Computational Efficiency Maximization for UAV-assisted MEC Network with Energy Harvesting in Disaster Scenarios

by

Reda Khalid

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Examining Committee Membership

The following served on the Examining Committee for this thesis.

Supervisor:	Dr. Waleed Ejaz Assistant Professor, Dept. of Electrical Engineering, Lakehead University
Examiner:	Dr. Salama Ikki Associate Professor, Dept. of Electrical Engineering, Lakehead University
Examiner:	Dr. Farhan Ghaffar Assistant Professor, Dept. of Electrical Engineering, Lakehead University

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

Wireless networks are expected to provide unlimited connectivity to an increasing number of heterogeneous devices. Future wireless networks (sixth-generation (6G)) will accomplish this in three-dimensional (3D) space by combining terrestrial and aerial networks. However, effective resource optimization and standardization in future wireless networks are challenging because of massive resource-constrained devices, diverse quality-of-service (QoS) requirements, and a high density of heterogeneous devices. Recently, unmanned aerial vehicle (UAV)-assisted mobile edge computing (MEC) networks are considered a potential candidate to provide effective and efficient solutions for disaster management in terms of disaster monitoring, forecasting, in-time response, and situation awareness. However, the limited size of end-user devices comes with the limitation of battery lives and computational capacities. Therefore, offloading, energy consumption and computational efficiency are significant challenges for uninterrupted communication in UAV-assisted MEC networks. In this thesis, we consider a UAV-assisted MEC network with energy harvesting (EH). To achieve this, we mathematically formulate a mixed integer non-linear programming problem to maximize the computational efficiency of UAV-assisted MEC networks with EH under disaster situations. A power splitting architecture splits the source power for communication and EH. We jointly optimize user association, the transmission power of UE, task offloading time, and UAV's optimal location. To solve this optimization problem, we divide it into three stages. In the first stage, we adopt k-means clustering to determine the optimal locations of the UAVs. In the second stage, we determine user association. In the third stage, we determine the optimal power of UE and offloading time using the optimal UAV location from the first stage and the user association indicator from the second stage, followed by linearization and the use of interior-point method to solve the resulting linear optimization problem. Simulation results for offloading, no-offloading, offloading with EH, and no-offloading no-EH scenarios are presented with a varying number of UAVs and UEs. The results show the proposed EH solution's effectiveness in offloading scenarios compared to no-offloading scenarios in terms of computational efficiency, bits computed, and energy consumption.

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Dedication

This is dedicated to my father, late Lt. Col. (R) Khalid Mateen Khan, who lit up when I told him about going back to school to pursue an MSc. in Electrical and Computer Engineering. Unfortunately, he could not live to see the day I complete it.

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List of Abbreviations

Acronyms	Description
2D	Two-dimensional
3D	Three-dimensional
3GPP	3rd Generation Partnership Project
5G	Fifth-generation
6G	Sixth-generation
APIs	Application programming interfaces
BSs	Base stations
CSMA/CA	Carrier sensing multiple access with collision avoidance
D2D	Device-to-device
DDPG-MC	Deep deterministic policy gradient-based maneuver control
DQN	deep Q-network
DTN	Delay-tolerant networking
ECONOMY	Energy efficiency in point-cloud-based autonomous UAV navigation
EH	Energy harvesting
eMBB	enhanced mobile broadband
ETSI	European telecommunication standards institute
IoT	Internet of Things
IPM	Interior point method
LoS	Line of sight
M2M	Machine-to-machine
MDP	Markov's decision process
MEC	Mobile edge computing
MILP	Mixed integer linear programming
MINLP	Mixed-integer nonlinear programming
ML	Machine learning
NOMA	Non-orthogonal multiple access
NP-hard	Non-deterministic polynomial-time hard

OSI	Open Systems Interconnection
PLOT	Perturbed Lyapunov optimization-based offloading and trajectory
QoS	Quality-of-service
RF	Radio frequency
RL	Reinforcement learning
SCA	Successive convex approximation
T-UAVs	Tethered UAVs
TB	Tethered balloon
TDMA	Time division multiple access
U-UAVs	Untethered UAVs
UAV	Unmanned aerial vehicle
UAV-BS	Unmanned aerial vehicle base stations
UE	User equipment
URLLC	Ultra-reliable and low-latency communication
V2I	Vehicle-to-infrastructure
V2V	Vehicle-to-vehicle
VANET	Vehicular Ad-hoc NETworks
WFPP	Weighted flight path planning
WSN	Wireless sensor network

List of Symbols

Symbol	Description
M	Number of UAVs
N	Number of Users
χ_{nm}	Offloading indicator of UE n
T	All tasks have same Time block T requirement
t_{mn}	Time to offload from UE to UAV
σ^2	Noise power
B	System Bandwidth
μ_m^{max}	Maximum number of UEs allowed to be associated with UAV m
g_0	Channel power gain at the reference distance $1m$
ζ	Positive coefficient
ρ	Power splitting ratio for transmission
p_{mn}	Transmission power of UE n to offload to UAV m
p_n^{max}	Maximum battery power for UE n
$\mathbb{C}_n$	Total used computation capacity of UE n
$\mathbb{C}_n^{max}$	Total computational capacity for UE n
R_{nm}	Offloading transmission rate of UAV m allocated to UE n
ω	Positive coefficient
α_n	Positive coefficient
η	Energy harvesting coefficient
β_n	Minimum bits requirement
E_{th}	Maximum available energy of the system
$E_n^{C_{ir}}$	Total circuit energy of UE n
γ_n	Cycles per bit for UE n
(x_m,y_m,h_m)	Coordinates of UAV m
θ_m	Half power beam width of antenna for UAV m
(x_n,y_n,0)	Coordinates of UE n
(x_m^{min},y_m^{min},h_m^{min},θ_m^{min})	Minimum values for UAV m to be in feasible range

(x_m^{max},y_m^{max},h_m^{max},θ_m^{max})	Maximum values for UAV m to be in feasible range
D_{mn}	Horizontal distance between of UE n and UAV m

Chapter 1

Introduction

Disasters bring voluminous human casualties and property losses and severely affect the communications infrastructure around the globe every year [1]. In 2021 alone, the emergency event database recorded 432 disastrous events that affected 101.8 million people worldwide, causing 10,492 deaths and approximately $252.1 billion in economic losses [2]. However, the inevitably long amount of time it takes to recover the original communications infrastructure is purely dependent on the severity levels of disasters. In certain critical situations such as tsunamis, flooding, and earthquakes, urgent deployment of communications infrastructure may save thousands of precious lives. Recently unmanned aerial vehicles (UAVs) have been considered useful in every field of life, such as public safety, energy, agriculture, remote sensing, disaster management, aerial delivery, surveillance, and communications [3]. European telecommunication standards institute (ETSI) created a mobile edge computing (MEC) paradigm, in which computing services and capabilities are implemented at the edge of the networks. The decentralized attribute of MEC can enable the deployment of the edge node as per the requirement in disaster scenarios [4]. Thus, integrating both technologies, such as UAV and MEC, can play a crucial role in leveraging the performance of wireless networks. It has excellent potential for rapid deployment of communications infrastructure, which can be highly beneficial in emergencies, especially in disaster management [5].

UAV-assisted MEC networks can offer low cost, high applicability and rapid deployment to provide MEC computation services in disaster-struck regions. The users trapped in the affected areas can offload their computational tasks to the UAV-mounted mobile edge nodes, which act as base stations (BSs) on demand without any network infrastructure installation delays. Another challenge is the limited battery power of user equipment (UE) and charging it in unprecedented disaster situations. A potential solution to charge UE in such situations is by incorporating radio frequency (RF) energy harvesting (EH) [6]. RF EH relies on electromagnetic waves transmitted wirelessly by a power source and converted back to electrical energy at the receiver. Thus, UAV-assisted MEC networks have the desired capabilities to support the industry and society needs of future communications. For instance, Motlagh et al. in [7] solved the problem of computation offloading of video processing tasks by introducing a UAV-assisted MEC architecture for the Internet of Things (IoT) services to achieve facial recognition based crowd surveillance. Similarly, Ahmed et al. proposed a scheme for joint placement and user association of UAVs for IoT networks [8]. Sekander et al. investigated the potential of drones for fifth-generation (5G) and beyond cellular networks and presented a multi-tier UAV-assisted cellular architecture for measuring the spectral efficiency of downlink transmissions [9].

In [10], Huang et al. proposed an efficient EH scheduling scheme for EH empowered device-to-device (D2D) relay networks. They formulated an optimization problem for energy scheduling and proposed a two-stage directional water-filling algorithm to solve it. Similarly, in [11, 12] Liu et al. proposed a hybrid architecture that combines the multihop D2D relay and UAVs to extend the coverage of IoT devices, along with a resource allocation scheme for UAV-assisted machine-to-machine (M2M) communications for disaster management. In [13], Bor-Yaliniz et al. introduced a revenue maximization scheme for the cellular network using the placement of UAV BSs. They formulated a mixed-integer nonlinear programming (MINLP) problem and solved it using a heuristic algorithm. Similarly, in [14], the deployment of UAV-BS based scheme is designed to investigate energy-efficient communication for mobile ad-hoc networks.

Computational offloading, energy limitation and computational efficiency are the main challenges of UAV-assisted MEC networks, particularly in disaster situations. In this thesis, we formulate an MINLP optimization problem to maximize the computational efficiency of a UAV-assisted MEC system in disaster situations. To achieve this objective, we jointly optimize user association with the nearest UAV, transmission power of UE, offloading time, and optimal location of UAV while adopting EH to replenish the power of energy-constrained UEs and maintain long-term energy sustainability.

1.1 Motivation

Due to the resource-constrained design of UEs, they require assistance to offload computation tasks. UAV-assisted MEC networks with EH are an efficient and effective solution to the offloading problem, particularly in disaster management in terms of monitoring, forecasting, in-time response, and situation awareness. Although using UAVs provide better LoS communication compared to terrestrial BSs, UAVs have limited computation capacity and battery life. It is still greater than the computation capacity and battery life of the UEs offloading the computation tasks to the UAV-assisted MEC node. Therefore, computational offloading, energy limitation and computational efficiency are the main challenges of UAV-assisted MEC networks, particularly in disaster situations. This motivates the proposed three-stage scheme to maximize the computation efficiency in UAV-assisted MEC networks with EH, where UEs are recharged using the downlink RF signal to increase their battery lives and promote long-term energy sustainability.

This EH in UAV-assisted MEC networks applies to the access communication links to provide power transfer while providing network connectivity to ground users. This will particularly help in disaster recovery scenarios, emergency relief, and battle-struck areas, where the terrestrial infrastructure may be damaged or unavailable. Deployment of UAV-BS once the UAVs determine network gaps will particularly help users stay connected to the network and communicate their needs to survive during unprecedented difficult times. Thus, to solve the problem of energy-constrained devices connected to the UAV-assisted MEC network, this thesis proposes an MINLP optimization problem to maximize the computational efficiency of the UAV-assisted MEC network with EH in a disaster situation.

Computation offloading, energy limitation and computation efficiency maximization problems are considered in the MINLP problem. We solve them by jointly optimizing the UAV location for maximum connections and offloading, UAV and UE associations for computation offloading, UE energy consumption reduction through offloading computation tasks and EH, as well as time taken to offload tasks from UE to UAV.

1.2 Preliminaries of Computation Efficiency in UAV-assisted MEC Network with Energy Harvesting

This section will discuss components that build the computation efficiency maximization in a UAV-assisted MEC network with EH. Some of the preliminaries include UAV-assisted wireless networks, MEC networks and UAV-assisted MEC networks, computation offloading, computation efficiency, energy efficiency and EH.

1.2.1 Mobile Edge Computing (MEC)

With the increase in high bandwidth and high reliability requirements in communication networks, cloud computing and cloud servers have been adopted in both wireless and wired networks. However, some applications like vehicular ad-hoc networks (VANET) have high sensitivity to latency, so cloud computing may not be sufficient for shorter real-time latency and improved reliability requirements. Therefore, to bring the computing to servers installed and available at the network edge instead of the remote cloud servers, MEC paradigm was formulated. The 3^{rd} Generation Partnership Project (3GPP), ETSI and other standardization bodies are defining the service, architecture and application programming interfaces (APIs) for MEC, while researchers are proposing architectures and derivations to analyse the computational offloading to MEC servers [15].

MEC extends the cloud computing paradigm at the network edge, where resources can be re-used and the network can be extended by varying geographical locations of edge nodes. MEC is not a standalone technology and can be looked at from a network or service perspective. From a network perspective, due to the close proximity of MEC nodes, fewer hops are needed by data packets, leading to reduced network congestion and latency, as well as increased reliability and bandwidth with the increased resource availability. From a service perspective, the homogenous technology stack empowers and implements data-centric architectures with service constraints. MEC can be implemented from a network or service perspective, or a combination of both for best results. Use of MEC is particularly beneficial for services and applications requiring ultra-low latency, high bandwidth, service reliability and special privacy. Since load sitautions and network configurations are predictable and pre-planned for static environments, significant performance improvements can be seen. However, if UE move unpredictably and inter-MEC-zone movement takes place, adjustments need to be made accordingly in higher layers of the Open Systems Interconnection (OSI) reference model, therefore impacting communication performance [16].

1.2.2 UAV-assisted wireless networks

Future wireless networks (sixth-generation (6G)) are anticipated to provide fast, reliable, and efficient connectivity to a growing number of heterogeneous devices. This can be accomplished in three-dimensional (3D) space by integrating terrestrial and aerial networks. Deployment of unmanned aerial vehicle base stations (UAV-BS) and relays can integrate terrestrial and aerial networks to provide massive connectivity in 3D space. In a UAV-BS, UAV acts as the BS to provide network connectivity. UAVs can provide high mobility and increased flexibility and can be used as a rapid remedy to temporary surges in user demand for connectivity, such as flash crowds or disaster scenarios. Applications of 3D networks range from military to public operations, including military surveillance, medical emergency, natural disasters, search and rescue, detection of network coverage gaps and provision of temporary on-demand connectivity, delivering parcels, relaying data packages, gathering sensor information, and in many other sectors [17–20]. With the massive number of resource-constrained devices, diverse quality-of-service (QoS) requirements, and a high density of heterogeneous devices, efficient resource management in future wireless networks is becoming a challenge. Traditional resource management schemes cannot cope with the complexities of these challenges, leading to the demand for UAV-assisted networks with energy harvesting in such a resource-constrained environment [21].

Recently UAVs integrated with MEC are gaining popularity due to their flexible nature of service provision [22]. Due to the energy constraint of UAVs, there are recent studies on energy consumption reduction [23], energy harvesting [24], energy efficiency [25] and resource allocation [22], and computation efficiency [26] of UAV-assisted MEC systems. Due to the energy constraint of the user devices, there are studies on energy consumption reduction through computation offloading to UAV-assisted MEC [27], and RF energy harvesting from UAV-assisted MEC [28]. Other topics of interest in the UAV-assisted MEC include trajectory optimization [29], service QoS provision [30], user quality of experience [31], data secrecy [32] and latency [33].

1.2.3 Computation Offloading

Computation offloading is another key preliminary, as well as challenge to overcome in UAV-assisted MEC networks. It is a key technology of MEC, where all or part of the computation tasks for a UE are offloaded to the MEC server for computation. This in turn reduced the energy consumption of the UE. On the other hand, since MEC server has far superior computing power than a UE, the performance is enhanced too [34, 35].

There can be three possible computation offloading decisions, i.e. local execution, partial offloading, and full offloading [36]. In the local execution, the computation tasks for the UE are performed locally by the device itself. In partial offloading, some part of the computation is performed locally, while the remaining tasks are migrated to the MEC server to be processed there. In the full offloading case, all the computation tasks are migrated to the MEC server to be processed there. Due to the superiority of the computation capacity of the MEC server, the task computation takes less time than it takes at the UE. However, there is time and energy associated with the transmission of unprocessed tasks to the MEC server and processed tasks back from the MEC server. The main performance metrics for offloading include latency, energy consumption and the trade-off between the two, as attempting to reduce latency significantly increase energy utilization, and vice-versa.

Computation offloading approaches can be examined as single-user or in a multi-user scenario. In a single-user scenario, the offloading decision depends on the computing task queue's length, UE's executing state and the transmission unit's state. In a multi-user scenario, the offloading decision is more complex, as the offloading decision of one user affects the performance of others. Network bandwidth, MEC computing resources and the number of users also contribute to the offloading decision [37].

1.2.4 Energy Harvesting

For high-computation, low-latency and energy-hungry applications, computation offloading in MEC with EH are becoming increasingly popular [27]. While MEC supports energy and computation-constrained UEs by processing their tasks [38]. Energy harvesting supports the operating capabilities of the UE itself by overcoming the shortcoming of limited battery life [39]. By converting the captured energy from various environmental sources such as microbial fuel cells [40], photovoltaic cells [41], piezoelectronics [42], thermal energy [43] and radio-frequency (RF) energy [44] into electrical energy, the EH capabilities enhance the battery lives of energy-constrained UE devices [39]. The energy management of this harvested energy is the main component in EH-based wireless networks [27].

Since EH contributes to longer device battery life, it in turn supports prolonged operating capabilities. EH can reduce and potentially eliminate the need for batteries in user devices. Delgado et al. recently proposed an optimal energy-aware task scheduling to achieve batteryless IoT devices in [45], running on capacitors to store energy charged using EH. This also makes the devices environmentally friendly, with cheap maintenance, easy recycling, and temperature variations and recharging degradation resistance [45]. However, there is fluctuation and unpredictability in the nature of EH process [46]. Environmental changes and inconsistencies also impact the characteristics of EH process. Therefore, it is difficult to estimate EH in the complexities of the dynamic environment, especially if multiple MEC servers are involved [38].

Though EH over RF transmission is an efficient way for powering low-power wireless devices, for instance, sensors and IoT devices. This is particularly beneficial due to the ability to transmit power to multiple receivers simultaneously, even when the distance is more than several meters away compared to near-field transmission in magnetic induction and resonance [47] [48]. However, the drawback of RF signals is the exponential attenuation of microwave energy based on the propagation distance, leading to reduced energy transfer efficiency [49].

Research in energy efficient designs are either focussed on reducing energy usage through design changes [50] or using RF signals as an energy harvesting source to improve energy efficiency [25]. Many studies used a linear EH model with the assumption that harvested energy increases linearly with the increase in the input power of the received signals [51]. However, practically, the RF-based EH process has non-linear characteristics with non-linear power transfer and non-linear energy harvesting [38] [46] [52]. Therefore, for practical implementation of EH, the non-linear EH model should be considered [53].

Efficient energy management has its challenges due to the unpredictable EH and QoS requirements [54]. Interesting research was conducted by Zhang et al. for device-to-device EH as a reward for offloading assistance [55]. Overall, increasing the energy efficiency of mobile devices is becoming more and more important with increasing mobile usage and limited battery life, where EH is a promising paradigm for green computing and communication [56].

1.2.5 Computation Efficiency

Apart from computation offloading and energy consumption, computation efficiency is a major challenge in UAV-assisted MEC networks. Computation efficiency is derived from the energy efficiency of a system. Instead of the frequently used metric for efficiency of the system, i.e. either energy efficiency or the data processed, a new metric called computation efficiency was defined in [57]. Energy efficiency is still a popular metric in industry and academia for multi-hop systems and heterogeneous networks. It can measure the reduction in energy consumed for a certain level of quality of service maintained. However, with the increasing number of energy and computation capacity-constrained devices with computation-intensive and latency-sensitive tasks, computation offloading to MEC servers has become increasingly important for delay-sensitive tasks while communications throughput has become secondary. The combined efficiency of communication and computation can be determined using the computation efficiency metric, which is the ratio of bits computed vs the energy consumed to compute the data bits. This new metric, computation efficiency, measures the efficiency of the system in terms of bits computed per Joule for massive computation requirements. Maximizing the computation efficiency, therefore, entails the maximization of computed bits as well as the minimization of energy consumed, while considering local and offloaded computation [57].

Computation efficiency is now being widely used as a performance metric. In [58], Cang et al. aim at maximizing the minimum computation efficiency of all users fairly. Resource allocation strategies for partial and binary computation offloading are defined to maximize the computation efficiency of wireless-powered MEC networks in [36]. Similarly, Huang et al. used computation efficiency as the performance metric to better express the effectiveness of their proposed system in [59].

1.3 Thesis Objective

The main objective of this thesis is to develop a scheme to maximize computational efficiency for a UAV-assisted MEC network with EH in disaster scenarios. To maximize the computation efficiency, we jointly optimize UAV location, user association, UE's transmission power, and computation tasks offloading time. This leads us to the formulation of an MINLP optimization problem. To solve the MINLP problem, we develop a three-stage scheme to maximize the computation efficiency a of UAV-assisted MEC network with EH in disaster scenarios. Simulation results are presented to test the effectiveness of the proposed scheme in terms of computational efficiency, bits computed, and energy consumption with a varying number of UAVs and UEs.

1.4 Thesis Contributions

The main contributions of this thesis can be summarized as follows:

- We formulate an MINLP optimization problem to maximize the computational efficiency of the UAV-assisted MEC networks with EH for disaster situations, in which we jointly optimize user association, transmission power of UE, offloading time, and UAV's optimal location.

- We propose a three-stage scheme to solve the optimization problem. In the first stage, we adopt k-means clustering to determine the optimal locations of the UAV-BSs. In the second stage, the user association decision is made based on the distance from the UAV and the maximum available connections of the UAV. In the third stage, we divide the problem into two sub-problems. First, we adopt linear approximation to linearize the MINLP problem; then, we apply the interior point method (IPM) to solve the formulated linear optimization problem to maximize the computation efficiency while optimizing transmission power and offloading time.

- The effectiveness of the proposed scheme is evaluated based on simulation results obtained in terms of computational efficiency, bits computed, and energy consumption for different scenarios of offloading, no-offloading, offloading-EH, and no-offloading-EH with a varying number of UAVs and UEs.

1.5 Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 covers the state-of-the-art development in computational efficiency, EH, and task offloading in UAV-assisted MEC networks and their challenges. Chapter 3 discusses the system model adopted to formulate the MINLP optimization problem in UAV-assisted MEC networks. Chapter 4 presents the proposed three-staged scheme to solve the optimization problem, followed by the simulation results and their analysis. Finally, Chapter 5 concludes the thesis and presents the future research directives.

Chapter 2

Background and Literature Review

In this chapter, we highlight some of the recent research and development trends, leading to the formulation of our work on computation efficiency maximization of UAV-assisted MEC networks with EH. Some areas of research include computational efficiency, user energy efficiency, energy harvesting, partial and binary computational offloading, location optimization or a combination of them in UAV-assisted MEC networks. In the summary section, we discuss how the proposed work is different and adds value to the existing literature on challenges faced with computation offloading, energy scarcity and computation efficiency in UAV-assisted MEC networks.

2.1 Related Work

2.1.1 Energy consumption and efficiency

There exists some work in different aspects of enhancing computational efficiency, EH, and task offloading in UAV-assisted MEC networks. Few papers discuss one or a combination of these optimization problems. For instance, in terms of energy consumption, Lin et al. proposed a two-stage optimization scheme in [60] to minimize the transmission energy consumption and service latency for a UAV-assisted MEC network. In the first stage, a non-cooperative offloading game problem is formulated and solved via an online non-cooperative computation offloading scheme using mobile users' individual rationality, long-term queue stability, and mobile users' mutual interference constraints. In the second stage, a UAV workload scheduling algorithm is presented to optimize the provision of UAVs' computational resources and minimize the UAVs' energy consumption. Similarly, in [61], Liu et al. formulated a non-convex optimization problem to minimize the total energy required for a UAV to jointly optimize the CPU frequencies, sensor devices' offloading amount, transmit power, and the UAV trajectory as constraints. They further used Taylor expansion to convert their optimization problem into a convex optimization problem. However, in the proposed scheme, with the increase in the number of idle sensor devices, the number of optimization variables also increases, which causes a longer convergence time.

Li et al. presented an optimization problem to maximize the UAV energy efficiency. They proposed energy-efficient resource allocation and trajectory schemes for UAV-assisted MEC networks by considering UAV communication energy budget, UAV computation capacity, and mechanical operation of the UAV constraints [25]. In [62], Manzoor et al. discussed an energy-efficient scheme consisting of ruin-theory followed by a water-filling based scheme for a UAV-assisted cellular network, with EH. The objective is to maximize data rate of enhanced mobile broadband (eMBB) users, enhance the cellular network capacity and increase flight duration of UAVs while considering latency and reliability constraints of ultra-reliable and low-latency communication (URLLC) applications. They jointly optimized user association, and power allocation for 5G. They discussed the energy sustainability, however, accounting for trajectory optimization of UAVs can make the solution more realistic as a significant amount of energy is utilized in maneuvering the UAVs. A multi-stage stochastic programming problem is formulated by Yang et al. to minimize the UAV propulsion energy. This is solved in a semi-closed loop form by splitting EH, allocation of computational resources (i.e., CPU frequencies and offloading times), and UAV trajectory control into sub-problems, while considering battery causality and data queue stability constraints [63]. Further, the authors presented an online perturbed Lyapunov optimization-based offloading and trajectory (PLOT) control algorithm to solve it as a deterministic optimization problem per time slot.

Resource scheduling to maximize the weighted global energy efficiency of a UAV-assisted MEC system consisting of 2-D multi-lane platooning vehicles was discussed in [64]. The effect of driving behaviour on ground-to-air communication and task offloading were taken into account. The authors also considered user preference in energy consumption to determine optimal energy utilization and maximize the global energy efficiency of the system. In [65], the authors formulated a joint optimization problem based on customized price and power control for energy-efficient wireless networks. The constraints included finding the right balance of uplink transmission power based on the pricing model for the best possible channel gains and QoS in the limited bandwidth. Using a generic net two-variable utility function, the S-modular theory is used to find a distributive and iterative algorithm for a Nash equilibrium point. This energy-efficient solution leveraged the price of service users were willing to pay for the maximum power they can transmit.

A summary of the discussions is given in Table 2.1. The table shows which papers adopted EH, and a brief description of the research problem, objective, constraints, problem type and solution approach of each paper. All the authors worked on improving the energy efficiency of the system. This was either done by reducing the energy consumption of the UAVs [61] [64] by minimizing UAV propulsion energy [63], increase flight duration [62], or adopting EH [61] [62] [63] or by introducing computation offloading [25] [60] [61], reducing transmission energy consumption [60], or introducing a price and power scheme for reduced power consumption and bandwidth allocation [65]. An interesting model with computation offloading to and EH from idle devices in the system was proposed in [61].

Table 2.1: Summary of Energy efficiency and consumption related work.

Ref.	EH	Research Problem	Objective	Constraints	Problem Type	Solution
[25]	✗	UAV aerial cloudlet collects and processes the ground users' offloaded tasks	Maximize UAV energy efficiency	Communication and computation requirements and resources	Non-convex joint optimization	Dinkelbach algorithm, SCA.
[60]	✗	Energy-efficient computation offloading for UAV-assisted MEC	Minimize transmission energy consumption and service latency	User rationality, long term queue stability, mutual interference	Optimization of UAV computation resource provision	Online non-cooperative computation offloading scheme; workload scheduling of UAV

✓ [61]	Wireless energy transmitter enabled UAVs and idle devices provide energy and computation offloading services	Minimize the total required energy of UAV	Active computing tasks, information and EH causality; UAV trajectory	Non-convex	Taylor expansion, SCA-based algorithm
✓ [62]	Ruin-based energy-efficiency scheme for UAV-assisted cellular network	Maximize data rate of eMBB users, increase UAV flight duration	Latency and reliability for URLLC applications	Joint optimization	Ruin theory, water-filling scheme.
✓ [63]	Offloading and trajectory control in UAV-enabled MEC with EH UE devices	Minimize UAV propulsion energy	UAV operational constraints; long-term data queue stability; Battery causality of EH devices	Multi-stage stochastic optimization	Online PLOT control algorithm; semi-closed-form solution of per-slot optimization problem.

✗ [64]	UAV assisted-MEC system with multi-lane platooning vehicles	Maximize weighted global energy efficiency	UAV energy consumed, quality of service, throughput	Non-convex energy optimization	Sequential quadratic programming.
✗ [65]	Custom price and power control in multi-service wireless networks	Maximization of QoS utility	Price and power, QoS	Joint optimization of price and power	S-modular theory.

2.1.2 Latency and computation offloading

In [66], the authors formulated an optimization problem with the objective of maximizing the latency fairness for UAV-assisted MEC systems by jointly considering the constraints of minimum control link rate, total power, and ground user device's battery power. In order to jointly optimize the given parameters, the authors devised an iterative algorithm in which the location of the UAV is determined using the guided pattern search algorithm, the altitude of the UAV by elevation angle, and the UAV power is allocated by using the bisection method, respectively. Further, a deep reinforcement-based method for solving the UAV-assisted computation offloading problem with a cost-efficient offloading policy for dynamic UAV mobility patterns and UAV failure is presented in [67]. The core objective of the optimization is to maximize the sum of rewards, improve energy efficiency, and reduce the average processing time while satisfying the computation capacity, UAV mobility, and UAV failures ratios constraints. Further, the authors proposed a distributed deep reinforcement learning-based method with cooperative exploring and prioritized experience replay to solve the formulated optimization problem.

In [68], Wang et al. formulated a non-convex optimization problem for finding an optimal computation offloading policy under an uncontrollable and dynamic UAV environment. The objective is to minimize the processing delay by jointly considering the user scheduling, task offloading ratio, UAV flight angle, and speed. Moreover, the authors derived a computation offloading algorithm based on the deep deterministic policy gradient using reinforcement learning to satisfy the aforementioned objective. In [69], Ye et al. worked on the allocation of optimal sub-bands and power for message transmission in unicast and broadcast vehicle-to-vehicle (V2V) communications in a decentralized manner. There are stringent latency constraints for V2V communication and the amount of vehicle-to-infrastructure (V2I) communication capacity and interference. The authors proposed a deep reinforcement learning (RL)-based decentralized and automated resource allocation method for this optimization problem. This led to little transmission overhead associated with local information and observations made by the decision-making agent of the V2V link or vehicle. However, deep learning adds computational complexity to the implementation. Luckily there are studies to reduce this computational complexity that can be considered with this proposed approach.

A summary of the discussions is given in Table 2.2. The table shows that none of the papers adopted EH, and provides a brief description of the research problem, objective, constraints, problem type and solution approach of each paper. All the authors worked on offloading computation tasks except [69], where power and bandwidth were optimized for latency-sensitive V2V links. Generally, reducing the communication latency [68] fairly [66], maximization of sum of reward through a cost-efficient offloading policy [67], and the latency sensitivity of V2V links [69] are summarized in the table.

Table 2.2: Summary of Latency and Computation offloading related work.

Ref.	EH	Research Problem	Objective	Constraints	Problem Type	Solution
[66]	✗	Resource optimization of randomly distributed ground users and a UAV-MEC	Maximize the latency fairness	Minimum control link rate and power limitations	Joint optimization	Iterative algorithm: guided pattern search; bisection method
[67]	✗	UAV-assisted MEC with cost-efficient offloading policy	Maximize sum of reward	Computation capacity, dynamic UAV mobility pattern and UAV failures	Joint optimization	distributed deep reinforcement learning-based method with cooperative exploring and prioritized experience replay

✗ [68]	Finding optimal computation offloading under an uncontrolled dynamic environment	Minimize the processing delay	User scheduling, task offloading ratio, UAV flight angle and speed	Non-convex joint optimization	Computation offloading algorithm based on the deep deterministic policy gradient using reinforcement learning
✗ [69]	Decentralized resource allocation of optimal sub-band and power levels for transmission in unicast and broadcast V2V Communications	Minimize interference of V2V links to V2I links	Latency constraints in V2V links, V2I capacity and interference threshold in broadcast	Sub-band and power optimization	Deep RL based resource allocation framework.

2.1.3 Energy harvesting

In [70], Liu et al. presented a UAV-connected and autonomous vehicles cooperation model for EH in UAV-assisted MEC networks. An optimization problem is formulated to maximize the overall computational capacity by jointly optimizing communication and computation resources. In the proposed successive convex approximation (SCA)-based joint communication and computation resource scheduling optimization method, the cloudlet-mounted UAVs harvest energy from the platooning vehicles and assist them with computational offloading while satisfying the energy, time, communication, and computational resources constraints. In [71], Li et al. presented a UAV-based wireless power transfer for the MEC networks to minimize the UAV's transmission power and developed a cooperative MEC scheme, in which a closer user assists the other users who are away from the UAV. In [6], the mobile UAV acts as a wireless energy source as well as a mobile fog server for the ground sensors. Xiong et al. jointly optimize UAV trajectory, task offloading, and computing resource allocation for UAV-assisted wireless-empowered fog computing networks, while considering non-linear EH, UAV velocity and sensor charging requirements' constraints. First-order Taylor expansion and a SCA theory-based iterative method were used to solve this non-convex joint optimization problem with a piecewise non-linear EH model [6].

In [72], Khairy et al. presented WiFi broadcast charging in carrier sensing multiple access with collision avoidance (CSMA/CA)-based IoT networks with a limitation of only charging, detecting or active period at any given time due to the use of a single antenna. In [73], Lu et al. compared power splitting and time switching architectures for RF EH performance in cellular networks. They demonstrated how the power-splitting architecture generated better results than the time-switching architecture regarding transmission outage probability, as the transmission outage led to service disruptions. In both [72, 73], the challenges of service disruption faced could be solved by the use of multiple antennas with designated communication or EH capabilities. Benkhelifa et al. used stochastic geometry and queuing theory in [74] to develop a spatiotemporal mathematical model of self-sustainability in IoT networks that recycle RF-energy in a downlink cellular network. The two-dimensional (2D) discrete-time Markov chain model tracks the time evolution of battery and data buffer of self-sustainable IoT devices. Simulation results showed that the network is unsuccessful in sustaining itself, possibly due to energy scarcity, overwhelming interference, or both. The spatiotemporal traffic intensity, cellular network density, and network self-sustainability are analyzed to quantify the required packet delay and buffer size in the design of IoT devices for different network parameters. However, the authors used a single antenna where the assumption is made that information transfer gets priority over EH.

Energy efficiency in point-cloud-based autonomous UAV navigation (ECONOMY) system is investigated in [75] for the unknown environment. The problem is decomposed into UAV communication optimization and UAV trajectory and velocity optimization with a constraint on colliding probability caused by point cloud uncertainties. The proposed scheme is based on the gradient ascend, then deterministically exploiting convex sets' tight-upper bound. The autonomous navigation scheme can be significant in search and rescue missions where dynamic obstacles are involved. However, ambient charging through EH on top of the articulated energy-efficient autonomous navigation in [75] can facilitate an uninterrupted mission. Joint optimization of communication schedule and continuous autonomous maneuvering in UAV-assisted data collection is discussed in [20]. A deep deterministic policy gradient-based maneuver control (DDPG-MC) is proposed for learning in online maneuver control. Li et al. formulated the data capture schedule to reduce buffer overflows at the sensors, which resulted in the dropping of newer data packets. A large number of sensors or poor trajectory planning can cause data buffers at the sensors to overflow. The queuing and buffer time at the sensors could be reduced by using multiple UAVs instead of one or improving the UAV's battery life through EH for continuous data collection.

A summary of the discussions is given in Table 2.3. The table shows that all the papers adopted EH, and provides a brief description of the research problem, objective, constraints, problem type and solution approach of each paper. All the authors worked on EH to maximize computation efficiency [70] and throughput [72], minimize energy consumption [6] [71], analyze RF EH architectures [73] and recycle RF energy [74] for long term energy sustainability. Some papers account for the non-linearity of EH process.

Table 2.3: Summary of Energy Harvesting related work.

Ref.	EH	Research Problem	Objective	Constraints	Problem Type	Solution
[70]	✓	Cloudlet-mounted UAVs harvest energy from platooning vehicles in return for computing services	Maximize system-wide computational capacity	Energy, time, communication and computation resources	Non-convex joint optimization	SCA-based joint communication and computation resource scheduling optimization method
[6]	✓	UAV-assisted wireless powered fog computing sensor network for a green communication system design	Minimize UAVs energy consumption	Nonlinear EH model, UAV velocity, sensor charging requirements	Non-convex joint optimization	SCA theory based iterative method

✓ [71]	UAV-based wireless power transmission in a collaborative MEC network, closer user assisting user further away from UAV	Minimize UAV transmission power	Offloading and local calculation delay, offloading task size	IoT device power optimization	UAV-based wireless power transmission and cooperative MEC scheme.
✓ [72]	EH performance analysis of a Wi-Fi based IoT network for communication and energy transfer	Maximize throughput; ensure long-term energy sustainability	Battery life; single antenna	Optimization	Probability theory and statistical geometry; distributed algorithm

✓ [73]	Performance analysis of time and power-splitting architectures for self-sustainable communications with general fading channels over cellular networks.	Analyze RF EH architectures	Interference	Comparative performance analysis	Ginibre model-based stochastic geometry
✓ [74]	Attempt to self-sustain IoT network relying on EH from downlink cellular network.	Recycle RF-energy	Data buffer; battery levels;	Multi-objective optimization	Stochastic geometry and queuing theory

2.1.4 UAV-assisted Networks with trajectory planning and tethering

Detection of network coverage holes using UAVs and mitigating them through reinforcement learning using UAV-BS is studied in [17] while providing optimal wireless backhaul rates in a time and resource-effective manner. With the main constraints of UAV coverage, capacity, position, and user requirements to be met, the operators then decided how to mitigate the holes, making the solution partially autonomous. Deployment of UAV-BSs autonomously can reduce human dependency as proposed in [19], where authors discussed maximizing the user coverage proactively by deploying autonomous UAV-BS to connect UE in cellular networks and minimize the cost of relay communication between UAVs. The challenge is to optimize with the trade-off between the maximum coverage ratio and the communication cost. The authors proposed a distributed algorithm with UE density function and communication graph to maximize coverage. Here, the autonomous UAV-BS are deployed at a fixed altitude, assuming data transmission over different frequencies to minimize the interference and reduce the complexity of the problem.

Aerial networks are also discussed in [76] with an objective to model and compare the cellular coverage probability when using tethered UAVs (T-UAVs) versus traditional untethered UAVs (U-UAVs) to assist in offloading network traffic of a densely populated area. Through stochastic geometry-based analysis and a user association policy, it is determined that T-UAVs outperformed traditional U-UAVs in terms of network coverage probability. However, T-UAVs are restricted to a search space radius based on the tether length and ground station location, whereas the U-UAVs are mobile. Therefore a combination of the two can overcome the challenges faced in each type, providing uninterrupted coverage over a longer distance.

UAV flight paths optimization is investigated in [18] for autonomous multi-hop UAV communication networks to conserve time and energy. Data packets are prioritized by assigning weight based on the destination, time remaining to live, same as delivery deadline, physical weight and size, priority, the delivery deadline and energy utilization. Iranmanesh et al. proposed a delay-tolerant networking (DTN)-based algorithm and heuristic weighted flight path planning (WFPP) algorithm for the path optimization problem. Routing is done based on calculating the safe return of the UAV before battery exhaustion, a significant constraint along with the UAV's weight-lifting capacity. Better delivery efficiency could be achieved through intermittent charging stations or wireless charging over RF communication channels. A resource and placement optimization for multiple UAVs is proposed in [77] to maximize end-to-end throughput in the absence of terrestrial infrastructure. A central tethered balloon (TB) determines the backhaul link association, and each UAV is associated with one TB. EH over the RF link between UAVs and TB can make the solution proposed in [77] sustainable for disaster scenarios.

In [78], Jung et al. proposed a combined use of convolutional neural networks, single-shot detection and LoS algorithm to quickly and reliably navigate the autonomous UAV across the gates in UAVs racing. The gates could be stationary or moving, and this navigation is performed indoors in non-optimal lighting conditions. They successfully navigated through a nine-door track, demonstrating its significance in search and rescue missions, where dynamic obstacles are involved. In [79], the authors worked on the trajectory optimization of the mobile sensor for long-term energy sustainability in an autonomous wireless sensor network (WSN). The constraints include the maximum distance between the static chargers and the mobile sensor as the radiated energy used in EH fades over distance, and the mobile sensor's battery capacity before it requires a recharge. For this real-time trajectory optimization problem, the authors proposed modelling the movement of the mobile sensor as a Markov's Decision Process (MDP) and using deep Q-network (DQN) where the mobile sensor learns the optimal position by tracking the received signals over time, i.e., combining neural networks with RL. The optimal trajectory to move to the best charging location was determined and followed to enable long-term energy sustenance in WSN.

A summary of the discussed papers is given in Table 2.4. The table shows which papers adopted EH, and provides a brief description of the research problem, objective, constraints, problem type and solution approach of each paper. The authors either worked on trajectory planning of UAVs, T-UAVs or other aerial-related work.

Table 2.4: Summary of Trajectory Planning, T-UAV and Aerial related work.

Ref.	EH	Research Problem	Objective	Constraints	Problem Type	Solution
[17]	✗	3-D UAV-BS placement to mitigate autonomously detected coverage holes.	Detect and mitigate coverage holes	UAV coverage capacity; position.	Optimization	Reinforcement learning; hole detecting UAV
[19]	✗	Autonomous placement of UAV-BS in cellular networks.	Maximize user coverage and minimize UAV relaying cost.	UAV coverage range; communication cost	Optimization of coverage and cost.	Distributed algorithm with UE density function and communication graph.
[18]	✗	Autonomous UAV flight path routing based on mobility.	Maximize data transfer and package delivery	Energy budget; length of travel; package weight	Path optimization.	New DTN based algorithm; heuristic WFPP algorithm; Travelling salesman problem solver.

✗ [20]	Aerial data capture scheduling and UAV maneuvering for wireless sensor networks.	Minimize data loss	Buffer overflow; fading airborne channels	Joint optimization	DDPG-MC; sensor data capture scheduling
✗ [75]	Energy-efficient and cloud-assisted autonomous UAV navigation in urban environment.	Maximize energy-efficiency	Probabilistic; collision-free constraints	Non-convex joint optimization	ECONOMY; including suggest-and-improve framework, gradient ascend
✗ [77]	Backhaul link for UAV optimized by TB, determining optimal UAV transmit power and UAV placement with reduced complexity.	Maximize end-to-end throughput	Access and backhaul UAV associations	Non-convex; Multi-objective optimization	Backhaul tethered balloons; Shrink and realign process based heuristic algorithm; benchmarks

✗ [76]	Performance analysis of T-UAV without resource constraints of U-UAV.	Analyze T-UAV and U-UAV-assisted offloading; maximize signal-to-noise ratio	Battery life; wireless backhaul link capacity	Comparative performance analysis	Stochastic geometry-based analysis (Joint probability density function); User association policy
✗ [78]	Indoor autonomous drone navigation with dynamic routing	Maximize gate detection and minimize collision	Non-optimal lighting and moving gates	Dynamic path optimization	Convolution neural networks; single-shot detection and LoS guidance algorithm.
✓ [79]	Trajectory planning of mobile sensor for energy sustainability in WSN	Maximize long-term achievable energy per slot from two static chargers	Radiated energy fading over distance and battery capacity of mobile sensors	Online trajectory optimization	MDP; new DQN based on RL and neural networks.

2.1.5 Computation efficiency

Zhou et al. discussed the resource allocation and computation efficiency for wireless empowered MEC networks under partial computation offloading and binary computation offloading modes in [36]. They compared the time division multiple access (TDMA) and non-orthogonal multiple access (NOMA) schemes for offloading transmission with the non-linear EH model to maximize the computation efficiency under the max-min fairness criterion by satisfying the minimum bits, EH, and energy consumption constraints.

In [80], Xu et al. presented a computation efficient aerial-ground multi-server cooperation system to maximize the weighted computation efficiency of the system. In this formulated non-convex optimization problem, they jointly optimized user's computation task allocation, time-slot partitioning, transmit power allocation, transmission bandwidth allocation, UAV's CPU frequency allocation, and UAV's trajectory control. They proposed an alternative computation efficiency maximization algorithm using Dinkelbach's method, the Lagrange duality, and the SCA concepts. Similarly, in order to maximize the computational efficiency for multi-UAV assisted MEC networks with partial offloading, a non-convex optimization problem is formulated by jointly optimizing the user association, CPU cycle frequency allocation, power and spectrum resource allocation, and the trajectory scheduling in [81]. Zhang et al. proposed a multi-loop iterative computation efficiency maximization algorithm. They used the Dinkelbach method for computation efficiency in the outer loop. Then a binary cut-and-branch method is adopted for optimizing user association, followed by a primal-dual interior point method for optimization of resource allocation and UAV trajectory scheduling in the inner loop. However, the performance gap between the baseline solution and the proposed scheme is quite small. Zhang et al. also presented a computation-efficient UAV-enabled MEC system under partial computation offloading and formulated a non-convex optimization problem in [5]. A two-stage optimization solution based on the Lagrangian dual and SCA methods is presented to solve the optimization problem by satisfying the maximum consumed energy, user offloading time, CPU frequencies, user's transmit power, UAV's mobility, and position constraints.

A summary given in Table 2.5, shows the research problem, objective, constraints, problem type and the solution proposed for computation efficiency related work. It also shows if EH was adopted in the implementation.

Table 2.5: Summary of Computation Efficiency related work.

Ref.	EH	Research Problem	Objective	Constraints	Problem Type	Solution
[80]	✗	Computation efficient aerial-ground multi-server cooperation	Maximize weighted computation efficiency of system	Communication and computation requirements	Non-convex joint optimization	Dinkelbachâs method, Lagrange duality and SCA
[81]	✗	Resource optimization for multi-UAV assisted MEC with partial offloading	Maximize computational efficiency of the system	Power and spectrum resources	Non-convex joint optimization	Multi-loop iterative computation efficiency maximization algorithm

[5]	✗	Computation efficient system for UAV-enabled MEC under partial computation offloading	Maximize the computational efficiency of the system	Communication and computation requirements and resources	Non-convex joint optimization	Two-stage optimization: Lagrangian dual method, then SCA
[36]	✓	Wireless-powered MEC networks with different computation offloading and transmission modes	Maximize system's computation efficiency under max-min fairness criterion	Minimum bits, EH causal constraint, energy consumption	Non-convex joint optimization	Two iterative algorithms and two alternative optimization algorithms.

2.2 Summary

In summary given in Tables 2.1, 2.2, 2.3, 2.4, 2.5, the existing works are either in the domain of computational efficiency, user energy efficiency, computational offloading or a combination of them in UAV-assisted MEC networks. The authors in [76, 77] showed an interesting view on using TB for backhaul link association. However, there is still a need to make the network self-sustainable without being location-bound to access the power supply. Therefore, in this thesis, we have considered computational efficiency maximization while jointly optimizing UAV location, user association, task offloading time, and transmission power of UE. We propose a three-stage scheme and simulation results are presented to test the effectiveness of the proposed scheme in terms of computational efficiency, bits computed, and energy consumption with a varying number of UAVs and users.

Chapter 3

Computational Efficiency Maximization in UAV-Assisted MEC Network with Energy Harvesting in Disaster Scenarios

By now we have established that the main challenges of UAV-assisted MEC Networks are computation offloading, energy scarcity of UE and computation efficiency. Our work focuses on offloading and computation services, along with energy harvesting provided by UAV to UE. We assume that UEs are resource-constrained devices and offload their computation tasks to UAVs. The UEs perform EH by receiving the RF signals from UAV-BSs to perform their operations and offloading. The UEs can either perform the computation tasks themselves or offload to UAVs. The decision that *n-th* UE can offload computation task to *m-th* UAV can be represented as χ_{nm} which is 1 if there is offloading and 0 otherwise. In an urban environment, there could be obstacles, therefore, we used probabilistic LoS channel model.

In this chapter, we define the system model architecture and formulate a mixed integer non-linear optimization problem to maximize the computation efficiency. Computation efficiency represents the ratio of computed bits vs the energy dissipated by UE, whether to compute the tasks locally if there is no offloading or to offload the tasks to be computed by the UAV-BS in the

UAV-assisted MEC network with EH. We jointly optimize user association, UE power utilized, offloading time duration and UAV's location. The formulated optimization problem is a mixed-integer nonlinear programming problem due to the non-linearity and mixed-integer nature of the objective function and some constraints, which are also defined in this chapter.

3.1 System Model and Problem Formulation

We consider a UAV-assisted MEC network architecture that consists of M number of UAV-BSs and N number of UEs with EH in a disaster scenario as shown in Fig. 3.2. Due to lack of ground communication infrastructure in such unprecedented scenarios, UAV-BS are a quick, flexible and reliable solution to provide network connectivity [3]. We assume that the UEs are resource constrained devices and can offload their computational tasks to UAVs for computational efficiency. The UEs also perform EH by receiving the RF signals from the UAV-BS. The received signal is split into two components with the power splitting ratio, ρ. Therefore ρ amount of the signal is used for EH with EH efficiency, η, and the remaining $1-\rho$ is utilized for communication signal processing. This can also be seen in Fig. 3.1.

The execution time is the total number of CPU cycles required to process any task divided by the total utilized computational capacity $\mathbb{C}_n$ of the n^{th} UE. We further assume that the UAV is equipped with directional antenna where the antenna gain outside of the beam width of antenna is approximately equal to zero [82]. The UAV mainly has three types of communication links: i) UAV-to-ground link, ii) UAV-to-UAV link, and iii) UE-to-UAV link. We use the probabilistic line of sight (LoS) channel model (p_{LOS}) at elevation angle ϕ_m [83] given as follows:

$$p_{LOS} = \frac{1}{1+a\exp\left(-b[\phi_m - a]\right)}. \tag{3.1}$$

where a and b are the channel parameters dependent on the environment. We have assumed block fading channel model and TDMA model, in which the channel remains the same for each time block of duration T. If the n^{th} UE is offloading some data, the portion of time block T for m^{th}

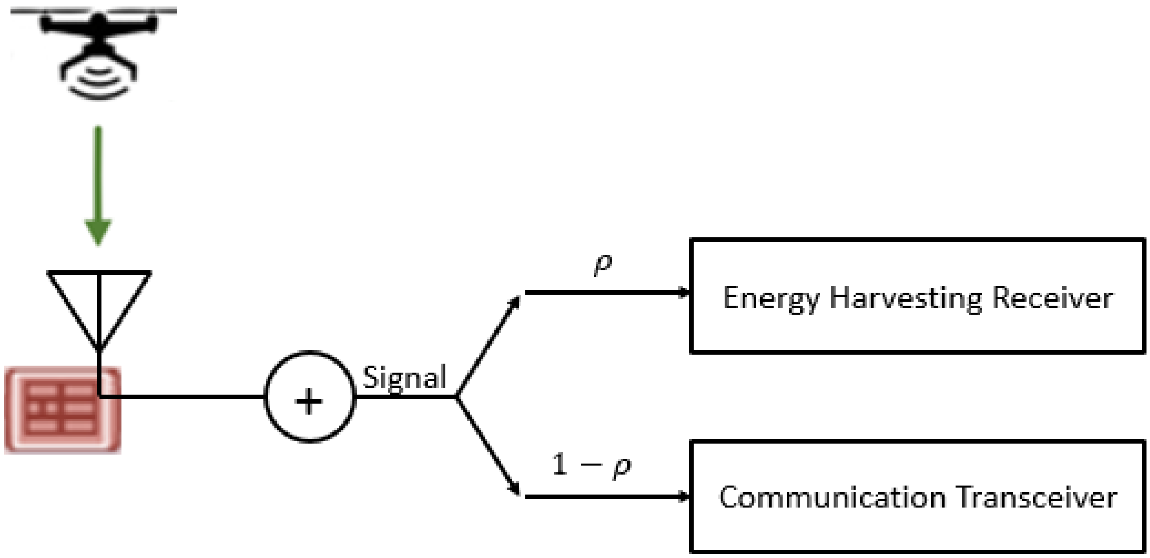

Figure 3.1: Power-splitting architecture.

UAV is assigned to the n^{th} UE, which is denoted by t_{mn}.

The data rate at which the n^{th} UE offloads tasks to the m^{th} UAV is denoted by R_{nm}. Here R_{nm} is calculated as follows:

$$R_{nm} = B \log_2 \left(1 + \frac{\zeta \eta (1-\rho) p_{mn}}{\theta_m^2 (h_m^2 + D_{mn}^2)}\right), \quad \forall n \in N,\ m \in M. \tag{3.2}$$

where B is the channel bandwidth, η is the EH efficiency. θ_m is the half power beam width of antenna for the m^{th} UAV. p_{mn} is the transmission power for the n^{th} UE associated with the m^{th} UAV and ζ is the positive coefficient calculated as follows:

$$\zeta = g_0 G_0 / \sigma^2, \tag{3.3}$$

where σ^2 is the noise power, g_0 is the channel power gain at reference distance $1m$ and $G_0 \approx 2.2846$ [82]. h_m is the height of the m^{th} UAV and D_{mn} is the horizontal displacement between the

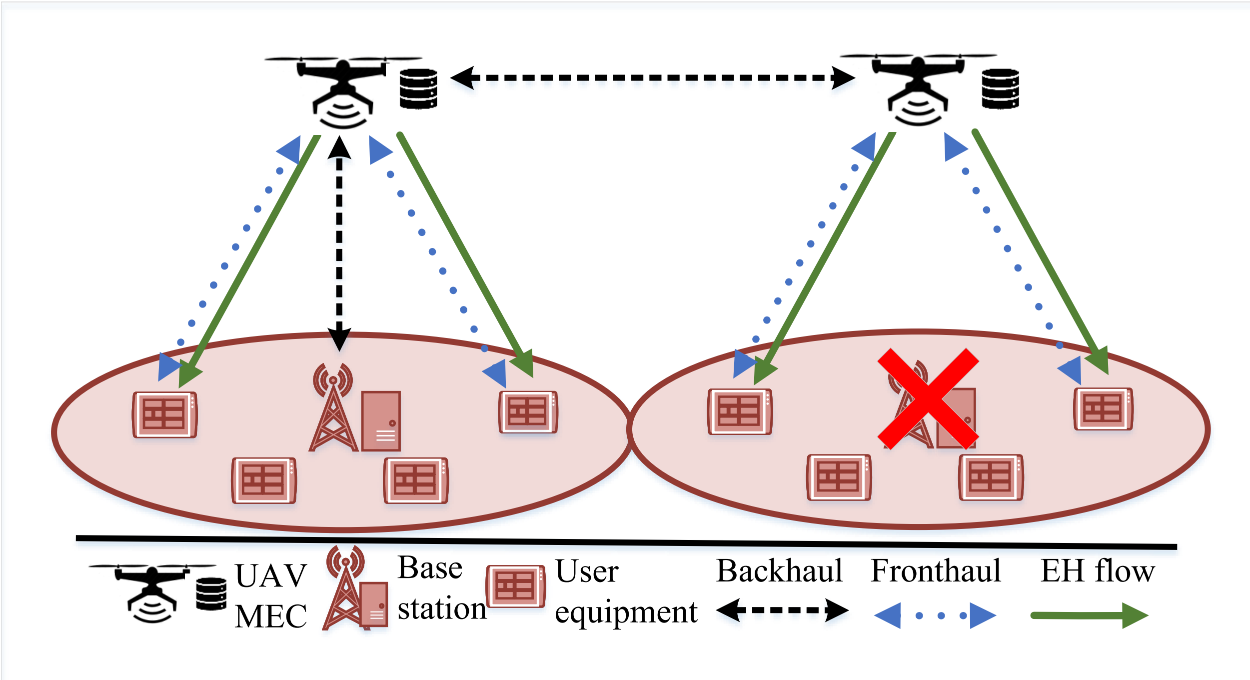

Figure 3.2: UAV-assisted MEC network architecture with EH in a disaster scenario.

n^{th} UE and the m^{th} UAV and is calculated as follows:

$$D_{mn} = \sqrt{(x_m - x_n)^2 + (y_m - y_n)^2}, \tag{3.4}$$

where x_m and y_m are the horizontal coordinates of the m^{th} UAV and x_n and y_n are the horizontal coordinates of the n^{th} UE in a 3D Cartesian coordinate system. Here the coordinates of the n^{th} UE and the m^{th} UAV are represented as (x_n, y_n, 0) and (x_m, y_m, h_m), respectively. It is assumed that the height of the n^{th} UE is zero whereas h_m denotes the height of UAV.

3.1.1 Problem Formulation

The objective of this thesis is to maximize the computational efficiency of UAV-assisted MEC network with EH in a disaster scenario. We jointly optimize the user association, transmission power of UE, offloading time, and UAV location while fulfilling the quality of service requirements of the UAV-assisted MEC network. The decision that the n^{th} UE offloads the computation tasks to the m^{th} UAV can be represented as χ_{nm} which is 1 if there is offloading and 0 otherwise.

$$\chi_{nm} = \begin{cases} 1 & \text{if } n^{th} \text{ UE offloads task to } m^{th} \text{ UAV} \\ 0 & \text{otherwise.} \end{cases} \tag{3.5}$$

We consider following constraints to formulate optimization problem for computational efficiency maximization for UAV-assisted MEC networks.

C1: The n^{th} UE can either perform task locally or can offload the task to only one UAV, such that the computation of a given task can be done only once. This can be written as:

$$\sum_{m=1}^{M} \chi_{nm} \leq 1, \forall n. \tag{3.6}$$

C2: Only a limited number of UEs can be associated to each UAV as shown below:

$$\sum_{n=1}^{N} \chi_{nm} \leq \mu_m^{max}, \forall m, \tag{3.7}$$

where μ_m^{max} represents the maximum number of UEs allowed to be associated with m^{th} UAV.

C3: The total computational capacity required by the n^{th} UE, represented by $\mathbb{C}_n$, should be less than or equal to the total available computational capacity of the n^{th} UE, $\mathbb{C}_n^{max}$. This can be mathematically represented as:

$$\mathbb{C}_n \leq (1 - \chi_{nm})\mathbb{C}_n^{max}, \forall n. \tag{3.8}$$

C4: Time required for offloading the tasks, t_{mn}, is constrained by the TDMA block size T. This can also be written as:

$$\sum_{n=1}^{N} t_{mn} \leq T, \forall m, \tag{3.9}$$

$$t_{mn} \leq \chi_{nm} T, \forall m, n. \tag{3.10}$$

C5: The total number of bits computed locally and offloaded, combined, should be greater than β_n bits. This can be mathematically expressed as:

$$\frac{\rho T \mathbb{C}_n}{\gamma_n} + \sum_{m=1}^{M} \chi_{nm} R_{nm} t_{mn} \geq \beta_n, \forall n. \tag{3.11}$$

where β_n represents the minimum number of bits computed, γ_n represents cycles per bit for the n^{th} UE.

C6: The energy consumption of the n^{th} UE is constrained by the maximum available energy (E_{th}). This can be mathematically explained as:

$$E_n^{C_{ir}} + \alpha_n (\mathbb{C}_n)^{\omega} T + \sum_{m=1}^{M} \zeta \eta (1-\rho) p_{mn} t_{mn} \leq E_{th}, \forall n. \tag{3.12}$$

where E_{th} represents the maximum available energy of the system, $E_n^{C_{ir}}$ is the total circuit energy of the n^{th} UE, ω is a positive coefficient, and α_n is also a positive coefficient.

C7: The transmission power of the n^{th} UE is constrained by the maximum available power, p_n^{max}, of the n^{th} UE itself. This can be written as:

$$p_{mn} \leq \chi_{nm} p_n^{max}, \forall m, n. \tag{3.13}$$

C8: The m^{th} UAV should be in the coverage range of n^{th} UE for task offloading, as shown below:

$$\chi_{nm} D_{mn} \leq h_m \tan \theta_m, \forall m, n. \tag{3.14}$$

C9: The locations of both the n^{th} UE and m^{th} UAV should be in feasible range. This can be written as:

$$x_m^{min} \leq x_m \leq x_m^{max}, \forall m, \tag{3.15}$$

$$y_m^{min} \leq y_m \leq y_m^{max}, \forall m. \tag{3.16}$$

where x_m^{min} and x_m^{max} represent the minimum and maximum values for x_m to be in the feasible range, y_m^{min} and y_m^{max} represent the minimum and maximum values for y_m to be in the feasible range.

C10: The height of the m^{th} UAV and half power beam width must also lie in the feasible range, as given below:

$$h_m^{min} \leq h_m \leq h_m^{max}, \forall m, \tag{3.17}$$

$$\theta_m^{min} \leq \theta_m \leq \theta_m^{max}, \forall m. \tag{3.18}$$

where h_m^{min} and h_m^{max} represent the minimum and maximum values for h_m to be in the feasible range, θ_m^{min} and θ_m^{max} represent the minimum and maximum values for θ_m to be in the feasible range.

Total number of bits computed can be written as the sum of bits computed locally by the UE as well as the bits offloaded to the UAV-BS for computation offloading.

$$\sum_{n=1}^{N} \left(\frac{\rho T \mathbb{C}_n}{\gamma_n} + \sum_{m=1}^{M} \chi_{nm} R_{nm} t_{mn} \right), \tag{3.19}$$

The total energy consumed can be written as the amount of energy consumed to power the UE, the energy required to compute the task locally by UE, and the energy required to offload the task to the UAV.

$$\sum_{n=1}^{N} \left(E_n^{C_{ir}} + \alpha_n (\mathbb{C}_n)^w T + \sum_{m=1}^{M} \zeta \eta (1-\rho) p_{mn} t_{mn} \right), \tag{3.20}$$

The utility function, U, can be defined as the total bits computed per energy consumed to show computation efficiency:

$$U = \frac{\sum_{n=1}^{N}\left(\frac{\rho T \mathbb{C}_n}{\gamma_n} + \sum_{m=1}^{M} \chi_{nm} R_{nm} t_{mn}\right)}{\sum_{n=1}^{N}\left(E_n^{C_{ir}} + \alpha_n (\mathbb{C}_n)^w T + \sum_{m=1}^{M} \zeta\eta(1-\rho) p_{mn} t_{mn}\right)} \tag{3.21}$$

The optimization problem to maximize the computation efficiency of UAV-assisted MEC networks with energy harvesting is given as:

$$\begin{aligned} &\max_{\chi_{mn},\rho,p_{mn},t_{mn},x_m,y_m,h_m} : U, \\ &\text{Subject to: } C1 - C10 \\ &\qquad \chi_{nm} == \{0,1\}, \forall m, n. \end{aligned} \tag{3.22}$$

The formulated optimization problem is an MINLP problem. The formulation in (3.22) is an MINLP optimization problem that belongs to the class of problems that is generally Non-deterministic polynomial-time hard (NP-Hard) [84]. Thus, due to NP-Hard nature of the problem, we cannot get its optimal solution in polynomial time. Therefore, a brute force search-based algorithm for the optimization problem would enumerate all discrete decision variables. However, the complexity of enumerating all discrete decision variables grows exponentially with the increase in number of UAVs and UEs. Thus, we propose a three-stage scheme to solve the optimization problem in (3.22).

3.2 Summary

In this chapter, we defined the system model architecture for a UAV-assisted MEC network with EH. We formulated an MINLP optimization problem to maximize the computation efficiency of the system, where computation efficiency represents the ratio of computed bits vs the energy dissipated by UE. We jointly optimize user association, UE power utilized, offloading time duration and UAV's location. The objective function and constraints considered are also explained in this chapter.

Chapter 4

Proposed Scheme and Simulation Results

The three-stage solution approach is explained in this chapter. Details of the simulations performed and results obtained are then presented in terms of bits computed, energy consumed and the computation efficiency, which is also referred to as the utility of the system.

4.1 Solution Approach

We propose a three-stage scheme to solve the MINLP optimization problem (3.22) as shown in Fig. 4.1. In the first stage, we adopt k-means clustering to determine the optimal locations of the UAV-BSs. In the second stage, the user association decision is made based on the distance from the nearest UAV and maximum available connections of the UAV. In the third stage, with the known realization of placement of UAVs and their associated UEs, we divide the remaining problem into two sub-problems. First, we adopt linear approximation to linearize the MINLP problem, then we apply the IPM to solve the formulated linear optimization problem to maximize the computational efficiency while optimizing UE transmission power and offloading time.

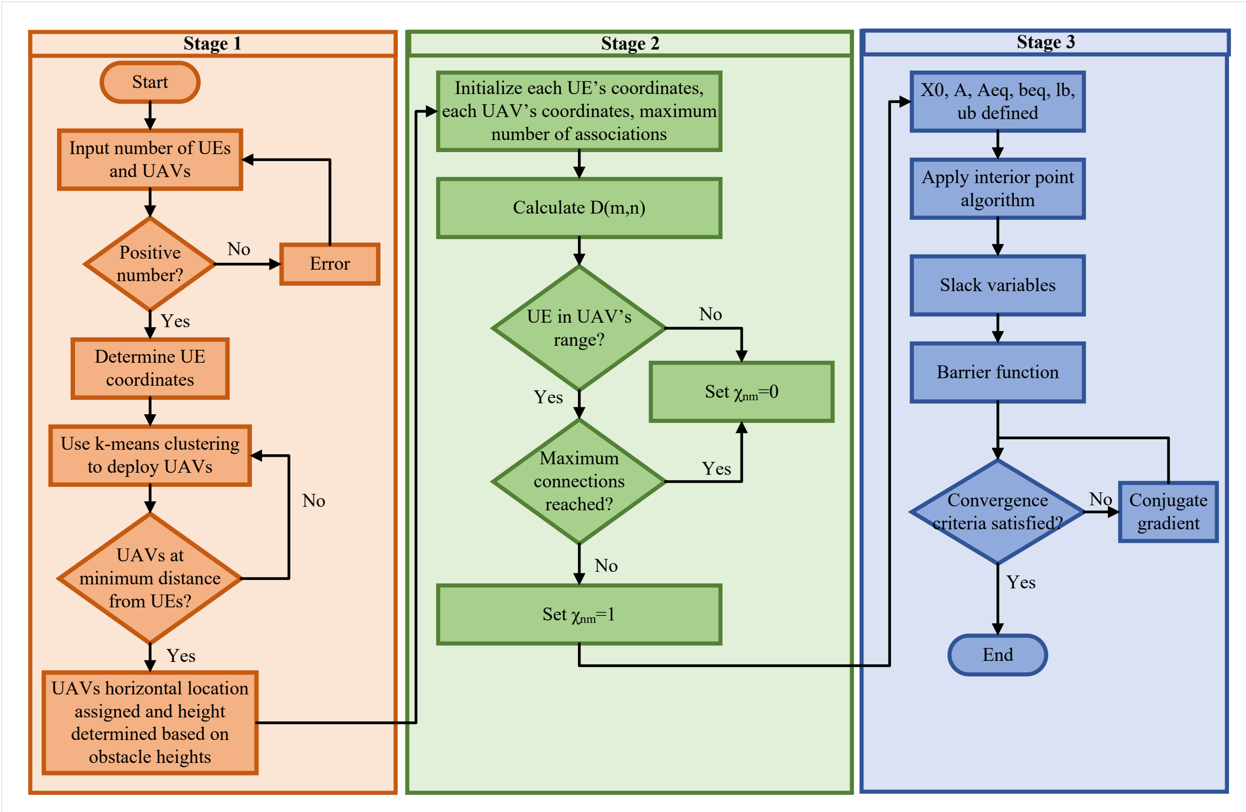

Figure 4.1: Proposed three-stage scheme.

4.1.1 UAV location determination

We consider the total number of N UEs and M UAVs as input of the proposed three-stage scheme. In the first stage, the coordinates of m^{th} UAV are determined with respect to their surrounding UEs. Then all N UEs are randomly assigned location coordinates. Following that, they are divided into M clusters using a k-means clustering algorithm. The k-means clustering algorithm is a classic statistic algorithm for cluster formation, where the samples are divided into a certain number of clusters based on their proximity. The solution generated by using this algorithm is guaranteed to be locally optimum with respect to error compared with the entire sample size. There have been many variations of it such as the k-means++ and the balanced k-means, which are less biased but computationally intensive. The results from these derivative algorithms are also similar to the classic k-means algorithm with less bias [85]. Therefore, we have used the k-means algorithm to determine the cluster formation for UEs based on the number of UEs in each cluster. Following which, the optimal horizontal coordinates (x_m, y_m) of the m^{th} UAV are determined based on the being placed in the cluster centers. The height of the m^{th} UAV, denoted as (h_m), is determined based on the obstacle heights in the algorithm in order to achieve LoS communication.

4.1.2 UE association decision

Once the UAVs' optimal location coordinates (x_m, y_m, h_m) are determined, the algorithm moves into the second stage, where it makes the UE association decision. This stage is initialized by inputting the maximum number of allowed connections for the m^{th} UAV. In this stage, association of each n^{th} UE is determined with the m^{th} UAV. This is subject to the proximity of the n^{th} UE from the m^{th} UAV and the predefined maximum number of allowed connections for the m^{th} UAV. Thus, the distance matrix, $D(m, n)$, is calculated for the distance between the n^{th} UE and the m^{th} UAV. Based on the distance matrix $D(m, n)$ for the n^{th} UE, a connection is established with the closest UAV and the binary variable χ_{nm} is set to be 1 considering the m^{th} UAV has not reached its maximum connections yet. This continues for the next n^{th} UE to associate with the m^{th} UAV until the maximum number of connections for the m^{th} UAV reaches its predefined maximum number of allowed connections. Hence, for the remaining UEs whose connection is not established, the binary association variable, χ_{nm} is set to be 0. Therefore, if the n^{th} UE is in the m^{th} UAV's range and the m^{th} UAV has not reached its maximum connections yet, then χ_{nm} is set to 1 based on the established association. If either the maximum number of associations for the m^{th} UAV are reached or the n^{th} UE is not in range, χ_{nm} is set to 0 representing no established association between the m^{th} UAV and the n^{th} UE.

4.1.3 Optimization when $\chi_{nm} = 0$

If the number of maximum connections for a UAV is already reached, or if $D(m, n)$ is not in the feasible range, the association indicator, χ_{nm} is set to 0. Therefore, to establish the connection for the n^{th} UE, the new optimal coordinates of the m^{th} UAV are calculated, and denoted by (x^*_m, y^*_m, h^*_m). In that case, the optimization problem becomes:

$$
\begin{aligned}
\max_{\chi_{mn}, p_{mn}, t_{mn}, x^*_m, y^*_m, h^*_m} &: U, \\
\text{Subject to:} & \\
C1 - C7 &: \text{from (3.22)} \\
C8 &: \chi_{nm} D^*_{mn} \leq h^*_m \tan\theta^*_m, \forall m, n. \\
C9 &: x^{min}_m \leq x^*_m \leq x^{max}_m, \forall m \\
& \quad y^{min}_m \leq y^*_m \leq y^{max}_m, \forall m. \\
C10 &: h^{min}_m \leq h^*_m \leq h^{max}_m, \forall m \\
& \quad \theta^{min}_m \leq \theta^*_m \leq \theta^{max}_m, \forall m.
\end{aligned} \tag{4.1}
$$

where $D(m, n)$ is given by:

$$
D^*_{mn} = \sqrt{(x^*_m - x_n)^2 + (y^*_m - y_n)^2}, \tag{4.2}
$$

and R_{nm} is given by:

$$
R_{nm} = B \log_2 \left(1 + \frac{\zeta\eta(1-\rho)p_{mn}}{\theta^{*2}_m (h^{*2}_m + D^{*2}_{mn})} \right), \quad \forall n \in N,\ m \in M. \tag{4.3}
$$

4.1.4 Linearization and optimization through IPM when $\chi_{nm} = 1$

Due to the non-linearity of the constraints the formulated optimization is an MINLP problem. At this stage, we divide the problem into two sub-problems. In the first sub-problem, we use linear approximation to linearize the MINLP into a mixed integer linear programming (MILP) problem.

The multi-tree outer approximation for convex MINLPs was originally proposed in [86]. There have been few enhancements to it, including in [87] and [88]. The convex MINLP problem is divided into two sub-problems. The first one is a mixed-integer linear relaxation of the original convex MINLP, tightened with linear outer approximation cuts subsequently for the convex nonlinearities. The second sub-problem is a convex non-linear sub-problem resulting from fixing all integer variables to the solution of the first sub-problem. With the correct assumptions, all feasible integer solutions are visited once at most, and the algorithm terminates after a finite number of iterations [89].

Subsequently, in the second sub-problem within the third stage of the optimization scheme proposed, we use IPM to solve the MILP optimization problem. The problem is initialized with a feasible value, and checked for convergence. If it converges under a certain tolerance level, we conclude the search. However, if it is not under the tolerance level, the search direction needs to be computed with the linearized barrier problem, using slack variables. The optimal value is determined by decreasing the merit function for backtracking line search, and checking for convergence under the tolerance level again.

4.1.5 Complexity of the proposed algorithm

The proposed three-stage algorithm comprises of k-means learning algorithm in the first stage to form clusters and find optimal locations for M UAVs with respect to N UEs. The complexity of this stage is determined by $\mathcal{O}(N^2)$ [90], where N is the number of UEs. In the second stage of the proposed algorithm, the user association is optimized, denoted by the association indicator, χ_{nm}. The complexity of this stage is determined by $\mathcal{O}(MN)$, where M is the number of UAVs and N is the number of UEs. In the third and last stage of the proposed algorithm, a linear approximation is applied followed by IPM to maximize the objective function by jointly optimizing user transmission power, and offloading time duration. The complexity of this stage of the algorithm is determined by $\mathcal{O}(N^{3.5}\log(1/\epsilon)$ with precision accuracy of ϵ [91]. So the total complexity of the proposed algorithm becomes $\mathcal{O}(N^2 + MN + N^{3.5}\log(1/\epsilon)$, which can be written as $\mathcal{O}(N^{3.5}\log(1/\epsilon)$.

Table 4.1: Simulation parameters

Parameter	**Value**
Number of UAVs, M	4-20
Number of UEs, N	20-300
TDMA time block T [82]	2 ms
System bandwidth B [82]	1 MHz
Offloading indicator, χ_{nm}	0 / 1
Positive coefficient, α_n	10^{-2e^9+1}
Positive coefficient, a	9.61
Positive coefficient, b	0.16
Positive coefficient, ω	2
Noise power, σ^2	-80 dBm/Hz
Maximum associations allowed with UAV m, μ_m^{max}	15
Maximum computation capacity of UE n, $\mathbb{C}_n^{max}$	1GHz
Maximum available energy E_{th} of UE n	20 dBm
Constant circuit energy of UE n, $E_n^{C_ir}$	0.00001 W
Minimum height of UAV m, h_m^{min}	10
Maximum height of UAV m, h_m^{max}	20
Minimum half power beam width, θ_m^{min}	$\pi/6$
Maximum half power beam width, θ_m^{max}	$\pi/3$
Half power beam width of antenna for UAV m, θ_m	pi/6 - pi/3 rad
Horizontal distance between UAV m and UE n, D_{mn}	$\leq$ 500m

4.2 Simulation Results

We simulate the proposed solution in MATLAB by considering the different scenarios of UAV-assisted MEC networks with EH while varying the number of UAVs and UEs. The scenarios we have first considered include a set of 4, 12, and 20 UAVs, then for each set of UAVs, we consider 100, 200, and 300 UEs. The scenarios are: for 4 UAVs we consider 100 UEs (scenario 1), 200 UEs (scenario 2), and 300 UEs (scenario 3). Then, sets of scenarios 4, 5, and 6 as well as scenarios 7, 8, and 9 follow the same number of UEs as scenarios 1, 2, and 3. However, scenarios 4, 5, and 6 have 12 UAVs and 7, 8, and 9 have 20 UAVs. The channel bandwidth considered is $1MHz$, the noise power is set to $-80dBm/Hz$ and the range is set to $500m$. The constraint on latency is $6ms$ and the TDMA time block, T is set to $2ms$. The minimum number of bits transmitted is set to 50. The maximum computation power of a UAV is considered $1GHz$ and the maximum number of UEs connected to a given UAV are 15. Detailed simulation parameters are given in Table 4.1.

Fig. 4.2 shows the performance comparison in terms of utility, bits computed, and energy consumption for different scenarios mentioned above. Within each scenario, we have four different use cases in a disaster scenario, such that (i) no offloading nor EH, (ii) offloading but no EH, (iii) offloading with EH, and (iv) no offloading with EH.

Bits computed

It can be observed from Fig 4.2 for all four use cases, that with the increase in the number of UEs from 100 UEs in scenario 1 to 200 UEs in scenario 2, then to 300 UEs in scenario 3, there is an increase in the number of bits computed. This is as expected, as there are more computation tasks associated with the newly introduced UEs in each scenario. The same trend of increase in bits computed is observed with the increase in the number of UEs from 100 UEs in scenario 4 to 200 UEs in scenario 5, then to 300 UEs in scenario 6, where the number of UAVs stays constant at 12 UAVs. Similarly for the increase from 100 UEs in scenario 7 to 200 UEs in scenario 8, then to 300 UEs in scenario 9, with the number of UAVs constant at 20 UAVs, a significant amount of increase can be seen in offloading cases due to the added offloading assistance from UAVs, compared to the increase in no offloading cases with a gradual increase in amount of bits computed locally.

When comparing scenarios 1, 4 and 7, the number of UEs remains constant at 100 UEs. However, number of UAVs increases from 4 UAVs in scenario 1 to 12 UAVs in scenario 4, and 20 UAVs in scenario 7. From Fig. 4.2, it can be seen that the number of bits computed remains the same for no offloading cases, as expected as the 100 UEs are processing the same amount of tasks as their limited capacities allow. On the other hand, for the offloading cases, there is a significant increase in the number of bits computed with offloading assistance from a greater number of UAVs in scenario 4 with 12 UAVs compared to scenario 1 with 4 UAVs. Along the same lines, a significant increase in bits computed can also be observed for scenario 7, with the number of UAVs increased to 20 UAVs. Similarly, the pattern for bits computed is repeated for offloading and no offloading cases for scenarios 2, 5 and 8 with the number of UEs constant at 200 UEs but UAVs increasing from 4 UAVs to 12 UAVs and again for scenarios 3, 6 and 9 with the number of UEs constant at 300 UEs but UAVs increasing to a constant 12 UAVs. The computed bits for EH and no EH cases remain the same within scenarios as energy harvesting does not impact task computation. However, offloading cases compute a significantly larger number of bits within each scenario due to the greater computation capacities of the UAVs the data is offloaded to.

Energy consumption

For the energy consumption based on the results shown in Fig. 4.2, there is a general trend of an increase in the amount of energy consumed for all four use cases with an increase in number of UEs. For scenarios 1, 2, and 3 with 4 UAVs, with the increase in the number of UEs from 100 UEs in scenario 1 to 200 UEs in scenario 2, the number of powered devices nearly doubles, hence the energy utilized nearly doubles for all four use cases. Then to 300 UEs in scenario 3, the number of powered devices nearly triples compared to scenario 1, hence the energy utilized nearly triples too, reflecting the amount of energy consumed to locally execute and offload a greater number of tasks to UAVs. Similarly, a significant increase in energy consumption can be observed for scenarios 4, 5, and 6 with the same number of 12 UAVs but an increase in UEs from 100 UEs in scenario 4 to 200 UEs in scenario 5, then to 300 UEs in scenario 6, where the number of UAVs stays constant at 12 UAVs. Similarly, with the number of UAVs constant at 20 UAVs, the increase from 100 UEs in scenario 7 to 200 UEs in scenario 8, then to 300 UEs in scenario 9 impacts the energy consumption significantly for all four use cases.

Despite an increase in number of UAVs from 4 UAVs in scenario 1 to 12 UAVs in scenario 4, and 20 UAVs in scenario 7. It can be seen from Fig. 4.2 that since the number of UEs is constant, the energy consumed remains the same for no offloading cases due to the same amount of computation happening locally and no energy used for EH. The same applies to the increase in UAVs for a constant number of UEs in scenarios 2, 5 and 8 at 200 UEs, and again in scenarios 3, 6 and 9 at 300 UEs for no offloading cases. However, for the offloading cases the energy utilized is slightly higher for powering a larger number of UAVs in scenario 4 with 12 UAVs compared to 4 UAVs in scenario 1 with no EH and a constant 100 UEs. Similarly, the energy utilized for

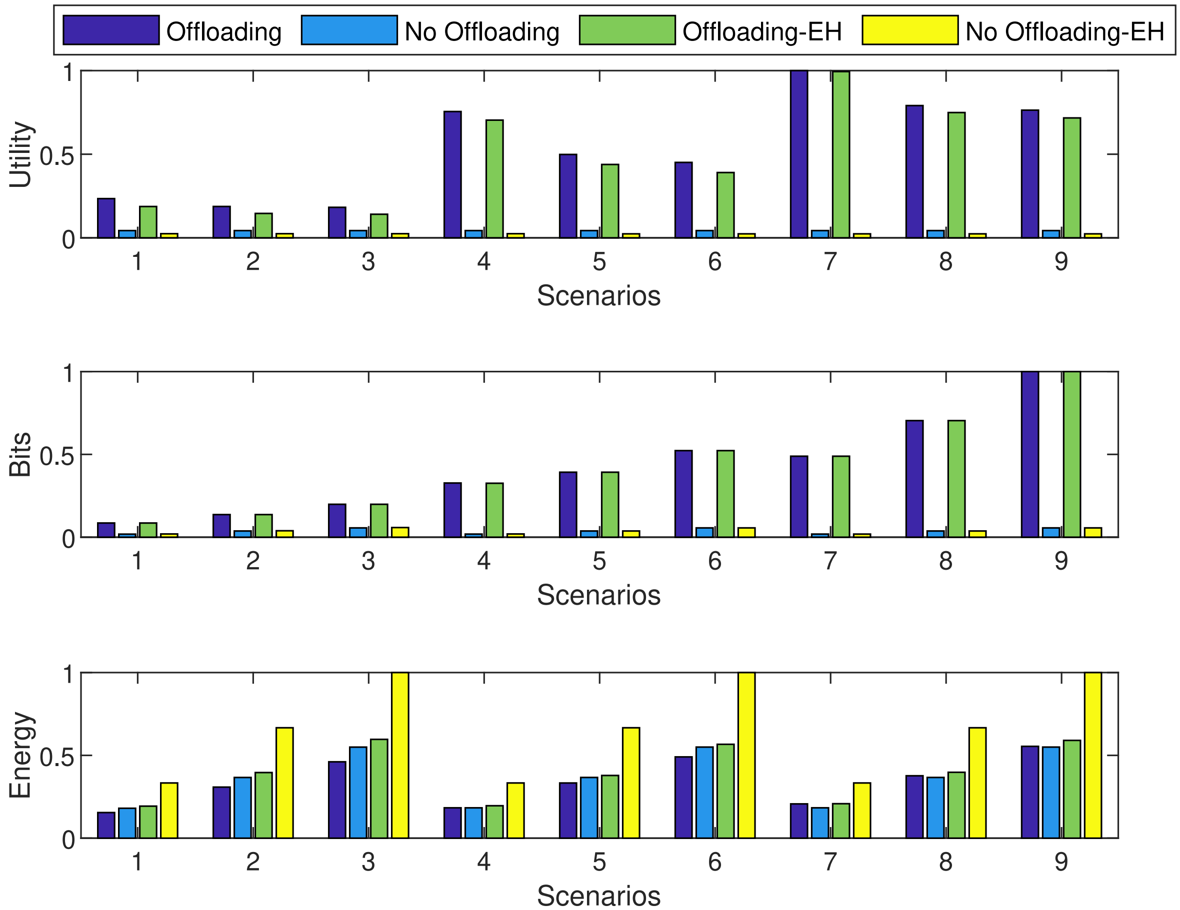

Figure 4.2: Performance comparison of offloading and no-offloading scenarios with/without EH in terms of i) utility, ii) number of bits computed, and iii) energy consumption.

offloading cases is slightly higher for powering a larger number of UAVs in scenario 7 with 20 UAVs compared to 12 UAVs in scenario 4 with no EH and a constant number of 200 UEs. The same applies again to scenarios 3 with 4 UAVs, 6 with 12 UAVs and 9 with 20 UAVs with a constant 300 UEs for offloading cases.

An interesting observation from Fig. 4.2 is that since the energy consumed for no offloading no EH cases remains the same across scenarios 1, 4, and 7 with the same number of 100 UEs but an increasing number of UAVs, the energy consumption for offloading with no EH to 4 UAVs in scenario 1 is less than the no offloading case, for 12 UAVs in scenario 4 is about the same as the no offloading case and for 20 UAVs in scenario 7, it is greater than the no offloading case due to the increase in the number of offloaded tasks. The same applies to scenarios 2, 5 and 8 due to the increase in offloaded tasks to the increased number of UAVs, as well as to scenarios 3, 6 and 9 due to the increase in offloaded tasks to the increased number of UAVs.

The cases with offloading and EH have a slightly greater increase in energy utilized compared with the cases with offloading and no EH, due to the energy consumed to harvest the energy. It may seem like EH consumes a greater amount of energy. However, the energy generated is far greater. This phenomenon is evident from the no offloading and enabled EH cases, where the energy consumed is far greater due to the consumption of the harvested energy in computing the tasks locally. It remains the same across the increase in number of UAVs from 4 UAVs in scenario 1 to 12 UAVs in scenario 4 and 20 UAVs in scenario 7 due to no offloading. Similarly for the increase in number of UAVs from 4 UAVs in scenario 2 to 12 UAVs in scenario 5 and 20 UAVs in scenario 8. Then again for the increase in number of UAVs from 4 UAVs in scenario 3 to 12 UAVs in scenario 6 and 20 UAVs in scenario 9. However, the energy consumed increases with the number of UEs from 100 UEs in scenarios 1, 4 and 7 to 200 UEs in scenarios 2, 5 and 8, and again with the increase in UEs to 300 UEs in scenarios 3, 6 and 9 because of the increased number of tasks requiring computation for the increased number of UEs.

Computation efficiency (utility)

The net computation efficiency, referred to as utility in Fig. 4.2 is calculated by the ratio of bits computed to the energy consumed. For no offloading cases across all 9 scenarios, the bits computed locally gradually increased with increments of 100 UEs in scenarios 1, 2 and 3, then again in scenarios 4, 5 and 6, and again in scenarios 7, 8 and 9. The same gradual increase applied to the amount of energy consumed to compute the tasks of 100 UEs in scenarios 1, 2 and 3, 200 UEs in scenarios 4, 5 and 6, and 300 UEs in scenarios 7, 8 and 9. Upon calculating the computation efficiency, since the energy consumed was directly proportional to the bits computed with everything performed locally, the computation efficiency came out to be the same across all 9 scenarios in no offloading cases.

For the offloading cases, the utility decreases with the increase in the number of UEs from 100

UEs in scenario 1 to 200 UEs in scenario 2, and again to 300 UEs in scenario 3 due to the increased number of tasks to be computed, requiring an increased amount of energy to offload and compute the tasks for the same number of UAVs that the tasks can be offloaded to. Similarly, for scenarios 4 with 100 UEs, 5 with 200 UEs and 6 with 300 UEs, even though the utility is significantly higher with the increased number of UAVs to 12 UAVs due to the closer proximity of the UAVs leading to less energy consumed to offload the tasks to with a greater number of tasks offloaded, the same decrease in utility applies to scenarios 4, 5 and 6 as the number of tasks to be offloaded increases in each scenario with the increased number of UEs. The same applies to scenarios 7 with 100 UEs, 8 with 200 UEs and 9 with 300 UEs. The utility decreases as the number of tasks to be offloaded increases in each scenario with the increased number of UEs. However, the utility is significantly higher with the increased number of UAVs to 20 UAVs due to the closer proximity of the UAVs leading to less energy consumed to offload the tasks to, but more tasks offloaded. For offloading cases with EH, more energy is required to harvest the energy for the same amount of bits to be computed when offloading without EH, leading to a slight decrease in computation efficiency of offloading cases with EH compared to offloading cases without EH. However, the energy harvested is far greater than the energy consumed to harvest it.

In the comparative analysis, we achieve better computational efficiency (utility) results during offloading compared to no offloading cases. We also achieve a greater number of bits computed when offloading than without offloading. However, the energy consumed is greater when offloading, as it involves sending and receiving data related to UAVs' computational tasks. In the EH cases, the bits transmitted remain the same as without EH cases. However, net utility is slightly less in EH cases as some level of computation is required for enabling EH. The energy utilized in EH cases is slightly greater to enable EH. However, the energy generated is significantly greater. It can be seen from the results that the most inefficient case in terms of energy is when there is no offloading nor EH. The overall computational efficiency, i.e., maximization of bits computed and minimization of energy utilized, is significantly greater for scenarios with offloading compared to scenarios without offloading.

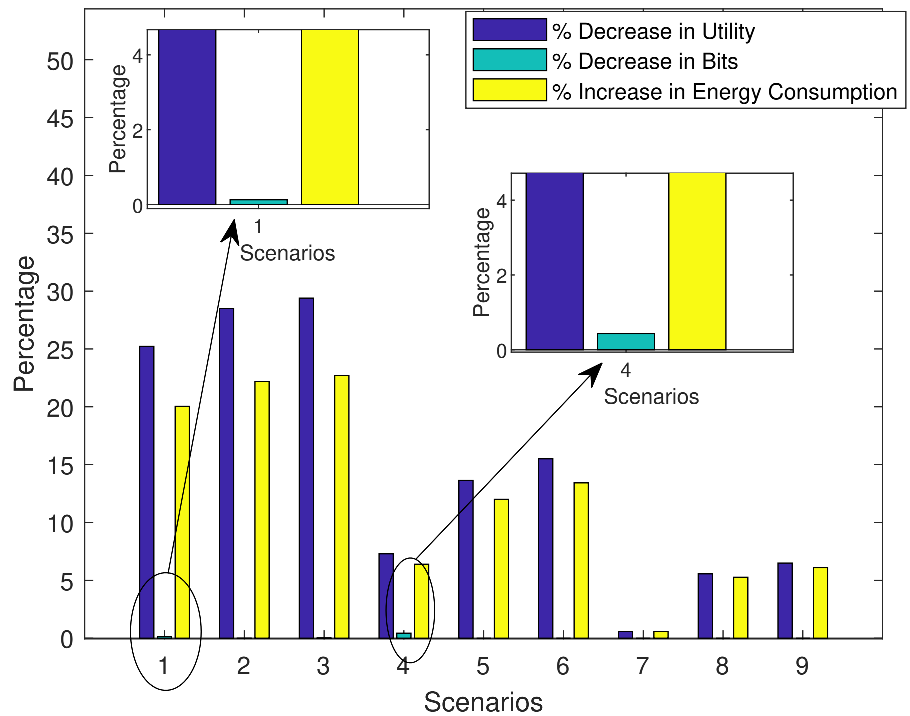

Figure 4.3: Impact analysis of offloading scenario with EH in comparison with only offloading.

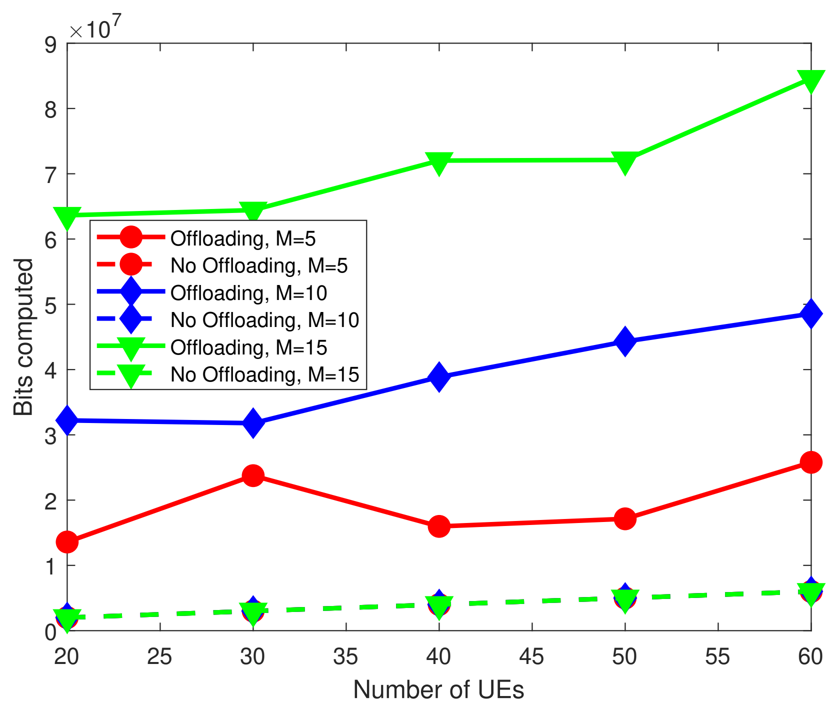

Figure 4.4: Performance analysis in terms of bits computed for offloading and no-offloading scenarios with a varying number of UAVs.

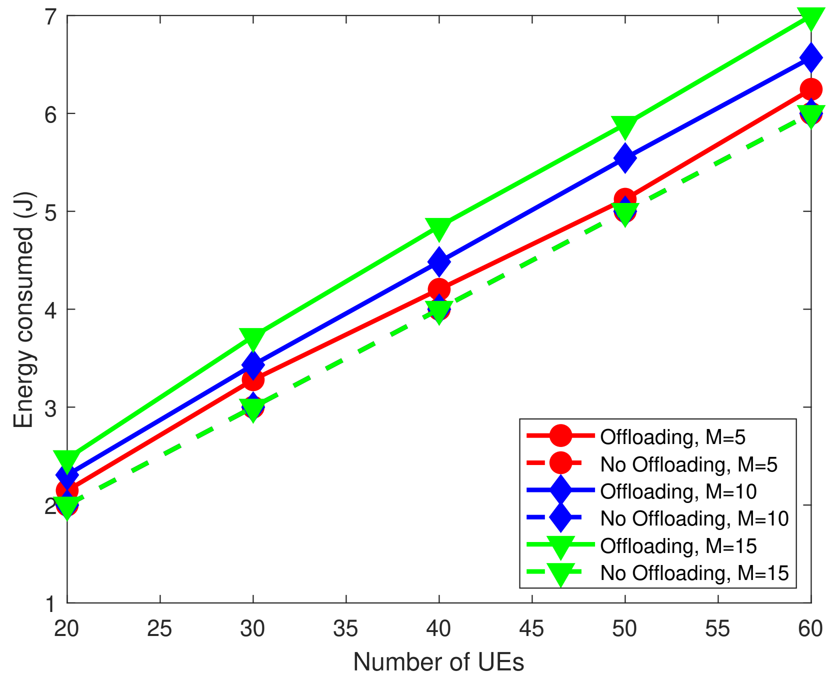

Figure 4.5: Performance analysis in terms of energy consumed for offloading and no-offloading scenarios with a varying number of UAVs.

Fig. 4.3 shows the percentage increase or decrease for offloading with EH compared to offloading without EH in terms of net utility, bits computed, and energy consumption. As the number of UAVs increases, the utility gap reduces, demonstrating the increase in energy harvested and the increase in bits computed. Since the number of bits computed is similar with and without offloading, it can be noted that despite the increase in energy consumption for offloading scenarios with less number of UAVs, the overall percentage increase in energy consumption is reduced with the increase in the number of UAVs in scenarios with EH.

Since we observed the superiority of EH over no EH cases, we now evaluate the performance for offloading and no offloading cases with EH. For Figs. 4.4, 4.5 and 4.6, we have considered offloading and no offloading scenarios with EH in the cases of 5, 10 and 15 UAVs catering for 20, 30, 40, 50 and 60 UEs. Fig. 4.4 presents the performance analysis in terms of bits computed for offloading and no-offloading scenarios with EH for a varying number of UEs and UAVs. Similar to Fig. 4.4, Fig. 4.5 shows the performance analysis for offloading and no offloading cases with EH

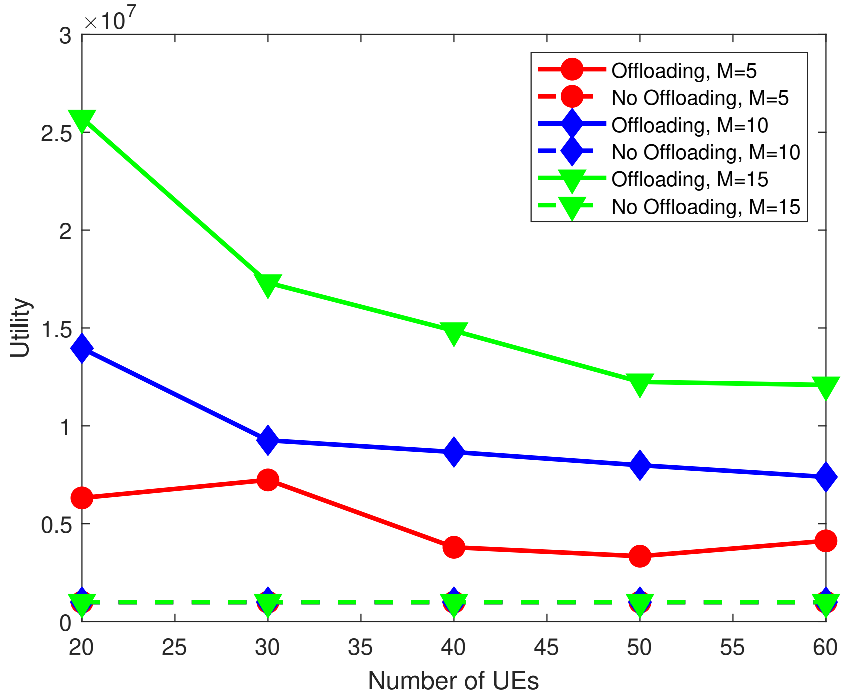

Figure 4.6: Performance analysis in terms of utility for offloading and no-offloading scenarios with a varying number of UAVs.

for a varying number of UAVs and UEs in terms of energy consumed. Similarly, Fig. 4.6 shows the performance comparison in terms of utility for offloading and no-offloading scenarios with EH for a varying number of UAVs and UEs.

It is clear from Fig. 4.4 that better performance is achieved in terms of bits computed for offloading than in no-offloading cases. The results show that for no offloading scenarios, the total number of bits computed gradually increases with the increase in the number of UEs from 20 UEs to 60 UEs as task computation is performed locally by each UE. The overlap for the three no-offloading scenarios also implies that increasing the number of UAVs has no impact on the number of bits computed in the scenarios without offloading, as the computation tasks are still locally performed by UEs. On the contrary, for offloading cases, the number of bits computed does not necessarily increase with the increase in the number of UEs as discussed previously, it can also decrease. This could be due to the widespread UEs and UAVs leading to $D(m, n)$ not being in feasible range for offloading, or the maximum number of associations being reached for UAVs so

UEs are unable to associate nor offload computation tasks. Therefore capping the maximum bits computed by certain UEs. An increase in the number of UAVs from 5 UAVs to 10 UAVs, and from 10 UAVs to 15 UAVs leads to UAVs being more readily available in 3-D space. Hence, provide more offloading opportunities for the UEs. Therefore, a greater number of computation tasks are performed by UAV leading to a higher number of total bits computed.

Similar to Fig. 4.4, it is evident from results in Fig. 4.5 that for cases without offloading, the energy consumed for local task computation gradually increases with the increase in the number of UEs from 20 UEs to 60 UEs. However, regardless of the increase in the number of UAVs, the energy consumed during no-offloading cases remains the same as all computation is locally performed by the UEs. This is why the increase in number of UEs directly impacts the energy consumed in no-offloading cases. However, for the offloading cases, the increase in number of UAVs and UEs both impact the energy consumption. The increase in energy consumption with an increase in the number of UAVs from 5 UAVs to 10 UAVs, and from 10 UAVs to 15 UAVs for a fixed number of UEs is caused by energy dissipated while offloading tasks from UEs to UAVs, since a greater number of UAVs provides with a greater opportunity to offload tasks. The increase in energy consumption with an increase in number of UEs from 20 UEs to 60 UEs for a fixed number of UAVs is caused by the operational energy of UEs as well as the increased number of tasks to be computed with a greater number of UEs. The rate of increase in energy consumed is consistent for the increase in the number of UEs from 30 UEs to 60 UEs for offloading scenarios with 10 UAVs and 15 UAVs. However, the offloading scenarios with 5 UAVs have a steep incline from 20 UEs to 30 UEs, then a lesser increase from 30 UEs to 40 UEs and 40 UEs to 50 UEs. This is likely due to the maximum number of associations being reached for the UAVs, leading to no offloading and local computation for some UEs, while the rest continue to offload tasks to UAVs. The overall energy consumption for offloading cases is greater than the energy consumption for cases without offloading as some energy is utilized to facilitate offloading.

Since the utility is measured by the ratio between bits computed and energy consumed, it can be observed form Fig. 4.6, that the utility or computation efficiency increases with an increase in bits computed as well as a decrease in energy consumed. In no offloading cases, since both the energy consumed and bits computed consistently increase with the increase in number of UEs from 20 UEs to 60 UEs, the utility remains the same. However, in the offloading scenarios, an increase in utility can be observed with an increase in number of UAVs from 5 UAVs to 10 UAVs, and from 10 UAVs to 15 UAVs as task offloading and bits computed increase significantly with a slight increase in energy consumed to facilitate the offloading. A trend of decreasing utility with the increase in number of UEs from 20 UEs to 60 UEs can be observed for the 10 UAVs and 15 UAVs scenarios with offloading, as expected, as even though the bits computed and energy consumed both increased, the number of bits computed did not increase as much as the increase in amount of energy dissipated. Moreover, the UAVs can only assist a certain maximum number of UEs. Therefore, the UEs computing tasks locally have a limited computation capacity, leading to less bits computed while circuit energy utilized for UAVs and UEs operation gradually increases with the number of UAVs and UEs. However, despite the decrease in utility with an increase in UEs, the overall utility increases significantly in offloading cases, compared to no offloading cases, and in 15 UAVs scenario compared to 10 UAVs scenario as well as in 10 UAVs scenario copmared to the 5 UAVs scenario. An anomaly in utility's overall decreasing trend for 5 UAVs can be seen at 30 UEs and 60 UEs in Fig. 4.6. Since utility is calculated by the ratio of bits computed to energy consumed, the peaks in Fig. 4.6 are a result of peaks formed in Fig. 4.4 where bits computed can potentially be higher due to the spread of UEs being such that most UEs are able to offload tasks to UAVs.

4.3 Summary

In this chapter, we discussed the solution approach, followed by a discussion on the results obtained from the simulations performed. To solve the MINLP problem at hand, we devise a three-stage solution. In the first stage, we optimize UAV location. In the second stage, we determine the user association. In the third stage, we divide the problem into two sub-problems, where we linearize the MINLP, followed by using the interior-point method to solve the MILP problem and optimize the UE energy consumption and offloading time. To summarize the findings, bits computed increased with the aid of UAVs, as the processing tasks at UE can be offloaded to accommodate for more tasks. The energy consumed increased with the operation of UAVs. However, the energy harvested is significantly greater. This leads to the overall significant increase in utility for cases where computation tasks were offloaded to UAVs, compared to cases with local computation at UEs.

Chapter 5

Conclusion and Future Work

5.1 Conclusions

In this thesis, we formulated an MINLP problem for UAV-assisted MEC networks with EH. The proposed work focused on access communication in disaster scenarios, where due to a lack of communication resources, UAV-BS are deployed to assist UEs with the network connection and computation task offloading. To simplify and solve the MINLP at hand, we formulate a three-stage optimization algorithm to maximize the computational efficiency of the system while jointly optimizing user association, transmission power of UE, offloading time, and UAV's optimal location. We find optimal UAV location in the first stage based on k-means clustering. In the second stage, we determine the UE association variable for offloading. In the third stage, we divide the remaining problem into two sub-problems for transmission power and offloading time optimization by linearization and using the IPM. Simulation results are presented to compare offloading with no-offloading scenarios with and without EH. The impact of increasing the number of UAVs and UEs is also analysed in terms of bits computed, energy consumption and computational efficiency of the system. It is evident from the results that EH scenarios provide better computational efficiency. This is because, despite the increase in energy consumed to harvest energy, the energy generated is far greater. It is also noted that the bits computed, and therefore computational efficiency of the system is far greater in offloading cases. This is because the limited computation capacity of the UEs is compensated by the greater capacity of the UAV-assisted MEC network. We can further improve the formulation by incorporating the use of any idle UEs in the near vicinity to offload computation tasks in case the UE is unable to associate with the nearest UAV for offloading.

5.2 Future Research Directions

We conclude the following open research issues and future research directions based on the presented study and its analysis.

Possible future research directions for UAV-assisted MEC networks with EH are:

- Using k-means clustering generates a sub-optimal solution for the considered optimization problem. Therefore, we can incorporate genetic algorithms or reinforcement learning instead of k-means clustering to further improve the discussed solution approach.

- With the anticipated increase in complexity of future communication networks, an ever-evolving solution is the application of machine learning (ML) to various aspects of wireless communications, ranging from signal detection, resource allocation, channel estimation, prediction and channel compression, channel encoding and decoding, end-to-end communication and standardization. Using this phenomenon can further enhance the efficiency and futuristically self-sustain the UAV-assisted MEC networks with EH.

- We have assumed that a control center is deploying UAVs to avoid collisions. Furthermore, due to the high mobility of UAV-BS, the optimal location for wireless access and backhaul links needs to be readjusted over time. The computational offloading to UAV-BS, trajectory design for optimal positioning and resource allocation in a swarm of UAVs with a shift from centralized optimization to distributed optimization can be a direction for future works [92].

- A linear EH model is considered in the current research. Therefore, we can consider non-linear EH model to address the non-linear nature of the EH process.

- Another futuristic directive is battery-less massive access. Currently, we rely on UAV-BS having a small battery and supporting EH. Removing the battery of UEs altogether and relying on EH entirely [45] through THz frequencies for direction or intelligent, reflective surface technology [93] [94] for transmission or relaying, actively or passively, in battery-less devices is an exciting direction for future networks.

- In UAV-assisted MEC networks with EH, we focus on air-to-ground communication to enhance the coverage and connectivity in the presented framework. To accommodate the various QoS requirements based on the type of service provided, further investigation can be performed on integration with satellite communication to automate and self-sustain the space-air-ground integrated networks.

- Reliability and characterization of an aerial communication channel through channel measurement and modelling is a significant milestone for secure and stable transmission in highly dynamic heterogeneous networks such as UAV-assisted MEC networks with EH. Similarly, the cost-effective and commercially available emerging cloud robotics platforms are readily being used to provide mobile communication services to flash crowds and other applications. Therefore, integrating UAV-assisted MEC networks with EH and robotics can address interference and mobility management issues.

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