O-RAN networks. UAVs equipped with cameras and sensors can provide aerial inspections of RUs and DUs, helping to identify and resolve issues more quickly and efficiently than traditional methods. Overall, UAVs can significantly enhance the flexibility, adaptability, and efficiency of C-RAN and O-RAN architectures, playing a vital role in the future development and operation of these networks.

B. CELLULAR-CONNECTED UAV AS UE

UAV can also act as user equipment of the wireless infrastructure, and this type of application is currently the most convenient and widespread use of UAVs. Because of the high adaptability of UAVs to different scenarios, it has the ability to combine with more emerging technologies to achieve cutting-edge applications, such as delivery, surveillance, remote sensing, virtual reality applications and so on. When UAVs are used as UE There are various benefits to utilising it: First, UAVs can eliminate the majority of distance and location limitations. Cellular-connected UAVs allows ground pilots to remotely command and control UAVs with an almost infinite operational range, as well as execute completely autonomous or semi-automatic control with the aid of artificial intelligence. Second, its mobility and adaptability enable it to undertake cooperative duties with other user equipment. As an expanded sensor in the network for autonomous driving, a temporary mobile traffic command centre, etc. This form of UAV usage has contributed significantly to the growth of the Internet of Things and smart cities.In the work of [54], author customized the recently emerging Cognitive Internet of Things framework for amateur UAV surveillance. He brought up one of the roles of UAVs in smart city systems. As a result of the adaptability of UAVs, there is likely to be closer collaboration with intelligent systems and the development of new sensors. Last but not least, UAVs may take over numerous risky or difficult jobs formerly performed by people. UAVs provide benefits that cannot be matched in fields like disaster aid and the identification of potentially hazardous regions. UAVs have more promising prospects in long-distance detection and emergency rescue now that the sensor system is more complete, especially when other UAVs are used as base stations to provide temporary remote communication connections.

Another notable usage of UAV user equipment is to let the UAV act as a mobile caching-enabled device to link with other user equipment/UAV user equipment [61]. Caching-enabled UAVs are a promising solution for users with high demand for location mobility, as the requested content needs to be stored in a new base station when the user moves to a new area. UAVs can serve the mobile location of users in real time and reduce the content requests of frequent updates of mobile users to reduce the complexity of caching. The application of UAV UE also faces many challenges, because unlike other UE-to-UE, UAV UE usually experiences different channel states when linking, which makes it difficult to meet the requirements for reliable and low-latency communication. And due to the energy limitation of UAVs, it is necessary to consider whether the mission can be completed in a short time or whether new UAVs can be replaced in time.

C. LESSONS LEARNED

The role of UAVs in communication has witnessed significant growth across various sectors, including medical, commercial, entertainment, and disaster response. UAVs offer reliable and cost-effective wireless communication solutions, making them indispensable in real-world scenarios, such as natural disasters or congested traffic areas, where they can supplement existing infrastructure and enhance performance. UAV BS, as aerial Base Stations, provide several advantages, including rapid deployment, mobility, higher chance of LoS connectivity, and flexibility in network arrangement. These attributes lead to improved communication quality and increased freedom in arranging network nodes. The advantages of UAV BS also extend to being cost-effective, as they eliminate the need for expensive tower and infrastructure deployments. They are faster and easier to deploy compared to traditional ground-based stations, making them suitable for temporary or emergency communication needs. These advantages make UAV BS a valuable tool in achieving efficient and adaptable wireless communication.

Moreover, UAV serve as wireless relays, offering connectivity and coverage enhancements in regions where building full cellular infrastructure is costly or challenging, such as areas with uncertain locations or geographical obstacles. Additionally, other UAV that function as cellular-connected UE can link with UAV relay, which presents numerous benefits such as overcoming distance limitations, providing extended operational ranges, and enabling cooperative missions with other user equipment. As a part of the Internet of Things and smart city systems, UAVs contribute to closer collaborations with intelligent systems and the development of new sensors.

As research continues and UAV technology advances, the role of UAVs in communication is poised for significant expansion, offering a multitude of advantages and diverse applications in the future. The integration of UAVs in C-RAN and O-RAN architectures enables them to function as mobile base stations, optimizing network flexibility and efficiency. Moreover, the inclusion of Intelligent Reflecting Surfaces (IRS) on UAVs introduces intelligent signal optimization, enhancing spectral efficiency. UAVs' adaptability to support various hardware and sensors fosters their use as UE in wireless infrastructure, opening up possibilities in delivery, surveillance, and smart city systems. Addressing challenges related to link reliability, low-latency requirements, and energy limitations will be crucial for realizing UAVs' full potential in communication networks and driving innovation across sectors.

Despite their advantages, UAV applications still face challenges, for example, UAV performance related to different channel states during linking and energy limitations, necessitating consideration of mission completion time and the replacement of UAV. Efficient trajectory design and channel optimization techniques are essential to improve UAV performance, especially in dynamic environments. In the forthcoming section, the intricacies of UAV-related applications will be explored, highlighting the unique challenges and obstacles encountered. To effectively address these issues, an analysis will be conducted to identify the most suitable types of ML methodologies for enhancing the performance and efficiency of UAV applications. By comprehensively understanding the specific needs and constraints of UAVs, innovative ML solutions can be devised, paving the way for more robust and reliable UAV communication and usage across a variety of scenarios and industries.

IV. SIMULATION AND VALIDATION METHODOLOGIES

The progression from theoretical models to practical applications in UAV technology heavily relies on a comprehensive validation process. This process employs various tools and methodologies, each with its unique advantages and applications. The main pillars of this validation process include simulators, emulators, and real-world deployments [68]. These methodologies not only affirm the viability of UAV technologies but also ensure their efficiency, safety, and reliability in operational environments. In this section, the diverse tools and methodologies employed for validating proposals aimed at advancing UAV communications will be reviewed.

A. SIMULATORS

Simulation platforms play a pivotal role in the early stages of UAV development, particularly for AI and ML applications. These platforms provide a risk-free environment to test algorithms, flight dynamics, and control strategies without the physical constraints and risks associated with real-world testing. Some researchers turn to Software In The Loop (SITL) simulations to mitigate these costs [69], [70]. SITL enables the testing of Plane, Copter, or Rover functionalities without requiring physical hardware by executing the autopilot code, typically written in C++, directly on a computer. This self-contained simulation is especially valuable for identifying potential in-flight issues, thereby preventing dangerous situations and protecting valuable equipment from damage. Gazebo is another powerful simulator, integrated with ROS (Robot Operating System), offer realistic physics and environmental conditions, enabling researchers to fine-tune UAV behaviors in various simulated scenarios [71]. Additionally, FlightGear and Microsoft AirSim, leveraging the Unreal Engine, are instrumental in propelling UAV technologies forward, especially in areas like AI-enhanced navigation, obstacle evasion, and strategic mission planning. FlightGear [72], recognized for its open-source flexibility, delivers a simulation landscape that not only supports but enhances the testing of AI integration under a spectrum of conditions, also facilitating targeted scenario assessments to gauge AI's decision-making prowess [73]. In contrast, AirSim [74] shines with its superior visual and physical simulation quality, pivotal for AI applications in vision-based navigation, enriched by its comprehensive support for AI and machine learning advancements via its API offerings [75]. The simulation of an extensive array of sensors by both platforms generates valuable datasets, crucial for the training and validation of AI models designed to decipher sensor data for the purpose of autonomous navigation.

Incorporating these insights, MATLAB and Python, alongside Octave, Scilab, Julia, R, and the ROS framework, enrich the UAV simulation and analysis landscape. MATLAB's toolbox and Simulink platform allow for detailed modeling and simulation of UAV dynamics [76], while Python, with libraries like DroneKit, facilitates automation for simulation control and data processing. These tools extend beyond basic flight simulations to complex, mission-specific scenario testing, highlighting their indispensable roles in UAV technology development.

B. GROUND CONTROL STATIONS

Ground Control Stations [77] are crucial for managing UAV operations, offering real-time control, monitoring, and communication with UAVs across commercial, research, and military applications. These systems range from software-based platforms to hardware setups, designed to cater to various operational needs. Key software-based Ground Control Stations

(GCS) platforms include Universal Ground Control Software (UGCS), MAVProxy, and Mission Planner (MP), each providing unique features. UGCS is renowned for its user-friendly interface and multi-UAV control capabilities, making it ideal for complex flight missions. MAVProxy, a command-line-based GCS, excels in extendability and supports multiple UAVs, suited for developers and field operations with its lightweight design. Mission Planner specializes in flight planning and configuration for ArduPilot users, offering a graphical interface for easy mission planning and simulation, enhancing pre-flight preparation and safety. Hardware-GCS are designed to offer robust and reliable control interfaces for UAV operations, particularly in mission-critical or demanding environments. An example of a hardware-based GCS is the DJI Smart Controller, which is tailored for use with DJI's range of UAVs. The Smart Controller features a built-in screen, offering high brightness for clear visibility in outdoor conditions, integrated controls for UAV piloting, and dedicated software that provides access to flight settings, data, and live video feeds.

The integration of GCS with simulation tools significantly benefits training and mission planning, reducing physical risks. Additionally, the latest GCS platforms are embracing AI and machine learning to automate tasks like path planning and obstacle avoidance, simplifying UAV operations.

C. REAL-WORLD DEPLOYMENTS AND TEST

Ultimately, the effectiveness and reliability of UAV technologies are validated through real-world deployments. These deployments are crucial for testing UAV systems in operational environments, offering insights into their performance under unpredictable conditions, user interactions, and compliance with regulatory standards. Real-world testing helps in identifying unforeseen challenges, such as environmental impacts on sensor accuracy, battery performance under different weather conditions, and the effectiveness of AI-driven decision-making processes. Case studies, such as the deployment of UAVs for agricultural monitoring, search and rescue missions [78], and infrastructure inspection, illustrate the adaptability and resilience of UAV systems in fulfilling their intended functions outside controlled environments.

V. ML SOLUTIONS IN UAV-BASED COMMUNICATIONS

As low-latitude UAVs are used, they are typically small unmanned aircraft that are flown for short periods of time (up to a few hours). This allows for the rapid deployment of multi-hop communication backbones in challenging applications without the need for any human involvement, such as public safety, search and rescue missions, surveillance inspections, emergency communications in post-disaster situations or emergencies, photographic reconnaissance, urban traffic monitoring, precision agriculture, and media. And different types of UAV applications have different needs and different levels of intelligence. This is making their demand for technology more multidimensional. While using UAV-BS, the key design considerations include performance characterization, optimal 3D deployment of UAVs, wireless and computational resource allocation, flight time and trajectory optimization, and network planning. Meanwhile, in the UAV-UE scenario, handover management, channel modeling, low-latency control, 3D localization, and interference management are among the main challenges. This part divides the main problems and difficulties that need to be faced in the application of low-altitude UAVs in the communication field into four categories, Positioning and trajectory, Physical Layer management, Resource Management and Network Planning and Security and Safety for UAV. Table 3 provides an overview of machine learning solutions in UAV-based communications, detailing their applications and various roles in enhancing UAV communication systems.

A. POSITIONING AND TRAJECTORY

It is good to start with mentioning that initial works used classical optimisation, some of them even considered a fixed height for UAVs and solved a 2D positioning [63]. However, when the problems become more realistic and considered more parameters the placement problems become to complex to be addressed by classical optimisation approaches. In order to achieve optimal or near-optimal performance, one of the most difficult aspects of building UAV based communication systems is determining the ideal location and trajectory of the UAV in relation to other ground or flying objects. Determining the target position of the UAV is a very high priority task of the UAV system which increase the probability that the channel between ground users is mainly a direct link, this potentially leads to a significant performance improvement over communication. After the ideal destination position of the UAV, the trajectory planning to complete the task and the path planning to reach the destination are also important indicators that affect the performance of the UAV. The trajectory is not only related to the planning and completion of the task, but also helps UAV system to manage energy more efficiently.

Simultaneously, the trajectory of the UAV will have a direct impact on both the safety of the UAV and the effectiveness of mission accomplishment. Therefore, the intelligence of a UAV system may be deduced from its location and trajectory planning. For instance, a reasonable UAV trajectory planning involves task scheduling, energy management, UAV safety, handover planning, and joint management with other aircraft, among other factors. During this process, it can also assist the system in turn, such as establishing a radio map.

1) POSITIONING FOR UAVS BSS

An essential aspect of the design involves optimizing the locations of UAVs to achieve optimal communication performance. Unlike the conventional 2D cell planning used with ground-based BSs that usually have predetermined heights, the altitude of UAV BSs can be dynamically determined. This gives rise to a novel challenge of 3D BS placement problems. The authors of [104] study how to minimize the

TABLE 3. Applications of UAV Communication

UAV Application Type	Paper	Year	Description	ML Type
Positioning and trajectory	[81]	2018	UAV navigation in indoor corridor environments	CNN
	[82]	2018	Reduce processing time of positioning	RL
	[83]	2018	maximize the number of covered users	Q Learning
	[84]	2018	minimize the transmit power	GMMs
	[85]	2019	Navigation through massive MIMO	DQL
	[86]	2019	Trajectory prediction of UAV in smart city	RNN
	[87]	2019	Path planning with radio map	RNN
	[88]	2019	Joint trajectory design and power control	Multi-agent Q learning
	[89]	2020	Trajectory Design in Wireless UAV Networks	Meta-RL
	[90]	2020	trajectory control for cellular Internet of UAVs	Q learning
	[91]	2020	Trajectory for UAV-aided time-sensitive IoT networks	DQN
	[92]	2020	Caching placement and content delivery in UAV NOMA networks	DDPG
	[93]	2020	Evolving spiking neuro controllers for UAVs	SNN
	[94]	2021	Persistent cruise control in UAV-aided data collection	DDPG
	[95]	2021	Trajectory Tracking Framework for UAVs under Degraded Conditions	Meta-learning
	[27]	2023	path planning in 6G and mmWave	DQN, TL
Physical Layer management	[96]	2018	Air-to-air path loss prediction	Random Forest,KNN
	[97]	2019	Smart monitoring of crops	GAN
	[98]	2019	Rapid 3D Channel Modeling for UAV Communication	K-means
	[99]	2019	UAV measurements for mobile communications	ANN
	[98]	2019	UAVs' opportunistic channel access	Clustering
	[100]	2020	Generate a radio map of the airspace	DDQN
	[101]	2021	Data-driven millimeter wave communications	GANs
	[102]	2021	FL for Latency Minimization	FL
Resource and Network Management	[103]	2017	Remaining useful battery life prediction	Multi-Layer Perceptron
	[104]	2017	Radio Maps	Clustering,Regression
	[105]	2017	Nonlinear controller for Mission Planning	Echo state network
	[106]	2018	Minimizing the power needed for transmission and mobility	K-means
	[107]	2019	Anomaly detection for UAV sensor data	DL,RL
	[108]	2020	Energy-efficient UAV navigation optimization	DQN
	[109]	2020	Joint Power Allocation and Scheduling	FL
	[110]	2021	UAV emergency communication with limited user equipment energy	DQN
	[111]	2021	Energy minimization for UAV constrained scheduling optimization	Actor-critic
Security and Safety	[112]	2018	UAV Pilot Identification	SVM
	[113]	2018	Learning-Based Defense against Malicious UAV	RL
	[114]	2018	UAV Pilot Identification	Classification
	[115]	2020	Cognitive Detection of Jamming Attack	FL
	[116]	2021	Secure Federated Learning for UAV-Assisted Crowd-sensing	FL

power consumption of UAVs to offload ground base stations to achieve optimal placement. The author uses GMMs in unsupervised learning to predict congestion in wireless networks, and then optimizes the placement of UAVs. In this case the UAV does not need to constantly change position for optimal communication. Under the condition that data distribution can be modeled by the Gaussian distribution, the author uses the K-means algorithm to perform the weighted expectation maximization algorithm to find the optimal parameters of the GMMs. The optimal deployment is then derived by formulating a power minimization problem for UAV base stations. Besides that, promising utilization of ML techniques would enable the UAV to learn the environment by intelligently process the data that it can collect. As an example, the UAV could learn in real time the channel model parameters of the area it is surveying and create a map to determine interference or channel gain at a spatial location where a UAV has not been before. In this way, the author of [102] tried to build a structured radio map studies the optimal location of UAV base stations. UAV user links are partitioned into a finite number of disjoint segments, each of which may have different propagation environment in terms of the channel modelling parameters such as path loss exponent, average channel power at the reference distance and shadowing variance. Reconstruction the channel from few data sample collected at different locations is not trivial and involve the use of unsupervised learning techniques. Both [102], [113] use a maximum likelihood approach for a joint clustering and regression. The remaining x positions are then used to build the radio map. First they are classified into one of the K segments based on the parameter θ learned from the segmented regression algorithm, then the segmented channel model is applied to compute the path loss. Since the Received Signal Strength (RSS) is the result of different effect, path loss and shadowing, the authors utilize a segmentation approach to describe them. Here, ML techniques help to develop a clustering and regression algorithm to learn the segmented model from a few training examples (the system needs a clustering algorithm to partition the training data into K groups according to group-specific models with unknown channel parameters to be learned). Finally, a k-nearest neighbors (KNN) classifier classifies each position into one of the K segments based on the parameters learned from the segmented regression algorithm.

[80] considers users' mobility and processing time in addition to the above positioning methods. In real-world applications, the user's location is likely to change over time, especially in the case of future access to self-driving cars or UAV UEs, providing the required QoS is unstable or may take longer processing time. The authors used a ML approach of reinforcement learning to cope with users moving with different speeds and having different requirements and optimize the algorithm and reduce processing time. Compared with the previous paper, the author [81] considered multiple UAV situations, optimized the positioning of multiple UAV small cells (DSCs) in an emergency scenario in order to maximize the number of covered users in an emergency situation. Q learning in RL was used to train UAVs to explore the affected area and find the best possible position which maximize total network coverage. Another author in [82] investigate the optimal deployment of UAV is to minimize the transmit power needed to satisfy the communication demand of users in the down-link, while also minimizing the power needed for UAV mobility, based on the predicted cellular traffic. ML techniques, here in the form of GMMs and a weighted expectation maximization (WEM) predict network congestion using data that describe the cellular traffic.

2) TRAJECTORY FOR UAVS

Trajectory tracking and planning are also areas of interest to researchers because of their impact on the overall performance of the UAV communication system. Reinforcement learning has been extensively used for the UAV navigation. In contrast to supervised ML, reinforcement learning does not rely on accurate prior knowledge of the environment or historical labeled data. Instead, in reinforcement learning, the agents can automatically learn from the environment and their own past experience through the rewards they obtain in order to improve their policy. This property makes reinforcement learning suitable for application in the cellular internet of UAV, where the UAV faces a dynamic and complex environment. Especially, Q-learning, that does not require models of the sensing and transmission, is suitable for the trajectory control problem. For applying Q-learning, the flight space can be abstracted into a finite set of discrete spatial points, and the trajectory can be considered as a path through these spatial points. The state of each UAV is its location, and the action is its trajectory in each cycle.

Following these guidelines, [88] addresses a trajectory control problem for cellular network of UAVs through the utilization of a Q-learning algorithm. In this approach, the UAVs are regarded as agents, their positions represent the states, and each cycle constitutes a time step. The feasible action set for a given UAV encompasses all potential direct trajectories towards spatial points that satisfy the condition of being within the maximum flying distance during one cycle. State transitions involve mapping the current locations and actions of UAVs to their respective locations at the commencement of the subsequent cycle. The reward mechanism assigns a value of 1 when the BS successfully receives valid sensory data from the UAV, and 0 otherwise.

In the study conducted by Huang [83], a novel approach based on deep reinforcement learning is introduced for enhancing UAV navigation using massive MIMO. The implementation of MIMO, which involves multiple antennas at both the transmitter and receiver ends, aims to enhance communication performance by enabling higher data rates. This advancement proves particularly advantageous for UAVs engaged in tasks such as video streaming and remote sensing, which demand robust high-bandwidth communication links. Additionally, MIMO contributes to enhancing communication reliability by mitigating the impacts of fading and interference. The research proposes a Learning Mechanism for Processing the DQN, followed by the utilization of DQN to optimize UAV navigation through the selection of the most suitable policy. In this context, the agent's decision-making process is informed by received signal strengths, which results in an improved trajectory planning performance for the UAV.

The author in [98] proposed a Learning Mechanism for Processing The DQN, then DQN is used for optimizing the UAV Navigation by selecting the Optimal Policy. The author proposes that in reality, it is difficult to find accurate and tractable end-to-end communication model in practice. The authors choose to use a dueling double deep Q network (dueling DDQN) with multi-step learning which the signal measurement at the UAV is utilized to directly train the navigation policy's action-value function. At the same time, the author also improved the use of signal measurement data and proposed a framework called simultaneous navigation and radio mapping (SNARM). The system can learn and generate a radio map of the airspace where the UAVs are operating while making trajectory planning decisions.

These radio coverage maps can also be well utilized. For example, the author of [85] uses aerial coverage maps to formulate a path planning problem that takes into consideration the coverage holes to find the shortest path given a connectivity quality constrained. At the same time, the trade-off between the path length and connectivity quality of UAVs is also considered in this process. However, this training method consumes too much time and training times. In order to solve the related limitations, the authors of [25] used the cutting-edge TL method to solve the problem of path planning. The authors successfully alleviate the problem of slow convergence of RL algorithms by employing a TL method to facilitate the agent's path learning in the new domain using the teacher policy previously trained in the old domain. It is worth mentioning that the author considers the situation of 6G and mmWave for simulation, which is more in line with the expectation of future communication conditions. Among them, the teacher path policy of the old domain is solved by Lyapunov-based model-free DQN. The results show that TL can significantly reduce the training time of mmWave.

Additionally, the UAVs trajectories could be jointly optimized with communication resource allocation for various performance metrics, such as spectral efficiency, or energy efficiency, by taking into account the UAVs's propulsion energy consumption. [86] formulate the problem of joint trajectory design and power control of UAVs to improve the users' throughput while satisfying their rate requirements. The problem is solved via three different steps: a multi-agent Q-learning placement algorithm to define the initial deployment of UAVs, an echo state network prediction algorithm for predicting the mobility of users, a multi-agent Q-learning-based trajectory acquisition an power control algorithm. A continuous learning approach for joint trajectory and coverage optimisation has been proposed in [114].

B. PHYSICAL LAYER MANAGEMENT

The physical layer in UAV communication is a key component of the entire communication system, which can directly affect the performance and reliability of the communication system. The task of the physical layer is mainly responsible for the physical transmission of data between the UAV and the ground station, and this process determines the range, data rate and quality of the communication link. The construction of accurate channel models in urban areas and the reduction of path loss (PL) by topology prediction are the primary objectives of wide communication enhancement. Dealing with intense interference from other UAVs and ground nodes is a further crucial factor to consider. ML solution play an important role in these processes. The physical layer must be meticulously designed and optimised to ensure reliable and efficient communication in the complex and demanding environments encountered by UAVs.

1) CHANNEL MODELING UAVS

In a wireless communication system, channel modelling is the process of building a model that describes the communication channel between the transmitter and receiver. Channel modelling is of utmost importance in the case of UAV communication, since UAVs often operate in conditions where communication channels are extremely dynamic and susceptible to a variety of interference and signal distortion. A good signal model is highly useful for performance evaluation, network planning, and optimising UAV trajectory design. During the process, it is necessary to consider the impact of UAV motion on the communication channel, including Doppler frequency shift, antenna direction changes, and other factors that may affect signal quality, such as the characteristics of the physical environment, obstacles that may cause signal reflection, diffraction, and attenuation, and The presence of topographical features.

Path loss is an important indicator of channel modeling for UAV communication. [94] uses the basic KNN and Random Forest algorithms in supervised learning to predict path loss. The labeled data used for prediction includes propagation distance, transmitter height, receiver height and elevation angle etc. Finally, the effects of the two methods are compared. Embodies the initial application of ML in UAV communication. The authors of [99] used the Generative Adversarial Networks (GAN) method in unsupervised learning to simulate and estimate the air-to-ground channel characteristics of UAV networks. The communication conditions are set in the case of using mmWave, so the data of the channel measurement are distributed data sets and are used for the training of the distributed conditional GAN architecture. The results show that the use of conditional GAN allows UAV down-link mmWave communications to have a larger average data rate.

The authors in Reference [96] note that existing channel models for UAV communication networks are often based on physical models that rely on assumptions about the environment, such as the location and height of buildings, which may not accurately reflect the complex and dynamic nature of the wireless channel. These physical models are also computationally expensive and may not be practical for real-time applications. To address these limitations, The authors use a deep learning architecture based on ANN to map input parameters, such as the UAV's position, altitude, and orientation, to the output channel parameters. The ANN is trained using a large data set of channel responses generated using a ray tracing simulator, which takes into account the physical characteristics of the environment. In additional detail, a clustering approach is applied to assess the 3-D wireless channel LoS and Non-Line of Sight (NLoS) channel states based on measurement by the UAV. In addition, shadowing characteristics are determined to provide a suitable temporary 3-D channel model. As an online learning strategy is implemented, changes to the communication environment are included into the temporary 3-D channel, therefore enhancing its precision. The work in reference [97] mentioned that

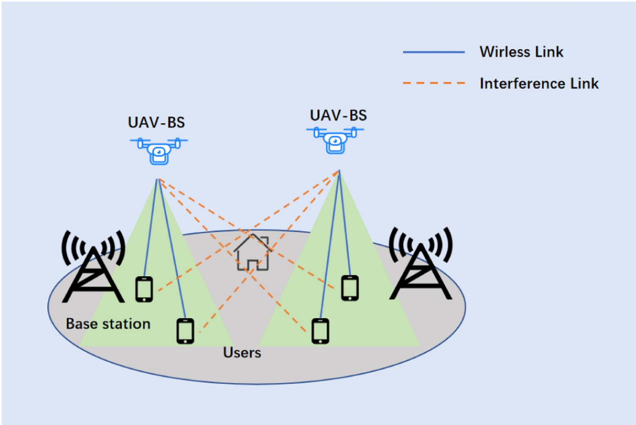

FIGURE 10. Scenario where the UAV is interfered by other BS and UE during flight.

optimization of UAV measurements is crucial to improving the performance and efficiency of the system such as received signal strength (RSS). The authors propose a novel approach that combines ANNs and the L-SHADE algorithm to optimize UAV measurements for mobile communications. The L-SHADE algorithm is used to optimize the input parameters to the ANN, such as the UAV's altitude, position, and orientation, to maximize the performance of the system. The authors demonstrate the effectiveness of their approach by comparing the performance of the proposed method with existing approaches. At the same time, their approach can be applied to other areas of UAV communications, such as UAV-based sensing and surveillance.

2) INTERFERENCE FOR UAVS

One major challenge to ensure the efficient coexistence between ground and aerial UE lies in the severe aerial-ground interference (Fig. 10). And that interference management is crucial to improving the performance and efficiency of the system. The existing literature on interference management in cellular-connected UAVs, and note that traditional approaches such as power control, resource allocation, and interference coordination are limited in their ability to adapt to the dynamic and complex nature of the network. ML algorithms can be used to detect interference in UAV communication by analyzing the received signal and identifying patterns that indicate the presence of interference. or can be used to implement adaptive filtering techniques that remove unwanted noise from the received signal.

The article in [96] examined UAVs' opportunistic channel access. Considering the different properties of data traffic and UAV clustering, this challenge was structured as a non cooperative interference mitigation game. After putting these qualities into the utility function, the weight coefficients are given to each feature, and then the features are added linearly. In addition, a distributed log-linear learning technique is used to reach the Nash equilibrium (NE) of the interference mitigation game. The learning algorithm is based on the fact that a UAV experiencing intra-cluster interference is chosen at random to update its joint channel-slot selection based on its experienced interference level, slot interval, and cluster rewards in each step, and that the channel selection is determined stochastically. Simulations focused on convergence behavior, selection behavior, and performance evaluation. This showed how important it is to set the right weights for the log-linear algorithm's enhanced interference control. In this manner, the proposed method quickly converges to the best network utility and the lowest possible interference level.

The authors in [115] propose a novel approach that uses Deep Reinforcement Learning (DRL) to optimize interference management in cellular-connected UAVs. The proposed approach uses a neural network to model the UAV's environment and learns the optimal policy for interference management through trial-and-error. Their approach is effective in managing interference in cellular-connected UAVs and has the potential to improve the performance and efficiency of the system. Another problem in the process of channel modeling for UAV communication is that channel changes are difficult to estimate. Many previous channel studies and interference simulations assume that the channel is block-fading channel or invariant channel.

C. RESOURCE AND NETWORK MANAGEMENT

Many conflicting requirements, such as low latency, increased throughput, low overhead, supporting a large number of devices, and dynamic conditions, must be taken into account when performing resource management, network planning, content caching, and user association tasks in UAV cellular networks. In this way, ML frameworks have been implemented to support highly effective resource management. In this process, judging the current status of the UAV is the first step, including network status, energy remaining, environmental status and so on. The authors of reference [116] sought to estimate the success and failure rates of UAV networks using ML techniques based on linear regression and Support Vector Machine (SVM). Due to the time-varying nature of the UAV connection caused by its mobility, the chance of successful transmission diminishes with increasing wireless link distance. In this context, ML techniques may be used to teach UAVs to identify whether connections to surrounding nodes are possible. Simulations demonstrate that accurate training of LR and SVM may be done with the increased precision and speed offered by SVM. Multi-UAV networks may be optimally deployed with early training, and correct clustering can increase wireless transmission reliability. In addition, for energy management based on the UAV status and link status, the scheduling of the goals that need to be completed are also important to improve the performance of UAV systems.

1) ENERGY EFFICIENCY AND POWER CONTROL

Energy efficiency and power control are important considerations in UAV communication, particularly for applications that require long flight times and limited battery capacity. Energy efficiency refers to the ability of a UAV communication system to minimize energy consumption while maintaining reliable communication performance. This can be achieved through a variety of techniques, such as adjusting the transmit power of system based on channel conditions, receiver distance, and interference levels. By using lower transmit power levels when possible, UAVs can conserve energy and extend their battery life, while still maintaining reliable communication performance. Transmission scheduling is another technique used to improve energy efficiency in UAV communication. By avoiding unnecessary transmissions and using energy-efficient transmission modes, such as additional transmission.

According to [117], the author specifies the scope of use of the UAV and then provides a communication link for ground users. Use the DQL of reinforcement learning to determine what height and position can minimize energy consumption while ensuring that the UAV can cover a certain range. And experiment in two situations of planned flight and unplanned flight respectively. Finally, the results are compared with traditional schemes that do not use ML. The results show that the combination of reinforcement learning and deep neural network can greatly improve the performance, including average coverage, average energy consumption, and time to complete tasks.

2) SCHEDULING

Beyond energy efficiency and power control for smart UAVs, one can think about smart event scheduling for a UAV network. It refers to the process of determining the optimal timing and frequency of data transmissions between the UAV and the ground station or other nodes in the communication network. The goal of scheduling is to ensure efficient and reliable communication while minimizing energy consumption and latency, performance metrics [60]. Good scheduling optimizes the use of available bandwidth and resources. For example, by scheduling transmissions at optimal times and frequencies, UAVs can avoid collisions and interference with other nodes in the network, while still ensuring timely data delivery. Scheduling can also help to minimize latency and delay in UAV communication. By scheduling transmissions in advance and using techniques such as predictive control and adaptive modulation, UAVs can reduce the time required to transmit and receive data, improving overall performance and response. And these also mean a reduction in overall energy consumption, which enhances energy management.

Within this context, the study outlined in [118] introduces a spatio-temporal scheduling framework tailored for self-governing UAVs. This RL solution, as proposed by the authors, operates on a model-free basis, harnessing the widely recognized Q-learning algorithm. The algorithm systematically addresses unforeseen occurrences by iteratively assessing their presence during each time slot and subsequently adjusting the UAVs schedule. This adjustment prompts a corresponding update in the UAV trajectory based on the Q-learning strategy. Notably, the approach considers a multitude of parameters associated with each event, encompassing aspects like commencement time, duration, location, and priority. The study holds several noteworthy aspects, encompassing its incorporation of diverse factors like efficient management of unexpected incidents, battery level considerations, and operation within a collaborative UAV ecosystem. Nonetheless, optimal selection of certain parameters remains less elucidated. For instance, the temporal parameter presents a trade-off between computational complexity and time efficiency. A decision-making process that maximizes the efficiency of the next event unavoidably prolongs processing time, potentially detrimentally impacting UAV coverage rates. Additionally, the research could potentially enhance its realism by considering multiple docking stations instead of focusing solely on a single station across the entire network. Such an extension would require the UAVs to factor in proximity when determining potential station shifts.

3) HANDOVER FOR UAVS

The support of mobility is a fundamental aspect of wireless networks. Handover (HO) is one of the key aspect in UAV mobility management when UAVs are integrated in existing cellular networks. The high speed and three dimensional motion of UAVs make HO management more difficult compared to ground UEs. Given the intrinsic characteristics of the ground to air link, researchers need to develop efficient HO management algorithms that can provide a robust UAV mobility support in the sky. UAVs face frequent HOs leading to undesirable outcomes such as radio link failures, ping pong HOs, and large signaling overheads. The authors of [119] explored the RL algorithm to maximize the received signal quality at a cellular-connected UAV while minimizing the number of HOs.

D. SECURITY AND SAFETY FOR UAV

It is anticipated that UAVs would play a significant role in several sectors of 5G and beyond networks, enabling not only better communication but also safety applications and essential infrastructures. Both security and safety are essential to ensure that UAV communication systems operate effectively and can be trusted to perform their intended functions without causing harm or damage. In addition, the huge expansion of the UAV business will result in many heterogeneous air-to-ground deployments with greater densities of UAV nodes, requiring their security against cyber-attacks across several network levels. At the same time, ensuring safety is one of the important indicators that UAV base station applications can be used in practice, but the level of safety is difficult to confirm from simulation or a small number of experiments. XAI can play an important role in this process, because it enables a clear understanding of how and why the UAV makes decisions. This means that the level of security can be more clearly identified. The author of [48] proposed a way to use XAI. Use XAI to judge and adjust when the UAV deviates from the established trajectory. The explainable model is presented on a visual platform in the form of if-then rules produced from a fuzzy inference model of the Sugeno type. The model is evaluated using data collected from three separate missions. Over the course of each operation, bad weather, Circumstances, and target locations are added at random.

In the study by [109], a defensive system was introduced to counteract malicious UAV activities. This system employed diverse UAV detection methods, including jamming, GPS spoofing, transmission of hacking signals, and laser-based interventions. The interaction with malicious UAVs was framed as a dynamic defense game, wherein the suitable defense strategy was selected based on the attack mode of the UAV and the significance of the protected zone. To model this strategy selection, the author employed the MDP framework and utilized Q-learning to identify the optimal defense approach without prior knowledge of the ongoing UAV attack mode in the dynamic game. Simulations revealed that the proposed RL-based malicious UAV interception approach substantially reduced the risk in the safeguarded area and enhanced the utility of the defense system compared to a random defense policy.

Another consideration is UAV detection, detection in UAV communication refers to the ability to identify and track UAVs in the communication network, typically using specialized sensors and algorithms. The goal of detection is to improve situational awareness and enable efficient and reliable communication with UAV, while also providing safety and security to protect against unauthorized or malicious UAVs. But for the urban environment, the environment is more complex which has more physical obstacles, environmental noise. Although the use of UAVs can increase the probability of LoS, traditional methods such as radar, electro-optical sensors, and computer vision still have a lower-than-expected effect. In this case, reinforcement learning can better assist the system to achieve better detection results.

E. ISAC UAV

UAVs are emerging sensing technologies that, thanks to their flexibility and their possibility of keeping a privileged LoS point of view, are often adopted for localization and sensing in time-critical applications [120], [121], [122], [123].

The advantages of using UAVs with Integrated Sensing and Communication (ISAC) are several, but, at the extreme, one can find two significant aspects. From one side, the 3D mobility of UAVs permits Dual Function Radar Communication (DFRC) tasks in an optimized fashion: apart from setting the best beam-forming and waveform design, the UAV the trajectory can further increase the performance of the ISAC system. On the other side, ISAC is an integrated solution that supports easy and low-complexity hardware deployment onboard battery-constraint agents.

For these reasons, the ISAC theoretical framework has been recently applied to UAVs [124], [125], [126], [127], [128], [129], [130], [131]. For example, in [127], a rotatory-wing UAV transmits the ISAC signal during its flying process, to simultaneously provide downlink communication service to a ground user and sense a target. The location of the user and the UAV are a priori known, whereas the location of the target is unknown. The trajectory design problem is to determine the next UAV waypoints, its hovering points and flying velocities to maximize the average communication rate while minimizing the Cramer-Rao Lower Bound (CRLB) of target location estimation. In [130], a ground BS is deployed to deliver downlink wireless services to cellular users. A cellular-connected UAV equipped with a side-looking synthetic-aperture radar (SAR) flies and collects the echoes of communication signals originated from the ground BS, to sense objects and gain situational awareness. The UAV minimizes the overall propulsion energy consumption during the considered time horizon, while maintaining acceptable sensing resolution by reusing cellular communication signals. Nevertheless, it has not been accounted for the fact that, due to its high altitude, the UAV might associate to several candidates ground BSs at different distances. Thus, the UAV-BS association should be carefully considered when designing the UAV trajectory. The work in [132] applies neural networks (NN) to derive the best joint UAV-BS and beamforming weights in a dual function radar-communication THz UAV, outperforming the conventional methods based on optimization techniques.

The authors in [131] consider a UAV equipped with a Uniform Linear Array (ULA) vertically deployed w.r.t. the horizontal plane. The UAV is at the same time serving ground users on the ground and radar sensing towards potential ground targets. The objective is to maximize the average weighted sum–rate throughput by jointly optimizing the UAV trajectory, as well as the transmit information and sensing beam-forming subject to the sensing requirements and transmit power constraints over different time slots. In [133], the considered UAV is required to execute multiple sensing tasks in sequence within the cell coverage. Finally, in [134], the authors consider a UAV-ISAC system where the objective is to maximize the achievable rate, subject to the beam-pattern gain constraint and the maximum transmit power constraint.

Other related papers of interest deal with ISAC design for mobile networks [135], Reconfigurable Intelligent Surface (RIS)-aided UAVs [136], physical layer security in UAV enabled wireless networks [137], and distributed target tracking by networks of UAVs [138].

VI. INTELLIGENT UAV WITH 6G AND BEYOND

6G is expected to offer significant improvements in terms of data rates, latency, and reliability compared to existing wireless communication systems. This could enable UAVs to transmit high-quality video and sensor data in real-time, even in challenging environments such as urban areas or disaster zones. Also, 6G is expected to support a massive number of connected devices, including UAV, which could help alleviate congestion in existing wireless networks. This could enable

TABLE 4. Intelligent UAV With 6G and Beyond

Application area	Paper	Year	Description
C-RAN and O-RAN	[145]	2021	O-RAN for Data-Driven NextG Cellular Networks
	[146]	2023	O-RAN Intelligent Controller with Multi-UAV Enable Wireless Network
	[147]	2023	Task Scheduling and Resource Sharing for O-RAN-empowered UAV Sensor Networks
Intelligent Edge Computing	[148]	2018	Joint offloading and trajectory design for UAV mobile edge computing networks
	[149]	2019	Energy efficient for UAV-enabled mobile edge computing networks
	[150]	2022	Deep-Graph-Based RL for Joint Cruise Control for Aerial Edge Internet of Things
	[151]	2022	A Survey on the Convergence of Edge Computing and ML for UAVs
	[152]	2022	Multi-UAV network assisted intelligent edge computing
Space-based networks (satellite)	[153]	2017	Space-based information service in Internet Plus Era
	[154]	2020	Cell Free Satellite assisted UAV networks for 6G wide area IoT
	[155]	2022	Satellite- and Cache-assisted UAV trajectory optimization for 6G aerial networks
	[156]	2024	UAV and satellite remote sensing for inland water quality
Swarm UAV system	[157]	2018	Review of UAV swarm communication and control architectures
	[158]	2018	Channel estimation and self-positioning for UAV Swarm syste,
	[159]	2022	Recent advances and future trends of UAV swarm communication
	[160]	2023	Comparative analysis of different UAV swarm control methods on unmanned farms
	[161]	2023	Air-to-ground relay communication planning method for UAVs swarm applications

UAV to operate in areas with high user demand, such as sports stadiums or large public events. Using 6G in UAV base stations could also open up new opportunities for applications and services. For example, UAVs equipped with 6G communication technology could be used for remote inspections of infrastructure, precision agriculture, or search and rescue missions. 6G could also enable new applications such as augmented and virtual reality, which require high-bandwidth and low-latency communication. Table 4 illustrates the integration of intelligent UAVs with 6G and beyond technologies, showcasing their advanced capabilities and potential applications.

A. C-RAN AND O-RAN

C-RA and O-RA are eye-catching network architecture that play important roles in the evolution of 6G networks which worth looking forward to. C-RA refers to the network architecture that concentrates the base band processing functions of multiple base stations into a public data center, which is also called "cloud". O-RA is a network architecture that aims to dis-aggregate and standardize the radio access network (RAN) components, including the hardware and software, to enable interoperability and innovation among vendors and operators [139]. C-RA has obvious advantages in increasing network capacity, improving network efficiency, improving energy efficiency, and simplifying network management. And the goal of O-RA is to promote a more open and flexible RAN ecosystem, while also reducing costs and improving performance [140]. The structure of O-RA is based on a set of functional blocks and interfaces that define how the RAN components interact with each other, which include Open RU, Open DU, and Open Central Unit (CU).

The DU performs base-band processing functions, such as digital signal processing, modulation/demodulation, and channel coding/decoding. It also handles the scheduling and coordination of radio resources. The CU provides control and management functions for the RAN, such as network management, traffic management, and service orchestration. It also performs higher-level functions such as radio resource management, mobility management, and security management. And the RU is responsible for the transmission and reception of radio signals over the air interface. It includes the antennas, radio transceiver, and other hardware components. These functions and interface structure of these modules are implemented through O-RAN Management and Control (OMC) for real-time and non-real-time intelligent management. Unlike traditional RAN systems, the structure of ORAN can be distributed and flexibly deployed. [141] mentioned that Using UAV as O-RUs allows to quickly deploy a 5G/6G network to assist the terrestrial network in a temporary period in which computing resources can fly closer to users to meet their stringent constraints. During this process, OMC in O-RAN can enable optimization and learning solutions for employing and controlling UAV-BSs to extend not only the coverage area but also the availability of computing resources. The author of [62] designed a control loop that defines the flows required to operate the UAV-BSs and manages the distributed elements of the O-RAN in order to perform offloading tasks. In order to resolve the proposed optimisation problem, apply learning solutions to the flying O-RAN architecture in order to optimise not only the UAV-BS trajectory for gathering sensing data, but also the distributed resources, such as the O-RAN RU, O-RAN DU, and ORAN CU, to serve offloading tasks requested by sensing devices.

B. INTELLIGENT EDGE COMPUTING

The concept of Mobile Edge Computing (MEC) finds its roots in the increasing demand for new applications like VR/AR and autonomous driving, which rely heavily on ultra low-latency communication, computation, and control across a multitude of wireless devices. Despite the intensive real-time computational tasks these applications entail, wireless devices are often constrained by their small size and limited computation and data storage capabilities. Consequently, MEC has emerged as a pivotal technology, aiming to augment the computational prowess of these small devices through computation task offloading to proximate MEC servers. However, for users situated at the cell's edge, this offloading strategy could inadvertently result in heightened transmission energy consumption and/or longer delays compared to local computation. This is due to the restricted communication rate with the Access Point/Base Station (AP/BS). To navigate this challenge, the strategic deployment of UAVs, endowed with substantial controllable mobility, has been proposed as a solution. These aerial entities, acting as flying cloudlets, can efficiently offload computations for users by dynamically approaching them, thereby circumventing the limitations associated with cell-edge offloading [143].

The research in [157] focuses on an intelligent caching approach for a heterogeneous aerial-terrestrial network in the context of 6G. This network comprises diverse base stations, including both UAV and terrestrial remote radio heads. The proposed technique leverages FL methods, eliminating the need for users to explicitly share their content preferences and reporting. Instead, a Hybrid Caching Predictor heterogeneous computing platform (HCP) accurately forecasts content caching across various base stations based on users' preferences. In this framework, the HCP serves as the central server, while network nodes securely share updates with the global model. A convolutional neural network (CNN) was employed to enable the HCP to learn the optimal files for caching in heterogeneous base stations. This FL-based HCP solution was evaluated using various datasets, demonstrating its effectiveness in comparison to other baseline techniques.

[145] presents an aerial Edge Internet of Things (EdgeIoT) system, where a drone is used as a mobile-edge server for processing tasks from ground IoT devices. It focuses on optimizing UAV cruise control and task offloading allocation, balancing the device's computing capabilities and the UAV's speed limits. The study introduces a deep-graph-based reinforcement learning framework to efficiently manage task offloading and UAV movement, leading to improved task handling and reduced task missing rates in EdgeIoT systems.

C. SPACE-BASED NETWORKS WITH SATELLITES

The core imperatives of 5G/6G mobile communication encompass not solely the establishment of a mobile communication network merging intelligence, perception, and security with communication functionalities at its core, but also the realization of a seamless, people-centric air-space-ground-sea coverage integrating various networks [148]. Within this framework, UAVs find application across space-based networks, satellite collaborations, terrestrial installations, and maritime communication users, facilitating multi-dimensional coverage across intricate scenarios while ensuring continuous, secure connections. The network architecture comprises space-based networks, aerial networks, and sea-based networks, each playing a distinct role in the ecosystem. Specifically, ground-based networks involve terrestrial communication equipment, encompassing terrestrial internet and wireless devices. Space-based networks consist of stationary satellites orbiting Earth, while aerial networks encompass temporarily deployed UAVs [149], airships, and similar entities. These aerial components serve as relays for sea-based users both on the ground and at sea, forwarding data to space-based satellites [150]. Sea-based networks refer to offshore platforms, ships, fishing vessels, and similar sea-based equipment. Owing to their considerable distance from the mainland, many offshore platforms lack communication connectivity within the range of existing ground-based station networks. The deployment of UAVs, however, enables effective communication between sea-based installations and terrestrial control centers.

D. SWARM UAV SYSTEM

Swarm UAV systems have gained significant attention in recent years due to their potential to perform various tasks that are difficult or impossible for a single UAV to accomplish. A swarm UAV system typically consists of multiple UAVs that work together to achieve a common goal. Compared with a single UAV, the swarm UAV system has many advantages, including improved efficiency, scalability, and robustness [152].

Swarm UAV base stations can support different swarm sizes and configurations, enabling flexibility and scalability in mission planning and execution. Especially when faced with a large coverage area, a single UAV cannot meet the demand. Meanwhile, another advantage of swarm UAV systems is their ability to perform complex tasks. For example, a swarm of UAVs can be used for search and rescue missions, where they can quickly and efficiently search large areas for survivors. Additionally, a swarm of UAV can be used for monitoring and surveillance tasks, where they can cover large areas and provide real-time data to a central hub.

The Swarm UAV system mainly has two common organizational structures: infrastructure-based swarm architecture and FANET [154]. Infrastructure-based swarm architecture utilizes a ground-based infrastructure to enhance the communication and coordination capabilities of the swarm. In this architecture, the swarm UAVs communicate with each other and with a ground-based infrastructure to enable efficient coordination. The control-based infrastructure typically consists of a base station, which serves as the central hub for controlling and coordinating the UAVs. The base station is equipped with advanced sensors and processing capabilities to enable real-time situational awareness and decision-making. The UAVs communicates with the base station and with each other through wireless communication links, such as WiFi, cellular, or satellite communication. One of the main advantages of the infrastructure-based swarm architecture is its ability to provide reliable and robust communication between the UAVs and the base station. This is particularly important in scenarios where the UAVs is operating in harsh environments with viruses or in areas with limited communication coverage. The ground-based infrastructure can also provide additional capabilities, such as power and data storage, which can enhance the endurance and mission capabilities of the swarm. Another advantage of the infrastructure architecture is its ability to enable more complex missions and applications. For example, the ground-based infrastructure can provide additional sensors and processing capabilities that can be used to support advanced applications, such as mapping and reconnaissance. The ground-based infrastructure can also be used for autonomous navigation and decision-making, enabling the UAVs to operate more independently and efficiently. A FANET is a type of ad-hoc network in which a group of UAVs communicate with each other to form a network. In a FANET, UAVs act as nodes in the network, communicating with each other to exchange data and coordinate their actions. One of the key advantages of FANET is their flexibility and adaptability. FANET can be rapidly deployed and reconfigured as needed, allowing them to respond to changing conditions in real-time. Another advantage of FANET is their scalability. FANET can be composed of many UAVs, allowing them to cover large areas and perform complex tasks. By working together, the UAVs can perform tasks more efficiently and effectively than a single UAVs could on its own.

VII. FUTURE RESEARCH DIRECTION

The rapid advancement of communication technologies and the increasing adoption of UAVs in various applications have opened up new avenues for future research in the field of UAV communication. In this section, several promising research directions are outlined that can further enhance the capabilities and potential of UAVs in communication systems.

- Energy constraints: Addressing the energy constraints of UAVs is a pivotal area of research that significantly enhances their prolonged operational capabilities. Key strategies involve the development and integration of innovative energy harvesting, storage, and transfer techniques, including wireless or laser-based energy transfer methods. Such advancements, as noted by [9], are essential for increasing the flight duration and operational efficiency of UAVs. This progress is vital for expanding the potential applications of UAVs, making them more effective for long-duration missions such as surveillance, environmental monitoring, and other tasks that require extended operational times. Furthermore, ML plays a crucial role in optimizing UAV energy management. It aids in the strategic placement of charging stations and the efficient scheduling of charging operations, thereby enhancing overall mission sustainability and reducing downtime. These developments collectively push the boundaries of UAV capabilities, enabling more robust and versatile deployments.
- Thethered UAVs: Exploring a wider range of UAVs, including tethered UAVs, for specific occasions and scenarios can unlock new possibilities in UAV communication. Tethered UAVs, connected to the ground by a cable, can provide continuous power supply and extended flight duration, making them suitable for prolonged, but static, missions [158]. There will be a need to assess the advantages and challenges of using specialized UAVs for different applications, such as disaster response, surveillance, and communication in remote areas. Additionally, investigating the integration of UAVs in new 6G architecture such as O-RA systems presents a promising research direction.
- non-terrestrial networks (NTN)-integration: Additionally, combining UAV networks with satellite systems to create comprehensive non-terrestrial networks represents a groundbreaking advancement. Such networks, supported by both terrestrial and aerial components, promise to deliver superior communication capabilities, broader coverage, and increased network resilience [159]. ML can be instrumental in the efficient formation and management of these complex networks, optimizing the coordination and operation of UAV swarms within this integrated system. This holistic approach could transform communication strategies, especially in areas where terrestrial infrastructure is lacking or has been compromised.
- Digital Twin: The integration of Digital Twin (DT) technology with UAVs presents significant opportunities to advance UAV operations, especially within the context of emerging 6G networks. DT technology enables real-time simulation of UAV operations, improving safety and operational efficiency, while predictive maintenance capabilities help extend the lifespan of UAVs. Additionally, DTs can provide detailed training environments, enhance decision-making by integrating with IoT and Big Data, and ensure regulatory compliance. According to [10], DT technology is expected to drive 6G research and development due to its modular capabilities and the potential for remote intelligence. This technological synergy between DT and 6G will enable proactive use of artificial intelligence, enhance network resilience, and open up new avenues for UAV applications in sectors like Industry 4.0 and aviation. As detailed in [160], a novel DT-based framework has been proposed for UAV swarms that reflects their physical entities with high fidelity throughout their life cycle. This framework integrates machine learning algorithms to optimize decision-making and control UAV behaviors effectively, demonstrating its efficacy in applications like intelligent network reconstruction. The relationship between DT and 6G outlines a promising research trajectory that could transform UAV operations and broader telecommunications frameworks.
- Blockchain: Blockchain technology significantly enhances UAV operations with its decentralized, secure

record-keeping and autonomous execution capabilities, as outlined by [161] and further supported by a comprehensive survey in [162]. This technology enhances the security and privacy of UAV communications through encrypted data stored on an immutable ledger, a crucial feature as UAVs find broader application in civilian and commercial fields. By improving traceability and accountability, blockchain is vital for ensuring regulatory compliance and effectively managing disputes. Blockchain enables autonomous UAV operations through smart contracts that automatically execute transactions, such as payment processing or maintenance protocols, once predefined conditions are met. It also significantly improves the coordination of UAV swarms, enabling efficient and secure communication without the need for a central authority, ensuring synchronized operation of the entire swarm. Additionally, blockchain helps streamline regulatory compliance by maintaining an immutable record of all UAV operations, streamlining the reporting process required by regulators. The research by [162] highlights the versatility of blockchain in UAV networks, facilitating applications in network security, decentralized storage, inventory management, and surveillance. As UAV technology continues to advance, integrating blockchain can unlock new applications and business models, particularly in the logistics, agriculture and emergency response sectors, making operations more robust, safe and able to handle complex tasks.

These research directions, complemented by real-world deployments and case studies in diverse application domains, will play a crucial role in shaping the future of UAV communication and the role of ML in it. They will revolutionize various industries and enhance communication capabilities across different sectors, paving the way for more robust, efficient, and adaptable UAV communication solutions.

VIII. CONCLUSION

In summary, a comprehensive study was conducted on the use of UAV in wireless networks, discussing the various roles that UAVs play in the field of wireless communication. This survey has also highlighted the critical role that ML techniques play in optimizing UAV operations, enhancing network efficiency, and addressing the challenges inherent to UAVs deployment. It can be noticed that the emerging cutting-Edge ML has greatly improved the potential and applicable dimensions of UAV applications. Deeper integration of UAVs in wireless communication networks opens up more possibilities for new network paradigms with higher flexibility and performance. Through an in-depth examination of existing literature, the potential of UAVs to serve as versatile communication tools has been elucidated, ranging from acting as aerial BS to enabling rapid disaster response and environmental monitoring. The popularization of these technologies and applications can reflect the fact that the convergence of UAVs, ML, and advanced communication technologies holds the promise of more efficient, adaptive, and resilient communication solutions. It is clear that UAVs are poised to play an increasingly pivotal role in the communication landscape, and the seamless integration of these technologies has the potential to redefine the way we connect, communicate, and respond to the dynamic demands of the modern world.

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CHENRUI SUN (Student Member, IEEE) received the undergraduation degree in system and control engineering from the University of Sheffield, Sheffield, U.K., and the master's degree in electrical and electronic engineering from the University of Sussex, Brighton, U.K. He is currently working toward the Ph.D. degree with the University of York, York, U.K., specializing in machine learning applied to Unmanned Aerial Vehicles and advanced wireless communication technologies, particularly focusing on 6G and beyond.

GIANLUCA FONTANESI (Member, IEEE) received the Ph.D. degree from the RF Microwave Research Group, School of Electrical, Electronic Engineering, University College Dublin, Dublin, Ireland, in 2021. He has several years of industrial experience as consultant for Nokia and as a Software and Radio Integration Engineer with Azcom Technology, Assago, Italy. He joined the SNT Communications and Networking Systems Group headed by Prof. Symeon Chatzinotas. His research interests include UAV and satellite communication, focusing on potential applications of machine learning techniques.

BERK CANBERK (Senior Member, IEEE) is currently a Professor with the School of Computing, Engineering and The Built Environment, where he leads interdisciplinary research and initiatives in AI-enabled Digital Twins, IoT Communication, and Smart Wireless Networks. He has been an Adjunct Professor with the Department of Electrical and Computer Engineering, Northeastern University, Boston, MA, USA, since 2017, and an Adjunct Faculty with the Department of Artificial Intelligence and Data Engineering, Istanbul Technical University, since 2022. He was an Associate Professor with the Department of Computer Engineering, ITU during 2016–2021, and a Full Professor during 2021–2022. He acts as an active Associate Editor for several world-leading academic journals, such as IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY (Scopus Q1 Quartile) since 2016, *Elsevier Computer Networks Journal* (Scopus Q1 Quartile) since 2013, *Elsevier Communication Networks Journal* (Scopus Q1 Quartile) since 2017, and IEEE COMMUNICATIONS LETTERS (Scopus Q1 Quartile) during 2018–2021. He's actively involved in several conferences as a TPC chair and organizing committee member.

AMIRHOSSEIN MOHAJERZADEH (Member, IEEE) is currently an Assistant Professor with Sohar University, Sohar, Oman. He has coauthored 80 published peer-reviewed research papers including six papers in different IEEE journals. He has had extensive collaboration with industry which resulted in 15 granted projects. He supervised or hosted in his lab more than 20 postgraduate highly qualified students. His research interests include communications technologies with emphasis on wireless cellular networks and smart systems. Dr. Mohajerzadeh was the recipient of several awards for his research, teaching, and service. He has served on academic venues including seminars, keynotes, panel talks, and tutorials in the last five years.

SYMEON CHATZINOTAS (Fellow, IEEE) received the M.Eng. degree in telecommunications from the Aristotle University of Thessaloniki, Thessaloniki, Greece, and the M.Sc. and Ph.D. degrees in electronic engineering from the University of Surrey, Guildford, U.K., in 2003, 2006, and 2009 respectively. He is currently a Full Professor/Chief Scientist I and the Head of the Research Group SIGCOM, Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg, Esch-sur-Alzette, Luxembourg. He is also an Adjunct Professor with the Department of Electronic Systems, Norwegian University of Science and Technology, Trondheim, Norway, and a Collaborating Scholar of the Institute of Informatics and Telecommunications, National Center for Scientific Research 'Demokritos'. In the past, he has lectured as a Visiting Professor with the University of Parma, Parma, Italy, and contributed in numerous R&D projects for the Institute of Telematics and Informatics, Center of Research and Technology Hellas and Mobile Communications Research Group, Center of Communication Systems Research, University of Surrey. He has authored more than 700 technical papers in refereed international journals, conferences and scientific books. He was the recipient of numerous awards and recognition, including the IEEE Fellowship and an IEEE Distinguished Contributions Award. He is currently serving on the editorial board of IEEE TRANSACTIONS ON COMMUNICATIONS, IEEE OPEN JOURNAL OF VEHICULAR TECHNOLOGY, and THE INTERNATIONAL JOURNAL OF SATELLITE COMMUNICATIONS AND NETWORKING.

DAVID GRACE (Senior Member, IEEE) received the Ph.D. degree from the University of York, York, U.K., in 1999. He is currently a Professor (Research) and leads the Challenging Environments Research Theme with the School of Physics, Engineering and Technology, and is pillar lead for advanced communications with the university's Institute for Safe Autonomy, and the Director of the Centre for High Altitude Platform Applications. His research interests include 5G/6G O-RAN systems, application of artificial intelligence to wireless communications, dynamic spectrum access, and interference management. He leads the €5.5 M REACH and is a work package lead for the York-led €7.8 M YO-RAN, which are projects developing 5G open radio access networks in collaboration with industry and funded by U.K. Government. He is an author of more than 300 papers, and author/editor of two books. He is a member of U.K. Telecom Infrastructure Network's Expert Working Group on Non-Terrestrial Networks, which influences government policy and brings together disparate strands of expertise. He was the Former Chair of IEEE Technical Committee on Cognitive Networks from 2013 to 2014, and a founding member of the IEEE Technical Committee on Green Communications and Computing. From 2014 to 2018, he was a non-executive Director of Stratospheric Platforms Ltd., which is developing high altitude platform based wireless systems.

HAMED AHMADI (Senior Member, IEEE) received the Ph.D. from National University of Singapore, Singapore, in 2012. He is currently a Reader in digital engineering with the School of Physics, Engineering and Technology, University of York, York, U.K. He is also an adjunct academic with the School of Electrical and Electronic Engineering, University College Dublin, Dublin, Ireland. He was a SINGA PhD Scholar with the Institute for Infocomm Research, A-STAR, National University of Singapore. Since then he was with different academic and industrial positions in the Republic of Ireland and U.K. He has authored or coauthored more than 90 peer reviewed book chapters, journal and conference papers. His research interests include digital twins, the application of machine learning in cyber-physical systems, open radio access and networking, green networks, airborne networks, and Internet-of-Things. He is a member of editorial board of *IEEE Communication Standards Magazine*, IEEE SYSTEMS AND SPRINGER WIRELESS NETWORKS. He is a Fellow of Higher Education Academy, U.K. He has been the Networks working group chair of COST Actions CA15104 (IRACON) and CA20120 (INTERACT).