Holistic Resource Management in UAV-assisted Wireless Networks

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Publications

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Abstract

Unmanned aerial vehicles (UAVs) are considered as a promising solution to assist terrestrial networks in future wireless networks (i.e., beyond fifth-generation (B5G) and sixth-generation (6G)). The convergence of various technologies requires future wireless networks to provide multiple functionalities, including communication, computing, control, and caching (4C), necessary for applications such as connected robotics and autonomous systems. The majority of existing works consider the developments in 4C individually, which limits the cooperation among 4C for potential gains. UAVs have been recently introduced to supplement mobile edge computing (MEC) in terrestrial networks to reduce network latency by providing mobile resources at the network edge in future wireless networks. However, compared to ground base stations (BSs), the limited resources at the network edge call for holistic management of the resources, which requires joint optimization. We provide a comprehensive review of holistic resource management in UAV-assisted wireless networks. Integrated resource management considers the challenges associated with aerial networks (such as three-dimensional (3D) placement of UAVs, trajectory planning, channel modelling, and backhaul connectivity) and terrestrial networks (such as limited bandwidth, power, and interference). We present architectures (source-UAV-destination and UAV-destination architecture) and 4C in UAV-assisted wireless networks. We then provide a detailed discussion on resource management by categorizing the optimization problems into individual or combinations of two (communication and computation) or three (communication, computation and control). Moreover, solution approaches and performance metrics are discussed and analyzed for different objectives and problem types. We formulate a mathematical framework for holistic resource management to minimize the linear combination of network latency and cost for user association while guaranteeing the offloading, computing, and caching constraints. Binary decision variables are used to allocate offloading and computing resources. Since the decision variables are binary and constraints are linear, the formulated problem is a binary linear programming problem. We propose a heuristic algorithm based on the interior point method by exploiting the optimization structure of the problem to get a sub-optimal solution with less complexity. Simulation results show the effectiveness of the proposed work when compared to the optimal results obtained using branch and bound. Finally, we discuss insight into the potential future research areas to address the challenges of holistic resource management in UAV-assisted wireless networks.

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List of Abbreviations

Acronyms	Description
ADMM	Alternating direction method of multipliers
AI	Artificial intelligence
BCD	Block coordinate descent
B5G	Beyond fifth generation
BS	Base station
BSUM	block successive upper bound minimization
CoCaCo	Computing caching and communication
CNN	Convolutional neural network
CPU	Central processing unit
CRAN	Cloud radio access networks
DF	Decode-and-forward
D2D	Device to device
DRL	Deep reinforcement learning
FL	Federated learning
HCP	Heterogeneous computing platforms
IoT	Internet of things
I/O	Input or output
KKT	Karush-kuhn-tucker
LEO	Low earth orbit
LoS	Line of sight
MAC	Medium access control
MDP	Markov decision problem
MEC	Mobile edge computing
MMKP	Multiple choice knapsack problem
MIMO	Multiple input multiple output
MINLP	Mixed integer non linear programming
MINP	Mixed integer linear programming
MISO	Multiple-input single-output

MSE	Mean square error
NOMA	Non orthogonal multiple access
NP-hard	Non-deterministic polynomial-time hard
OFDMA	Orthogonal frequency division multiple access
SAT	Satellite aerial terrestrial
QoE	Quality of experience
QoS	Quality of service
SC	Small cell
SCA	Successive convex approximation
SINR	Signal to interference and noise ratio
SNR	Signal to noise ratio
SWIPT	Simultaneous wireless information and power transfer
TSN	Terrestrial satellite networks
UAVs	Unmanned aerial vehicles
UDs	User devices
URLLC	Ultra-reliable low-latency communications
V2V	Vehicle-to vehicle

List of Symbols

Symbol	Description
K	Number of IoT devices
L	Aerial-assisted networks layers L0,L1
M	Number of base stations and UAVsM0,M1
M_0	Number of base stations
M_2	Number of UAVs
T_k	IoT device task
s_k	Size of data(Bits)
τ_k	computation deadline
w_k	Computation workload (in CPU cycles/bit)
$\Phi_{k,m,l}^{OF}$	Offloding binary variable
$\Upsilon_{k,m}^{CO}$	Computing binary variable
$R_{k,m,l}$	Instantaneous data rate
$h_{k,m,l}$	Channel gain
σ_k^2	Power of the Gaussian noise
$a_{k,m,l}$	Fraction of bandwidth
$B_{m,l}$	Bandwidth
$L_{k,m,l}^{OF}$	offloading Transmission latency
O_{ml}	Communication resources of mth device of lth layer
$o_{k,m,l}$	Computation allocation
$\sum_g^{K_g} Q_g$	Computation workload used by other devices
$L_{k,m,l}^{CO}$	Computing Latency to perform task T$_k$
$Y_{m,l}$	Cache capacity of mth device on lth layer

Chapter 1

Introduction

Future wireless networks are expected to provide connectivity to an ever-increasing number of heterogeneous and resource-constrained Internet of things (IoT) devices [1–5]. To achieve this, future wireless networks must support communication in three-dimensional (3D) space by integrating ground and aerial networks [6]. On-demand deployment of unmanned aerial vehicles (UAV) base stations (BSs) can provide dynamic and flexible networks, leading to more complex interference management and requires efficient resource management. Deployment of UAV BSs and relays can integrate terrestrial and aerial networks to provide massive connectivity in 3D space [7–10]. Further, mobile edge computing (MEC) has been considered a promising solution to these challenges by deploying cloud servers at the edge of the network [11]. With the help of MEC, energy consumption and latency can be minimized by offloading the intensive computations to the nearby edge servers, which results in computational complexity. For effective utilization of computing and caching resources in MEC and finite physical bandwidth of wireless channels, task control and resource allocation are required, especially in the presence of a large number of delay-sensitive tasks [12]. Recently, UAV-assisted MEC networks have been considered for flexible and on-demand deployment to provide cost-effective computation offloading and caching services for resource-constrained devices [13–16]. However, UAVs have limited resources, backhaul capacity, and battery life—thus, there is a need to optimize resources, energy, power, bandwidth, trajectory etc. These limitations put a daunting challenge for the operational lifetime of UAVs and the quality of service (QoS) of UAV-assisted MEC networks.

Network entities such as IoT devices, mobile users, and UAVs need to make local and autonomous decisions about different resources, e.g., bandwidth allocation, transmit power, spectrum and interference control, caching decision, to achieve the goals including throughput maximization, power optimization, bandwidth minimization, etc. The resources of network entities can be categorized as communication, computing, caching, and control (4Cs) and are necessary for the success of UAV-assisted MEC networks [17, 18]. There has been research on the resource management of UAV-assisted MEC networks with the goal of optimizing system latency [12, 16, 19–21], energy consumption [13, 15, 22–26], power minimization [14, 27] and maximization of secure computing and computation efficiency [28, 29].

1.1 Motivation

Resources associated with each 4Cs functionality play a vital role in enhancing network performance. Considering a large number of heterogeneous and resource-constrained devices, it is crucial to optimize resources, including energy, power, bandwidth, trajectory, etc. The communication resources (such as bandwidth and power, etc.) need to transmit data through the wireless channels [11, 30, 31]. The computing resources (such as memory, CPU cycle, etc.) are required for computational jobs [1, 2, 32]. Caching makes the computing jobs faster if the cache is located near the user or edge of the networks [8, 33, 34]. The selection of cache location and size depends on the network infrastructure and user applications. If joint communication and computing or caching resources are considered, then the control parameters (such as managing input/output data rate, timing, synchronization) need to be set up according to the network infrastructure as well as the quality of service (QoS) requirements [11, 35]. User applications depending on wireless networks need 4Cs resources to full fill the QoS requirements of users and network operators. The tremendous growth of online data traffic, diverse parameters and applications, as well as heterogeneous and resource-constrained devices, require holistic management of resources.

In IoT networks, each computation task is either processed locally at the IoT device or offloaded to the centralized cloud server, which offers enormous storage and computation resources. The IoT devices' computing resources (e.g., battery power, memory, etc.) are limited; thus, IoT devices can offload computational tasks to the centralized cloud server in the network. However, cloud computing may cause a delay due to relatively large distance between the IoT devices and the cloud servers [11] which may not meet the requirements of some latency-sensitive applications. Also, the massive amount of data transmissions may cause traffic congestion in the core networks [1, 2, 11]. To address these problems, UAV-assisted MEC is proposed where computing and caching is performed at the edge of the network and UAVs are used to assist the edge devices of the networks [8, 36, 37]. The UAVs equipped with MEC capability (with computing and caching resources) can reduce the bandwidth requirement of the network. UAV-assisted MEC is considered as a low latency computing service for IoT devices [8, 36, 37]. The UAV devices can be used to handle the offloading task in a network architecture where UAVs are deployed as mobile cloudlets, edge enabled UAV wireless networks, and UAV assisted multi-hop relays etc. On the other hand, the minimization of the network bandwidth requirement and network latency while satisfying user-perceived quality of experience (QoE) becomes one of the most critical concerns of network operators [11, 30, 38, 39].

Radio resource management becomes more challenging with the integration of UAVs to support the computing and caching requirements of the users. UAVs have limited communication, computation, and storage capabilities; there is always a need to optimize resources, energy, power, bandwidth, trajectory etc. Although the placement of UAVs provides a promising solution to these 4Cs issues of the wireless networks, still there are limitations on endurance, backhaul capacity, and power [40, 41]. Recently, non-orthogonal multiple access (NOMA) has been explored to improve the communication throughput in UAV-assisted networks [42, 43]. However, a UAV cannot be available for a long duration as it is required to charge or replace its battery and return to its hotspot region. The backhaul link capacity of the UAV is restraining its deployment region to a space around the ground BS. Tethered balloons are considered to overcome these limitations by providing continuous power and data via a tethered from the ground station to tethered balloons, and through backhaul link to UAVs [41, 44]. Also, tethered balloons are placed at fixed locations at a higher altitude than UAVs, increasing the probability of having a line of sight (LoS).

Several radio resource management schemes have been developed for UAV-assisted wireless networks while considering different objectives and constraints, including network scalability, reliability, efficiency (spectral usage and energy consumption), QoS requirements, coverage, and reducing complexity. The majority of existing work considers the developments in 4Cs individually or a combination of two, which limits possible gain that could be achieved through the cooperation of 4Cs [1, 2, 45]. The limited resources in the UAV-assisted wireless networks and MEC needs holistic management of the resources, which requires joint optimization [4]. Joint optimization of resources (spectrum, energy, computation), trajectory, content caching, interference, and user association is needed to fully utilize the UAV-assisted wireless networks. On the other hand, the multi-dimensional optimization problems can enable intelligent control to meet stringent end-to-end delay requirements [11].

1.2 Preliminary of 4Cs in UAV-assisted Wireless Networks

This section will discuss two architectures of UAV-assisted wireless networks (i.e., UAV as relay and UAV as a BS). Also, we present the significance and utilization 4Cs resources in UAV-assisted wireless networks.

1.2.1 Architectures for UAV-assisted Wireless Networks

The UAVs can be used either as a BS or relay node in a UAV-assisted wireless network, depending on the application. Thus, UAV-assisted wireless applications (i.e., airborne BS, aerial delivery service, etc.) are grouped into two types of architecture, as shown in Fig 1.1. The use of tethered balloons can further enhance the performance of UAV-assisted wireless networks. As shown in

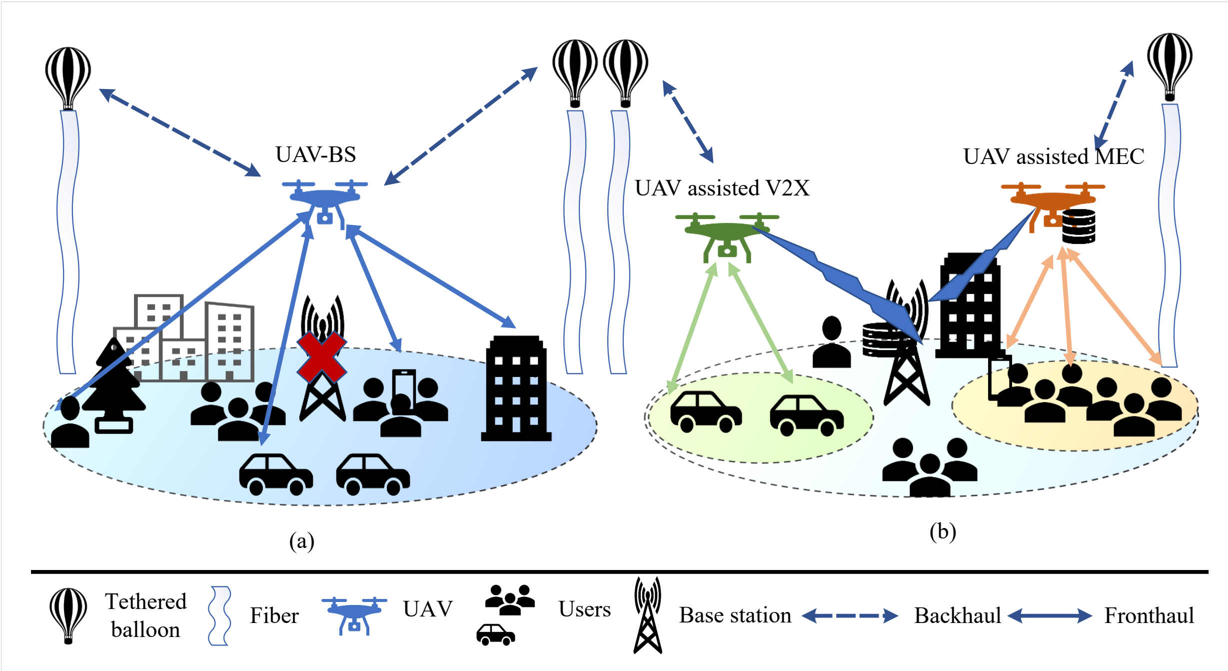


Figure 1.1: Architectures of UAV-assisted wireless networks (a) UAV-destination (UAV as BS) and (b) source-UAV-destination (UAV as relay).

Fig. 1.1, tethered balloons are connected with a link with ground BS and through a backhaul link to UAV which will increase the data rate of the ground users associated with UAVs and tethered balloons [41, 44].

- **Source-UAV-Destination (UAVs as Relay):** UAVs can be considered as a relay node in source-destination network [37, 46] as shown in 1.1(a) . For example, UAVs can relay the data collected from IoT nodes to the data center in IoT networks. Further, the performance can be enhanced using tethered balloons. There are two types of association: (i) the access association between UAVs and IoT devices and (ii) a backhaul association between UAVs and tethered balloons. In the case of multi UAVs, each UAV is associated with one tethered balloon. On the other hand, each tethered balloon can associate with multiple UAVs. There are many scenarios in which single or multiple UAVs acts as relays to provide better coverage, data offloading, backhauling and hotspots. UAV relaying is an important application that can efficiently extend the communication coverage [37]. By utilizing a UAV as a relay, two users with blockage communication channels can be linked. This gives a new method to help local resource-limited users access remote resources. Also, in [47] UAV acts as a relay to offload the user's computation tasks to the BS to minimize total energy consumption and efficient completion of the task.

- **UAV-destination (UAV as a BS):** Here, the UAVs are considered as BSs for data transmission, computing, and storage devices for wireless communication [8, 48]. UAV-BSs are different from terrestrial BSs because the location of BS is fixed in terrestrial networks, while in the case of UAV-assisted BS, both user and BS are mobile. The air to the ground path between user and UAV depends on user location and UAV-BS location. In UAV-assisted BS networks, UAV placement is a 3D problem to deal with. In [8] authors considered a 6G integrated aerial-terrestrial network model where UAVs and terrestrial remote radio heads jointly serve as heterogeneous BSs of a cloud radio access network serving different mobile users. Authors in [49, 50] considered UAVs with small cell capabilities to work as UAV-BS. Particularly, in [49], the UAV movement, charging, and coverage action are considered in terms of jointly optimizing the energy and throughput through revenue and cost components. Whereas throughput maximization is considered in [50] in terms of buy or sell decisions of energy consumed and produced by the cellular network integrating renewable energy generation. In [51], a downlink cellular network with multiple UAVs has been proposed where UAVs are acting as BS, which wireless charging stations on the ground power. In [52], UAVs as mobile base stations provide video streaming services within a cellular macro area. Authors formulated a Q-learning-based UAV flight planning algorithm to improve the QoE of video users. A distributed heterogeneous computing platform across the UAVs and terrestrial BSs has been proposed to improve the cache capacity and minimize the cache miss ratio. In [36], UAVs integrating computing platforms act as small distributed clouds where data is offloaded to minimize the computation and transmit powers of all users in the system.

1.2.2 4Cs in UAV-assisted Wireless Networks

The main obstacle to fully enable the collaboration of cloud computing, MEC, IoT, and UAVs exhibit 4Cs problems. This subsection discusses 4Cs resources in UAV-assisted wireless networks

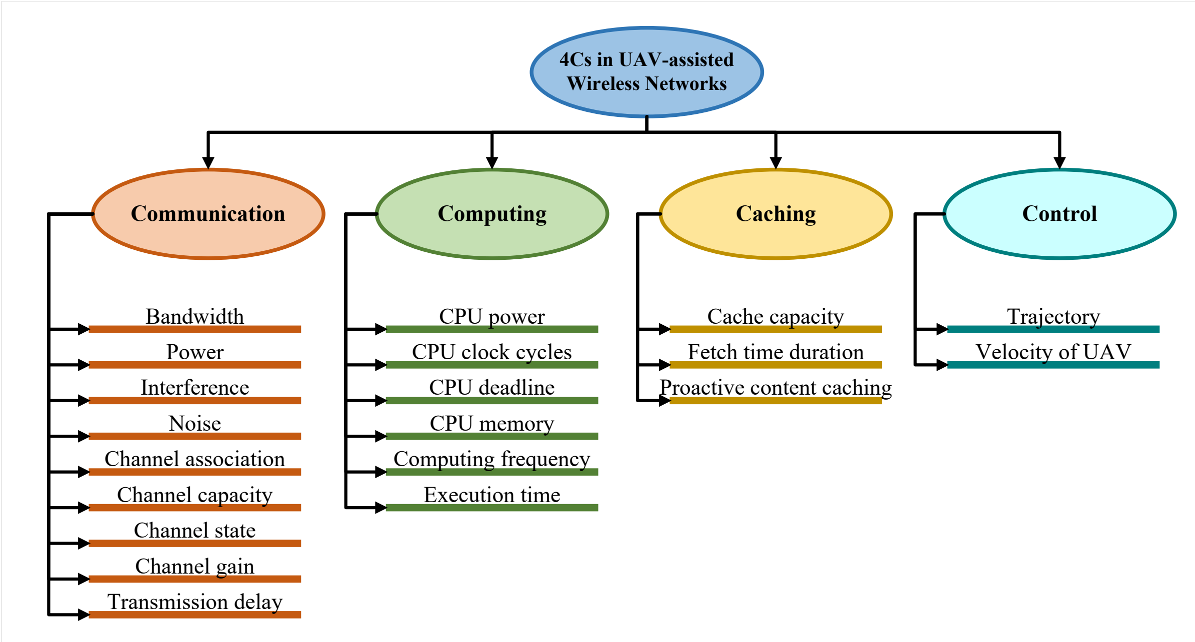


Figure 1.2: 4Cs resources in UAV-assisted wireless networks.

as shown in Fig. 1.2 and how these resources are utilized and optimized in the existing literature for wireless networks.

Communication

In general, channel, bandwidth, power, and transmission rate are considered as communication resources in wireless networks. When UAVs are integrated into the terrestrial networks, the bandwidth sharing and power optimization become more challenging due to the heterogeneity of the networks [47, 53]. For example, in the source-UAV-destination-based architecture, two communication channels are utilized: (i) from source to UAVs and (ii) UAVs to destination. UAVs' different altitudes, speeds, and LoS communication generate UAV-related interference, which imposes challenges in the communication resource allocation problems. In wireless communication, UAVs have been applied in various scenarios, such as UAV-assisted heterogeneous computing platform [8], UAV relaying to expand the communication coverage [37, 46], UAV-assisted mmWave communications to increase the transmission probabilities of the communication links and system throughput [54]. To offload a task from users to the MEC servers or UAVs, the network will incur communication cost, which requires optimizing uplink and downlink bandwidth, transmission rate, transmission power, channel gain, noise, etc. Moreover, UAVs' mobility and energy-constrained nature pose many communication challenges in UAV-based systems to meet strict requirements such as low latency, low cost, and high transmission capacity. In [36] multiple-input multiple-output (MIMO) technology is discussed to increase the uplink capacity of the UAV system. Authors in [47, 55] introduced the NOMA-based UAV system to improve the spectrum efficiency and system capacity.

Computing

Computing efficiency is one of the objectives of optimizing computing resources. Computing efficiency is estimated based on the CPU energy, execution time, flying latency, the velocity of UAV, trajectory, etc. UAV trajectory and acceleration play an essential role in minimizing the total required energy of the system and energy of UAV, hence improving the computing efficiency of the system [40]. The computing resource can be of three types in UAV-assisted wireless networks:

- Local computing: Data is processed at the IoT device/mobile user. In the UAV-destination-based architecture, the UAVs are worked as a local computing device.
- Edge computing: When the computing resources (e.g., battery power, CPU cycles, memory, and input/output data rate) of the IoT devices are limited, the computational tasks can be offloaded to the edge devices [11]. In this case, UAVs are used as the edge devices which contain the computing servers. For example, UAV-assisted MEC where UAV equipped with energy transmitter and a MEC server provides both energy and computing services to IoT devices [46].
- Cloud Computing: The remote cloud is used for big data processing. In the source-UAV-destination architecture, UAVs are utilized in the middle of the communication process among the remote cloud data centers and wireless users to minimize communication delay. Tethered balloons can also be utilized as computing servers in which UAVs can act as

a relay between IoT devices and tethered balloons. Moreover, remote cloud computing with UAV uses AIâs cognitive functions to enhance QoE [31].

In [9], a random best and better response algorithm has been proposed to avoid the computational complexity considering the distributed character of UAV swarms. In this kind of network, the location of the servers (i.e., UAVs) is changeable so that the channel quality of offloading links can be adjusted and impact other offloading behaviours. In [46], the UAV-assisted wireless powered cooperative MEC system has been introduced to minimize the total required energy of UAV. In order to avoid co-channel interference, computation task offloading is implemented over orthogonal frequency bands. The authors in [40] investigated a new application scenario where a cellular-connected UAV offloads its computing tasks to multiple ground BSs along its trajectory to minimize mission completion time. UAV trajectory is designed using maximum speed, location, and computation capacity constraints to achieve this goal.

Caching

In both architectures (source-UAV-destination and UAV-destination), UAVs are utilized as a storage device to cache the most frequently used data. In the UAV-assisted MEC system, MEC server caches data after the task has been offloaded. This data can be retrieved from the cache storage based on the demand. However, due to limited cache capacity/resources, the least recently used data can be replaced by new data. The well-known least frequently used cache replacement is one of the solutions to this limited cache capacity problem [11]. The other solutions are cache data in the collaboration space [56], and proximity to destination nodes (i.e., BSs, user terminals) in order to reduce the fetching delay and backhaul load [1, 2, 11, 45]. The group of UAVs can be utilized as UAV swarms which can provide one collaboration space to cache data. The surge of mobile traffic increases communication delay while placing a tremendous burden on the backhaul links. To address this issue, content caching has reappeared as an exciting topic in beyond 5G/6G networks, particularly in the network edge serviced by heterogeneous BSc (network model in which UAVs and remote radio heads works jointly) [8]. The content caching-enabled BSs in 6G feature a vast deployment of UAVs acting as flying BSs [8, 57–59]. The deployment of cache enabling UAVs to offload the data in the peak hours of some hotspots provides a low-cost and rapid-deployment solution for content distribution applications with high data rate and low latency requirements [60]. However, the solutions have ignored the limited battery life as well as the limited storage capacity of the UAV.

Control

The control or scheduling methods are essential when two or more resources (i.e., communication, computing, caching) are utilized in the data communication process. It is challenging to control autonomous IoT systems in UAV-assisted wireless networks to accommodate environmental dynamics and make intelligent decisions or actions in real-time. There are two types of control methods considered from the resource management perspective: i) centralized control method and ii) distributed control method. In [11], the authors proposed distributed control method in which resource demands that are not satisfied at one MEC server can be satisfied by other MEC servers in the same collaboration space. The BS-based MEC systems utilized a centralized control method. In contrast, the UAU-assisted MEC system requires distributed control method due to the mobility and the distributed nature of UAV [11, 40, 61]. In [62], authors proposed a resource-sharing model for multiple learning services for both centralized and decentralized approaches. The centralized resource management is based on CPU allocation, bandwidth allocation, and hyper-learning rate decision, while the decentralized algorithm allows each learning service to manage the resources independently. According to the authors, the decentralized approach requires many iterations to convergence; it provides more flexibility and scalability to resource allocation procedures without revealing the learning service information. Authors in [63] which investigates the optimization questions related to the use of UAVs employed as flying antenna arrays granting improved wireless services to users. The authors investigate the minimization of the transmission and control time of the UAVs within flying antenna arrays. Optimal locations of the UAVs are derived such that transmission time and control time for the user are minimized by controlling the speed of the

UAVs.

1.3 Thesis Objective

The main objective of this thesis is to develop an efficient 4Cs resource management scheme for UAV-assisted MEC networks to minimize the latency and cost. The tremendous growth of online data traffic, diverse parameters and applications, as well as heterogeneous and resource-constrained devices, require holistic management of resources. Data and computational task offloading to nearby UAV servers can enhance the system performance by increasing the resources. In other words, data will be offloaded, processed, analyzed, and cached at the available UAV, if the associated base station is unavailable. To achieve this, we need to have caching storage, big data platform, and analytics software in the UAV server. Furthermore, since offloading data for being processed, analyzed, and cached at the UAV server requires communication resources, rather than considering each C (Computing, Caching, Communication, or Control) independently, we need to have a joint 4Cs model that reduces communication delay, computational delay, and backhaul bandwidth consumption.

1.4 Thesis Contributions

Following are the main contributions of this thesis:

- We provide a comprehensive survey on the state-of-the-art progress of 4Cs resource optimization issues in UAV-assisted wireless networks mainly investigated in the last five years.

- We provide a comprehensive discussion on optimization of 4Cs in UAV-assisted wireless networks in terms of four categories of joint problems: i) joint communication, computing and caching (3C) resource optimization, ii) joint communication and computing (2C) resource allocation, iii) joint trajectory and communication resource allocation, and iv) joint computing and caching (2C) resource allocation. The joint problems are analyzed with different objectives, parameters and constraints settings. We also present the solution approaches and performance metrics for different joint optimization problems in UAV-assisted wireless networks.

- We propose a mathematical framework for holistic resource management in UAV-assisted MEC networks to schedule resource-constrained devices on the ground for data offloading. The objective is to minimize the network's communication and computation latency and cost by jointly optimizing 4Cs resources. Constraints on bandwidth, computation resources, and caching resources are considered.

- We first solve the joint optimization problem using branch & bound algorithm to obtain optimal results. Then, we propose a heuristic algorithm to solve the joint optimization problem with less complexity.

- Simulation results demonstrate the effectiveness of the proposed framework, and the results of the proposed heuristic algorithm are compared with the branch & bound algorithm, which is used as a benchmark.

- Lastly, we discuss the challenges and future research directions for holistic resource management to deploy UAV-assisted wireless networks successfully.

1.5 Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 provides background and literature review on 4Cs resources of UAV-assisted wireless networks. This chapter includes a detailed review of existing surveys and a comprehensive discussion on joint optimization of UAV placement or trajectory with 4Cs, 3Cs, and 2Cs. We discuss the solutions and techniques for joint optimization problems as well as performance metrics and measurements used in the literature to access the solutions discussed. Chapter 3 provides the system model and optimization problem for holistic resource management in UAV-assisted MEC networks to schedule resource-constrained devices on the ground for data offloading. Chapter 4 presents a proposed heuristic algorithm to solve the formulated optimization problem. This chapter also provides simulation results of the proposed heuristic algorithm and its comparison with the optimal (branch & bound algorithm) in terms of connected devices and active BSs and UAVs. Finally, the thesis concludes and future research directions are highlighted in Chapter 5.

Chapter 2

Background and Literature Review

This chapter provides a comprehensive survey of the state-of-the-art progress of 4Cs (communication, computation, cache and control) resource optimization issues in UAV-assisted wireless networks. We discuss details about 4Cs individually, a combination of three (joint communication, computation, caching), a combination of two (joint communication and computing/joint computing and caching) individually and with UAV trajectory. We provide available solution techniques, algorithms and performance metrics to solve 4Cs optimization problems for UAV-assisted wireless networks.

2.1 Existing Surveys

This section reviews existing surveys on joint optimization of terrestrial and aerial networks resources. Authors in [35] presented a survey on the application of deep reinforcement learning (DRL) for communication, caching, and security from both terrestrial and aerial IoT networks. The network issues such as dynamic spectrum access, joint user association, data control in dynamic and unpredictable environments, caching and energy consumption have been discussed. Various deep reinforcement learning extensions are proposed to solve these issues. This survey motivates the use of MEC close to end-users having computational resources and caching capabilities that significantly improve the users' energy efficiency and QoS requirements. In [64], the authors proposed a general DRL model for autonomous IoT systems. Computation complexity and storage capacity requirements in autonomous IoT systems are also discussed. Resources control actions using DRL techniques, e.g., partially observable Markov decision process-based deep reinforcement learning and multi-agent deep reinforcement learning, are also presented. The survey is categorized from the perspective of the proposed DRL model. In [65], the authors discussed DRL algorithms to enhance the scalability and elasticity in 4Cs problems in terrestrial networks. The application of DRL algorithms is discussed in several IoT applications, including intelligent transportation services and smart grids. Authors in [66] presented an overview of artificial intelligence (AI) systems in increasingly complex environments. They introduced several typical DRL algorithms such as deep Q-network, policy search, and actor-critic network to address communication and caching issues. The above-mentioned surveys [35, 64–66] provided insights into the 4Cs problems of IoT-supported terrestrial networks using DRL algorithms. However, the 4Cs problems are not discussed from the perspective of UAV-assisted wireless networks and are limited to the application of DRL in terrestrial networks.

In [67], the authors presented a comprehensive survey of resource allocation schemes with a holistic view of objectives, constraints, problem types, and solution strategies in cloud radio access networks (CRAN). They presented several emerging use-cases for CRAN, challenges, open issues, and application-specific objectives. They only discussed communication and computing resource allocation problems in detail. In [68], authors investigated the resource management problem for large-scale UAV-assisted wireless networks from a game-theoretic perspective. Several game-theoretic models (including mean-field game, graphical game, Stackelberg game, coalition game, and potential game) for resource management in large-scale UAV-assisted wireless networks. An interference-aware online channel selection game and joint task and allocation game are presented to show the usefulness of game theory models. In [18] authors provided a detailed survey on resource management (placement of UAVs, UAV trajectory, backhaul, path planning, charging, spectrum, and data offloading) in UAV assisted wireless networks while considering communication and computation parameters. Only two aspects out of 4Cs are considered in this paper. A survey on communication and networking technologies for UAV-assisted wireless networks is presented in [69]. The communication technologies are analyzed for both hardware and algorithm-based software, including antenna arrays, signal management, and utilization of centralized and decentralized techniques. The authors in [70] presented a comprehensive survey on AI-enabled resource management considering communication, computing, and caching resources. The main focus of this survey is the AI-empowered resource management framework which is one of the critical drivers for future wireless networks.

In [71], authors discussed 3D placement of UAVs, trajectory planning, channel modelling, backhaul connectivity, energy limitations, resource management issues, existing solutions, and challenges in 5G/B5G wireless networks. This survey is focused on 2Cs problems (communication and computation). In [72] authors examine the intrinsic connection between the game theory, machine learning, their applications and open issues for UAV wireless communication networks. They covered several game theory formulations for task allocation, coverage maximizing, beaconing schedule, energy optimization and machine learning tools for channel modelling, resource management and UAV positioning problems. This survey provides comprehensive details of 2Cs (communication and computing) problems for UAV-assisted wireless communication. The authors in [73] studied two applications of UAVs, namely, aerial base stations and cellular-connected users. For each application of UAVs, the key challenges such as 3D deployment, performance analysis, and channel modelling are presented. The authors also presented the energy efficiency of UAV-assisted wireless networks in terms of communication resource allocation with some insightful results. In [74], the authors discussed the major limitation of providing connectivity to rural and underprivileged areas. In providing rural connectivity, the UAVs are considered one of the potential solutions for fronthaul and backhaul communication for the 6G networks. Similarly, in [75] considers energy-efficient management of a fleet of UAVs that operate as flying 5G base stations to provide continuous coverage of user nodes in rural areas.

In summary, given in Table 2.1, the holistic resource management in UAV-assisted wireless networks is not given sufficient attention. Most of the existing surveys either focused on (i) the machine learning, AI, or game-theoretic solutions for the resource management [35,64–66,68,70] or (ii) focusing on the individual or combination of two (communication and computation) [71,72], or three (communication ,computation and control) [18,69]. In comparison, our survey covers all the 4Cs problems in UAV-assisted wireless networks and how these problems are solved using different algorithms in recent literature.

Table 2.1: Existing surveys [UAV= UAV-assisted wireless networks;C1=Communication; C2=Computing; C3=Caching, C4=Control].

Ref.	**UAV**	**C1**	**C2**	**C3**	**C4**	**Remarks**
[35]	✗	✓	✓	✓	✓	Studied the applications of DRL with a focus on communications and networking problems in terrestrial networks.
[64]	✗	✓	✓	✓	✓	Different learning methods in autonomous IoT systems in terrestrial networks are discussed.
[65]	✗	✓	✓	✓	✓	Provided a detailed review of DRL algorithms and their applications in terrestrial networks. Also, the application of DRL to solve 4Cs in IoT applications is discussed.
[66]	✗	✓	✓	✗	✓	The role of deep enforcement learning in communication, computing and control management in terrestrial networks is discussed.
[67]	✓	✓	✓	✗	✗	This survey is related to the communication and computing resource allocation issues,objectives,problems types for CRAN network.They didn't discuss UAV networks and their problems in detail.
[68]	✓	✓	✗	✗	✓	Investigated the distributed resource management problems for large-scale UAV communication networks, providing cost-effective and reliable applications.

[18]	✓	✓	✓	✗	✓	A comprehensive review on resource management, path planning, backhauling, charging, and channel association in UAV-assisted wireless networks is presented.
[69]	✓	✓	✓	✗	✓	Communication technologies in UAV networks and a review of 3Cs resource management are presented.
[70]	✗	✓	✓	✓	✗	An AI-empowered resource management framework is presented and elaborates on the functions of AI in some key drivers of this framework through current research.
[71]	✓	✓	✓	✗	✗	Focused on UAV 3D placement and resource allocation (mainly communication and computation) problems in 5G/B5G wireless networks.
[72]	✓	✓	✓	✗	✗	The role of game theory and machine learning in communication and computation problems for UAV-assisted wireless networks is discussed.
[73]	✓	✓	✗	✗	✗	Challenges, open problems and mathematical model for UAV base stations and cellular connected UAVs are discussed.
[74]	✓	✓	✗	✗	✗	This survey discussed the directions of the future evolution of rural connectivity. The authors also highlighted how to integrate UAVs for granting wireless communications in zones where the deployment of traditional base stations is not possible.

Our survey	✓	✓	✓	✓	✓	Our survey reviews 4Cs resource allocation and optimization in terrestrial and aerial networks. The problems related to joint optimization of resources, their solution methods and performance metrics have been discussed and analyzed.

2.2 Optimization of 4Cs in UAV-assisted Wireless Networks

The integration of UAVs in terrestrial wireless networks raises several challenges related to the coordination of UAVs, mobile users, services, UAV placement, trajectory optimization, etc. Since mobile users' resources (i.e., power, bandwidth, energy, memory, I/O data rate, etc.) are limited, there is always a need to optimize these resources to increase the efficiency of the network. Therefore, the joint 4Cs problems for UAV-assisted networks are crucial. To get the best performance of the system, it is necessary to jointly optimize all the resources such as communication, computing, and caching and have an efficient control method for all these resources as discussed in [11]. Authors jointly optimized all the resources (communication, computing and caching) in a terrestrial network and used the distributed control to minimize the edge cloud network's bandwidth consumption and network latency. However, most of the existing literature is focused on either 3Cs (joint communication, computing and caching), 2Cs (joint communication and computing, joint computing and caching along with UAV trajectory), or 1C (joint trajectory and communication) problems. In subsequent subsections, we will discuss joint 3Cs, 2Cs, and 1C for terrestrial and non-terrestrial networks. However, there is no existing work for the joint 4Cs problems for the UAV networks.

2.2.1 Joint Communication, Computing and Caching (3Cs) Optimization

This subsection provides the joint optimization of 3Cs resources along with UAV placement. There exists literature on joint 3Cs resource optimization in terrestrial networks. In [1], authors considered the minimization of energy consumption and execution delay taking into account service caching and device-to-device (D2D) communication and introduced opportunistic networks in multi-access networks simultaneously. They formulated the offloading decision as a sequential game problem with lower time complexity. In [2], the energy minimization problem has been formulated by jointly optimizing caching, offloading, and time allocation policy subject to caching and deadline constraints for the MEC network. The formulated optimization problem is mixed-integer non-linear programming (MINLP) problem and NP-hard. In [45], authors formulate an MINLP to minimize the computation delay and energy consumption of the mobile user that jointly optimize the service caching placement, computation offloading decisions, and system resource allocation (e.g., CPU processing frequency and transmit power) in MEC systems. Here, service caching refers to pre-sorting the necessary programs for executing computation tasks at MEC servers. It reduces the real-time delay and bandwidth cost of acquiring and initializing service applications.

In [32], the authors considered frequency-division multiple access setups for minimizing the weighted-sum energy of the BS and the users by jointly optimizing cache placement and bandwidth allocation subject to caching and computing capacities of BS, limited bandwidth and computation latency constraints for each type of task. Authors in [33] proposed a computing task caching strategy to minimize the processing delay of tasks by jointly optimizing communication, computing, and cache resource allocation at the edge cloud in terrestrial network. In [30], authors considered the bidirectional computation task model, where each task is served via three mechanisms, i.e., local computing with local caching, local computing without local caching, and computing at the MEC server. They formulated the average bandwidth minimization problem by jointly optimizing the caching and computing resources under the latency, cache size, and average power constraints. Based on the problem structure and optimal properties, they transform the problem into a multiple dimensional multiple-choice knapsack problem (MMKP) which is NP-hard.

In [31] authors considered AI-enabled smart edge with heterogeneous IoT architecture that combines edge computing, caching, and communication. The authors proposed the Smart-Edge-CoCaCo algorithm to minimize total delay and confirm the computation offloading decision by joint optimization of the wireless communication model, the collaborative filter caching model in edge cloud, and the computation offloading model. They experimented in a real environment on the affective interaction through wearable computing and cloud technology emotion interaction system and observed the delay of the proposed algorithm. In [76], authors jointly considered 3Cs to reduce infotainment content retrieval delay and enhance the QoE of the smart car users and formulate the problem as a mix-integer, non-linear, and non-convex optimization. UAV mounted storage and computing servers perform the caching and computing operation to improve communication and computing efficiency. Due to the limited communication and computing facility in the UAV devices, the joint optimization of UAV placement (i.e., UAV location, altitude, speed, and distance) with 3Cs resource allocation are considered in [8, 77, 78]. UAV-assisted heterogeneous computing platforms (HCP) are considered in [8], where content cache placement and traffic distribution problem is considered in the optimization problem. Authors in [9] considered UAV deployment with communication resources (i.e., power control and channel access) and computing decision (i.e., computation offloading) in the optimization problem where maximum power budget, minimum data rate and computation requirements of UAV are considered as main constraints.

In [60], the authors considered cache enabling UAV-assisted network where user association problem with joint cache placement and UAV deployment is considered to maximize the QoE of users. Authors in [79] addressed the learning-based joint scheduling and 3C resource management in UAV networks. An asynchronous advantage actor-critic-based joint device selection, UAVs placement, and resource management algorithm is proposed to enhance the federated convergence speed and accuracy. In order to enhance the performance of UAV-assisted wireless communication, MEC technology is used by appropriately utilizing communication and computing resources jointly at the edge of the network to decrease response delay and increase the efficiency of network resources utilization [77]. In [80] authors jointly considered NOMA with wireless cache and simultaneous wireless information and power transfer (SWIPT) for UAV communication by utilizing communication and caching resources to enhance energy harvesting and information transmission in UAV based IoT networks. In [81], a multi-resource management architecture of terrestrial satellite networks (TSN) towards 6G has been proposed. The uplink capacity of the user has been improved by joint optimization of the satellite service period and 3C power allocation considering user fairness and data security in the uplink transmission of TSN. The downlink transmission capacity improved by introducing terrestrial and aerial relays and observed the influence on the overall system throughput. In [82], the authors proposed a next-generation aerial delivery network architecture based on the 3D connectivity of the 3Cs resources. In [83], the energy consumption of UAVs has been minimized by jointly optimizing its trajectory and resource allocation, and task decision and bits scheduling of users considering fairness. The problem is formulated as a mix-integer nonlinear programming problem with strongly coupled variants and further transformed into three more tractable subproblems, i.e., trajectory optimization, task decision and bits scheduling and resource allocation.

Lessons Learnt: In summary, given in Table 2.2, the main lessons are:

- Joint 3Cs problems are either bandwidth minimization or energy minimization problems.
- Most of the current literature on 3Cs resource allocation problems is related to terrestrial networks.
- Joint 3C problems for UAV assisted networks also consider UAV placement, user association, and path planning, making it more challenging.

Table 2.2: Objectives and constraints for joint communication, computing, and caching (3C) resource optimization.

Ref.	Objectives	Parameters/constraints	Problem type
[1]	Offloading strategy based on game theory to decrease overall computation overhead, energy consumption, and execution delay	• Parameters: Computation task parameter, decision-making parameter, the overhead of mobile user. • Constraints: Delay, storage capacity, cache capability of the server, computational offloading strategies.	Non convex
[11]	Minimize bandwidth consumption and network latency	• Parameters: Vectors of cache, computation allocation and communication resource allocation. • Constraints: Sum of spectrum allocation less than total available spectrum, computation, and caching resources limit, task execution frequency.	Non-convex
[2]	Energy minimization	• Parameters: Caching action, system state, offloading vector, time allocation vector. • Constraints: caching, deadline.	MINLP non-convex

[32]	Weighted sum energy minimization	• Parameters: Energy consumption, dual variables, input and output data length. • Constraints: Computation offloading deadline, caching and computation capacity, transmission bandwidth, latency.	MINLP
[33]	Minimizing processing delay of the task through the deployment of task caching	• Parameters: Four video tasks, task requests, task duration, uplink data rate, edge caching, and computing capacity. • Constraint: Caching capacity.	Mixed-integer linear problem
[30]	Minimize average bandwidth	• Parameters: Number of tasks, caching and computing policy, average bandwidth, energy, cache, bandwidth cost. • Constraints: Latency, cache size, average power.	MMKP and NP hard, auxiliary problem
[31]	Reduce network congestion; decrease computing and communication delay; better user QoE	• Parameters: AIWAC emotion recognition system, data(image), number of users, the average delay. • Constraints: Caching and computation.	Convex

[76]	Minimize the total delay for the smart cars in the service area	• Parameters: Speed of cars, data rate, computation and cache capacity, delay. • Constraints: Cache allocation, computation and resource constraints.	NP-hard, MINL
[8]	Minimize cache-miss ratio	• Parameters: User equipment identifier, weight vector, control parameter, context information, stochastic gradient descent (SGD). • Constraints: Same learning model for user equipment and HCP	Two-step federated problem
[9]	Deployment, computation offloading, power control, and channel access in coalition-based UAV swarms	• Parameters: Channel parameters, power level, coalition head location, SNR threshold. • Constraints: Time, any two offloading members in the same coalition should choose different sub-channels, highest local computing frequency.	Energy saving optimization problem

[60]	Maximize the QoE of users in the networks, optimization problem of UAV deployment, caching placement	• Parameters: Cache capacity, SINR, transmission delay, the distance between user and UAV. • Constraints: Coupling constraint (binary variables coupled).	Non-convex
[79]	Minimize the federated learning model execution time and the learning accuracy loss	• Parameters: Data sample vector, learning model, loss function, probabilistic loss model, SINR, data rates, bandwidth, transmit power. • Constraints: Maximum transmit power UAV sub-channel, computation capacity range.	MINLP
[77]	Minimize response delay	• Parameters: Power, distance, transmission probability, delay, packet arrival rate. • Constraints: Payload and energy, Communication and computation resources constraints.	Lower and upper convex

2.2.2 Joint Communication and Computing (2C) Optimization

The enormous growth of smart devices and applications in beyond 5G/6G networks emerges into computation-intensive and delay-sensitive tasks. MEC with the integration of UAVs is considered a promising solution to provide the communication and computing resource platform for computation-intensive and delay-sensitive tasks. However, the joint decision of offloading and the transmission power controlling is still one of the challenges in the UAV-assisted MEC systems. As shown in Table 2.3, joint optimization of communication and computing resources considered time, power, bandwidth and energy in terrestrial networks, while the integration of UAVs includes UAV location, speed, trajectory and UAV battery power as a parameter in the optimization problems.

In [84], authors considered dynamic user pairing NOMA-based offloading to deal with the massive access and different offloading requirements of IoT devices in terrestrial networks. The minimization of energy consumption is obtained by jointly optimizing user pairing, communication and computing resources (i.e., transmission power, CPU energy and frequency). The joint multi-user offloading and transmission power control optimization problem to minimize the system-wide computation overhead in a multi-channel wireless interference scenario is studied in [85]. Authors in [86] comprehensively discussed the cooperative communication and computation of vehicular systems and established a stochastic model of vehicle-to-vehicle (V2V) communication using probability theory. Further, they combine V2V communication and vehicle computing to characterize the coupling reliability of cooperative communications and computation systems. In [87], fairness of users has been ensured by joint pilot transmission, data transmission, and resources allocation during the computation execution process to minimize the maximum offload computing delay of all users in the massive MIMO MEC network. The optimization problem is considered constraints on user energy consumption, signal to interference and noise ratio (SINR), and computing resource.

A joint computation offloading and multi-user scheduling algorithm has been proposed to minimize the long-term average weighted sum of delay and power consumption in narrow-band-IoT edge computing system [88]. A semi-distributed dynamic optimization problem is formulated where the offloading is performed locally at the IoT devices. At the same time, the scheduling is auction-based, in which the IoT devices submit bids to the BS to make the scheduling decision centrally. In [89], authors formulated a stochastic optimization problem, which maximizes the system utility and ensures the queues stability subject to the power, subcarrier and computation resources constraints by the joint congestion control and resource allocation in the MEC system. In [90], authors considered both transmission and computation resources to decide on the resource allocation scheme to minimize data loss and maximize the number of completed missions for space network missions. In [91, 92], authors considered joint optimization of communication (i.e., transmission power and bandwidth) and computing resources (i.e., CPU frequency, offloading decision) of both the mobile user and MEC server to minimize the energy consumption of all the users.

An incentive mechanism based on joint non-convex optimization problem of opportunistic computation offloading under delay and cost constraints is formulated in [93] for 5G integrated satellite-ground framework in vehicular network. A vehicular user can either be a service requestor or a service provider. A service requestor is allowed to offload workload to nearby vehicles via V2V channels while effectively controlling the cost and a service provider provides computing services while protecting profit. Joint resource management for D2D communication-assisted multi-tier fog computing is studied in [94], and a joint power control, link scheduling integration, channel assignment and multi-dimensional resource optimization problem has been formulated to maximize the network management profit. In [95], authors proposed joint optimization of the cooperative computation offloading decision and resource allocation cooperative computation offloading to maximize the weighted sum of the computation rate and the transaction throughput for blockchain-enabled MEC systems. In [96], authors considered a multi-user MEC-enabled wireless communication system, where the user equipment suffers limited communication and computation resources. To achieve higher energy efficiency and a better QoE, they formulate an NP-hard MINLP problem, aiming to maximize the number of offloaded tasks in uplink communication while maintaining the computation resources of MEC at an acceptable level.

The computation offloading problem for the hierarchical MEC system with UAVs is studied in [36]. The hierarchical MEC, which exploits both centralized and distributed computing architectures, is promising to support computation offloading in emerging computationally expensive mobile applications. In this study, UAVs integrating computing platforms act as small distributed clouds while the macro BS integrates a more powerful central cloud server. Furthermore, the MIMO technology is employed for data communication. The authors considered the joint task offloading, user-cloud/cloudlet association, transmit power allocation, and path planning to minimize the total weighted consumed power of the system. The computation efficiency maximization problem is discussed in [97] by addressing the joint optimization of communication and computation resources (i.e., transmit power, offloading times, CPU frequencies and trajectory of UAV) for UAV enabled MEC systems. In [90], authors discussed both transmission conflict and system performance improvement for the space networks by joint transmission and computation resource allocation. The authors in [62] discussed the joint resource optimization and hyper learning rate control method to minimize the energy consumption of mobile devices and overall learning rate in the MEC system. The authors proposed a resource-sharing model for both centralized and decentralized resource management. In [98], authors considered a UAV-assisted MEC system in which a mobile UAV equipped with computing resources is employed to help user devices (UDs) compute their tasks. They formulated an optimization problem to minimize the weighted-sum energy consumption of the UAV and UDs by jointly optimizing the UAV trajectory and computation resource allocation under the constraint of the number of computation bits for orthogonal and non-orthogonal access modes.

Lessons Learnt: In summary, given in Table 2.3, the main lessons are:

- The objective of all the joint communication and computation problems are either energy and power minimization or maximization of the weighted sum of computational offloading.
- Majority of the problems are MINLP and dynamic optimization.
- Limited literature is available on joint communication and computation is discussed for UAV-assisted wireless networks.

Table 2.3: Objective and constraints for joint communication and computing (2C) resource optimization.

Ref.	Objectives	Parameters/constraints	Problem type
[99]	Minimize energy consumption	• Parameters: Power, time, task offloading, transmission rate. • Constraints: Time resources, offloading task to MEC server, transmission delay.	Non-convex
[84]	Minimize energy consumption	• Parameters: Transmission power, offloading data size, transmission energy, CPU frequency, SINR. • Constraint: Time.	MINLP
[85]	Minimize computation overhead	• Parameters: Execution latency, energy consumption, power, channel parameters. • Constraints: Transmission power, multi-dimensional discrete space.	Non-convex, MINLP
[86]	Maximize the estimated success probability of computation offloading	• Parameters: Time, data, feasible scheduling solution, SINR, privacy tolerance threshold, bandwidth. • Constraints: Reliability, end-to-end delay	Convex

[87]	Minimizing the maximum offload computing delay for all users	• Parameters: CPU frequency, total computing delay, transmission rates, energy consumption. • Constraints: User energy consumption, computing resource constraints, SINR.	Non-convex
[88]	Minimize the weighted sum of the average delay and power consumption for the IoT devices	• Parameters: System state, transmission queue length, processing queue length, and offloading decision. • Constraints: Average delay and power consumption.	Dynamic optimization
[89]	Maximizes the system utility and ensures the queues stability by the joint congestion control and resource allocation	• Parameters: Bandwidth, time, Transmission power, CPU frequency, execution time. • Constraints: Power, sub-carrier and computation resources.	Convex optimization problem
[90]	Maximize number of completed missions while minimizing data loss	• Parameters: Antenna size, data size, compression ratio, mission index. • Constraints: State transition, run time, completed mission constraint.	MILP

[91]	Minimize energy consumption	• Parameters: Bandwidth, data rate, upload time, AWGN power, path loss, the reference distance. • Constraints: Task delay constraints, transmission power, maximum CPU frequency.	Non-convex
[93]	Opportunistic computational offloading and price per resource block	• Parameters: Weight factors, completion time, CPU cycles. • Constraints: Delay and cost.	Non-convex, NP-hard
[94]	Maximization of network management profit	• Parameters: Link scheduling, channel assignment, power. • Constraints: Energy consumption cost, computation and communication, SINR, power.	MINLP
[95]	Maximize weighted sum of computation rate and transaction throughput for MEC systems	• Parameters:State space, channel conditions, computing resources, power. • Constraints: Maximum frequency (Dynamic voltage and frequency scaling), latency time to finality.	MDP

[92]	Minimization of energy consumption and time delay	• Parameters: Energy Consumption, execution delay, transmission power, bandwidth limit, offloading decision. • Constraints: Frequency of CPU, power, bandwidth, computing resources, the stability limit.	Convex optimization
[96]	Maximize the number of offloaded tasks	• Parameters: Radio remote heads, SINR, Transmitted data rate, power, bandwidth. • Constraints: Time cost, computation, communication, power.	MINLP
[36]	Minimize the total weighted computation and transmit powers of all users in the system	• Parameters: Distance/coverage radius, time, CPU clock speed, path loss, maximum allowable speed. • Constraints: Computation resources, minimum transmission rate, maximum allowable consumed powers.	MINLP
[97]	Maximization of computational efficiency of UAV-enabled MEC system	• Parameters: UAV trajectory. • Constraints: Energy, offloading time, CPU frequencies, transmit power, UAV's mobility, position of UAV.	Non-convex

[62]	Minimize the running time cost and the energy consumption of user equipment	• Parameters: Hyper learning rate, cost of learning service,CPU frequency, bandwidth. • Constraints: CPU frequency, bandwidth, uplink transmission time, shared CPU resources.	Non-convex

2.2.3 Joint Computing and Caching (2C) Optimization

Joint optimization of cache and computing resources in terrestrial and aerial networks consider content cache placement and computing task offloading decision as shown in Table 2.4. Edge service caching is considered a promising solution to reduce real-time delay in MEC-supported applications. Authors in [45] considered terrestrial networks where mobile users contain single servers that cache pre-sorted initial service for real-time applications. MEC networks provide more computing and storage capability for latency-sensitive mobile applications. However, the computation and caching resources at the edge servers are limited, so there is a need to optimize these resources to increase the efficiency of the network. In [100], the authors proposed a joint task offloading and data caching scheme to minimize the overall computation latency of all mobile devices while maintaining the lowest energy consumption. Introducing UAVs in the MEC network is another solution to increase the computing and caching resources of the network. UAV-mounted cloudlet distribution and data computation in location-based social networks are considered in [101], where computing and traffic load reduction are the main objectives for the optimization problem in the UAV-cloudlet distribution.

Lessons Learnt: In summary, given in Table 2.4, the main lessons are:

- Joint computing and cashing resource optimization consider CPU frequencies, computation time, energy, power and caching capacity parameters.

- The joint computing and caching problems can be MINLP, linear programming, and convex optimization.

- MEC, cloud computing and UAVs in the network plays a vital role in maximizing caching and computing efficiency.

Table 2.4: Objectives and constraints for joint computing and caching resource optimization.

Ref.	**Objectives**	**Parameters/constraints**	**Problem type**
[45]	Minimize the overall computation delay and energy consumption of the mobile user	• Parameters: Computation time, CPU frequency, energy efficiency, power. • Constraints: Time and energy consumed while computing tasks, caching capacity.	MINLP
[100]	Minimize the overall computation latency	• Parameters: Task arrival rate, storage size, amount of data, power, service rate. • Constraints: Energy consumption, per-slot computation delay, bandwidth, deadline requirements.	Binary programming problem
[101]	Optimization of energy consumption and cache placement	• Parameters: Time, latency, energy consumption. • Constraints: Storage, popular file library,CPU and link bandwidth resources.	Convex

2.2.4 Joint Trajectory, Communication and Computation Optimization

This subsection is about joint optimization of UAV trajectory and 2Cs, i.e., communication and computation resource allocation. As shown in Table 2.5, UAV trajectory optimization considers the parameters of UAV mass, velocity, acceleration, altitude and its location parameters along with power, signal-to-noise ratio (SNR), bandwidth, CPU frequencies, energy consumption and offloading rate etc.

The future wireless networks in which UAVs can be used to assist computing in MEC systems pose new opportunities to solve the challenges in communication and computation design, and several prior related works have been done for this [37, 40, 46, 47, 102]. Particularly, the work in [37] considers that UAV is deployed as a helper that not only helps compute the bits offloaded from terminal devices but also acts as a decode-and-forward (DF) relay to assist task bits to transmit from terminal devices to BS and minimize the sum energy of communication-related energy, computation-related energy, and UAVâs flight energy. In [47], the UAV-assisted MEC system is studied, in which the UAV serves as a relay between the offloading users and the BS. Furthermore, NOMA is introduced to improve the spectrum efficiency and joint trajectory and computation offloading optimization is done to minimize the total delay of all users. Authors in [46] formulated the non-convex joint optimization of the CPU frequencies, the offloading amount, the transmit power, and the UAVâs trajectory to minimize the required energy of UAV in UAV-assisted wireless powered cooperative MEC. This work also shows that trajectory optimization plays a dominant factor in minimizing the total required energy of the system and optimizing acceleration has a significant effect on the required energy of the UAV.

In [40], the authors aim to minimize the UAVâs mission completion time by optimizing its trajectory jointly with the computation offloading scheduling, subject to the maximum speed constraint of the UAV and the computation capacity constraints at ground BSs. Authors in [102] investigated a multiple UAVs-assisted two-stage MEC system in which the computation-intensive and delay-sensitive tasks of mobile devices are cooperatively executed on both MEC-enabled UAVs and terrestrial BSs attached with the MEC server. A joint task offloading, communication and computation resource allocation problem has been formulated to minimize the energy consumption of mobile devices and UAVs while considering the limited communication resources for the uplink transmission, the computation resources of UAVs and the tolerable latency of the tasks. In [103], a novel framework is proposed to exploit the flexibility of the UAV for legitimate monitoring via joint trajectory design and energy management. The UAV can adjust its positions and send the jamming signal to the suspicious receiver to ensure successful eavesdropping. To achieve energy-efficient UAV operations in practice, authors further consider a solar-powered rotary-wing UAV-enabled monitoring system, including propulsion power consumption.

In [104], authors designed the UAV trajectory to minimize the total energy consumption while satisfying the requested timeout requirement and energy budget, which is accomplished via jointly optimizing the path and UAVâs velocities along with subsequent hops. The corresponding optimization problem is challenging to solve due to its non-convexity and combinatorial nature. In [105], joint communication and computation resource allocation and UAV trajectory optimization have been studied for maximizing the total energy efficiency in UAV-based NOMA downlink wireless networks with the QoS requirements. The UAV-assisted cellular network where multiple UAVs serve as aerial BSs to provide wireless connectivity to ground users through frequency division multiple access scheme has been discussed in [106]. Joint optimization for user association, communication and computing resource allocation, and UAV placement is investigated to maximize the downlink sum rate.

Lessons Learnt: In summary, given in Table 2.5, the main lessons are:

- Joint UAV trajectory, communication, and computation resource allocation problems are mainly non-convex optimization and MINLP.
- Communication resources and trajectory optimization have a significant impact on the network's total energy consumption.

Table 2.5: Objectives and constraints for joint UAV trajectory, communication, and computation resource optimization.

Ref.	**Objectives**	**Parameters/constraints**	**Problem type**
[37]	Minimize total energy consumption	• Parameters: Time, bandwidth, SNR, offloading rate, power, speed, location, CPU frequency. • Constraints: Communication, computation resource allocation, computation causality, UAV trajectory.	Non-convex
[47]	Joint trajectory and computation optimization	• Parameters: Data rate, power, interference, energy, commutation capacity, UAV mass, QoS requirement. • Constraints: UAV energy, latency, transmit power, transmission rate, requirements of successive interference cancellation.	Non-convex

[46]	Minimize the total required energy at the UAV	• Parameters: CPU frequency vector, computational bits offloading vector, UAV trajectory, velocity, acceleration, Transmit power vector. • Constraints: Sensor device computing task constraints, the information and energy harvesting causality, UAVâs trajectory.	Non-convex
[40]	Computation offloading and trajectory optimization of UAV	• Parameters: Number of tasks, CPU cycles, UAV altitude, horizontal locations, mission completion time, UAV's speed, computational offloading. • Constraints: Maximum speed of UAV, computation capacity.	Non-convex
[102]	Minimize the energy consumption of mobile devices and UAVs	• Parameters: Channel assignment variable, approximation function, channel gain, SNR, the thrust of UAV, energy consumption, weight and penalty parameters. • Constraints: Task execution time, task data size, maximum computing capacity, channel association.	MINLP

[103]	Minimizing total energy consumption	• Parameters: UAV location, travel distance, maximum speed, transmit power. • Constraints: UAVâs mobile activity constraints (location and speed), SINR.	Non-convex
[104]	Minimize UAV energy consumption	• Parameters: Power consumption, flying velocity, UAV path. • Constraints: Feasible set of paths, HOP (trajectory line segments) velocities, energy budget, maximum latency.	Non-convex
[107]	Minimize power consumption	• Parameters: Trajectory, beam-forming vector, time, power, frequency. • Constraints: Semi-infinite constraint, disjunctive constraint.	Non-convex

2.2.5 Joint Trajectory and Communication Optimization

The employment of UAVs in wireless communication provides better communication channels and mobility, which provides flexibility in deployment. The trajectory optimization and acceleration of UAV plays a dominant factor in minimizing the total required energy of the system [46]. On the other hand, the unique characteristic of UAVs also poses challenges in resource allocation, such as mobility, trajectory, speed and energy, which are enlisted in the parameters and constraints column in Table 2.6. This subsection is about communication resource allocation along with UAV trajectory optimization. Communication resource allocation and optimization mainly consider spectrum efficiency, power control and interference management. In order to tackle UAV-related challenges and communication resources (i.e., transmission power, bandwidth etc.) optimization issues in UAV-assisted wireless networks, the proper design of UAV trajectory is necessary.

In [34, 108], authors considered the optimization of the communication resource allocation by minimizing the interference and protection cost in terrestrial networks. In [34], authors investigate the resource allocation and power control problems in which the D2D pairs utilize the uplink resources of cellular users in 5G networks. In [34], joint channel and power allocation algorithm with deep Q-learning has been investigated to maximize the system capacity and spectrum efficiency while minimizing interference in D2D communication in terrestrial networks. In [108], a multicast routing algorithm has been investigated to provide working communication paths for staged load control by jointly organizing the load control terminals in source grid load systems, optimizing the dispatching of power supply, power grid, and power load. In [86], the authors proposed an optimization problem to minimize the total energy consumption, including communication energy, computation energy and UAVâs flight energy, by optimizing communication resources (i.e., bits allocation, time slot scheduling, and power) and UAV trajectory. Authors in [109] applied Q-learning method for trajectory optimization problem. The joint trajectory and sum-rate maximization problem is considered in [109] where the UAV works as a machine learning agent that updates the trajectory that maximizes the sum rate of the transmission based on q-learning techniques.

In [110], UAV trajectory and power allocation scheme is proposed to maximize the downlink achievable sum rate of all users by considering UAV mobility, information causality, and transmit power constraints. Authors in [53] proposed a UAV-assisted multi-carrier wireless communication model to maximize the minimum achievable rate in the uplink among all IoT nodes by jointly optimizing the UAV trajectory, subcarrier, power, and subslot allocation. Authors in [111] considered a generic optimization problem to maximize the UAV communication utility by jointly designing the continuous-time UAV trajectory and communication. Power-efficient resource allocation is significant in UAV-assisted communication systems due to limited onboard battery capacity. In [104], authors optimized UAV trajectory to minimize the total energy consumption while satisfying the

UAV mobility (i.e., location and speed), maximum latency, and SINR in UAV enabled communication system. The optimal path is selected as the designed trajectory of the UAV for best UAV performance. Authors in [107] considered the minimization of the total power consumption by jointly optimizing the 2D trajectory and the transmit beamforming vector of the UAV. In [112], authors considered a single cell multi-user orthogonal frequency division multiple access (OFDMA) network with one UAV, which works as an amplify-and-forward relay to improve the QoS of the user equipment in the cell edge. In order to improve the throughput while guaranteeing user fairness, they jointly optimized the communication mode, sub-channel allocation, power allocation, and UAV trajectory, which is an NP-hard problem.

Lessons Learnt: In summary, given in Table 2.6, the main lessons are:

- Interference management, power, and spectrum allocation play a vital role in communication resource optimization problems along with UAV trajectory.
- The problems in this category of resource allocation are either non-convex optimization or mixed integer linear programming (MILP).
- The goal of communication resource optimization is to maximize the system capacity, spectrum efficiency and achievable sum rate.

Table 2.6: Objectives and constraints for joint UAV trajectory and communication resource optimization.

Ref.	Objectives	Parameters/constraints	Problem type
[34]	Maximize system capacity and spectrum efficiency while minimizing interference to cellular users	• Parameters: State transition probabilities, reward function, environment state, CPU capacity. • Constraints: SINR, power, bandwidth.	State space problem

[108]	Improve the resource utilization rate of the communication for load control, minimize protection cost	• Parameters: Cost, the working capacity of the link, number of protection paths. • Constraints: Bandwidth, total energy consumption, CPU capacity, the deadline requirement, computation offloading.	MILP
[110]	Maximize the downlink achievable sum rate of all users by jointly optimizing UAV trajectory and BS/UAV power	• Parameters: Flight speed, UAV distance. • Constraints: UAV mobility and information causality, flight speed, BS/UAV transmit power.	Non-convex
[53]	Maximize the minimum achievable rate in the uplink among all IoT nodes	• Parameters: Antenna gain, altitude, UAV speed, location of UAV, bandwidth, energy. • Constraints: Achievable sum rate, UAV flight speed, power.	Non-convex
[111]	Maximizing the UAV communication utility	• Parameters: Number of segments by path and time discretization, communication utility function, conventional path discretization, flexible path discretization, flight time. • Constraints: Maximum UAV speed, UAV communication, UAV trajectory.	Non-convex

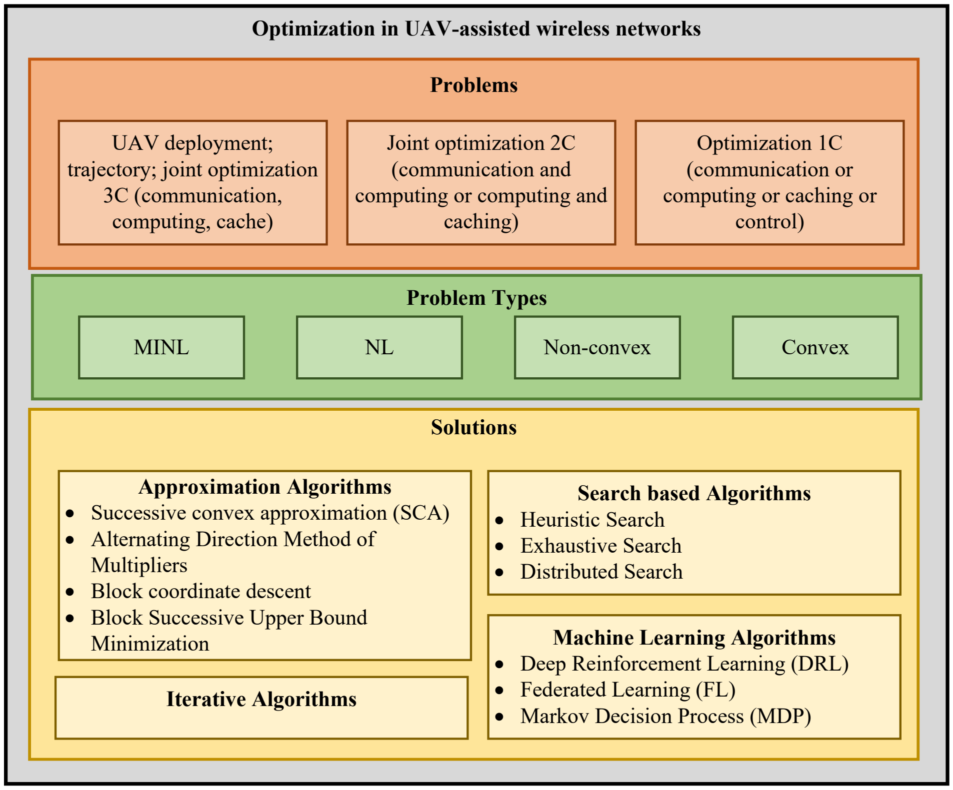


Figure 2.1: Solution and techniques for optimization problems in UAV-assisted wireless networks.

2.3 Solutions and Techniques

This section discusses the solution methods and techniques for optimization issues presented in the considered in Section 2.2. We classify the solutions methods and techniques for the joint 3Cs resource optimization, joint 2Cs resource optimization, joint trajectory and 2Cs resource optimization, joint trajectory and communication resource optimization can be divided into the categories shown in Fig. 2.1. Mainly, we divide the solution methods and techniques into approximation algorithms, iterative algorithms, search-based algorithms, and machine learning algorithms. These categories are further categorized into different approaches. The optimization problems identified in the literature include convex, non-convex, linear programming, MINLP, and MILP. However, most of the work considered non-convex optimization formulations. The solution methods for non-convex problems utilize relaxation, approximation, and multipliers, converting non-convex problems to convex problems.

2.3.1 Approximation Algorithms:

The approximation algorithms are utilized in non-convex optimization problems such as energy efficiency. In aerial networks, UAV-related problems such as UAV trajectory, path planning and UAV placement are solved using approximation methods. The approximation algorithms can be further classified into the following:

Successive Convex Approximation (SCA)

Successive convex approximation (SCA) converts the non-convex problem into a convex or linear problem by introducing slack variables into the function until it becomes linear. Authors in [37] formulated the energy minimization problem by optimizing the UAV trajectory as a part of the main problem, i.e., joint communication and computing resource optimization. The formulated problem is non-convex optimization that is challenging to be solved. Lagrange duality and the SCA method are used to convert the problem into convex optimization and obtain a local optimal solution. Similarly, in [40] alternating optimization and the SCA techniques are applied in computation offloading and trajectory optimization problems which return the sub-optimal solution to the offloading decision problem.

Authors in [85] developed distributed power control algorithm for MEC using SCA by optimizing auxiliary variables and the transmission power in a distributed way, given the convergence threshold and learning rate. In [47], joint optimization of UAV trajectory and power allocation problem is addressed by leveraging the SCA to obtain a sub-optimal solution. The SCA-based algorithms should be adopted to find an optimal solution due to increased computational complexity, relatively large amount of data and mobility of UAVs in 6G networks. In [46], the total required energy of UAV is minimized by jointly optimizing the CPU frequencies, the offloading amount, the transmit power, and the UAVâs trajectory by using the SCA-based algorithm. In [97], the authors proposed the two-stage alternative optimization algorithm to solve the non-convex computation efficiency maximization problem for UAV-assisted MEC network. In the first stage for any given UAV trajectory, they applied the Lagrangian dual method to obtain the closed expressions of the optimal transmitted power and CPU frequencies. In the second stage, the SCA method is used to obtain the optimized trajectory of the UAV.

To improve the performance of UAV-assisted wireless networks, the joint design of UAV trajectory and communication is considered in [111]. Authors have to deal with the challenge of many design variables arising from the continuous-time UAV trajectory optimization. The SCA is used to optimize the UAV trajectory with piecewise-linear path segments connected via a finite number of waypoints in a 3D space to obtain a sub-optimal solution. In [103], the authors considered joint trajectory design and energy management of UAV. Authors model and include the propulsion power to minimize the overall energy consumption of the UAV, and using the SCA, an effective iterative approach is developed to find a feasible solution fulfilling the Karush-Kuhn-Tucker (KKT) conditions. Authors in [107] investigated the total power consumption minimization problem by jointly optimizing the 2D trajectory and the transmit beamforming vector of the UAV for multi-user downlink multiple-input single-output (MISO) UAV communication systems. They proposed a sub-optimal iterative low-complexity scheme based on the SCA to balance optima and computational complexity.

Alternating Direction Method of Multipliers (ADMM)

The alternating direction method of multipliers (ADMM) is a simple but powerful first-order method for solving convex optimization problems with a large number of variables and constraints. Using this method, one can decompose the complex problem into a series of sub-problems containing only a small number of variables and constraints. These sub-problems are independent of each other and can be solved in a distributed manner.

In [2] authors considered joint caching, offloading, and time allocation (3C resource allocation), which is a non-convex and MINLP problem for the MEC system to minimize the weighted sum energy consumption using caching and deadline constraints. The authors converted it into equivalent convex MINLP using some appropriate transformations to solve this problem. They obtained a sub-optimal solution using the alternating direction method of multipliers and the penalty convex-concave procedure. To address the complexity issue in large size terrestrial networks, authors in [113] proposed an ADMM based technique that jointly optimizes the mode selection and time allocation. Joint computing and communication resources with cache allocation are considered in [76]. The authors applied the ADMM method for MINLP to find the optimal global solution for resource allocation. In [62], the authors investigated multi-service federated learning problem to jointly optimize communication, computation and control parameters while minimizing the learning time energy consumption of users. The authors developed a decentralized algorithm that leverages the parallelism structure for sub-problems update of Jacobi-Proximal ADMM into multi convex ADMM (i.e., JP-miADMM). It allows each learning service to independently manage the local resource and learning process without revealing the learning service information.

Block Coordinate Descent (BCD) method

Block coordinate descent (BCD) is a simple iterative algorithm for non-convex optimization that sequentially minimizes the objective function in each block coordinate while the other coordinates are held fixed. Joint optimization of UAV trajectory and resource allocation problems are non-convex optimization problems in which continuous-time variables are coupled together. A non-convex optimization problem due to the coupling among the 2D UAV waypoints, travelling duration on line segments, and UAV communication scheduling has been proposed in [111]. To address the coupling, a BCD method is used for the joint UAV trajectory and communication design. The BCD method decoupled the variables into multiple blocks (non-convex) and solved them in iterations to get the sub-optimal solution. Practically, BCD cannot be applied directly to non-convex problems and guarantees the convergence of the objective function, so another approximation method is always used in combination with BCD to convert the non-convex function to convex. In UAV trajectory optimization problems, the BCD method is used in combination with successive convex approximation to get the finest trajectory as discussed in [104].

Block Successive Upper bound Minimization (BSUM) method

The block successive upper Bound minimization (BSUM) method is a distributed algorithm for big-data optimization and solving separable smooth or non-smooth convex optimization problems with linear coupling constraints. The BSUM method allows the decomposition of the formulated optimization problem into small sub-problems that can be addressed separately by minimizing the proximal upper-bound function by updating the variables' blocks until it converges to both a coordinate-wise minimum and a stationary solution. In [11], the authors developed a BSUM based distributed optimization control algorithm to jointly optimize a linear combination of the bandwidth consumption and network latency in big data MEC. They investigated BSUM for the 4Cs with a cyclic rule, Gauss-Southwell rule and randomized rule. In [102], the authors formulated a joint offloading, communication, and computation resource allocation problem to minimize the energy consumption of mobile devices and UAVs by considering limited communication and computing resources. The formulated problem is mixed-integer non-convex due to coupling among the variables, so they applied the BSUM method to get the stationary points of the non-convex objective function. The non-convex objective function is decomposed into multiple sub-problems, which are then solved in a block-by-block manner, and finally, the optimal solution is obtained.

Lessons Learnt: The main findings of this sub-section are:

- Approximation algorithms are mainly used to convert the non-convex optimization problem into convex and divide the main problem into subproblems to reduce the complexity.
- Approximation algorithms play a vital role in trajectory optimization or path selection of UAVs.
- Approximation algorithms alone cannot solve joint 3Cs or 2Cs problems. BCD, BSUM, and SCA methods are mostly used for 2Cs resource allocation.

2.3.2 Iterative Algorithms

The complex non-convex problems with higher computational complexity are solved using mathematical evaluations of the iterative algorithms. This method computes the results using approximation from the previous answer or an initial guess. Iterative algorithms are mostly used in UAV-assisted wireless networks where energy consumption minimization is needed to optimize the UAV trajectory.

Two steps iterative method

The two-step procedure invokes the iterative method that divides the joint problems into two phases. It is very popular in two parameters optimization problems, e.g., joint bandwidth and power allocation problems. The first phase keeps one variable (e.g., power) fixed and iteratively updates other parameters (e.g., bandwidth). In the next phase, use the updated parameters (i.e., bandwidth) to find the solution for the first parameter (i.e., power).

In [36], authors considered the joint task offloading, user-cloud association, transmit power allocation, and path planning to minimize the total weighted consumed power of the system. They proposed an iterative two-phase algorithm to tackle the underlying non-convex MINLP. In [37], an iterative algorithm is used to optimize the computation bits allocation jointly, power allocation, time slot scheduling, and UAV trajectory optimization after converting the problem into convex optimization as discussed in Section 2.3.1. The user-cloud or cloudlet association problem is solved in the first phase, and the joint resource allocation, path planning problem is solved in the second phase. The iterative optimization algorithm is designed to solve the joint optimization problem of time delay and energy consumption in [92]. According to the authors, as the number of algorithm iterations increases, the task execution energy consumption tends to converge fewer times. In [110], an iterative algorithm is proposed to optimize the UAV trajectory and BS/UAV transmit power to obtain the approximately optimal solution. The formulated problem contains multiple constraints such as flight speed, information causality, and BS/UAV transmit power, which is difficult to solve directly. Therefore, the problem is divided into two parts and solved iteratively until the optimal value of the objective function is achieved.

Authors in [53] proposed a low complexity iterative algorithm to solve non-convex optimization problem discussed in Section-III. The optimization problem is challenging to solve directly because it involves multiple discrete variables and includes UAV flight speed, subcarrier, and power allocation constraints. Therefore, the problem is divided into two steps. Firstly, a resource allocation algorithm based on joint subcarrier, power and subslot allocation is designed for a fixed UAV trajectory. Secondly, the UAV trajectory for different flight modes is optimized for fixed resource allocation. The solution is effective for both one flight and periodic flight mode. In [107], authors investigated robust resource allocation algorithm design for multi-user downlink multiple-input single-output UAV communication systems. The proposed non-convex optimization problem is first solved optimally by employing monotonic optimization theory and semi-definite programming relaxation, yielding the optimal 2D trajectory and beamforming policy. The developed optimal resource allocation algorithm is of high computational complexity, so a low complexity iterative scheme is proposed. The results proved that the proposed algorithms confirm their robustness with respect to UAV jittering, wind speed uncertainty, and user location uncertainty. In [114], the authors formulated the MINLP problem to minimize the task latency of all devices by jointly optimizing caching and offloading decisions. They proposed an iterative algorithm to obtain the joint solution of resource allocation and UAV placement.

Lessons Learnt: The main summary of this sub-section includes:

- Iterative algorithms effectively optimize the UAV trajectory, significantly enhance the achievable rate among all nodes, and improve the achievable sum rate.
- Iteration algorithm has good convergence compared with conventional resource allocation schemes.

2.3.3 Search based Algorithms

This subsection discusses search-based algorithms and their applicability in UAV networks. In the existing literature, these algorithms are mostly used to find maximum coverage, maximum sum rate, minimum power consumption, and optimum height of UAV.

Heuristic Search

In [84], a heuristic algorithm is applied for user scheduling to get the sub-optimal solution. A sub-optimal cache placement scheme is proposed in [32] to solve the MILP problem by using a greedy heuristic algorithm to reduce the complexity caused by exhaustive search. Authors in [96] formulated a task scheduling and resource allocation problem as non convex mixed integer problem.They proposed a low complexity heuristic algorithm to achieve a near optimal solution. In [104], the authors designed the UAV trajectory by solving a non-convex joint optimization problem using heuristic search and dynamic programming to obtain a feasible set of paths. They compared the proposed heuristic search and dynamic programming with exhaustive search and travelling salesman problem. While the exhaustive search achieves the best performance at a high computation cost, the heuristic algorithm exhibits relatively poor performance with low complexity. As a result, dynamic programming is proposed as a practical trade-off between exhaustive and heuristic algorithms.

Exhaustive Search

Exhaustive search is a high computational complex algorithm that checks every possibility to obtain the best solution. In the existing literature, exhaustive search is mostly used in UAVs placement problems concerning user locations, bandwidth allocation, and cache placement problems. In [32], the authors found the optimal caching decisions and bandwidth allocation to minimize the weighted-sum energy of the edge server and the users using exhaustive search. The exhaustive search algorithm provides global optimal solution; its exponential computation complexity might limit its applicability in practical applications. Therefore, the authors proposed the greedy cache placement algorithm to find the sub-optimal solution to the problem.

Distributed Search

In [9], authors proposed a distributed learning algorithm to optimize the joint deployment, computation offloading, power control, and channel access in coalition-based UAV swarms. The algorithm compared multiple offloading strategies in one iteration, which can fasten the convergence speed and avoid the cost of searching the whole strategy space.

Lessons Learnt: The main summary of this sub-section includes:

- The heuristic algorithm exhibits relatively poor performance with low complexity.
- Exhaustive search exponential computation complexity may limit its applicability in practical applications.

2.3.4 Machine Learning (ML) Algorithms

This section briefly presents the role of machine learning algorithms such as federated learning, DRL, and Markov decision process in UAVs joint optimization problems and 4Cs problems in B5G and 6G networks.

Deep Reinforcement Learning (DRL)

With the dynamic nature of UAVs and uncertain environment conditions, UAVs need to improve the QoS of sensing and communication without complete information, which makes reinforcement learning suitable for use in the cellular Internet of UAVs [115]. In [79], the authors used DRL to deal with uncertain channel conditions of multi UAV enabled network. Model-free reinforcement learning is one of the dynamic programming techniques capable of tackling the decision-making problem by learning an optimized policy in dynamic environments. In [116], a model-free DRL-based collaborative computation offloading and resource allocation scheme has been proposed in an aerial to ground network to minimize task execution delay and energy consumption. In

[117], authors formulated the optimization problem considering backhaul rate, transmission power and transmission mode. They proposed a DRL-based method to enhance the backhaul rate with limited information exchange and avoid malicious power exchange. In [118], authors formulated the complex optimization problem for joint communication and computation resource allocation in a space-air-ground-sea integrated network architecture. In the integrated network, satellites and UAVs provide the users with edge computing services and network access. A complex decision process and DRL solution is designed to provide better QoS. In [119], the authors formulated the MINLP problem for joint communication and computing resource allocation for hybrid MEC networks. Hybrid deep learning-based online offloading algorithm has been proposed to provide the user association and computing resource allocation under the practical latency requirement of the task and limited computing resources of the MEC network. The global optimal solution has been found while speeding up the decision-making through a deep neural network. The simulation results have shown that the proposed solutions have better computational efficiency and accuracy.

Federated Learning (FL)

Federated learning (FL) emerges as a promising paradigm aiming to protect device privacy by enabling devices to train AI models locally without sending their raw data to a server. Instead of training the AI model at the data server, FL enables devices to execute local training on their data. In [8], the authors proposed a two-stage FL algorithm among the users, UAVs/BSs, and distributed heterogeneous computing platform to collaboratively predict the content caching placement by jointly considering traffic distribution, user mobility, and localized content popularity in 6G networks. An asynchronous weight updating method is adopted to avoid redundant learning transfer in FL. Authors in [79] developed an asynchronous FL framework for multi-UAV-enabled networks. The proposed framework can provide asynchronous distributed computing by enabling model training locally without transmitting raw and sensitive data to UAV servers to achieve fast convergence speed and high learning accuracy for multi-UAV-enabled wireless networks.

Markov Decision Process (MDP)

The UAVs or IoT devices must determine the best action based on their current state in reinforcement learning techniques. 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. An MDP model consists of possible states, a set of actions, a transition model, and a reward value function. In [88], the authors formulated a continuous-time MDP problem for the multiuser narrow band-IoT MEC system considering stochastic task arrivals to minimize the average delay and power consumption of processing the sensed data for the IoT devices. Authors in [95] considered a cooperative computation offloading and resource allocation framework for blockchain-enabled MEC systems to maximize the computation rate and transaction throughput. Due to the dynamic characteristics of the wireless fading channel and the processing queues at MEC servers, the joint optimization is formulated as an MDP.

In [120] authors investigated the joint task generation and computational offloading policy by using the average energy constraint at the device in a MEC system. Using the Lagrangian method, they solved the constrained MDP problem by transferring it into the unconstrained MDP. They showed that the optimal policy for the constrained MDP with a single constraint is a randomized mixture of two deterministic policies for the unconstrained MDP. By jointly considering the evolution of the age of obtained status updates and the energy consumption of computation offloading for minimizing the average age of obtained status updates under the average energy constraint at the device. In [121], authors formulated the resource management of UAV-assisted wireless powered IoT networks and data collection as MDP to get an optimal solution, where states consist of battery levels and data queue lengths of the IoT nodes, channel qualities, and position of UAV.

Lessons Learnt: The main summary of this sub-section includes:

- Machine learning-based solutions such as DRL, FL, and MDP are used for channel modelling, resource management, and UAV positioning problems.

- Machine learning makes the problems model-free and easier to analyze the consumer behaviour and requirements.

- Federated learning is used to protect the privacy of data.

- Reinforcement learning is effective in a dynamic environment.

2.4 Performance Metrics

The performance metrics for joint resource optimization in UAV-assisted wireless networks are shown in Fig. 2.2 and are measured based on the optimization objectives with joint resource allocation problems. The performance metrics are designed based on either individual resource components or overall networks. For example, the overall networks or applications related performance such as throughput, sum rate, energy efficiency and spectrum efficiency are considered in UAV placement, and joint 3Cs resource allocation problems [8, 9, 60, 77, 79]. Individual component-based performance metrics are described below:

Communication Performance Metrics

UAV path planning, placement, trajectory optimization problems, and joint transmission power and bandwidth allocation problems have significantly affected the communication performance of the UAV networks. The main objectives of the UAV communication side are to minimize communication delay and extend the coverage. Communication latency, path-loss, weighted consumed power, system throughput, as well as spectrum and energy efficiency are considered as key performance metrics for communication resources in UAV-assisted wireless networks [36, 47, 58, 80]. UAV communication distance and trajectory are also used to measure its performance. UAVs tend to move to locations to support the users better, increasing the SNR. However, UAVs try to balance the benefits of moving to minimize the communication distance and the consumed flying power to achieve the best solution while effectively supporting users' computation demands [9]. Maximum transmit power and UAV speed are used to measure the communication performance and it is observed that the flying power of UAV increases with the UAV speed for OFDMA UAV

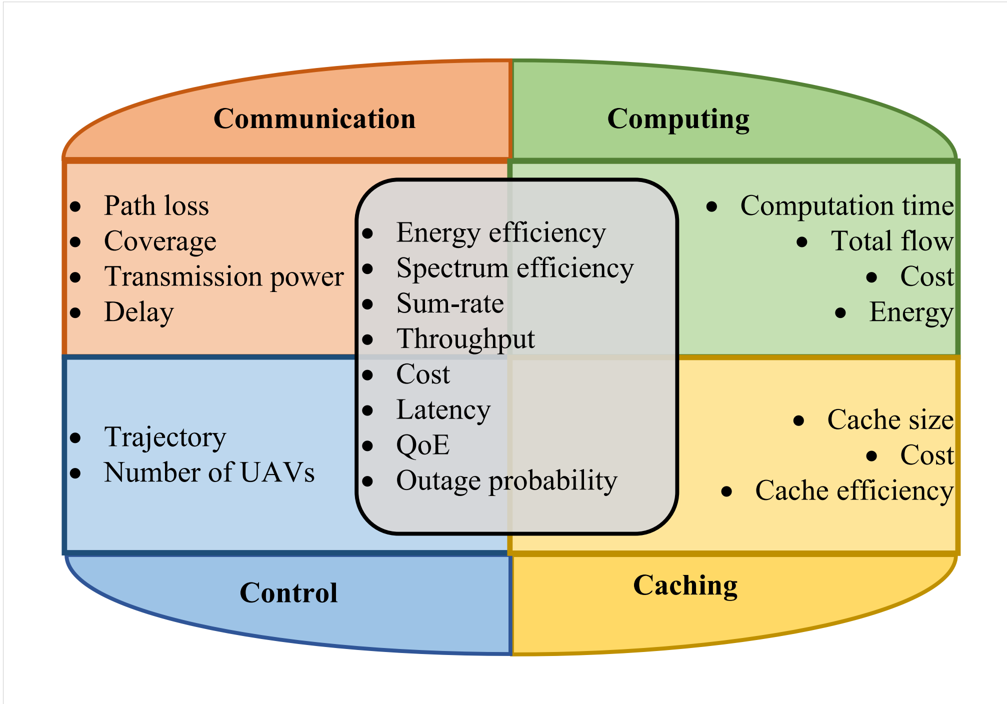


Figure 2.2: Performance metrics.

relay networks [112]. In [38], the authors presented the performance of the power optimization for low interference and throughput enhancement scheme for 6G future networks by measuring the delay of the transmitted packet. The probability of the user receiving the requested file from its associated UAV is the crucial performance measurement criterion for UAV deployment and power optimization schemes [55]. Simulation results in [59] showed that the proposed trajectory design could improve the network throughput and UAV-to-device link utilization compared to the conventional reinforcement learning algorithms.

Computing Performance Metrics

When UAVs are installed with computing processors, they can provide computing services as MEC servers. The UAV trajectory and acceleration optimization play a dominant factor in minimizing the total required energy of the UAV. The UAV computation efficiency can be analyzed by computation overhead, total energy consumption, computation time, energy cost, average CPU cycles to complete the task, and the flying UAV BS computation capacity. Average system-wide computation overhead is usually measured with the different number of users, data sizes and

CPU cycles and compared with the baseline results to see the convergence of the proposed solutions [9, 36, 40, 85]. For example, in [47], the performance of the proposed multi-dimensional computing resource allocation is measured by comparing the computation capacity of the different schemes. In [46], CPU frequency is used as a performance parameter, where data received at the UAV is allowed to compute in the subsequent time slots to minimize the energy required for the computation. The number of bits offloaded to the UAV and UAV's CPU frequencies in each time slot are jointly optimized to achieve computation equilibrium. In [118], the proposed DRL-based scheme performance is measured with the required CPU cycles for computing a task and compared with the different schemes in the integrated network where satellites and UAVs provide the users with edge computing services and network access.

Caching Performance Metrics

Content caching at the network edge and deployment of cache enabling UAVs at hot spots has been extensively used in recent years to alleviate network traffic load [8, 60]. The caching size, cache hits, misses and cost are usually used to measure the UAV caching efficiency. A cache hit occurs when the requested content is retrieved from cache storage available at the UAV-BS. It contributes to bandwidth saving as it reduces the data exchange between UAV BS and the data centre (cloud or edge user). On the other hand, a cache miss occurs when requested data is unavailable at the UAV-BS or ground BS. The total number of cache hits and cache misses measures the cache efficiency. In learning-based content caching algorithms, performance is evaluated using the proposed algorithm's convergence and mean square error with baseline algorithms. In [8], a heterogeneous computing platform for FL-based collaborative content caching algorithm is used to improve the caching efficiency and its performance evaluated using two real-world data sets. Simulations are conducted to evaluate the learning accuracy using the proposed FL approach with a convolutional neural network (CNN) layer and two baseline FL methods. The results showed that the proposed scheme has minimum loss or mean square error (MSE) and convergence compared to baseline. NOMA scheme is used to increase the caching efficiency for UAV-assisted caching networks [55], and its performance is measured by comparing its convergence with the baseline schemes.

Other Performance Metrics

QoE is a subjective evaluation of the userâs media experience, used as the performance monitor of mobile networks [60]. In order to meet the requirement of high-quality data transmission of video applications, a certain QoE of users needs to be guaranteed. The usersâ QoE maximization is studied in UAV-assisted cellular networks for content distribution. One potential application scenario is a stadium that hosts a large-scale sports event, which deploys cache-enabling UAV BSs outside the stadium for hotspots coverage to reduce the traffic load of ground BSs. In [61], authors used QoE as a performance parameter to evaluate the convergence of proposed joint spectrum, computing, and caching resource allocation for UAV-assisted vehicular networks.

2.5 Summary

This chapter has discussed the resource optimization issue in singleton and joint 4Cs resources in UAV-assisted wireless networks. We presented two architectures for UAV-assisted wireless networks, i.e., UAV as a BS and UAV as a relay. The state of the artwork for each use case in B5G/6G wireless communication is presented. The architectures of UAV-assisted wireless networks have been presented along with tethered balloons to increase the data rate and backhaul capacity of the UAVs. To investigate the role of 4Cs resource management in future UAV-assisted wireless networks, we studied the joint optimization of resources in terrestrial and aerial networks. To the best of our knowledge, there is no current research in which all 4Cs resources are considered holistically along with UAV placement and trajectory optimization. We analyzed all the related problems, their types, parameters, constraints, solution types, and commonly used performance metrics for each use case. It is worth mentioning that UAV path planning, 3D placement and trajectory optimization have a significant role in communication and computing resources optimization in the UAV networks. Also, network efficiency can be increased by adding multiple UAVs to the network. We studied the problem types and their solution methods, especially for the UAV-assisted networks and concluded, based on current research, that approximation and iterative algorithms are widely used in combination with machine learning algorithms to solve the high complexity resource allocation problems.

Chapter 3

4Cs Resource Management in UAV-assisted MEC Networks

3.1 Introduction

The limited resources in the UAV-assisted MEC networks need holistic management of the resources, which requires joint optimization [4]. However, the majority of existing work considers the developments in 4Cs individually or a combination of two, which limits possible gain that could be achieved through the cooperation of 4Cs [25, 28]. Joint optimization of resources (spectrum, energy, computation), trajectory, content caching, interference, and user association is needed to utilize the UAV-assisted MEC networks fully. On the other hand, the multi-dimensional optimization problems can enable intelligent control to meet stringent end-to-end delay requirements [11]. Thus, a joint communication, computing, and caching resources, along with the control parameters (such as managing input/output data rate, timing, synchronization), need to be set up according to the network infrastructure as well as the quality of service (QoS) requirements [11, 22].

3.2 Related Work

Recently, there have been several efforts in joint resource management in UAV-assisted MEC networks. There exists some literature on joint 3C resource optimization in UAV assisted MEC networks but there is no such work in which all 4Cs have been jointly optimized. However, joint 4Cs optimization have been found in terrestrial networks. For example, authors jointly optimized communication, computing and caching in a big data MEC network and used the distributed optimization control to minimize the edge cloud network's bandwidth consumption and network latency in [11]. In [24], UAV's energy consumption has been minimized by jointly optimizing its trajectory and 3C resource allocation, and task decision and bits scheduling of users considering fairness. The formulated mixed-integer nonlinear programming problem transformed into three more tractable sub-problems, i.e., trajectory optimization, task decision, and bits scheduling and resource allocation. The branch & bound algorithm is used to solve the task and bit scheduling problem, while a penalty-based method is used to reduce the complexity. An iterative algorithm based on SCA and BCD is used to deal with all three sub-problems. Service caching in a multi UAV-assisted MEC system has been investigated in [20], where each UAV equipped with an edge server can cache offloaded data from the ground devices. A joint service caching, task offloading, resource allocation, and UAV placement optimization problem is formulated to minimize the latency of all the devices while guaranteeing the task delay requirement and the energy budget of all devices and UAVs. The mixed-integer non-linear programming problem is decoupled into two sub-problems, i.e., a joint service caching, offloading decision and resource allocation problem and a UAV placement. An iterative algorithm is proposed to obtain the joint solution.

Joint 2C resource management is the combination of two resources, such as communication and computing, communication and caching and computing and caching etc. Here, the existing literature on joint 2C resources optimization of UAV assisted MEC networks have been discussed in detail. Extensive research efforts have been made from the academia to employ UAVs as different kinds of wireless communication platforms. For example, in [19] authors consider the 3D wireless communication scenario in UAV enabled MEC network. They aimed to minimize the weighted sum of the service delay of all IoT devices and energy consumption of a single UAV by jointly optimizing UAV position, communication and computing resource allocation, and task splitting decisions. The non-convex problem is solved by converting it into convex subproblems and getting the sub-optimal solution using successive convex approximation. A non-convex problem of minimum secure computing capacity maximization division multiple access (TDMA) and non-orthogonal multiple access (NOMA) schemes [28]. A block coordinate descent (BCD)-based and a penalized BCD (P-BCD) based algorithms are proposed to solve the problems for TDMA and NOMA schemes, respectively. In [13], authors studied the joint optimization of trajectory, the power of the users, user scheduling and computation offloading in a UAV-assisted MEC network with NOMA. The constraints on UAV's energy consumption and QoS of the users are considered. The successive convex approximations (SCA) approach is adopted to solve the optimization problem. The sum power minimization problem is considered in [14] by jointly optimizing offloading decisions, resource allocation, user association, and power control in a MEC system with multiple UAVs. To solve the mixed-integer and non-convex optimization problem efficiently, the authors reformulated it as a Markov decision process and proposed a deep reinforcement learning-based algorithm named as multi-agent reinforcement learning and a semi-distributed multi-agent federated reinforcement learning algorithm with the integration of federated learning and deep reinforcement learning.

The UAVs are deployed for computation tasks offloaded from terminal devices as well as for decode-and-forward relay to assist tasks between terminal devices and BS in [15]. Energy consumption for communication, computation, and UAV flight is minimized by optimizing the UAV trajectory. The non-convex optimization problem is solved using Lagrange duality and the SCA method by converting the problem into convex optimization and obtaining a local optimal solution. Authors in [16] considered the problem of cooperative computation offloading for UAVs such that energy consumption and task execution latency can both be reduced. Transmission data rate and communication and computation resource allocation are optimized to satisfy energy consumption and task execution latency. The convex optimization problem is solved using simulated annealingbased particle swarm optimization for optimal data allocation. A UAV-assisted MEC network with consideration of priority constraints among tasks is designed in [21]. The objective is to minimize the maximum processing time of tasks to guarantee the response time in forest fire monitoring. A learning-based cooperative particle swarm optimization with a Markov random field-based decomposition strategy is adopted to solve the optimization problem. UAV energy efficiency is maximized by jointly optimizing the UAV trajectory, user transmit power, and computation load allocation in [22]. The constraints on user communication energy budget, computation capability, and the mechanical operation of the UAV are considered. The optimal resource allocation results are obtained by exploiting the SCA technique and Dinkelbach algorithm to transform the non-convex fractional programming problem into a solvable form and by further decomposing it using the alternating direction method of the multipliers technique. In [23], the authors proposed an energy-efficient resource allocation and computation offloading strategy in a UAV-assisted MEC network to minimize energy consumption. Two heuristic algorithms are proposed to obtain the sub-optimal solutions to the proposed problem.

In [25], authors considered the minimization of weighted sum energy consumption of UAVs and users in a UAV-assisted MEC network by jointly optimizing the bit allocation, transmit power, CPU frequency, bandwidth allocation and UAV trajectories. The non-convex problem is decomposed into two sub-problems, and a joint resource allocation and trajectory design algorithm is proposed based on the SCA technique and alternative optimization. A UAV-assisted MEC network is considered in [26] in which a moving UAV equipped with computing resources is deployed to computer the tasks of user devices. The weighted-sum energy consumption of the UAV and user devices is minimized by jointly optimizing the UAV trajectory and computation resource allocation under the constraint of the number of computation bits for orthogonal and non-orthogonal access modes. The non-convex problem is solved using the proposed alternating iterative algorithm based on the block alternating descent method. In [27], authors formulated the sum power minimization problem with latency and coverage constraints by jointly optimizing user association, power control, computation capacity allocation and location planning in a UAV-assisted MEC network. The non-convex problem is decomposed into three subproblems and solved iteratively. The compressive sensing-based algorithm is used for the user association. At the same time, the one-dimensional search method is adopted for computation capacity allocation or location planning optimal solution. The computation efficiency maximization problem is studied in [29] to jointly optimize communication and computation resources (including transmit power, offloading times, and CPU frequencies) in a UAV-assisted MEC network. The non-convex problem is solved using the proposed two-stage optimization algorithm, in which first the Lagrangian dual method is applied to obtain the closed expression of the optimal transmitted power and CPU frequencies. Then the SCA method is used to obtain the optimized trajectory of the UAV. In summary given in Table 3.1, several resource management schemes have been developed for UAV-assisted wireless networks while considering different objectives and constraints,including network scalability, reliability, efficiency (spectral usage and energy consumption), QoS requirements, coverage, and reducing complexity. The majority of existing work considers the developments in 4Cs individually or a combination of two, which limits possible gain that could be achieved through the cooperation of 4Cs.

Table 3.1: Summary of related work

Ref.	**UAV**	**4C**	**Objective**	**Constraints**	**Problem Type**	**Solution**
[11]	✗	4C	Minimize bandwidth consumption and network latency	Spectrum, computation, and caching resources limit, task execution frequency	Non-convex	Block successive upper bound
[24]	✓	3C	Minimize energy consumption of UAVs	Offloading, channel conditions,latency requirements, task scheduling	MINLP	Iterative, SCA, BCD

[20]	✓	3C	Minimize the sum of the total latency	Energy requirement, latency	MINLP	SCA, Iterative algorithm
[19]	✓	2C	Minimize service delay and energy consumption of UAV	Computing delay	Non-convex	SCA, iterative algorithm
[28]	✓	2C	Maximize minimum secure computing capacity	UAV mobility and second order cone (SOC) constraints	Non-convex	BCD,P-BCD
[13]	✓	2C	Minimize the energy consumption of all the UEs	Data rate, interference, energy of UAV	Non-convex	DCP, SCA, Two step iterative algorithm
[14]	✓	2C	Power minimization problem	UE power, weight and latency	Non-convex	Markov decision process, MARL
[15]	✓	2C	Minimize total energy consumption	Communication, computation resources, computation causality, UAV trajectory	Non-convex	Lagrangian duality, SCA
[16]	✓	2C	Energy consumption and task execution latency minimization	Latency, transmission power, time	Convex optimization	SAPSO, Lagrange multiplier method

[21]	✓	2C	Minimize the maximum processing time of tasks	Task priority, decision variables	Discrete optimization problem	LCPSO, MRF-based decomposition
[22]	✓	2C	Maximize UAV energy efficiency	Communication energy, computation capability, second order cone (SOC)	Non-convex	SCA, Dinkelbach algorithm, ADMM
[23]	✓	2C	Energy consumption minimization	Offloading, delay, computational resources, data rate	Single variable optimization	Golden-section search method (GSSM), heuristic algorithm
[25]	✓	2C	Energy consumption minimization of users and UAVs	CPU frequencies, information causalities, transmission data rate, bandwidth, energy consumption	Non-convex	SCA, alternative optimization
[26]	✓	2C	Energy consumption minimization	Number of computation bits	Non-convex	Block alternating descent method, iterative algorithm

[27]	✓	2C	Sum power minimization problem	Latency and coverage constraints	Non-convex	Fuzzy c-means clustering, One-dimensional search
[29]	✓	2C	Maximization of computation efficiency	Energy consumption, offloading time, CPU frequencies, transmit power, UAV mobility and position	Non-convex	Lagrangian duality, SCA
This chapter	✓	4C	Minimize the latency and cost	Size of data, data rate, computational workload, deadline, computing resources and allocation	Linear programming	Heuristic algorithm

3.3 System Model

We consider a UAV-assisted MEC network that consists of K number of IoT devices on the ground and a set of $L = \{L_0, L_1\}$ layers to represent a ground network and aerial network, respectively, as shown in Fig. 3.1. The layer L_0 consists of M_B number of base stations and L_1 consists of M_U number of UAVs, both equipped with MEC capabilities. We assume that IoT devices have applications that need computation and caching resources. However, IoT devices are resource-constrained with limited computation, caching, and battery capability. It is also assumed that MEC server resources are virtualized and shared by multiple IoT devices. A 3D coordinate system is considered in which the coordinates of *m-th* UAV are $\varphi_m^{M_U} = [x_m^{M_U}, y_m^{M_U}, z_m^{M_U}]$, where $x_m^{M_U}$

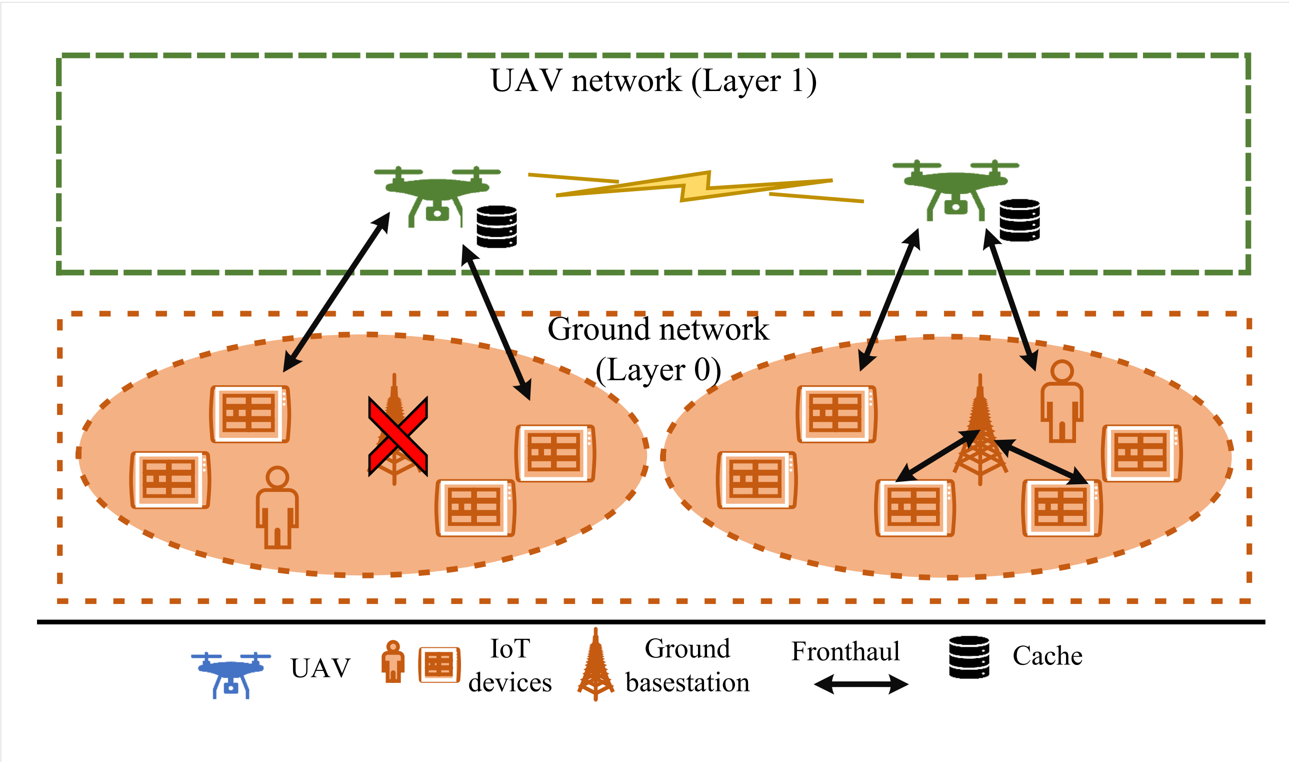


Figure 3.1: Architecture of UAV-assisted MEC network.

,$y_m^{M_U}$ are horizontal coordinates and $z_m^{M_U}$ is the vertical coordinate which is height in meters. The coordinates for the base stations and IoT devices are considered as $\varphi_m^{M_B} = [x_m^{M_B}, y_m^{M_B}]$ and $\varphi_k^K = [x_k^K, y_k^K]$, respectively. To avoid interference between backhaul and access links, we assume that all communication occurs on orthogonal frequencies [122]. Also, we consider the communication between UAVs and IoT devices using orthogonal frequency division multiple access (OFDMA).

We consider a task offloading model in which IoT devices offload their tasks for computation and caching to the appropriate MEC server in the network, depending on their residual energy. A task from a *k-th* IoT device can be defined as $T_k = (s_k, \tau_k, w_k)$, where s_k represents the size of the data for computation (in bits), τ_k is the computation deadline, and w_k is the computation workload (in CPU cycles/bit). It is assumed that the resource demand of each user is independent. We assume that the IoT device will forward the task to the control center. The control center will then find the appropriate base station or UAV for the offloading and/or computation. The control center is assumed to have information about available resources from the ground base stations and UAVs through a resource allocation table (RAT) that keeps track of available resources, including CPU utilization and cache capability. The ground base station and UAVs share their RAT updates with the control center. Based on the task demand, a control center can decide whether to assign a task to ground BS or offload it to one of the UAVs. To offload a task from an IoT device, communication resources are required (to transfer data to the UAV or base station), computation resources are required to process this data, and caching resources are required to store the most frequently used data. Control resources are required to coordinate allocating communication, computation, and storage resources for a given task.

Table 2 details the list of acronyms used in this chapter .

3.4 Proposed Joint 4Cs Resource Allocation

In our proposed work, each IoT device k transmit its task $T_k = (s_k, \tau_k, w_k)$ to the control center as shown in Fig. 3.2. The control center then maps the demands into the resource allocation required by *k-th* IoT device. When $\tau_k = 0$ and $w_k = 0$, we consider that the *k-th* IoT device only needs communication (to offload the task) and caching (to store the data) resources for data of size s_k [11]. On the other hand, when $\tau_k \neq 0$ and $w_k \neq 0$, we consider that the *k-th* IoT device need communication, computation, and caching resources for the data of size s_k.

The task of *k-th* IoT device can be offloaded to the *m-th* device in the *l-th* layer. This can be defined using a binary variable $\Phi^{OF}_{k,m,l}$:

$$\Phi^{OF}_{k,m,l} = \begin{cases} 1 & \text{if } T_k \text{ is offloaded to } m\text{-}th \text{ device} \\ & \text{in } l\text{-}th \text{ layer,} \\ 0 & \text{Otherwise.} \end{cases} \tag{3.1}$$

Once the *k-th* IoT device offload a task T_k to the *m-th* device in *l-th* layer as decided by control center, it must send the s_k bits as an input for the task (which incurs communication cost); after receiving the data, the MEC server only cache the data if $\tau_k = 0$ and $w_k = 0$ (caching cost).

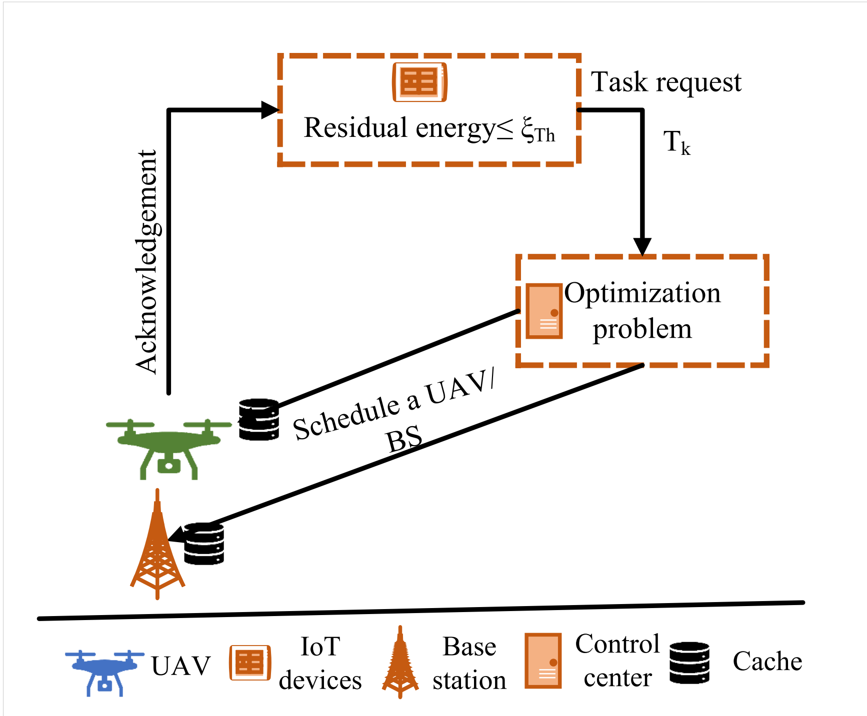


Figure 3.2: Proposed scheduling scheme.

Otherwise, the MEC server processes the data, which means it must allocate resources (computation cost). We define a binary variable $\Upsilon^{CO}_{k,m,l}$ that specifies whether the *k-th* IoT device's data is computed on the the *m-th* device in the *l-th* layer.

$$\Upsilon^{CO}_{k,m,l} = \begin{cases} 1 & \text{if } T_k \text{ is computed to } m\text{-}th \text{ device} \\ & \text{in } l\text{-}th \text{ layer,} \\ 0 & \text{Otherwise.} \end{cases} \tag{3.2}$$

Thus, we need to discuss communication, computation, caching, and control models to calculate all of these costs.

Communication Model

When *k-th* IoT device offloads data, there will be communication cost in terms of bandwidth. Thus, the data rate of the *k-th* IoT device is given as [11]:

$$R_{k,m,l} = a_{k,m,l} B_{m,l} \log_2 \left(1 + \frac{P_k h_{k,m,l}}{\sigma_k^2} \right), \; \forall \, k, m \tag{3.3}$$

where P_k is the transmission power of *k-th* IoT device, $h_{k,m,l}$ is the channel gain between the *k-th* IoT device and *m-th* device of *l-th* layer, and σ_k^2 is the power of the Gaussian noise at *k-th* IoT device. $a_{k,m,l}$ is the fraction of bandwidth $B_{m,l}$ allocated for communication between *k-th* IoT device and *m-th* device in *l-th* layer. We assume that the available spectrum is divided into orthogonal resource blocks. Therefore, there is no interference among the users.

The transmission delay in offloading data can be represented as:

$$L_{k,m,l}^{OF} = \Phi_{k,m,l}^{OF} \frac{s_k}{R_{k,m,l}}, \; \forall \, k, m, l. \tag{3.4}$$

We assume that the signalling delay for the communication between the IoT device and the control center is negligibly small. The cost for offloading the data is considered as a linear function of bandwidth [123].

$$C_{k,m,l}^{OF} = f(\Phi_{k,m,l}^{OF} s_k), \tag{3.5}$$

where f is a linear function.

Computing Model

If the task of *k-th* IoT device needs computation after offloading (i.e., $\tau_k \neq 0$ and $w_k \neq 0$), it needs computation resources and incurs latency. We represent the available computation resources at *m-th* device of *l-th* layer by $O_{m,l}$. The computation allocation of $o_{k,m,l}$ can be calculated as [11]:

$$o_{k,m,l} = O_{m,l} \frac{w_k}{\sum_g^{K_g} Q_g}, \; \forall \, m, l. \tag{3.6}$$

where $\sum_{g}^{K_g} Q_g$ is the computation workload used by other devices.

The latency to perform task T_k can be written as [11, 124]:

$$L_{k,m,l}^{CO} = \Upsilon_{k,m,l}^{CO} \frac{s_k w_k}{o_{k,m,l}}. \tag{3.7}$$

The cost for computation of data is also considered as a linear function of resources allocated to IoT devices as:

$$C_{k,m,l}^{CO} = f(\Upsilon_{k,m,l}^{CO} o_{k,m,l}). \tag{3.8}$$

Caching Model

The cache capacity of *m-th* device on *l-th* layer is represented by $Y_{m,l}$. Thus, the total cache capacity of *m-th* device in *l-th* layer must satisfy:

$$\sum_{k} \Phi_{k,m,l}^{OF} s_k \leq Y_{m,l}, \forall m, l. \tag{3.9}$$

Control Model

We propose a centralized optimization control model that coordinates and integrates the communication, computation and caching models. We consider the total delay and cost for the task from *k-th* IoT device to complete offloading and computing. The total latency required for the task from *k-th* IoT device can be written as:

$$L_{k,m,l}^{TOT} = \Phi_{k,m,l}^{OF} L_{k,m,l}^{OF} + \Upsilon_{k,m,l}^{CO} L_{k,m,l}^{CO}. \tag{3.10}$$

Similarly, the total cost for the task from *k-th* IoT device can be written as:

$$C_{k,m,l}^{TOT} = \Upsilon_{k,m,l}^{CO} C_{k,m,l}^{CO} + \Phi_{k,m,l}^{OF} C_{k,m,l}^{OF}. \tag{3.11}$$

Thus, the utility function for the task of *k-th* IoT device can be written as:

$$U(\Upsilon_{k,m,l}^{CO}, \Phi_{k,m,l}^{OF}) = \alpha L_{k,m,l}^{TOT} + (1-\alpha) C_{k,m,l}^{TOT}. \tag{3.12}$$

where $\alpha = (0, 1)$ is the weight associated with latency and cost.

3.4.1 Problem Formulation

We formulate a joint 4Cs optimization problem to minimize the network delay.

$$\begin{aligned}
&\min_{\Phi_{k,m,l}^{OF}, \Upsilon_{k,m,l}^{CO}} : \sum_k \sum_m \sum_l U(\Upsilon_{k,m,l}^{CO}, \Phi_{k,m,l}^{OF}), \\
&\text{Subject to:} \\
&\qquad C1 : \Upsilon_{k,m,l}^{CO} \le \Phi_{k,m,l}^{OF}, \forall l, m, k \\
&\quad C2 : L_{k,m,l}^{CO} \le \tau_k, \forall l, m, k \\
&\quad C3 : \sum_m \sum_l \Phi_{k,m,l}^{OF} \le 1, \ \forall k \\
&\quad C4 : \sum_m \sum_l \Upsilon_{k,m,l}^{CO} \le 1, \ \forall k \\
&\quad C5 : \sum_k \Phi_{k,m,l}^{OF} a_{k,m,l} \le 1, \ \forall l, m \\
&\quad C6 : \sum_k \Upsilon_{k,m,l}^{CO} o_{k,m,l} \le O_{m,l}, \ \forall l, m_l \\
&\quad C7 : \sum_k \Phi_{k,m,l}^{OF} s_k \le Y_{m,l}, \forall m, l \\
&\quad C8 : \Phi_{k,m,l}^{OF} = \Upsilon_{k,m,l}^{CO}, \forall k, m, l
\end{aligned} \tag{3.13}$$

where C1 ensures that computation will be done only when the task is offloaded. C2 implies that the computation deadline should be met. C3 and C4 ensure that a task can be offloaded to and computed by only one device of any layer, respectively. C5 deals with bandwidth allocation, which should be a fraction of the total bandwidth available. C6 and C7 ensure that the computation and caching resources required by the task are less than the available resources, respectively. Lastly, C8 implies that computing and offloading should be done on the same device.

3.5 Summary

This chapter proposes a 4Cs resource management framework for user association in UAV-assisted MEC networks. This framework uses MEC servers (Bs/UAV) to satisfy users' demands. We have formulated the problem as a joint optimization problem that aims to minimize a linear combination of network latency and cost under the constraints of offloading, computational resources and caching capability.

Chapter 4

Proposed Scheme and Simulation Results

4.1 Solution Approaches

The formulated problem in (3.13) is a binary linear programming problem, and such problems are generally convex. We adopt a branch and bound algorithm to obtain optimal results to solve this binary linear programming problem. In general, given a convex problem, a branch & bound algorithm explores the entire search space of possible solutions and provides an optimal solution. However, the worst-case complexity of the branch and bound algorithm is high, which limits the scalability of the network [125]. Thus, we propose a heuristic algorithm to obtain near-optimal results with low complexity. The results for heuristic algorithm are almost equal to branch & bound in most of the cases.

4.1.1 Heuristic algorithm

We also solve binary linear programming problem using the proposed heuristic algorithm based on the interior point method. We use the primal-dual interior point method as a basis of the heuristic algorithm. The main advantage of the interior point method is that the number of iterations of the constraint condition is not sensitive to polynomial time complexity [126]. First, we applied the primal-dual method, and the problem formulated in (3.13) can be written as:

$$\begin{aligned} \text{Primal :} \quad & \min_{x} U(X) \\ \text{Subject to :} \ & A_{\Theta}X = b \\ & X^{min} \leq X \leq X^{max} \\ & X = \{1, 0\} \end{aligned} \tag{4.1}$$

$$\begin{aligned} \text{Dual :} \quad & \max_{\pi, S} \ U(\pi) \\ \text{Subject to :} \ & A_{\Theta}^{T}\pi + S = c \\ & S \geq 0 \end{aligned} \tag{4.2}$$

where U(X) is the objective function, X is the primal variable, A is the non-linear constraints matrix, X^{min} and X^{max} are the upper and lower limits of variable X.To write the dual of 4.1, we consider π and S dual variables. $X \in \{\Upsilon \text{ and } \Phi\}$ are binary decision variables, and Θ is a set of constraints from C1 to C8. This method approximates the optimization problem by adding the slack variables to a sequence of sub-problems. The primal-dual search direction is found using modified Karush-Kuhn-Tucker (KKT) conditions. KKT conditions for the primal-dual interior point method are:

$$r_{pd}(X, \pi, S) = \begin{pmatrix} A^{T}\pi + S - c \\ diag(X)\pi - (1/t)1 \\ AX - b \end{pmatrix} \tag{4.3}$$

The interior point method solves the problem 4.1 (or the KKT conditions 4.4) by applying Newton's method to a sequence of the modified version of KKT conditions. The search directions in a primal-dual interior-point method are obtained from Newton's method, applied to modified KKT equations as [126]: set $0 = r_{pd}(y + \Delta y) \approx r_{pd}(y) + Dr_{pd}(y)\Delta y$,(where y is the search direction ($y = (X, \pi, S)$) and D is the derivative) i.e, solve:

$$\begin{bmatrix} 0 & I & A^T \\ diag(\pi) & diag(X) & 0 \\ A & 0 & 0 \end{bmatrix} \begin{pmatrix} \Delta X \\ \Delta\pi \\ \Delta S \end{pmatrix} = -r_{pd}(X, \pi, S) \tag{4.4}$$

and take step:

$$y^+ = y + s\Delta y \tag{4.5}$$

(with line search for $s \geq 0$), but only once , Then update:

$$t = \mu t \tag{4.6}$$

where parameter t is set to factor μ times the current duality gap. If X, π, and S were central, with parameter t, then we would increase t by the factor μ. Values of the parameter μ on the order of 10 appear to work well. Once backtracking allows for $s = 1$, primal-dual iterates will be primal and dual feasible from that point onward. To see this ΔX , π , S are constructed so that:

$$A^T\Delta\pi + \Delta S = -r_{dual} = -(A^T\pi + S - c) \tag{4.7}$$

$$A\Delta X = -r_{prim} = -(AX - b) \tag{4.8}$$

Therefore after one step

$$X^+ = X + \Delta X, \qquad \pi^+ = \pi + \Delta\pi, \qquad S^+ = S + \Delta S \tag{4.9}$$

We have

$$r_{dual} = A^T\pi^+S^+ - c = 0 \tag{4.10}$$

$$r_{prim} = AX^+b = 0 \tag{4.11}$$

so our iterates primal and dual feasible.

Algorithm 1 : Heuristic algorithm.

Given: X that satisfies $U(X) \leq 0$, $\pi \geq 0$, $\mu \geq 1$, $\epsilon_{feas} \geq 0$, $\epsilon \geq 0$.
repeat:
Step 1:
Determine $t := t\mu$
Step 2:
Compute primal-dual search direction Δy_{pd}.
Step 3:
Line search and update.
Determine step length $s \geq 0$ and set $y := y + sy_{pd}$S.
Until: $\parallel r_{prim} \parallel_2 \leq \epsilon_{feas}, \quad \parallel r_{dual} \parallel_2 \leq \epsilon_{feas}$, and $\eta \leq \epsilon \, r_{feas} = (\parallel r_{prim} \parallel_2^2 + \parallel r_{dual} \parallel_2^2)^1/2$
Output $X_{relaxed}$
IRA:
Step 4:
$Input \leftarrow Output(X_{relaxed})$
Step 5:
Assign connection matrix $\bar{X} = 0$
Step 6:
Iteratively discretized the relaxed value of $X_{relaxed}$ to assign each user with its corresponding BS/UAV.
Update corresponding $\bar{X}$
Step 7:
if (termination criteria satisfied) **then**
X=$\bar{X}$
end if

The heuristic algorithm is given in Algorithm 1. In step 1, the parameter t is set to a factor μ times t, which is the value of t associated with the current surrogate duality gap η. The primal-dual interior-point algorithm terminates when X is primal feasible and π, S are dual feasible. A threshold is applied at the output of the primal-dual algorithm by using the interior rounding algorithm (IRA). The output from the interior point method is compared with the threshold, if its greater than threshold value than connection value will be set as 1; otherwise, it will be 0. This strategy restricts IoT devices from offloading data at the BS/UAV when there are insufficient resources.

4.1.2 Complexity Analysis

We can find the solution to the problem (3.13) using branch & bound; however, the computational complexity is high. The worst-case complexity of the branch & bound algorithm is equal to exhaustive search [125]. For a linear program (4.1) where constraint matrix $A_\Theta \in \mathbb{R}^{\Theta,n}$ (Θ is the number of constraints and n is the number of variables) the interior point computational complexity is $O(n^3)$ [127, 128].

The computational complexity of heuristic algorithm can be calculated based on the number of flops (basic unit of computation) [129]. In our proposed heuristic algorithm , computational complexity can be calculated as;

$$\text{Number of Flops} \approx 2 + M(M + 3 + KLogK + 8 + K)$$

$$\approx 2 + (11 + M^2 + MKLogK + MK)$$

$$\approx O(M^2 + MKLogK)$$

$$\text{Total Computational Complexity} \approx IPM + IRA$$

$$\approx O(n^3) + O(M^2 + MKLogK)$$

$$\approx O[(n^3) + (M^2 + MKLogK)] \tag{4.12}$$

where (4.12) is the complexity of the proposed heuristic algorithm in polynomial time. In contrast, the complexity of optimal (B and B) is $O(2^{MK})$. Where $M = M_B + M_U$. The difference between the heuristic and optimal computational complexity can be seen in Table 4.1. Optimal (branch & bound) algorithm computational complexity increases very rapidly with the increase in the number of variables $n = K * M$. Without loss of generality, we choose small values of K and M for illustration purposes.

Table 4.1: Complexity analysis

Parameters	Heuristic	Optimal
$K = 4$, $M = 3$, $n = K * M = 12$	5855.006	262144
$K = 6$, $M = 4$, $n = K * M = 24$	13858.675	16777216
$K = 8$, $M = 4$, $n = K * M = 32$	32812.899	4294967296

4.2 Simulation Results

In this section, we evaluate the performance of the proposed framework using the branch & bound algorithm and heuristic algorithm. Branch & bound algorithm provides optimal results with high computation complexity. Thus, the results obtained using the branch & bound algorithm are used as a benchmark to evaluate the performance of the proposed heuristic algorithm. We consider a UAV-assisted MEC network with the number of IoT devices varying from $K = 20 - 100$, the number of base stations varying from $M0 = 5-15$, the number of UAVs varying from $M1 = 6-9$ with computing and caching capabilities. We consider network layers $L = L0, L1$ where $L0$ is the ground network and $L1$ is the aerial network. The objective of assigning a BS or UAV for the task $T_k = (s_k, \tau_k, w_k)$ is to minimize network latency and cost (offloading and computing). We consider the simulation parameters similar to [11] and are given in Table 4.2.

Table 4.2: Simulation parameters

Parameter	value
Number of IoT devices, K	20-100
Aerial-assisted networks layers, L	2
No of base stations M_B	5-15

No of UAVs M_U	6-9
size of data s_k	2-7 Mega Bits
Computation deadline τ_k	1-12 sec
Computation workload w_k	452-737 cycles/bit
Offloading cost for BS $C^{OF}_{k,m,l}$	90
Offloading cost for UAV $C^{OF}_{k,m,l}$	120
Computing cost for BS $C^{CO}_{k,m,l}$	100-150
Computing cost for UAV $C^{CO}_{k,m,l}$	400-1500
Computation capacity $O_{m,l}$	3000-9000
Caching capacity $Y_{m,l}$	100-500 Mega bits

Figs. 4.1(a)-(e) show the number of IoT devices served versus the total number of IoT devices for $K = \{20, 40, 60, 80, 100\}$. We consider the number of base stations $M_B = 5$ in all cases, whereas the number of UAVs varies from $M_U = 6$ in Figs. 4.1(a)-(c) and $M_U = 9$ in Figs. 4.1(d)-(f). Figs. 4.1(a) and (d) are for users served by BSs ($M_B = 5$) only. On the other hand, Figs. 4.1(b) ($M_U = 6$) and (e) ($M_U = 9$) are for users served by UAVs only and the lastly Figs. 4.1(c) and (f) are combined results for users served when both UAVs and BSs deployed in both cases. In Fig. 4.1(a) $M_B = 5$, it is observed that users served by the BS increases with the increase in users from $k = 20$ to $K = 100$. Although in Fig. 4.1 (b) when $M_U = 6$ and $K = 20$, there is no user served by UAVs. However, as the number of users increased, the number of served users increased. Fig. 4.1 (c) $M_B = 5$ and $M_U = 6$, is the combined result when $M_B = 5$ BSs and $M_U = 6$ UAVs are available. It is observed that more users have been assigned to UAVs (M_U) as the number of users (K) increases. Also, the combined results for the optimal and heuristic algorithm are nearly equal. A similar pattern has been observed in Figs. 4.1 (e) and (f) when we increase the number of UAVs from 6 to 9.There is no sign of increasing user association with UAVs as the cost of UAVs is high

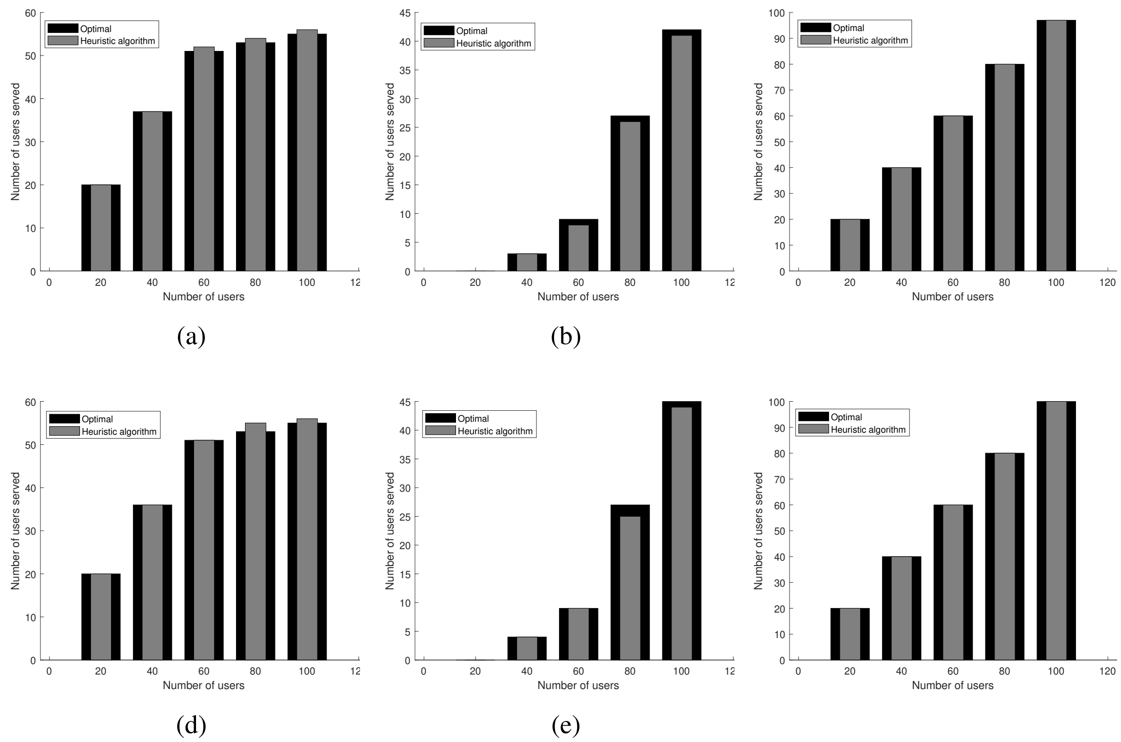
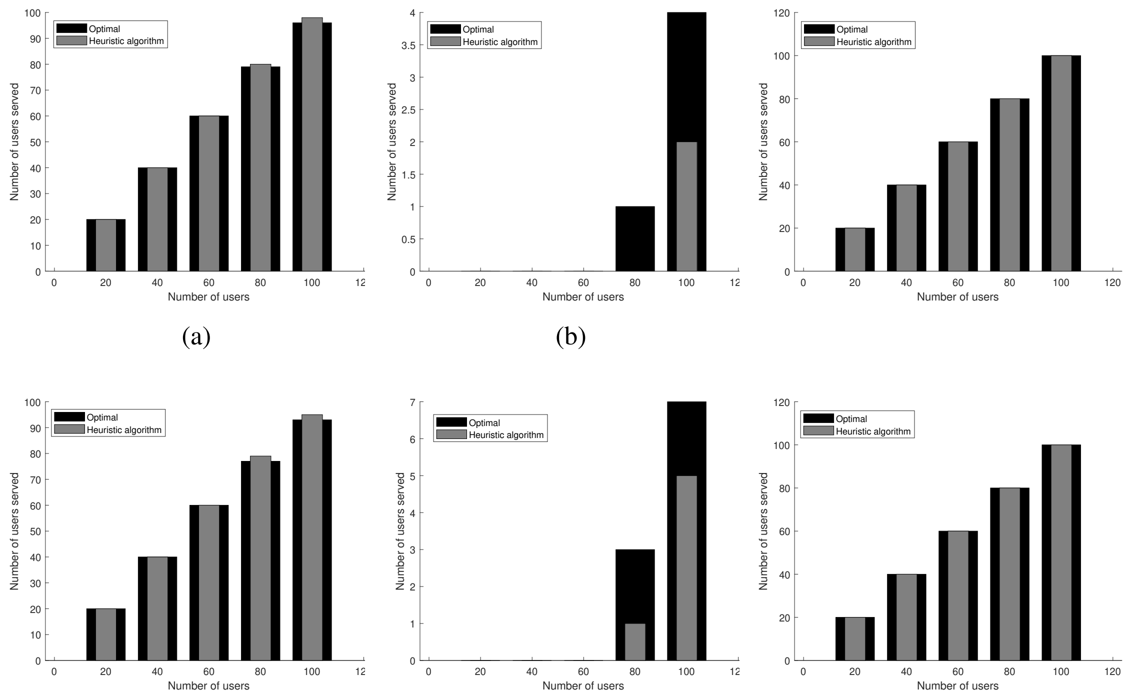


Figure 4.1: Number of users served when number of BS $M_B = 5$ and number of UAVs (a) $M_U = 6$ with BSs only, (b) $M_U = 6$ with UAVs only, (c) $M_B + M_U = 5 + 6$ with both BSs and UAVs, (d) $M_U = 9$ with BSs only, (e) $M_U = 9$ with UAVs only, (f) $M_B + M_U = 5 + 9$ with both BSs and UAVs.

and one of the objectives is to minimize the cost. Thus, users preferably associate with the BSs if they are available.

Figs. 4.2(a)-(e) show the number of IoT devices served versus the total number of IoT devices for $K = \{20, 40, 60, 80, 100\}$. We consider the number of base stations $M_B = 10$ in all cases, whereas the number of UAVs varies from $M_U = 6$ in Figs. 4.2(a)-(c) and $M_U = 9$ in Figs. 4.2(d)-(f). In Fig. 4.2(a) $M_B = 10$, (b) $M_U = 6$, (c) $M_B = 10$ and $M_U = 6$, it is observed that with the increase in number of BS (M_B) user (K) association with the UAVs (M_U) has bee decreased (as we can see from last fig. 4.1 (b) and (e)) and with the BS (M_B) is increased.The combined results for heuristic and optimal are nearly equal. Figs. 4.3(a)-(e) show the number of IoT devices served versus the total number of IoT devices for $K = \{20, 40, 60, 80, 100\}$. We consider that the number of base stations $M_B = 15$ in all cases, whereas the number of UAVs vary from $M_U = 6$



(a) (b)

(d) (e)

Figure 4.2: Number of users served when number of BS $M_B = 10$ and number of UAVs (a) $M_U = 6$ with BSs only, (b) $M_U = 6$ with UAVs only, (c) $M_B + M_U = 10 + 6$ with both BSs and UAVs, (d) $M_U = 9$ with BSs only, (e) $M_U = 9$ with UAVs only, (f) $M_B + M_U = 10 + 9$ with both BSs and UAVs.

in Figs. 4.3(a)-(c) and $M_U = 9$ in Figs. 4.3(d)-(f). In Figs. 4.3(a) $M_B = 15$, (b) $M_U = 6$, (c) $M_B = 15$ and $M_U = 6$, with the increase in number of deployed BSs, there is significant change in the user association with UAVs. This shows that if we increase the $M_B = 15$, there are enough BSs available for the users to be served, so no user has been served by the UAVs.

Comparing Figs. 4.1-4.3, it is observed that by increasing the number of UAVs with the same number of BSs, there is little change in the association. In contrast, if we increase the number of BS with the same number of UAVs, there is a significant effect on the user association. The BS has served more users, so in the last case, no user has been served by the UAVs. Overall, if we see individual cases, the heuristic algorithm occasionally performs better than optimal. However, if we see combined results, then optimal and heuristic are performing nearly equal. The complexity of the heuristic algorithm is less than optimal; thus, the heuristic algorithm is more suitable for

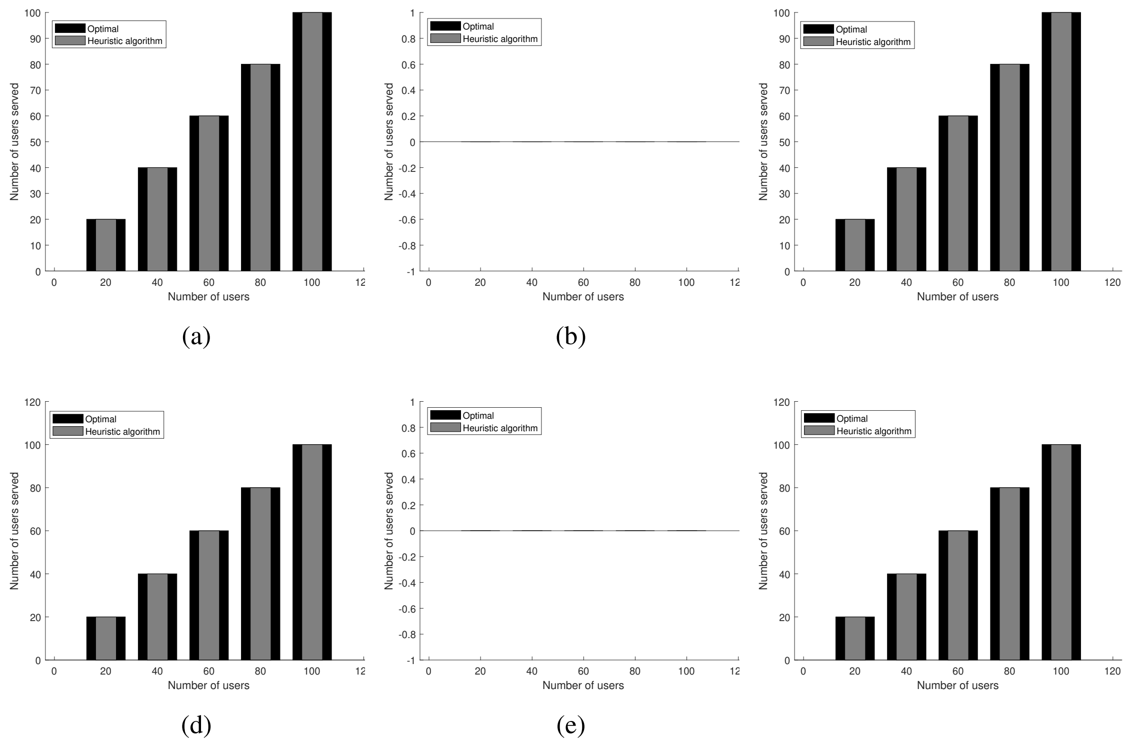


Figure 4.3: Number of users served when number of BS $M_B = 15$ and number of UAVs (a) $M_U = 6$ with BSs only, (b) $M_U = 6$ with UAVs only, (c) $M_B + M_U = 15 + 6$ with both BSs and UAVs, (d) $M_U = 9$ with BSs only, (e) $M_U = 9$ with UAVs only, (f) $M_B + M_U = 15 + 9$ with both BSs and UAVs.

scalable future wireless networks. Since the objective is to minimize the latency and cost of the network, we see that by increasing the number of UAVs in the network (UAVs have more cost and latency than the BS), there is no significant effect on users' connectivity with the UAVs.

Figs. 4.4 to 4.6 show the number of active BSs/active UAVs versus number of users $K = \{20, 40, 60, 80, 100\}$ for optimal and heuristic algorithm. Fig. 4.4(a) and 4.4(c) it is observed that all the BS ($M_B = 5$) have been active in serving IoT devices while in Figs. 4.4(b) $M_U = 6$ and (d) $M_U = 9$, it is observed that there is little increase in number of deployed UAVs (M_U) with increase in users. This is mainly because the objective is to minimize latency and the cost of deployment. The connectivity cost of UAVs is considered higher compared to BSs. Thus IoT devices connect with UAVs only when the overall objective function is minimized. Figs. 4.5(a) and (c), the number of active BS has been increased to $M_B = 10$ while in Figs. 4.5(b) and (d) active UAVs are $M_U = 6$

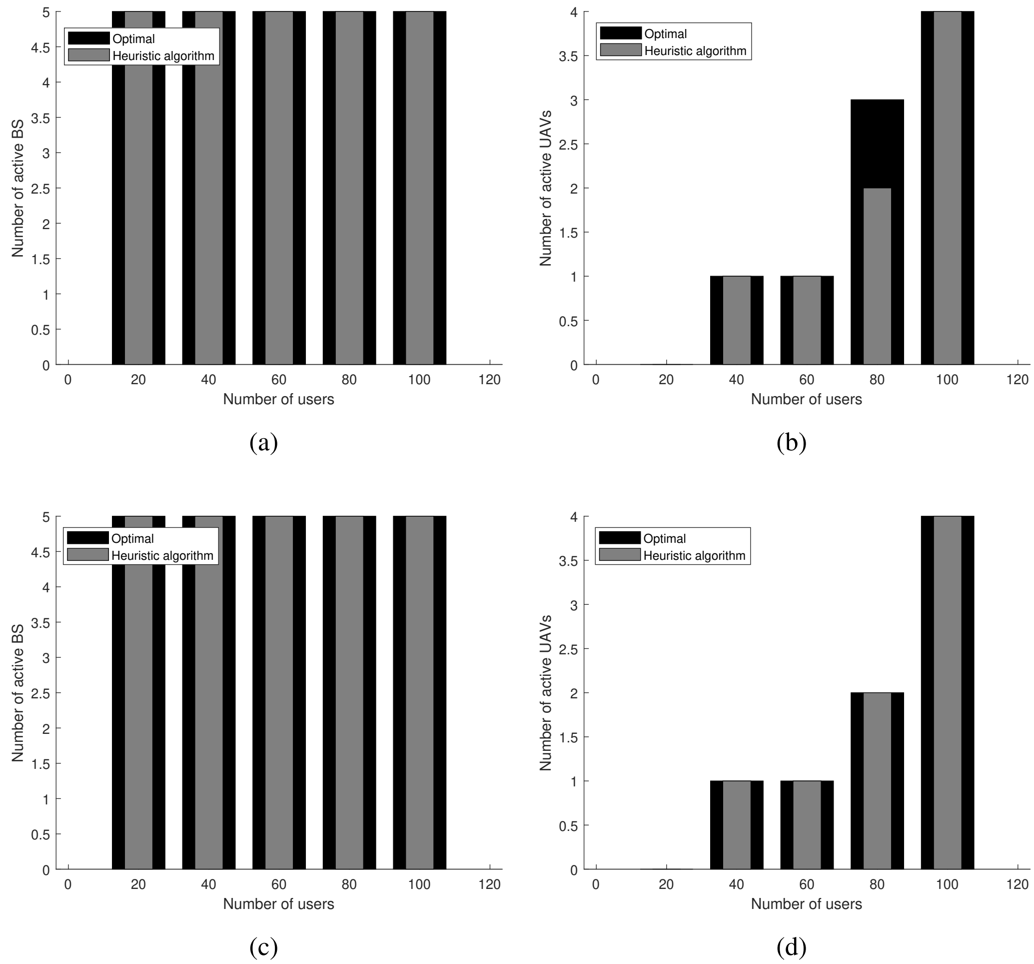


Figure 4.4: Number of active BSs and UAVs when total available number of BS $M_B = 5$ (a),(c) and number of UAVs $M_U = 6$ (b) and $M_U = 9$ (d) (a) number of active BSs, (b) Number of active UAVs, (c) number of active BSs , (d) Number of active UAVs.

and $M_U = 9$ respectively. In Figs. 4.5(a) and (c), it is observed that with the increase in the number of users from left to the right number of deployed BS (M_B) increases; when $K = 100$ all the BS have been deployed to meet the demand of increased users also deployment of UAVs have been increased when users increases as can be seen in Figs. 4.5(b) and (d). In Figs. 4.6(a)-(d), the number of BSs has been further increased to $M_B = 15$ while in 4.6(b) and (d) UAVs are $M_U = 6$ and $M_U = 9$ respectively. It is observed in Figs. 4.6(a) and (c) that with increases in the number of users from left to right number of deployed BS (M_B) increases. Moreover, when $K = 100$, all the BSs have been deployed to meet increased user demand. In Figs. 4.6(b) and (d) no UAV has

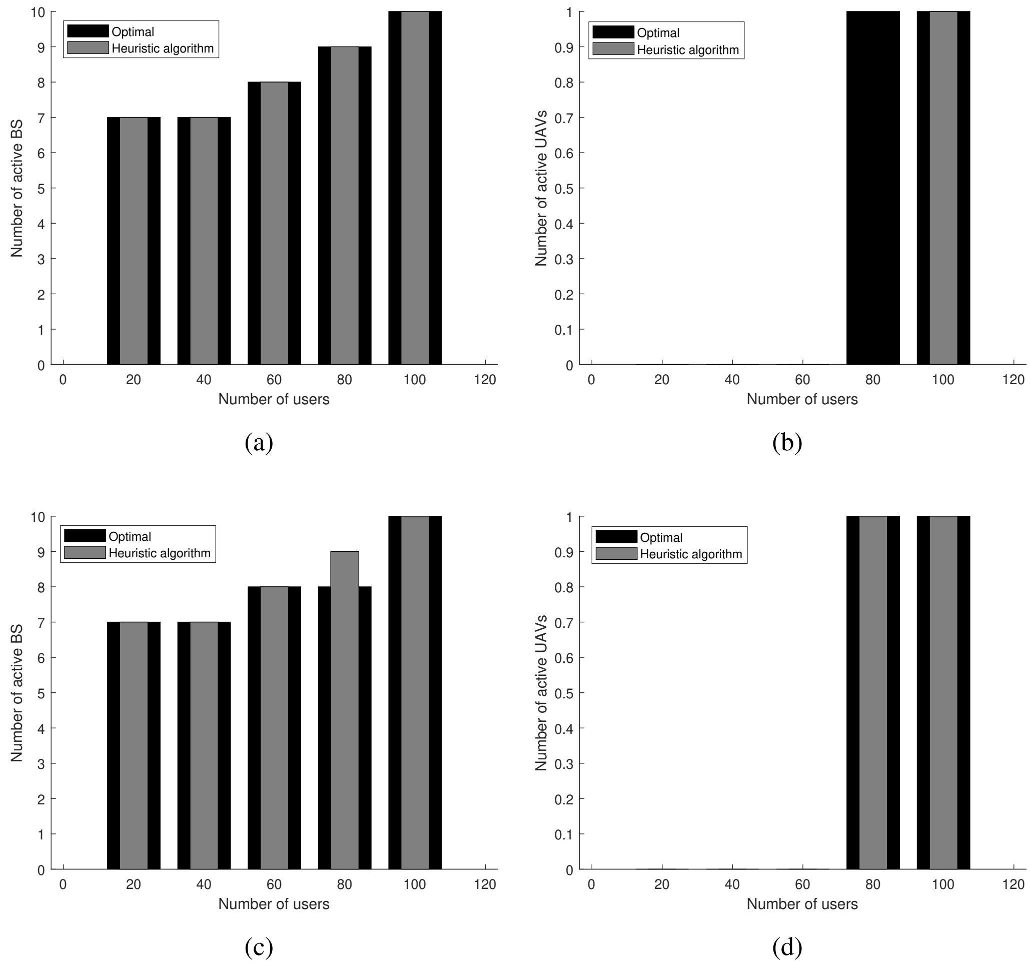


Figure 4.5: Number of active BSs and UAVs when total available number of BS $M_B = 10$ (a),(c) and number of UAVs $M_U = 6$ (b) and $M_U = 9$ (d) (a) number of active BSs, (b) Number of active UAVs, (c) number of active BSs , (d) Number of active UAVs.

been deployed as there is enough active BS available for the users. Overall, we can see that the performance of the heuristic algorithm is comparable with optimal.

Figs. 4.7(a)-(e) show connections of BS (M_B=15) and UAVs (M_U=9) with different number of users ($K = 20, 40, 60, 80$) using heuristic algorithm. We have randomly deployed BS and UAVs in an area of $5000m \times 5000m$. In 4.7(a) users are $K = 20$, active BS are $M_B = 15$ and active UAVS are $M_U = 9$, it is observed that almost all the users are associated with the BS (M_B). As the number of users increases to $k = 40$ in Fig. 4.7(b), there is little increase in association with the UAV to meet the user demand, while in Fig. 4.7(e) significant users are associated with the

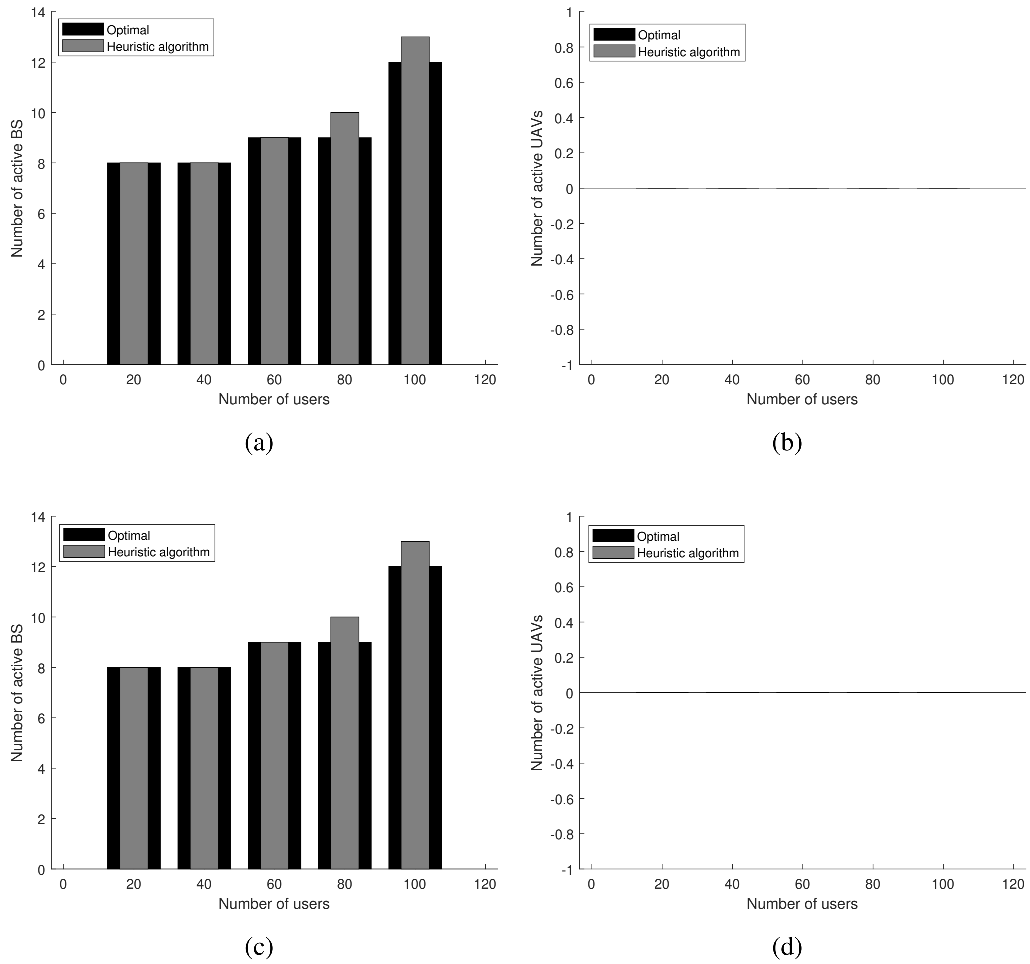


Figure 4.6: Number of active BSs and UAVs when total available number of BS $M_B = 10$ (a),(c) and number of UAVs $M_U = 6$ (b) and $M_U = 9$ (d) (a) number of active BSs, (b) Number of active UAVs, (c) number of active BSs , (d) Number of active UAVs.

UAVs in addition to BSs as the demand of users increases. We can say that our proposed heuristic algorithm satisfies the users' connectivity demands in most cases.

4.3 Summary

In this chapter, we have discussed the proposed solution and simulation results to show the effectiveness of the proposed framework. We proposed a heuristic algorithm based on the interior point method to solve the formulated optimization problem. We also discussed the proposed algorithm's

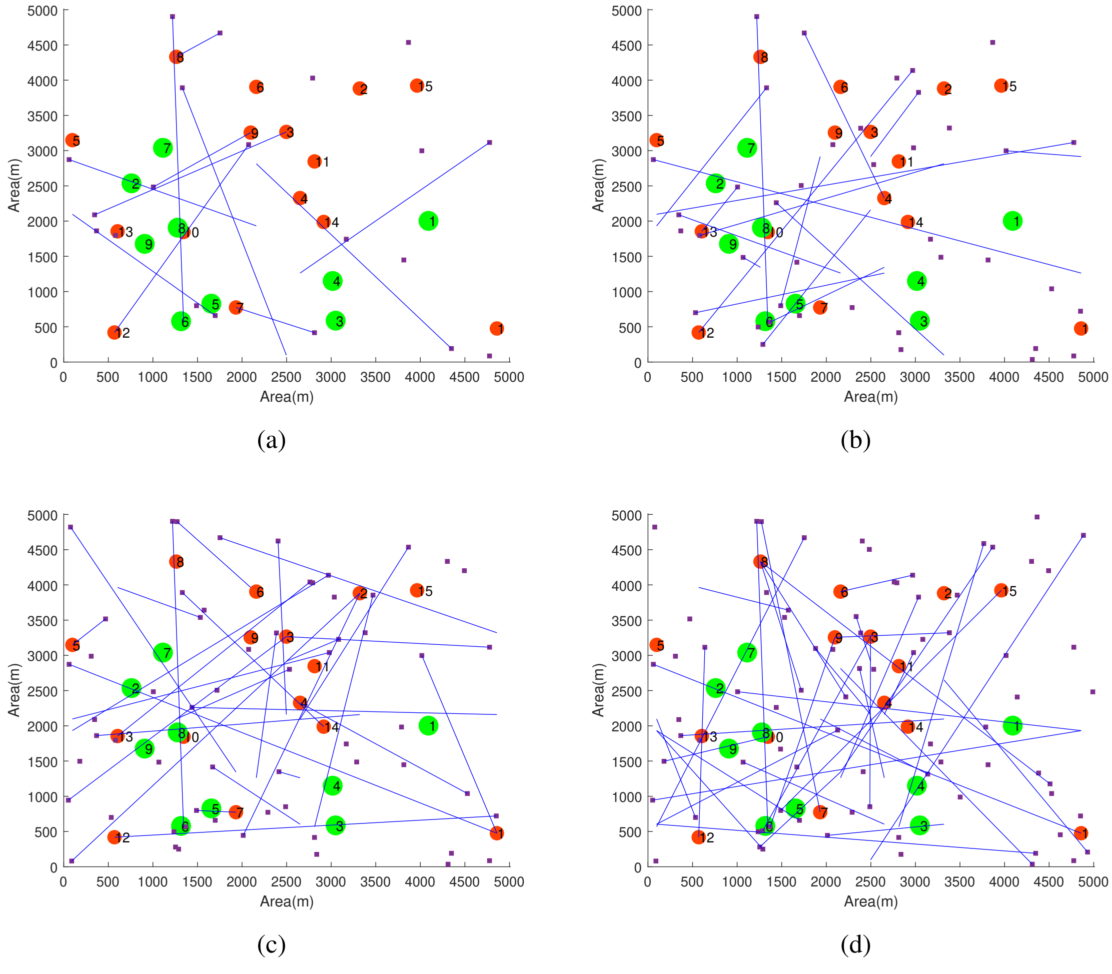


Figure 4.7: Heuristic: Association of users with base stations and UAVs (a) $K = 20$, (b) $K = 40$, (c) $K = 60$ and, (d) $K = 80$.

computational complexity and compared it with the branch & bound. The branch & bound (optimal) algorithm is considered as a benchmark that provides optimal results with high complexity. We compare the results from the heuristic algorithm with those computed via the branch & bound method (optimal). The results of the proposed heuristic are comparable with optimal with less complexity.

Chapter 5

Conclusion and Future Work

5.1 Conclusions

Increasing demand for wireless connectivity, high data rate, and improved QoS requirements impose various challenges to traditional terrestrial networks. To fulfill the requirements of future applications, integrated aerial and terrestrial networks are considered game-changer. This thesis has discussed 4Cs resources, their optimization issues, current literature proposed solutions, and their performance parameters for UAV-assisted MEC networks. Also, we propose a mathematical framework for user association in UAV-assisted MEC networks while considering 4Cs resources. The formulated problem as a joint optimization problem aims to minimize a linear combination of network latency and cost subject to offloading, computational resources and caching constraints. The heuristic algorithm based on the interior point method has been proposed to solve the formulated optimization problem. The branch & bound algorithm is considered as a benchmark that provides optimal results with high complexity. The results from the heuristic algorithm have been compared with those computed via the branch & bound method (optimal). We have concluded that the performance of the proposed heuristic is comparable with optimal with less complexity.

5.2 Future Research Directions

Based on our study of 4Cs resource management in UAV-assisted wireless networks, there are still open research areas which need attention:

5.2.1 Dynamic 4Cs Resource Management

Dynamic 4C resource allocation in the integrated UAV and cellular system is an interesting future work to improve system efficiency. The efficient design of dynamic 4Cs resource management in integrated networks needs to satisfy asymmetric QoS requirements of UAVs and terrestrial networks with the stringent constraints imposed by the size, weight, power, control, deployment of UAVs, and the limitations imposed by the cellular networks. In the 4Cs resource allocation protocol design, researchers focus on the dynamic spectrum, interference management, multiple access schemes for cellular-connected UAVs, channel measurement for UAV-to-UAV and UAV-to-ground communication, UAV cache placement, and edge computing design. Authors in [31] highlighted that the caching in the edge computing nodes and offloading model is a potential future research topic that requires comparative verification experiments on cache hit ratio, coverage, and offloading delay to optimize network architecture and algorithm performance. In [91], authors suggested user cooperation on joint communication and computation optimization problems. In [92], the authors suggested investigating the execution order of computing tasks with different latency requirements to improve the QoE. Moreover, AI algorithms and technologies can improve system performance and intelligence [130]. In dynamic 4Cs resource management, the use of DRL can also play a critical role in improving the network's performance. 4Cs resource management in the perspective of self-organization and autonomous techniques for sustainable UAV-assisted networks are the new research horizon.

5.2.2 Multi-UAV, MEC, and IoT devices

UAV-assisted MEC systems are utilized for on-demand LoS computing services. In this category, multi-UAV-supported multi-MEC is one of the potential research areas. Multiple UAV-based MEC systems need to design the UAV movement control, cooperation, and communication resource allocation of multiple UAVs. The computation efficiency maximization problem in [97] can be extended into the multi-UAV and multi-user scenarios. In [11], authors focused on intra-cooperation between MEC servers that belong to one collaboration space. One interesting future work could be to extend the framework to account for inter-cooperation between MEC servers that belongs to different collaboration spaces. The work in [30] can be extended into the joint design of caching at the MEC server and the mobile device and the joint caching and computing policy design in a multicast-enabled scenario with multiple MEC servers and multiple mobile devices. The authors in [79] pointed out that multiple UAVsâ trajectory optimization without collision and power control can be an exciting work to investigate.

5.2.3 4Cs Resource Management in Satellite-Aerial-Terrestrial Networks

Integrated satellite-aerial-terrestrial (SAT) are envisioned to support the multidimensional requirements of future wireless networks. Integrated 3D SAT architecture using low orbit satellites, high altitude tethered balloons, high altitude platforms, UAVs, and cellular networks can meet the high data rate and multi-QoS demands and improve coverage and capacity in various applications. The future improvement of SAT networks needs to address the following points:

- Proper design and requirement analysis of channels (LEO-to-UAV, UAV-to-UAV, and UAV-to-ground) model and air interface, interference models.
- Address the 4Cs resource management in SAT networks regarding QoS requirements of different applications.
- Address the 4Cs resource management in SAT networks regarding resource scheduling, load balancing, multiple access, and different channel model points of view.

- Integrate AI/ML techniques in managing 4Cs components in SAT networks.

5.2.4 Blockchain-enabled 4C Resource Management

Developing low complexity distributed consensus and blockchain-enabled 4Cs resource management is another potential research area in UAV-assisted wireless networks. Blockchain provides lightweight, secure and consensus distributed security solutions to content distribution, network monitoring, and security-related applications. In [95], interference management in blockchain-enabled MEC systems is explored. Blockchain-enabled 4Cs resource management can address the challenges associated with using blockchain-based services (e.g., monitoring, security, content distribution, etc.) and the challenges related to integrated networks. The blockchain-enabled 4Cs resource management needs to address the following as future research works:

- Data integrity and security using blockchain UAVs.
- Blockchain-enabled UAVs-based secure content delivery.
- Computing and caching solutions for multi-UAV multi-MEC communications using Blockchain.
- Low complexity blockchain solutions for flying automation.

5.2.5 Green 4Cs Technologies for 6G Networks

It is anticipated that 6G networks consist of a large number of devices with smarter and energy-efficient resource management of edge computing, caching and ultra-reliable low-latency communications with machine learning capability. The new research direction horizon includes technologies associated with overcoming the energy barriers in radio access, computing, and caching sides and making the 6G networks more green and sustainable. For example, authors in [131] considered energy-efficient solution in next-generation delivery networks using UAVs. The high-altitude platforms are used as hybrid energy sources, including wind and solar energy and possible RF energy harvesting approaches. Similarly, in [132], authors considered the DRL-based charging mechanism for UAVs battery. The UAVs' optimal locations are utilized to improve the performance of wireless power transfer in UAV networks. Novel technologies, architecture and design related to energy harvesting, energy supply for UAVs in 6G networks, and energy-efficient UAV-assisted MEC are the potential research areas for green 6G networks.

Bibliography

[1] J. Li, H. Zhang, H. Ji, and X. Li, “Joint computation offloading and service caching for MEC in multi-access networks,” in *IEEE 30th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, pp. 1–6, IEEE, 2019.

[2] W. Wen, Y. Cui, T. Q. Quek, F.-C. Zheng, and S. Jin, “Joint optimal software caching, computation offloading and communications resource allocation for mobile edge computing,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 7879–7894, Jul. 2020.

[3] A. Manzoor, D. H. Kim, and C. S. Hong, “Energy efficient resource allocation in UAV-based heterogeneous networks,” pp. 1–4, Nov. 2019.

[4] F. Tariq, M. R. Khandaker, K.-K. Wong, M. A. Imran, M. Bennis, and M. Debbah, “A speculative study on 6g,” *IEEE Wireless Communications*, vol. 27, no. 4, pp. 118–125, Aug. 2020.

[5] H. Peng and X. S. Shen, “DDPG-based resource management for MEC/UAV-assisted vehicular networks,” in *2020 IEEE 92nd Vehicular Technology Conference (VTC2020-Fall)*, pp. 1–6, IEEE, 2020.

[6] M. R. Ramzan, M. Naeem, M. Altaf, and W. Ejaz, “Multi-criterion resource management in energy harvested cooperative UAV-enabled IoT networks,” *IEEE Internet of Things Journal*, Feb. 2022.

[7] R. Masroor, M. Naeem, and W. Ejaz, "Efficient deployment of uavs for disaster management: a multi-criterion optimization approach," *Computer Communications*, vol. 177, pp. 185–194, Sept. 2021.

[8] Z. M. Fadlullah and N. Kato, "HCP: Heterogeneous computing platform for federated learning based collaborative content caching towards 6G networks," *IEEE Transactions on Emerging Topics in Computing*, Apr. 2020.

[9] K. Yao, Y. Xu, J. Chen, Y. Gong, Y. Yang, C. Yao, and Z. Du, "Distributed joint optimization of deployment, computation offloading and resouce allocation in coalition-based UAV swarms," in *International Conference on Wireless Communications and Signal Processing (WCSP)*, pp. 207–212, IEEE, Dec. 2020.

[10] H. Yang and X. Xie, "Energy-efficient joint scheduling and resource management for UAV-enabled multicell networks," *IEEE Systems Journal*, vol. 14, no. 1, pp. 363–374, Mar. 2020.

[11] A. Ndikumana, N. H. Tran, T. M. Ho, Z. Han, W. Saad, D. Niyato, and C. S. Hong, "Joint communication, computation, caching, and control in big data multi-access edge computing," *IEEE Transactions on Mobile Computing*, vol. 19, no. 6, pp. 1359–1374, Jun. 2020.

[12] F. Jiang, K. Wang, L. Dong, C. Pan, W. Xu, and K. Yang, "Deep-learning-based joint resource scheduling algorithms for hybrid MEC networks," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6252–6265, Jul. 2020.

[13] F. Guo, H. Zhang, H. Ji, X. Li, and V. C. Leung, "Joint trajectory and computation offloading optimization for UAV-assisted MEC with NOMA," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 1–6, IEEE, 2019.

[14] Y. Nie, J. Zhao, F. Gao, and F. R. Yu, "Semi-distributed resource management in UAV-aided MEC systems: A multi-agent federated reinforcement learning approach," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 12, pp. 13162–13173, Dec. 2021.

[15] T. Zhang, Y. Xu, J. Loo, D. Yang, and L. Xiao, "Joint computation and communication design for UAV-assisted mobile edge computing in IoT," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 8, pp. 5505–5516, Aug. 2020.

[16] S. Zhu, L. Gui, J. Chen, Q. Zhang, and N. Zhang, "Cooperative computation offloading for UAVs: A joint radio and computing resource allocation approach," in *IEEE International Conference on Edge Computing (EDGE)*, pp. 74–79, IEEE, 2018.

[17] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, pp. 2322–2358, Aug. 2017.

[18] R. Masroor, M. Naeem, and W. Ejaz, "Resource management in uav-assisted wireless networks: An optimization perspective," *Ad Hoc Networks*, vol. 121, p. 102596, Oct. 2021.

[19] Z. Yu, Y. Gong, S. Gong, and Y. Guo, "Joint task offloading and resource allocation in UAV-enabled mobile edge computing," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 3147–3159, Apr. 2020.

[20] G. Zheng, C. Xu, H. Long, and Y. Sheng, "Service caching based task offloading and resource allocation in multi-UAV assisted MEC networks," in *IEEE/CIC International Conference on Communications in China (ICCC)*, pp. 1024–1029, IEEE, 2021.

[21] L. Sun, L. Wan, and X. Wang, "Learning-based resource allocation strategy for industrial IoT in UAV-enabled MEC systems," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 7, pp. 5031–5040, Jul. 2020.

[22] M. Li, N. Cheng, J. Gao, Y. Wang, L. Zhao, and X. Shen, "Energy-efficient UAV-assisted mobile edge computing: Resource allocation and trajectory optimization," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3424–3438, Mar. 2020.

[23] U. A. Khan, W. Khalid, and S. Saifullah, "Energy efficient resource allocation and computation offloading strategy in a UAV-enabled secure edge-cloud computing system," in *IEEE International Conference on Smart Internet of Things (SmartIoT)*, pp. 58–63, IEEE, 2020.

[24] M. Zhao, W. Li, L. Bao, J. Luo, Z. He, and D. Liu, "Fairness-aware task scheduling and resource allocation in UAV-enabled mobile edge computing networks," *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 4, pp. 2174–2187, Dec. 2021.

[25] X. Qin, Z. Song, Y. Hao, and X. Sun, "Joint resource allocation and trajectory optimization for multi-uav-assisted multi-access mobile edge computing," *IEEE Wireless Communications Letters*, vol. 10, no. 7, pp. 1400–1404, Jul. 2021.

[26] J. Ji, K. Zhu, C. Yi, and D. Niyato, "Energy consumption minimization in UAV-assisted mobile-edge computing systems: Joint resource allocation and trajectory design," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 8570–8584, May 2021.

[27] Z. Yang, C. Pan, K. Wang, and M. Shikh-Bahaei, "Energy efficient resource allocation in UAV-enabled mobile edge computing networks," *IEEE Transactions on Wireless Communications*, vol. 18, no. 9, pp. 4576–4589, Sept. 2019.

[28] Y. Xu, T. Zhang, D. Yang, Y. Liu, and M. Tao, "Joint resource and trajectory optimization for security in UAV-assisted MEC systems," *IEEE Transactions on Communications*, vol. 69, no. 1, pp. 573–588, Jan. 2021.

[29] X. Zhang, Y. Zhong, P. Liu, F. Zhou, and Y. Wang, "Resource allocation for a UAV-enabled mobile-edge computing system: Computation efficiency maximization," *IEEE Access*, vol. 7, pp. 113345–113354, Aug. 2019.

[30] L. Zhang, Y. Sun, Z. Chen, and S. Roy, "Communications-Caching-Computing Resource Allocation for Bidirectional Data Computation in Mobile Edge Networks," *IEEE Transactions on Communications*, vol. 69, no. 3, pp. 1496–1509, Mar. 2021.

[31] Y. Hao, Y. Miao, L. Hu, M. S. Hossain, G. Muhammad, and S. U. Amin, "Smart-Edge-CoCaCo: AI-enabled smart edge with joint computation, caching, and communication in heterogeneous IoT," *IEEE Network*, vol. 33, no. 2, pp. 58–64, Mar./Apr. 2019.

[32] J. Chen, H. Xing, X. Lin, and S. Bi, "Joint cache placement and bandwidth allocation for FDMA-based mobile edge computing systems," in *ICC 2020-2020 IEEE International Conference on Communications (ICC)*, pp. 1–7, IEEE, Jul. 2020.

[33] M. Chen, Y. Hao, L. Hu, M. S. Hossain, and A. Ghoneim, "Edge-CoCaCo: Toward joint optimization of computation, caching, and communication on edge cloud," *IEEE Wireless Communications*, vol. 25, no. 3, pp. 21–27, Jun. 2018.

[34] D. Wang, H. Qin, B. Song, K. Xu, X. Du, and M. Guizani, "Joint resource allocation and power control for D2D communication with deep reinforcement learning in MCC," *Physical Communication*, vol. 45, p. 101262, 2021.

[35] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang, and D. I. Kim, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3133–3174, May. 2019.

[36] N. T. Ti and L. B. Le, "Joint resource allocation, computation offloading, and path planning for UAV based hierarchical fog-cloud mobile systems," in *IEEE Seventh International Conference on Communications and Electronics (ICCE)*, pp. 373–378, IEEE, Nov. 2018.

[37] T. Zhang, Y. Xu, J. Loo, D. Yang, and L. Xiao, "Joint computation and communication design for UAV-assisted mobile edge computing in IoT," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 8, pp. 5505–5516, Aug. 2020.

[38] S. Mandelli, A. Lieto, A. Weber, and T. Wild, "Power optimization and throughput enhancement in 6G networks by delay-aware resource leverage," in *Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, pp. 176–181, IEEE, 2021.

[39] U. J. W. E. Z. Shah, M. Naeem and M. Altaf, “”A compendium of radio resource management in UAV-assisted next generation computing paradigms”,” pp. 1–40, Mar. 2022.

[40] X. Cao, J. Xu, and R. Zhang, “Mobile edge computing for cellular-connected UAV: Computation offloading and trajectory optimization,” in *IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, pp. 1–5, IEEE, Aug. 2018.

[41] O. M. Bushnaq, M. A. Kishk, A. Celik, M.-S. Alouini, and T. Y. Al-Naffouri, “Optimal deployment of tethered drones for maximum cellular coverage in user clusters,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 3, pp. 2092–2108, 2020.

[42] H. M. Hariz, S. Sheikhzadeh, N. Mokari, M. R. Javan, B. Abbasi-Arand, and E. A. Jorswieck, “AI-based Radio Resource Management and Trajectory Design for PD-NOMA Communication in IRS-UAV Assisted Networks,” *arXiv preprint arXiv:2111.03869*, 2021.

[43] Y. Xu, T. Zhang, D. Yang, Y. Liu, and M. Tao, “Joint resource and trajectory optimization for security in UAV-assisted MEC systems,” *IEEE Transactions on Communications*, vol. 69, no. 1, pp. 573–588, Jan. 2021.

[44] A. Alzidaneen, A. Alsharoa, and M.-S. Alouini, “Resource and placement optimization for multiple uavs using backhaul tethered balloons,” *IEEE Wireless Communications Letters*, vol. 9, no. 4, pp. 543–547, 2019.

[45] S. Bi, L. Huang, and Y.-J. A. Zhang, “Joint optimization of service caching placement and computation offloading in mobile edge computing systems,” *IEEE Transactions on Wireless Communications*, vol. 19, no. 7, pp. 4947–4963, Jul. 2020.

[46] Y. Liu, K. Xiong, Q. Ni, P. Fan, and K. B. Letaief, “UAV-assisted wireless powered cooperative mobile edge computing: Joint offloading, CPU control, and trajectory optimization,” *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 2777–2790, Dec. 2019.

[47] F. Guo, H. Zhang, H. Ji, X. Li, and V. C. Leung, "Joint trajectory and computation offloading optimization for UAV-assisted MEC with NOMA," in *IEEE INFOCOM 2019-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 1–6, IEEE, Jun. 2020.

[48] H. Yang, J. Zhao, J. Nie, N. Kumar, K.-Y. Lam, and Z. Xiong, "UAV-assisted 5G/6G networks: Joint scheduling and resource allocation based on asynchronous reinforcement learning," pp. 1–6, Jul. 2021.

[49] L. Chiaraviglio, F. DâAndreagiovanni, W. Liu, J. A. Gutierrez, N. Blefari-Melazzi, K.-K. R. Choo, and M.-S. Alouini, "Multi-area throughput and energy optimization of UAV-aided cellular networks powered by solar panels and grid," *IEEE Transactions on Mobile Computing*, vol. 20, no. 7, pp. 2427–2444, Jul. 2021.

[50] L. Chiaraviglio, F. Dâandreagiovanni, R. Choo, F. Cuomo, and S. Colonnese, "Joint optimization of area throughput and grid-connected microgeneration in UAV-based mobile networks," *IEEE Access*, vol. 7, pp. 69545–69558, May 2019.

[51] S. Yin, L. Li, and F. R. Yu, "Resource allocation and basestation placement in downlink cellular networks assisted by multiple wireless powered uavs," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 2, pp. 2171–2184, Feb. 2020.

[52] S. Colonnese, F. Cuomo, G. Pagliari, and L. Chiaraviglio, "Q-SQUARE: A Q-learning approach to provide a QoE aware UAV flight path in cellular networks," *Ad Hoc Networks*, vol. 91, p. 101872, Aug. 2019.

[53] Z. Na, M. Zhang, J. Wang, and Z. Gao, "UAV-assisted wireless powered Internet of Things: Joint trajectory optimization and resource allocation," *Ad Hoc Networks*, vol. 98, p. 102052, 2020.

[54] Y. Zhu, G. Zheng, and M. Fitch, “Secrecy rate analysis of uav-enabled mmwave networks using matÃ©rn hardcore point processes,” *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 7, pp. 1397–1409, 2018.

[55] Y. Yin, M. Liu, G. Gui, H. Gacanin, H. Sari, and F. Adachi, “Cross-layer resource allocation for UAV-assisted wireless caching networks with NOMA,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 4, pp. 3428–3438, Apr. 2021.

[56] K. Bilal, E. Baccour, A. Erbad, A. Mohamed, and M. Guizani, “Collaborative joint caching and transcoding in mobile edge networks,” *Journal of Network and Computer Applications*, vol. 136, pp. 86–99, Mar. 2019.

[57] F. Tang, Z. M. Fadlullah, B. Mao, N. Kato, F. Ono, and R. Miura, “On a novel adaptive uav-mounted cloudlet-aided recommendation system for lbsns,” *IEEE Transactions on Emerging Topics in Computing*, vol. 7, no. 4, pp. 565–577, 2018.

[58] S. Chai and V. K. N. Lau, “Multi-UAV trajectory and power Optimization for cached UAV wireless networks with energy and content recharging-demand driven deep learning approach,” *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 10, pp. 3208–3224, Jun. 2021.

[59] Y.-J. Chen, K.-M. Liao, M.-L. Ku, F. P. Tso, and G.-Y. Chen, “Multi-agent reinforcement learning based 3D trajectory design in aerial-terrestrial wireless caching networks,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 8, pp. 8201–8215, Aug. 2021.

[60] T. Zhang, Y. Wang, Y. Liu, W. Xu, and A. Nallanathan, “Cache-enabling UAV communications: Network deployment and resource allocation,” *IEEE Transactions on Wireless Communications*, vol. 19, no. 11, pp. 7470–7483, Jul. 2020.

[61] H. Peng and X. Shen, “Multi-agent reinforcement learning based resource management in MEC- and UAV-assisted vehicular networks, year=Jan. 2021, volume=39, number=1, pages=131-141, publisher=IEEE,” *IEEE Journal on Selected Areas in Communications*.

[62] M. N. Nguyen, N. H. Tran, Y. K. Tun, Z. Han, and C. S. Hong, "Toward multiple federated learning services resource sharing in mobile edge networks," *arXiv preprint arXiv:2011.12469*, pp. 1–20, Nov. 2020.

[63] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Communications and control for wireless drone-based antenna array," *IEEE Transactions on Communications*, vol. 67, no. 1, pp. 820–834, Sept. 2018.

[64] L. Lei, Y. Tan, K. Zheng, S. Liu, K. Zhang, and X. Shen, "Deep reinforcement learning for autonomous internet of things: Model, applications and challenges," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 1722–1760, Apr. 2020.

[65] W. Chen, X. Qiu, T. Cai, H.-N. Dai, Z. Zheng, and Y. Zhang, "Deep Reinforcement Learning for Internet of Things: A Comprehensive Survey," *IEEE Communications Surveys & Tutorials*, Apr. 2021.

[66] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, "A brief survey of deep reinforcement learning," *arXiv preprint arXiv:1708.05866*, vol. 34, no. 6, pp. 26–38, Nov. 2017.

[67] W. Ejaz, S. K. Sharma, S. Saadat, M. Naeem, A. Anpalagan, and N. A. Chughtai, "A comprehensive survey on resource allocation for cran in 5g and beyond networks," *Journal of Network and Computer Applications*, vol. 160, p. 102638, Jun. 2020.

[68] J. Chen, P. Chen, Q. Wu, Y. Xu, N. Qi, and T. Fang, "A game-theoretic perspective on resource management for large-scale UAV communication networks," *China Communications*, vol. 18, no. 1, pp. 70–87, Jan. 2021.

[69] A. Sharma, P. Vanjani, N. Paliwal, C. M. W. Basnayaka, D. N. K. Jayakody, H.-C. Wang, and P. Muthuchidambaranathan, "Communication and networking technologies for UAVs: A survey," *Journal of Network and Computer Applications*, p. 102739, Oct. 2020.

[70] M. Lin and Y. Zhao, "Artificial intelligence-empowered resource management for future wireless communications: A survey," *China Communications*, vol. 17, no. 3, pp. 58–77, Apr. 2020.

[71] R. Shahzadi, M. Ali, H. Z. Khan, and M. Naeem, "UAV assisted 5G and beyond wireless networks: A survey," *Journal of Network and Computer Applications*, p. 103114, Sep. 2021.

[72] M. Zhou, Y. Guan, M. Hayajneh, K. Niu, and C. Abdallah, "Game theory and machine learning in uavs-assisted wireless communication networks: A survey," *arXiv preprint arXiv:2108.03495*, 2021.

[73] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE communications surveys & tutorials*, vol. 21, no. 3, pp. 2334–2360, Thirdquarter 2019.

[74] E. Yaacoub and M.-S. Alouini, "A key 6G challenge and opportunityâConnecting the base of the pyramid: A survey on rural connectivity," *Proceedings of the IEEE*, vol. 108, no. 4, pp. 533–582, Apr. 2020.

[75] L. Amorosi, L. Chiaraviglio, F. D'Andreagiovanni, and N. Blefari-Melazzi, "Energy-efficient mission planning of UAVs for 5G coverage in rural zones," pp. 1–9, Mar. 2018.

[76] Kazmi, SM Ahsan and Dang, Tri Nguyen and Yaqoob, Ibrar and Ndikumana, Anselme and Ahmed, Ejaz and Hussain, Rasheed and Hong, Choong Seon, "Infotainment enabled smart cars: A joint communication, caching, and computation approach," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 9, pp. 8408–8420, Sep. 2019.

[77] Q. Zhang, J. Chen, L. Ji, Z. Feng, Z. Han, and Z. Chen, "Response delay optimization in mobile edge computing enabled UAV swarm," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3280–3295, Mar. 2020.

[78] S. Zheng, Z. Ren, X. Hou, and H. Zhang, "Optimal communication-computing-caching for maximizing revenue in UAV-aided mobile edge computing," pp. 1–6, Jan. 2021.

[79] H. Yang, J. Zhao, Z. Xiong, K.-Y. Lam, S. Sun, and L. Xiao, "Privacy-Preserving federated learning for UAV-enabled networks: learning-based joint scheduling and resource management," *arXiv preprint arXiv:2011.14197*, Nov. 2020.

[80] H. Li, J. Li, M. Liu, Z. Ding, and F. Gong, "Energy harvesting and resource allocation for cache-enabled UAV based IoT NOMA networks," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 9, pp. 9625–9630, Jul.2021.

[81] M. Lin and Y. Zhao, "Artificial intelligence-empowered resource management for future wireless communications: A survey," *China Communications*, vol. 17, no. 3, pp. 58–77, Apr. 2020.

[82] G. Kurt and H. Yanikomeroglu, "Communication, computing, caching, and sensing for next generation aerial delivery networks," *arXiv preprint arXiv:2011.13224*, vol. 14, no. 8, pp. 1–7, Jun. 2020.

[83] M. Zhao, W. Li, L. Bao, J. Luo, Z. He, and D. Liu, "Fairness-aware task scheduling and resource allocation in UAV-enabled mobile edge computing networks," *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 4, pp. 2174–2187, Dec. 2021.

[84] J. Li, F. Wu, K. Zhang, and S. Leng, "Joint dynamic user pairing, computation offloading and power control for NOMA-based MEC system," in *2019 11th International Conference on Wireless Communications and Signal Processing (WCSP)*, pp. 1–6, IEEE, Dec. 2019.

[85] J. Liu, P. Li, J. Liu, and J. Lai, "Joint offloading and transmission power control for mobile edge computing," *IEEE Access*, vol. 7, pp. 81640–81651, May. 2019.

[86] X. Han, D. Tian, Z. Sheng, X. Duan, J. Zhou, W. Hao, K. Long, M. Chen, and V. C. Leung, "Reliability-Aware joint optimization for cooperative vehicular communication and computing," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–20, Dec. 2020.

[87] W. Feng, J. Zheng, and W. Jiang, "Joint pilot and data transmission power control and computing resource allocation algorithm for massive MIMO-MEC networks," *IEEE Access*, vol. 8, pp. 80801–80811, Apr. 2020.

[88] L. Lei, H. Xu, X. Xiong, K. Zheng, and W. Xiang, "Joint computation offloading and multiuser scheduling using approximate dynamic programming in NB-IoT edge computing system," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 5345–5362, Jun. 2019.

[89] S. Li, Q. Wang, Y. Wang, D. Tan, and W. Li, "Delay-aware task congestion control and resource allocation in mobile edge computing," in *IEEE 30th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, pp. 1–6, IEEE, Nov. 2019.

[90] L. He, J. Li, M. Sheng, R. Liu, K. Guo, and J. Liu, "Joint allocation of transmission and computation resources for space networks," in *IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1–6, IEEE, Jun. 2018.

[91] S. Li, W. Sun, Y. Sun, and Y. Huo, "Energy-Efficient task offloading using dynamic voltage scaling in mobile edge computing," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 1, pp. 588–598, Dec. 2020.

[92] S. Yang, "A joint optimization scheme for task offloading and resource allocation based on edge computing in 5G communication networks," *Computer Communications*, vol. 160, pp. 759–768, Jul. 2020.

[93] M. LiWang, S. Dai, Z. Gao, X. Du, M. Guizani, and H. Dai, "A computation offloading incentive mechanism with delay and cost constraints under 5G satellite-ground IoV architecture," *IEEE Wireless Communications*, vol. 26, no. 4, pp. 124–132, Apr. 2019.

[94] C. Yi, S. Huang, and J. Cai, "Joint resource allocation for device-to-device communication assisted fog computing," *IEEE Transactions on Mobile Computing*, Nov. 2019.

[95] J. Feng, F. R. Yu, Q. Pei, X. Chu, J. Du, and L. Zhu, "Cooperative computation offloading and resource allocation for blockchain-enabled mobile-edge computing: A deep reinforcement learning approach," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6214–6228, Dec. 2019.

[96] Y. Liao, L. Shou, Q. Yu, Q. Ai, and Q. Liu, "Joint offloading decision and resource allocation for mobile edge computing enabled networks," *Computer Communications*, vol. 154, pp. 361–369, Feb. 2020.

[97] X. Zhang, Y. Zhong, P. Liu, F. Zhou, and Y. Wang, "Resource allocation for a UAV-enabled mobile-edge computing system: Computation efficiency maximization," *IEEE Access*, vol. 7, pp. 113345–113354, Aug. 2019.

[98] J. Ji, K. Zhu, C. Yi, and D. Niyato, "Energy consumption minimization in UAV-assisted mobile-edge computing systems: Joint resource allocation and trajectory design," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 8570–8584, May 2021.

[99] Z. Yang, J. Xie, J. Gao, Z. Chen, and Y. Jia, "Joint optimization of wireless resource allocation and task partition for mobile edge computing," in *2020 IEEE/CIC International Conference on Communications in China (ICCC)*, pp. 1303–1307, IEEE, Nov. 2020.

[100] N. Zhang, S. Guo, Y. Dong, and D. Liu, "Joint task offloading and data caching in mobile edge computing networks," *Computer Networks*, vol. 182, p. 107446, Aug. 2020.

[101] Y. Sai, D.-z. Fan, and M.-y. Fan, "Cooperative and efficient content caching and distribution mechanism in 5G network," *Computer Communications*, vol. 161, pp. 183–190, Jul. 2020.

[102] N. N. Ei, M. Alsenwi, Y. K. Tun, Z. Han, and C. S. Hong, "Energy-Efficient resource allocation in multi-UAV-assisted two-stage edge computing for beyond 5G networks," *arXiv preprint arXiv:2011.11876*, pp. 1–11, Nov. 2020.

[103] S. Hu, Q. Wu, and X. Wang, "Energy management and trajectory optimization for UAV-enabled legitimate monitoring systems," *IEEE Transactions on Wireless Communications*, pp. 1–33, Apr. 2020.

[104] D.-H. Tran, T. X. Vu, S. Chatzinotas, S. ShahbazPanahi, and B. Ottersten, "Coarse trajectory design for energy minimization in UAV-enabled," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 9, pp. 9483–9496, Jun. 2020.

[105] Y. Li, H. Zhang, K. Long, C. Jiang, and M. Guizani, "Joint resource allocation and trajectory optimization with QoS in NOMA UAV networks," pp. 1–5, Dec. 2020.

[106] S. Yin, L. Li, and F. R. Yu, "Resource allocation and basestation placement in downlink cellular networks assisted by multiple wireless powered UAVs," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 2, pp. 2171–2184, Feb. 2020.

[107] D. Xu, Y. Sun, D. W. K. Ng, and R. Schober, "Multiuser MISO UAV communications in uncertain environments with no-fly zones: Robust trajectory and resource allocation design," *IEEE Transactions on Communications*, vol. 68, no. 5, pp. 3153–3172, Jan. 2020.

[108] L. Liu, B. Li, B. Qi, X. Ye, Y. Sun, S. Tian, C. Zhu, and P. Xi, "Optimization of communication capacity for load control considering shared risk link group in source-grid-load system," *International Journal of Electrical Power & Energy Systems*, vol. 122, p. 106166, May 2020.

[109] H. Bayerlein, P. De Kerret, and D. Gesbert, "Trajectory optimization for autonomous flying base station via reinforcement learning," pp. 1–5, Aug. 2018.

[110] Z. Na, B. Mao, J. Shi, J. Wang, Z. Gao, and M. Xiong, "Joint trajectory and power optimization for UAV-relay-assisted Internet of Things in emergency," *Physical Communication*, vol. 41, p. 101100, Apr. 2020.

[111] Y. Guo, C. You, C. Yin, and R. Zhang, "UAV trajectory and communication co-design: flexible path discretization and path compression," *arXiv preprint arXiv:2010.07068*, pp. 1–30, Oct. 2020.

[112] S. Zeng, H. Zhang, B. Di, and L. Song, "Trajectory optimization and resource Allocation for OFDMA UAV relay networks," *IEEE Transactions on Wireless Communications*, vol. 20, no. 10, pp. 6634–6647, Oct, 2021.

[113] S. Bi and Y. J. Zhang, "Computation rate maximization for wireless powered mobile-edge computing with binary computation offloading," *IEEE Transactions on Wireless Communications*, vol. 17, no. 6, pp. 4177–4190, Apr. 2018.

[114] G. Zheng, C. Xu, H. Long, and Y. Sheng, "Service caching based task offloading and resource allocation in multi-UAV assisted MEC networks," in *IEEE/CIC International Conference on Communications in China (ICCC)*, pp. 1024–1029, IEEE, Jul. 2021.

[115] J. Hu, H. Zhang, L. Song, Z. Han, and H. V. Poor, "Reinforcement learning for a cellular internet of UAVs: Protocol design, trajectory control, and resource management," *IEEE Wireless Communications*, vol. 27, no. 1, pp. 116–123, Feb. 2020.

[116] A. M. Seid, G. O. Boateng, S. Anokye, T. Kwantwi, G. Sun, and G. Liu, "Collaborative computation offloading and resource allocation in multi-UAV-assisted IoT Networks: A deep reinforcement learning approach," *IEEE Internet of Things Journal*, vol. 8, no. 15, pp. 12203–12218, Aug. 2021.

[117] W. Xu, H. Lei, and J. Shang, "Joint topology construction and power adjustment for UAV networks: A deep reinforcement learning based approach," *China Communications*, vol. 18, no. 7, pp. 265–283, Jul. 2021.

[118] F. Xu, F. Yang, C. Zhao, and S. Wu, "Deep reinforcement learning based joint edge resource management in maritime network," *China Communications*, vol. 17, no. 5, pp. 211–222, May. 2020.

[119] F. Jiang, K. Wang, L. Dong, C. Pan, W. Xu, and K. Yang, "Deep-learning-based joint resource scheduling algorithms for hybrid MEC networks," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6252–6265, Jul. 2020.

[120] L. Liu, X. Qin, Y. Tao, and Z. Zhang, "Timely updates in MEC-assisted status update systems: Joint task generation and computation offloading scheme," *China Communications*, vol. 17, no. 8, pp. 168–186, Sep. 2020.

[121] K. Li, W. Ni, E. Tovar, and A. Jamalipour, "Deep Q-Learning based resource management in UAV-assisted wireless powered IoT Networks," pp. 1–6, Jul. 2020.

[122] J. Gora and S. Redana, "In-band and out-band relaying configurations for dual-carrier LTE-advanced system," in *IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1820–1824, IEEE, 2011.

[123] C. W. Zaw, N. N. Ei, H. Y. Reum Im, Y. K. Tun, and C. S. Hong, "Cost and latency trade-off in mobile edge computing: A distributed game approach," in *2019 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pp. 1–7, Apr. 2019.

[124] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, pp. 2322–2358, Fourthquarter 2017.

[125] N. Thakoor and J. Gao, "Branch-and-bound for model selection and its computational complexity," *IEEE Transactions on Knowledge and Data Engineering*, vol. 23, no. 5, pp. 655–668, May 2011.

[126] S. Boyd, S. P. Boyd, and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.

[127] F. A. Potra and S. J. Wright, "Interior-point methods," *Journal of computational and applied mathematics*, vol. 124, no. 1-2, pp. 281–302, 2000.

[128] S. J. Wright, *Primal-dual interior-point methods*. SIAM, 1997.

[129] D. S. Watkins, *Fundamentals of matrix computations*, vol. 64. John Wiley & Sons, 2004.

[130] S. U. Jamil, M. Arif Khan, and S. u. Rehman, "Intelligent task off-loading and resource allocation for 6G smart city environment," pp. 441–444, Jan. 2021.

[131] M. Amjad, A. Ahmed, M. Naeem, M. Awais, W. Ejaz, and A. Anpalagan, "Resource management in energy harvesting cooperative IoT network under QoS constraints," *Sensors*, vol. 18, no. 10, p. 3560, 2018.

[132] Z. Ullah, F. Al-Turjman, U. Moatasim, L. Mostarda, and R. Gagliardi, "UAVs joint optimization problems and machine learning to improve the 5G and Beyond communication," *Computer Networks*, p. 107478, Aug. 2020.