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Review article

UAVs joint optimization problems and machine learning to improve the 5G and Beyond communication

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ABSTRACT

Recently, unmanned aerial vehicles (UAVs) have gained notable interest in various applications such as wireless coverage, aerial surveillance, precision agriculture, construction, power lines monitoring and blood delivery, etc. The UAVs implicit attributes e.g., rapid deployment, quick mobility, increase in flight duration, improvements in payload capacities, etc. , place it as an effective candidate for many applications in 5G and Beyond communications. The UAVs-assisted next-generation communications are determined to be highly influenced by various techniques and technologies like artificial intelligence (AI), machine learning (ML), deep reinforcement learning (DRL), mobile edge computing (MEC), and software-defined networks (SDN). In this article, we develop a review to investigate the UAVs joint optimization problems to enhance system efficiency. We classify the joint optimization problems based on the number of parameters used in proposed optimization problems. Moreover, we explore the impact of AI, ML, DRL, MEC, and SDN over UAVs joint optimization problems and present future research challenges and directions.

1. Introduction

Due to the vibrant and rapid mobility nature of UAVs, they can be generally employed in a range of applications varying from civilians to the military. The reduced manufacturing cost, accuracy in flight trajectory control, expanding payload capacities, effective energy harvesting strategies, as well as convenience of implementation, make the UAV a potential tool. The prior prospective features of UAVs caused a rise in UAVs fostering for commercial purpose and is also forecasted to progress in future [1–4]. In literary works, UAVs are also labeled as unmanned aerial systems (UAS) and most typically regarded as “drones”. Growing UAVs applications in the telecommunication industry as relay BSs, live information streaming and communication gateways, applications in search & rescue procedures, earthquake zones, monitoring the woodland fire, building, and construction, show business, oil wells, and power lines, and so on, are predicted to model the surge in UAVs market gain [5,6]. The 3GPP has issued a research study to understand the existing obstacles, challenges, requirements, and possibilities in UAVs adaptation to LTE and 5G & B5G communication networks [7]. The UAVs potential use in a hot spot and congested areas as relay-BSs make it a fundamental part of the next-generation communication [8,9]. Recently, deep learning is performing an outstanding role in effectively solving many intricate issues related to automated tasks in the areas of control engineering, understanding, decision making, drug discoveries, and also localization. Research study shows that the increasing interest of machine and deep learning techniques utilization helps in resolving complex UAVs applications like regular handover in network communication, landing on the mobile platform, accuracy in agriculture, surveillance, network access, designing optimum UAVs trajectory and energy optimization [10]. In [11], the authors discussed in detailed the current advances in UAVs applications from a medical care perspective varying from blood shipment missions to testing packages and medications, development in UAVs communication algorithms, the UAVs deployment strategies, and the UAV’s efficiency from the security perspective. The authors in [12] arranged a survey that discusses UAVs networking concerns and requirements from the civil application’s perspectives. Hazim et al. [6] organized an extensive study that focuses on vital obstacles concerning UAVs civil applications, energy harvesting, crash evasion, networking & safety as well as provides different significant understandings to handle it. The writers in [13], evaluated various protocols and strategies regarding UAVs communication at

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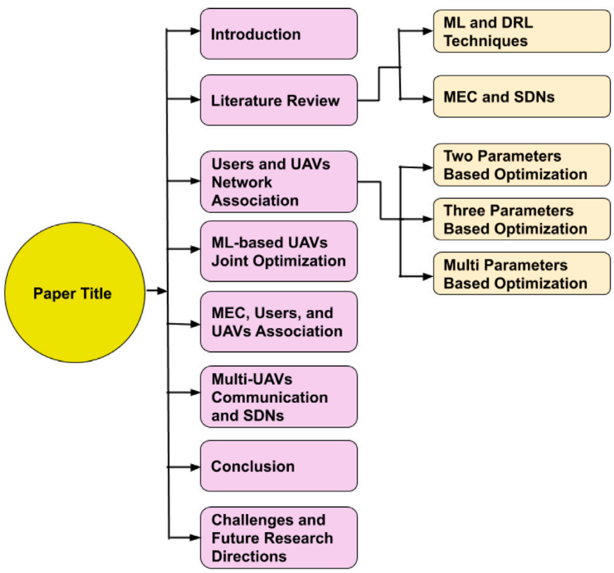

Fig. 1. A generalized overview of the article layout.

low amplitude platform, high amplitude platform as well as incorporated air-borne UAVs communication systems. In [14], Gupta et al. investigated UAVs wireless communication problems e.g., air-borne trajectory, routing protocols, energy efficacy, and hand over in UAVs-assisted wireless communication networks. Azad et al. [3] established a detailed survey that focuses on UAVs growth, difficulties, as well as possibilities. They explained numerous key problems and affiliated feasible approaches of UAVs like UAVs interference, airborne UAVs based relay BS, UAVs prototyping, regulations, and cyber-physical safety and security. The writers in [15], analyzed various challenges from spectral performance perspective related to multi-level UAVs communication networks. A joint optimization problem is composed of an upper-level and with one or many lower-level optimization problems. The upper and lower-level problems ratify their strategies to optimize their respective rewards [16]. The efficiency of any UAVs-assisted mission is jointly dependent on various parameters (e.g., flight trajectory, power consumption, payload capacity, etc.) that gives birth to the need for effective handling of arising joint optimization issues. To the best of our knowledge, there does not exist any survey that entirely focuses on the joint optimization problems of UAVs, concerning flight trajectory, time scheduling, altitude optimization, aerial and relay BSs, energy harvesting, power transfer, optimal power consumption, and resource allocations. In this article, we have provided an in-depth study regarding the prior non-convex joint optimization problems in the view of various successive optimization algorithms, mobile edge computing (MEC) techniques, and software-defined network (SDN). We have provided the most recent improvements concerning AI, ML, and DRL-assisted UAVs applications that play a vital role in 5G and B5G communication (see Fig. 1).

The article layout is structured in the following, Section 1 provides a brief introduction about UAVs development, different literature reviews, and the objective of this article. Section 2 offers a brief literature reviews of ML techniques, MEC, and SDNs, Section 3 discusses different joint optimization issues of users and UAVs association, Section 4 describes the role of AI, ML, and DRL in joint UAVs communication architecture, Section 5 explains about MEC role in UAVs joint optimization problems and network efficiency, and Section 6 talks about the use of SDN in UAVs applications. Section 7 explains conclusion of the article while Section 8 explores current challenges and future research directions.

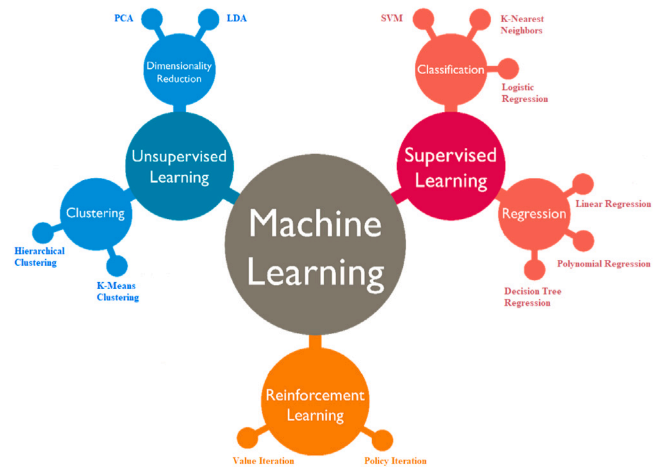

Fig. 2. Categorization of machine learning techniques.

2. Literature review

In this section, we provide a brief review of various ML and DRL techniques, mobile edge computing (MEC), and software-defined networks (SDNs). The prior algorithms and technologies are playing a significant role in efficiently handling UAVs joint optimization problems and improve the respective system's performance.

2.1. A brief literature review of ML and DRL techniques

Machine learning techniques are categorized into three tiers i.e., supervised learning, unsupervised learning, and reinforcement learning (RL). The RL is consists of various protocols, shown in Fig. 2 [10,17]. A brief literature review of the aforementioned learning techniques is provided with respective examples and applications. In AI and ML, supervised learning is defined as a set of techniques that find a predictive model by using input data to a known output. In other words, its a process of training an AI model by providing input data to attain a predefined output. Supervised learning is categorized into regression and classification techniques, and some of its examples are support vector machine, linear regression, and random forest. In unsupervised learning, an unclassified and non-labeled input dataset is provided to train the AI network to find concealed patterns, outcomes, and distributions. The technique's objective is to cluster unsorted data based on hidden patterns without any prior training data set. Unsupervised learning problems include clustering and dimensionality reduction. Some of its examples are hierarchical clustering, the k-means, PCA, and auto-encoder algorithm.

Markov Decision Process (MDP) In RL techniques, an agent is supposed to determine the best action based on its current state, and the repetition of this process in any problem is known as a Markov Decision Process (MDP). The goal of an MDP is to look for an optimal solution to sequential decision problems (SDP). In cases where the SDPs are stochastic, an MDP is highly improbable to provide an optimal solution but could strive for the best among available set of solutions. An MDP model is consists of a set of possible states (S), a set of actions (A), a transition model, and a reward value function (R). The Reward (R) and the transition is dependent on the current state (suppose S1), chosen action (suppose A1), and the resulting state (suppose S2).

Reinforcement Learning (RL) The objective of an RL agent is to enhance its long term accumulated reward through its interactions with the environment. The step of an RL technique that performs interactions and learns is called an agent and it achieves this goal (of learning) through an optimal policy. A policy is defined to be an array of actions for a predefined set of states and a policy that improves the overall long-term reward is regarded as an optimal policy. The crucial job for an agent is to effectively utilize the known actions and probe new actions that may lead to better rewards over the available best actions. For an agent, a core issue is to maintain a balance between the new exploration or utilizing the existing actions. In other words, improving the reward using an existing set of actions or to investigate for new best possible actions that could possibly lead to a better reward.

RL techniques can be organized into two different categories i.e., model-based and model-free. The model-based RL algorithms make use of function approximator and regarded as sample efficient. Various techniques that effectively handle model-based RL problems are policy search, value function, transition models, and return function. Examples of model-free RL algorithms are Monte Carlo and Temporal Difference methods while SARSA and Q-Learning techniques fall under the categories of the TD method.

Dynamic programming Dynamic Programming (DP) is a mathematical technique to solve complex problems by dividing it into a set of simple subproblems. The DP method was developed by Richard Bellman in the 1950s to solve optimization problems. DP is an iterative optimization technique that breaks down a complex problem into an array of simpler and uncomplicated subproblems to be solved efficiently. DP offers a generalized approach to analyze and assess various sorts of problems. Implementing a DP based approach over a problem requires extensive observation and understanding of the concerned environment. Most often, it needs creativity and subtle intuition to identify and formulate a DP problem. In an environment of the MDP model, DP is used to identify an optimal policy using suitable iterative methods [18,19].

Monte Carlo (MC) method Monte Carlo (MC) methods are a group of computational techniques that depends on iterative random sampling to attain numerical results. In fact, MC methods utilize randomness to attain the solution to complex problems that could be deterministic in nature. To implement MC methods, its necessary to have a set of random numbers. The MC methods are effectively being used in the areas of Physics, Biology, Computer Science, etc. to efficiently handle complex problems. The MC methods are used in the scenarios of optimization, probability distribution, and numerical integration. The major advantages of MC methods over DP techniques are, (i) MC methods are easy to implement (ii) MC methods could be utilized in sample models (iii) MC methods achieve optimal solutions using direct interaction [20].

Temporal difference methods In the case of MC methods, a new update takes place after completion of the existing episode, and it involves a waiting problem. This problem is handled by the Temporal difference (TD) techniques, a group of model-free RL techniques. The TD techniques learn through the bootstrapping process and are widely used techniques for assessment and accurate prediction of the policy. The TD techniques are a sort of unsupervised learning technique where the agent learns to predict the value of a variable resulting at the end of an array of states [21,22]. In the case of RL problems, the TD methods are used to anticipate long-term future rewards.

SARSA The authors in [23] developed a new RL-based TD technique initially called 'modified Q-learning' and later on the Rich Sutton named it State-Action-Reward-State-Action (SARSA). The proposed method is somewhat an advanced form of the Q-learning technique. Unlike Q-learning, the SARSA is an on-policy learning technique. The SARSA learns the optimal value through the actions carried out by the current policy. Each time, the policy updates take place when the agent performs actions or interacts with the environment.

Q-Learning The Q-learning method is regarded as a stochastic DRL technique. Q-learning is a model-free and off-policy TD learning algorithm [23]. Q-learning technique attains the optimal policy by utilizing off-policy e.g., the updating policy of the method is unlike the action policy and may involve taking random actions. Q-learning algorithm seeks to discover the best action to decide, having the current state. The primary aim of the Q-learning algorithm is to find out and learn a policy that leads to optimization of the total reward.

Actor–Critic algorithm The actor–critic technique is a well-known RL algorithm and a combination of value function and policy. The critic section of the technique assesses the value function while the actor part updates the policy according to the critic estimate. The actor–critic algorithm appraises both i.e, the policy, and value function and can be applied to small and large action-state spaces. The critic part makes use of an approximation framework and simulations to estimate the value function that is further applied to update the actor's policy [24].

Bayesian methods In DRL methods, an agent learns rewards from different states and increases it over time. The agent learns and adjusts to swap from low to high rewards states. Environmental uncertainty plays a crucial part in optimizing the reward. The Bayesian models offer an analytical framework to evaluate and analyze a model uncertainty [25]. Bayesian techniques can handle exploitation–exploration problems due to its capability of acquiring uncertainty in the model's learning parameters. Moreover, the Thompson sampling method can be utilized to deal with exploration–exploitation problems.

Deep Q Network The Deep Q-Network (DQN) [23] technique is based on Neural Network to guess the value function in case of large state space. The network training is accomplished using the Q-learning update mechanism. The DQN technique solves the issues related to large state space and concerned actions.

2.2. A brief literature review of mobile edge computing and software defined networks

The existing cloud computing architecture is insufficient to fulfill the needs of low latency, user mobility, support for high data rate, and user location-awareness [26]. To solve the preceding issues, the researchers introduced a new approach called Mobile Edge Computing (MEC). The researchers and engineers aim at integrating the networking, servers, and computing power with the base stations to better answer the aforementioned issues. The MEC offers a distributed computing paradigm that divides a task into sub-tasks. Various issues and challenges can arise during the process of sub-task distribution. After the distribution phase, the mobile edge cloud decides about the various relevant issues e.g., low latency, bandwidth, etc. The delay-sensitive operations can be carried out at MEC servers while delay-tolerant high data processing should be performed on the cloud server [27]. With the steady deployment of 5G commercial infrastructure, the telecommunication industry is highly determined to integrate the IoT and cellular internet to the upcoming 5G communication network. In this regard, a UAV is a potential choice for MEC nodes as it is controlled by ground controllers. The UAV has the capacity to acquire high-resolution images and offer onboard data storage and computation facilities for the MEC system [28,29]. Since UAVs are equipped with limited energy resources that make airborne UAVs unable to offer consistent MEC services for a long time. However, advanced technologies like AI, ML, and DRL can help in optimizing data storage, processing, and communication services of airborne UAVs and offer improved MEC services to the network.

The software-defined network (SDN) mechanism is centralized network management by distributing the network data and control planes [30]. The SDN approach offers the capability to control a network framework in a centralized manner using different software applications [31]. The ML algorithms can naturally fit well in SDNs due to the availability of a high amount of network data, particularly in efficiently handling problems like fault detection, network traffic estimation, etc. UAVs can perform the autonomous mission, either by predefined mission planing or through intelligent automation systems. In such scenarios, inter-UAV understanding and coordination techniques should be constructed to optimize the UAVs swarm efficiency. The techniques organize UAVs-UAVs communication, UAVs-BS communication, UAVs trajectories, and control links [32]. The centralized nature of SDN can handle various UAVs control functionalities including sustainability of control links, collision avoidance, network handling, etc. Consequently, SDN based approach can effectively contribute and optimize the UAV-assisted network performance.

In this section, we attempted to offer a concise literature review of different ML and DRL techniques, as shown in Fig. 2. We tried to briefly explore the emerging technologies including, mobile edge computing (MEC) and software-defined networks (SDNs), that have a significant impact on futuristic UAVs application. The prior algorithms and techniques are vital to efficiently deal with UAVs joint optimization issues and optimize the system's productivity.

3. Users and UAVs network association

In this section, we present various joint UAVs network optimization scenarios to achieve optimal network efficiency. We have divided this section into two, three, and more than three (multi) parameters based optimization problems and have summarized each subsection through tabular representation (see Table 1).

3.1. Two parameters based optimization

In this subsection, we provide the UAVs joint optimization study where the number of prime governing variables are limited to two only. The research efforts of various researchers are as follow. In [33], the researchers proposed a framework to assign optimal locations to UAVs-enabled aerial relays. The proposed problem is composed of UAVs-user association and UAVs-aerial placement. The prospective problem is based on probabilistic and deterministic LoS classification, making efficient use of city map. A low-complexity based technique is used to estimate the best UAVs placement concerning user locations. The attained performance is approximately equal to the high-complexity based exhaustive search techniques. In [34], the Koulali et al. proposed the idea to schedule the beaconing periods to optimize energy consumption during UAVs-GUs communication. The proposed optimization problem is efficiently handled through a learning algorithm to achieve convergence while maintaining the especial Nash equilibrium operating point. The authors in [35], introduced user association through UAVs-enabled network using D2D communication. The primary objective is to improve the weighted sum-rate of the UAVs-assisted and D2D-connected GUs by the optimization of user association. The resultant NP-hard problem is efficiently solved using the proposed (e.g., cluster-based and relaxed optimization) algorithms. The simulation results depict the outstanding performance of the proposed protocol. The researchers in [36] investigated the joint optimization problem of UAVs-user association and UAVs aerial placement to enhance achievable data rates at GUs. The proposed architecture results in a mixed-integer non-convex optimization problem (MINCOP). The proposed problem is decomposed into integer optimization and a non-convex optimization sub-problems. The resultant sub-problems are efficiently solved through successive convex approximation. The comparative performance analysis of the proposed technique to the benchmarks verifies the preceding technique's significance. In [37], the authors proposed a UAV-based network communication scheme where UAV conduct fixed trajectory-based periodic operations and one-time fly operation to serve the GUs (Fig. 3). The proposed paradigm aims to optimize UAV flight duration during each scenario while maintaining the required data rate of GUs. The authors jointly optimized the UAV trajectories and resource allocations and proposed recursive algorithms to find the optimal solution using block coordinate descent and successive convex optimization techniques. The analytical results signify the performance of the proposed architecture over the benchmark techniques.

The researchers in [38] formulated a scheme to collect confidential data from scheduled SNs through UAV while avoiding the interception of unscheduled SNs. The authors developed various measuring parameters (e.g., secrecy outage probability and reliability outage probability) at a constant data rate to construct an optimization problem. The resultant optimization problem is reduced to a convex optimization problem using penalty and first-order restrictive approximation approaches. Further, the penalty method based recursive procedure is devised to achieve the optimal solution to the proposed problem. The analysis shows the significant performance of the proposed model over the benchmark techniques.

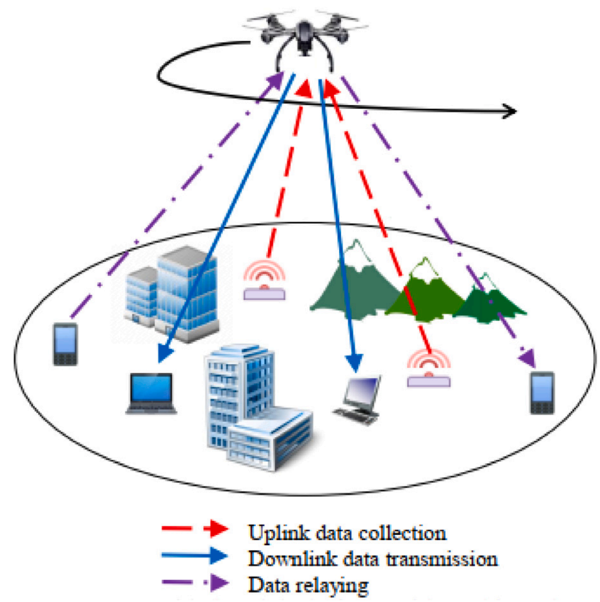

Fig. 3. A UAV-based architecture with multi-mode network communications [37].

The authors in [39] introduced a UAV-enabled network paradigm to enhance the system throughput using UAV trajectory and transmit power. The initial UAV-GU communication is constrained in the sense that UAV can only communicate when it is in the vicinity of the GU. Initially, an alternating directional method of multipliers (ADMM) is utilized to find the power transmit and UAV trajectory respectively. The authors also proposed a secondary algorithm to successively estimate the transmit power and UAV trajectory. The simulation results signify the performance of the ADMM-based technique over the relevant baseline approaches. Zhang et al. [40] proposed a UAVs-enabled wireless communication system to enhance the system capacity by joint optimization of UAVs trajectories and power allocation. The authors reduced the non-convex optimization problem into two sub-problems and proposed SCA and block coordinate update algorithms to efficiently solve it. The obtained simulation results portray that the proposed paradigm greatly improves system capacity. The researchers [41] proposed UAVs-enabled communication architecture to improve the secrecy rate of the proposed scheme. In the preceding problem, a UAV playing the role of an aerial BS to communicate with confidential GNs and simultaneously, a jammer UAV is also deployed to thwart the existing eavesdroppers. The proposed problem is a non-convex optimization problem that is reduced to two subproblems and solved by SCA and alternating iterative techniques. The attained results depict the sufficient performance of the proposed paradigm. The authors in [42] designed an architecture of two-tier hovering UAVs to efficiently use resource allocation. The preceding model is a joint optimization problem of UAVs aerial altitude and power control in the presence of cross-tier interference of the proposed network model. The prior problem is solved through the concave–convex procedure (CCCP) and Lagrange dual decomposition technique, supported by a greedy search algorithm. The proposed model effectively improves the overall throughput of the system (see Tables 2 and 3).

Table 1
Acronyms used in this article.

Acronym	Text	Acronym	Text	Acronym	Text
ML	Machine Learning	DRL	Deep reinforcement learning	UAV	Unmanned Air Vehicle
UAV	Unmanned Air Vehicle	UAS	Unmanned Aerial System	BS	Base Station
MDP	Markov Decision Process	Relay-BS	Relay Base Station	UE	User equipment
LTE	Long Term Evolution	AI	Artificial Intelligence	R&d	Research and development
3GPP	3rd generation partnership project	SDN	Software defined network	ITS	Intelligent transportation systems
RL	Reinforcement Learning	B5G	Beyond 5G	MEC	Mobile edge computing
DP	Dynamic Programming	LoS	Line of Sight	ESN	Echo state network
GBSs	Ground Base Stations	C-RAN	Cloud Radio Access Network	CRN	Cognitive Radio Network
TDMA	Time Division Multiple Access	ICT	Information and communication technology	GUs	Ground Users
MTs	Mobile Terminals	IoT	Internet of Things	MEC	Mobile edge computing
D2D	Device to Device	NOMA	Non-orthogonal Multiple Access	OMA	Orthogonal Multiple Access
OFDMA	Orthognal Freq. Division Multiple Access	SNs	Sensor Nodes	SCA	Successive Convex Approximation
LSM	Liquid state machine	MCC	Mobile Cloud Computing	FDMA	Frequency Division Multiple Access
F-MEC	Flying Mobile Edge Computing	NFV	Network Functions Virtualization	FANET	Flying Adhoc Network

Table 2
Two network parameters based optimization problems to improve the network efficiency.

Reference	Year	Optimization parameters	Objectives
[33]	2018	UAVs-User association and UAVs-Aerial placement	Computational efficiency
[35]	2019	User association,D2D communication	Throughput
[36]	2019	UAVs-User association and UAVs-Aerial placement	Throughput
[37]	2018	UAVs trajectory and resource allocations	Flight duration
[38]	2020	Secrecy and Reliability outage probabilities	Collection of confidential data
[39]	2019	UAV Trajectory and transmit power	Throughput
[40]	2019	UAVs Trajectories and power allocations	System capacity
[41]	2019	UAVs-GNs communication, Eavesdropper	Improvement in secrecy rate
[42]	2018	UAVs altitude and power control	Throughput

Table 3
Three network parameters based optimization problems to improve the network efficiency.

Reference	Year	Optimization parameters	Objectives
[43]	2018	Users association, UAVs trajectory, Power consumption	Throughput
[44]	2019	User association, 3-D locations, and UAVs power	Throughput
[45]	2018	UAVs trajectory, Users scheduling, and bandwidth allocations	Throughput
[46]	2019	UAVs trajectories, Scheduling of GNs, and Power allocation	QoS
[47]	2019	UAV trajectory, GNs association, and downlink power transmission	Improvement in secrecy rate
[48]	2019	UAVs altitude, UAVs 2D placements, and UAVs-users associations	Throughput
[49]	2019	UAVs trajectory, Power allocation, Static NOMA	System performance
[50]	2020	Channel model, UAV trajectory, and transmit power	Network coverage
[51]	2019	Resource allocation, User association, and aerial BSs placements	Sum rate

3.2. Three parameters based optimization

In the following study, we provide three parameters-based joint optimization problems that are hard to solve. A brief research study of complex problems formulations and technical methodologies to effectively handle them are as follows.

The researchers in [43], briefly analyzed the two primary cellular architectures e.g., GBSs-assisted cellular-enabled UAVs acting as aerial users, and Cellular-assisted UAVs to UAVs communication to serve GUs as shown in Fig. 4. The Fig. 4 shows various use cases of UAVs including, expansion in cellular coverage without the ground communication architecture; instant service recovery in case of bug or malfunctioning of a ground communication system; serving temporary hotspot zones; aerial relaying, etc. The authors focused on the former platform to formulate a problem and assess the role of UAVs trajectory to ensure reliable communication between UAVs and GBSs during the mission. The objective is to accomplish the mission in the least possible time by following an optimum trajectory while ensuring the defined link quality between UAVs and GBSs during the mission. The analytical study shows the effectiveness of the proposed techniques and provides a near-optimal solution. The simulation results validate the analytical findings against existing benchmark techniques. The authors in [44] proposed a joint optimization architecture of user association, 3-D locations, and UAVs power allotment to enhance data rate at GUs while ensuring their energy requirements.

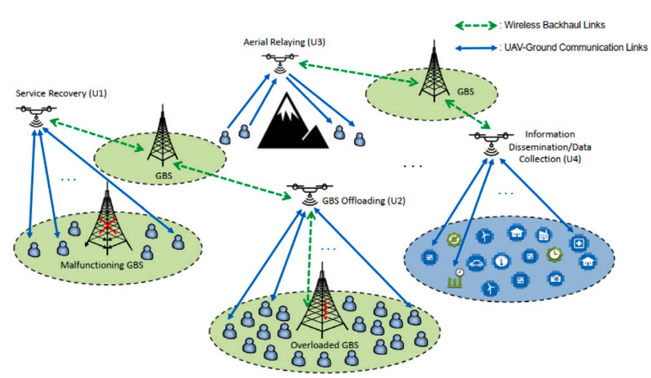

Fig. 4. UAVs-based aerial communication system where UAVs perform in four different roles.

The proposed non-convex problem is decomposed into convex sub-problems and solved using a multi-variable recursive algorithm. The simulation results under various configurations confirm the effectiveness of the proposed scheme over traditional benchmark techniques. The researchers in [45] proposed a joint network paradigm of UAVs-enabled BSs and mobile terminals (MTs) to enhance the throughput at the cell-edge MTs. In the proposed architecture, UAVs fly around the cell-edge MTs and the system throughput is enhanced by joint

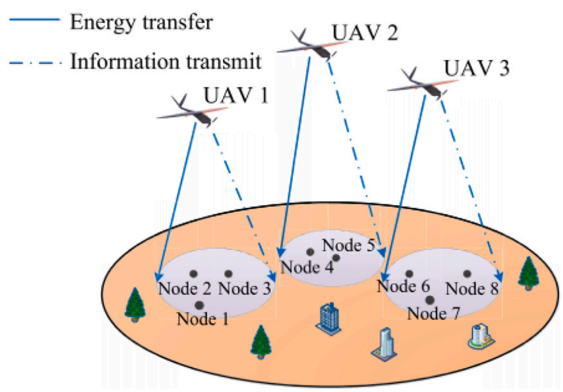

Fig. 5. A generalized overview of UAVs-based simultaneous wireless information and power transfer [44].

optimization of UAVs trajectory, user appointments, and bandwidth allocations. The attained results demonstrate the effectiveness of the proposed scheme and improve system performance in comparison to the GBS-only network. The authors in [46] introduced a scheme to construct a communication network where UAVs are subject to collect data from a set of scheduled ground nodes (GNs) in an environment where jammers are deployed to stop communication. The primary goal of the proposed paradigm is to enhance various QoS e.g., minimum, average, and delay-conditioned minimum throughput. The resultant non-convex optimization problem is composed of UAVs trajectories, a schedule of GNs, and power assignments. The optimization problem is handled through two block coordinate descent techniques supported by successive convex approximation and S-techniques. The analytical results demonstrate significant performance in terms of QoS. Li et al. [47] proposed a joint optimization model comprised of UAV trajectory, GNs association, and downlink power transmission in the presence of Eves. The proposed architecture aims to enhance the secrecy rate while maintaining fairness in GNs. The authors employed SCA and alternating techniques to efficiently solve the non-convex optimization problem. The attained results show the effectiveness of the proposed architecture and significantly enhance the secrecy rate relative to the existing baseline techniques. The authors in [48], designed a UAVs-enabled network based on UAVs 3D placements and UAVs-users association. The proposed problem is decomposed into three subproblems (i.e., UAVs altitude optimization, UAVs 2D placements, and UAVs-users associations) and solved using low-complexity recursive algorithms. The proposed approach performance is superior to baseline techniques. The researchers in [49] conducted various studies to assess the impact of non-orthogonal multiple access (NOMA) in the UAVs-enabled network. The authors implemented a stochastic geometry based approach to model the UAVs and GUs positions and analyzed the proposed system performance. In a second attempt, a joint problem of UAVs trajectory design and power distribution for static NOMA users at constant UAVs altitude is analyzed. Furthermore, the authors utilized ML-based techniques to study the system performance by assuming movable GUs followed by UAVs to track GUs and adjust their locations accordingly. The authors in [50] coined a hybrid communication system of UAV, satellite-terrestrial, and maritime. The objective of the proposed system is to enhance the UAV's coverage for the maritime transport system. The proposed optimization problem is composed of channel model, UAV flying trajectory, and transmit power while preconditioning various factors like acceptable interference, UAV energy consumption dedicated to communication, etc. The non-convex optimization problem is handled using successive convex and bisection search optimization techniques. The results analysis depicts that the proposed system performs well and can be an integrated part of the existing communication systems. The Yin et al. [51] constructed a multi-UAVs based downlink cellular communication model that aims to enhance the sum rate while serving GUs through frequency division multiple access (FDMA) technique. The UAVs are assumed to be recharged by wireless recharging facilities available on the ground. The resultant non-convex optimization problem is composed of resource allocation, user association, and aerial BSs placements. The optimization problem is efficiently handled through various iterative algorithms like alternating and successive convex optimization techniques. The proposed scheme performance is significantly superior to compared baseline techniques (see Fig. 5).

3.3. Multi parameters based optimization

In a multi-parameters based optimization study, we have tried to explore much more complex problems, consisting of more than three parameters that are much harder to formulate and solve. In the following, we provide many such complex optimization problems and their respective solutions.

The researchers in [52], investigated the data rate capacity of a broadcast channel of two ground users (GUs) and a UAV-based aerial BS while considering the joint architecture of UAV trajectory and communication techniques. The results show that data rate capacity can be enhanced using different factors e.g., optimal variation in UAV speed, optimal placement of UAV in case of low-mobility, and UAV hover-fly-hover (HFH) trajectory in case of high-speed mobility. The authors have also investigated the impact of communication techniques (e.g., TDMA and SC) to analyze the relative variation in channel capacity. In [53], the authors proposed a joint architecture of user associations, beamforming, and UAVs-altitude control mechanism for cellular-enabled UAVs and multiple GBSs. To enhance the UAVs achievable rate, the experts proposed a hierarchical bi-layer iterative protocol to jointly optimize users association, GBSs, beamforming vectors, and UAVs vertical altitude. The analytical results showed that the proposed technique can enhance the UAVs achievable rate to the benchmark UAVs association scenarios. The authors in [54] introduced an aerial UAV-based multi-users communication system where UAV serve GUs to improve the throughput using non-orthogonal multiple access (NOMA) techniques. The proposed problem is a non-convex joint optimization problem consists of total bandwidth, UAV vertical altitude, antenna beamwidth, and power. The problem is developed using dirty paper coding based max–min rate optimization and handled through path-following techniques. The comparative analytical study of the proposed NOMA-based scheme outperforms the corresponding OMA (Orthogonal Multiple Access) techniques. In [55], the Xie et al. designed wireless powered communication networks where two UAVs charge two ground IoT devices and gather the required data during uplink transmission. In the proposed paradigm, the UAVs collaborate during energy transfer and data collection process through interference mitigation strategy and coordinated multi-point mechanism. The primary goal of the proposed idea is to enhance the uplink data rate communication during time-constrained UAVs missions. The joint optimization problem is composed of UAVs trajectories, the downlink/uplink transmissions, UAVs speed, collision avoidance, and energy constraint at ground IoT devices. Under the defined pattern of interference coordination and coordinated multi-point mechanism, optimal solutions were attained for a long duration UAV mission. For the short time UAVs mission, the successive convex approximation (SCA) and alternating optimization techniques were employed to achieve the quality solutions. The authors in [56] come up with a communication architecture where UAVs-enabled aerial BSs provide communication services to certain GUs in the presence of many eavesdroppers (Eves). In the proposed scheme, some UAVs acting as BSs make efficient use of orthogonal frequency division multiple access (OFDMA) to communicate with the desired GUs at dedicated subcarriers while other UAVs perform as jammers during the mission to provide necessary security support. To enhance the average secrecy rate per user during communication, a non-convex

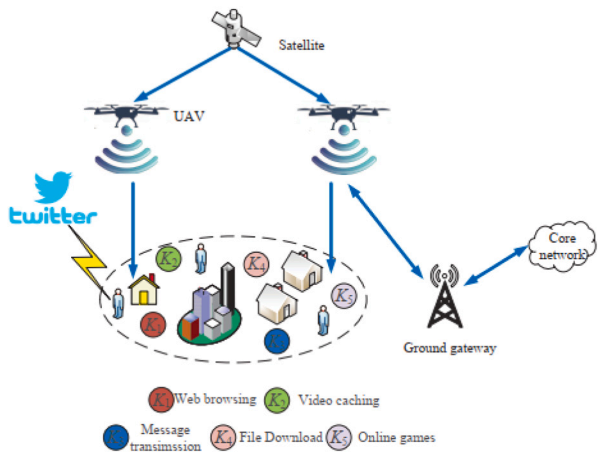

Fig. 6. UAVs, deep learning, and GUs mobility information based smart communication network.

joint optimization problem is developed. The preceding optimization problem consists of UAVs hovering speed, safety distance among UAVs, initial and final positions of UAVs, UAVs trajectories, and the existence of no-fly zone. The prior problem is solved through an efficient iterative algorithm and the average minimum secrecy rate has been significantly improved in comparison to existing baseline approaches.

4. Machine learning based UAVs joint optimization

In this section, we briefly present the role of AI, ML, and DRL in UAVs joint optimization problems regarding 5G and B5G communication, a crucial aspect of any smart city project. Here we have provided all the joint optimization problems irrespective of the number of governing parameters.

The authors [57] formulated a machine learning-based novel framework to optimize UAVs trajectories by estimating the user's mobility data. The proposed architecture is shown in Fig. 6 [57]. The joint problem consists of UAVs trajectories and power control to improve the sum rate and maintain data rate requirements of GUs. The authors employed a multi-agent Q-learning based technique to find an optimal initial UAVs placement locations w.r.t the GUs. The GUs real-time mobility is gathered from Twitter to develop GUs trajectories and an echo state network (ESN) based estimation technique is utilized to predict the GUs future positions using training data as evident from Fig. 6. Furthermore, a multi-agent Q-learning based technique is used to predict the real-time UAVs aerial placements w.r.t GUs movements. The analytical results show that with an increasing amount of training data, the prediction performance of the ESN-based technique is improved.

The authors in [58], considered a scheme to jointly study the multi-UAVs deployment and their dynamic movements to improve the sum mean opinion score of GUs. The proposed scheme is a non-convex optimization problem and is worked out in three phases. In the first phase, the authors employed a K-means algorithm to cluster the GUs. In the second phase, Q-learning based technique is utilized to enable UAVs to autonomously decide about their 3D position. In the final phase, Q-learning based movement protocol is applied to deal with dynamic GUs. The results analysis reveals that the proposed architecture performs significantly in terms of complexity and convergence (see Tables 4 and 5). The authors in [59], proposed a UAVs-based network communication system that primarily focused on caching and resource allocation to serve the GUs. The GUs are supposed to allow to use of licensed and unlicensed bands to retrieve data from UAVs-enabled cache or server-assisted UAVs. The proposed optimization problem is consists of user association, cache contents, and spectrum allocation. The prior problem is efficiently solved using the liquid state machine

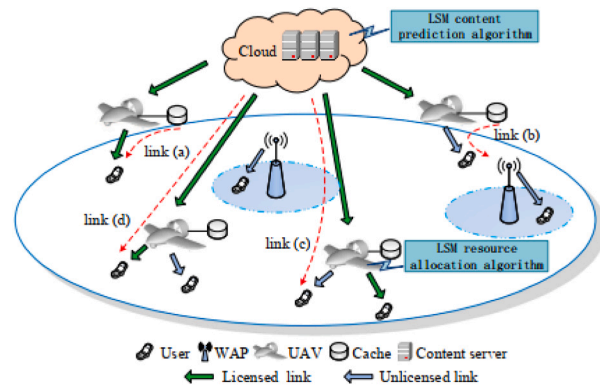

Fig. 7. UAVs-assisted communication system that make use of caching and resource distribution to serve GUs.

(LSM) technique. The LSM technique effectively estimates the GUs content request and resource allocation approach to optimize system performance. The proposed architecture (Fig. 7 [59]) performance is superior to the baseline techniques (e.g., Q-learning with and without cache). Wang et al. [60] formulated a platform called flying mobile edge computing (F-MEC), where UAVs are outfitted with computational resources and offer task offloading services to UEs. The primary goal of the proposed architecture is to optimize UAVs aerial trajectory, user association, and resource allocation. The optimization problem is solved through the Trajectory control algorithm, supported by the block coordinate descent algorithm. An additional reinforcement learning-based approach is proposed to enhance the convergence of the training process. The simulation results show that the proposed techniques outperform the corresponding benchmark algorithms. In [61], Li et al. devised an intelligent technique called reinforcement learning handoff (RLH) to minimize unnecessary handoffs in a UAV-assisted communication network. To enhance the proposed system throughput, mobility control techniques are proposed using K-mean and SNR estimation methods. The proposed technique significantly reduced handoffs.

5. Mobile edge computing and UAVs, users association

In this section, we present the performance of advanced technology i.e., MEC in UAVs joint optimization problems to improve the efficiency of next generation communication networks.

The authors in [62], proposed an innovative communication paradigm to fulfill the needs of 5G and beyond cellular network applications. The proposed architecture is consists of multi-access edge computing (MEC), ultra-dense networking (UDN), and virtual infrastructure manager where UAVs can provide an efficient network services to necessitous GUs (see Table 6).

The preceding architecture is equipped with advanced communication techniques such as NOMA, energy efficient strategies, etc. that enables UAVs to adjust with GUs mobility to enhance the system performance. The results analysis signifies the user connectivity performance of the proposed scheme. The authors in [63] explored the joint optimization problem of resource allocation and task offloading in MEC-based dense cloud radio access network (C-RAN) to improve network efficiency. The proposed optimization problem is decomposed into four subproblems through the Lyapunov optimization technique. The resultant subproblems are efficiently solved through convex optimization and matching game techniques. Under various conditions, the trade-off between network energy efficiency and service delay has been analyzed that validate the efficacy of the proposed technique. In [64], Zhang et al. constructed a joint optimization model of UAVs based communication and computation. The proposed network is composed of two-tier MEC-enabled UAVs, where the upper layer UAV acts as a

Table 4
Multi network parameters based optimization problems to improve the network efficiency.

Reference	Year	Optimization parameters	Objectives
[52]	2018	UAV trajectory, UAV Speed, UAV placements, Communication techniques	Throughput
[53]	2019	Users association, GBSs, Beamforming vectors, and UAVs altitude	Throughput
[54]	2019	Bandwidth, UAV Altitude, Antenna beam width, and Power	Throughput
[55]	2020	UAVs trajectories, Downlink/Uplink transmissions, UAVs speed, Collision Avoidance, and energy constraint at IoT Devices	Improvement in uplink data rate
[56]	2020	UAVs speed, UAVs Placements, Safety distance among UAVs, UAVs trajectories, and no-fly zone	Improvement in average secrecy rate per user

Table 5
Machine learning based optimization problems to improve the network efficiency.

Reference	Year	Optimization parameters	Objectives
[57]	2019	UAVs trajectories and power	Improvement in sum rate
[58]	2019	UAVs Deployment and dynamic movements	Complexity optimization
[59],	2019	User association, cache contents, and spectrum allocation	System efficiency
[60]	2019	UAVs aerial trajectory, user association, and resource allocation	System efficiency
[56]	2020	UAVs Speed, UAVs Placements, Safety distance among UAVs, UAVs trajectories, and no-fly zone	Improvement in average secrecy rate per user

Table 6
MEC role in UAVs joint optimization problems to enhance the network efficiency.

Reference	Year	Optimization parameters	Objectives
[62]	2020	MEC, UDN, UAVs-GUs association, and virtual infrastructure manager	System performance
[63]	2020	Resource allocation, Task offloading using C-RAN	System efficiency
[64],	2020	UAVs based Communication and computation	Delay optimization
[65]	2016	Multi-level clusters, MCC, and software	Improving the usage capacity of idle mobile gadgets
[66]	2019	UAV trajectory, time slot and power allocation	Energy consumption
[67]	2020	Cache-assisted UAVs and Cognitive Radio Network (CRN)	Improving data rate using redundant data optimization
[68]	2019	Resource allocation and Task scheduling	Trade-off between power consumption and delay
[69]	2018	Resource allocation, computation tasks offloading	Energy optimization

centralized UAV while the down layer performs as UAVs swarm. To attain the network optimal delay, a closed-form solution is employed by utilizing queueing theory and stochastic geometry. The system performance in terms of optimal delay has been analyzed through testbed and simulation results. In [65], the authors proposed a new paradigm called Mobilouds, comprising of multi-level clusters processing capabilities and control software. Mobilouds architecture facilitates the collaborative use of mobile devices in mobile cloud computing (MCC) and maximizing the usage capacity of idle mobile gadgets. The proposed framework provides an effective balance between energy and time through efficient use of all available resources. In this article [70], the Cheng et al. proposed a joint architecture of air-ground integrated mobile edge network (AGMEN), shown in Fig. 8. In the proposed scheme, scheduled airborne UAVs support network communication in terms of caching and MEC. The authors have investigated the most feasible and practical applications of the AGMEN paradigm. The authors in [66] developed a non-convex joint optimization problem consisting of UAV aerial trajectory, time slot arrangement, bits and power allocation. The objective of the proposed technique is to optimize the overall energy consumption concerning communication, computation and UAV flight trajectory. The proposed problem is reduced to two subproblems and effectively handle using less-computationally recursive algorithms. The numerical results have confirmed the superior performance of the proposed scheme over the compared baseline techniques.

The researchers in [67] formulated a cache-enabled UAV collaboration paradigm in the cognitive radio network (CRN) to improve its data communication efficiency while optimizing the CRN's redundant data traffic. The experimental results show the effectiveness of the proposed scheme in improving the achieved data rates. In [68], the Duan

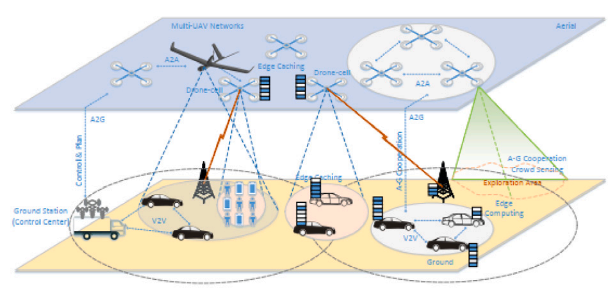

Fig. 8. A generalized architecture of the proposed AGMEN.

et al. proposed an architecture jointly composed of MEC and cloud computing techniques to offload tasks from the UAVs-enabled communication system. The joint optimization problem is constituted of resource allocation and task scheduling to establish a trade-off between power consumption and delay. A low-complexity recursive algorithm is used to attain a closed-form solution to the joint optimization problem. The results signify the importance of heterogeneous cloud structure to enhance UAV-assisted network performance. The authors in [71], proposed an innovative architecture to make the source UAV capable to offload tasks from ground sensors and assign them to nearby airborne UAVs for further processing. The proposed scheme aims to enhance the capability of system computation by jointly exploiting the system communication and computational latency. The joint optimization problem is effectively handled through an online greedy algorithm, followed

Table 7
SDN role in UAVs optimization problems to improve the network efficiency.

Reference	Year	Optimization parameters	Objectives
[72]	2019	User association, Time scheduling, 3D UAVs placements, and spectrum resource utilization's	System performance
[73]	2018	Load balancing protocols and SDN-assisted architecture	Network efficiency
[74],	2019	SDN-assisted UAVs architecture	System performance optimization
[75]	2017	SDN, NFV-assisted Communication architecture	Improvement of UAVs speed and dynamics
[76]	2017	SDN-assisted FANET	Video transmission feasibility
[77]	2020	SDN-assisted FANET	Network overhead optimization
[78]	2019	Centralized SDN architecture	UAVs-based continuous services
[79]	2019	SDN-assisted Paradigm	Communication security to UAVs-assisted services

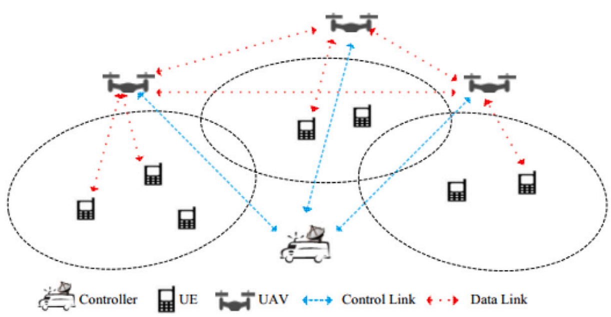

Fig. 9. Depiction of an SDN-assisted UAVs communication network [73].

by the primal–dual technique. The simulation results reveal the effectiveness of the proposed scheme in terms of achieving near-optimal task distribution (see Table 7). The researchers in [69], formulated UAV-based MEC architecture to optimize the energy consumption of UAV and mobile devices. The non-convex joint optimization problem is consists of resource allocation, computation offloading tasks, and UAV flight trajectory. The proposed problem is decomposed into three subproblems and solved through a proposed iterative algorithm. The obtained results signify the performance of the proposed technique over the concerned benchmark algorithms.

6. Multi-UAVs communication and software defined networks

SDN is an emerging field in ICT and in this section, we explore its performance in UAVs joint optimization issues to enhance the performance of future network communication.

The authors [72] studied to possibilities to enhance the efficiency of UAVs-assisted software-defined networks (SDNs). The non-convex joint optimization problem is composed of user association, time scheduling, 3D UAVs placements, and spectrum resource arrangements. The authors proposed an alternating maximization (AM) recursive algorithm to solve the optimization problem. The proposed optimization problem is reduced to three subproblems and solved through SCO and alternating direction method of multipliers techniques. The attained analytical results signify the performance of the proposed architecture from a throughput perspective. In [73], Zhang et al. constructed a scalable SDN-assisted architecture to efficiently organize and analyze the data from UAVs-based communication networks (shown in Fig. 9). A load balancing protocol is proposed that utilizes the prior attained results to sustain the required network efficiency.

The authors in [74] proposed a framework for software-defined UAVs network that efficiently employs Software-defined Network (SDN) to realize UAVs-assisted various missions. The researchers in [75] formulated a novel SDN-based and NFV-assisted lightweight architecture to support UAVs high speed, dynamic movements, and situational-awareness. The joint programmatic use of SDN and NFV can attain swift and smooth transfer of UAV-oriented services among various ground BSs and network operators. The authors have effectively shown the applicability of the proposed framework. The authors in [80] conducted a detailed survey to explore various SDN-based UAVs applications including aerial BSs, cybersecurity, surveillance, etc. that are crucial to smart cities' development. Besides a rich literature review of SDN and UAVs integration, the authors have provided future research directions and challenges. The Rametta et al. [76] proposed a flexible SDN-assisted FANET of UAVs to make feasible the video transmission capabilities. The proposed framework is composed of dynamic and fixed UAVs video transmitters to serve the desired users with the requested content. A numerical model has been formulated to analyze the computational efficiencies of various nodes, present in the network. The Cumino et al. [77], proposed an SDN-assisted FANET clustering protocol called CAPONE. The CAPONE aims to optimize network overhead while assuring UAV control messages transmission and management. CAPONE utilizes the Gap statistics technique to cluster the UAVs network and corresponding cluster heads are defined by the Fuzzy C-means algorithm. The assessment and acknowledgment approach optimizes the number of control messages and enhances their transmission capability.

In [78], the authors proposed an SDN-based location-aware paradigm to offer UAVs-enabled seamless network services. The UAVs-assisted communication network is monitored through a centralized SDN system. The proposed scheme efficiency is superior to the traditional baseline monitoring system. The authors in [79] formulated an SDN-assisted framework to provide security services to the UAVs-enabled network communication system. The performance of the proposed architecture has been validated through comparative analysis with the existing benchmark AODV routing protocol. The attained results endorse the use of SDN as an effective tool in UAVs-assisted networks.

7. Conclusion

Unmanned aerial vehicles (UAVs) have accomplished an impressive interest in different applications ranging from civilian to military due to its outstanding aspects e.g., rapid deployment, robust maneuverability, increase in airborne flight time, payload capabilities, etc. We constructed a detailed study to analyze the UAVs joint optimization problems to improve the performance of 5G and Beyond 5G communication networks. The joint optimization problems are categorized based on the parameters used in proposed UAVs architectures. The role of machine learning (ML), deep reinforcement learning (DRL), and state-of-the-art technologies such as mobile edge computing (MEC), and software-defined networks (SDN) over UAVs joint optimization problems have explored. Finally, we provide a set of existing research challenges and future research directions.

8. Challenges and future research directions

Based on the presented study and its analysis, we concluded the following open research issues and future research directions,

- Analysis of medium blockage effects on UAVs communication range and UAVs-GUs communication, during joint optimization architecture.
- Design of scalable UAVs-based communication networks as the number of users, ground nodes, and demand for high data rates are increasing.
- Considering UAVs-enabled data filtering techniques to avert false locations and minimize redundant data.
- Joint optimization of UAVs-GUs mutual separations and size of caching data should be considered.
- Measurement study to model the UAVs-UAVs, UAVs-GBs, and UAVs-GUs channel, etc. with different UAVs velocities in different wind speed, in the presence of regular and irregular shaped objects.
- For precise decision-making, a sufficient amount of training data (e.g., vehicle speed, GUs position, UAVs altitude, etc.) is needed to better utilize the ML and DRL techniques.
- Joint optimization architecture of UAVs onboard facilities (e.g., caching, processing, sensing and communication resources), UAVs-GUs distances, UAVs optimal hovering positions and UAVs trajectory using ML-techniques can significantly improve the data rate at GUs.
- Designing a mechanism to charge a UAVs battery using the ML and DRL techniques. The UAVs optimal location should be find out using prior techniques to improve the performance of wireless power transfer from charging sources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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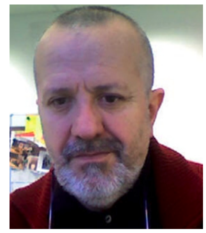

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