Multi-objective resource optimization of unmanned aerial vehicles and internet of things devices in time critical applications using evolutionary approaches

by

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Abstract

In this thesis, investigations are done on the use of UAVs to support IoT devices on the ground in time critical applications. Due to advancements in aerial and sensor technology, a team of UAVs can be used to bring about a collaborative effort in supporting IoT devices due to their flexibility and versatility. However, both UAVs and ground IoT devices have limited energy resources since they are powered by battery and as a result, there exists a need to effectively manage their operation. The first part of the investigation involves the use of UAVs to provide aerial services such as video or image data to get more information about the situation on the ground. A multi-parameter encoded model based on a multi-objective optimization algorithm is developed to generate a set of 3D waypoints for each UAV to visit within an expected time frame using variable speeds to maximize service provision without violating any mission constraints and also minimizes the total energy consumed and response time by the UAV team. The proposed model is able to give solutions that improve the energy consumption by 8%. The second part of the investigation involves the use of UAVs as aerial base stations to collect data from IoT devices in the absence of critical communication infrastructure. Another model employing an improved hybrid multi-objective optimization algorithm, is developed to jointly determine the UAV-IoT device association, UAV locations, UAV speeds and hovering durations and the transmit power used by the IoT devices when sending data. The aim is to minimize the energy consumption of both the UAVs and IoT devices as well as maximize the data collected by UAVs. An improvement of 12% is seen in the amount of data collected when compared to similar approaches.

To my lovely father
Mr Gaopalelwe Godfrey Seane Pule

This one is for you. Love you always and forever.
Rest in Peace

"Psalm 23 - Jehova ke modisa wa me"

Declaration of Authorship

I, Kabo Elliot Pule, declare that this thesis titled, 'Multi-objective resource optimization of unmanned aerial vehicles and internet of things devices in time critical applications using evolutionary approaches' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date: 27/12/23

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Chapter 1

Introduction

Over the past two decades, the vast advancement of sensor technology has seen a rapid increase in innovation in both industry and academia. A large number of devices can connect to the Internet to access various services and as a result, the development of more intelligent applications have become more pervasive. This has given birth to the concept of the Internet of Things (IoT) which puts ”smart” at the epicentre of all the technological developments and helps deliver efficient services to different application domains in an effort to improve operational activities [3, 4]. This has changed the traditional way of life into a high technology and smarter way of life [5]. The wide accessibility of sophisticated and futuristic hardware which consumes low power and is available at relatively low costs [6], has greatly improved prototyping efforts to facilitate the timeous delivery of solutions. IoT, being one of the main drivers of the Fourth Industrial Revolution (4IR), gives rise to remote monitoring capabilities and allows a multitude of devices, which are mostly static, to be remotely deployed and connected over a common network to enable information sharing with the aim of creating a more holistic view of the situation and finally deliver that information to a Data Analysis Center (DAC) for intelligentization to help improve decision making efforts. There has been an increase in the amount and quality of data generated since it is more granular and accurate, and also the data collection efforts are timely as the IoT network often operates in real or near real-time [7].

This allows for better tracking of the situation which improves awareness. Some potential application domains include manufacturing, mining, agriculture, healthcare, and smart cities [8–11]. Furthermore, the improvement in aerial technology and robotics has resulted in an emergence of a new form of devices called Unmanned Aerial Vehicles (UAVs), commonly known as drones. UAVs have improved computing and networking capabilities, can be equipped with antennas, sensors and cameras making them highly sophisticated and well suited for cutting edge research. This can be seen from the rise in interest from both academia and industry. Initially, UAVs were mainly used for military applications, but over the years a number of countries including USA, Russia, France and Canada have been involved in UAV development [12]. Most of the current development is around multi-rotor UAVs which are more versatile and smaller in nature. The general public also have access to these UAVs since they are available at relatively lower costs and this is attributed to cost-cutting and miniaturization of equipment. The ability of a UAVs to be quickly deployed makes them suitable for short term or ad-hoc missions [13]. Companies such as Amazon and Embention have integrated IoT in UAVs for their logistics operations [14, 15] and this has greatly improved efficiency. Other UAV applications include precision agriculture, asset inspection, mapping and surveying and aerial photography and videography [16, 17].

1.1 Problem Statement

In this thesis, investigations are carried out on the use of UAVs to support IoT devices on the ground in time critical applications. In time critical applications, there is usually a stringent requirement for pertinent and effective response because any missed deadlines could result in serious repercussions such as loss of property, injury or even death [18, 19]. Examples include floods, hurricanes, earthquakes, wild fires, work place accidents, terrorist attacks, just to mention a few [20]. In such scenarios, due to events taking place suddenly, there is a need for timely support and reporting to allow enough time for decisions to be made effectively to cope with the emergency event immediately. An investigation is done on a pre-disaster scenario where IoT devices are deployed on the ground to continuously monitor data in geographical areas of interest and send that data through fixed terrestrial communication infrastructures called Base Stations (BSs) to the DAC for analysis. By continuously monitoring data in an area, the IoT devices can detect early signs for disasters, raise events and send them to the DAC. As soon as information about the event locations reaches the DAC, a team UAVs can then be deployed to provide services at those locations in an effort to gain a more accurate depiction of the situation on the ground. The UAV team is able to cover larger areas in a short period of time which makes them one of the preferred choices for a fast response. Their high maneuverability and rapid deployment allows for a prompt assessment of the situation to be made available at the DAC for analysis and thus increasing the probability of providing rescue services and humanitarian relief [21] in time. Although there are many benefits of using multiple UAVs, there still exists some challenges for their effective deployment in critical scenarios. UAVs have limited energy since they are powered by battery and this restricts their flight time [22,23], therefore an efficient utilization of their limited resources is paramount. Also, to get the best out of a team, there has to be an effective structure that will help improve the team performance through coherent and efficient coordination and cooperation [24] in task execution. This ensures that tasks are assigned to the best suited UAVs taking into account their positions, available energy and any spatio-temporal requirements of the application. Given efficient management of the aforementioned issues, this can lead to an overall level of success for the whole team. Given these challenges, the following research questions have been noted:

- How best can UAVs be coordinated and assigned tasks that have spatial and temporal characteristics while efficiently utilizing the limited resources?
- How can the task assignment ensure that UAVs operate within the resource and time constraints of the mission?
- What can be done to allow UAVs to operate for extended periods of time to maximize the service provision?

Figure 1.1 shows a basic scenario where UAVs interact with IoT devices on the ground to help deliver data to the data analysis centre. The operation needs to consider the availability and importance of the data as different events emerge or unfold. A mechanism for prioritising the different data sources will help to ensure the more important data is collected first and in the shortest time possible while the less urgent data is dealt with at a later time. All of this needs to be done, taking into account the resource constraints of the system.

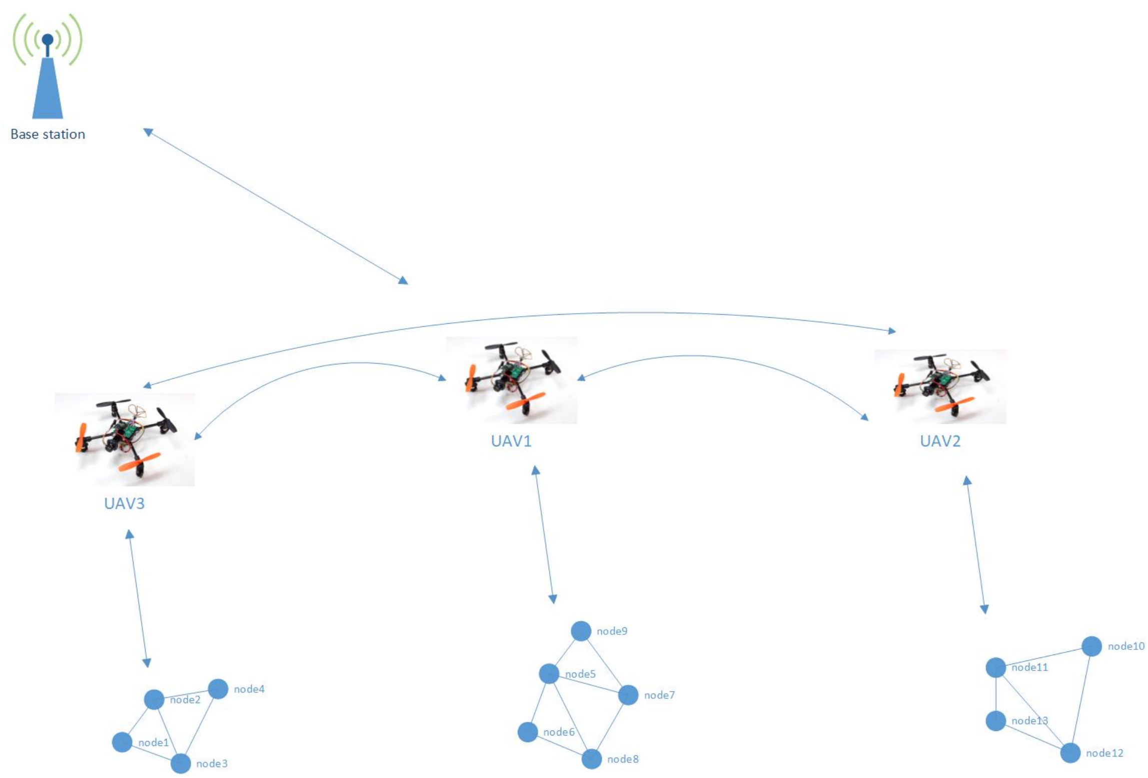

Figure 1.1: Basic Architecture

Furthermore, investigations are also carried out for a post-disaster scenario. Once a disaster hits, many unfortunate things happen and an example of such a calamity is the damage to critical communication infrastructure. In the context of an IoT network, such a misfortune can be the damage of BSs which creates a gap in IoT device communication. In such a case, the data collected by the IoT devices will not be able to reach the DAC, making it completely blind to what is happening on the ground. One way to address this is through the use of cooperating UAVs that can help bring a coordinated effort to facilitate the remote collection of data from IoT devices. Developments in aerial robotics, embedded computing platforms, communication technology and peripherals has seen a growth in the use of UAVs being equipped with antennas and sensors and cameras. A group of UAVs can be used as aerial mobile BSs to collect data from remotely deployed IoT devices, to provide temporary communication infrastructure for ground users seeking immediate help or to provide a visual insight of the situation on the ground through image and video data capture. This UAV collective can work collaboratively to cover large areas and carry out complex missions in a shorter period of time. Due to their flexibility and size, they are able to maneuver through small areas and can reach places deemed too dangerous for any human contact. By having autonomous capabilities, UAV missions can be automated to further improve their operations. To enable a productive collaboration between the IoT devices and UAVs, several issues need to be addressed. Firstly, both the UAVs and IoT devices have limited energy as they generally powered by a battery, and therefore, their operation needs to be optimized to avoid wastage in the limited resources. For IoT devices, most of their energy is spent through data transmissions. The further they have to communicate, the more transmit power they use and the more energy they consume. For UAVs, most of their energy is consumed during flight, therefore the management of their flight path becomes paramount to allow them to operate for longer periods of time. Secondly, since UAVs are highly mobile and dynamic, their position changes frequently, which makes it a challenge to have consistent communication links and as a result, it becomes important to manage the communication between them and the IoT devices to facilitate reliable data collection. Taking these factors into consideration, the following research questions came to light:

- How best can the UAVs be distributed in 3D space to collect data from the IoT devices
- What speeds should the UAVs employ when moving from one location to another to minimize their energy consumption
- What transmit power should the IoT devices use to send data to the UAVs to minimize their energy consumption
- How long should each UAV hover at a specific location while collecting data to maximize the data collected

- How best can both the UAVs and IoT devices operate within the constraints of the mission

All these aforementioned issues can be difficult to track individually and therefore there exists a need to manage them concurrently given the requirements of the mission. This is where computational techniques could be used to optimise the real-time operation of the UAVs and IoT devices and create a system that is efficient and robust to handle real-world applications. The work in this thesis includes the development of novel techniques to address the aforementioned issues for pre and post disaster applications. These techniques facilitate the efficient and intelligent operation of both the IoT devices and UAVs to promote the adaptive management of coverage, service provision and the limited energy of these devices.

1.2 Motivation

Prior studies have been done to investigate how UAVs can effectively provide aerial services for IoT devices on the ground [25–31]. These studies focused mostly on optimization of the UAV mission by individually addressing issues affecting the effective deployment of UAVs such as limited energy of the UAVs, UAV task execution order, or UAV coverage. Issues were not considered as a collective and as a result the outputs from the optimization were solutions that addressed one issue instead of a set of issues. In other studies, the focus was on either minimizing UAV energy or maximizing task execution, without a consideration for the temporal aspects of the mission. The tasks were spatially distributed with no timing constraints defined, such as task start time and duration. Those that did consider temporal aspects did not take into account the limited energy of the UAVs. In this thesis, the aim is to simultaneously address a set of the issues affecting effective UAV operation when supporting IoT devices on the ground. The focus is on tasks that have both temporal and spatial characteristics, while taking into account some mission constraints such as the limited energy of the UAVs and temporal constraints associated with the mission tasks. In other works, the cooperating UAVs employed a constant speed and altitude to execute the mission, by so doing, it put hard constraints on parameters that can be variably exploited (speed, altitude) to improve the UAV efficiency in terms of task execution. In this thesis, we exploit variable speeds and altitudes, with the intention to optimize the UAV operation even further. Some situations may require UAVs to travel at different speeds from one location to another in order to meet the temporal constraints of the tasks, or serving IoT devices from a different altitudes to help avoid collisions. The intention is for this work to be applicable when handling real-world scenarios such as emergency first aid delivery, emergency inspection of critical infrastructure and others.

In the case of employing UAVs for data collection from IoT devices, previous works [32–34] used UAVs to fly at a constant altitude and speed over an area of interest, in predetermined paths which were usually circular or rectangular, and each IoT device would send data only when the UAV is in its vicinity. When the distribution of IoT devices on the ground is not uniform, it resulted in some IoT devices not being able to send data during the time window when the UAV is in vicinity. It was more of a hit and miss situation. To improve on these approaches, other studies considered a fly-hover-collect approach [35–37]. This is an approach where a UAV flies to a location, hovers for a set period of time to collect data, then move on to the next location to do the same. This was repeated until all locations were visited. This was a much better approach because by hovering at a location, more devices were able to send data to the UAVs. However, in all these works, IoT devices were clustered in different groups and each group could only communicate with one UAV. For devices at the edge of the cluster, this sometimes became detrimental as data packets got lost due to collisions, and the reception signal was weaker as they were the furthest away from the UAV when compared to other members of the cluster. In this thesis, we further improve on this by allowing one IoT device to send data to more than one UAV to improve the data reception ratio by the UAVs. This is done in an effort to increase the probability of data reception. If one UAV does not receive the data packet, then the others will. It is a system that implements redundancy at its core, making it robust and resilient.

To develop a system that requires multiple conflicting objectives to be optimized, with constraints in place, choosing the right algorithm or computational technique is imperative. The algorithm should be able to simultaneously optimize all the objectives while ensuring that constraints are not violated. Intelligent multi-objective optimization algorithms are able to find global optimal solutions for such cases. Specifically Multi-Objective Evolutionary Algorithms (MOEA) are best suited for this work due to their stochastic optimization technique which greatly helps with the exploration process. There are a variety of MOEA including genetic algorithms, genetic programming, strength pareto evolutionary algorithm and many more. In this thesis, different versions of the Non-Dominated Sorting Genetic Algorithm (NSGA), introduced by Deb et al. [38], specifically NSGA-II and NSGA-III are adapted to fit the application use case. The original version of NSGA [39] had good success in a variety of problems, however the drawback was its high computational complexity. On the contrary, NSGA-II and NSGA-III, being elitist NSGAs, are able to perform faster [40,41], because only the best individuals in the solution set are kept at each iteration of the algorithm.

1.3 Contributions

The first investigation is the intelligent operation of UAVs when providing aerial services to support IoT devices on the ground. To this endeavour, the contribution of this thesis is the development of a multi-parameter encoded task assignment model for UAVs to support IoT devices which are spatially and temporally distributed based on an EA called Non-Dominated Sorting Genetic Algorithm II (NSGA-II). NSGA-II was developed by authors [38] and uses a chromosome to represent a potential solution. The structure of the chromosome is usually used to represent one parameter type such as waypoints in the case of the travelling salesman problem. Then a solution becomes an optimal route that traverses the waypoints found in the solution chromosome. In this work, a multi-parameter encoded chromosome structure is developed to define the task assignment solution to determine more than just the UAV waypoint order but also other operational parameters such as speed and hovering altitude. From the solution, a model that assigns the best UAVs to provide aerial services at various event locations is generated. The model ensures that constraints such as event start times and limited UAV energy are not violated. It is generic and can be applied to a multitude of UAV operations such as search and rescue, emergency deliveries and inspections. The model considers factors such as the UAV position and remaining energy, task location, start time and duration to distribute the tasks accordingly among the UAVs. Conflicting objectives are optimized, which are the UAV energy consumption and the UAV task response time. For a shorter response time, UAVs have to employ faster speeds but this results in the consumption of more energy during travel and thus a shorter operation time. On the other hand, if UAVs employ very slow speeds then they consume considerably less amounts of energy but their response time becomes very poor. A balance becomes very imperative and this is where NSGA-II performs best to find an acceptable trade-off between the conflicting objectives that simultaneously optimizes both of them. The algorithm optimizes the assignment of tasks to UAVs, the speed employed by UAVs when moving from one task location to another as well as the altitude at which the UAVs is providing the aerial services. A charging dock was considered to replenish the UAV energy to allow the UAVs to perform for longer periods of time. By doing so, this introduced an additional parameter to be optimized, which is the charging duration and this increased the complexity of the problem. By developing the multi-parameter encoded chromosome structure, we were able to capture all these parameters as decision variables in the model and NSGA-II generated a task assignment schedule that simultaneously optimized the objectives, without violating any constraints.

The second investigation is on optimizing the UAV operation when collecting data from IoT devices. More complexity is added by considering more objectives to simultaneously optimize. To deal with this increase in the number of objectives, the optimization part of the algorithm is handled by NSGA-III, which is an improved version of NSGA-II [38]. With NSGA-III, three or more conflicting objectives can be optimised efficiently [42]. NSGA-III also performs better when considering the exploitation versus exploration trade-off which results in better quality solutions. To allow one IoT device to send to more than one UAV, a soft clustering algorithm for IoT devices was adopted, called Fuzzy C-Means (FCM). The contribution of this work involves the development of a hybrid algorithm that merges the operation of FCM and NSGA-III. The algorithm uses as decision variables, the UAV-IoT device association, the 3D deployment of UAVs, the UAV speeds, the hover duration when collecting data and the transmission power and rate used by IoT devices when sending data to the UAVs. Similar to the first investigation that used NSGA-II, a chromosome structure is developed to capture all these decision variables. The hybrid algorithm generates solutions that minimize the energy consumption of both the UAVs and IoT devices and also maximize the data collected by the UAVs.

1.4 Objectives

The objectives of the thesis involves developing the following:

- A task assignment model to simultaneously optimize the energy consumption and response time of UAVs when providing aerial services at event areas.
- A technique that optimizes the energy consumption of UAVs when collecting data from IoT devices on the ground
- A strategy that optimizes the energy consumption of IoT devices when sending data to the UAVs
- An algorithm that maximizes the data collected by the UAVs
- A model that ensures that none of the constraints of the mission are violated.

1.5 Thesis Outline

To gain better under understanding of the scope of the work, the thesis is organised as follows. Chapter 2 is the literature review which gives a background into our work. This chapter explains the concept of IoT, the role of IoT devices and how UAVs have been integrated to support IoT devices to improve efficiencies. It also highlights the gaps that exist in past literature which influenced the direction of this thesis. Chapter 3 is the research methodology which is used to explain the techniques adopted to address the research gaps. It gives more information about the underlying algorithms employed and how they work to optimise the operation of both UAVs and IoT devices. Chapter 4 defines the problem investigated when UAVs are providing aerial services in support of events raised by IoT devices. It further shows the performance of using a multi-parameter encoded chromosome for NSGA-II, when compared to other implementations. Chapter 5 defines the second problem investigated when using UAVs to collect data from IoT devices. The performance of the hybrid algorithm that uses FCM and NSGA-III is assessed and compared with other implementations. Finally chapter 6 is the conclusion which shows how the work in the thesis addressed the research questions, the challenges and limitations of the work and suggests the directions for future research.

Chapter 2

Literature Review

2.1 Internet of Things (IoT)

IoT refers to the global network of machines, devices and people to facilitate interaction and exchange of valuable information [43] [44] [45]. It is a network of the future which has gained massive interest in previous years. The ability for things to be connected and communicate with each other makes integration between heterogeneous systems seamless which allows the application of business intelligence and analytics to be done with a more holistic view. A thing was defined to be an real object with physical characteristics or a virtual object which belongs to the information world, provided it has an identity and can be integrated into the network [46]. Physical things can can have sensing capabilities, be controlled to perform desired actions while being connected, whereas virtual things such as data objects or multimedia content can be stored, processed and shared throughout the network. A mapping can be created between the physical and virtual things in the information world through relationships but some virtual things are able to exist independently. IoT was envisioned to create a plug and play technology which provided the system user with benefits of remote access and control as well as configuration to ease the operation of the system [47]. It was also envisaged to be used at an individual level as well as a professional level. At the individual level, IoT improves the living standards through smart services such as smart learning, smart homes, e-health and so forth. At the professional level, it can be used in various industries such as manufacturing, supply chains, logistics and mining just to mention a few. The vision was to have a world that is communicating and sharing insights. To successfully implement and IoT system, there is a need for high connectivity, impeccable privacy and security, ultra-high reliability, low latency, efficient power consumption and interoperability [44]. By being a broad concept, there is no uniform architecture for an IoT system. Several researchers have proposed different architectures but they have similar components. The European FP7 Research Project [48] used a tree analogy to describe the architecture of an IoT system. At the root level, these are the technologies which facilitate interoperability. These include communication technologies and the devices or things. At the trunk level is the set of enablers and buildings and at the leaf level is the applications. The International Telecommunication Union (ITU) [46] considers the architecture to consist of four horizontal layers which all have management and security capabilities. At the top layer is the application layer, followed by the service and application support layer which could be generic or application specific. The network layer is the third layer for all networking and transport to connect things. This is where access control and allocation of resources is done. The device layer forms the bottom layer. Xiaocong et al. [49] proposed a structure for a business operation support platform (BOSP) formed by three layers. At the bottom is the access layer, then the devices management layer and at the top is the ability formation layer. The access layer defines protocols and controls the traffic in the network. The device management layer manages the devices through a management portal. The ability formation layer encapsulates the capabilities of the applications.

As mentioned before, most of these architecture components are similar and therefore for our investigation we refer to an IoT system with the following components:

- IoT devices
- Base Stations (BS)
- Cloud

At the bottom layer is the IoT devices, at the middle layer is the BS and at the top layer is the cloud. Figure 2.1 shows a depiction of the IoT system and the bi-directional data flow between the different layers.

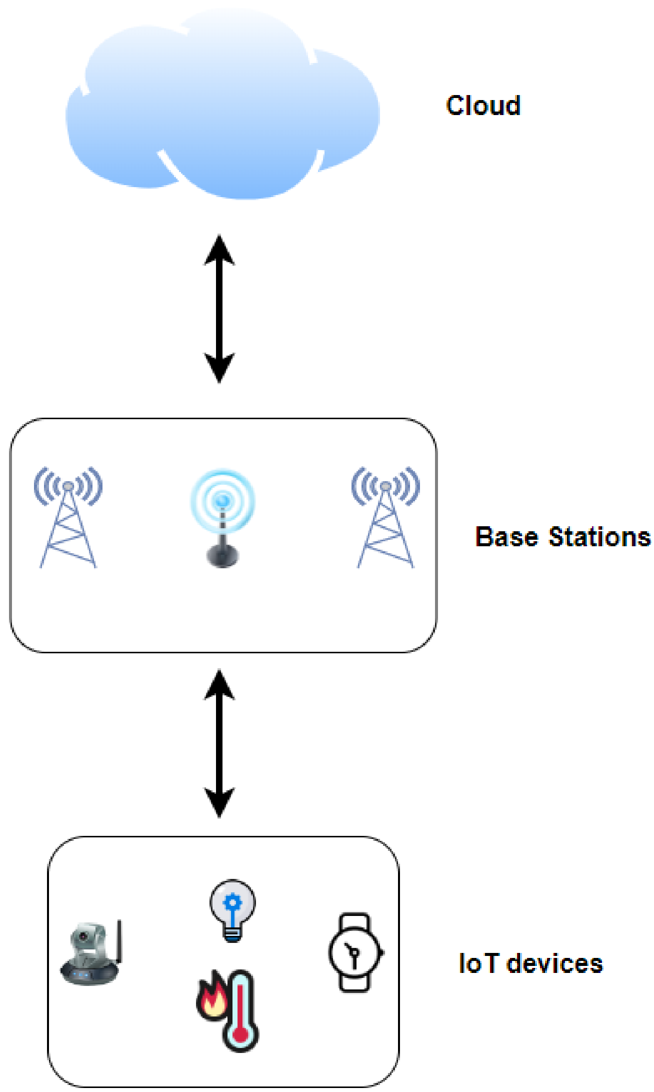

Figure 2.1: Key IoT components

2.1.1 IoT Devices

In architecture, [50] the IoT devices have sensing, processing and communication capabilities. They can be referred to as autonomous devices that carry out measurement tasks by using sensors. Examples of sensors include temperature sensors, smoke sensors, infrared sensors, motion sensors, level sensors, Global Positioning System (GPS) sensors and so forth. Past literature [51, 52], shows that the number of businesses using IoT devices have increased from 13 percent in 2014 to about 25 percent in 2019. This is a significant uptake in the number of devices in just 5 years. It is estimated that in 2023, the number of IoT devices connected will increase to an astonishing 43 billion. IoT devices are deployed remotely to create a ubiquitous sensing system [53] of smart devices connected over a network to share and exchange information with each other through Machine-to-machine (M2M) communications [54], without the need for human intervention. Communication technologies include Radio Frequency Identification (RFID), Zigbee, LoRaWAN, 802.15.4, Bluetooth, Near Field Communication (NFC), Cellular, Wireless Fidelity (WiFi) and so on [55–57]. This collected data needs to be processed and analysed so that intelligent, informed decisions and actions could be made.

2.1.2 Base Stations

A BS which is sometimes referred to as a gateway an intelligent component in the IoT system and is typically employed between the network of IoT devices and the Internet where the application servers reside. It supports different protocols that IoT devices might use to communicate and mitigates the diversity of the devices through the consolidation of data and passing it to and from the internet. It takes the complexity that is required to connect to the internet, away from IoT devices allowing them to perform their basic functionality and save energy. They provide flexible connections between the IoT devices and the cloud to allow the analysis of data and data driven decision making [58–60]. The BS acts as a proxy for the sensing domain. BS can be classified into three main types, namely, passive, semi-automatic and fully automatic. A passive gateway is one that requires settings to be manually configured for new IoT devices. A semi-automatic BS automatically generates a link between the IoT device and itself but device functionality has to be configured manually. Automatic BS automatically connect the IoT devices to themselves and configures the functions of the devices [61]. Data from the IoT devices can be stored locally on the gateway database for later delivery or sent to the cloud immediately.

2.1.3 Cloud

The Cloud resides in the internet and consists of multiple application servers that receive data from the BS [62–64], stores it in a database efficiently and processes it to gain intelligent insight to facilitate informed decision making by the end users. The servers usually communicate via Hypertext Transfer Protocol (HTTP) or Message Queuing Telemetry Protocol (MQTT), which are used on top of the TCP/IP protocol. HTTP is energy intensive and therefore not suitable for IoT since the devices have limited energy but MQTT is a lightweight protocol specifically designed for resource constrained IoT devices [65]. The application servers have high computing power and can run complex algorithms on the data. Users are able to use cloud applications to interact with IoT devices. The data flows from the cloud to the BS and finally the IoT device and vice versa. There are many IoT applications that have been developed and they include the following:

2.1.3.1 IoT Applications

There are many real world application that are driven by the efficient use of IoT devices. These applications are used in various industries such as healthcare, agriculture, military, manufacturing, transport, residential and so forth. Examples include smart mobility and smart transportation systems [66, 67] which involves enabling seamless, flexible and efficient travel using different modes. It is sometimes referred to as the Internet of Vehicles (IoV) and helps reduce accidents by improving road safety and optimizing transportation routes. Another application is smart grid which is an electricity supply network that uses IoT communication technology to monitor and detect changes in usage and hence make adjustments as a reaction to the changes in usage [68]. Smart Home allows the remote monitoring and control of various devices for heating, lighting, cooling and any other electronics. Environmental monitoring for areas affected by pollution, smart agriculture [69] through real time monitoring of soil properties, smart cities [70, 71]. Additionally IoT supports military applications for assistance and surveillance of soldiers in a battlefield [72, 73]. It makes it easy to know health parameters such as temperature and heart rates as well as environmental parameters such as air quality. Industrial applications such as construction site monitoring [74–76] involving the monitoring of parameters such as air temperature, air pressure, particulate matter (PM), emissions and so forth. These applications help improve the safety of workers and also improve the operation of the equipment and entire construction site.

All these applications are different in nature and therefore have different timely requirements. Some applications such as smart agriculture can tolerate delays in delivering data captured for analysis as a prompt response may not necessarily be required. Other applications such as the military operations are very time crucial and need to operate in almost real time. This means that the data collected from sensors needs to reach the data analysis component (cloud) as quick as possible. This will allow enough time to formulate an appropriate response to an emerging event that was caused by violations of thresholds previously set. Traditionally, the set up of these IoT systems make use of terrestrial BS. The initial placement of these BS is very crucial as it affects the lifetime of the IoT device network. There can be times when some IoT devices are within range of the BS but also some find themselves out of range. In any case, the IoT devices have limited battery power, and their operation needs to managed efficiently to ensure the longevity of the network. The further the devices are from the BS, the greater the transmission range and hence there will be more energy consumption during data transmissions. Also during unfortunate events such as fires, floods or any other disaster, the critical BS can be damaged resulting and so data would not reach user applications in the cloud. This is when the use of alternative BS becomes necessary and quick deployment is paramount. UAVs are able to assist with the alleviation of these issues because they can be deployed quickly and can act as aerial BS to facilitate data collection and also provide aerial services for situational analysis.

2.2 Unmanned Aerial Vehicles (UAVs)

UAVs commonly known as drones refers to aerial vehicles that can be controlled without a human pilot onboard. Their control can be completely autonomous with the aid of sensors, microprocessors and other electronic equipment available on the UAVs [77, 78] or they can be controlled through a human operated remote control. Manual control of UAVs has a risk of being inefficient and prone to human error, so it becomes beneficial to operate them autonomously. The architecture of a UAV system typically comprises of satellites, ground control stations (GCS), UAVs, computers and mobile phones which all interact using communication links. Due to their flexibility and autonomy, UAVs can operate in areas that are dangerous for humans or hard to access. Improvements in UAV technology has seen a great increase in the uptake for a vast array of applications. Figure 2.2 shows the growth of revenue for commercial UAVs in USA used in different sectors. A key feature of UAVs is the vertical takeoff and landing (VTOL) which allows them to operate a high speeds and have the capability to hang vertically in the air. This improves the efficiency of UAVs.

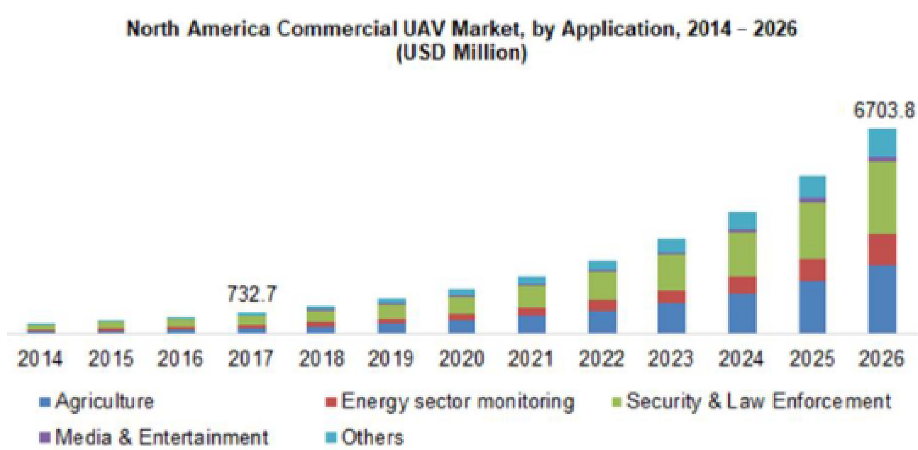

Figure 2.2: Commercial UAV market for North America [1]

2.2.1 Classification of UAVs

UAVs can be classified into different categories depending on their specifications, size, range and shape [79,80]. They have different wing structures and engines. They can communicate using short range or long range wireless technologies. UAVs are usually equipped with a GPS, sensors used for stability and cameras. There are 4 main categories for UAVs, namely fixed-wing, fixed-wing hybrid, single rotor and multi-rotor [81]. The key features of each category are shown in Table 2.1. Fixed-wing UAVs have wings instead of rotors, a main body, motor and propeller. They are more difficult to operate and are able to balance vertically in the air for long periods of time. However they cannot hover, move backward or rotate. This limits their capabilities in some applications. Fixed-wing hybrid UAVs can be automated and manually glide. They suffer when flying forward and when hovering. Single rotor UAVs have one rotor and require special training to operate. Their mechanical makeup is complex making them expensive and vibrations easily affect them. However they are able to hover and have a long endurance. Multi-rotor UAVs are the cheapest and widely used in literature. They are easy to manufacture and used widely in many applications. They have multiple rotors numbers ranginf from 3 to 8. Tricopters have 3 rotors, quadcopters have 4, hexacopters have 6 and octocopters have 8. Out of them all, quadcopters are the most popular and commonly used. They have VTOL, high agility, small size and are cheaper to manufacture.

UAV Category	Key Features
fixed-wing	long operation time, high speed
fixed-wing hybrid	long operation time, VTOL
single rotor	long operation time, VTOL, hovering
multi-rotor	short operation time, VTOL, hovering

Table 2.1: UAV Categories

2.2.2 UAV Flight Time

For smaller UAVs such as quadcopters, the maximum speed is between 10 - 20 m/s. The speed used by the UAV greatly impacts the battery life and ultimately the flight time. Faster speeds consume more energy as compared to lower speeds. Additionally the size of the UAV, weather conditions such as wind, and the weight, affects the flight time. Quadcopters usually have a flight time of between 30-50 minutes. The size and weight of the UAV depends heavily on the payload. Payload can be defined as the capability of a UAV to lift and carry a load. UAVs with a larger payload can carry more accessories such as sensors, cameras, cellular equipment and so forth. The heavier the payload, the higher the battery consumption and the shorter the flight range.

2.2.3 UAV altitude

Altitude is the height at which a UAV can fly. There are generally two categories that depend on altitude, namely low altitude platforms (LAP) and high altitude platforms (HAP). LAP can achieve heights of between 50m and 3000m while HAP can reach heights of between 3000m and 20,000m.

2.2.4 UAV Applications

Advancements in technology has seen a great improvement in the quality of sensors and other electronic equipment deployed on UAVs allowing them to be used in various applications. Their autonomy and flexibility also further their range of applications. UAVs have been used in monitoring and surveillance applications [82–84] for detecting enemies in a battlefield, detecting poachers as well as border control. They have also been used in remote sensing and mapping [16, 85, 86]. Remote sensing and mapping helps in the detection of diseases in plants, surveying of terrains, and forest mapping just to mention a few. Also 3D environmental maps can be created to be used in crowd sourced mapping. Other applications include precision agriculture [16] by spraying pesticides and monitoring the growth of crops. Forest restoration [87–89] such as the supply of seeds and monitoring of forest species. Infrastructure inspection is also a great application for UAVs as they are able to get a good picture from above. Examples include inspecting power lines, bridges, buildings for any damages [90–92].

Despite all the benefits of using UAVs there are still some issues that need to be addressed. UAV battery life is limited and as mentioned earlier, it can last up to 30 minutes. Increasing the size of the battery increases the weight of the UAV and hence will also drain the battery at a higher rate. Their rapid mobility also influences the communication between UAVs as line of sight (LoS) links change frequently and the signal does not stabilize. Our research involves using UAVs to assist IoT devices on the ground and we investigate techniques that can help address issues that exist on both the IoT devices and UAVs side that hinders the cooperation between these two platforms. Their intelligent operation is of prime importance.

2.2.5 UAV Enabled IoT Applications

This section reviews previous works regarding the use of UAVs to support ground devices. UAVs have been previously used to support Wireless Sensor Networks (WSNs), ground user equipment (UE), social networks and IoT devices just to mention a few [93–96]. This is due to their salient attributes such as rapid deployment, strong line of sight links and flexible mobility. Nonetheless, due to their rapid mobility, line of sight links fluctuate which affects the quality of service and by so doing the optimal placement of UAVs becomes an important factor to consider. Zorbas et al. [97] investigated the optimal placement of UAVs with regards to altitude, to cover GNs, having conflicting objectives which are minimizing the number of UAVs and minimizing the UAV energy consumption. They considered a minimum and maximum altitude for the UAVs. They showed that when UAVs take higher altitudes, it increases the coverage area an hence fewer UAVs are needed. Consequently, the higher the UAV flies, the more the energy consumption and that is why the two objectives are conflicting. They solved the problem using mixed integer linear optimization model. However, the speeds of the UAVs were kept constant which limits the flexibility of the system, as variable speeds could further enhance the performance of the system. Authors in [98] investigated the use of a single UAV for search and rescue applications such as floods and bomb blasts. The goal was find the optimal position to deploy a UAV that acts as a bridge between two static ground nodes (GNs). The UAV was hovering over an area in a spiral trajectory to receive location data from GNs and use that data as well as the received signal strength (RSS) to find an optimal position to act as a bridge. Results showed an improvement in the throughput and a lower bit error rate (BER). Nonetheless the system was limited to just two GNs and did not consider any energy constraints which makes it intractable when dealing with a large number of GNs. Chen et al. [99] studied the optimal altitude to place a UAV acting as a relay between a GN and a remote ground station. They proposed a model that considers Air-to-Ground (A2G) path loss model as well as the hop from the UAV to the remote station. As with [98], they considered a single UAV case which greatly limits the potential of the system in terms of coverage area. Sabino et al. [100] investigated UAV placement schemes by finding optimal positions for UAVs to maintain connectivity and improve the network performance. It was a centralized placement scheme where a single entity selects the UAV positions and conveys them to the UAVs through a radio interface. They employed a Multi-Objective Evolutionary Algorithm (MOEA) technique for optimal placement of UAV nodes with the objective of minimizing the number of UAVs needed to provide service to ground nodes (GN) as well as minimizing the dissatisfaction of the data rate required by the GN subject to multiple constraints. Simulations showed that the algorithm was able to optimize the placement of UAVs given the data requirement and position of GNs and since there were conflicting objectives considered, there was a trade-off in between the number of UAVs and the coverage quality. However, they considered only the positions the UAVs needed to take and did not consider other parts of the UAV mission which include travelling from the base to the placement points and returning to the base once the mission is complete. As a result, the analysis was incomplete and therefore not a true reflection of a real scenario. Choi et al. focused on an energy efficient communication for a small fixed wing UAV using circular maneuvering [101]. The role of the UAV was to act as a relay to connect two stationery GNs. They defined an energy metric as the ratio of the network capacity to the power consumption during maneuvering and communication and formulated a maximization problem that optimizes two variables, namely speed and load factor. A closed-form sub-optimal solution was found with a negligible loss of energy efficiency compared with the optimal solution. Since they considered a fixed wing UAV, it was unable to hover at an optimal position and had to maneuver in a circular manner and this results in the consumption of more energy. Additionally, the altitude of the UAV remained fixed, but this could also be optimised to create a more efficient relay system. They also considered a single UAV and only two GNs and did not show how scalable such a system is when dealing with a multitude of GNs which will require multiple UAVs as well. In [102], a mobility model for interconnected UAVs having an area exploration mission was investigated. The UAVs were to explore an area while maintaining connectivity between themselves and the base station. The energy of the UAVs was considered as an important criteria along with coverage area and connectivity. It was a decentralised system where each UAV determined its next move based on information from its neighbours. Due to the scarcity of the UAV energy, its management proved to be beneficial to ensure a longer network lifetime and ensure mission success. However, they only considered UAV movements in a 2D environment, therefore neglecting optimal UAV altitude for carrying out the area exploration mission. Additionally, there were no timing constraints relating to the mission. Say et al. [103], proposed the use of a fixed wing UAV to increase the data gathering effort in sensor networks. Sensors in the coverage area of a UAV were classified into different transmission priorities by adjusting the contention window used in the IEEE 802.11 media access control (MAC) protocol. Higher priority sensors had a lower contention window while lower priority ones had a higher contention window to reduce packet collisions and minimize packet loss. They considered the movement of the UAV to be in the forward direction, with a constant speed and altitude and without any hovering capability. This can lead to packet loss when some sensors lose direct links with the UAV as result of being in the rear edge of the UAVs coverage area, but they minimized that through the priority based activation of the sensors. Similar to other works, the inability of the UAV to hover, use different altitudes and employ variable speed limited the system. Also, they considered a single UAV which results in longer mission times and less coverage area as compared to when a team of UAVs performed in the mission. Authors in [104] employed UAVs to survey and communicate sensed images. The sensed images were sent to a static BS by survey UAVs through a relay UAV. The survey UAVs had predetermined routes and a set of waypoints for the relay UAV were computed to allow the reception of the sensed images. A markov decision process (MDP) was used to compute a stochastic planning model that finds the best schedules for the relay UAV to maximize the image acquisition rate, and an improvement in terms of end-to-end delay and frame delivery ratio was realised. Results showed the effectiveness of approach by an improvement of 8% and 12 % in terms of image acquisition rate and frame delivery respectively. Similar to other works, they considered using one relay UAV which is a single point of failure and having multiple relay UAVs could improve the robustness of the system. Ang et al. [105], investigates the use of a mobile data collector (MDC) for big data collection over spatially separated geographical regions. A large scale WSN is partitioned into multiple groups called clusters and the optimal number of clusters is determined to minimize the sensor energy consumption. Once the clusters are found, the MDC travels to each one to collect data and transmit the data to the BS. Authors proposed the use of analytical approaches for calculating the sensor energy consumption and determining the optimal cluster number. Similar to other previous works, they considered a single MDC which creates a single point of failure. Additionally, they did not consider the energy consumption of the MDC and assumed the energy could not be exhausted. It is impractical for real world scenarios to consider perpetual energy for the MDC. Say et al. [106] explored a cooperative partnership for data forwarding in WSN by employing a UAV. They presented an architecture for data acquisition to subdue limitations in traditional WSNs. The sensor nodes were classified into different frames and had the capability to pair with other nodes in the network to simultaneously send data to the UAV. The aim was to reduce the packet loss in the rear side of the UAV's area of coverage. However, in their analysis, they did not consider the energy of the IoT devices or the UAV during this data collection mission. Also, when sensor readings are stagnant, the UAV still maintains its path and energy is wasted on capturing redundant readings. Pang et al. [107] explored the use of UAVs to replenish the energy of the sensors using wireless power transfer technology. The UAVs visit the sensor clusters to collect data and recharge the sensors in the clusters. They formulated an optimization problem with constraints for the distance between the UAVs and sensor clusters, data collected by the cluster sink as well as the remaining energy of the sensors in the cluster. A one side matching algorithm and a greedy algorithm was developed to maximize the system utility. They were able to verify that data can be collected efficiently and also recharging the sensors. However, in this study, the UAVs limited energy was not considered which is a very important aspect in real world deployments. Authors in [108] developed a crop monitoring system using wireless sensors and a UAV. They considered a scenario of dynamic data collection which results in a dynamic path for UAVs. Field sensors were clustered at runtime and a Bayesian classifier was used to find the best node to act as a cluster head. The UAV did most of the processing which involved activating the sensors, shunting them, locating all active ones and nominating the cluster head. However, they too considered a single UAV which limits the throughput and creates a single point of failure and also most of the processing was done by the UAV which further consumes the limited energy available onboard the UAV. They focused more on the sensors and did not take the energy of the UAV as an additional constraint to ensure robustness in the data collection process. Hua et al. [109] proposed the use of a UAV acting as a flying base station for power efficient communications with sensor nodes (SNs). The objective was to minimize the total power consumption of the UAV while guaranteeing the required transmission rate of SNs through the optimization of the scheduling scheme and power allocation as well as the path of the UAV. They employed a block coordinate descent and successive optimization technique to break the problem into two sub-problems. Numerical results showed that their approach performed better in terms of the transmission power which greatly saved the limited power of the UAV. Nonetheless, the UAV employed a constant altitude which restricts the system. Wang et al. [110] proposed a cloud based UAV system to process the data from sensors. They analyzed the on-demand service capability of the UAVs and cloud to determine the maximum data the UAVs can generate . They used the Jackson network theory to investigate the queuing system and verification was done through simulations. Authors in [111] proposed a leader-follower coalition model for UAVs to identify targets on the ground. The UAV to first locate the target becomes the leaser and selects a group of follower UAVs to complete the task with the identified target. The aim is to ensure that resources utilization is minimized. However there was no priority for targets to be identified. Authors in [112] investigated a real time coordination system to enable UAV collaboration. They looked at UAV swarm formation and bandwidth management. smart phone attached to a UAV was responsible for local processing, wireless communication, sensing the position of the UAV and relaying flight control signals to the UAV. UAVs could fly in patrol mode or swarm mode. The former mode used a predetermined path while the latter used a leader-follower approach. The system was able to find reliable and timely message delivery. However energy of the UAVs was not considered and was assumed to be enough for both the patrol and swarm flight modes. In [113], the efficiency of the data collection by a UAV was improved by using in-network pre-processing of sensor data for local UAV task planning. The sensor network had cluster heads which collected and aggregated data from other sensors while a team of UAVs collected data from cluster heads and communicated that data to a network control centre. UAVs were assumed to have enough on-board storage and computing resources to run the task planning algorithm. Results showed a good response to event detection but the in network processing consumes more power and as a result will shorten the mission time. In [114], an energy efficient cooperative relaying scheme was investigated to extend the lifetime of a wireless sensor network while guaranteeing success of the mission. The objective was to minimize the energy consumption while guaranteeing the bit error rates.

When dealing with applications that require close to real time monitoring, it is important to deploy UAVs in the quickest possible manner to allow prompt data capture and reporting. Ueyama et al. [115] proposed the use of UAVs to help with resilience of a WSN during failures and natural disasters. The roles of the UAV were twofold, one was to act as a router in a multi-hop transmission and another was to act as a data mule and create a delay-tolerant network (DTN). The system was evaluated based on the energy consumption of the sensor nodes and UAVs, the packet loss rate and the round trip time (RTT). They were able to create a resilient network employing UAVs but since they considered one UAV, this limited the resilience for multiple areas that may need assistance. Also they used ZigBee as their radio protocol of choice which is unsuitable for certain types of data such as image data as it employs very low data rates. They also did not consider the response time of the UAV in their analysis which is very key when dealing with time sensitive applications such as disasters. Tuna et al. [116] proposed the use of UAVs to create an emergency communication system in disaster affected areas. This team of UAVs works post disaster to bring about a communication infrastructure for ground nodes/stations and also organises itself into a mesh network to maintain connectivity between the ground station and each UAV in the network. The ground station is the central coordinator and brain of the operation. Ensuring connectivity is maintained is key as data collected by each UAV can be made available at the ground station and commands sent out from the ground station can reach the intended UAVs in a timely manner. This is very important in real time monitoring. One issue to address is the single point of failure due to having centralised control at the ground station. Trasvina et al. [117] proposed the use of UAVs as part of a wireless sensor network to monitor marine environments .

The wireless sensor network was composed of sensing buoys, low power, long range communications and a UAV as the data collector. The network used Low Power Wide Area Networks (LPWAN) as a communication protocol, LoRa to be exact. This is quite beneficial when energy is a scarce resource and its consumption is to be minimized as well as when low data rates are needed. The long range communication meant the UAV could travel a short distance to establish communication with the buoy hence saving the limited energy of the UAV. Using a single UAV though reduced area coverage when searching for the buoy which meant more time was needed to locate it. This could end up depleting the limited energy. UAVs have also been used for Crowd Surveillance applications, [118] to monitor and report on objects of interest. UAVs have limited onboard processing capabilities so as an alternative, video data collected was offloaded to a Mobile Edge Computing Cloud (MEC) node to save the limited energy of the UAVs and also for faster processing of data. An MEC node has far superior processors and help bring computation close to the network edge to allow faster processing and for timely decisions to be made. This is a real time application so the processing time needs to be minimal to efficiently identify and track suspicious persons. Offloading to the MEC node required the use of Wifi or LTE which is energy consuming so this is one issue that needed to be managed well. Only one MEC node was investigated so that also has a single point of failure flaw. UAVs being used as data collectors [119] has gained so much popularity to improve the life of remotely deployed wireless sensor networks. For large scale sensor networks, energy efficient data collection is needed and a group of UAVs have been sought to provide just that. Multiple UAVs ensure data can be collected over spatially separated geographical regions. For this application, authors proposed UAVs as mobile collectors following predetermined paths. The network is divided into clusters with each UAV servicing a cluster in a stop and collect protocol approach at the cluster centroid. In situations when data demand is dynamic, predetermined paths will not work. Certain areas may have different priorities and so the flight path cannot be planned ahead of time and would require for it to be determined on demand. Some authors have looked into a Cloud-assisted UAV data collection effort [120] in Wireless Sensor Network (WSN) clusters. Their main area of focus was on emerging events and how such a system reacts to that. Analytic done in the cloud helped derive the UAV's optimal flying and data acquisition path in the WSN clusters. Through this approach, they managed to cut down on the UAV's flight time, energy consumption and ensure the integrity of the data collected. As with other single UAV applications, they lacked on benefiting from coverage that comes with multi-UAV systems to allow the task to completed in the shortest time possible. Emerging events were monitored but the UAV had to get data from all the clusters, send it to the base station before the cloud computing platform could kick in to determine the UAV's next flight mission. This wastes time as the UAV has to complete its current mission before the emergent event could be detected. The main issue to address when using UAVs is the limited available energy. This is the bottleneck of all things that can be done using UAVs. The energy is mostly consumed by two factors, travel and communication. Past researchers have done a lot of work trying to address these, ranging from planning an optimal flying path to planning the best transmission schedule to prolong the lifetime of a UAV aided system. In [121], they proposed an energy-efficient cooperative relaying algorithm for UAVs to use when sending data to the base station. The UAV transmission schedule was optimized under guaranteed bit error rates to minimize the maximum energy consumption. The UAV flight trajectory was was pre-determined making it inefficient to changing data demands from emerging events. In [122], an optimal UAV path was developed using multi-objective bio inspired algorithms. It used a genetic algorithm and ant colony optimization algorithms. The aim was to maximize the value of the collected data and minimize the energy cost incurred by the UAV during travel. The algorithm worked well in determining the UAVs next point of data collection. The flight path is dynamic so would be good to adapt to changing data demands. One limitation that is evident is that there is one UAV doing the data collection and so coverage capacity is limited especially when considering a large wireless sensor network scenario.

A lot of work has been done to assign targets and tasks to a group of UAVs. Shima et al. [123] proposed the use of genetic algorithms (GA) to handle the task assignment problem. The scenario was unique because there were constraints such as task precedence, timing constraints and limitations to trajectory. The GA proved to find good feasible solutions however all targets had the same priority. There was not a requirement for other tasks to be done before others. The UAV energy was also not considered when assigning these tasks, something that is very important and affects the mission operation time. Wang et al. [124] proposed using a GA with double chromosome encoding to handle the Multi-UAV reconnaissance task allocation. The objective was to minimize the task execution time and UAVs total consumptions. The algorithm proved to be efficient in large scale task allocation in the face of limited resources. Ghazzai et al. [125] investigated the sequential and parallel UAV scheduling for applications with multiple events by treating it as a Mixed Integer Linear Programming problem. The objective was to minimize the total energy consumption. One of the major contributing factors to energy consumption was the energy used when a UAV is waiting at an event area before serving it. This is something that can be avoided by carefully planning the UAV task sequence and can be improved further.

In [126], the authors investigated the use of UAV mounted BS to provide wireless services. An optimal placement algorithm that maximizes the number of covered users using the minimum transmit power was proposed and the performance was evaluated. Downlink communications were investigated. They focused on minimizing the distance between the UAVs and IoT device to save the limited energy of IoT devices during transmissions. This results in more travel for UAVs which was not analysed. Assessing how much energy the UAVs use and including that in the decision making could be beneficial. In [127], the authors looked into how best to deploy UAVs to serve a large number of user equipment (UE) using the least interference. However a local optimal solution resulted and the UAV altitude was kept constant which limited the behaviour of the system. In [128], authors investigated how to deploy UAVs to serve UE's and minimize relay costs between them. They too considered a fixed altitude for UAVs and the service times of the UAVs were not limited. The transmit power was kept constant which can lead to misuse of the limited energy. Authors in [129] proposed a mobility model that chooses UAV waypoints intelligently to improve coverage for Wireless Sensor Networks (WSNs). In [130], the authors investigated the optimal trajectory of UAVs equipped with multiple antennas for maximizing sum-rate in uplink communications. In [131], they investigated the optimal deployment and movement of a UAV for supporting downlink wireless communications However, these works considered a single UAV in their models. Authors in [132] proposed a path planning approach that deploys UAVs for faster data collection. However, UAVs collected data from the nearest sensors which is a greedy approach and not always the most efficient because it uses a narrower search space for solutions and suffers from falling into a local minima. [133]. The energy remaining was not considered in the decision making and this could lead to unrealistic solutions for practical scenarios. In [134], authors investigated how a team of UAVs can be used to maximize the coverage for ground devices while deploying a minimum number of UAVs.

As mentioned above, some issues still exist when using UAVs with IoT devices. In critical applications, resource efficient response is needed to deliver services. During data collection, the right parameters need to be selected to effectively collect the data. Issues that have been identified include the following:

- Limited energy of UAVs and IoT devices
- Handling IoT device generated events with different priorities
- Limited speed of the UAVs
- Limited transmission power of IoT devices
- Unstable communication links between UAVs and IoT devices due to frequent topology changes of the UAVs.

To address these issues, EA models are developed. The first one employs a multi-parameter encoded chromosome for NSGA-II. Decision variables are determined to minimize the UAV energy consumption, minimize the UAV response time for events based on priority. The model determines the order of waypoints for each UAV and speeds employed from one waypoint to another. The altitude at a particular waypoint is determined and varied to help reduce collisions in the UAV team. The charging duration is also calculated to ensure UAVs have enough energy to provide the required service. The second model is composed of a hybrid algorithm using FCM and NSGA-III. Decision variables such as UAV speed, UAV altitude, IoT transmission power and UAV hover duration are determined to simultaneously minimize the energy consumption of both the UAVs and IoT devices as well as maximizing the data collected from IoT devices.

The above models work to promote cooperation and collaboration among UAVs to achieve a common goal. Constraints such as UAV energy, IoT device energy, charging power, UAV speeds, task start time and duration are all handled to provide solutions that are not in violation. The most suited UAV is selected to do the right job and operation of the IoT device is optimized to conserve resources and guarantee an acceptable throughput.

Chapter 3

Methodology

In this thesis two models are developed for effective employment of multiple UAVs to support IoT devices on the ground. The models find solutions that simultaneously optimize multiple conflicting objectives. The objectives are conflicting because there is no one solution that optimizes all the objectives. An improvement of one objective comes at the expense of the other objectives [135]. As a result, the models generate a set of Pareto-optimal solutions, commonly referred to as the Pareto front. Pareto front is a set of non inferior solutions in the objective space defining a boundary beyond which none of the objectives can be improved without sacrificing the others. These were named after engineer and economist Vilfredo Alfredo, who noticed that many economic solutions helped some people while hurting others and therefore became interested in finding solutions that helped some people without hurting anyone else [136, 137].

Figure 3.1 shows the Pareto-optimal solutions in the case of two conflicting objectives. Objectives are to minimize both F_1 and F_2. Pareto-optimal solutions are shown on the red line. None of these solutions are superior to one another. The far left solution has the least value for objective function F_1, but has the highest value when looking at objective function F_2. The next solution has a higher value for objective function F_1, but has a lower value for objective F_2 when compared to the first solution. All the solutions in the Pareto front are non-dominated to each other but are superior to the rest of the solutions in the search space.

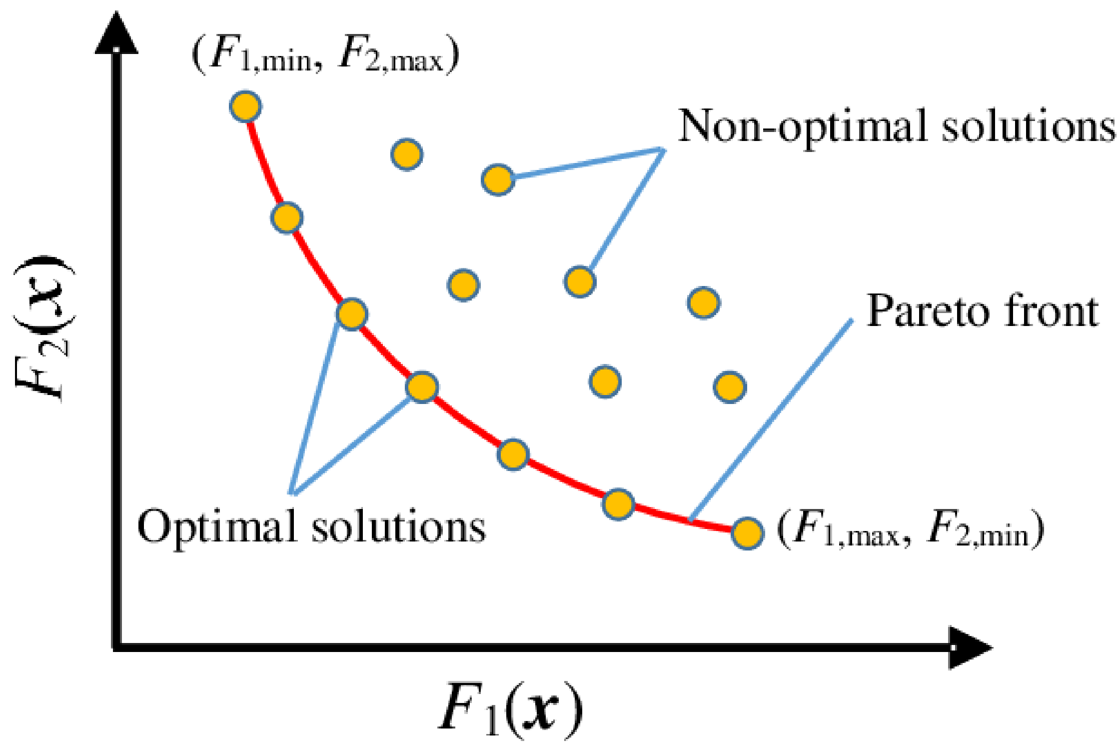

Figure 3.1: Pareto optimal solutions [2]

The two models developed in this thesis are discussed below.

3.1 Multi-Parameter Encoded NSGA-II Model

In this model, a multi-parameter encoded chromosome is developed to represent a potential solution based on decision parameters of interest. Objectives that are to be simultaneously optimize, influence the choice of decision parameters. For this model, two main conflicting objectives are considered, and they are as follows:

- Minimize the UAV energy consumption
- Minimize the UAv response time

UAVs consume the most energy during travel, and this is dependent on the distance between UAV waypoints and the speed employed by UAVs. The response time depends mainly on the UAV speed. Therefore, to minimize the UAV energy, UAVs have to employ a lower speed when moving from one waypoint to another. By doing so, the response time increases as the UAVs move slower. On the other hand, if UAVs employ higher speeds, the energy consumption increases, but the response time decreases. That is why these objectives are conflicting.

The following decision parameters are selected for this model:

- UAV waypoint visitation order, according to priority of events. This influences the distance travelled by the UAV and thus the UAV energy consumption.
- UAV operating altitude, which also affects the UAV travel distance. It also helps towards reducing chances of UAV collisions by ensuring that no two UAVs operate at the same altitude in any time period. A safe distance is selected to determine the minimum difference between the operating altitude of any combination of UAVs.
- UAV speed, which determines the response time and energy consumption of the UAVs.
- UAV departure time, which determines the response time.
- UAV recharging time, which helps UAVs replenish their remaining energy to allow extended operation.

These decision parameters are captured in a chromosome structure used by NSGA-II as a potential solution. NSGA-II find the values for these parameters that simultaneously optimizes our two objectives, being the UAV energy consumption and UAV response time.

3.1.1 Chromosome Encoding

The chromosome is usually in the form of an array or a matrix. As mentioned, the chromosome represents a potential solution which in this work represents a task assignment schedule for UAVs. For this model, we used a multi-dimensional array to represent the task assignment of the UAV team.

Time periods (k)

	0	e1	e1	0	0	0	e5	e5	0	0
UAVs	0	0	e4		e2	e2	0	0	e5	0
	0	e3	0	e4	e4	0	0	0	e6	0

Figure 3.2: Multi-parameter encoded chromosome

Figure 3.2 shows an example of the chromosome structure, where rows represent UAVs and columns represent time periods of the UAV mission. Individual cells of the chromosome are referred to as genes and they are encoded using the above mentioned decision variables. Non zero genes such as gene $e1$, contain information needed to respond to IoT events, whereas the 0 gene represents information about the "HOME" event of the UAVs. This is where the charging dock is located, so in addition, it has battery charging information such as duration.

The information contained in non-zero gene is as follows:

- UAV waypoint for event 1
- UAV speed to use when moving to the waypoint
- UAV departure time
- UAV altitude

The information contained in zero (0) gene is as follows:

- UAV waypoint for "HOME"
- UAV speed to use to go back "HOME"

- UAV departure time
- UAV altitude which is zero since they arrive and leave "HOME" from their charging stations, assumed to be on the ground.
- UAV charging duration

Figure 3.2 represents the chromosomes using three rows and ten columns. This means that three UAVs are employed over ten time periods and at each time period, the appropriate event is assigned to the UAV. The UAV uses information about the event to know when and where to go next, which speed to employ and the altitude to provide the service.

Once the solution chromosome has been well defined, then the optimization process can commence and this is handled by NSGA-II. The algorithm is named as Discrete Non-Dominated Search Genetic Algorithm with different type genes (D-NSGA-II-DTG) because the chromosome uses genes of different types as seen above. The pseudocode for the optimization algortithm is shown as Algorithm 1.

3.1.2 Multi-objective Optimization

The algorithm starts with a random population of individual solutions, P_0 of size N. The individual solutions are represented using the chromosome structure defined in section 3.1.1. Random waypoints, speeds, departure times, altitudes and charging durations are generated for each UAV in the chromosome throughout all the time periods of the mission. Objective functions are then calculated for each solution in the population P_0. Objective functions to be minimized are the UAV energy consumption and UAV response time. Once the objective functions are calculated, a non-dominated sort of the population is performed. A rank(fitness) is assigned to each solution of P_0 depending on how it performed in the non-dominated sorting. This helps rank the best individuals according to rank. The best solutions are then selected using binary tournament selection and they take part in the next step of the algorithm which is genetic crossover and mutation. Crossover and mutation are genetic operators that combine the better solutions in the population to create a new set of offspring solutions of size N. A union of the offspring population and

Algorithm 1: Pseudocode-D-NSGA-II-DTG

```
Input: Population_size, Problem_size, P_crossover, P_mutation
Output: Children
Population ← InitializePopulation(Population_size, Problem_size)
EvaluateObjectiveFunctions(Population)
FastNonDominatedSort(Population)
Selected ← SelectParentsbyRank(Population, Population_size)
Children ← CrossoverAndMutation(Selected, P_crossover, P_mutation)
while (!StopCondition()) do
    EvaluateObjectiveFunctions(Children)
    Union ← Merge(Population, Children)
    Fronts ← FastNonDominatedSort(Union)
    Parents ← Ø
    Front_L ← Ø
    for (Front_i ∈ Fronts) do
        CrowdingDistanceAssignment(Front_i)
        if (Size(Parents) + Size(Front_i) > Population_size) then
            Front_L ← i
            Break()
        else
            Parents ← Merge(Parents, Front_i)
        end
    end
    if (Size(Parents) < Population_size) then
        Front_L ← SortByRankAndDistance(Front_L) for (P_1 to P_{Population_size} − Size(Front_L)) do
            Parents ← P_i
        end
    end
    Selected ← SelectParentsByRankAndDistance(Parents, Population_size)
    Population ← Children
    Children ← CrossoverAndMutation(Selected, P_crossover, P_mutation)
end
return (Children)
```

the parent population is then performed to generate a new population of size $2N$. The population is then sorted based on non-domination according to different fronts. The solutions belonging to the first front F_1 are the best solutions. For the next iteration of the algorithm, the non-dominated sorted population becomes the initial population and must be a size of N. All solutions from F_1 are chosen if the size is smaller than N. The rest of the population is taken from the next following fronts which is F_2, then F_3, F_4 and so on. If the count of solutions from F_1 to the last front F_x is greater then N, then a crowding distance operation is done to remove the excess solutions in order to have exactly N solutions. Genetic crossover and mutation are performed on the new solutions to create a child solution population Q_{t+1} of size N and the cycle repeats until a maximum number of iterations is performed or when there is no improvement in the quality of solutions.

3.1.2.1 Genetic Crossover

Crossover is analogous to the creating of an offspring through sexual reproduction. Crossover is done based on some probability, called the probability of crossover, P_c. An random index is calculated, which marks the split locations in the parent chromosomes. The left part in parent 1 is combined with the right part from parent 2 and vice versa. with some probability and this is the location at which the parent solutions are split to be exchanged to combine the left and right portions of the parents' chromosomes. See Figure 3.3 below. During this process, event information is exchanged between parents. Event information includes the waypoints, speeds, departure times, altitudes and charging duration if it is the "HOME" event.

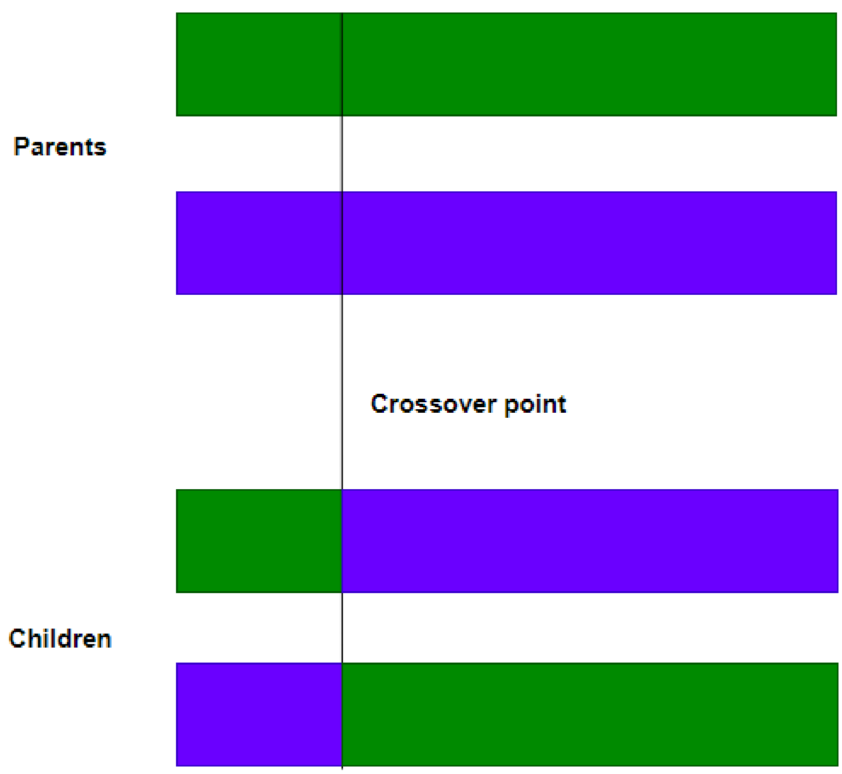

Figure 3.3: Genetic crossover operator

3.1.2.2 Genetic Mutation

Mutation is used to randomly change the individual genes of a solution based on some probability called the probability of mutation (P_m). This is done to to introduce diversity in the solutions to improve the exploration of the optimization process. This is illustrated in Figure 3.4.

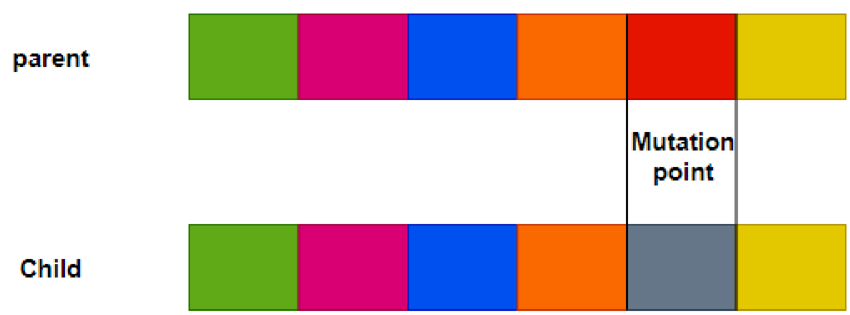

Figure 3.4: Genetic mutation operator

3.1.2.3 Crowding distance Operator

The crowding distance operator is a diversity preserving operator. Solutions with a higher crowding distance are preferred over other solutions in the same rank. This is done to eliminate excess solutions to ensure that the population at the beginning of each iteration is exactly N. Figure 3.5 shows how it is calculated.

To summarise this model, Black box is shown in Figure 3.6. This will help visualise the model in terms of inputs and outputs. The model's main focus is on optimizing the multi-UAV task assignment, given the objectives of energy and response time to be minimized, subject to constraints.

The output is the task assignment schedule that shows the position each UAV needs to be at each time period, the speed used when moving from one location to another, the altitude the uAV takes when providing service, the UAV departure time from

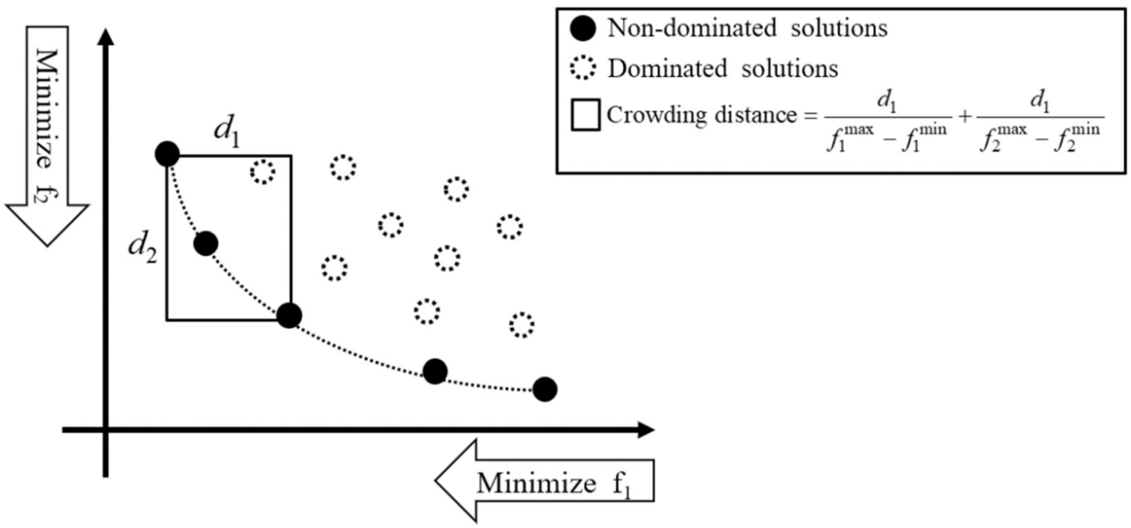

Figure 3.5: Crowding distance calculation

one location to another and in some cases the charging duration when the UAV has returned "HOME" to replenish its energy.

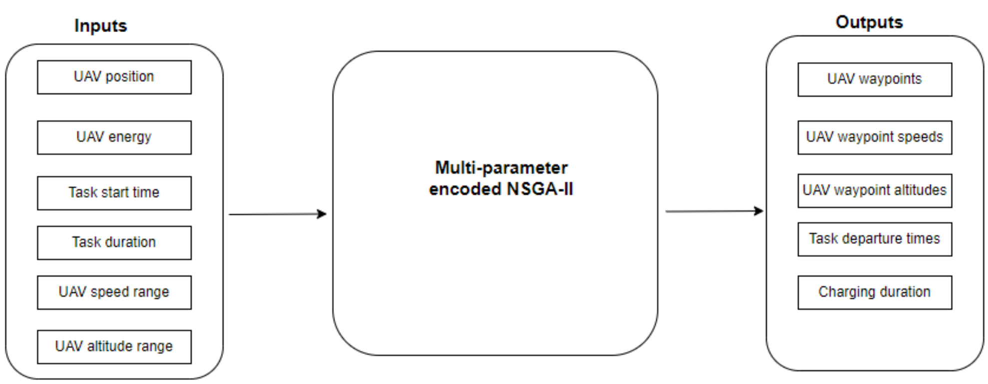

Figure 3.6: Black box model

3.2 Fuzzy C-Means NSGA-III Model

In this model, a hybrid algorithm is developed based on FCM and NSGA-III. The model works to simultaneously optimize multiple conflicting objectives, and they are as shown below:

- Minimize the UAV energy consumption
- Minimize the IoT devices energy consumption
- Maximize the data collected by the UAVs

During data collection, UAVs consume energy when travelling and when hovering to collect data. For IoT devices, most of energy is consumed during transmissions. The further the receiver is, the more energy is consumed during transmissions. To minimize the IoT energy consumption, UAVs will travel more distance so as to be closer to the IoT devices. This results in UAVs energy consumption increasing. Additionally to maximize the data collected by the UAVs, the hovering time needs to be longer. This results in in an increase in the UAV energy consumption due to hovering. This shows why these objectives are conflicting, and why an EA such as NSGA-III is appropriate to find non-dominated solutions. NSGA-III is chosen over NSGA-II because it performs better when considering more than two objectives to simultaneously optimize.

The following decision variables are selected for this model:

- Number of clusters for IoT devices, which determines the UAV waypoints and thus the UAV energy consumption.
- Cluster centers which represent the UAV waypoints, which affects the UAV energy consumption.
- UAV speed when moving from one cluster center to another, which affects the UAV energy consumption.
- UAV altitude when hovering which affects bothe the UAV and IoT device energy consumption.

- IoT device transmit power which affects the IoT device energy consumption and data collection rate.

3.2.1 Fuzzy C-Means (FCM)

FCM is a clustering algorithm in the field of machine learning proposed by Bezdek et al. in 1984. A clustering algorithm assigns a set of data points into groups called clusters. Generally, there are two categories which are hard clustering and soft clustering. With hard clustering (e.g k-means), the data points are divided into distinct clusters, where each data point belongs to only one cluster. However, with soft clustering (e.g FCM), the data points can belong to more than one cluster [138], as seen from Figure 3.7. Each IoT device will have membership leevls for clusters. The membership levels are represented with a fuzzy membership matrix. FCM has been shown to suffer from a local minima and requires the number of clusters to be provided in advance. [139].

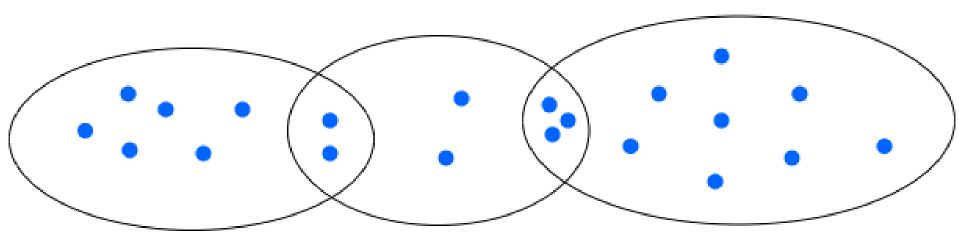

Figure 3.7: Overlapping clusters

To help deal with these shortcomings, NSGA-III is incorporated since it has uses exploration and exploitation capabilities to escape the local minima and making it a good fit for global optimization problems. Additionally, when using NSGA-III, there is no need to specify the number of clusters in advance as the cluster number can be one of the decision variables determined by NSGA-III. FCM is employed to aggregate IoT devices into overlapping clusters, where the cluster centre represents a potential UAV hovering location when collecting data. NSGA-III is employed to find acceptable values for the decision variables, that can simultaneously optimize all objectives of interest. The hybrid algorithm developed in this work is called F-NSGA-III to show that it uses concepts from both FCM with NSGA-III. The pseudocode is as shown in Algorithm 2.

Algorithm 2: Pseudocode: F-NSGA-III

Input: $N, P_{crossover}, P_{mutation}, H, MaxIterations$
Output: P_t
(1) Initialize hyperplane reference points and initial population P_0 which with random number of clusters c and random initial cluster centers (c_x, c_y, c_z). The cluster centers represent the UAV waypoints
(2) Decode each individual in the population to obtain cluster centers and calculate the fuzzy membership degrees U of each IoT device to the clusters (UAV-IoT) device association
(3) Calculate new cluster centers of each individual using fuzzy rules
(4) Evaluate the objective functions to calculate the fitness values of each individual in the population
(5) Non-dominated sorting of the population
(6) Generate offspring solution population using genetic operators (crossover and mutation)
(7) Combine parent and offspring population to create a total population T of size $2N$
(8) Non-dominated sorting of population T into different levels $(L_1, L_2, ..., L_l)$
(9) Select individuals from each level until the size of the new population is of size¿=N. Take note of the last level L_{last} which satisfied this
(10) Apply reference based niching to select individuals from L_{last} to ensure that the new population P_t is of size N.
(11) If stopping criteria is not met, go to step (2)
(12) **Return** P_t

3.2.2 Multi-objective Optimization

A set of predefined reference points is used to help with diversity and convergence of the solutions. Based on this consideration, we developed a fuzzy inspired multi-objective optimization algorithm that combines concepts from FCM and NSGA-III and we call it F-NSGA-III.

The proposed F-NSGA-III algorithm, as shown by Algorithm 2 starts with a random population of size N and a set of M dimensional reference points H on a unit hyperplane that covers the entire region, R^M_+. Reference points are selected on the hyperplane such that they intercept the objective function's axis at one. The total number of reference points, H in an M-objective problem is given by equation (3.1), where p is selected by the user and represents the number of divisions. N is calculated to the the smallest multiple of four greater than H. The initial population consists of random number of clusters and cluster centers. These represent the UAV hovering waypoints while collecting data. Each individual in the population is then decoded to extract the cluster centers and then fuzzy membership degrees for each IoT device is calculated. This shows the UAV-IoT device association. Next, the cluster centers are updated according to fuzzy rules. Objective functions are then evaluated for each member of the population and this represents the fitness of the solutions. Once the fitness is calculated, non-dominated sorting of the population is done. After that, genetic operators are applied to create a new child population of size N. The parent and child populations are then combined to form a total population T of size $2N$. The new population is then sorted to different domination levels $(L_1, L_2, ..., L_l)$. Thereafter, individuals are selected from each domination level starting with L_1 until the size of $T \geq N$. Suppose the last level to be included in the population is L_x, then individuals from that level will be sorted using a reference based niching technique that uses the M dimensional reference points. Based on the sorting, the top individuals from this level are added to the population T such that the size no becomes exactly N. If the stopping criteria is not met, which in our case is the number of iterations of the algorithm, then these steps are repeated. Once the stopping criteria is met, then the newly created population is returned and considered to be the most optimal.

$$H = \binom{M + p - 1}{p} \tag{3.1}$$

3.3 Ground-to-Air Path Loss Model

Since there is no information relating to obstacles or anything that can cause signal attenuation and degradation, randomness associated with LoS and non-line-of-sight (NLoS) links in the communication system is considered. For ground-to-air communications, each IoT device will have a LoS view towards a specific UAV with some probability. The probability depends on the environment(rural, urban, suburban etc), the locations of both the IoT device and the UAV as well as the elevation angle. *IntelliCloud* is assumed to have information about the ground device's locations and the type of environment. As expressed in [140], the LoS probability is as shown in (3.2):

$$P_{\mathrm{LoS}}^{ij} = \frac{1}{1 + \psi \exp(-\beta \left[\theta_{ij} - \psi\right])}, \tag{3.2}$$

where ψ, β are constants that depend on the frequency and type of environment. θ_{ij} is the elevation angle between device i and UAV j. As seen from Figure 3.8, θ is calculated using (3.3). The distance between device i and UAV j is d_{ij}, and it is calculated using (3.4).

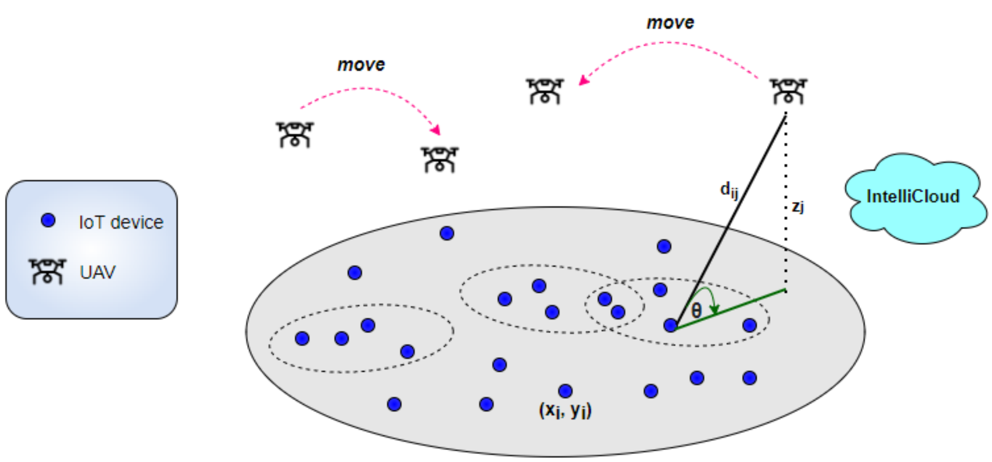

Figure 3.8: LoS Model diagram

$$\theta = \frac{180}{\pi} * sin^{-1}(\frac{h_j}{d_{ij}}) \tag{3.3}$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + h_j^2} \tag{3.4}$$

The path loss model for LoS and NLoS links between device i and UAV j as given by [141] is shown in (3.5) and (3.6) respectively:

$$L_{ij}^{LoS} = \eta_1 (\frac{4\pi f_c d_{ij}}{c})^{\alpha} \tag{3.5}$$

$$L_{ij}^{NLoS} = \eta_2(\frac{4\pi f_c d_{ij}}{c})^{\alpha} \tag{3.6}$$

where f_c is the carrier frequency, α is the path loss component, η_1 and η_2 are the excessive path loss coefficients in LoS and NLoS and c is the speed of light. The NLoS probability is $P_{NLoS}^{ij} = 1 - P_{LoS}^{ij}$. The path loss average which considers both LoS and NLoS can be used for device-UAV communications allows SNR expressions to be easier to deal with. This can be expressed by (3.7):

$$\bar{L}_{ij} = P_{LoS}^{ij}\eta_1(\frac{4\pi f_c d_{ij}}{c})^{\alpha} + P_{NLoS}^{ij}\eta_2(\frac{4\pi f_c d_{ij}}{c})^{\alpha} \tag{3.7}$$

3.4 Channel Assignment

We assume that the devices transmit data to UAVs using frequency division multiple access (FDMA) over R orthogonal channels. Different channels will be assigned to devices that are in close proximity to one another to mitigate the effects of interference when two closely located devices are communicating at the same time.

Chapter 4

Multi-Parameter Encoded Genetic Algorithm (D-NSGA-II-DTG)

In this chapter, the feasibility and performance of the D-NSGA-II-DTG algorithm, which is at the core of the model developed in this research, is tested on a scenario that requires multiple UAVs to provide aerial services under time and energy constraints.

A geographical area of size $X \times Y \times Z$ km^3 is considered, which is served by N UAVs as shown in Figure 4.1. The UAVs are used collaboratively to cover E events during a time horizon T. Each event has a priority that is based on task start times for tasks associated with that event. A higher priority event would naturally have an earlier start time to allow for prompt response. We refer to the start time as the response time and it is denoted by $t_{response}$. The task duration, which we refer to as the task coverage time is denoted by t_{cover}.

The location of each event is expressed using the 2D geographical position (x_i, y_i) for $i = 1, 2, 3, ..., E$. UAVs provide aerial services at the event location from a determined altitude h, so for an event i located at (x_i, y_i, z_i), the UAV would service it from a position (x_i, y_i, h). All UAVs are assumed to start at the same initial position referred to as "HOME" and will return "HOME" once the mission is complete. The battery capacity of each UAV is denoted by B_{full}.

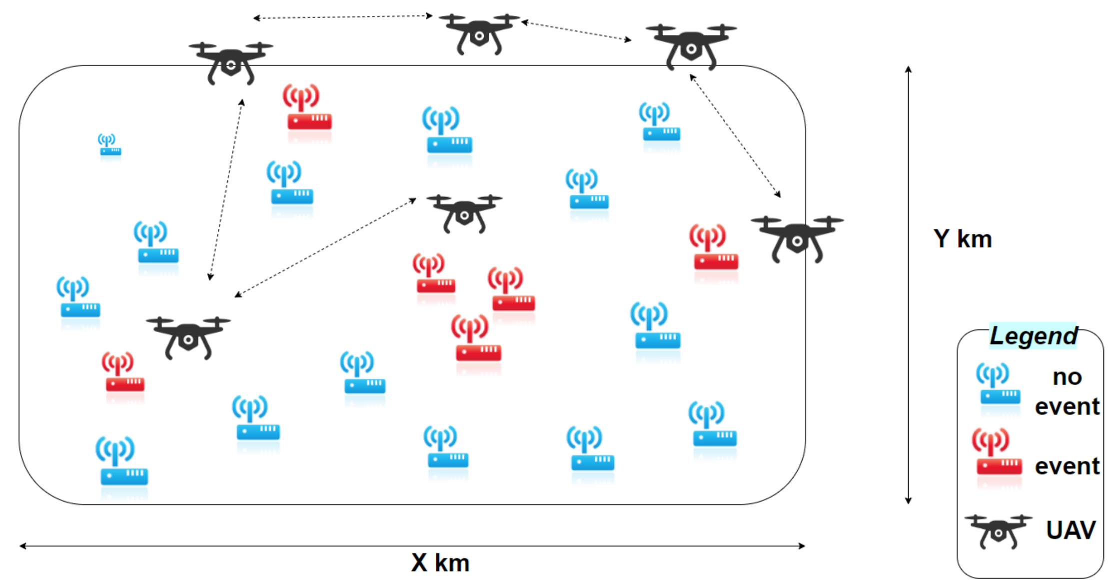

Figure 4.1: Events generated by IoT devices in area of interest

The power consumption of the UAV is composed of the power when travelling, power when hovering, power when waiting for an event to start and power when serving at an event. This is as shown below:

- Power when hovering denoted by P_{hover}
- Power when travelling denoted by P_{tr}
- Power when waiting at an event denoted by P_{wait}
- Power when serving an event denoted by P_{serve}

The equations for each different power consumption (hovering, travelling, waiting, serving) are adopted from a promising study by Ghazzai et al. [125]. These equations are adopted because they gave good results when considering implementation on real physical devices. Additionally, it allows the approach in this research to be directly compared with Ghazzai et al. approach since the same equations are used to calculate the power consumption of the UAV team. The equations are as shown below.

The hovering and transition power consumption is calculated as shown below.

$$P_{hover} = \sqrt{\frac{(m_{total}g)^3}{2\pi r_p^2 n_p \rho}} \tag{4.1}$$

$$P_{tr} = \frac{P_{full}}{v_{max}}\bar{v} \tag{4.2}$$

where:

- m_{total} is the total mass of the UAV in kg
- g is the acceleration due to gravity in m/s^2
- ρ is the air density in kg/m^3
- r_p is the radius of a UAV's propeller
- n_p is the number of propellers on each UAV
- P_{full} is the hardware power level when the UAV is moving at maximum speed in $Watts$
- v_{max} is the maximum speed of the UAV in m/s
- $\bar{v}$ is the average speed of a UAV in m/s

The energy consumption of the UAVs is calculated as shown.

(a) Energy consumed when moving from one event to another

$$E_{fly} = (P_{hover} + P_{tr}) \cdot T_{fly} \tag{4.3}$$

where, $T_{fly} = \frac{\Delta d}{\bar{v}}$ and Δd is the distance between two events.

(b) Energy consumed when waiting at an event

$$E_{wait} = P_{hover} \cdot T_{wait} \tag{4.4}$$

(c) Energy when serving events

$$E_{serve} = (P_{hover} + P_{serve}) \cdot T_{serve} \tag{4.5}$$

$T_{fly}, T_{wait}, T_{serve}$ are durations of time the UAV takes to fly from one event to another, wait at an event and serve at an event respectively.

4.1 Problem Formulation

In this study, a team of UAVs is employed to support multiple events raised by IoT devices on the ground. These events are spatially and temporally distributed in the geographical area of interest during a defined time horizon, T. The time horizon is divided into K time periods of the same length. The aim of this study is to determine how best we could deploy the available UAVs given the spatio-temporal characteristics of events and the availability of a charging dock to replenish the available UAV energy. We investigate how UAVs can be used cooperatively to improve the efficiency, given the time and energy constraints of the mission. The intent is to jointly optimize the UAV speed, altitude, hover duration, waypoint order and departure time, as well as the charging duration, in an effort to minimize the energy of the UAV team as well as the response time. This is put in place to improve the efficiency of the mission in terms of energy and time, while ensuring that non of the constraints are violated. Consequently, this problem is formulated as a multi-objective optimization problem, subject to constraints, as shown below:

(objective 1) : minimize

$$\sum_{u=1}^{N} E_{u,K}^{fly} + E_{u,K}^{wait} + E_{u,K}^{serve}$$

(objective 2) : minimize

$$\sum_{u=1}^{N}\sum_{i=1}^{E} t_{u,arrival} - t_{i,response} \quad \forall k = 1, 2, \ldots, K$$

The 1st objective minimises the total energy consumption incurred by all UAVs during the mission and the 2nd objective minimises the response times of all the UAVs. This helps create a task assignment model that allows UAVs to adequately serve at the different event locations.

4.1.1 Decision variables

The decision variables for this problem include:

- $\delta_{i,u,k}$ is a binary variable which shows if event i has been assigned to UAV u during time period k.

$$\delta_{i,u,k} = \begin{cases} 1, & \text{if } i \text{ is assigned to } u \text{ at time period } k \\ 0, & \text{otherwise} \end{cases} \tag{4.6}$$

- Average speed of the UAV, $\bar{v}$
- UAV altitude, h
- UAV departure time
- UAV hovering time
- UAV charging time

4.1.2 Constraints

The constraints of the mission are as follows:

$$
\begin{aligned}
&E^{fly}_{u,K} + E^{wait}_{u,K} + E^{serve}_{u,K} \leq B_{full} \quad \forall u = 1, 2, \dots, N && \text{(a)}\\
&\sum_{u=1}^{N} \delta_{i,u,k} = 1 && \text{(b)}\\
&\sum_{k=1}^{K} N_{total,k} \leq N && \text{(c)}\\
&\bar{v} \leq 20m/s && \text{(d)}\\
&30m \leq h \leq 100m && \text{(e)}\\
&|h_u - h_v| \geq 0.2m \quad \forall u, v = 1, 2, \dots, N \quad s.t \quad u \neq v && \text{(f)}
\end{aligned}
\tag{4.7}
$$

Constraint (a) is added to ensure that the UAV has enough energy to complete its tasks. The energy consumption during flying, waiting and serving at an event should not exceed the energy available on the UAV.

Constraint (b) ensures that only one UAV is assigned to an event i at each time period k. This helps avoid a situation where two or more UAVs are assigned to the same event during the same time period.

Constraint (c) ensures that the number of UAVs employed at any time period is less than or equal to the total available UAVs, N.

Constraint (d) ensures that the maximum possible speed of any UAV is $20m/s$. This is the maximum speed for most quad rotor UAVs.

Constraint (e) ensures that the altitudes that the UAVs can take are restricted between 30m and 100m during the mission.

Constraint (f) ensures that no two UAVs have the same altitude and the minimum difference between the altitude of any two UAVs is greater or equals to 20cm. This was calculated based on the typical size of a quad rotor UAV.

4.1.3 Assumptions

The following assumptions have been made,

- It is assumed that all UAVs will fly at an average speed $\bar{v}$, and this speed may change from one waypoint to another.
- The 2D coordinates of each event are known.
- UAVs do not consume energy when "HOME".
- All UAVs start from "HOME" and return "HOME" once the mission is complete.

To allow UAVs to operate for longer periods of time, a charging dock is added to the system, located at $HOME, (x_{home}, y_{home}, z_{home})$, which UAVs can use to recharge their batteries during the mission. UAVs recharge their batteries with a charging power of $P_{charging}$. The energy replenished by the UAVs charging for a period, $t_{charging}$ would then be:

$$E_{gain} = P_{charge} \cdot t_{charge} \tag{4.8}$$

Given that at the beginning of the mission, UAVs have an initial energy $B_{initial}$, this results in the modification of constraint (a) to the following:

$$B_{initial} + E_{gain} - (E^{fly}_{u,K} + E^{wait}_{u,K} + E^{serve}_{u,K}) \leq B_{full} \tag{4.9}$$

4.2 Results and Discussion

To assess the performance of the proposed model based on D-NSGA-II-DTG algorithm, numerical simulations are done and comparison is made to similar implementations by Ghazzai et al. [142] and Tran et al. [143]. Ghazzai et al. used MILP to create a schedule to deploy multiple UAVs to cover events that are spatially and temporally distributed while keeping the speed of all UAVs constant and taking into account the limited energy of the UAVs. Tran et al. designed a UAV trajectory to minimize the total energy consumption while meeting the temporal requirements and energy budget of the associated tasks by optimizing the UAV velocities along subsequent hops. UAVs employed a constant altitude along subsequent hops.

In this investigation, the geographical area size measures $10 \times 10\ km^2$ and the total mission time is 7.5 hours, which is divided into 15 time periods, each 0.5 hours long. UAVs start at $HOME$, located at $(5000, 5000, 0)$. The locations of the events are as shown in Figure 4.2.

The temporal characteristics of each event is shown in Table 4.1.

Table 4.1: Event Start times and Service Duration

Event Number	**Start time (s)**	**Duration (s)**
1	1800	1800
2	14400	3600
3	10800	5400
4	9000	3600

Table 4.2 shows the system parameters while Table 4.3 shows the D-NSGA-II-DTG parameters.

Table 4.2: System Parameters

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
$m_{total}(kg)$	2	$\rho(kg/m^3)$	1.225	n	4
$g(m/s^2)$	9.8	r_p	0.18	$P_{tr}(W)$	20
$B_{full}(Wh)$	111	$v_{min}(m/s)$	10	$v_{max}(m/s)$	20
$P_{serve}(W)$	10	$P_{charge}(W)$	140		

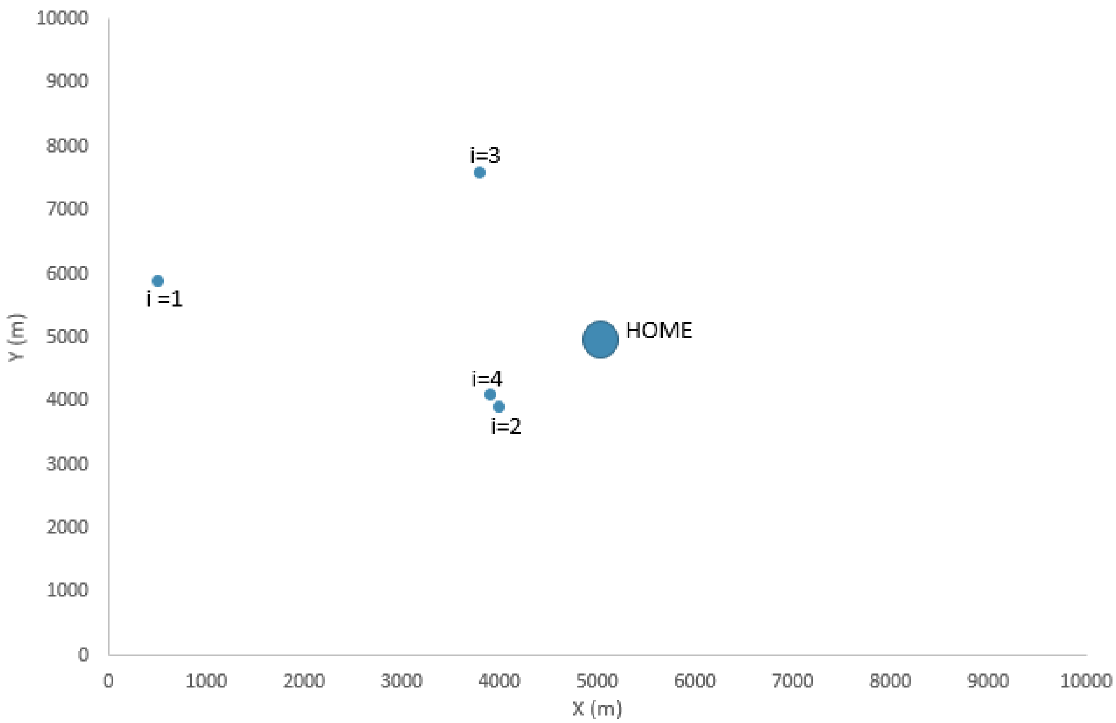

Figure 4.2: Scenario of event locations and the UAVs' start and end positions (HOME)

Table 4.3: D-NSGA-II-DTG Parameters

Parameter	**Value**	**Parameter**	**Value**
p_m	0.03	p_c	0.8
$populationSize$	200	$numberOfGenerations$	200

Figure 4.3 shows the total energy consumed by the UAV team during the mission. As seen from the figure, the total energy consumed by the UAV team is less when comparing the implementation of D-NSGA-II-DTG to both MILP and DP making the proposed algorithm more energy efficient. This is attributed to efficiency in optimising the speed, charging times and the 3D positions of the UAVs when serving at the event areas. DP performed slightly better than MILP due to optimizing of the UAV speed when moving from one event to another. D-NSGA-II-DTG outperforms DP by optimizing the response time and ensuring that energy incurred due to waiting at an event is minimized. Also by allowing UAVs to operate at variable altitudes,

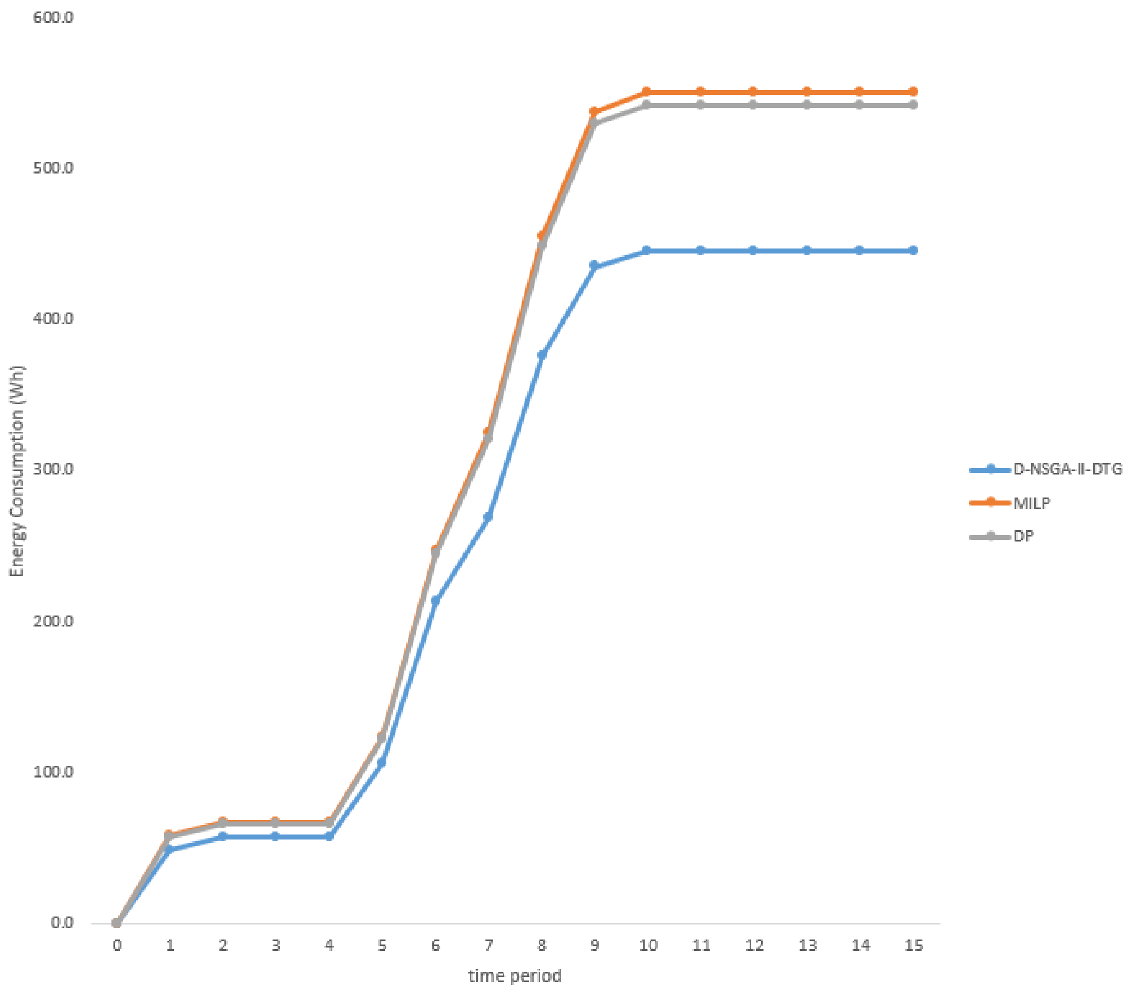

Figure 4.3: Cumulative Energy Consumed by all UAVs during the mission

this resulted in more energy savings for D-NSGA-II-DTG when compared to both the MILP and DP algorithms.

Figure 4.4 shows the energy consumed by each UAV. All algorithms used 4 UAVs for the mission. Overall, the D-NSGA-II-DTG algorithm was more energy efficient. The total energy consumption when using D-NSGA-II-DTG was 445.6Wh whereas MILP and DP were 550.4Wh and 541.9Wh respectively.

To validate solutions, a more in-depth analysis was done by comparing the energy consumed against the energy remaining for all UAVs in the mission at each period.

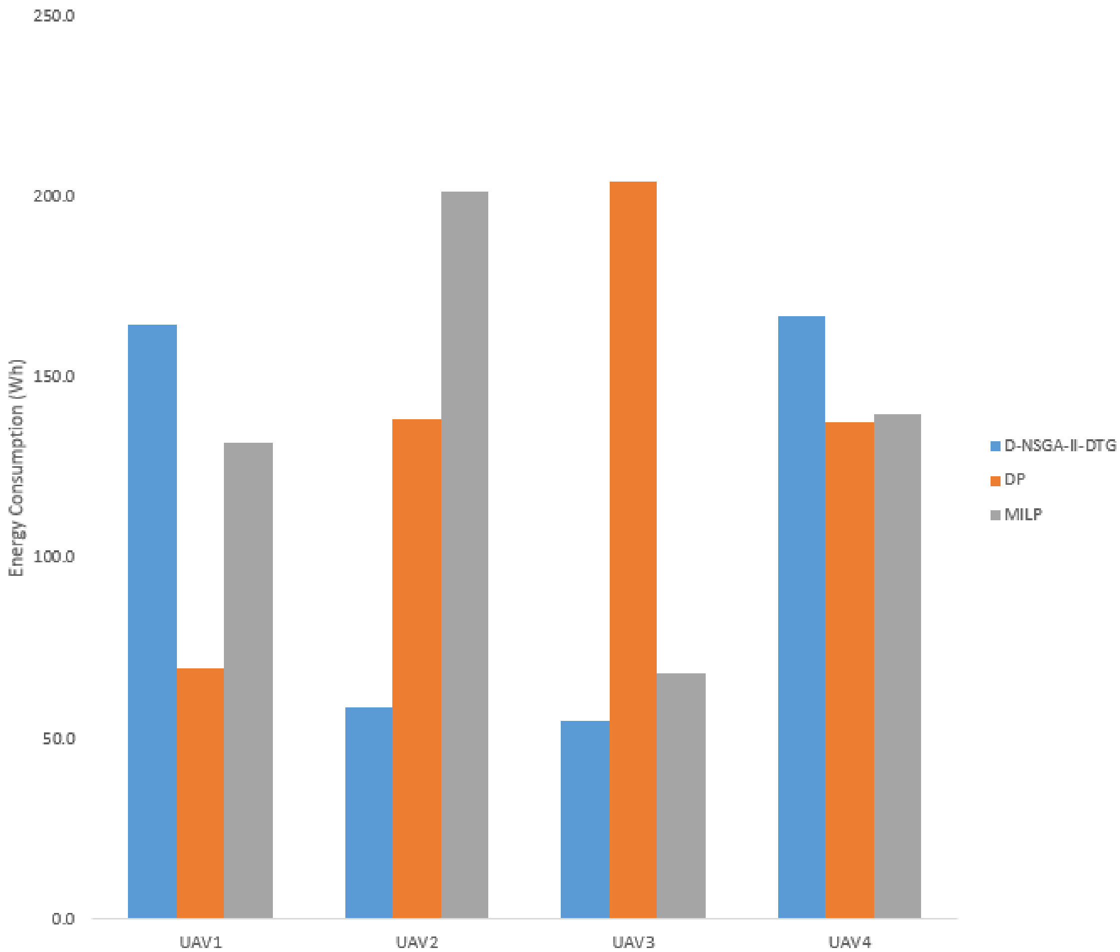

Figure 4.4: Total Energy Consumed by each UAV

Table 4.4 shows that the energy consumed by each UAV at each time period is less than the available energy of the UAVs. This is supported by a residual of energy at the end of each time period. This proves that all UAVs had enough energy to provide the required services.

Table 4.5 shows the start times of each event which coincide with the expected response times for the UAV team. A UAV incurs an energy cost if it arrives at an event earlier than the start time, because it has to hover and wait until the set start time. To reduce the overall energy consumption, the waiting time is minimized. For a successful mission, there should be no UAVs that are late to serve at an event.

Table 4.4: Energy consumed vs Energy remaining for each UAV

Algorithm	UAV	Energy	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
			Time Periods															
D-NSGA-II-DTG	UAV 1	Remaining Energy (Wh)	70.0	21.6	71.5	111.0	111.0	111.0	62.6	14.1	59.5	111.0	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	48.4	8.7	0.0	0.0	0.0	48.4	48.4	10.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	UAV 2	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	111.0	111.0	111.0	62.6	108.1	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	48.4	10.6	0.0	0.0	0.0	0.0	0.0	0.0
	UAV 3	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	111.0	62.6	111.0	111.0	111.0	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	0.0	48.4	6.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	UAV 4	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	62.6	106.3	111.0	62.6	14.1	60.1	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	48.4	11.4	0.0	48.4	48.4	10.4	0.0	0.0	0.0	0.0	0.0
			0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
MILP	UAV 1	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	111.0	111.0	52.1	97.8	111.0	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	58.9	10.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	UAV 2	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	111.0	52.1	84.1	25.2	71.0	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	0.0	58.9	10.5	58.9	10.5	0.0	0.0	0.0	0.0	0.0	0.0
	UAV 3	Remaining Energy (Wh)	70.0	12.3	60.9	111.0	111.0	54.4	105.5	111.0	111.0	50.4	92.3	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	57.7	9.3	0.0	0.0	56.6	8.2	0.0	0.0	60.6	12.2	0.0	0.0	0.0	0.0	0.0
	UAV 4	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	111.0	54.4	89.5	28.9	70.8	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	0.0	56.6	8.2	60.6	12.2	0.0	0.0	0.0	0.0	0.0	0.0
			0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
DP	UAV 1	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	54.8.0	93.9.0	35.5	82.5	111.0	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	56.2	7.8	58.4	9.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	UAV 2	Remaining Energy (Wh)	70.0	12.8	62.5	111.0	111.0	111.0	54.8	106.9	111.0	51.0	94.4	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	57.2	8.8	0.0	0.0	0.0	56.2	7.8	0.0	60.0	11.5	0.0	0.0	0.0	0.0	0.0
	UAV 3	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	111.0	111.0	111.0	52.6	99.7	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	58.4	9.9	0.0	0.0	0.0	0.0	0.0	0.0
	UAV 4	Remaining Energy (Wh)	70.0	111.0	111.0	111.0	111.0	111.0	52.6	84.5	24.6	67.9	111.0	111.0	111.0	111.0	111.0	111.0
		Consumed Energy (Wh)	0.0	0.0	0.0	0.0	0.0	0.0	58.4	9.9	60.0	11.5	0.0	0.0	0.0	0.0	0.0	0.0

Table 4.5: Expected response times for each event

Event Number	Expected Response Time (s)	Time period (k)	Cumulative Expected response time (s)
1	1800	1	1800
4	9000	5	10800
3	10800	6	21600
2	14400	8	36000

Figure 4.5 shows the event response times of the UAV team. All the schedules from MILP, DP and D-NSGA-II-DTG met the temporal requirements of the tasks. However, for DP, some UAVs arrived earlier at some events. The drawback for DP was that the UAV team incurred more energy due to waiting and this is seen from Figure 4.3 which shows the cumulative energy consumption of the UAV team from the different algorithms. MILP and D-NSGA-II-DTG had similar event response times, resulting in their plots overlapping as seen in Figure 4.5. Looking at Figure 4.5 and comparing the response time to the cumulative response time in Table 4.5, we

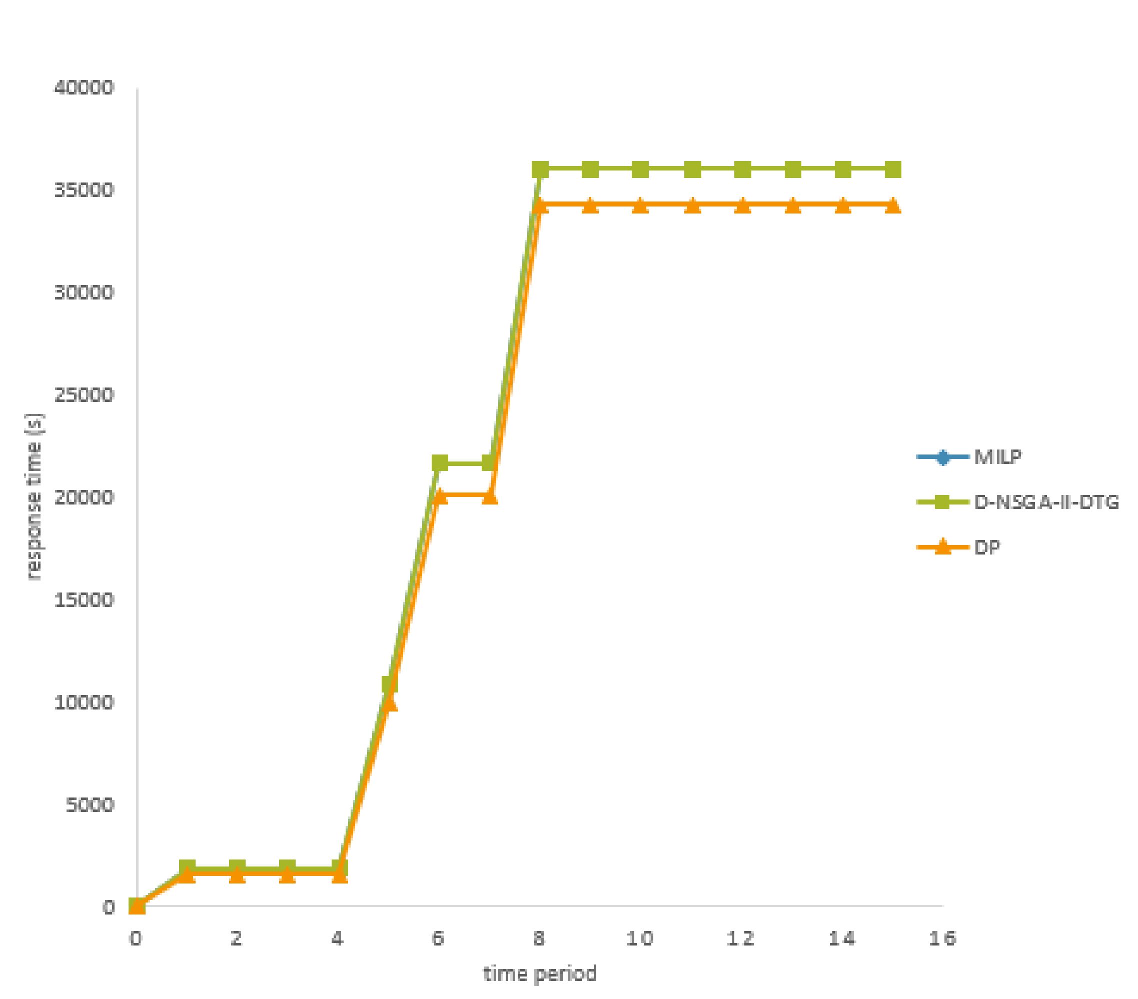

Figure 4.5: Cumulative Response time during the mission

prove the feasibility of the schedule produced by the proposed approach in ensuring that UAVs are not late to provide service at an event. At $k = 1$, the cumulative response time is $1800s$, and remains unchanged for $k = 2, 3, 4$. At $k = 5$, it increased to $10800s$ and at $k = 6$ it went to $21600s$. It remains the same for $k = 7$ and finally increases to $36000s$ at $k = 8$. Since all events are served, the cumulative response time remains unchanged for the rest of the time periods. Since the UAV team's response time was equal or less than the expected event response times, it showed that the UAVs responded efficiently and in time to sufficiently provide the required service. The task assignment schedule from all algorithms ensured that the temporal requirements were met.

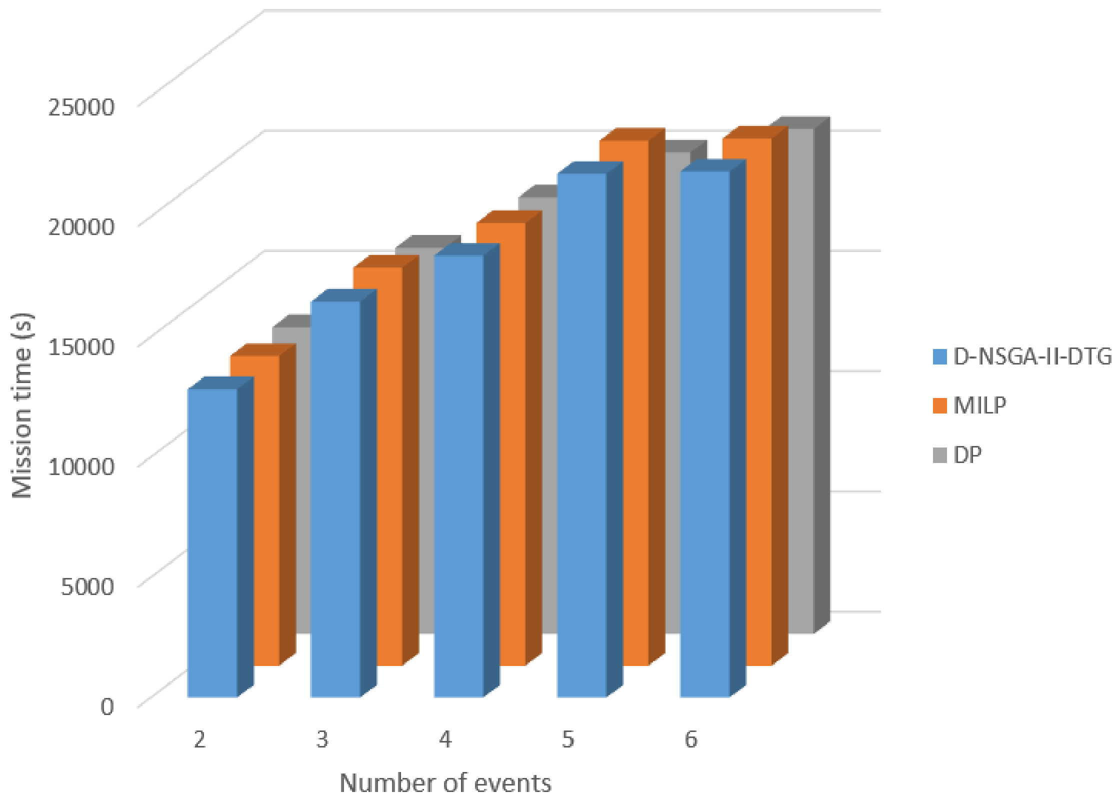

Figure 4.6: Mission time for different number of events

Figure 4.6 shows the mission times for different number of events. Events are increased in the order of the start times. As seen from the figure, D-NSGA-II-DTG and DP outperform MILP in terms of the mission operation times. By optimizing the UAV speed when moving from one event to the next, the mission operation times were minimized as compared to MILP which employed a constant speed for all UAVs which limited the behaviour of the system in exploiting various acceptable speeds in achieving an optimal task assignment schedule. DP performed better than D-NSGA-II-DTG because D-NSGA-II-DTG found a balance between the energy consumption and the operation time. It was outperformed in terms of the mission operation time but was superior in terms of energy consumption.

In Figure 4.7, a simple scenario consisting of 3 events was considered and the impact of modifying the UAV's battery capacity was investigated. The number of available UAVs is 4 and other system parameters were kept the same.

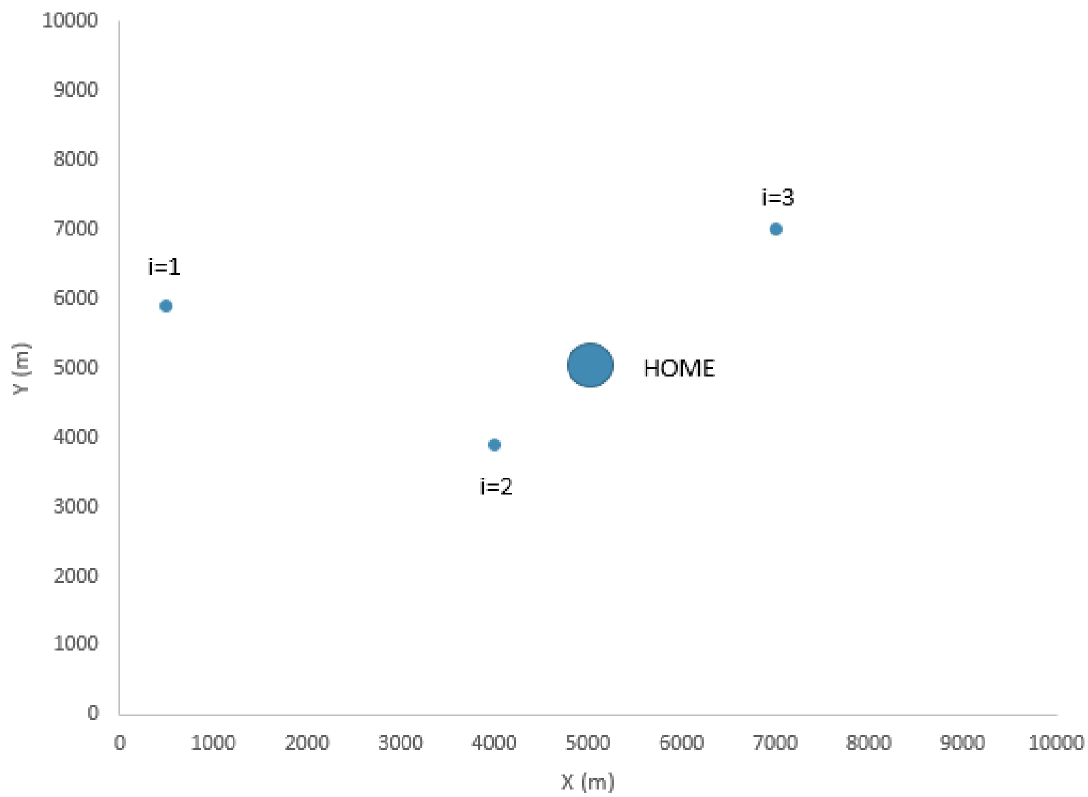

Figure 4.7: Scenario to show the impact battery capacity and charging power have on the system

Figure 4.8 shows changes in the energy consumption as we vary the battery capacity. When using different batteries with a lower capacity, UAVs would quickly run out of battery, operate for a shorter time and will require more trips back HOME to replenish the energy during task execution. This results in more trips and thus more energy being consumed. Also can lead to incomplete tasks as temporal requirements for some tasks might not be met. When the capacity is increased, the UAV's are able

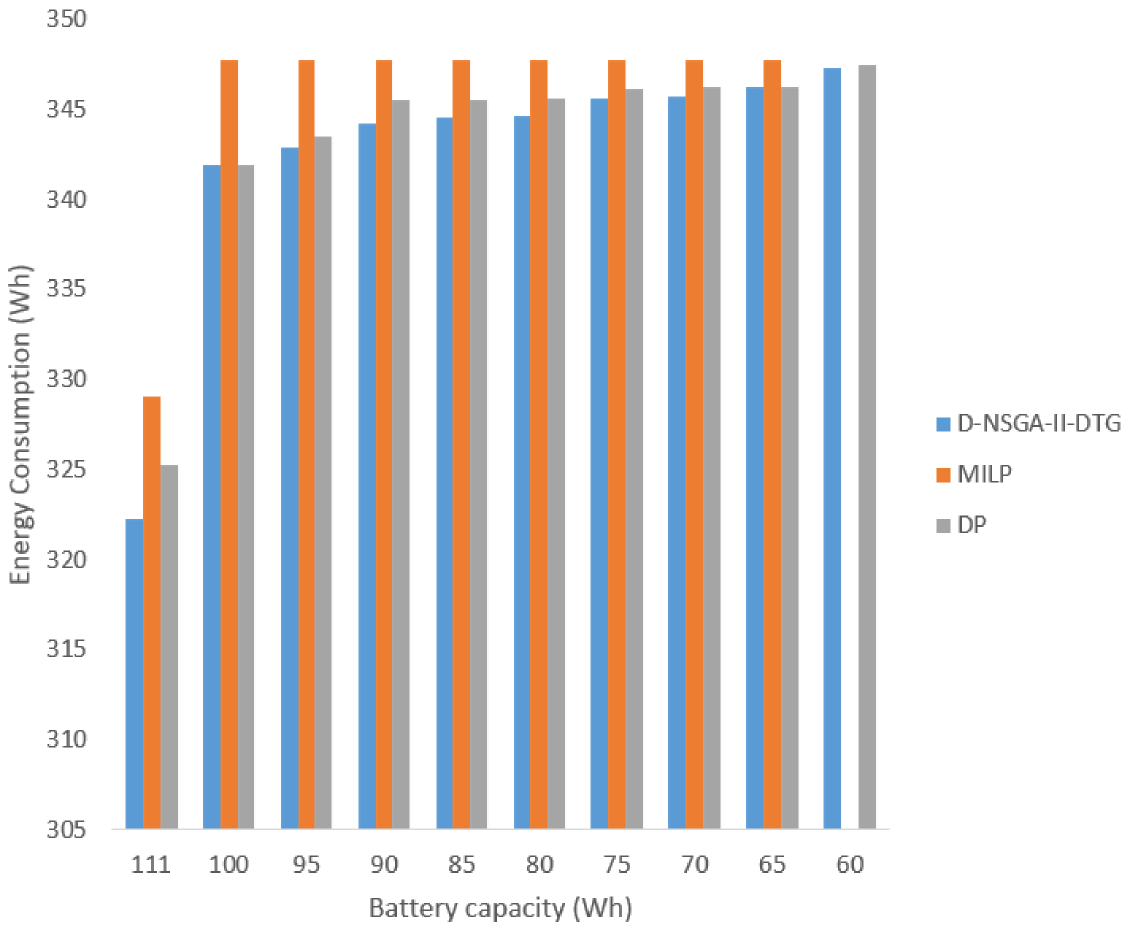

Figure 4.8: System behaviour for different battery capacities

to perform more tasks before they have to return to the charging dock to replenish the energy. This allows more tasks to be executed sufficiently in a shorter time. The battery capacity range was from 60 Wh to 110 Wh. When using MILP, battery capacities below 65Wh result in infeasible solutions for the scenario in Figure 4.7 due to energy constraint violations. However, for D-NSGA-II-DTG and DP, the lowest battery capacity for which a feasible solution could be found was 60Wh. This further shows the strength D-NSGA-II-DTG and DP have over MILP in using a smaller battery capacity to successfully complete the mission. This showed how robust our proposed D-NSGA-II-DTG algorithm can be to varying battery capacities.

Figure 4.9 shows the impact of the charging power on the total energy consumption

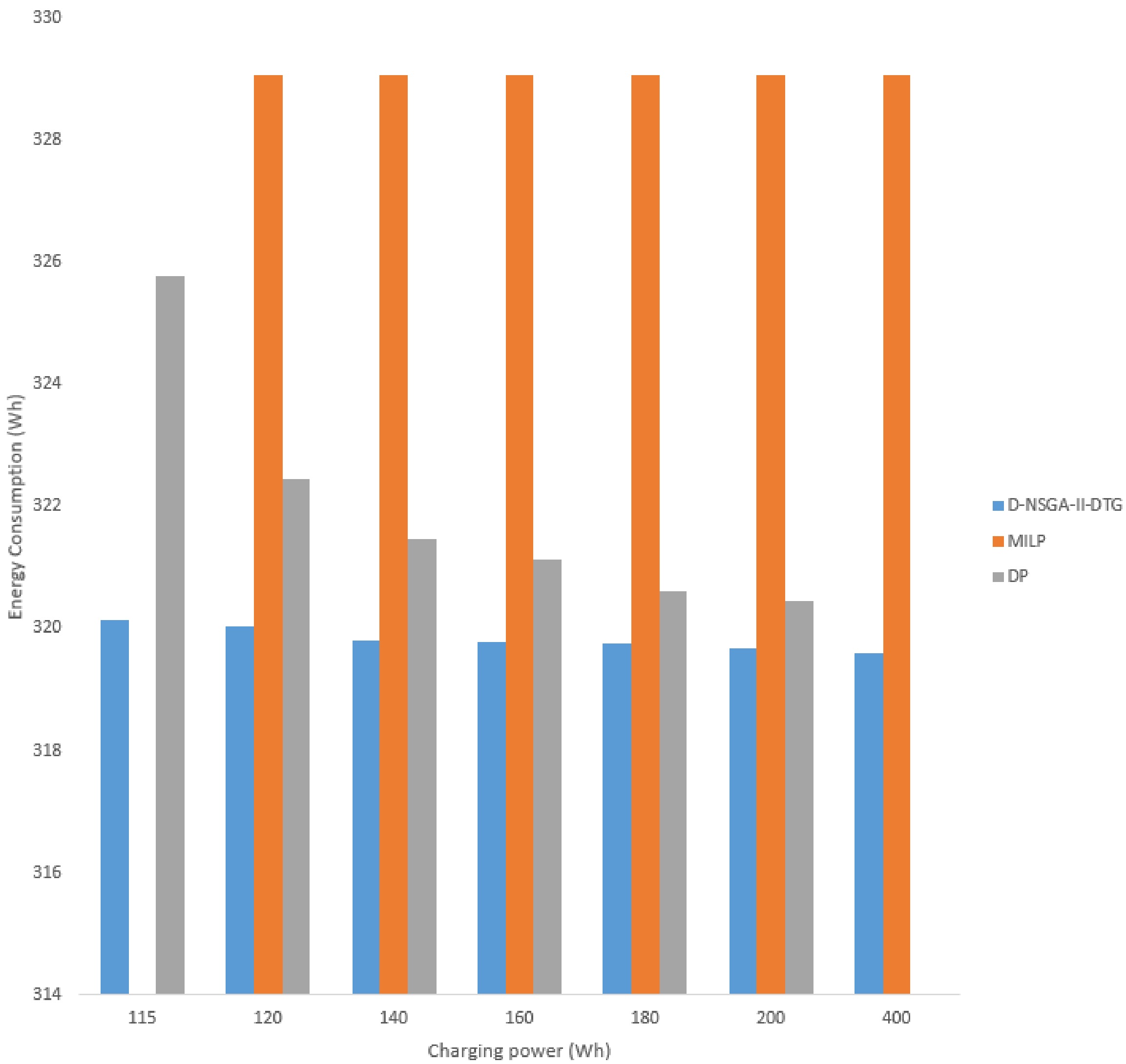

Figure 4.9: Behaviour of the system as the charging power varies

of the mission. The other system parameters were kept unchanged. A lower charging power means the battery will be recharged slower leading to lower energy capacity of the UAV and a high likelihood of many trips back to $HOME$ for the recharge. A higher charging power ensures the battery is charged faster to full potential allowing for more events to be attended with less frequent trips $HOME$ to recharge. This is clearly depicted in Figure 4.9, with power charge of 400 Wh resulting in less energy consumption as compared to the power charge of 120 Wh. D-NSGA-II-DTG and DP were able to find a feasible schedule when the charging power was $115Wh$ whereas MILP failed. The minimum charging power required for the MILP assignment schedule is $120Wh$ whereas for D-NSGA-II-DTG and DP was $115Wh$. This means a lower charging power ($115Wh$) could be employed when using D-NSGA-II-DTG and DP without compromising the success of the mission. Furthermore, this adds to the robustness of the system and adaptation to different power levels when charging.

Table 4.6: D-NSGA-II-DTG System behaviour as events increase

Number of events	No of UAVs available	Number of UAVs used	Overlapping events	Violates constraints
2	4	2	0	no
3	4	3	2	no
4	4	4	3	no
5	4	4	4	yes
5	5	5	4	no
6	6	5	4	no
6	20	6	4	no
20	20	20	18	yes
20	22	22	18	no
20	24	22	18	no

Table 4.6 shows the scalability of our proposed D-NSGA-II-DTG. Its shows how the system handles an increasing number of UAVs. The number of events is increased from 2-20, and D-NSGA-II-DTG calculates the number of UAVs needed to serve at different events. In most cases, the model was able to deduce the number of required UAVs to ensure that non of the constraints were violated. Only 20% of the tests failed as constraints were violated. In 80% of the tests, the system provided a task assignment schedule for UAVs without violating any constraints. This shows the scalability of the proposed work.

Chapter 5

Fuzzy C-means Genetic Algorithm (NSGA-III-FCM)

In this chapter, the problem of using UAVs as aerial base stations to collect data from IoT devices on the ground is investigated. There are multiple IoT devices distributed over a geographical area of size $A \times B$ km^2. The location of each IoT device in the set $K = \{k_1, k_2, k_3, ...K\}$ is represented by $(x_i, y_i, 0)$. There is a team of UAVs that act as aerial base stations and their role is to collect data from these devices. The positions that the UAVs in the set $U = \{u_1, u_2, u_3, ...U\}$ will hover from while collecting data can be represented by (x_j, y_j, z_j), where z_j is the flying altitude of the UAV which should be within the transmission range of the IoT devices. This is all shown in Figure 5.1. The assumption is that all UAVs will start their mission from a position called $HOME$ and return there once the mission is complete. Both the UAVs and IoT devices have limited energy denoted by E_{UAV} and E_{IoT} respectively. The time a UAV spends hovering at a location collecting data will be dependent on the amount of information stored in the IoT device.

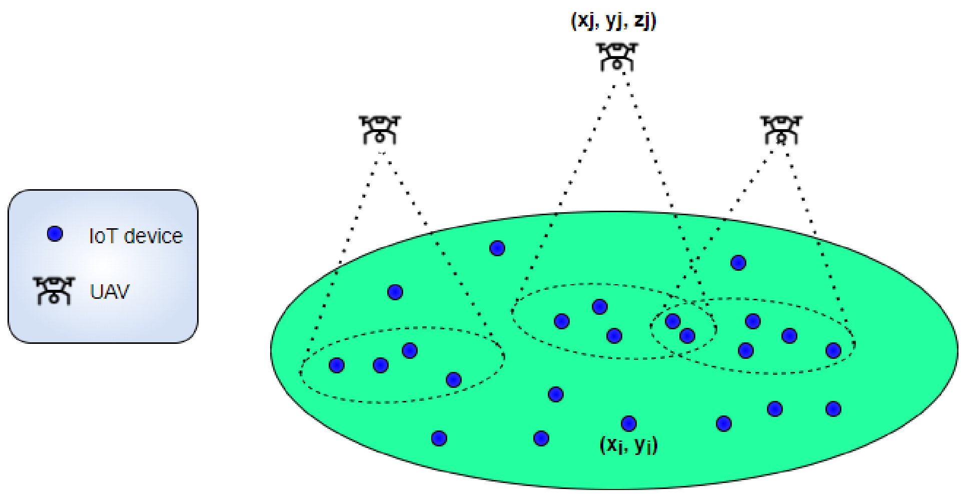

Figure 5.1: System model diagram

5.1 Problem Formulation

The optimization problem involves finding IoT device associations, UAV locations and the transmit power of IoT devices with the following objectives:

- Minimize the total energy consumed by the IoT devices
- Minimize the total energy of the UAVs
- Maximize the data collected by the UAVs

The energy consumed by the IoT devices, E_{IoT} during transmissions is as shown in (5.1), where P_{comms} is the transmission power used by the IoT device and T_{comms} is the transmission time.

$$E_{IoT} = P_{comms} * T_{comms} \tag{5.1}$$

For successful transmissions, the power received by the UAV must be greater or equals to the UAVs receiver sensitivity denoted by P_{th}. The received power is calculated using (5.2)

$$P_r = P_{comms} - \bar{L}_{ij} \tag{5.2}$$

According to the Shannon-Hartley theorem [144], the channel capacity, C can be calculated as follows:

$$C = B \log_2(1 + \frac{P_r}{N}) \tag{5.3}$$

B is the channel bandwidth, P_r is the received signal power at the UAV and N is the noise power.
The UAVs consume energy during travel and when hovering at a location to collect data. The energy consumed during travel and when hovering is as shown in (5.3) and (5.4) respectively.

$$E_{travel} = P_{travel} * T_{travel} = \frac{P_{full}}{v_{max}} \bar{v} * T_{travel} \tag{5.4}$$

$$E_{hover} = P_{hover} * T_{hover} = \sqrt{\frac{(m_{total} g)^3}{2\pi r_p^2 n_p \rho}} * T_{hover} \tag{5.5}$$

P_{full} is the hardware power that is consumed when the UAV is moving at a maximum speed, while v_{max} and $\bar{v}$ are the maximum possible UAV speed and the average speed employed by the UAV respectively. m_{total} is the total mass of the UAV, g is the acceleration due to gravity, ρ is the ir density, r_p is the propeller radius and n_p is the number of propellers. T_{travel} and T_{hover} shows the time the UAV takes during travel and the time when hovering respectively.

The multi-objective optimization problem is formulated as follows:

$$\min \quad \sum_{i=1}^{K} E_i^{IoT} \tag{5.6}$$

$$\min \quad \sum_{j=1}^{U} E_j^{UAV} \tag{5.7}$$

$$\max \quad \sum_{i=1}^{K} C_i * T_{comms} \tag{5.8}$$

(5.6) minimizes the total energy consumed by the IoT devices. (5.7) minimizes the total energy consumed by the UAV team. (5.8) maximizes the data collected by the UAVs.

5.1.1 Decision variables

The decision variables for this problem include:

- $\delta_{i,u}$ is a binary variable which shows if cluster i has been assigned to UAV u

$$\delta_{i,u} = \begin{cases} 1, & \text{if } i \text{ is assigned to } u \\ 0, & \text{otherwise} \end{cases} \tag{5.9}$$

- Average speed of the UAV, $\bar{v}$
- UAV altitude, h
- UAV hovering time
- IoT device transmit power

5.1.2 Constraints

We aim to simultaneously optimize these objectives without violating any of the system constraints and they include the following:

$$
\begin{aligned}
E^u_{travel} + E^u_{hover} &\leq B_{full} \quad \forall u = 1, 2, \dots, U && \text{(a)}\\
P^u_r &\geq P_{th} \quad \forall u = 1, 2, \dots, U && \text{(b)}\\
P^k_{comms} &\leq P_{max} \quad \forall k = 1, 2, \dots, K && \text{(c)}
\end{aligned}
\tag{5.10}
$$

Constraint (a) ensures that UAVs do not consume more energy than which is available. The energy the UAVs spend when travelling and while hovering should be always less than the energy they have available.

Constraint (b) ensures that the received power at the UAV is greater than the UAV's receiver sensitivity to allow for successful reception of data from the IoT devices.

Constraint (c) ensures that the optimized transmit power of the IoT device is acceptable and will always be less than the highest possible transmit power the device can employ.

5.2 Results and Discussion

In this section, we evaluate the effectiveness of the proposed NSGA-III-FCM approach. An urban environment of a geographical area size of 1km $\times$ 1 km is considered with $\psi, \beta = 11.95$ and 0.14 respectively. Simulation parameters are shown in Table 5.1. Table 5.2 shows the UAV parameters. These were kept the same as in [141] to allow for easier comparison with related study. They are the specifications of the UAV model investigated in the related study. Table 5.3 shows the NSGA-III-FCM parameters. The rule of thumb is to use a low mutation rate to avoid solutions being random, and a high mutation rate to allow good parent genes to transfer to the child population. Population size and number of generations were selected to be more than 100. This helps the algorithm generate better solutions over time. For a population and number of generations, greater than 200, the quality of the solutions did not change. This work investigates the determination of key decision parameters such as UAV locations, UAV-IoT device association and IoT device transmission power with the objective of minimizing the energy energy consumption of both the UAVs and IoT devices and maximizing the UAV packet reception ratio. We compared our proposed approach to implementations involving:

1. Stationary Base Stations (BS)
2. K-Means clustering for deducing optimal UAV waypoints and UAV-IoT device association while minimizing the transmit power of the IoT devices [141]
3. Heuristic algorithm to maximize the data collected in IoT Sensor networks [145]
4. Genetic algorithm for multi-UAV collaborative data collection [32]

The experiments were done over 100 independent runs and the results were averaged to compare the efficiency and shortfalls for all approaches.

Table 5.1: Simulation Parameters

Parameter	**Description**	**Value**
f_c	Carrier frequency	2 Ghz
α	Path Loss exponent	2
N	Noise Power	-130 dBm
η_1	Additional path loss for LoS links	3dB
η_2	Additional path loss for NLoS links	23 dB

Table 5.2: UAV Parameters

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
$m_{total}(kg)$	2	$\rho(kg/m^3)$	1.225	n	4
$g(m/s^2)$	9.8	r_p	0.18	$P_{tr}(W)$	20
$B_{full}(Wh)$	111	$v_{min}(m/s)$	10	$v_{max}(m/s)$	20

We began our investigation with 5 UAVs serving 100 IoT devices uniformly distributed over the geographical area of interest and using 20 communication channels.

Table 5.3: NSGA-III-FCM Parameters

Parameter	**Value**	**Parameter**	**Value**
p_m	0.03	p_c	0.8
$populationSize$	200	$numberOfGenerations$	200

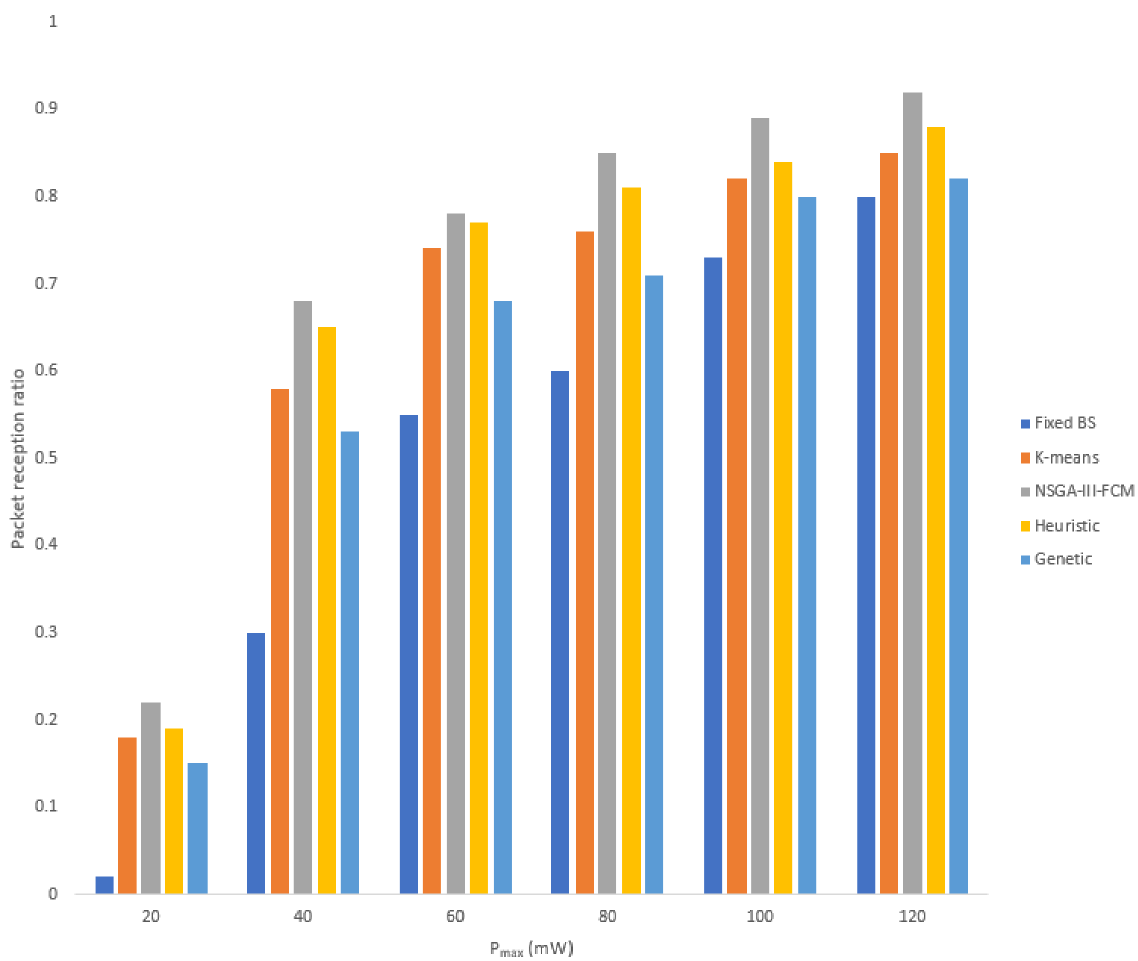

Figure 5.2: Packet reception ratio for different maximum transmit power of the IoT devices

The aim was to compare how the packet reception ratio changes as we vary the maximum transmit power, P_{max} of the IoT devices. The packet reception ratio depends heavily on the UAV waypoints when serving the IoT devices as well as the transmit power employed by those IoT devices. In Figure 5.2, it can be seen that as the transmit power of the IoT devices is increased, the packet reception also increases. This is because for higher P_{max} values, the probability of the data packet to reach the UAV is also high. From Figure 5.2, our proposed approach improves the packet reception ratio as compared to the other implementations. This is heavily attributed to the flexibility of FCM used in our approach by having the same IoT device belonging to multiple clusters and as a result, can send data to more than one UAV. This increases the probability of receiving that data packet. With all the other approaches, one IoT device could only send data to one UAV which makes the system less tolerant to any faults incurred during communication and thus resulting in a lower packet reception ratio. Following our implementation, in terms of packet reception ratio performance, the order in decreasing values of packet reception was Heuristic implementation, k-means implementation, genetic algorithm implementation, and lastly the fixes BS. At lower values of P_{max}, the improvement is significant and as we increase P_{max} the improvement is less because now packets are able to reach base stations which are further away. When increasing the P_{max} from $20mW$ to $120mW$ the reception ratio increased from 0.02 to 0.8 for fixed BS, 0.17 to 0.82 for genetic algorithm, 0.18 to 0.85 for k-means, 0.19 to 0.88 for the heuristic implementation and 0.22 to 0.92 for our approach.

Next we investigated a scenario where we still have 100 IoT devices, 20 channels and P_{max} is fixed at $100mW$. In Figure 5.3, we show how the total IoT device energy consumption relates to the number of deployed UAVs. We can see that as the number of UAVs is increased, the energy incurred by the IoT devices during transmissions decreases. This is because as the number of UAVs increases then the total UAV team can travel to more waypoints which can be closer to the IoT devices. Therefore the IoT devices can employ less transmit power during communication with the UAV team and thus consume less energy. The implementation by k-means algorithm performed the best because their main objective was to minimize the IoT device energy consumption by employing a lower transmit power during communications. Our implementation was the next best and was outperformed by k-means implementation because the algorithm simultaneously optimizes conflicting objectives and that results in a trade-off. The genetic algorithm performed the third best, while the heuristic was the fourth best and the fixed BS implementation performed the worst. There is

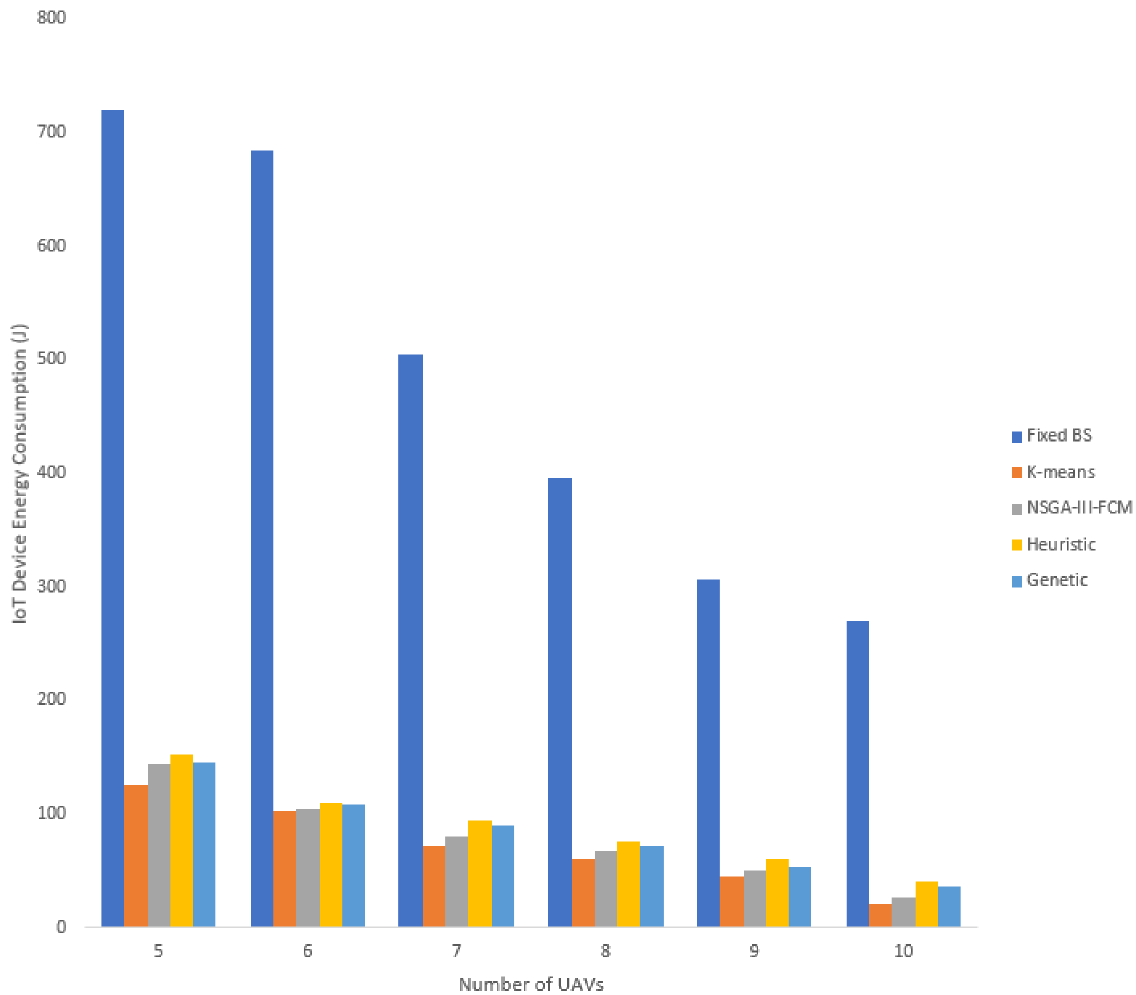

Figure 5.3: Total IoT device energy Consumption for different number of UAVs

a huge jump for fixed BS because it is heavily reliant on a good distribution of IoT devices. If the distribution is unfavourable, then IoT devices have to send data across large distances. There is no way for the BS to move closer to the devices to save their energy. The total IoT device energy consumption decreases from 720 Joules to 270 Joules for fixed BS, 126 Joules to 22 Joules for K-means, 144 Joules to 27 Joules for NSGA-III-FCM, 153 Joules to 41 Joules for heuristic and 146 Joules to 36 Joules for the genetic algorithm implementation. By intelligently optimizing the UAV locations and transmit power of the IoT devices, our approach, (NSGA-III-FCM) was able to realise improvements in the energy consumption of the IoT devices even though it was outperformed by k-means.

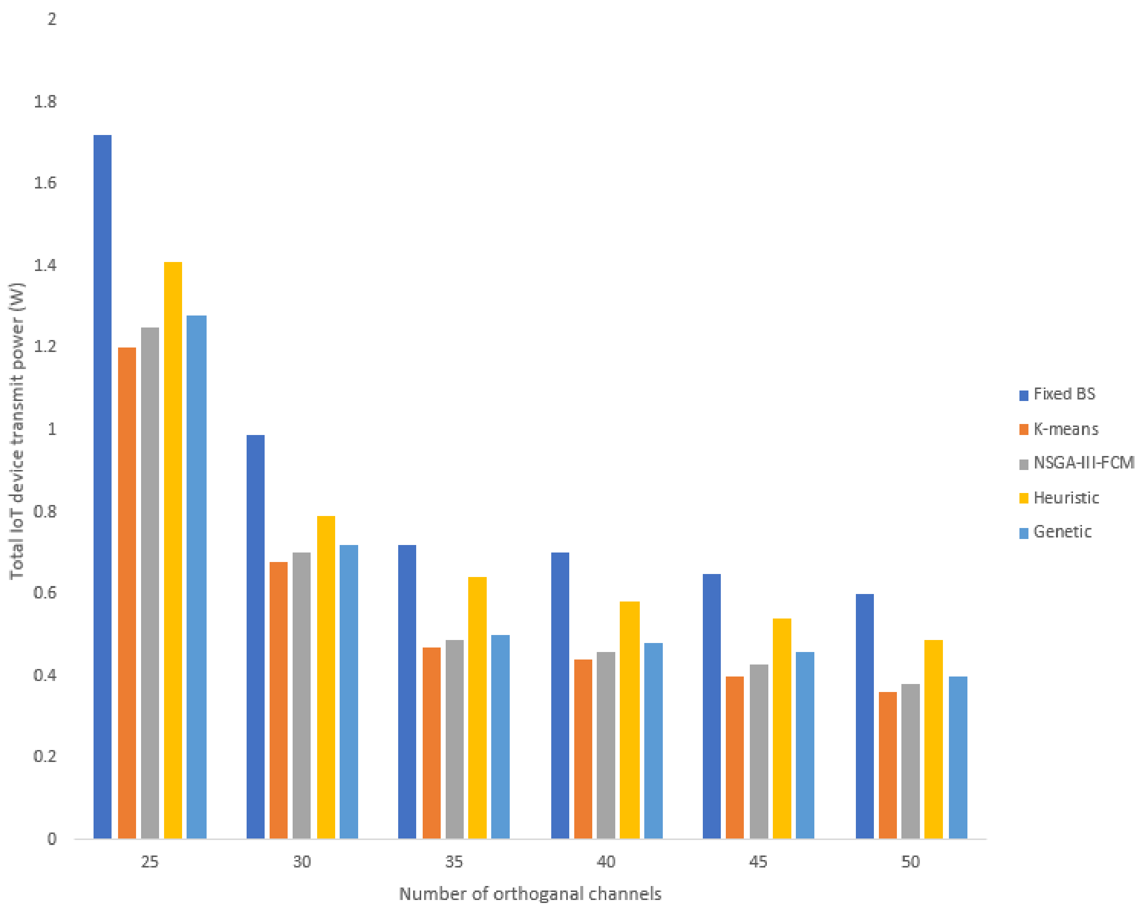

Figure 5.4: IoT device transmit power for different number of communication channels

Figure 5.4 shows the total transmit power used by all IoT devices for successful uplink communication as the number of available orthogonal channels varies. We had 100 IoT devices served by 5 UAVs. As the number of channels increases, the total transmit power decreases. This is because, when there are more channels, then interference between IoT devices will be lower. When the interference is lower, the IoT devices are able to use less transmit power to achieve successful uplink communication with the UAVs. The order in which the algorithms perform is similar to that shown by Figure 5.3 because the transmit power highly influences the energy consumption of the IoT devices. When we vary the number of channels from 25 to 50, the total IoT device transmit power decreases from 1.72 W to 0.6W for fixed BS, 1.2W to 0.36W for K-means, 1.25W to 0.38W for NSGA-III-FCM, 1.41W to 0.49 W for heuristic and 1.25W to 0.4W for the genetic algorithm implementation. Our approach is outperformed by k-means implementation but also outperforms all the other implementations.

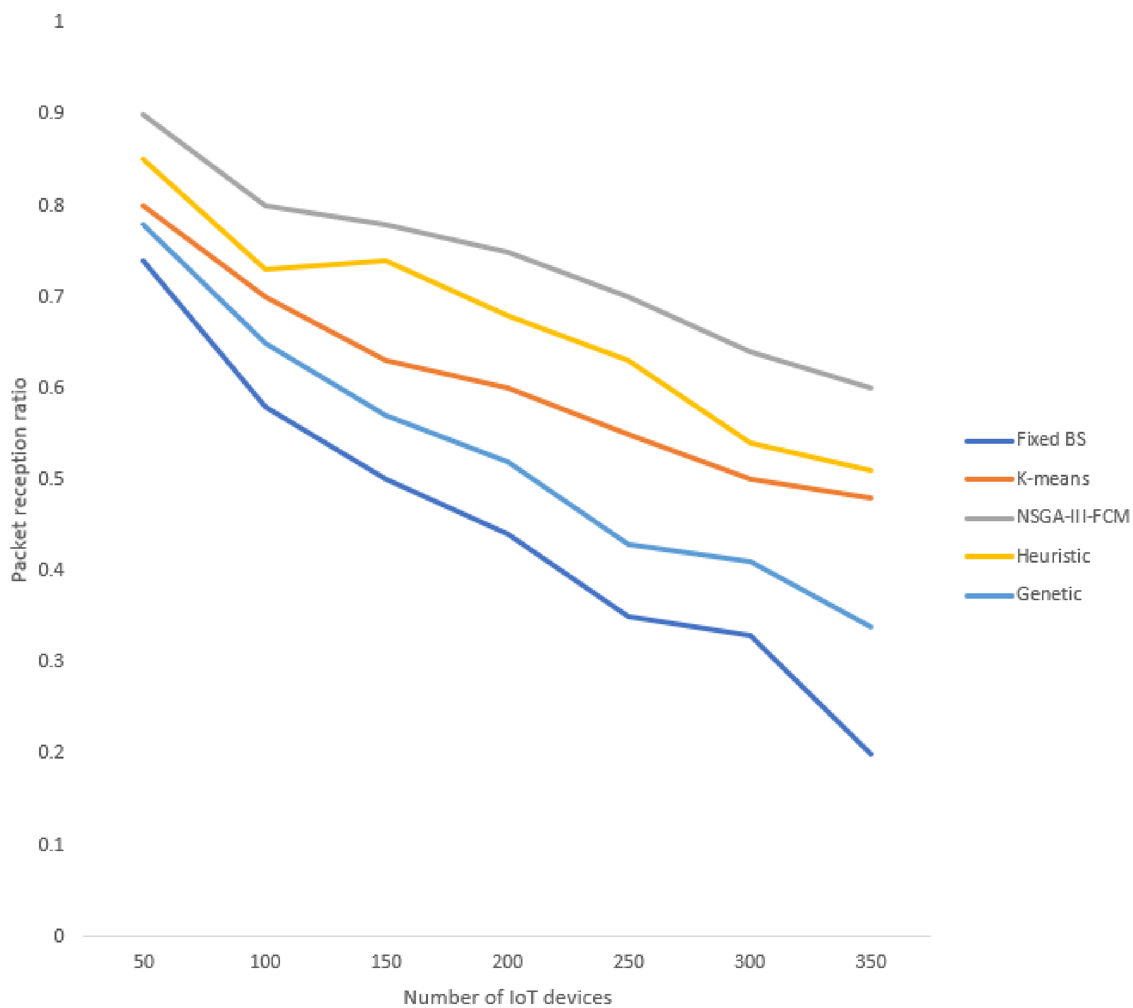

Figure 5.5: Packet reception ratio for different number of IoT devices

Figure 5.5 shows how the packet reception ratio changes as the number of IoT devices varies for all the approaches. P_{max} was kept at $100mW$ as the number of orthogonal channels used was 20. From the investigation, the packet reception ratio decreases as the number of IoT devices increases. This is due to interference and collisions as some devices used the same channel for uplink communications. As the number of

IoT devices was increased from 50 to 350, the packet reception ratio decreased from 0.74 to 0.2 for fixed BS, 0.8 to 0.48 for K-means, 0.9 to 0.6 for NSGA-III-FCM, 0.85 to 0.51 for heuristic and 0.78 to 0.34 for the genetic algorithm approach. From these results, our proposed algorithm performed the best because the IoT devices are able to send data to multiple UAVs thereby increasing the likelihood of receiving the data packet successfully. Also the probability of reception also increases with more retries. As for the rest of the implementations, the IoT device can only send to one UAV, increasing the likelihood for lost packets.

Figure 5.6 shows the number of UAVs required as the number of IoT devices increases. Generally as more devices are present, more UAVs will be needed in order to collect as much information as possible. Our approach performed the best in terms of requiring less UAVs followed by k-means implementation then heuristic, then genetic and lastly the fixed BS implementation. One of the objectives our algorithm aims to minimize is the energy consumption of the UAVs which has translated to a fewer number of UAVs required. This has shown to be the case. When the number of IoT devices is increased from 50 to 350, the number of UAVs required varies from 10 to 60 for fixed BS, 6 to 47 for k-means, 5 to 43 for NSGA-III-FCM, 7 to 50 for heuristic and 8 to 55 for the genetic algorithm implementation.

Figure 5.7 shows how the UAV team's energy consumption changes when the number of IoT devices increases. This is heavily influenced by the total distance travelled by the UAV team. As seen from Figure 5.6, the fixed-BS implementation incurred the least amount of UAV energy because the UAVs moved the least. Our approach performed second best followed by k-means then heuristic and lastly the genetic algorithm implementation. As mentioned before, our system works to minimize the UAV energy consumption by optimizing the UAV waypoints, speed and hovering times when collecting data. For other approaches, the objectives were to minimize the IoT device energy which meant UAVs had to travel more. Another of the objectives was to maximize the data collected which resulted in UAVs spending more time hovering to collect the data and another was to minimize the data collection time which resulted in UAVs employing high speeds to complete the mission in a shorter period of time. All these led to high energy consumption for the UAV team as

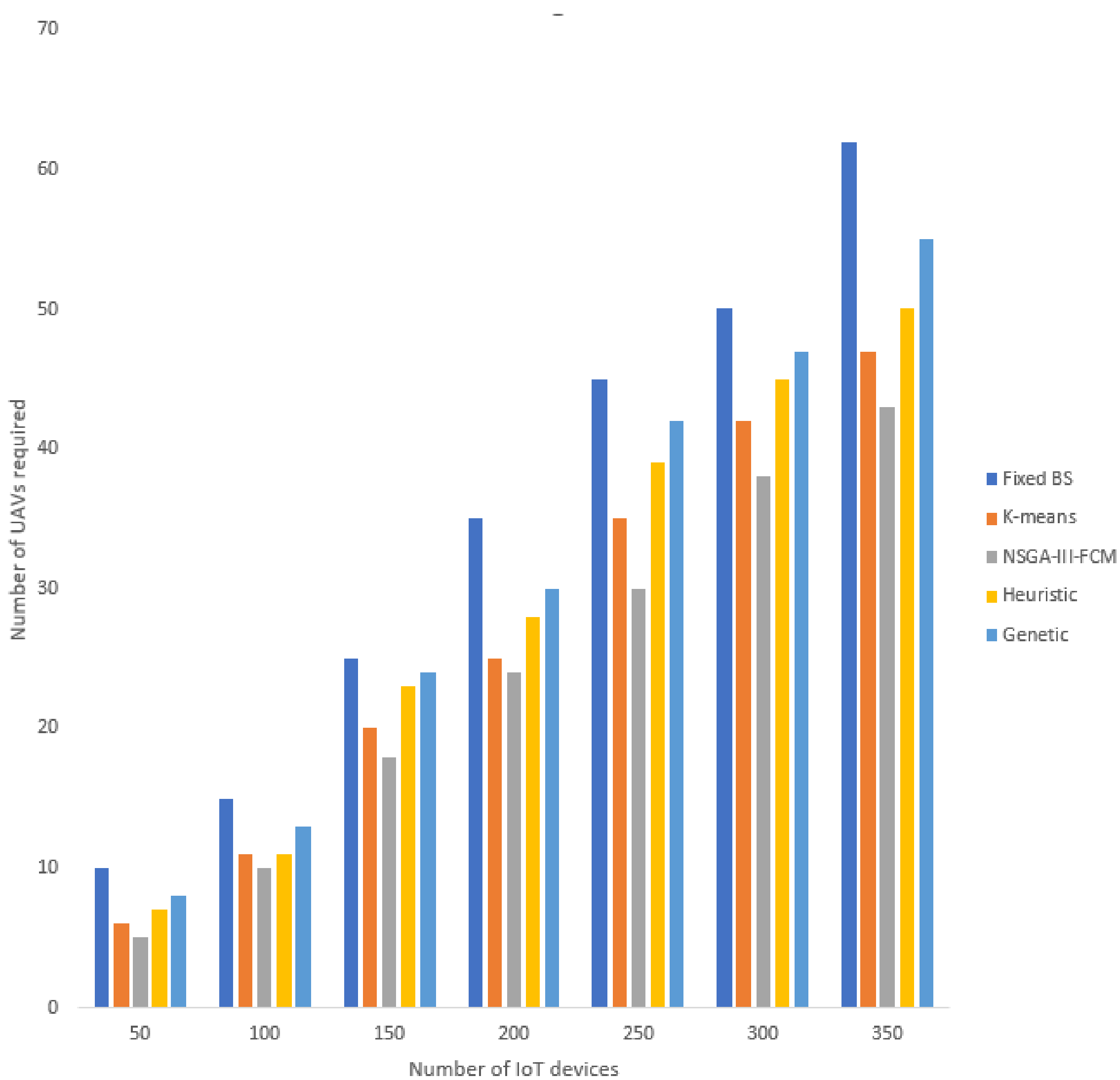

Figure 5.6: UAVs required for different number of devices

compared to our approach. When the number of IoT devices was varied from 50 to 350, the total UAV energy consumption changed from 6500 Joules to 45000 Joules for fixed BS, 8500 Joules to 52457 Joules for k-means, 8345 Joules to 50365 Joules for NSGA-III-FCM, 8556 Joules to 52475 Joules for heuristic and 9211 Joules to 52894 Joules for the genetic algorithm implementation.

Figure 5.8 shows how the battery capacity influenced the amount of data collected. We consider a scenario with 100 IoT devices and this number ws kept constant for

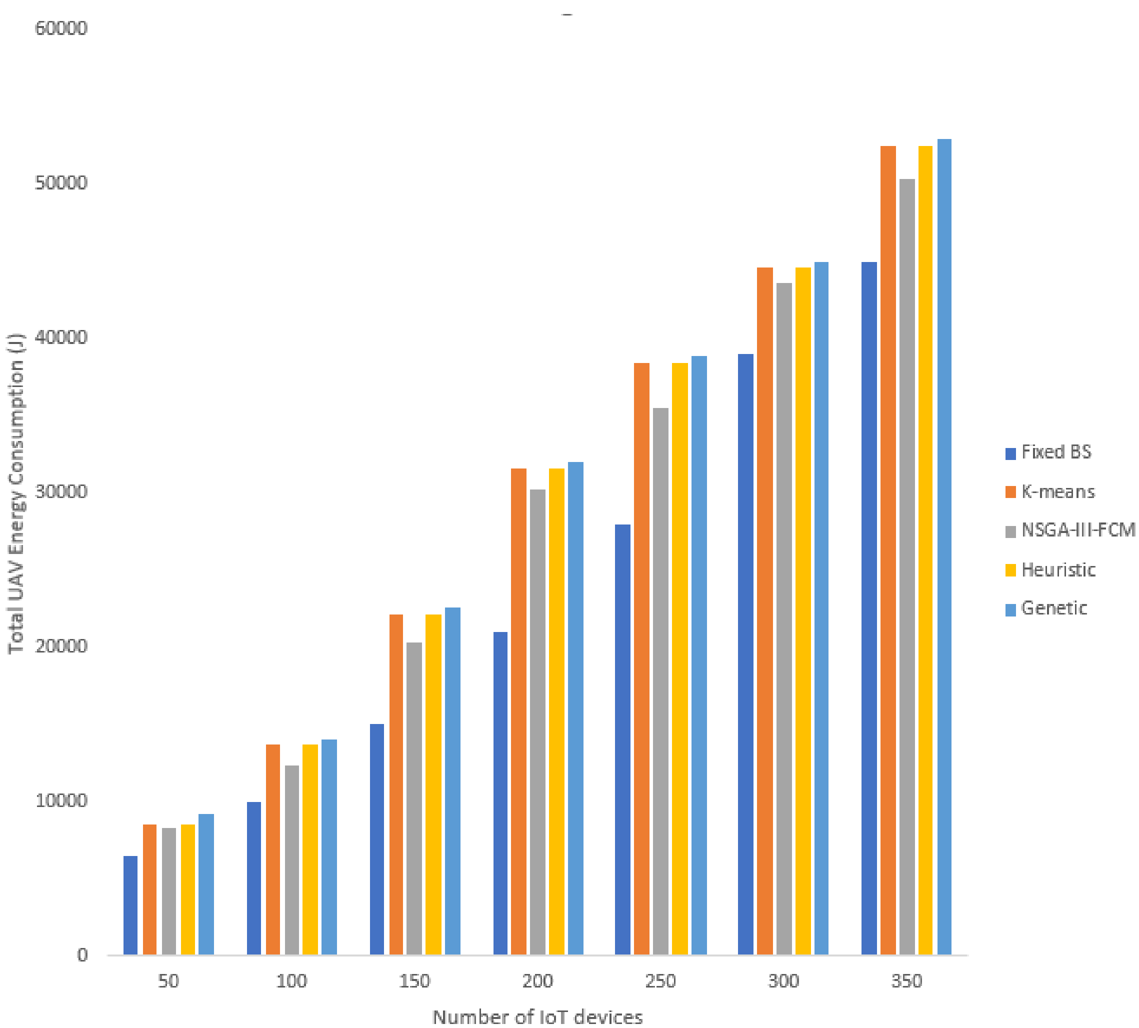

Figure 5.7: UAV energy consumption for different number of devices

this part of the investigation. Generally when the UAV battery capacity is increased, the amount of data collected also increased. This is due to the fact that UAVs can travel more to get even closer to the IoT devices which allows the devices to employ larger data rates and push more data to the UAVs. Also the UAVs can hover for longer periods of time and as a result, they can collect more data. The heuristic implementation collected the most data because their main objective was to maximize the amount of data collected. Our approach came in third when comparing the data collected. As mentioned previously, the nature of our algorithm is to simultaneously

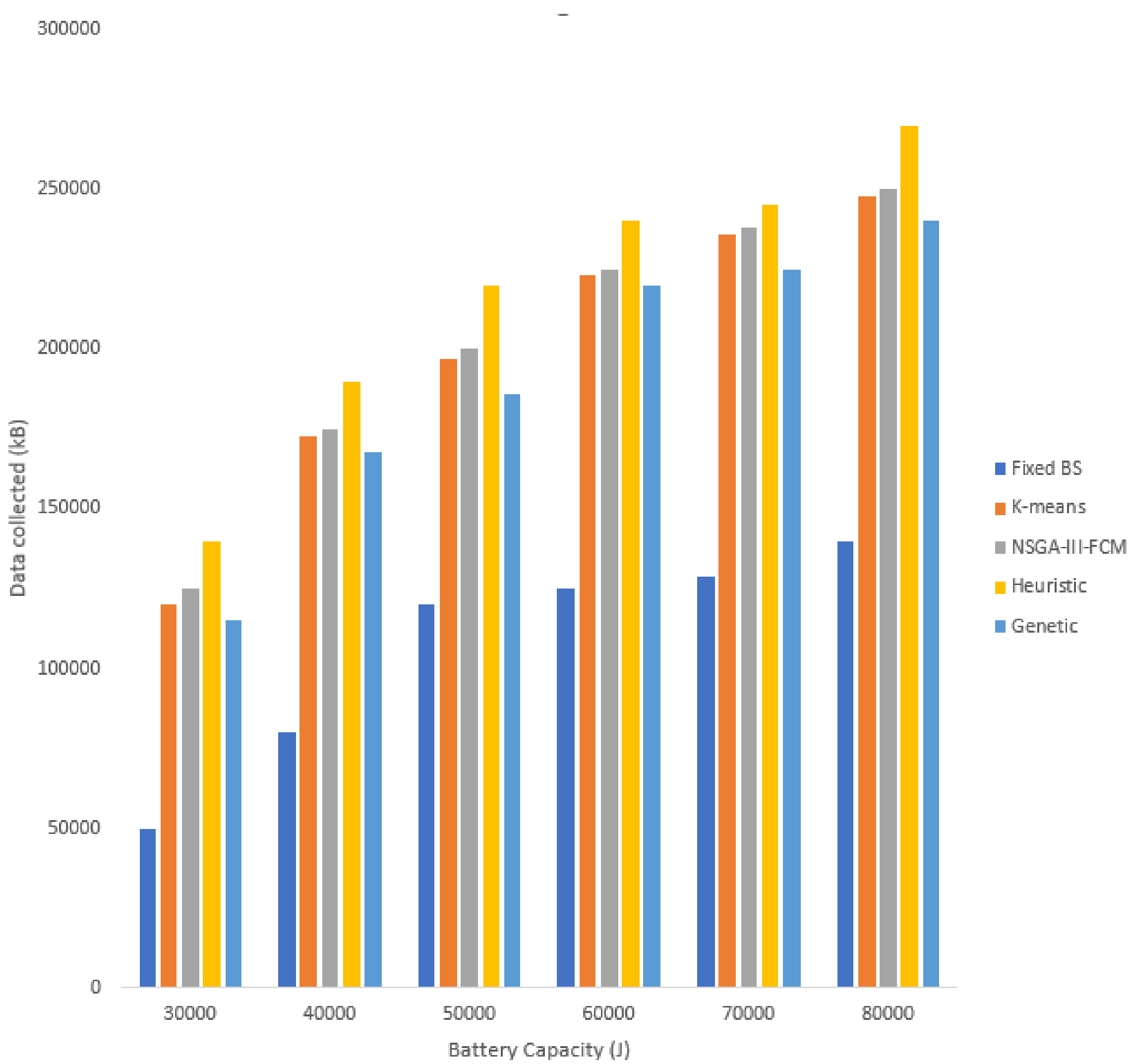

Figure 5.8: Data collected for different number of devices

optimize conflicting objectives and by so doing there was a trade-off in the amount of data collected by the UAV team. When varying the battery capacity from 30000 J to 80000 J, the data collected by the UAVs increased from 50000 kB to 14000 kB for fixed BS, 120000 kB to 248000 kB for K-means, 125000 kB to 250000 kB for NSGA-III-FCM, 140000 kB to 270000 kB for heuristic and 115000 kB to 240000 kB for the genetic implementation.

Figure 5.9 shows the amount of data collected as the number of IoT devices increases.

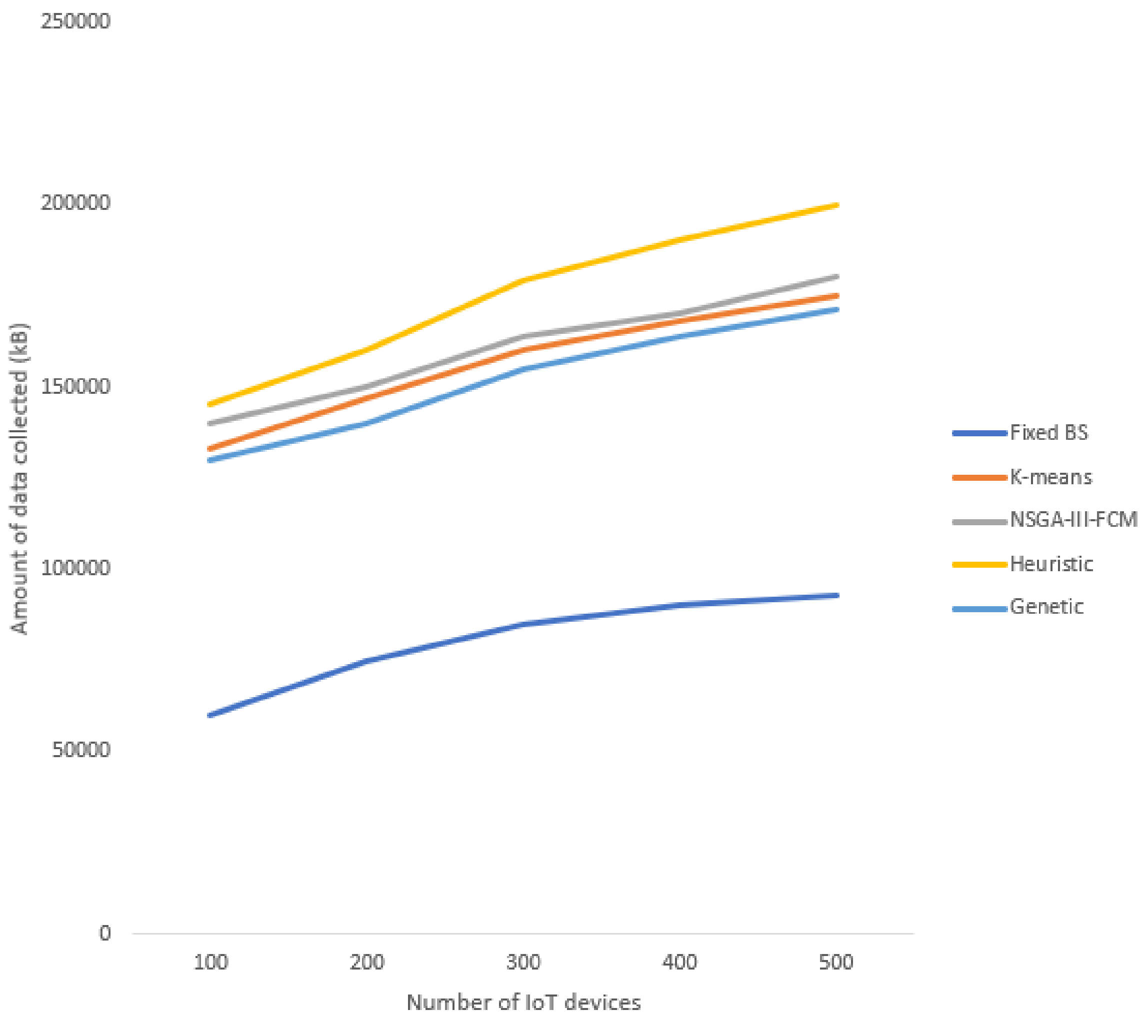

Figure 5.9: Total Data collected for different number of IoT devices

The number of UAVs used in this investigation is 10. Generally as the number of devices increases, then the amount of data to be transmitted to the UAVs also increases. As seen from the figure, for all the implementations, there is a positive correlation between the number of IoT devices and the data collected by UAVs. The heuristic implementation collected the most data followed by NSGA-II-FCM, then k-means, then genetic and lastly the fixed BS implementation. Our approach might not perform the best in terms of data collected but performs relatively well as compared to the rest of the approaches. As mentioned before, the heuristic implementation focused more on maximizing the amount of data collected hence why the performance is best. Our approach also maximizes the amount of data collected but in addition it also minimizes the energy of the IoT devices and UAVs which would mean less time for transmissions and possibly less time for hovering hence why it is outperformed by the heuristic implementation.

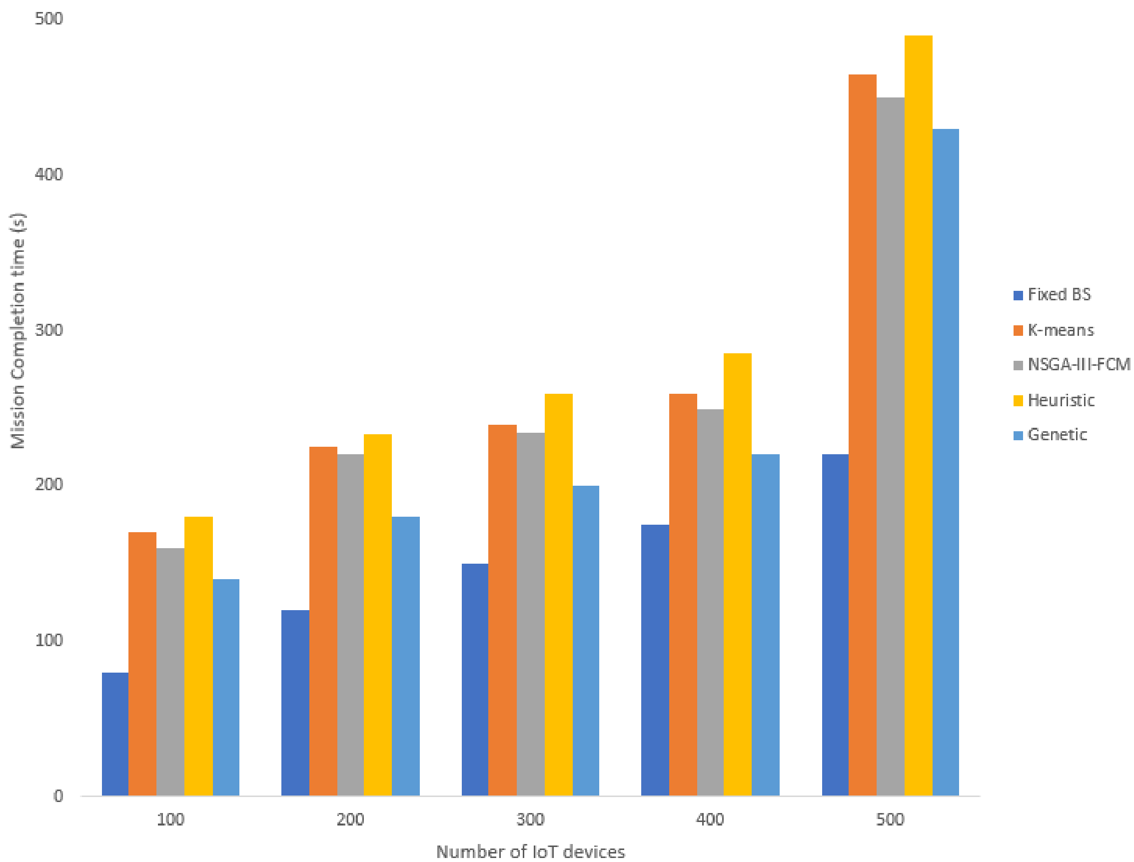

Figure 5.10: Completion time for different number of IoT devices

Figure 5.10, shows how the mission completion time changes as the number of IoT devices increases. As the number of IoT devices increases, the information available for collection by UAVs also increases. This will therefore prolong the data collection time and inevitably the mission completion time. Figure 5.10 shows this positive correlation between the number of IoT devices and mission completion time. The fixed BS implementation performed best in terms of mission completion time because the UAVs travel less distance as they only have one waypoint to reach. This also meant the IoT devices had to employ larger transmit powers for successful reception leading to larger data rates and shortening the UAVs hover time when collecting data. Taking all these into account will lead to lower mission times. The genetic algorithm implementation followed the fixed BS in terms of mission completion time as their main objective was to minimize the data collection time and hence mission completion time. Our approach came in third in comparison as a compromise was made in order to maximize data collected as well as reduce the energy consumption of IoT devices and UAVs. Following our implementation was k-means and lastly the heuristic implementation.

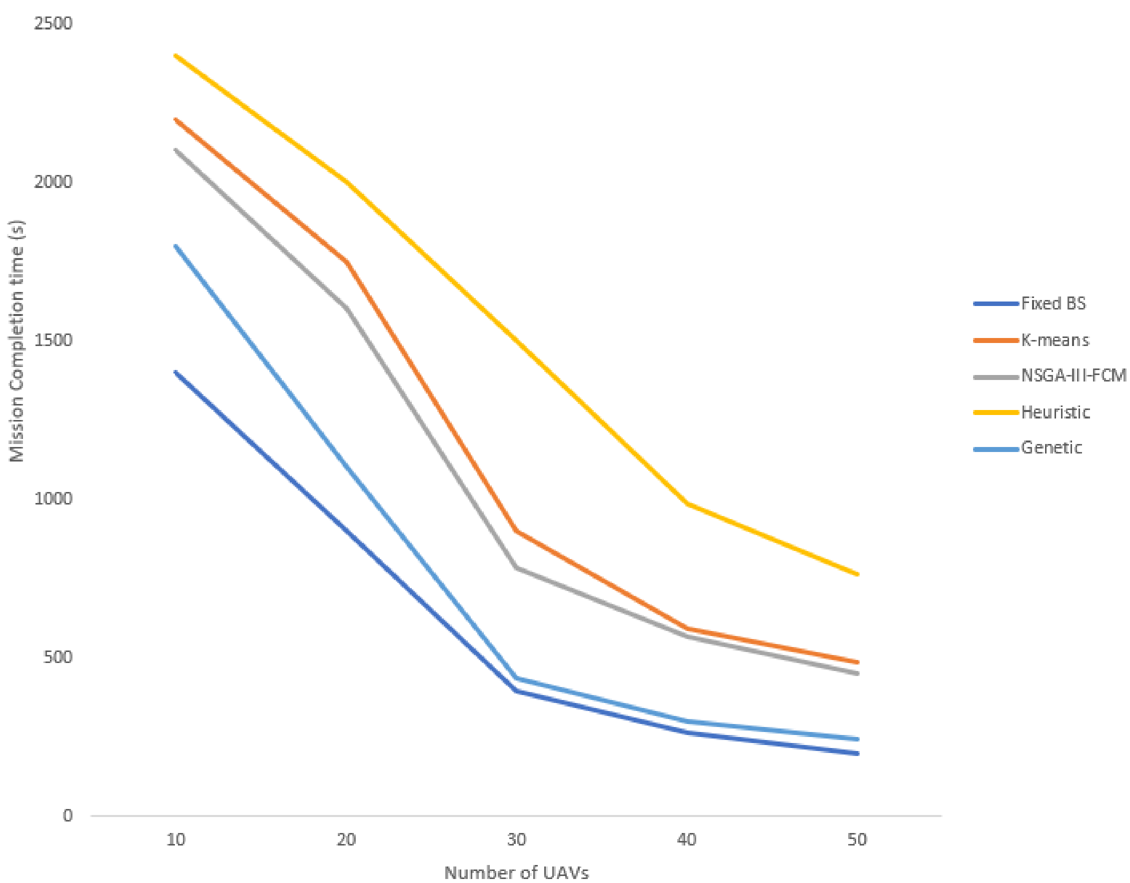

Figure 5.11: Completion time for different number of UAVs

Figure 5.11 shows how the mission completion time is affected by the number of available UAVs. As the number of UAVs is increased, there is more division of labour and hence data can be collected in a shorter period of time. As the number of UAVs was varied from 10 to 50, the mission completion time decreased from 1400s to 200s for fixed BS, 2200s to 487s for k-means, 2100s to 450s for NSGA-III-FCM, 2400s to 765s for heuristic and 1800s to 245s for the genetic algorithm implementation. Our approach performed fairly well and the compromise of having conflicting objectives was acceptable given the comparison with the other approaches.

In this chapter, we have proposed an optimization algorithm that combines concepts from FCM and NSGA-III to optimize the UAV-IoT device association, IoT device transmit power, UAV waypoints and UAV speeds and UAV hovering time in an effort to minimize the energy consumption of the UAV team and the IoT devices as well as maximizing the amount of data collected. A balance was sought since the objectives are conflicting. The concept of FCM proved to be beneficial since more than one UAV could receive data from the same IoT device which improved the packet reception ratio. Our approach also performed better than other in terms of minimizing the UAV team's energy consumption. The k-means implementation which focused mainly on minimizing the transmit power of the IoT devices outperformed our approach in terms of the energy consumption of the IoT devices. The heuristic approach outperformed our approach in terms of the maximum data collected by the system. The genetic algorithm approach outperformed our approach with regard to the mission completion time. Taking all these into consideration in their totality, our approach performed well for all objectives which is promising for real world applications as we considered different conflicting objectives. We were also able to show how our system responds to varying number of UAVs, IoT devices as well as UAV battery capacities.

Chapter 6

Conclusion

The goal of the work done in this thesis is aimed at answering the research questions introduced in Chapter 1.

The following is the first set of research questions:

- How best can UAVs be coordinated and assigned tasks that have spatial and temporal characteristics while efficiently utilizing the limited resources?
- How can the task assignment ensure that UAVs operate within the resource and time constraints of the mission?
- What can be done to allow UAVs to operate for extended periods of time to maximize the service provision?

Chapter 3 provides a task assignment model that uses a multi-parameter encoded chromosome to represent a solution used by NSGA-II optimization algorithm, called D-NSGA-II-DTG. The multi-dimensional chromosome was encoded to include information about UAV waypoints, UAV speeds, UAV altitudes and UAV task departure times. By having such a chromosome structure, tasks with spatial and temporal characteristics are assigned to the best suited UAVs, taking into account the limited energy of the UAVs, the UAV position, task start times and duration. The generation of the task assignment model allowed coordination of multiple UAVs when handling multiple tasks. In Chapter 4, Figure 4.3 and Figure 4.5 show the results our work, compared to similar studies, looking at energy consumption and response time of the UAV team. The proposed model performed better than others in terms of energy consumption. This is due to the exploitation of variable speeds when moving form one waypoint to another. Our proposed model was tied for first place with a similar implementation when looking at the UAV response time. By incorporating constraints into the algorithm, a task assignment schedule was generated without any violating any constraints. Table **??** tracks the UAV energy at each time period and proves that the energy consumed at each time period is always less than the energy onboard the UAV. In terms of start times, no UAVs are late at an event, allowing the provision of adequate service. A charging dock is provided to allow UAVs to operate for extended periods of time. This introduced extra complexity to the problem because the charging duration also becomes a decision variable to be calculated. Nonetheless, the proposed mole was able to handle that well since it was easily incorporated into the chromosome structure. Table **??** shows that the UAVs are able to operate for about 7.5 hrs. UAVs low on energy travel "HOME" to recharge and once replenished, they can further participate in the mission. All this was done while meeting the temporal requirements of the tasks. Figure 4.6 and Table 4.6 shows the scalability of the proposed model to handle an increasing number of UAVs and IoT devices. The model has about an 80% success rate, which is good considering that IoT devices are randomly distributed in the area of interest. Figure 4.8 and Figure 4.9 show the behaviour of the model when UAVs have varying battery capacities and use variable charging Power to replenish their energy. The model provided positive results, and showed its robustness in such scenarios.

The next set of research questions are as follows:

- How best can the UAVs be distributed in 3D space to collect data from the IoT devices
- What speeds should the UAVs employ when moving from one location to another to minimize their energy consumption
- When should IoT devices wake up to send data to the UAVs

- What transmit power should the IoT devices use to send data to the UAVs to minimize their energy consumption
- How long should each UAV hover at a specific location while collecting data to maximize the data collected
- How best can both the UAVs and IoT devices operate within the constraints of the mission

To address these questions, Chapter 3 proposed the development of a task assignment model that uses a hybrid algorithm of FCM and NSGA-III, called NSGA-III-FCM. More objectives to be optimized are considered. They include the UAV energy consumption, the IoT device energy consumption and the data collected by the UAVs. By incorporating the soft clustering of FCM, IoT devices are aggregated into multiple overlapping clusters, and the cluster centres are used by UAVs as hover waypoints when collecting data. The model determined the UAV speeds, UAV altitudes, transmit power of IoT devices and UAV hover duration during the data collection process. The task assignment model was able to find good positions for UAVs to take when collecting data such that their energy consumption was minimized and enough data was collected. In Chapter 4, Figure 5.5 shows that the proposed NSGA-III-FCM performed well in terms of packet reception ratio, when compared to other implementations. The soft clustering of FCM which allows IoT devices to send data to more than one UAV, greatly improved the packet reception ratio and more data was collected by UAVs. Figure 5.7 shows how the UAV energy consumption changes as the number of IoT devices increases. The proposed NSGA-III-FCM performed second best which is acceptable since it has many conflicting objectives. The scalability of the proposed model was shown in Figure 5.2. The packet reception ratio was second best overall when comparing to other implementations which is acceptable because of the other conflicting objectives. a good packet reception ratio for varying transmit power of IoT devices. Figure 5.3 shows the IoT consumption for varying number of UAVs. Overall the proposed NSGA-III-FCM model performed second best when compared to other implementations. This again is acceptable since other conflicting objectives are considered. The solutions generated by NSGA-III-FCM are able to find:

- Acceptable UAV speeds when moving form one location to another
- Acceptable UAV hovering durations to allow more data to be collected.
- Minimum transmit power required by IoT devices to successfully send data to the UAVs.

In summary, the proposed D-NSGA-II and NSGA-III-FCM models are able to answer all research questions adequately. These models generate generic task assignment schedules that can be applied to a multitude of real-world applications such as parcel deliveries, inspection of critical infrastructure and video production service. However, there are a couple of limitations to this work.

6.1 Limitations

This work employs the use of EA for multi-objective optimizations. These algorithms are computationally intensive and thus could not be run on edge devices. This is a huge blow because time critical applications require the fastest response possible and having to send data to the cloud and waiting for a response introduces some latency. Another limitation is on the choice of genetic parameters such as probability of mutation and crossover. These parameters heavily influence the performance of the algorithms and some metrics need to be considered to aid in choosing the right values for those parameters. Examples of metrics that can be used include the Hypervolume (HV), overall non dominated vector generation (ONVG) as well as the diversity metric. The population size and number of needs to be justified and not just selected to be a large number

6.2 Future work

The following areas are suggested in terms of future work:

- Investigate techniques to reduce the complexity of genetic algorithms to allow them to be run on edge devices

- Investigate how the probability of mutation and crossover can be adapted dynamically
- Task assignment of multiple UAVs to support IoT devices in dynamic scenarios.

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