

**NETWORK DEPLOYMENT AND UAV PATH
PLANNING IN UAV-ASSISTED IOT NETWORKS:
A JOINT OPTIMIZATION MODEL**

BY

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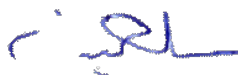
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*To my beloved mother, who has been my constant source of inspiration and
strength.
To my father, husband, sisters, and brother, for their continued encouragement;
and to my beloved son, Turki.*

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Abstract

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UAV-assisted IoT networks have become widely utilized in real-life applications, including smart cities. These networks leverage the intelligence of IoT devices and the mobility and flexibility of UAVs to provide a flexible deployment and extended coverage, especially in remote or inaccessible areas. However, deploying these networks with an energy efficiency constraint requires careful design and determination of the necessary number of cluster heads (CHs) and their placement, and a collision-free UAV trajectory plan. Therefore, this study proposes a hybrid full-joint optimization framework that simulates and decides the optimal count of CH, their coordination, and the design of a collision-free UAV route. The approach leverages the advantage of the Self-Organizing Map (SOM) to initialize the

CHs' placement. Then the approach integrates a two-phase evolutionary process: first, global discrete exploration by Genetic Algorithm (GA); second, continuous spatial refinement by Quantum-behaved Particle Swarm Optimization (QPSO). To reflect a real-world scenario, the study considers an obstacle avoidance constraint. To have a collision-free UAV path, we utilize the visibility-graph routing model with virtual nodes to guarantee obstacle avoidance and provide a smooth UAV route. Several experiments were conducted, focusing on multiple scenarios —node density variation, weight configuration, and obstacle complexity—to demonstrate the applicability of the hybrid GA–QPSO to enhance the network lifetime compared to the GA baseline algorithm. Moreover, the proposed framework has demonstrated its stable convergence and the ability to design geometrically efficient UAV trajectories. However, in some cases, the proposed solution illustrates slightly higher UAV energy consumption than the baseline algorithm, but it significantly enhances the lifetime of IoT nodes compared to the GA. This makes it a robust and reliable solution for next-generation IoT networks with UAV assistance.

ملخص الرسالة

الاسم الكامل:

غدير العزمان

عنوان الرسالة:

نشر الشبكات و تخطيط مسار الطائرة الممسيرة في شبكات إنترنت الأشياء المعززة بالطائرات

المسيرة: نموذج تحسين مشترك

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تعد شبكات إنترنت الأشياء المدعومة بالطائرات بدون طيار من أبرز الحلول المستخدمة لمراقبة وجمع البيانات في المدن الذكية. وذلك مما تقدمه هذه الطائرات من مميزات من أهمها مرونتها في الطيران وقدرتها على الوصول إلى المناطق البعيدة والصعبة. على الرغم مما تقدمه هذه الشبكات من مميزات إلى أن تشغيلها ونشرها في المدن الذكية يواجه بعض التحديات، من أبرزها أن هذه الشبكات تتكون من أجهزة ذات قدرات محدودة بالطاقة فيما يتعلق بطول عمر البطارية. لذلك تهدف هذه الدراسة إلى توفير حل شامل يساهم في تصميم ونشر هذه الشبكات بطريقة دقيقة تضمن تقليل استهلاك الطاقة وإطالة عمر الشبكة. لذلك قمنا بهذه الرسالة بتقديم حل هجين يدمج مميزات الخوارزمية الوراثية مع خوارزمية أسراب الجسيمات الكمية لتحسين يساعد في نشر هذه الشبكات في المناطق ثنائية الأبعاد بطريقة احترافية مع الأخذ بعين الاعتبار محدودية طاقة الأجهزة وتفادي العوائق الموجودة في المنطقة عند تصميم مسار الطائرة بدون طيار لضمان تجنب الاصطدام بها وضمان إكمال مهمة جمع البيانات. الحل المقترح يبدأ باختيار رؤوس العناقيد باستخدام خرائط التنظيم الذاتي ووضعها في مواقع مبدئية، ثم تقوم الخوارزمية الوراثية باستكشاف فضاء الحلول على مستوى عدد الرؤوس ومواقعها ومسار الطائرة ثم تقوم خوارزمية أسراب الجسيمات الكمية بتحسين جودة الحل المقدم من الخوارزمية الوراثية. تم دراسة وتقييم الحل المقترح باستخدام مجموعة واسعة من المحاكاة شملت دراسة فعالية الحلول مع زيادة عدد العقد الموجودة في الشبكة، وتقييم جودة دالة الملائمة من خلال تغيير الأوزان بين عمر الشبكة وطاقة الطائرة وأخيراً

زيادة عدد العوائق في المنطقة وضمان جودة تفاديها. كما تم تقييم الحل من خلال دراسة مؤشرات مختلفة مثل عمر الشبكة من خلال التركيز على الوقت الذي تموت فيه أول عقدة وأول رأس مجموعة في الشبكة، ودراسة طول المسار واستهلاك الطاقة للطائرة. أظهرت نتائج الدراسة أن الحل الهجين تفوق على الخوارزمية الجينية في إطالة عمر شبكة إنترنت الأشياء بنسبة ملحوظة مع زيادة بسيطة مقبولة في طول المسار واستهلاك الطاقة للطائرة بدون طيار. أظهرت النتائج جودة الحل المقترح وفعاليته كحل عملي لتحسين عملية جمع البيانات في المدن الذكية التي تحتوي على شبكات إنترنت الأشياء المدعومة بالطائرات المسيرة.

CHAPTER 1

INTRODUCTION

Nowadays, the Internet of Things (IoT) is playing a critical role in smart city applications by enabling real-time and intelligent decision-making through the deployment of interconnected devices [1]. IoT systems are widely deployed in domains that prioritize reliability, real-time monitoring, energy-efficient communication, and data collection, such as smart cities [2]. However, these networks generate massive amounts of data that need to be collected efficiently [3]. Traditional data collection methods typically face difficulties associated with restricted energy resources, communication constraints, and fluctuating environmental conditions [4]. Therefore, UAV-assisted IoT is considered a promising solution for enhancing data collection in such networks [5].

In UAV-assisted IoT, the UAV serves as a mobile agent, efficiently collecting the data from IoT devices [6]. The data collection role of the UAV can potentially lead to a reduction in the energy consumption of IoT devices [7]. This approach is beneficial for applications in which IoT devices are deployed over large geographical areas and communication with a central server is infeasible or inefficient [5], [4]. The integration of UAVs enhances the flexibility of monitoring, assessing, and collecting data from remote or hard-to-reach areas [8].

Despite these benefits, the integration of UAVs and IoT systems presents several challenges. For example, the energy-constrained nature of UAVs presents a limitation that must be considered when designing their path, ensuring the suc-

successful completion of their mission to collect data from all designated nodes [3]. Furthermore, IoT devices are battery-powered and have limited capacity [1]. They consume considerable energy during transmitting, receiving, and processing data, especially in large networks and long-distance transmissions [3]. To conserve energy, IoT devices alternate between two modes of operation: an active mode with high energy consumption and a sleep mode with very low energy consumption [9]. Nevertheless, developing protocols and strategies to maximize the lifetime of IoT devices remains essential.

Many research studies have considered clustering as an effective solution to handle the energy constraint of IoT devices [5]. In clustering, a special node called the cluster head (CH) is located near normal nodes and is responsible for collecting and processing data from all the nodes within the cluster [10]. This approach allows normal nodes to conserve energy by transmitting data to the nearby cluster head rather than to a distant node or base station. In addition, CHs can serve as data collection points for a roaming UAV.

Optimizing the number and placement of CHs is essential for extending the network lifetime. However, this is a complex task [11]. A small number of clusters and CHs may lead to excessive energy consumption of individual nodes since they may transmit over long distances to reach the CHs [1]. On the other hand, a large number of clusters and CHs leads to high communication overhead and inefficient UAV trajectories [11]. This scenario emphasizes the significance of a comprehensive optimization approach that takes into account these conflicting objectives.

Furthermore, UAV energy consumption is affected by flight, hovering, payload weight, and communication overhead [10]. In addition, environmental obstacles can significantly impact the flight distance and stability of communication with IoT devices, resulting in increased energy consumption [12]. Numerous studies have demonstrated that optimizing the UAV path can enhance its energy efficiency [13]. Several factors have been considered for UAV path optimization, such as obstacle avoidance and hovering points, to ensure efficient energy consumption

during data collection missions [8].

Many studies try to address these challenges separately, either focusing on increasing the IoT network lifetime or optimizing the UAV trajectory [14]. This research suggests addressing these challenges holistically by jointly optimizing the number of CHs, their placement, and the UAV path. It aims to enhance the overall energy of the system by utilizing clustering techniques, energy-aware cluster head selection, and trajectory planning with obstacle avoidance. This enhances the efficiency and sustainability of UAV-assisted IoT networks.

The expected outcomes of this study can be summarized as follows: Address the current limitations in the field of UAV-assisted IoT data collection and contribute to a comprehensive study that simultaneously optimizes the UAV's trajectory, the number of CHs, and their placement. Consider the energy constraints and obstacle avoidance constraints. Propose a Hybrid Genetic Algorithm and Quantum-behaved Particle Swarm Optimization (GA-QPSO) framework that is a unified optimization approach that addresses the limitation of simultaneously optimizing the IoT network deployment with designing the UAV path. The hybrid approach combines the advantage of GA global exploration and QPSO for continuous-space refinement. The main purpose of the proposed solution is to deploy an efficient UAV-assisted IoT network. However, all the design and evaluation of the proposed framework are discussed in this research.

The subsequent sections discuss the motivation of this research, highlighting the advantages and challenges in deploying UAV-assisted IoT networks. Further, the problem statement and the objectives of this study define the goal and scope of this research, and the contribution highlights the advantage of this study in overcoming some limitations in the field of UAV-assisted IoT. Finally, provide a roadmap for the document.

1 Motivation

Deploying UAV-assisted IoT in smart-city environments has some challenges, as IoT nodes and UAVs are energy-limited devices [15]. Therefore, deploying IoT nodes in large areas where the existence of obstacles makes the data collection by the UAV a challenging task [16]. Several solutions exist to solve these challenges, such as:

- Clustering is an efficient technique to reduce the energy consumption of UAVs and increase the lifespan of IoT sensors [17]. However, an excessive number of clusters can lead to an inefficient network, as the high number of UAV hovering points and the excessive communication overhead between CHs and the UAV increase the overall energy expenditure [1]. Conversely, a small number of CHs expand the consumption of the energy of the normal sensors within the cluster as they transmit data to the CH over a large distance [18]. Therefore, finding the optimal number of CHs ensures effective energy distribution across the network and balances energy consumption between the CHs and regular sensors, reducing the UAV hovering points [11].
- The CHs significantly contribute to enhancing the network performance [3]; they help to extend the network lifespan, increase the amount of delivered data, and expand the coverage region of the network [10]. However, identifying the optimal CHs is a complex process because it must meet specific criteria to guarantee effective performance [1]. However, considering the energy level of CHs ensures the efficient energy consumption of the CHs, thereby extending their lifespan [19].
- Placing a cluster head in an appropriate location can increase the energy efficiency of the UAV [14]. This work considers placing the cluster heads in a way that minimizes the UAV's path while ensuring its efficient connection to the sensors within the cluster.

- A UAV has a limited battery capacity, and it consumes a lot of energy during flying and hovering to aggregate the data from the node [20]. However, the CHs contribute to the field of optimizing the UAV's energy performance, as they enable it to hover over their positions to collect data rather than travel to all nodes in the network [21]. Thus, this study focuses on optimizing the trajectory of UAVs to efficiently aggregate the data from all CHs and conserve energy resources.
- In smart city scenarios, a variety of obstacles, such as trees, buildings, and more, affect the communication between IoT devices and UAVs, thereby altering the UAV path [12]. However, these obstacles add additional constraints in the field of UAV-assisted IoT [22]. Therefore, studying obstacle avoidance while proposing solutions leads to effective approaches that contribute to the energy efficiency of the whole network.

All of these factors provide an overview that the optimization of deploying UAV-assisted IoT networks never relies on one design variable. The count of cluster heads, their coordination, and the design of the UAV route in the presence of obstacles are all interconnected, and they all contribute to defining the overall stability and energy efficiency of the network. However, focusing on optimizing one aspect in isolation leads to degrading another [23]. Therefore, building a unified framework that simultaneously optimizes all these aspects provides a better network lifetime while reducing the UAV energy consumption [24]. This motivates this study to propose a full joint optimization framework that aims to enhance the overall UAV-assisted IoT network energy efficiency.

2 Problem Statement

The deployment of UAV-assisted IoT networks is constrained by several factors, such as the power limitation of IoT nodes and the geographical disparity in their placement [25]. Moreover, it is constrained by the power limitation of a UAV

and the design of its route in a way that preserves its energy [26]. However, IoT networks widely use clustering due to its effectiveness in energy efficiency and data aggregation [14]. Therefore, for the networks that utilize clustering, CHs, and UAVs, the energy-efficient data collection depends on independent aspects, which are determining the optimal number of CHs, optimally deciding their placement, and designing the UAV route with a consideration of its energy efficiency. Most existing approaches study these factors independently [18]. For example, optimize the clustering at the beginning, then design the UAV route afterward. In some sequential optimization approaches, when optimizing clustering before optimizing the UAV path, it may lead to imbalanced cluster size and communication distance; such imbalances may result in increasing the energy burden on some CHs and IoT nodes [14]. Further, irregular spatial placement of CH leads to infeasible long UAV trajectories [27]. Moreover, high energy consumption of UAVs results from unnecessary detours or obstacle violations, such as the path constraints imposed by restricted zones and rerouting due to obstacle avoidance [16].

However, all these limitations increase with dense deployment and in environments with rich obstacles, as the line-of-sight is restricted and the safety of the UAV must be considered. Therefore, having a unified framework that evaluates all decision variables at the same time rather than in isolation will contribute to overcoming these limitations. Related to these challenges, the main research problem addressed in this study is to design a full joint optimization approach that can simultaneously decide the optimal count of CHs, optimally determine their placement, and design a collision-free UAV route that increases the overall energy efficiency of the UAV-assisted IoT network in a smart urban city. As the problem consists of multiple objectives and involves mixed variables, it is nonlinear, and conventional metaheuristic algorithms, such as the genetic algorithm, often suffer from a lack of refinement or premature convergence [28]. Therefore, a proposed hybrid approach is required to effectively explore and refine the solution space, resulting in more robust results.

3 Objectives

The primary objective is to jointly optimize the number of CHs, their placement, and the trajectory of the UAV to enhance the overall energy efficiency of the UAV-assisted IoT network. We divide this objective into three sub-objectives: optimizing the number of CHs to extend the network lifetime, locating CHs optimally to shorten the UAV path, and designing an optimal collision-free UAV path to minimize its energy consumption.

To achieve these objectives, this study is structured around the following aims. First, develop a unified full joint optimization approach to simultaneously determine all the sub-objectives of this study. The advantage of this joint formulation is that, instead of using traditional sequential models, it provides an approach that globally coordinates decisions across clustering and UAV mobility [24]. Second, propose a hybrid full joint optimization approach that combines the genetic algorithm (GA) and quantum-behaved particle swarm optimization (QPSO). The GA is responsible for performing global exploration and jointly determining the count of CHs, their coordination, and designing a collision-free UAV trajectory. However, the QPSO refines the coordination of CHs, enhances the cluster geometry, and enhances the convergence. The purpose of hybridization is to overcome limitations of the metaheuristic algorithm and provide robustness in search spaces with high dimensionality [29]. Study some realistic constraints in UAV-assisted IoT urban environments by integrating obstacle-aware trajectory planning for the UAV. Reflecting a real scenario, add a safety margin around the obstacles, build a visibility graph to avoid obstacles, and use a virtual node as a waypoint that the UAV passes through to prevent collision. This ensures that our proposed framework designs the UAV route in a safe and energy-efficient manner. Moreover, integrate reliable energy and communication models considering the sending and receiving energy consumption of IoT nodes, the aggregation energy of cluster heads, and the hovering and flying energy usage of the UAV. This ensures a real representation of real-world scenarios. Moreover, develop a comprehensive

analysis of the proposed framework and compare it with the baseline algorithm, proving its contribution to the energy efficiency of the UAV-assisted IoT network.

4 Contribution

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

- We propose a full joint optimization framework that simultaneously optimizes the number of cluster heads and their placement and designs a collision-free UAV path within a unified fitness function.
- We develop a hybrid GA–QPSO optimization approach. We utilize the genetic algorithm to perform a global search over mixed variables, while QPSO refines continuous variables through a global attractor mechanism to improve convergence quality and solution stability.
- We initialize cluster-head placement by utilizing the self-organizing map (SOM) algorithm that initializes the CHs’ locations based on data density patterns. This helps to reduce the randomness of GA initialization and enhance clustering quality and convergence behavior.
- We propose a collision-free UAV route design based on a visibility-graph approach with virtual nodes and safety margins to provide an obstacle-aware UAV path planning solution in complex urban environments.
- We design a weighted multi-objective fitness function that captures the trade-off between UAV energy efficiency and IoT network lifetime, allowing the optimization framework to be tuned for different mission priorities.
- We evaluate the proposed framework under multiple scenarios, including varying node densities, fitness-function weight configurations, obstacle complexities, and baseline comparisons, using performance metrics related to IoT network lifetime and UAV energy efficiency.

5 Thesis Structure

This thesis is organized into five chapters:

In the introduction, it defines the objective, motivation, and problem formulation of this study and highlights the contribution of this thesis.

Chapter two provides a comprehensive background and literature review focusing on UAV-assisted IoT data collection, specifically clustering IoT nodes, designing UAV paths, and joint optimization studies.

Chapter three highlights the system model and design and presents the proposed full joint optimization framework.

Chapter four presents all conducted experiments, highlights the studied scenarios, evaluates all conducted experiments, and compares the proposed approach with baseline algorithms. Additionally, it provides a discussion and analysis of the results and highlights the thesis's limitations.

Chapter five concludes this thesis, highlights the main findings of this study, and discusses future work.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

1 Background

1.1 IoT Network

The Internet of Things is a system that consists of low-cost, low-power devices that communicate with each other and with a central system using the Internet or other communication networks [25]. IoT devices have the ability to sense, process, and communicate, enabling intelligent decision-making and automation [2]. The extensive deployment of IoT networks facilitates their broad applicability across many sectors, including smart cities, agriculture, healthcare, and beyond [30]. IoT networks commonly consist of three layers that facilitate communications and processing:

- Perception Layer: Consists of components that are responsible for sensing and collecting data from the physical environment [31]. The two primary components of this layer are sensors and actuators. Sensors are responsible for gathering the data, such as temperature, location, humidity, and others [32]. The collected data is then transmitted to the network for assessments and applying decision-making [33]. Actuators have the ability to convert

electrical signals into physical actions [34]. For example, in smart farming, sensors measure soil humidity level and detect when it falls below a specific threshold, prompting an actuator to open the water valve to increase soil moisture [21].

- Network Layer: It is responsible for connecting the IoT devices with the central system for data transmission [31]. Depending on the IoT applications and their requirements, various standard communications technologies can be used to enable network connectivity. They range from long-range standards such as Sigfox, LoRaWAN, and Narrowband IoT (NB-IoT) to short-range standards such as ZigBee, WiFi, or Bluetooth [25].
- Application Layer: It consists of platforms that allow user interaction, data visualization, and analytics [33]. These platforms can be customized based on the domain, such as agriculture, healthcare, industrial automation, etc. [25].

IoT devices are typically battery-powered and have limited capacity [1]. They consume a significant amount of energy in sending and receiving data, particularly in long-distance transmission [21]. In cases of inactivity, these devices switch to sleep mode to conserve energy [9]. Hence, energy-efficient design is one of the primary network design objectives in IoT applications [9].

1.2 UAVs

Unmanned Aerial Vehicles (UAVs), also referred to as drones, are aircraft systems that have the ability to function independently [35]. They can be remotely controlled without an onboard human pilot [36]. Initially, they were employed for military and surveillance services [5]. Their various advantages, such as flexibility, mobility, low operational cost, and the ability to access infeasible areas by humans, have led to their widespread utilization in several aspects of life [37]. This is particularly evident in tasks that are challenging for humans to perform,

such as agricultural data collection, monitoring, rescue operations, surveillance, telecommunications, medical supplies, military operations, etc. [38].

UAVs (drones) can be classified into three categories based on their design and operational capabilities: fixed-wing, rotary-wing, and hybrid models. The fixed-wing drones look like traditional airplanes, with a stiff wing configuration that produces lift as the vehicle traverses through the air [39]. This type of drone requires specialized training to operate, is expensive, and is not able to hover, rendering it useless in certain applications like surveillance [40]. Power line inspection and aerial mapping widely utilize these drones [40]. Rotary-wing aircraft, known as vertical take-off and landing (VTOL) aircraft or rotorcraft, provide a feature of stable flight in a fixed location while preserving maneuverability [39]. One known type, quadcopters, finds widespread use in various applications due to their ability to land vertically, rapid maneuverability, affordability, and low cost [7]. It is widely used in smart farming, smart cities, emergency services, etc. [41]. Table 2.1 below illustrates some examples of quadcopter drones with their features [41], [32]. Hybrid model drones combine the advantages of the previous two models: the vertical landing feature of rotary-wing drones and the fixed wing for flight [36]. Long-range and high-payload operations frequently utilize this type [36]. Table 2.2 provides a summary of comparisons for the three categories [42].

Model	Weight	Flight Time	Maximum Speed	Transmitting Distance	Payload
DJI Matrice 300	6.3 kg	Up to 43 minutes	82.8 km/h	Up to 8 km	2.7 kg
DJI Phantom 4 Pro V2.0	1.38 kg	Up to 30 minutes	72 km/h	Up to 7 km	0.5 kg
Freefly Alta 8	4.1 kg	Up to 30 minutes	56 km/h	Up to 5 km	4.5 kg

Table 2.1: Examples of Quadrotor UAV Models

Despite their advantages, UAVs face some challenges that have been the focus of research during the past few years. One of the most recognized limitations of UAVs is their limited battery capacity, which constrains their energy supply and, consequently, reduces their operational duration [43]. As a result, researchers have explored different solutions to optimize UAV energy efficiency, with path planning

Characteristics	Fixed-wing	Rotor-based	Hybrid
Energy Efficacy	Advanced	Basic	Advanced
Landing	Conventional	Vertical	Vertical
Autonomy	-	✓	✓
Hovering	-	✓	✓
Energy Source	Battery, fuel	Battery	Battery, fuel
Perseverance	60 up to 3000 meters	6 up to 180 meters	180 up to 480 meters
Payload Capacity	100 kg	50 kg	10kh

Table 2.2: Comparison of UAV Categories

as one of the most effective solutions [5].

1.3 UAV-Assisted IoT

Given the aforementioned potential benefits and challenges of IoT and UAVs across various applications, their integration has become a promising solution to addressing some of these challenges [32]. It has also created opportunities for new innovative solutions that address real-world challenges [44]. By utilizing the mobility of UAVs and the intelligence of IoT devices, the integrated system can outperform stationary IoT and reach hard-to-access areas such as forests, disaster areas, etc. [45]. Using the UAV as a sink node, data is collected from IoT devices, possibly processed, and delivered to the central unit, thereby preserving the energy of IoT devices and reducing latency [34]. In smart farming, sensors gather data about crops and irrigation, and the UAV sends this data to a central unit for analysis and monitoring [32]. Additionally, smart cities utilize UAV-assisted IoT to manage the traffic [2]. While in healthcare, it is used to remotely monitor patient vitals, and in emergency scenarios, it is used to send medicine, blood samples, vaccines, etc. [44]. However, disaster management utilizes it to gather information about the disaster’s location and situation and, in some cases, to transmit essential supplies to speed the disaster response [45].

2 Literature Review

Several studies have investigated data collection in UAV-assisted IoT. These studies tackle different related challenges and constraints, such as optimizing UAV trajectory, IoT clustering, and energy efficiency. In this section, we review the recent state of the art, focusing on clustering-based networks, UAV path planning, and relevant optimization problems.

2.1 Clustering

To extend the IoT network lifespan and increase the communication efficiency among deployed sensors, the researchers suggest clustering as a potential solution [46]. Ravi and Lokesh [46] introduced a novel algorithm that integrates K-means with their proposed algorithm, "cyclic rider optimization algorithm (C-ROA)," to apply clustering and optimize the CH selection. Subsequently, they employed the "delay-optimized data fusion tree" to reduce the fusion's impact on data transmission delay. The proposed solution showed improvement in the performance of IoT in terms of alive nodes, energy, delay, and deployment cost. Marwa et al. [47] proposed an enhanced particle swarm optimization (PSO) and utilized it to design a fuzzy logic (FL)-based low-energy adaptive clustering hierarchy (LEACH) protocol. For cluster formation, they incorporate both PSO and K-means algorithms. The primary and secondary cluster heads (CHs) are selected using the FL technique.

Furthermore, Dohare and Singh [48] proposed the "PSO-based deterministic energy-efficient clustering (PSODEC)" algorithm, which addresses the optimization of CH selection in IoT networks. In this work, K-means was employed to cluster the sensors, and the CH is selected by evaluating the residual energy, while PSODEC is used to select the primary CH. Sabitri et al. [49] proposed utilizing the evaluation of residual energy to optimize CH selection. Their algorithm calculates the residual energy of the CHs, then determines the size of the

cluster based on it. This leads to enhanced energy efficiency for sensor nodes and extended network lifetime. Afolayan et al. [50] studied the optimal number of clusters by comparing gap statistics and elbow methods. They found that the gap statistics method outperformed the elbow method.

2.2 UAV Path Planning

UAV-based data collection is an effective method for gathering data from randomly deployed IoT sensors in a large area [7]. Therefore, many researchers have proposed optimization solutions for UAV trajectories to efficiently collect data while considering energy constraints. Some papers utilized metaheuristic algorithms to address the UAV path planning. For instance, Jingcheng et al. [26] proposed an algorithm that integrates the Salp Swarm Algorithm (SSA) with Rapidly Exploring Random Trees (RRT) to enhance efficiency, reduce power consumption, and minimize the trajectory cost for UAVs. In contrast, Lin et al. [51] designed an approach that solves the combinatorial optimization task of minimizing the cost of flying multiple UAVs covering a designated area. The proposed approach is based on PSO heuristics combined with two techniques, which are local search and path encoding, to apply path planning.

Other research works have utilized reinforcement learning techniques in their solutions. Aliia and Sang-Jo [37] proposed an approach that employed a reinforcement learning technique to find the optimal UAV path in unknown environments, with the goal of enhancing data acquisition and reducing energy consumption. While Yunkai et al. [52] introduced the "Deep Q-Network algorithm with delayed reward (DR-MADQN)." They depended on Deep Reinforcement Learning (DRL), especially a multi-agent framework, to significantly minimize the Age of Information (AoI) and the charging wait time of IoT devices. Similarly, Shuo et al. [53] utilized the DRL algorithm for UAV path planning. The authors utilized Lyapunov optimization to develop an online determination policy. The resulting policy overcomes the data rate limitation by reducing the frequency of edge processors.

Several papers have addressed various constraints and proposed algorithms to solve them. Aditya et al. [54] improved the energy efficiency of UAVs within IoT networks by addressing energy harvesting and altitude constraints. Their algorithm utilized the sequential convex optimization method to find the best UAV altitude that contributes to increased energy usage efficiency. Additionally, Wang et al. [6] introduced a novel solution that utilized the differential evolution algorithm to ensure efficient energy consumption among all devices. This is accomplished by optimizing the UAV's flying trajectory and the devices' transmission timetable while ensuring reliable data acquisition and three-dimensional positioning precision.

Additionally, Hanbin et al. [55] proposed an algorithm utilizing the reformulation-linearization technique (RLT) and the alternating direction method of multipliers (ADMM) to optimize the UAV's visiting path and enhance energy efficiency. However, to decrease data latency in UAV-assisted IoT, Xiong [56] introduced a mechanism for data collection that employs an airborne collaborative relay and implements an Age of Information-sensitive Data Collection (ADC) framework. This approach allows for the iterative optimization of UAV flight paths by incorporating the design of a general AoI expectation function.

2.3 UAV-Assisted IoT Data Collection

Clustering and path planning are efficient techniques that enhance energy efficiency, data collection, and network lifetime in UAV-assisted IoT [18]. Therefore, many researchers have proposed optimization solutions that consider both techniques. This section reviews papers that focus on clustering and path planning. Each paper concentrates on data collection and addressing the energy consumption constraints. Table 3 is a summary of these papers.

Numerous studies consider clustering and UAV path planning, with the main focus on increasing the network lifetime. For example, Syed et al. [57] aimed to enhance the energy efficiency of WSN networks by considering the residual energy of sensors and reducing the communication length between CHs and the

UAV. They clustered the sensor nodes utilizing the K-means algorithm to cluster the sensors while they selected the optimal CHs based on the residual energy and positioned them at the midpoint of the cluster. For the UAV trajectory, they used the simulated annealing (SA) technique. While Huimin et al. [4] proposed a solution addressing the age of information AoI of SNs in UAV-assisted IoT. They used "Karush-Kuhn-Tucker (KKT) conditions" to optimize the energy transmission and data acquisition time. Further, they used the ant colony algorithm (AC) and dynamic programming (DP) to address the UAV path planning. For Sami et al. [21], they proposed a hybrid optimization technique, "Lion Mated with Cats Optimization (LMCO)," that optimizes CHs, trajectory planning, and resource distribution. They addressed several constraints: energy, distance, latency, trust, and quality of service (QoS). LMCO outperforms HEED and CMBO in terms of energy efficiency and network lifetime.

Other studies focus primarily on UAV path planning. Such as Nurul and Faiz [58] proposed an algorithm for energy-efficient coverage path planning (EECPP) for UAV-assisted IoT. It incorporates two algorithms: the PSO algorithm for path planning and the K-means algorithm to predict the stop points and clustering. Omer et al. [59] introduced an algorithm named "Quality and Energy-Aware Data Collection Strategy (QEADCS)" to address the challenges of energy consumption and data quality. They assumed that the CHs were predefined; there are two types of them: one for direct data collection by UAV and another, a non-visited CH that transmits its data through multiple hops to a direct CH. The proposed algorithm leverages the advantages of the genetic algorithm to select the UAV trajectories. While Tariq et al. [5] clustered the nodes based on their Received Signal Strength Indicator (RSSI) values and selected the CHs based on their centrality. Also, they planned the UAV path using Dijkstra's algorithm and GA.

However, Dongji et al. [60] worked on minimizing the flying time of the UAV. Therefore, they clustered the IoT devices using their proposed algorithm, the "novel Logarithmic Kernel-based Mean Shift (LKMS) clustering algorithm." Clustering, optimizing UAV trajectory, and bandwidth allocation are considered ways

to minimize the flying time. Thus, they used Block Coordinate Descent (BCD) to break the problem into subproblems, and Successive Convex Approximation (SCA) transforms non-convex subproblems into convex ones for effective optimization. For the UAV trajectory, they utilized GA. While Mengtang et al. [7] introduced a genetic algorithm and K-means (GAK-means) that dynamically optimize communication coverage radii to cluster IoT devices and enhance communication. Further, they developed the Fly-Circle-Communicate (FCC) trajectory design algorithm, where the UAV hovers over the cluster centers sequentially, utilizing circle flight and interaction.

Moreover, other studies aimed to enhance the overall network efficiency. Mohamed et al. [2] designed an energy-aware approach aimed at reducing the overall consumption of energy by UAVs and IoT devices by precisely optimizing the UAV deployment. They proposed an optimized population size mechanism, which determines whether to add, remove, or replace stop points by assigning an auxiliary variable to each one. Their approach incorporates two novel variants—DEoPS and GBoPS—based on differential evolution (DE) and gradient-based optimization (GBO) to effectively address the deployment problem. Chuan et al. [3] focused on balancing the data aggregation and ensuring energy efficiency within the cluster, as well as optimizing the UAV travel path. Their approach is a hybrid that integrates data compression and node clustering techniques. To further optimize energy consumption, the scheme integrates both exact and greedy approaches. ACO is employed for path planning.

Furthermore, Keiwan et al. [17]. They introduced the "sensor networks using dual cluster heads (UAVDCH) method," which consists of two CHs within each cluster: a primary cluster head (PCH) that collects data from all cluster sensors and a border cluster head (BCH) that forwards the collected data from the PCH to the UAV. The BCH serves as the UAV's hovering point to minimize its hover locations. Their approach collects the data from multiple clusters simultaneously using a multi-channel technique, resulting in improved operational efficiency. For Khanh-Van et al. [20], they proposed an approach called "Grounding Gathering

Data Assisted by Multi-UAV with a Balanced Clustering (GAMBAC)” that studied the data collection in joint clustering and multi-UAVs. This approach balances the sensors within the clusters to increase the sensors’ energy efficiency.

Further, Sivaram et al. [30] presented a low-complexity algorithm that is foundational in a mathematical proof, which establishes that the optimal way-points for a variant of the Traveling Salesman Problem (TSP) are restricted to the border regions of sensor communication ranges, thereby notably diminishing the solution space. By identifying the optimal communication range, the algorithm effectively minimizes the energy consumption of both the UAV and the sensors. While Botao et al. [27] proposed a novel method that integrated DRL with a sequence-to-sequence (Seq2Seq) model. Their aim is to jointly optimize CH selection and UAV trajectory. Their approach demonstrated its ability to scale and generalize. Rong et al. [18] introduced a novel parallel data collection to minimize the aggregation time. Their scheme consists of modified K-means for clustering, greedy optimization for CH mode selection, the SA algorithm for UAV path planning, and Convex for speed optimization. Additionally, Pravija et al. [13] proposed a novel algorithm known as ”game theory-based distributed RP selection (GTBRP)” to optimize the RP that acts as CH. They considered the residual energy, load, and node degree of RP. Also, they modified ACO to optimize UAV path planning. Their algorithm successfully extended the network’s lifetime and preserved energy.

For Oussama et al. [19], they optimized the number of CHs and UAV paths to reduce the overall cost of deploying UAV-assisted IoT systems. They proposed a customized K-means algorithm that applies clustering, deploys CHs, and adjusts CH locations to be near the dock station to reduce UAV energy consumption. Additionally, they introduced online and offline path planning for UAVs, utilizing near-optimal meta-heuristic methods for offline scenarios and deep reinforcement for online scenarios. Reducing the optimization and operational cost associated with data collection in a multi-UAV-assisted WSN network is the aim of Safwan et al. [61]. They optimized the number of CHs using the K-means algorithm. They

employed the "multiple Traveling Salesman Problem (mTSP)" and the "Traveling Salesman Problem with Neighbors (TSPN)" to determine the number of UAVs and their trajectories while utilizing GA to optimize the path. As a result of their work, they discovered that optimizing the UAV altitude, hovering near the CH instead of hovering directly above it, leads to reducing both UAV path distance and data collection time.

On the other hand, some papers focused on the process of jointly optimizing the UAV trajectory plan and energy efficiency of IoT nodes. Such as Xiao et al. [6]. Their paper focuses on optimization techniques rather than clustering or planning methods. They employed three methods, the Dinkelbach, Block Coordinate Descent (BCD) framework, and Successive Convex Approximation (SCA), to solve the problem iteratively. The simulation results proved that the proposed framework significantly enhanced system energy efficiency. While Run et al. [8] jointly optimized UAV trajectory planning, CH selection, and virtual node selection by using local search methods to iteratively apply the optimization. The aim is to reduce the energy consumption of IoT nodes and ensure the safe path of UAVs. To ensure the safe path of the UAV, they used a virtual node to guide it. Additionally, they developed a tiny machine learning algorithm (TinyML) to select the optimal location of a virtual node and enable the UAV to make real-time decisions during flight. Furthermore, Ning et al. [62] applied sequential joint optimization of the UAV route and data acquisition to extend the system energy efficiency. They developed a deep reinforcement learning algorithm with a multi-agent constraint to guarantee UAVs' safe route. Moreover, they propose an algorithm to ensure the fair utilization of energy among devices. However, Gouda and Thakur proposed a joint optimization framework that focuses on enhancing the energy efficiency of a UAV. They used the PSO algorithm to optimize the cluster formulation and select the CH based on three factors: residual energy, distance, and centrality. However, they use an ant colony system to design an energy-efficient UAV path. They demonstrated that their approach contributes to enhancing the throughput, energy efficiency, and path length of the network.

Despite all the advantages of reviewed papers, there are certain gaps and limitations in UAV-assisted IoT data collection, particularly when considering energy efficiency. Studies that proposed approaches utilizing both techniques—clustering and path planning—did not consider obstacles as a constraint. Moreover, these studies either focus on increasing the energy efficiency of UAVs or extending the network lifetime. However, even though the papers consider both optimizations, they optimize them sequentially without considering a full joint optimization. Furthermore, most of the reviewed solutions focus on homogeneous sensor nodes, which simplify their approaches and overlook the heterogeneity of real-world IoT systems. However, the joint optimization of UAV paths, the number of CHs, and the location of CHs to minimize path distance receives limited consideration. However, this thesis aims to address these limitations by proposing an efficient approach that jointly optimizes the UAV trajectory, the number of CHs, and their placement. Additionally, consider the heterogeneity in the sensor nodes, energy, and obstacle avoidance constraints.

Table 2.3: Summary of Literature

Ref	Objective	Technique	No. of UAV	CH	Network Models	Other constraints	Advantage	Drawback
[57]	Balance clusters and optimize UAV path planning for longer network lifetime.	K-means + SA	One	✓	Homo	Lifetime of WSN	Reduces data collection time, near-optimal GA solutions.	Limited adaptability to dynamic changes in the network.
[4]	Balance clusters and optimize UAV path planning for longer network lifetime.	KKT+DP+ACO	One		Homo	Time to collect data	Useful for maintaining the SNs data's freshness	Computational complexity increases with the number of SNs.
[21]	Optimize UAV trajectories, CH selection, and task scheduling.	LMCO	One	✓	Hetero	Collision-free of UAV paths, distance, latency, trust, and QoS	Outperforms HEED and CMBO in terms of energy efficiency and network lifetime.	Real-world applicability.
[58]	Energy-efficient coverage path planning.	EECPP + K-means + PSO	One		Homo	Flight Height, data Rate, and Communication Constraints	Outperformed the compared algorithm with 19.99%. Also, reduced energy usage by an average of 56.15% as opposed to E2PP.	Assuming only ideal conditions.
[59]	Address the challenges of the energy consumption and data quality of UAV-based data collection.	QEADCS	One	✓	Hetero	UAV battery	The optimized path reduced the cost by up to 50% compared to conventional approaches.	Limited adaptability to dynamic changes in the network.
[5]	To address the challenge of timely data collection and processing in smart farming environments with randomly deployed sensors.	Energy-Aware Clustering + Modified Dijkstra + GA	One		Homo	Real-time scheduling, nodes connectivity, and data buffering deployment	They have efficient performance, good energy efficiency, CPU-memory usage, and the number of control packets.	Limited adaptability to dynamic changes in the network.

Ref	Objective	Technique	No. of UAV	CH	Network Models	Other constraints	Advantage	Drawback
[60]	Jointly optimizing IoT clustering, UAV trajectory, and bandwidth allocation to minimize UAV flying time.	LKMS + BCD + SCA + GA	One		Homo	Bandwidth limitations, cluster balancing, and UAVs operate in a specified area with limited bandwidth resources and energy.	LKMS clustering outperformed k-means in terms of communication time with a degradation of 18.28%. Degradation in UAV flight time.	For real-world applicability, they did not consider UAV energy constraints.
[7]	Optimize energy consumption of IoT devices and UAVs through trajectory planning.	GAK-means + FCC	One		Homo	Altitude of UAV	The proposed method shortens communication times and effectively consumes energy from UAV batteries.	Assuming the unlimited availability and reliability of the communication between UAV and IoT devices within the defined coverage radii.
[2]	Reduce the energy UAVs consume while flying between stop points and hovering, as well as the energy IoT devices consume while transmitting data to the UAVs.	DEoPS + GBoPS	One		Homo	Stop points, bandwidth, and coverage	Enhances efficiency and demonstrates better performance than rival optimizers for different energy consumption formulations.	Do not consider the capabilities of the UAVs that may affect energy consumption.
[3]	Reduce the total energy consumption of both the UAV and IoT network.	ODC + Greedy + ACO	One	✓	Homo	Path planning	Efficiently collect data, arrange the UAV's route, and use low energy.	Scalability is not considered.
[17]	Enhance the efficiency of data collection by UAV while reducing its energy consumption and optimizing its flight trajectories.	UAVDCH	One	✓	Homo	UAV battery constraints	Reduce UAV hovering points, reduce its energy consumption, and trajectory path while maximizing the data collection rate.	They did not study its applicability in dynamic environments.

Ref	Objective	Technique	No. of UAV	CH	Network Models	Other constraints	Advantage	Drawback
[20]	Address energy consumption and data quality challenges.	QEADCS	One		Hetero	UAV battery	Load balancing and reduced energy use.	Assumes ideal conditions.
[30]	Optimize the communication range of the IoT sensors to increase total energy efficiency and ensure efficient data collection by UAV.	TSP	One		Homo	UAV Altitude	The total energy consumption of both the UAV and sensors is low.	Simplified the network model.
[27]	Optimize CH selection and UAV trajectory.	DRL + Seq2Seq	One	✓	Homo	UAV trajectory avoids loops	Achieved near-optimal energy efficiency.	Clustering methodology is not mentioned.
[18]	Reduce the overall data collection time planning.	Modified K-means + SA + Greedy	One	✓	Homo	Time-constrained	Parallel transmission enhances efficiency.	Energy Efficiency Tradeoffs.
[13]	Enhance energy efficiency and prolong network longevity while reducing data collection latency with optimal RP selection and UAV trajectory design.	GTBRP + ACO	One	✓	Homo	Load balancing of nodes, Communication range of sensors	Successfully extended the network's lifetime and preserved energy.	Real-world applicability.

Ref	Objective	Technique	No. of UAV	CH	Network Models	Other constraints	Advantage	Drawback
[19]	Reduce the deployment cost of the system and the energy consumption while collecting the data within a time restriction.	K-means + DRL + meta-heuristic	Multiple	✓	Hetero	UAV mission deadlines and battery capacity	Low energy consumption, applicable to large-scale networks.	In the online approach, the UAV wastes energy exploring the environment, so they reach the deadline without collecting all the data.
[61]	Minimize the total flight time for multi-UAVs while collecting the data from WSNs.	K-means + GA + mTSP and TSPN	Multiple	✓	Homo	Budget (number of CHs and UAVs)	Reduce the data collection time, and GA provides near-optimal solutions due to its degradation rate of 3.5%.	Does not consider real-world UAV energy constraints.
[6]	Enhance energy efficiency during communications.	Dinkelbach Method + BCD + SCA	One		Homo	IoT data amount	Improves system energy efficiency.	The method doesn't fully optimize the UAV's trajectory.
[8]	Plan the trajectory of the UAV, considering reducing the risks that the UAV faces and the energy consumption of the IoT network.	Local search + TinyML	One	✓	Homo	Flight safety	In a high-risk scenario, the efficiency of the performance is high.	Consider static risk maps.

"Homo" refers to homogeneous sensors; "Hetero" refers to heterogeneous sensors.

CHAPTER 3

SYSTEM MODEL AND DESIGN

In this chapter, we will discuss the system model, which defines the design components, communication assumptions, and the studied environment, as well as the energy models and the constraints of UAV mobility. Furthermore, we will highlight the problem formulation and the constraints.

1 Network Model

This study focuses on the deployment of UAV-assisted IoT networks in smart urban environments. The objective is to jointly optimize the number of CHs and their placement and design collision-free UAV trajectories to enhance the energy efficiency of the overall network. There are several assumptions considered while studying the solution. Below are the assumptions used; each assumption reflects the optimization framework, the design architecture, and the logic used in our approach.

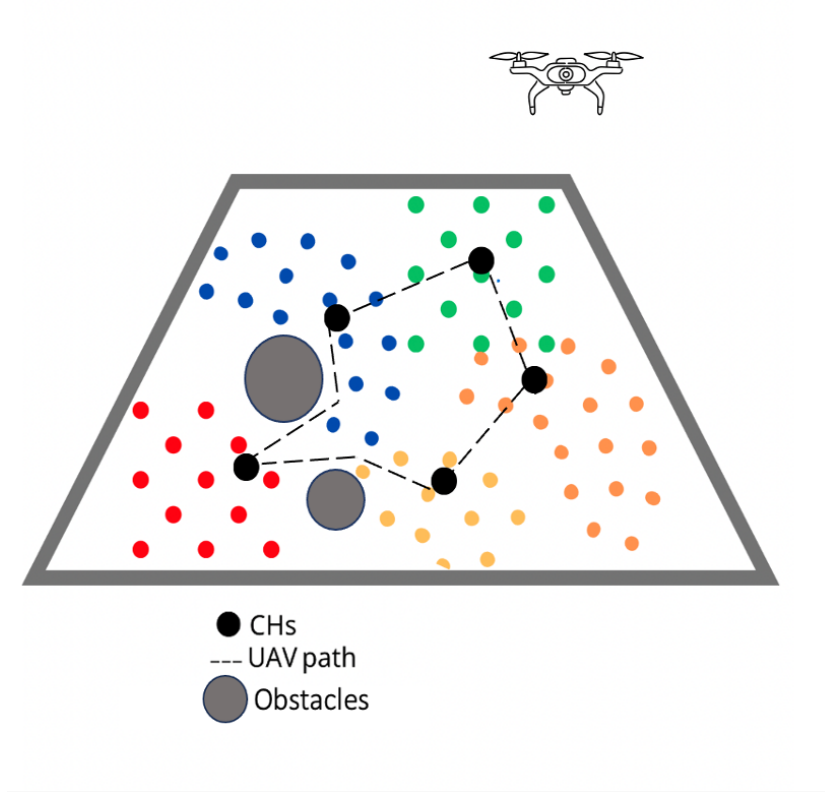


Figure 3.1: Network model

1.1 Environment

The proposed solution is an offline optimization approach. The considered environment is a 2D static smart-city environment. With static IoT nodes that are randomly distributed through uniform distribution, representing random sensor nodes deployed in several locations in smart cities, such as streetlights, bus stations, etc. [15]. Each node has a fixed task, such as sensing gas leakage, air quality, etc. There is one UAV that acts as a sink node without a fixed base station; it operates within a short time mission duration.

1.2 IoT Nodes

The IoT nodes reflect low-power devices that are uniformly distributed in a smart monitoring environment [39]. We assume the IoT nodes are equipped with a first-order radio model. Further, all nodes are identical with a fixed initial energy of 1J

[63]. However, they communicate using the first-order radio model that is widely used in UAV-assisted IoT literature [14]. We assume that in each regular time interval, each IoT generates one packet with a fixed size of 4000 bits and sends it to its CH [64]. In the simulation, in each round, each node sends one packet to the CH. Further, the communication between each IoT node and its corresponding CH is through a single hop. Each node has a fixed location.

1.3 Cluster Heads

The CH will be placed in an optimal location, and it has higher initial energy than other IoT nodes. We assume that in each communication round, each CH is responsible for aggregating all the received packets from IoT nodes under its cluster into one packet that represents the cluster's information. The CH sends the aggregated packet to the UAV when it hovers above or near it. Periodic aggregation has valuable benefits in enhancing the energy efficiency of the network, as it reduces the communication overhead of the network level and reduces redundant transmissions [47].

1.4 UAV

UAV has a lightweight gateway to communicate with CH [37]. It flies at a fixed altitude of 50 m that is used in several papers that focus on UAV data collection. This altitude preserves reliable and stable line-of-sight communication with the ground devices and simplifies designing optimal UAVs, while it is high enough to avoid small obstacles [14]. However, the design of the UAV path must be collision-free.

1.5 Obstacles

We assume that there are circular obstacles that reflect real downtown obstacles such as buildings, restricted zones, etc. [15]. The circular obstacles efficiently provide geometric operations for trajectory planning [65]. These obstacles should

be successively avoided while designing the UAV path. Additionally, we assume that there is no CH placed in the obstacle's region.

1.6 Obstacle Modeling and Virtual Nodes

In the real application of smart downtowns, the obstacles of buildings, towers, etc., are treated as substantial constraints that must not be violated by the UAV [65]. Much research that focuses on studying the collision-free path of the UAV has integrated obstacle avoidance indirectly [66]. They avoid collision through setting penalties or heuristic rejections. Further, they define the path directly without a geometric structure. This results in unrealistic trajectories where the UAV passes very close to the obstacles or leads to unstable convergence and infeasible paths [66]. To overcome these limitations, in our solution, we integrate the obstacle modeling in our optimization loop using a hybrid geometric graph. To prevent the UAV from violating the obstacle region, we utilize geometric safety by expanding the obstacles with safety margins to ensure that the UAV does not fly in an unsafe region. The UAV altitude and physical constraints influence the size of the margin. The advantage of this technique is to have a realistic physical representation. The inflated radius R' is defined as [67]:

$$R' = R + \Delta R$$

Where ΔR is the extra margin added upon the benefit of the safety margin to define the restricted flying area, it does not reroute the UAV to avoid the region. Therefore, we use several virtual nodes that surround each inflated obstacle. These nodes are considered as waypoints utilized to construct the linking of the visibility graph. The visibility graph is a mapping technique that is used to connect the points in the environment [68]. The visibility graph consists of several nodes in our solution: CH, the UAV depot, and the virtual nodes. If the straight line of sight between the two nodes is intercepted by an obstacle, the visibility graph captures the geometric structure of the environment and finds the shortest

possible diversions. Thereby, during the UAV path, it checks if the path between two CHs is blocked by an obstacle; if it is, it finds the shortest safe route through the virtual nodes. It utilized Dijkstra, which is a well-established method that finds the shortest paths with minimum cost and positive edge weights [69]. It guarantees a collision-free path, it is fixed, and it does not affect the optimization variable or increase the dimensionality of the GA or QPSO.

1.7 Network Deployment

The IoT sensor nodes are deployed in a unified random distribution in the 2D area with minimum spacing constraints that reflect the real-world scenario. However, the distribution of nodes should be restricted outside the obstacle and boundary regions. Further, the location of each node remains static after the distribution. Each node is responsible for generating a packet at every interval and sending it to its CH. The communication between the nodes and the CH follows the radio-energy dissipation model. Each CH is responsible for aggregating the received data and sending it to the UAV when it hovers above it. In our network, there are several clusters, and each cluster has a CH; the number of the CH is selected by the optimizer. However, the initial location of the CH is selected using the SOM algorithm, and then the optimal placement is selected by the optimizer. The UAV starts its collection mission from a fixed initial location, then it follows the path selected by the optimizer to visit each CH once, collect the data, and go back to its depot.

2 Application Scenario

Nowadays, smart urban cities utilize the UAV-assisted IoT due to its valuable benefits in smart monitoring [23]. Therefore, the application studied in this research is deploying a two-dimensional (2D) smart urban city. We consider that there is a static 2D area of a downtown smart-city intersection. The downtown intersections are one of the critical regions to monitor and manage, as they are

crowded with vehicular and pedestrian flows, and they are surrounded by a huge number of buildings [70]. Therefore, continuous monitoring of this region helps to smartly increase its management quality and enhance its safety. We consider that there are N low-power IoT nodes that are deployed in static locations of the city, such as deployed in intersections, bus stations, and the facades of buildings. These nodes are responsible for sensing crowd density, the quality of the air, the leakage of the gas, and vibration to smartly monitor the environmental, safety, and structural circumstances of the city. The type of IoT device considered in the scenario is a low-power wireless IoT sensor that is widely used for monitoring purposes in smart cities due to its scalable wireless technology with extremely low power and short range [38].

Moreover, we consider that IoT nodes are grouped into M clusters, and each cluster has a CH. The CH is a node that is responsible for collecting the data from the IoT nodes within its cluster. So, in each interval time, the IoT node generates a packet and sends it directly to its CH. We assume that in each round, each sensor will send one packet to its CH. Then the CH will aggregate the data and send it to the UAV while it is hovering above it. The advantage of CH is that it helps to extend the IoT network lifetime, as it lets the limited-power device send its data over short distances instead of multi-hop long distances, which leads to reduced energy consumption [46]. Additionally, it helps to enhance the energy consumption of UAV as it reduces their hovering points [17]. Smart urban areas widely use a UAV as a sink node without a base station, especially in the case of emergencies when the base station is crashed [14]. To smartly monitor the city even when disasters occur. Therefore, we assume that there is a DJI Matrice-100 UAV with a rotary wing that acts as a sink node and flies periodically at a fixed altitude from its depots, visiting each CH one time per round, collecting its aggregated data, and going back to its depots after completing its mission [71]. This type of UAV is selected due to its applicability to precise hovering above CHs. Moreover, it is efficient in navigating waypoints [23]. In a downtown smart-city intersection, there are several types of physical obstacles, such as buildings,

towers, and restricted areas, that affect both the quality of wireless communication and the navigation of UAVs [70]. In this research scenario, we assume that there are static obstacles, represented as circular regions (O_i). These obstacles generate non-line-of-sight (NLoS) and no-fly zones that the UAV must consider to safely complete its mission [12]. The main objective of this study is to jointly optimize the number of CHs, their placement, and the trajectory of the UAV to enhance the overall energy efficiency of the system. We divide this objective into three sub-objectives: optimizing the number of CHs to extend the network lifetime, placing CHs optimally to shorten the UAV path, and designing an optimal collision-free UAV to minimize its energy consumption.

There are several challenges to achieve our objective: The clustering approach that utilizes existing cluster heads creates an energy-efficient network because IoT nodes send their packets over short distances, which results in lower energy consumption [72]. Moreover, it increases the energy efficiency of the UAV, as it reduces the number of its hovering points and the overhead [73]. However, the increased number of CH results in increased hovering points, which raises the energy consumption of the UAV. Thereby, one challenge is to optimize the number of CHs that extend the network's lifespan while considering the UAV's path length and its energy consumption [14]. Moreover, optimally place the CHs to extend the network's lifetime and enhance the UAV's energy efficiency. Furthermore, designing an optimal collision-free trajectory of UAVs to efficiently aggregate the data from all CHs and conserve energy resources is one of the challenges of this study.

3 Communication Model

The communication between the UAV and CHs follows the air-to-ground (A2G) model presented in [19]. In the A2G model, the communication channel can either be line-of-sight (LoS) or non-line-of-sight (NLoS) [61]. However, the probability

of LoS between the UAV and CHs can be calculated as [8]:

$$P_{i,L} = [1 + a \times e^{-b(\phi-a)}]^{-1} \quad (1)$$

where, a and b are drone-specific parameters, and ϕ is the angle formed between the UAV and the CH given by [7]:

$$\phi = \frac{180}{\pi} \cdot \arcsin\left(\frac{H}{d_{i,j}}\right). \quad (2)$$

The probability of non-line-of-sight (NLoS) is given by [7]:

$$P_{i,NL} = 1 - P_{i,L}. \quad (3)$$

The average of the losing path between CH and UAV is [8]:

$$\bar{p}_{i,L} = p_{i,L} (k_0 + \lambda_L) + p_{i,NL} (k_0 + \lambda_{NL}) \quad (4)$$

where, λ_L represents the mean value of the losing path of LoS, while λ_{NL} is for the NLoS link, k_0 (path-loss index) = $10k \log_{10}\left(\frac{4\pi f_c H}{c}\right)$, where, c is the light speed and f_c is the frequency of the carrier.

The Shannon formula is used to find the average of the transmission rate of the data r_{data} between UAV and CHs [9]:

$$r_{data} = B \log_2 \left(1 + \frac{P}{\bar{p}_{i,LoS} N_0} \right) \quad (5)$$

B is communication bandwidth, while P is the transmission power, and N_0 represents the density of noise across the spectrum.

4 IoT Energy Model

In each data collection round, the sensor nodes send their data to the CH directly; this is called intra-cluster communication [74]. We assume that the communication

between the ground IoT nodes and their CH follows the technology of low-power wireless sensor networks, which is consistent with IEEE 802.15.4 [49]. In our study, we did not model the details of the protocol level, such as packet scheduling or MAC address; rather, we abstracted the energy usage of the communication using the first-order radio model. However, our simulation model controls the radio parameters based on the standard IEEE 802.15.4 used in the literature [72]. Chapter 4 discusses the details of the set values of the simulation. As the communication of IoT nodes is based on the first-order radio model, the IoT devices consume energy based on the principle of wireless hardware energy dissipation [8]. The transmitter wastes energy to operate the amplifier and the wireless electronics, while the recipient expends energy to operate the wireless electronics [17]. Focusing on power attenuation between the sender and recipient, which is caused by the distance between them, as represented by the free-space model. However, if the distance between the node and the CH is long, it consumes energy based on the multipath fading model. Multipath propagation occurs when the radio signals from the sender node reach the cluster head through several reflected, diffracted, or scattered paths, which enhances the fourth power distance due to the attenuation [75]. The two equations below (6) and (7) are used to calculate the amount of energy consumed by the sender (IoT nodes) in sending data in free space (6) and in multi-path (7) to the CH [57]:

$$E_{\text{sender}}^{\text{free-space}}(m, d) = mE_{\text{cir}} + mE_{\text{free-s}}d^2 \quad (6)$$

$$E_{\text{sender}}^{\text{multi-path}}(m, d) = mE_{\text{cir}} + mE_{\text{multi-p}}d^4 \quad (7)$$

E_{sender} represents the energy consumed in sending a packet, d is cross-over distance, m is the number of bits being transmitted for one packet, E_{cir} denotes the energy required to power the wireless electronics circuit, and while, $E_{\text{free-space}}$, is free-space amplifier energy. While it $E_{\text{multi-p}}$ is multi-path amplifier energy.

The crossover distance is a distance that specifies whether the packet is sent

in free space or multi-path distance. So, when the intra-cluster links are less than d_0 , the free-space model is used, while if they are longer than d_0 , they follow the multi-path model.

The crossover distance is calculated through:

$$d_0 = \sqrt{\frac{E_{\text{free-s}}}{E_{\text{multi-p}}}} \quad (8)$$

The energy consumed by the CH while receiving the packets from all IoT nodes within its cluster is represented as $E_{CH, \text{re}}$:

$$E_{CH, \text{re}} = n_k m E_{\text{cir}} \quad (9)$$

where n_k is the number of received packets from K number of nodes within its cluster.

Moreover, in our model, the cluster heads consume energy while aggregating all received packets from the IoT nodes:

$$E_{CH, \text{agg}, K} = n_k m E_{\text{agg}} \quad (10)$$

The distance between each sensor and target CH is calculated using Euclidean distance [52]:

$$d_{s, CH} = \sqrt{(x_s - x_{CH})^2 + (y_s - y_{CH})^2}, \quad (11)$$

Where (x_s, y_s) is the sensor coordinate and (x_{CH}, y_{CH}) is the cluster coordinate.

Furthermore, CH's energy expenditure to transmit the data to the drone can be calculated using [30]:

$$E_{CHT} = P_{ch} \frac{D_k}{r_{data}} \quad (12)$$

where, P_{ch} is the power consumed by CH to send data to the UAV, D_k is the total amount of transmitted data.

To calculate:

$$D_k = (N - 1) * \ell \quad (13)$$

ℓ is the bits that are messages received from sensors.

Therefore, the overall energy consumed by the CH is:

$$E_{CH, \text{ Total}} = E_{CH, \text{ re}} + E_{CH, \text{ agg}} + E_{CH, T} \quad (14)$$

Therefore, the overall energy consumed by the IoT network during a data collection round is:

$$E_{\text{IoT}} = \left(\sum_{k=1}^K \sum_{n=1}^N (E_{\text{sender}} + E_{CH, \text{ re}}) \right) + \left(\sum_{k=1}^K (E_{CH, \text{ agg}} + E_{CH, T}) \right)$$

5 UAV Energy Model

In the path planning process, the energy model plays a crucial role. UAVs are becoming increasingly popular due to their numerous advantages, but they still have a short operational lifespan due to the limitation of their onboard battery capacity. This limitation is one of the main drawbacks that affect the completion of desired missions [44]. To overcome this limitation, minimizing the UAV's energy consumption through an optimized path is one of the main objectives of this study. We will consider the energy consumption in three stages: flight energy, hovering energy, and energy used during communication with ground devices.

Flight energy represents the movement of the UAV between stop points [30]:

$$E_f = \sum_{j=i}^m P_f \frac{d_{j,j+1}}{v} \quad (15)$$

where, P_f denotes the power of the UAV during flight, v is the flight speed, and $d_{j,j+1}$ represents the Euclidean distance between two stop points j -th and $j + 1$.

The hovering energy can be calculated over a time period from t_1 to t_2 using

the following formula [61]:

$$E_{hov} = P_{hov} (t_2 - t_1) . \quad (16)$$

Where P_{hov} represents the power needed for hovering.

The energy consumption during data collection from all CHs [30]:

$$E_u = \sum_{i=1}^c E_i \quad (17)$$

Where E_i is the energy consumed for data collection from the i -th CH, defined as:

$$E_i = d(i) \cdot P_{hov} + P_c \cdot t_i \quad (18)$$

Where $d(i)$ is the distance to the i -th cluster, P_{hov} is the hovering power, P_c is the power required for the communication, and t_i is the time spent to collect the data from the CH.

Therefore, the UAV total energy consumption [76]:

$$E_{UAV} = E_f + E_{hov} + E_u \quad (19)$$

6 Problem Formulation

This study considers three objectives: optimizing the optimal number of CHs that extend the lifetime of the network, finding the optimal placement of CHs that shorten the UAV path, and optimizing the UAV trajectory with obstacle avoidance while reducing its energy consumption during data collection. To express the three objectives as a single objective, we sum the objective functions and use normalizing and weighting methods:

$$\text{P1: } \min (\alpha E_{UAV} + \beta E_{IoT})$$

In optimization problem P1, the objective function contains two elements:

first, the energy consumption of the UAV; second, the energy consumption of the IoT network. Each component is multiplied by its associated weight, α or β , which is manually selected according to its relevance in various scenarios. Increasing the weight of α leads to focusing more on optimizing the UAV path, while increasing β focuses on the enhancement of the network lifetime. These weights help manage the tradeoff between the objectives.

There are several constraints: The constraint (P1.a) guarantees the efficient residual energy E_{resid} of CHs to carry out their respective roles, where E_{min} , CH is the minimum required energy to accomplish their task. This prevents the CH from depleting its energy, which may disrupt the IoT network [30].

$$E_{resid} \geq E_{min,CH} \quad (\text{P1.a}),$$

The optimal number of cluster heads reflects the relationship between several aspects, which are the data aggregation efficiency, network density, and clustering overhead. Therefore, Constraint (P1.b) ensures an optimal number of CHs. The predefined numbers of N_{min} and N_{max} represent the minimum and maximum number of CHs.

$$N_{CH,min} \leq N_{CH} \leq N_{CH,max} \quad (\text{P1.b}),$$

The P1.C constraint ensures that the UAV visits each cluster once per data collection round [49]. Where the permutation vector π represents the order of the visiting sequence to each CH.

$$\pi \in \text{Perm}(CH) \quad (\text{P1.c})$$

P1.d. Each obstacle radius r_{obs} will be expanded with a safety margin Δ_{saf} in order to prevent the UAV from flying in the restricted area [66]. This forms an inflated radius $\widehat{r_{obs}}$:

$$\widehat{r_{obs}} = r_{obs} + \Delta_{saf} \quad (\text{P1.d})$$

Constraint (P1.e) ensures that for each obstacle $\forall O_i$ the UAV remains outside the inflated radius of the obstacle $\widehat{r_{obs}}$. The distance between the UAV and the center of the obstacle is computed using Euclidean distance, where $\Delta x = x_i - x_j$, $\Delta y = y_i - y_j$ [66].

$$\Delta x^2 + \Delta y^2 \geq \widehat{r_{obs}}^2 \quad \forall O_i \quad (\text{P1.e})$$

This study focuses on avoiding obstacles by construction, as each obstacle is surrounded by several virtual nodes that are used as waypoints that the UAV passes through in case of obstacle intersection on the path between two CHs. The visibility graph is responsible for using these virtual nodes to decide the best virtual node to pass through to avoid obstacles. So, constraint p1.f focuses on placing the virtual node v_{jk} in the inflated obstacle radius at angle θ_k . $\cos \theta_k$ and $\sin \theta_k$ represent the horizontal and vertical directions from the center of the obstacle [26].

$$v_{n_{j,k}} = O_j + \widehat{r_{obs}} [\cos \theta_k, \sin \theta_k] \quad (\text{P1.f})$$

(P1.h) ensures that the UAV does not exceed its battery capacity.

$$E_{UAV} \leq E_{\max} \quad (\text{P1.h}).$$

7 Proposed Solution

In this section, we will discuss the proposed solution in detail.

7.1 Motivation

In this section, we will discuss and justify the reasons for selecting metaheuristic algorithms to develop our design. As the primary objective of this research consists of three parts. First, find the optimal number of CHs to extend the IoT network lifetime; second, find the optimal placement for each CH to shorten the UAV path and extend the network lifetime; third, design the optimal UAV route with collision avoidance to enhance its energy efficiency. So, the main goal is to deploy a UAV-assisted IoT network in a smart city with efficient energy consumption, considering several metrics, such as the time of first and last node death, UAV energy consumption, and UAV path length. There are several demanding features that characterize this optimization problem:

- It is an NP-hard problem due to the joint optimization of clustering and path planning with collision-free [77]. Moreover, it consisted of mixed variables, such as discrete variables of the number of CHs and continuous variables for their coordination [17]. As well as UAV trajectory planning with collision avoidance, it is a mix of discrete and continuous variables [65]. Further, it is considered a non-convex and non-linear search space due to the infeasible region of the obstacles and the combined nature of the CHs placement and UAV path planning.
- The objective of this research consists of conflicting criteria. There is a conflict between the number of CHs and UAV energy consumption, as the increased number of CHs enhances the IoT network lifetime, while it may lead to high overhead and long UAV path distance [76]. However, decreasing the number of CHs leads to less overhead and better energy efficiency of the UAV, but it may lead to an inefficient IoT network lifetime [24]. Moreover, there is a conflict between shortening the UAV path with consideration of obstacle avoidance and visiting all CHs, especially in the case of scattered CHs. So, there is a conflict between network lifetime vs. UAV energy vs. path length vs. collision avoidance.

Traditional convex, gradient-based optimization techniques, or mixed-integer linear programming (MILP), are not applicable to solve our complicated optimization problem, as they are applicable to solve smooth objective functions and convex feasible regions [78]. In contrast, a metaheuristic algorithm is more suitable for our multi-objective function, with the required consistency of our trade-off goals. Metaheuristic algorithms are algorithms that are designed to solve stochastic optimization problems that have complex, large, and poorly structured spaces [79]. It solves NP-hard, nonlinear, and multi-modal problems utilizing exploration and exploitation mechanisms. The algorithms are inspired by nature’s behavior, such as evolution or swarms that use randomized operators to determine near-optimal solutions [80]. The global search capability using populations of candidate solutions of these algorithms leads to overcoming the local optima that exist in non-convex scenes [78]. The encoding technique allows handling mixed-variable decision spaces. Metaheuristic algorithms have a fitness function that helps to control and balance the trade-offs among multiple objectives. Their scalability and applicability to determine near-optimal solutions make them widely utilized in real-world deployment problems, such as IoT clustering and UAV path planning [80].

A Genetic Algorithm (GA) is a metaheuristic algorithm that is based on population and inspired by the nature of evolution and genetics [81]. It derives its near-optimal solution through iterative processes of selection, crossover, and mutation of the evolving population of solutions [15]. It has a fitness function that evaluates each solution and selects the best ones to generate new offspring. In the crossover, it focuses on useful traits of the parent solution and recombines them. The mutation is responsible for maintaining diversity and avoiding local minima by introducing randomness. However, the repeated evolutionary cycle in each generation leads to gradual convergence toward a near-optimal solution in complex optimization problems [82]. Therefore, it has been studied in several papers in the field of clustering and path planning. Due to its applicability to solve non-convex, mixed-variable, large search space, and complex constraint problems

[83].

The GA algorithm is selected to solve our optimization problem due to several reasons. The population-based mechanism effectively manages the complex relationships among the combinational structure of the cluster heads' count and indices, their placement, and geometric restrictions involved in the obstacle avoidance during UAV route design. It has a custom-designed fitness function that allows us to encode our three sub-objectives in one unified function, with the benefit of a weighted tradeoff that allows us to control, balance, and express the competitive objective without the need for mathematical reformulation. Its reliability is maintained even with the existence of a noisy, non-smooth, or complex objective function [74]. These features are critical for energy-dissipation and wireless communication models, as the computation of analytical gradients is commonly impossible. The genetic algorithm demonstrates its applicability in the field of optimization in UAV route planning, and IoT clustering makes it a suitable foundation for our full joint optimization problem [15].

The genetic algorithm has a significant global search advantage due to its population-based evolutionary composition [81]. That makes it better than the local optimization methods, as it works on diverse groups of individuals in each generation rather than a single candidate solution in each iteration [74]. Although it has significant global search applicability, GA fails in local refinement, especially in the case of continuous variables, which are, in our case, CH locations and UAV route points. Its mutation and crossover operators provide a diversity advantage; however, this high level of diversity may result in insufficient fine-grained exploitation, regression near optimal regions, and slow convergence [28]. However, the GA algorithm is prone to early convergence and is sensitive to its parameter settings, as it does not have a dedicated mechanism to guide solutions toward a global best [84]. Thus, it must have good fine-tuning of its parameters; however, its dependency on random operations results in instability in the final solution quality.

To overcome these limitations, we propose a hybrid optimization algorithm

that utilizes the advantages of the QPSO for local refinement. Quantum-behaved Particle Swarm Optimization (QPSO) is an enhanced version of the practical swarm optimization metaheuristic algorithm that is inspired by the social behavior of the birds and fish flocking [85]. It utilized the quantum mechanism to eliminate the velocity term of classical PSO, which leads to more efficiency in the continuous search space. However, in the optimization problems, each particle is considered a comprehensive candidate solution, and the swarm is a search space that explores several particles. In classical PSO, it uses the explicit velocities to move the particles, while in QPSO, each particle is modeled as situated inside a quantum delta-potential; this affords it an advantage to appear anywhere in the feasible space [86]. Leading to strong global coverage with a maintenance of the natural contraction respecting the best mean attractor, which is found by averaging the best solutions of the swarm’s personnel. It gradually reduces its quantum search radius (β parameter) to uncover its near-optimal solution. This feature allows the particle to explore widely in the first stages and then apply gradual coordination to move into precise local reinforcement; these gradual movements lead to a noticeable improvement in the solution quality [87]. Therefore, we use the QPSO as a post-GA refinement to effectively enhance the solution. As it overcomes the local reinforcement limitation of GA, fixing the fine-grained failure in cluster head placement and UAV route, the stochastic operators of the GA could not resolve it efficiently.

We leverage the complementary strengths of both algorithms and propose our hybridization of the GA and QPSO frameworks. Both are effective in handling the composite, NP-hard optimization problem of our research [78]. The GA gives our framework the advantage of global exploration, preserving the diversity of the population, and avoiding premature convergence by effectively searching the continuous and discrete design space to discover the promising areas. The QPSO refines the candidate that was generated by the GA by precise local exploitation utilizing a quantum mechanism, leading to more optimal CH placement and a shorter and optimal collision-free UAV route. By integrating the advantage

of evolutionary global search with the quantum-behaved swarm refinement, our framework enhances the solution quality, has better convergence stability, and avoids the recession of metaheuristic algorithm limitation [79]. Moreover, provide superior performance in terms of network lifetime, UAV energy efficiency, and UAV path planning with collision avoidance. That aligns with recent studies that demonstrated the effectiveness of hybrid metaheuristic algorithms in the field of optimization problems in UAV-assisted IoT networks [29]

7.2 Overview of the Proposed Hybrid GA–QPSO Framework

Most of the recently reviewed research that studies the deployment of UAV-assisted IoT data collection focuses either on optimizing the CH selection and placement to extend network lifetime or on optimizing the design of UAV paths [14]. However, several papers have studied the joint optimization of clustering and UAV trajectory planning, but they study it in isolation or in sequential stages. Therefore, in this research, we focus on full joint optimization where, during the search process, all design variables influence each other. We propose a hybrid metaheuristic optimization framework that simultaneously determines the optimal number of CH, their optimal placement in a 2D area, and the design of a collision-free UAV path within a unified fitness function. This, ultimately, led to a more efficient, consistent, and realistic system design. The proposed solution utilizes a hybrid GA-QPSO where the GA algorithm is responsible for global exploration and QPSO for continuous local refinement. Figure 3.2 below shows the flowchart of the proposed optimization framework.

7.3 System Initialization

To study the deployment of UAV-assisted IoT in a real downtown, we simulate a static two-dimensional area that reflects a smart urban area. We set the parameters of the network, including the number of nodes, traffic generation rates,

initial energies, radio parameters, and unified random distribution. We assume that all IoT nodes have identical initial settings, while the CHs have higher initial energy than other nodes within their cluster. However, initialize the parameter of the radio-energy model and consider the constant of a free space propagation [11]. Moreover, initialize all required parameters for the UAV, including its hovering and flying powers, air density, mass, and rotor specifications. All of these follow the accepted energy model from prior studies and represent realistic energy estimation, and preserve computational tractability [88].

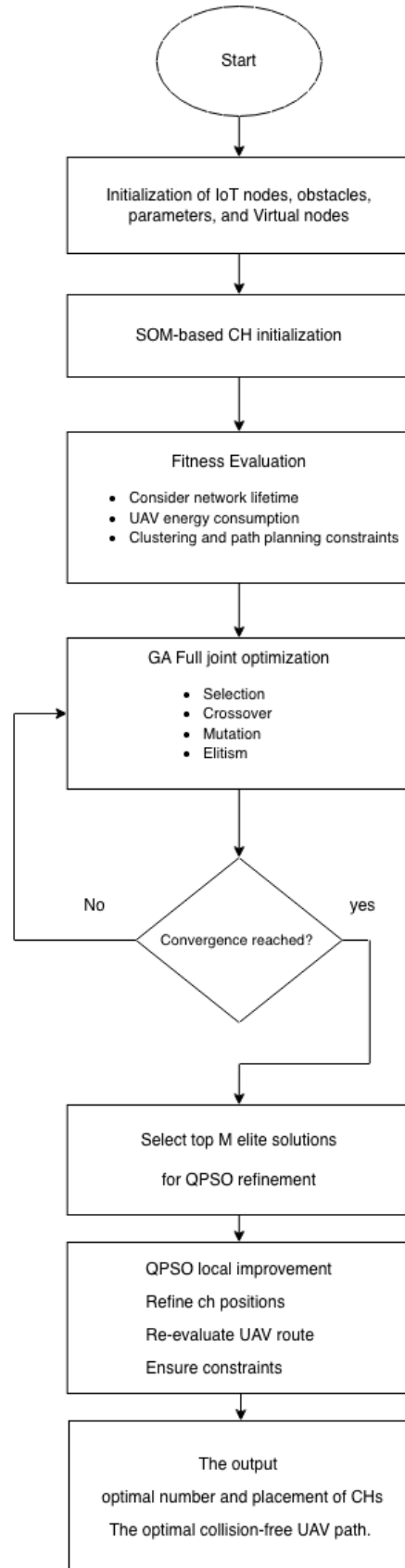


Figure 3.2: The flowchart of the proposed solution

7.4 Joint Fitness Function Design

The main objective of this research is to deploy an energy-efficient UAV-assisted IoT network considering three objectives: First, what is the optimal number of CH for use in a specific environment? 2. How to optimally place each CH in an allocation to extend the network lifetime and reduce UAV energy consumption. The third objective is to design an optimal collision-free UAV path. In our solution, we design a fitness function that covers our objective and constraints. The proposed fitness function of multi-objective optimization problems is [73]:

$$\text{Fitness} = \alpha(1 - L_{\text{norm}}) + \beta P_{\text{norm}} + \text{Pan}$$

where L_{norm} is the normalized network lifetime that represents the first and last IoT node and cluster head to die. However, P_{norm} represents the UAV energy usage of the collision avoidance route. α and β are control values that direct the optimization function to balance between UAV energy efficiency and IoT lifetime [89]. However, $\alpha + \beta = 1$. Furthermore, the penalties represent the cost added to enforce the required constraints. In our fitness function, the penalties ensure that each node is assigned to a CH, there is no CH without any assigned node, and both the UAV and CH do not intersect with the obstacle region. The main advantage of the fitness function is combining the three sub-objectives of this study: the number of CHs, their placement, and the collision-free UAV path. Moreover, the weights tuning handles the tradeoff between UAV energy efficiency and the network lifetime, while the penalties provide physical feasibility enforcement. The optimal number of cluster heads is determined by evaluating this fitness function for each value of N_{ch} within $[K_{\text{min}}, K_{\text{max}}]$ [50].

7.5 Initialization of the CH placement Using SOM

To initialize the CH placement in our proposed model, we utilized a Self-Organizing Map (SOM). SOM is an unsupervised neural-mapping algorithm that has the ad-

vantage of projecting high-dimensional data into a grid of low dimensions in an efficient way, as it preserves the relationships between the input samples [90]. It is widely used in the field of clustering due to its applicability to represent spatial density patterns in a smooth and self-organized way. The purpose of the SOM algorithm in our model is to initialize the cluster head positions before the GA begins its global search, providing the advantage of a density-aware initialization and consistent topology [91]. Thus, instead of using random initialization of the GA, which may result in a less efficient solution, such as empty clusters, high penalties in the fitness function, and sparsity in the placement of the CH, the SOM will generate the initial position of each CH that the GA starts with. However, that helps reduce the search space of the GA algorithm, leading to more efficient and stable optimization [92].

7.6 GA Algorithm for Global Search

In the hybrid optimization approach, the genetic algorithm is responsible for global optimization. It is primarily exploring the design space, which includes a wide mix of variables, such as cluster head number, the coordination of each CH, and the UAV visitation order. Its evolutionary operators provide it an advantage to preserve population diversity and avert premature convergence without the requirement of gradient information [29]. These benefits make it applicable to our joint optimization problem that consists of a non-convex, obstacle-constrained landscape in the field of deploying UAV-assisted IoT networks [78]. Figure 3.3 shows the flowchart of the GA algorithm.

Chromosome Representation

In our full joint optimization approach, we encode the number of CHs, the continuous coordination of each CH that is initialized by the SOM algorithm, which gives the advantage of diversity and density-aware starting points, and the permuted UAV visit order in one chromosome [93]. The equation below shows the

representation of each chromosome [94]. Each solution S consists of three parts: the number of CHs, the CH locations, and the UAV route.

$$S = (N_{ch}, CH_L, \pi)$$

Where N_{ch} is the number of CHs selected from the specified range of minimum and maximum number of CHs:

$$N_{ch} \in [N_{ch,min}, N_{ch,max}]$$

CH_L is the locations of all cluster heads in the 2D area:

π is the permutation that describes the order of the CHs in the UAV route.

$$\pi \in [\pi_{ch,1}, \pi_{ch,2}, \dots, \pi_{ch,k}]$$

Selection

In the selection stage, it evaluates the solutions (chromosomes), and the solution with a greater fitness score has a higher chance of being selected as a parent S_p for the reproduction stage [94].

$$S_p = \arg \max_{S_i \in T} \text{Fit}(S_i)$$

Crossover

It applied the BLX- crossover for the continuous CH coordinates. Resulting in a smooth inheritance from parents of CH placements and route-key values. BLX-

Crossover is a technique that is widely used for the optimization of the real valued. It generates the offspring gene by coordinating the parents and sampling the offspring from a larger area surrounding them [95].

$$x' \sim U(\min(x_1, x_2) - \alpha d, \max(x_1, x_2) + \alpha d)$$

$$d = |x_1 - x_2|$$

Where U is the uniform distribution across the interval, and d represents the distance between parent and alpha, it is the control value that prevents expansion beyond the interval of the parents. This helps in creating population diversity and encourages exploration, leading to overcoming premature convergence [81].

Mutation

In this stage, the algorithm preserves the diversity of the population and performs and applies smooth adjustments to its solutions [11]. In our problem, it mutates the cluster head coordination by adding small Gaussian noise, leading to a focused investigation of promising CH placement and providing an optimal UAV path.

$$CH_{L_j}' = CH_{L_j} + \text{Noise}(0, \sigma^2)$$

Where CH_{L_j} is the placement vector of the j -th CH.

Elitism and Termination

In each generation, the individuals with the best performance are forwarder elitists in order to guarantee monotonic improvement of the optimal solution [94]. The GA terminates when it reaches the maximum iteration, and the next best solutions are sent to the QPSO for further refining.

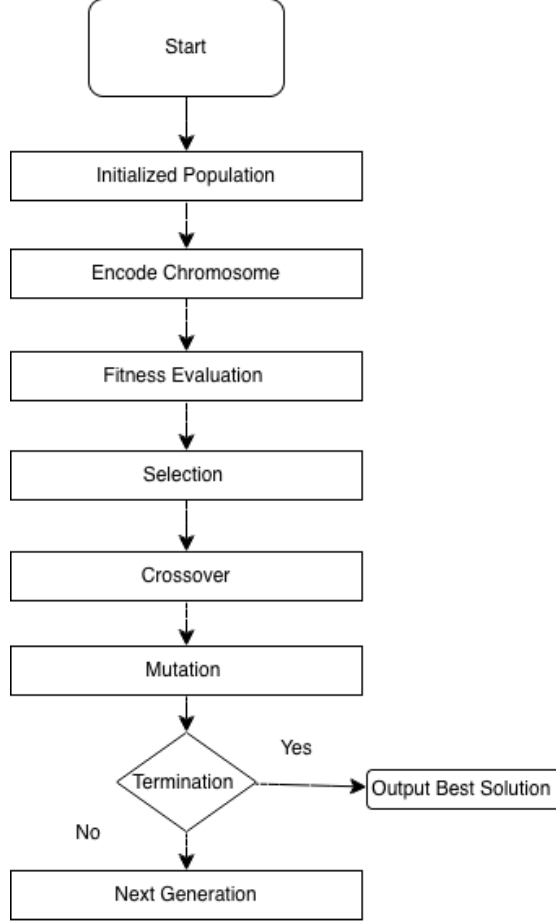


Figure 3.3: The flowchart of GA

7.7 QPSO for Local Refinement

In our model, GA will provide the globally optimized solution of the optimal number and placement of CHs and the UAV route order. The second stage of our hybrid solution uses the QPSO to apply fine-grained refinement. The QPSO is suitable for local refinement because it specializes in continuous optimization, and it is highly precise in exploitation [86]. These benefits provide better convergence toward optimal cluster head coordination and a smoother UAV path that the genetic algorithm cannot achieve alone [87]. In our solution, the QPSO is used to refine the continuous variables, which are the coordinates of CHs and the waypoints of the UAV. However, it keeps the number of CHs, their indexes, and the route order of the UAV fixed from the GA. In this way, we leverage the strength

of each algorithm, the excellence of the genetic algorithm to handle discrete global exploration, and the continuous local exploitation. The QPSO is excellent at handling it.

However, below is the pseudocode of the hybrid GA-QPSO full joint optimization approach.

Algorithm 1: GA-Based Joint Optimization Stage Part-1

Input: Nodes: places of IoT sensors;
Obstacles: barrier of obstacles;
 $K_{\min}, K_{\max}$: the number of minimum and maximum number of cluster heads;
GA parameters, parameters of the QPSO;
The parameters of network, energy and UAV models.
Output: Number of CH;
Final CH positions;
Final UAV route;
Performance metrics.

- 1 **1. Preprocessing: Obstacle Aware Distance Engine;**
- 2 BuildVisibilityGraph(Obstacles) and Virtual Nodes;
- 3 Define ObstacleAwareDistance(p, q);
- 4 Bestglobalfitness $\leftarrow -\infty$;
- 5 bestglobalsolution $\leftarrow$ null;
- 6 **2. Stage 1: The first step is the stage of GA-Based Joint Optimization Over K;**
- 7 **for** K **from** $K_{\min}$ **to** $K_{\max}$ **do**
- 8 CH-SOM SOMInitializeCH(Nodes, K);
- 9 Population P_0 in GA population;;
- 10 • Chromosomes around CH-SOM;
- 11 • Additional randomly inherited chromosomes;
- 12 **while** $GATerminated = false$ **do**
- 13 **foreach** chromosome z **in** P **do**
- 14 (CHs, Route) $\leftarrow$ Decode(z , K);
- 15 Fitness(z) $\leftarrow$ EvaluateFitness(CHs, Route, Nodes, ObstacleAwareDistance);
- 16 $P \leftarrow$ GAEvolve(P);
- 17 (CHGA, RouteGA) $\leftarrow$ BestSolution(P);
- 18 FitnessGA $\leftarrow$ BestFitness(P);
- 19 EliteSetK $\leftarrow$ ExtractElites(P);
- 20 **if** $FitnessGA > Bestglobalfitness$ **then**
- 21 Bestglobalfitness $\leftarrow$ FitnessGA;
- 22 bestglobalsolution $\leftarrow$ (K, CHGA, RouteGA, EliteSetK);
- 23 (K^* , CH_best_GA, Route_best_GA, EliteSet_best) is the best_global_solution;
- 24 MetricsGA $\leftarrow$ CHbestGA Evaluation Solution(RoutebestGA);

Figure 3.4: Hybrid GA-QPSO joint optimization-1

Algorithm 2: QPSO Refinement Stage Part-2

```
1 3. Stage 2: CH Refinement of QPSO Local Positions;
2 best_qpso_fitness ← best_global_fitness;
3 best_qpso_solution ← (CH_best_GA, Route_best_GA);
4 foreach (CH_init, Route_init) in EliteSet_best do
5   CH_refined ← QPSO_Optimize_CH(CH_init, Route_init, Nodes,
   ObstacleAware_Distance);
6   Metrics_refined ← Evaluate_Solution(CH_refined, Route_init);
7   Fitness_refined ← Metrics_refined.fitness;
8   if FitnessRefined > bestQPSOFitness then
9     best_qpso_fitness ← Fitness_refined;
10    best_qpso_solution ← (CH_refined, Route_init);
11 Return CH_final, Route_final, Metrics_final;
```

Figure 3.5: Hybrid GA-QPSO joint optimization-2

CHAPTER 4

PERFORMANCE EVALUATION

In this chapter, we conduct a comprehensive study and evaluation of the proposed solution, the hybrid GA-QPSO, for the joint optimization problem in UAV-assisted IoT networks. Unlike most joint optimization studies, which study optimization problems at separate or sequential levels, the proposed solution studies the full joint optimization. It simultaneously optimizes the number of CHs, their placement in 2D areas, and the UAV path planning with collision avoidance in a single unified objective function. The objective of this chapter is to demonstrate the effectiveness and the robustness of the proposed solution under realistic UAV-assisted IoT network deployment applications in smart urban cities. Moreover, in this chapter, we discuss the experimental environment and the simulation setup. Furthermore, to assess the proposed solution, several scenarios were conducted to study specific objectives. The main objective of the proposed solution is to increase the energy efficiency of the UAV-assisted IoT by increasing the network lifetime and decreasing the UAV energy consumption. Thus, the objective integrates two conflicting goals. Therefore, in this chapter, we analyze the tradeoff between the conflicting objectives by evaluating different weight configurations: lifetime-oriented, balanced, and UAV-oriented settings. All conducted experiments are evaluated using several evaluation metrics, such as the energy

consumption of the UAV, the UAV path length, the first/last node death, and the first/last CH death. The purpose is to provide a comprehensive assessment of the energy efficiency of the ground and aerial devices. However, the contribution of the hybrid GA-QPSO is studied in this chapter to demonstrate the enhancement of the proposed solution; therefore, several comparative evaluation assessments are conducted in this chapter. The chapter is concluded with a full discussion of the proposed solution and results.

1 Simulation Tool and Environment

We apply our deployment of UAV-assisted IoT networks using Python 3.10. Using Python to simulate our model presents us with the advantage of integrating numerical computation, geometric processing, and the optimization of hybrid GA-QPSO in an individual framework [96]. Further, enable flexible experimentation across several nodes and obstacle densities, and flexibly tune the optimization weight. In the implementation, several libraries were used, such as NumPy, which is a Python library that specializes in numerical computing. We utilize NumPy to apply random sampling, matrix operations, and the calculations of geometric distance, and to evaluate the energy model. The NetworkX library is used to construct the visibility graph and to use Dijkstra’s algorithm to determine the shortest UAV path with obstacle consideration [97]. This approach realistically reflects the physical obstructions in the deployment environment.

Furthermore, Matplotlib is a specialized library for visualizations. We use it to visualize the simulation results, such as the CH placement, clusters, UAV path, and the alive-nodes curves. Moreover, we use the MiniSom library to initialize the locations of CH; this initialization leads to enhanced GA convergence, as it provides topology-aware starting points. The hybrid GA-QPSO optimization engine is the core of the simulation tool; we implement it manually without utilizing any external libraries. To ensure that it covers all the objectives and constraints of our approach, and to ensure control of the multi-objective search. The hybrid

GA-QPSO consists of two stages: first, a global search by the GA focusing on the mixed-variable search space and jointly encoding the coordinates of cluster heads as continuous values and the UAV hovering order as a permutation. The fitness function combines the evaluation of the lifetime model, obstacle-aware UAV trajectory, and penalty fitness in a unified weighted multi-objective score. The second stage includes refining the best solutions obtained from the GA, utilizing quantum-inspired particle dynamics of the QPSO algorithm to enhance CHs placement. In the simulated framework, all numerical analysis we apply, such as computing the first and last node and cluster head, dies. All the experiments were conducted on Windows 10 platforms with 16 GB RAM. Furthermore, all the evaluation was done using ten seeds, enabling reproduction of the work. However, as the GA-QPSO optimization is CPU-intensive, we use ProcessPoolExecutor. So, we run each tree seed in parallel in independent processes, which reduces total runtime while maintaining reproducibility [97].

2 Simulation Setup

This section describes the conducted simulation environment to evaluate our proposed hybrid GA-QPSO solution. In the simulation, we aim to build an environment that closely resembles deploying UAV-assisted IoT data collection in realistic smart urban cities.

2.1 Area Size

To study our solution, we considered 2D areas of a square smart-city block of size 500×500 m². This helps us study the effectiveness of our solution in moderate spatial variation and different obstacle densities. This size is considered sufficient to study the non-trivial communication distance and suitable for a single UAV to travel around in a single mission [98].

2.2 IoT Node Deployment

We studied the node densities by considering four different quantities of IoT nodes: 100 nodes reflect low-density IoT nodes that sense the air quality. 200 nodes represent a moderate density that is used to monitor Ethernet traffic. Further, 300-400 nodes reflect dense deployment for structural monitoring. We assume that all IoT nodes are identical in terms of communication hardware and fixed initial energy (1J) [63]. We are studying the placement of cluster heads, which are responsible for aggregating the data from all nodes in their cluster and sending it to the UAV, which is considered energy-intensive; therefore, we assumed the cluster heads are more capable devices, so we set their initial energy to 2J. All IoT nodes are randomly distributed in the area using a unified random distribution with a minimum inter-node spacing of 2 meters. The inter-node spacing is implemented to avoid unrealistic clustering and overlapping coordinates while guaranteeing physically valid placement with the avoidance of short links that skew the models of energy consumption.

2.3 Traffic Generation and Energy Consumption Model

In our model, we assume that each IoT sends one fixed packet size to its CH during each round; during each round, the CHs aggregate the received packets. As many rounds as the nodes are alive, these steps are repeated. However, the UAV energy consumption and path length are evaluated based on one optimized data-collection mission. The UAV hovers above each cluster head and receives one aggregated packet from each of them. Therefore, the IoT network lifetime is evaluated per round, while the UAV energy is evaluated per mission. Table 4.1 below illustrates a summary of values in our simulation, including the values of all parameters that align with the literature in the field of UAV-assisted IoT [47], [37].

Table 4.1: Simulation Parameters

Parameter	Value
IoT packet size	4000 bits
Packet delivery rate	1
Rounds	8000
Energy of electronic circuit E_{cir}	50 nJ/bit
Free-space amplifier $E_{\text{free-s}}$	10^{-11} J/bit/m ²
Multipath amplifier $E_{\text{multi-p}}$	1.3×10^{-15} J/bit/m ⁴
CH data aggregation cost E_{agg}	5 nJ/bit
Carrier frequency	900 MHz
Bandwidth	125 kHz
CH transmission power $P_{\text{CH,trans}}$	10 dBm
Thermal noise	−174 dBm/Hz
Contact duration between CH and UAV	0.02 s

2.4 UAV Mobility Model

In our model, we assume that the UAV has a predefined depot from which it starts its mission, visits each CH to collect aggregated data packets, and then returns to its depot after completing its mission. We assume that the UAV energy consumption and path length are evaluated based on one optimized data-collection mission. However, the UAV must avoid obstacles using the waypoints' virtual nodes. Table 4.2 below summarizes the set values for the UAV parameters.

Table 4.2: UAV Mobility and Energy Parameters

Parameter	Value
UAV type	Quadrotor
UAV mass	0.5 kg
Rotor radius	0.2 m
Air density ρ	1.11 kg/m ³
Altitude	50 m
Speed	15 m/s
Maximum power	5 W

2.5 Obstacles

Obstacles represent a real urban smart city scenario; we consider several circular obstacles, reflecting buildings, restricted areas, etc., with different obstacle densities (0, 2, 4, and 6 obstacles) [99]. Obstacles imposed mobility constraints on the UAV, as it must have a collision-free trajectory to accomplish its task without crashing [100]. Safety margins of 10 meters around each obstacle with 12 virtual nodes are utilized to guide the UAV and avoid collision. In a real-world scenario, the UAV is usually affected by GPS drift of some meters, and it is affected by sensor noise and inertial estimation errors; these lead to inaccurate positions under practical flight conditions [101]. Therefore, we inflate the obstacles with 10 m safety margins to ensure that the UAV flies outside the obstacle region under worst-case conditions. The small size of safety margins results in insufficient coverage, while a large size leads to unnecessarily long detours; therefore, we set it to 10 [102]. For the virtual nodes, we set 12 virtual nodes and distributed them around the obstacles with equal space between them; these nodes were considered as verticals utilized in the visibility graph. It provides 30 degrees angular resolution; this number helps to balance between the computational efficiency and the geometric accuracy. However, using fewer virtual nodes leads to insufficient shortcuts and distorts the obstacle contour. Using a high number of these virtual

nodes causes a high computational cost with a slight improvement in optimizing the UAV path [16]. Therefore, we use a moderate number of virtual nodes.

2.6 Clustering Configuration

One of the primary objectives of this research is to determine the optimal number of cluster heads. Therefore, the number of cluster heads is not fixed. It is optimized using our proposed joint optimization approach. Based on the reviewed literature that focused on optimizing the number of CHs, they usually set the optimal number of cluster heads in the range of 5% to 10% of the overall number of IoT nodes [103], [75]. Therefore, we follow this range to set 6% of the overall nodes to the minimum required number of CHs, while 8% of the total nodes are set to the maximum number. Then the optimization approach will dynamically select the optimal required count of CHs based on the fitness function and the specified constraints. Moreover, we control the balance of each cluster by setting its maximum size at 25% of all IoT nodes. This is an essential control to extend the network lifetime and ensure balanced energy distribution among the network [104].

2.7 Optimization Parameters

This section demonstrates the parameter settings of the algorithms used.

SOM Parameters

The SOM algorithm is used in our proposed solution to initialize the locations of CHs, benefiting the GA algorithm by reducing its search burden and sufficiently enhancing its optimization convergence. It guarantees ordered spatial density mapping; it matches the specified number of cluster heads using a one-dimensional topology with K neurons, resulting in density-aware CH locations [91]. All parameter settings of the SOMs algorithm are shown in Table 4.3. These settings follow standard values that offer steady convergence while avoiding overfitting in

low-dimensional map training [93].

Table 4.3: SOM Parameters

Parameter	Value
Learning rate	0.3
Neighborhood width σ	0.3
Training iterations	100

GA Parameters

In our optimization approach, the GA jointly optimizes the number and placement of the cluster heads and the UAV trajectory. It is considered a global optimization algorithm in our framework. The GA algorithm has the ability to handle the mixed variable challenges in our problem as it explores the number of cluster heads, which is a discrete variable, and the coordination of CHs, which are continuous variables [82]. We set all the parameters following the reviewed papers that demonstrate that a moderate number of populations and controlled stochastic mutation results in sufficient diversity and global exploration while preserving runtime efficiency and avoiding premature convergence [81]. Therefore, the selected parameters denote stable performance among the seeds used, preserve the diversity of the solution, and balance the computational efficiency with optimization quality. Table 4.4 shows all the parameter settings during our simulations.

Table 4.4: GA Parameters

Parameter	Value
Population size	60
Crossover probability	0.5
Mutation probability	0.3
Iterations	100

QPSO Parameters

After the GA finds its optimal solutions, the QPSO is used to contribute to exploiting the continuous space, offering better local refinement accuracy. We set the particle number to 30, the contraction coefficient to $\beta_{\min} = 0.75$ and $\beta_{\max} = 1.0$, and the iteration to 100. These settings are appropriate for QPSO to efficiently converge to the global attractor point [105]. This effectively fine-tunes CH locations and UAV path geometry. Table 4.5 shows all the parameter settings during our simulations.

Table 4.5: QPSO Parameters

Parameter	Value
Number of particles	30
$\beta_{\min}$	0.75
$\beta_{\max}$	1.0
Iterations	100

3 Evaluation Metrics

To comprehensively evaluate the performance of our proposed hybrid GA-QPSO approach, we use a set of metrics that are especially designed for UAV-assisted IoT and align with recent literature. We focused on selecting metrics that effectively assess network lifetime, CH stability, the energy efficiency of the UAV, and the overall sustainability of the evaluated system in the presence of obstacles.

3.1 Network Lifetime Metrics

As mentioned in Chapter 3, the energy model of the IoT network that we follow in our framework is the first-order radio model [47]. Therefore, each node consumes its energy while transmitting data to the CH based on the packet size, the distance to the CH, and the radio propagation model [75]. However, each

cluster head consumes more energy than other IoT nodes, as it receives multiple packets from its cluster nodes, aggregates them, and sends them to the UAV [10]. The energy depletion of IoT nodes and cluster heads is calculated as a per-round cost and accumulated to study the overall energy performance of the IoT network. Therefore, in our simulations, we use the energy model to compute both the nodes' lifetimes and the CH's stability and lifetime. This procedure helps us to form the evaluation metrics used to assess our approach. Network lifetime is a crucial indicator of the performance of UAV-assisted IoT networks, as the powered nodes are energy-constrained devices, and their availability directly affects the smart monitoring in urban cities, influencing the quality of the UAV data collection mission, spatial coverage, and data complement [77]. To evaluate the IoT nodes' lifetime, we considered the First Node Death (FND) and the Cluster-Head Stability Metrics.

First Node Death (FND)

The survival of ground IoT nodes is one of the main indications of the network lifetime. First Node Death (FND) is one of the important metrics that provides an overall observation of the network degradation [106]. The cumulative energy depletion of the IoT node is calculated using its transmission energy consumption based on the first-order radio model mentioned in the methodology chapter. The FND is the first round, where the first node exhausted its battery [25]:

$$\text{FND} = \min_{i \in N} \{ \text{round} \mid E_{N\text{-res}}(\text{round}) = 0 \}$$

Where $E_{N\text{-res}}(\text{round})$ is the residual energy of node number i in each round. When it reaches 0, it is considered a dead node. This metric gives us an indication of the network stability period, specifying the interval time during which all nodes are functioning correctly and the full spatial coverage is preserved. This is a significant metric, as the early node depletion results in unbalanced clustering, coverage holes, and incomplete data collection missions [14]. Especially as it is

sensitive to the cluster head location, the distribution of the cluster, and the UAV route [106]. Therefore, it gives us a reliable and comparable indication of the IoT nodes' lifetime. However, the last node death (LND) is defined as the last round in which the last node exhausts its energy [49]. In our simulations, we care about optimizing the number of CHs to extend the network lifetime, balance the cluster size, and ensure the appropriate distance between the IoT nodes and their cluster heads. The IoT nodes that remain alive until the last simulation window, by default, will be given a lifetime equal to the simulation horizon. Therefore, we do not consider the LND as an evaluation metric, as it reflects the simulation duration rather than the actual physical depletion time of the network [106]. Moreover, the network may be inactive for a while before the last node dies; therefore, we do not consider it as an evaluation metric in our approach. However, FND impacts the UAV-assisted IoT, as it affects the data collection mission, clustering balance, and the quality of the network [25]. Therefore, we select the FND as the primary metric to evaluate the IoT node lifetime.

Cluster-Head lifetime Metrics

In our framework, cluster heads handle intensive energy functions, as they are responsible for receiving data packets from all IoT nodes within their cluster, aggregating all received data, and transmitting it to the UAV over a long distance. So, the cluster heads are the link between the IoT node and the UAV. Therefore, any depletion of CH energy significantly affects the quality of the UAV-assisted IoT data collection mission [57]. The primary evaluation metric of the CH stability is the First Cluster-Head Death (FCHD), which highlights the round in which the first CH exhausts its energy. However, the Last Cluster-Head Death (LCHD) may be affected by the simulation horizon when their energy is exhausted beyond the last simulation round, and does not really reflect the meaningful physical death. Consequently, we consider the FCHD as the primary evaluation metric of the CH's lifetime, as it demonstrates the reliability and stability metric of the

proposed clustering approach. The FCHD is represented as [25]

$$\text{FCHD} = \min_{j \in CH} \{ \text{round} \mid E_{CH\text{-res}}(\text{round}) = 0 \}$$

Where $E_{CH\text{-res}}(\text{round})$ is the residual energy of CH number j in each round. When it reaches 0, it is considered a dead Cluster head.

Optimal Number of Cluster Heads

One of the main objectives of this research is to identify the optimal number of cluster heads in deploying the UAV-assisted IoT network. An efficient number of CHs enhances the network lifetime, provides better cluster load, reduces the transmission distance, and balances the energy consumption [19]. Moreover, optimizing the number of UAV hovering points enhances its energy efficiency. Therefore, we focus on this study to evaluate the optimal number of cluster heads in the simulated area, where the optimal number of cluster heads is specified based on our joint fitness function:

$$N_{CH}^* = \arg \max_{N_{ch}} \text{Fitness}(N_{ch}, CH_L, \pi)$$

Where N_{CH}^* is the optimal number of CH, N_{CH} is the number of CH, CH_L is the locations of CHs, and π is the visit order to each CH.

3.2 UAV Evaluation Metrics

UAV Energy Consumption

The evaluation of the energy consumption of the UAV is based on its energy consumption model discussed in Chapter 3. The UAV plays a crucial role in UAV-assisted IoT, as it is responsible for applying data collection missions from the ground devices [60]. Therefore, preserving the energy needed to complete its mission is a significant constraint to the study. The UAV expends energy while hovering over each CH, exchanging packets, and avoiding obstacles [57]. However,

in this research, we assume that we use a multirotor UAV; it consumes more energy while doing both hovering and communication with the cluster heads. However, it consumes less energy while flying [76]. Therefore, in our simulation, we assume that the flight energy is low, and the UAV energy consumption is determined by the cumulative hovering duration for data collection, the stabilization time of the waypoint transitions, and the angle of approach. This aligns with recent research in this field, as it reflects real scenarios of UAV data collection where a UAV pauses above the cluster heads to build reliable communication with ground devices [61]. Moreover, stationary flight consumes more energy than moving between nodes over short distances. However, our proposed GA-QPSO framework influences these metrics by optimizing the placement of the CHs, the visiting order of these cluster heads, and smoothing the trajectory design. The refinements of the QPSO specifically enhance the visiting order, shorten the stabilization period, and minimize the unnecessary repositioning, leading to a reduction in the hovering time, thereby reducing the UAV energy consumption [55]. We evaluate the energy efficiency of the UAV to ensure that our model balances between improvements in the IoT lifetime and the UAV's energy consumption.

UAV Path Length

One of our evaluation metrics is to evaluate the UAV path length, which measures the overall displacement of the UAV platform while it follows the optimization sequence to visit all cluster heads. The evaluation of path length is essential to ensure the path efficiency, the optimality of the trajectory, and the existence of a balance between clustering and trajectory planning [27]. Moreover, it helps to assess the optimization functions' quality in effectively designing collision-free routes and avoiding unnecessarily long detours. These criteria are essential in the deployment of real UAV-assisted IoT networks [66]. We calculate the path length by computing the Euclidean distances between sequential cluster heads generated by the hybrid GA-QPSO [61]. There are several advantages of the short path, such as it minimizes the UAV mission duration, leading to serving ground devices

before reaching its operational limits. providing robust communication with the cluster heads. Moreover, provide a smooth and safe route; reduce the abrupt maneuvers or lateral adjustments [12]. These circumstances influence the stability and energy utilization of the UAV. This metric aligns with recent literature that focuses on UAV-assisted IoT [57]. In our study, the path length metrics are considered as complementary indicators to the energy consumption of the drone, where the energy consumption focuses on hovering and communication requirements, and the trajectory length study the quality of the optimized path. Provide a comprehensive evaluation of the UAV performance of the proposed optimization approach.

4 The Validation of the Deployed Simulation Environment

We validated the performance of our developed simulation environment before evaluating the proposed GA-QPSO optimization model. The purpose of the validation is to ensure that the developed environment performs accurately, reflects the behavior of IoT networks, and guarantees performance trends. However, to guarantee that the utilized energy model, clustering technique, and calculation of IoT node lifetime are implemented correctly, we compare the results of our simulator with a well-known benchmarking model under similar system parameters and assumptions. We reproduce the proposed model by Haris and Nam [75]. They utilize the PSO algorithm to optimize cluster head selection and perform IoT clustering. Therefore, it is ideal as a baseline algorithm for validating our simulators. However, we selected their model for validation due to several reasons: it focuses on enhancing IoT network lifetime by utilizing the optimization of CH, which aligns with this study's objective. They implement a similar first-order radio energy model to our study. They have similar assumptions to our study, such as the offline optimization approach in a 2D area, the IoT nodes, and the

CH being static. They use similar evaluation metrics that align with our metrics.

To apply the validation, we added the PSO validation algorithm to our simulation environment. However, we kept our communication model and energy dissipation mechanisms unchanged, as their values aligned with the paper’s assumption and values. Moreover, the paper follows our assumption that, in each round, each IoT node generates a packet of 4000 bits and sends it to its assigned CH. However, we set the environmental and network parameters to align with those in the reference study, such as the area size, the IoT nodes’ initial energy, the number of CHs, and the IoT nodes, ensuring a fair comparison. Table 4.6 below shows the summary of the conducted scenario following the paper [75].

Table 4.6: Validation Simulation Parameters

Parameter	Value
Network area size	100×100 m ²
Number of IoT nodes	100
Number of CHs	10
IoT nodes initial energy	0.5 J
IoT packet size	4000 bits
Packet delivery rate	1
Rounds	5000
Energy of electronic circuit E_{cir}	50 nJ/bit
Free-space amplifier $E_{\text{free-s}}$	10^{-11} J/bit/m ²
Multipath amplifier $E_{\text{multi-p}}$	1.3×10^{-15} J/bit/m ⁴
CH data aggregation cost E_{agg}	5 nJ/bit
PSO particles	36

We ran the scenario using ten random seeds and calculated the average of the results. Furthermore, we evaluated the performance of IoT lifetime using the same evaluation metrics used in the paper, including FND, half node die (HND), which is the number of rounds where half the number of nodes consumed all their energy, and LND. We found that our simulator shows a similar lifetime trend re-

ported in the reference study. Table 4.7 shows the results of the benchmark-based validation. While Figure 4.1 shows the alive nodes vs. the round curve. However, we observed that there are minor numerical differences, which are expected due to the stochastic initialization and random node deployment. The numerical deviations are within the range reported in studies that focused on simulating networks based on stochastic optimization [79]. Overall, the lifetime progression and general survival behavior remain constant, demonstrating the correctness of the energy model, communication assumptions, and IoT lifetime calculations in our deployed simulation environment.

Table 4.7: Summary of Network Lifetime Metrics—Benchmark-Based validation

Metric	Benchmark Study	Proposed Simulator
FND	1700	~ 1795
HND	3500	~ 2789
LND	4178	~ 4366

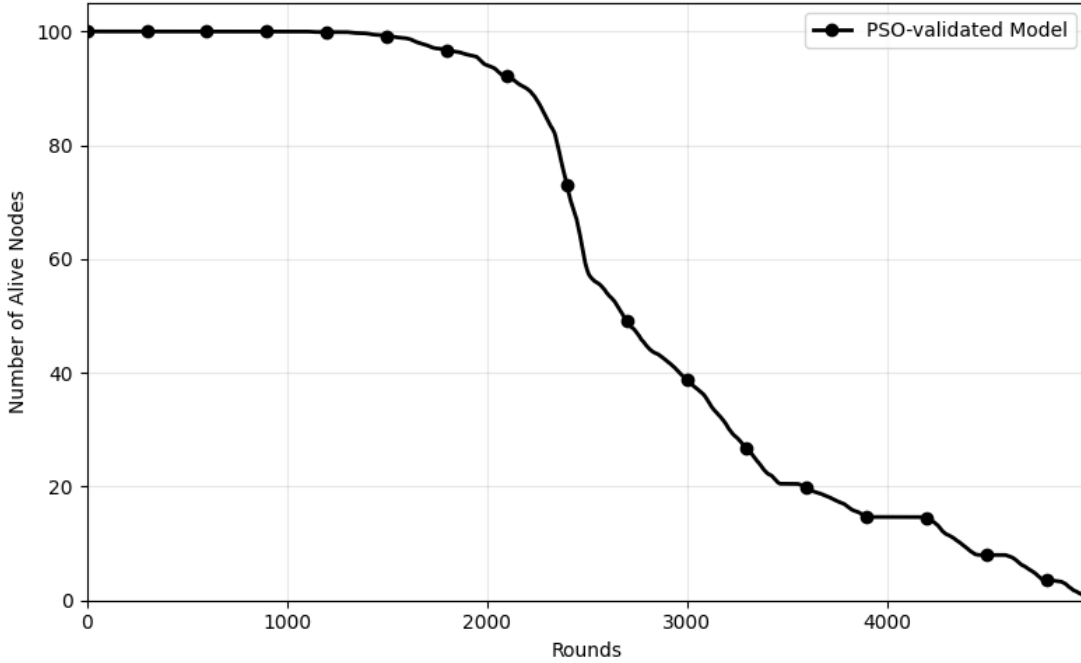


Figure 4.1: Alive-node curve of the PSO validation model

Based on the validation experiment conducted, we can conclude that our developed simulation environment is valid, reliable, and accurately reflects the IoT

communication models, representing the energy consumption and the behavior of the network lifetime. Therefore, we can use our simulator to evaluate our proposed hybrid GA-QPSO model.

5 Results and Discussion

In this section, we evaluate the performance of the proposed joint optimization approach, present, and analyze all the experiment results for all the studied scenarios. Evaluate the results based on the selected evaluation metrics. Compare our hybrid approach with baseline algorithms.

5.1 Study the Impact of IoT Node Density

In this scenario, we test deploying different IoT node densities in a fixed area size with a balanced fixed weight of 50% for both the UAV and IoT system, and in the same parameter settings. The purpose of this experiment is to study the impact of IoT node density on the performance of our proposed framework. Therefore, we conduct different experiments starting with a low node density of 100 nodes, then a moderate node density of 200 nodes, followed by a dense node density of 300, and finally with 400 nodes. We ensure that the trade-off between IoT lifetime and UAV energy efficiency is balanced; this gives us a clear observation of the effect of the node densities themselves, rather than bias toward one of the UAVs or lifetime efficiency. We conduct each experiment using ten independent seeds, and then we calculate the average of all seeds to ensure the robustness of the statistical results and to avoid the randomness associated with a single topology.

Optimal Number of CH

One of the main objectives of this study is to determine the optimal number of CHs. Therefore, we evaluate the range of candidate CHs optimized in each density level. As the extensive number of cluster heads leads to an increased overhead and

UAV energy consumption [77]. However, reducing the number of cluster heads resulted in poor IoT lifetime [27]. We followed the reviewed literature to set the tested range of the number of cluster heads in each density level. The literature that studied optimizing the number of CH found that the best number of cluster heads is in the range of 5-10% of overall node density [63], [103]. Therefore, in each experiment, we set the minimum and maximum number of CH using the range of 6-8% of the total number of nodes. For all results in the results and discussion section, we calculate the standard error (SE) of the mean across all reported results. The SE is computed as

$$SE = \frac{\sigma}{\sqrt{n}}$$

where σ is the sample standard deviation, and n is the number of conducted runs [107]. The purpose is to study the variability across runs. Figure 4.2 illustrates the mean optimal count of CHs with the SE in all node density scenarios. We found that in all node densities, the optimal number of CH is around 7% of the overall number of nodes, with a small range of SE, which remains remarkably stable. This percentage is scientifically reasonable, and it shows stability across the 10 seeds in four different density ranges. Moreover, this gives an indication that the proposed hybrid solution has a reliable convergence [108]. The results show a near-linear increase in the required number of cluster heads as the number of nodes grows. This is consistent with the principle of cluster-based data aggregation used in the UAV-assisted IoT networks [109]. At a node density of 100 nodes, it is illustrated that the cluster structure is simple with a little uncertainty in CH placement; however, the optimizer found that the optimal number of CH is 7. At 200 nodes, the distribution slightly increases, leading to an expanded required number of CHs of around 14 CHs. However, in the dense node density, it is illustrated that the count of cluster heads stabilizes in the range of 21 to 22 for 300 nodes and 27 to 30 for 400 nodes. The confidence interval illustrates that the proposed Hybrid GA-QPSO is applicable for achieving reliable conver-

gence among the independent seeds, resulting in stable, repeatable cluster head configurations that provide efficient intra-cluster communication with balanced load for aggregating data by UAV. However, this indicates that the proposed hybrid GA-QPSO optimizer learns the best CH ratio that effectively generalizes well with the node density [72]. Moreover, the observed minimal dispersion among all independent seeds demonstrated the effectiveness of the SOM-based initialization of the placement of CHs, resulting in an efficient start of GA that reduced the noise exploration and enabled QPSO refinement to converge quickly and produce stable cluster head placement [110].

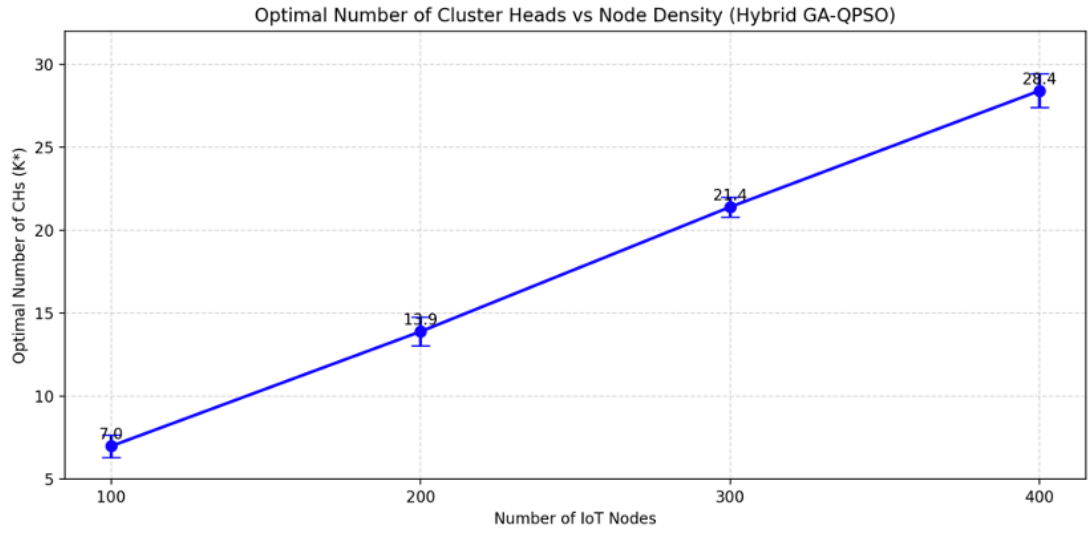


Figure 4.2: Optimal number of CH in different node densities of the proposed hybrid GA-QPSO

Lifetime Performance—Hybrid GA-QPSO

The FND is an evaluation metric that indicates the time when the first IoT node is exhausted, which determines the weakest energy pathway in the network [111]. It is an essential evaluation metric in the UAV-assisted IoT, as it helps to study the effectiveness of building balanced clusters that efficiently consume energy before the UAV starts collecting the data [27]. The FND is sensitive to both local communication patterns and randomness, thereby resulting in moderate to high variability [46]. Therefore, we conduct the experiments using ten independent

seeds, and then we calculate the mean of the results along with a SE to analyze the behavior of the proposed Hybrid GA–QPSO approach. This procedure helps study early network lifetime in a statistically sound manner. Hybrid GA–QPSO greatly improves the network lifetime whenever the density rises.

As shown in Figure 4.3, the FND at density 100 is around 107 rounds, which is considered extremely low compared to other densities. However, as the number of IoT nodes increased to 200, the FND increased to approximately 624 rounds. Further, it is noticeable from the graph that the most significant improvement of FND exists at 300 densities, where it is approximately a five-fold increase compared to 200 nodes. However, at 400 nodes, the survival rate of IoT nodes showed a slight increase compared to 300 nodes. This indicates that whenever the dense node increases, the FND improves due to the short intra-communication distance between the node and its CH, resulting in less energy consumption by the IoT nodes [111].

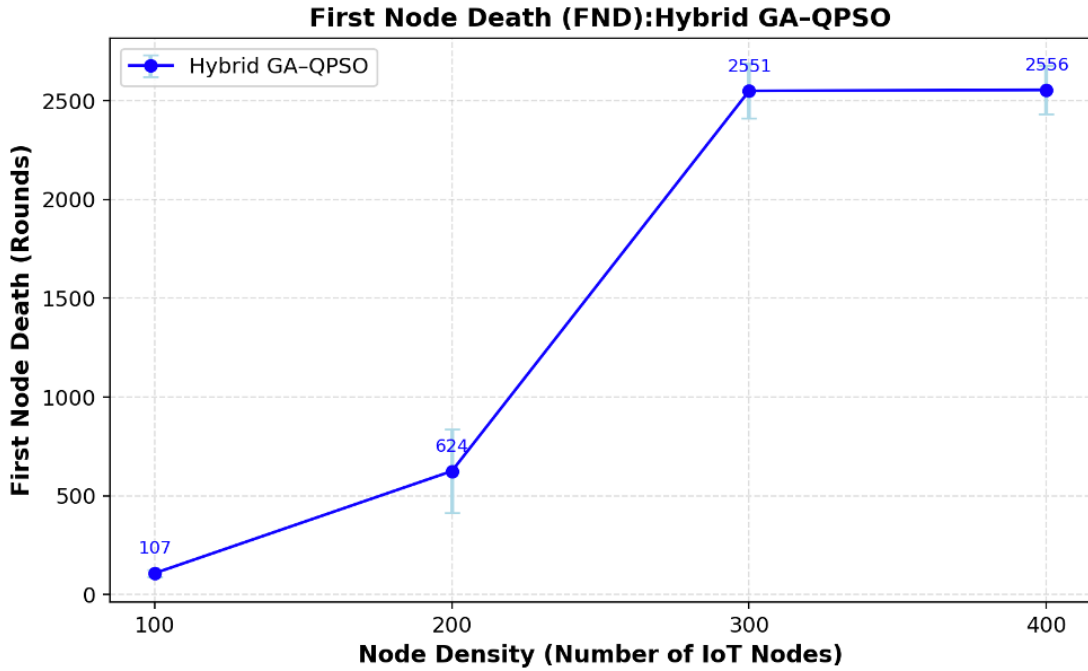


Figure 4.3: FND in node density scenario: proposed hybrid GA-QPSO

Lifetime Performance: GA vs Hybrid GA–QPSO Comparison

We compare the proposed hybrid GA–QPSO with the baseline GA algorithm to study the contribution in terms of FND [74]. However, to ensure statistical fairness, we evaluate both algorithms under the same parametric setting, environmental situation, and node density using SE. Figure 4.4 below illustrates that the hybrid approach showed noticeable improvement with a moderate range in low density and a high range in high densities.

However, it is noticeable that both algorithms have low FND at 100 nodes, due to inherent sparsity. This outcome is expected because distributing a small number of nodes over a large area generates sparse topologies, which result in a long distance between the nodes and their CH, which forces the IoT nodes to broadcast more frequently, raising depletion [112]. Although both algorithms show low FND, the hybrid approach provides an improvement of approximately 44.6% compared to the GA baseline. The enhancement becomes more pronounced at 200 densities, where the hybrid approach has a better lifetime of 624 rounds compared to the baseline, which has an FND of 410 rounds, which is around a 52.2% difference. There is a noticeable improvement at 300 nodes, where the GA baseline has a mean of FND around 1915, while the hybrid reaches around 2551, which is around a 33.2% difference. Both algorithms had high IoT survival at 400 nodes, with higher FND for the hybrid approach (2556 vs 2214). The variability of both nodes in the SE demonstrates the stochastic nature of FND. However, the hybrid algorithm is more consistent across seeds because it prevents the ultimate early-death situations that exist in some GA seeds. The comparative results in terms of FND confirm the main contribution of the hybrid GA–QPSO. The GA baseline often converges to a suboptimal cluster head, while the hybrid GA–QPSO takes advantage of GA for global search and QPSO for local refinement [29]. This results in reliability and resilience of clustering and an energy-aware solution with a better lifetime.

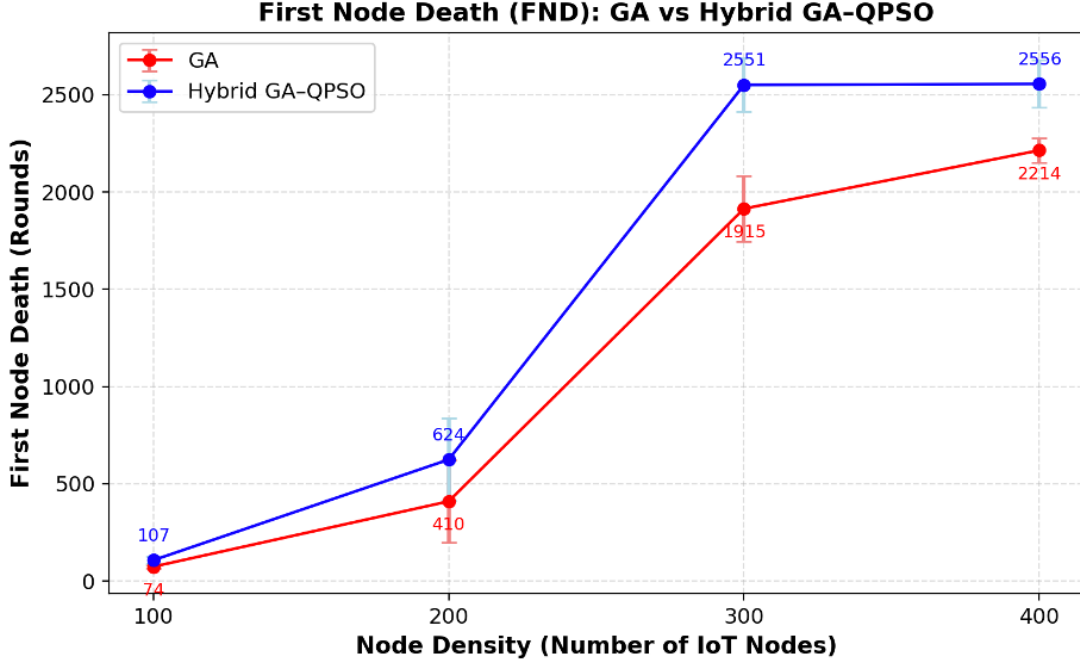


Figure 4.4: FND in node density scenario: GA vs proposed hybrid GA-QPSO

Figures 4.5 demonstrate a comparison between hybrid GA-QPSO and the GA baseline in terms of alive nodes over 8000 rounds. It is noticeable that the proposed solution maintains more alive nodes over all node densities compared to GA. Even though both algorithms follow the same trend as node increase, the hybrid solution provides better operational nodes during the first and mid-lifetime phases. By focusing on 100 nodes, we notice that in the middle rounds, our proposed GA-QPSO enhances the live node by approximately 20–40%. Moreover, at 200 nodes, our proposed approach noticeably enhances the lifetime of the nodes by roughly 15% and 30% in the middle rounds. Further, the upward shift in the hybrid curve in 300 and 400 nodes indicates the high energy balancing, stable CH placement, and decrease in early exhaustion in both densities. Overall, this confirms that compared to the GA algorithm, our proposed solution provides meaningful improvement in network stability and lifetime. Furthermore, it confirms the advantage of combining the GA with QPSO, illustrating the superior lifetime performance among different node densities.

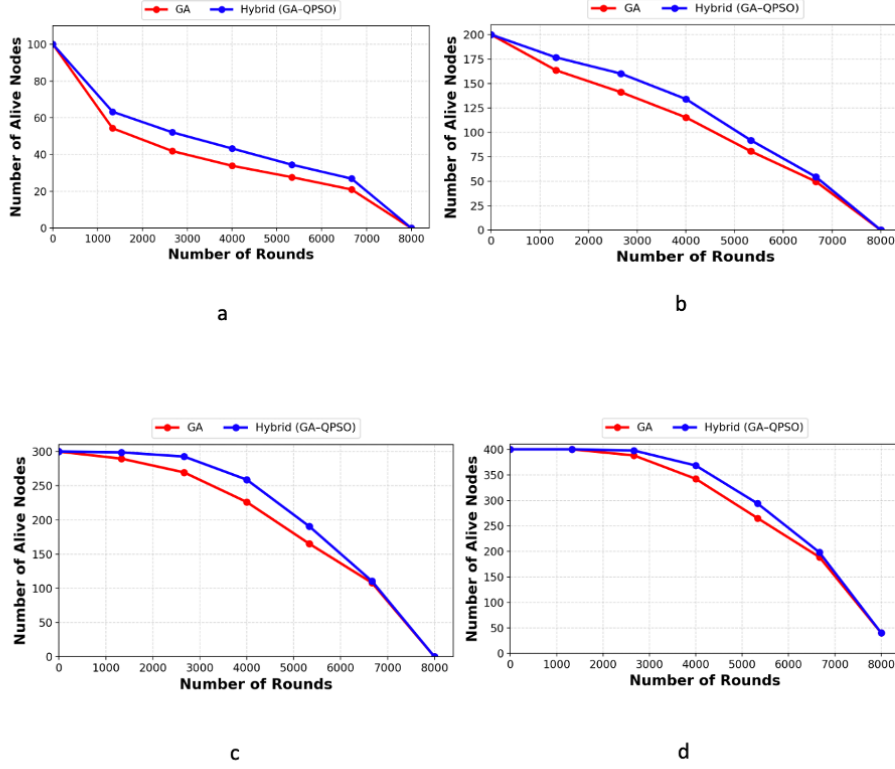


Figure 4.5: Alive-node curves for GA and Hybrid GA-QPSO under (a) 100 nodes, (b) 200 nodes, (c) 300 nodes, and (d) 400 nodes

Statistical Validation

We applied a statistical significance analysis using the paired t-test to verify that the enhancement of the FND by the hybrid GA-QPSO approach is not because of random variations among the conducted runs [113]. We focus on FND, as in all conducted runs, the hybrid solution showed improvement on it. Furthermore, we focus on balance weight configuration with 300 IoT nodes, which serves as a neutral and useful working scenario.

The observations are paired because both the GA baseline and the hybrid GA-QPSO were set using the identical set of random seeds to generate FND. The paired t-test is suitable. This is because of its ability to determine the statistical significance of the mean difference between two paired samples, which is based on the premise that the differences are roughly normally distributed [113].

We assume that the null hypothesis (H_0) states that the difference between

the FND of the baseline GA algorithm and the proposed Hybrid GA-QPSO is not significant, while in the alternative hypothesis (H_1), we assume that the proposed hybrid framework provides a higher FND value. We applied the paired t-test to the results collected from all 10 independent seeds.

Based on Table 4.8 below, the results of the paired t-test show that the hybrid approach provides a statistically significant enhancement of the network lifetime, focusing on the FND metric. The p-value of 0.0108 falls below the commonly used significance level of 0.05, which is the commonly used value to determine the significance level [114]. Thus, we can reject the H_0 and confirm that the improvement of FND is statistically significant, and it is not because of the random initialization effects. This test analysis is strong evidence of the effectiveness of the proposed hybrid optimization approach to extending the network lifetime compared to the GA baseline.

Table 4.8: Statistical Comparison of GA and hybrid GA-QPSO Based on FND

Metric	Value
Number of independent runs	10
GA mean FND	1915
Hybrid mean FND	2551
Mean improvement (Hybrid – GA)	636
<i>p</i> -value	0.0108

Cluster Head Lifetime- Hybrid GA-QPSO

However, the lifetime of the cluster head is an essential evaluation metric, as the survival of the CH is essential to guarantee the connection between ground devices and UAV, and to ensure the complete data collection mission [72]. To evaluate the CH lifetime, we focus on the time the first CH dies, FCHD. This metric is important because if the cluster heads die early, that indicates the poor optimization of CHs' placement, the imbalance of clusters, and the imbalance of

energy consumption [25]. However, it is observable from Figure 4.6 that whenever the node density increases, the CH lifetime decreases. It is noticeable that at 100 nodes, it achieved the highest FCHD of around 5856. This is due to the low number of served nodes in each cluster, which thereby leads to reduced traffic load in each cluster head. Furthermore, it is noticeable that at 200 nodes, the FCHD decreases sparingly to 5488 rounds. This downward trend continues at both densities, 300 and 400 nodes, as the FCHD is reduced to 4929 and 4231 rounds, respectively. With high node density, the CH is not only affected by the assigned number of nodes; it is also highly loaded with the frequent incoming data with the packet sizes [27].

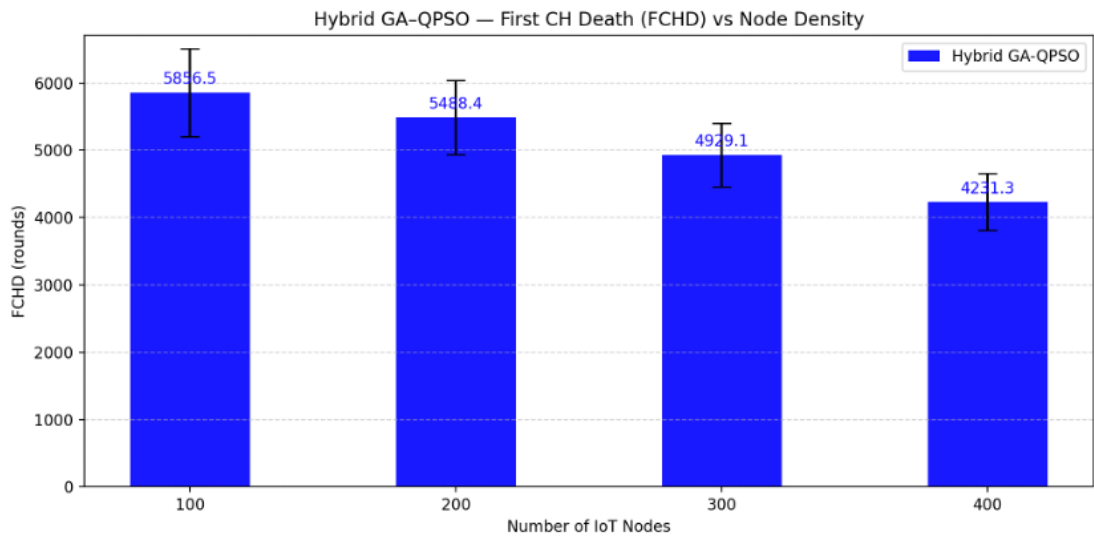


Figure 4.6: FCHD in node density scenario: proposed hybrid GA-QPSO

Cluster Head Lifetime: Compare GA vs Hybrid GA-QPSO

The bar chart in Figure 4.7 compares the FCHD between the baseline GA and the proposed hybrid GA-QPSO among all node densities. It is observable that the hybrid approach outperforms the baseline algorithm in all densities. This is an indication that the enhancement that the QPSO provides in refining the CH locations leads to a better lifetime of CHs and improved cluster geometry. This gives the deployed network the advantage of having better CH survival, even with the increased number of IoT nodes and the increased aggregation load and

communication. Both algorithms have the lowest FCHD at node 100; this is due to the moderate traffic load of cluster heads. However, the hybrid GA-QPSO increases the FCHD to around 5.84% compared to the GA baseline. However, at node 200, the enhancement of the hybrid GA-QPSO becomes clearer as it enhances the FCHD to around 14%. However, at dense node densities of 300 and 400 nodes, the network deployment becomes more challenging as, even if the cluster head ratio is stable, the cluster heads consume more energy due to the frequent transmission and contentions [46]. Although the GA baseline has high FCHD, the hybrid GA-QPSO refines the CH locations to have better stability and extends the cluster head lifetime at 300 and 400 nodes to 4929 rounds and 4231 rounds, respectively. Overall, it is noticeable that the proposed hybrid GA-QPSO contributes to providing better FCHD compared to the baseline.

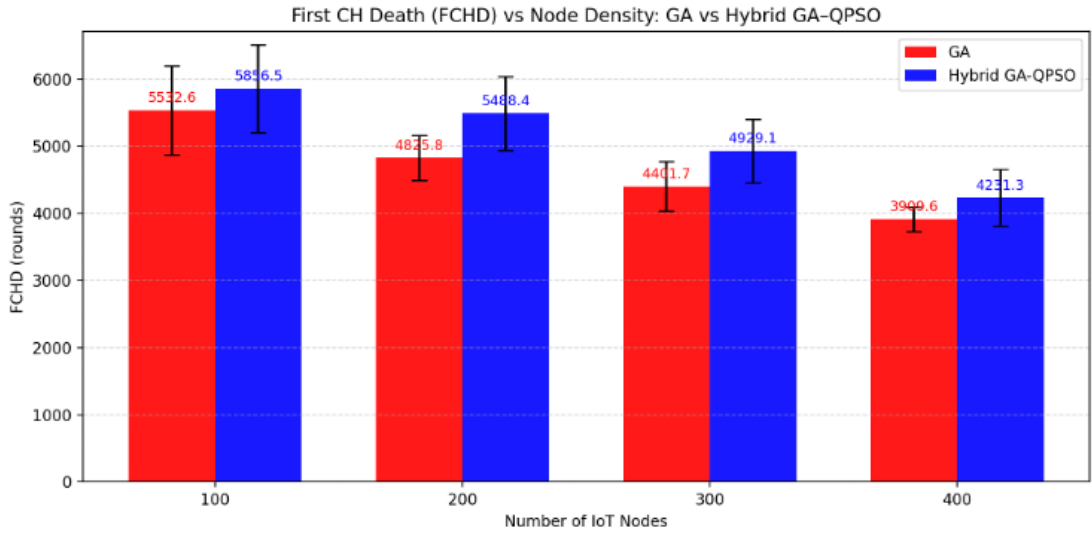


Figure 4.7: FCHD in node density scenario: GA vs proposed hybrid GA-QPSO

UAV Path Length and Energy Consumption—Hybrid GA-QPSO

In this research, the UAV's energy efficiency is one of the optimization objectives. Therefore, we evaluate the conducted experiments to investigate the performance of the GA-QPSO approach regarding UAV efficiency with different node densities. As shown in Figures 4.8 and 4.9, whenever the IoT size increases, proportionally the UAV energy consumption and the path length increase. However, this trend

occurs because as the node density expands, the number of required CH also expands, resulting in a higher hovering point of the UAV. This results in more energy consumption and an expanded path [6].

However, both Figures 4.8 and 4.9 for UAV energy consumption and UAV path demonstrate a smooth increase of path length and energy consumption with the expanded node densities. At 100 nodes, the energy consumption of the UAV is 1142 J; at 200 nodes, it increases to 1669 J, and at 300 and 400 nodes, it further increases to 2589 and 2968.5 joules, respectively. However, the path length is 920 m at 100 nodes; at 200 nodes, it is increased to 1336 m; then at 300 and 400 nodes, it becomes 2074 m and 2367 m, respectively. Although the hovering points expand with each node density, the UAV energy consumption and path length show a smooth increase.

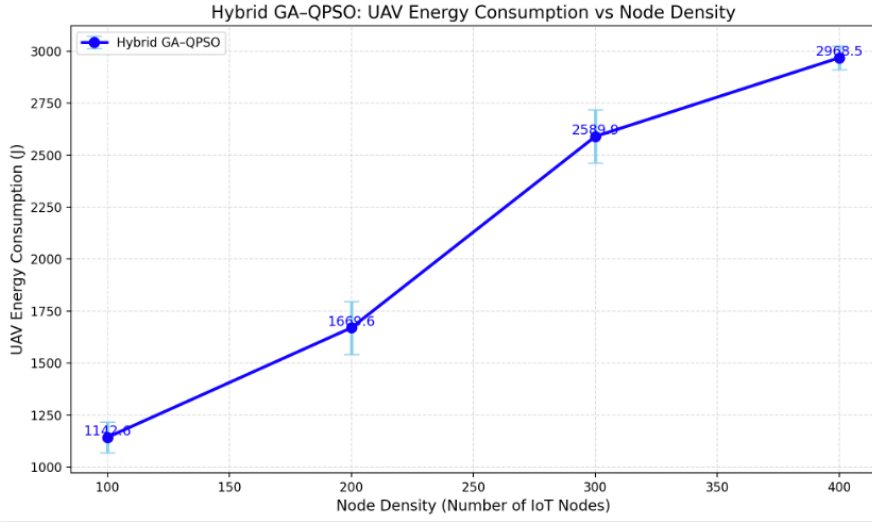


Figure 4.8: UAV energy consumption in node density scenario: proposed hybrid GA-QPSO

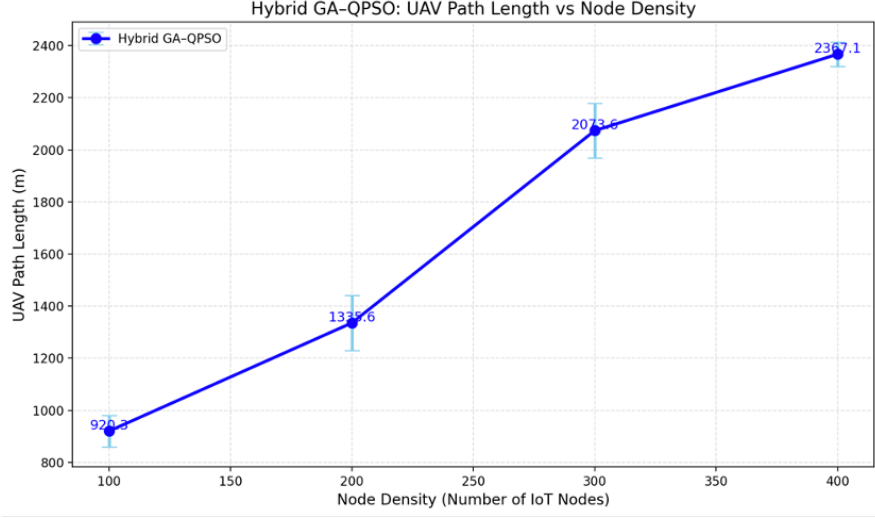


Figure 4.9: UAV path length in node density scenario: proposed hybrid GA-QPSO

UAV Path Length and Energy Consumption—GA vs Hybrid GA-QPSO Comparison

Figures 4.10 and 4.11 show the comparison between the GA baseline algorithm and the hybrid GA-QPSO in terms of UAV trajectory length and energy consumption. It is noticeable in the figures that the hybrid approach provides a slight increase in the UAV cost in some densities compared to the GA algorithm. This assertion is proved by both the mean of the seed values and the SE. Although the hybrid optimizer significantly enhances the network lifetime compared to the GA discussed above, it provides a noticeably shorter path length than GA at 200 node density, and it reduces the path length to approximately 6.0% with a narrow confidence interval. Moreover, it decreases the energy efficiency by around 5.8%. However, it shows a slightly longer path than GA at nodes 100 and 400, roughly 1.6%. In terms of power usage, it shows an increase as well, but the overlap between the SE intervals demonstrating the increase is low [107]. At node 300, both the path and energy usage are roughly unchanged. However, this slight increase in path length and energy consumption does not degrade network performance, as the refinement of CH contributes to extending the lifetime, providing load bal-

ancing, and enhancing the network stability. Overall, this confirms the hybrid framework's ability to significantly extend lifetime with minimal UAV overhead.

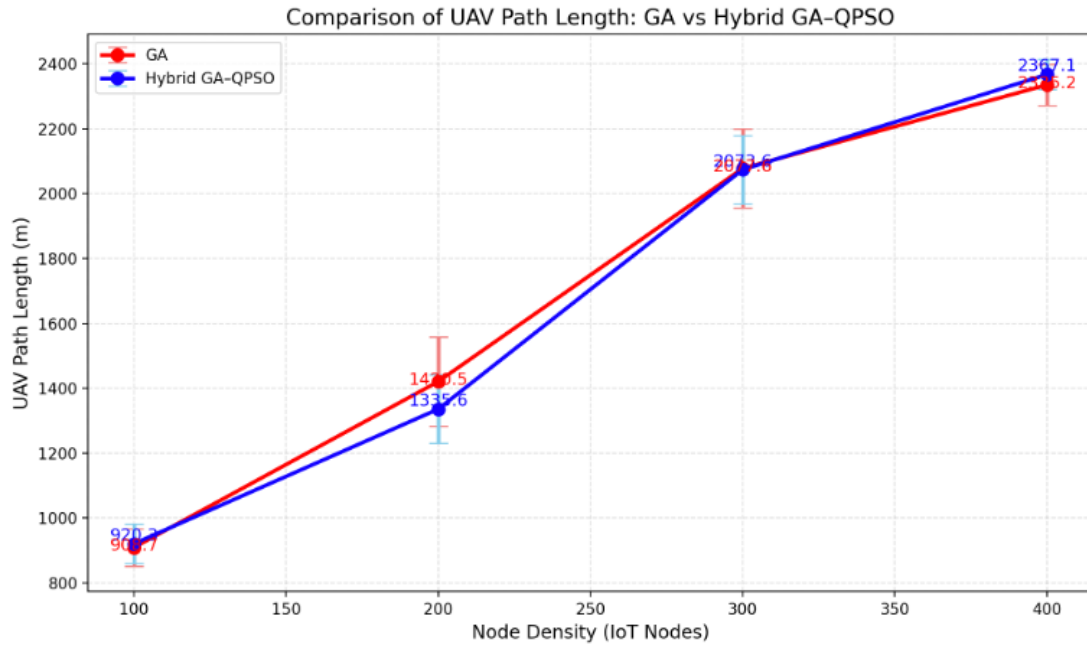


Figure 4.10: UAV path length in node density scenario: GA vs proposed hybrid GA-QPSO

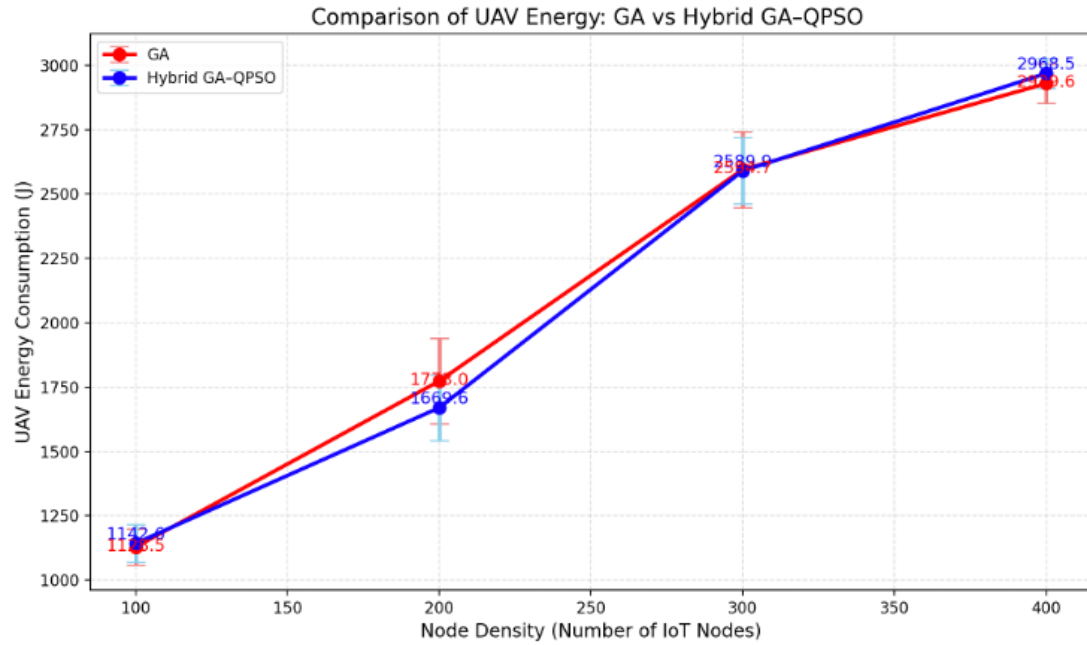


Figure 4.11: UAV energy consumption in node density scenario: GA vs proposed hybrid GA-QPSO

Discussion of Node Density Scenario

It is observable from the results of the conducted experiment that the increased node densities lead to higher FND, lower FCHD, and higher UAV path length and energy consumption. Across most of the node densities, the hybrid GA-QPSO demonstrated an enhancement in network lifetime with minimal overhead of UAV in some cases. This is mostly observable at high node densities. The findings indicate the advantage of QPSO refinement that results in balanced clusters, stable placement of CHs, and shorter communication distance between nodes and CH, leading to a long survival period of network nodes. However, even the hybrid solution showed a slight increase in UAV energy consumption and path length, which they considered very low compared to the great improvement in the lifetime. This indicates an effective energy-lifetime trade-off of the proposed solution. Overall, the enhancement of the hybrid approach with slight UAV overhead indicates that this approach is more dependable and offers a more energy-efficient clustering and routing solution compared to GA. Furthermore, the result confirms its applicability in deploying dense networks compared to GA. Table 4.9 illustrates the summary of conducted experiments.

Table 4.9: Summary of GA and Hybrid GA-QPSO Performance Across Node Densities.

Density	GA FND	Hybrid FND	GA Energy	Hybrid Energy	GA Path	Hybrid Path
100	74	107	1128.46	1142.58	908.73	920.32
200	410	624.0	1773.03	1669.57	1420.49	1335.61
300	1914.6	2551.7	2594.73	2589.92	2077.55	2073.61
400	2214.5	2556.0	2929.55	2968.48	2335.19	2367.13

5.2 Study the Impact of the Weights Configurations in the Fitness Function

In this scenario, we focus on investigating the effect of weight configurations on the optimization of multi-objective problems. We evaluate three different weight configurations:

- The first configuration is lifetime-oriented settings, which focuses on the network lifetime by giving it 70% weight focus while the UAV is 30%.
- For the second balanced- oriented setting, we set both the UAV and IoT lifetime weights to 50% for each of them.
- Third, the UAV-oriented approach that focuses on the UAV energy efficiency by giving it 70% weight and the lifetime 30%. Below is an analysis of the results of the conducted experiments.

Optimal Number of CH

Based on the experiments' results shown in Figure 4.12 below, among all seeds, the lifetime-oriented experiments had the most of the selected number of cluster heads in the range between 21 and 22, with the average around 21 CHs. In the balanced weight settings, the range of the optimal count of CH falls between 20 and 22, with an average of 21. In contrast, in the UAV-oriented case, it falls in the range of 18-22, with an average of 20. Therefore, the result demonstrates that when the focus is on lifetime, the optimizer focuses on selecting a higher number of CH in the range 21-22 compared with the other weights. This aligns with the fact that increasing the number of cluster heads decreases the cluster radius, resulting in better-balanced clusters, even if the increase will lead to more hovering points in the UAV route [24]. In a balanced setting, it tends to select in a range between lifetime-oriented and UAV-oriented; this indicates that the optimizer is trying to manage the tradeoff between the lifetime and UAV efficiency. However, it is observable in several UAV-oriented experiments that the optimal number of CH is 18, which is the lowest number selected among all conducted experiments. This aligns with the fact that decreasing the number of hovering points leads to shorter UAV paths, and therapy enhances its energy efficiency [24].

However, it is noticeable that, across all different weight configurations, the average of the required number of cluster head concentrators is in the range of 20 to 21 CHs. This demonstrates that the modification of the weight does not

significantly change the optimal number of cluster heads. Therefore, the results indicate that the hybrid optimization approach tends to edit the CH placement, distribution, balancing, and UAV visit order rather than increasing the number of CHs. However, the results provide an indication that the weight vector is mostly like a fine-tuning mechanism that changes the coordination of CH to enhance the lifetime or to reduce the UAV route [62]. This reflects the behavior of the GA-QPSO frameworks, where they concentrate more on refining the CH placement and UAV path rather than increasing the number of CHs. However, this behavior can be explained as follows: with a cluster-head ratio, while increasing the count of CHs, the lifetime performance of the IoT node is enhanced, and the UAV hovering cost increases as well. Consequently, in our approach, the optimizer refines the placement of the CHs instead of increasing them; this enables the balanced configuration to maintain approximately the same or a slightly higher number of CHs compared to the lifetime-oriented one.

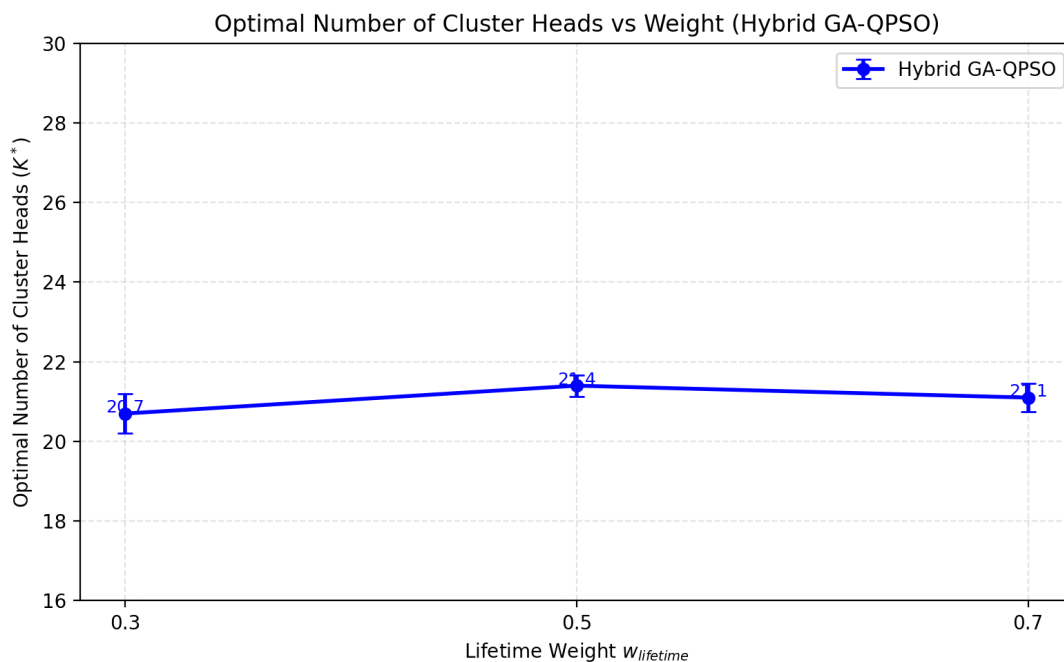


Figure 4.12: The optimal number of CH in hybrid GA-QPSO-weight scenario

Lifetime Performance- Hybrid GA-QPSO

Figure 4.13 illustrates that whenever the weight concentrates on the IoT lifetime, the FND increases, reflecting a higher node lifetime. The highest FND, with around 2796 rounds, is when the configuration focuses on the lifetime-oriented settings. However, in the balanced configuration of (50%/50%), the lifetime is approximately the same as the lifetime-biased configuration, with a slight decrease in FND of approximately 7.294%. In contrast, when the weight configuration prioritized the UAV path, the FND dropped to approximately 907 rounds. This reflects the decreased resilience of the network's lifetime when the cost of the UAV is prioritized.

The multi-objective functions influence the tradeoff behavior; the conducted experiments demonstrated how our optimization function manages the tradeoff of our objectives in terms of IoT node lifetime [18]. Our experiments illustrate that increasing the weight of nodes' lifetime results in better CH placement that enhances the intra-communication distance, ensures balanced energy consumption among the nodes, and delays their energy exhaustion. This is illustrated in Figure 4.14 where the CH become close to their sensor groups, resulting in short intra-communication distance and longer and more complex UAV routes. However, increasing the weight of the UAV energy efficiency forces the optimization function to place the cluster heads in locations that shorten the UAV route, even if the intra-communication between the CHs and IoT nodes becomes a long distance, thereby resulting in earlier energy exhaustion of IoT nodes [27]. This is shown in Figure 4.15, where the cluster heads are more inward and compact, resulting in a smooth and short trajectory. However, in balanced-oriented settings, the results demonstrated that the optimizer preserved a high number of FND compared to UAV-oriented settings and maintained a similarly high range of lifetime-oriented results. Figure 4.16 shows that the CHs in the balanced setting are placed centrally, leading to moderate path length. This indicated that the hybrid GA-QPSO strongly handled the balanced weight by providing a significant enhancement of

node survival compared to UAV-oriented and preserved a long lifetime interval close to lifetime-oriented.

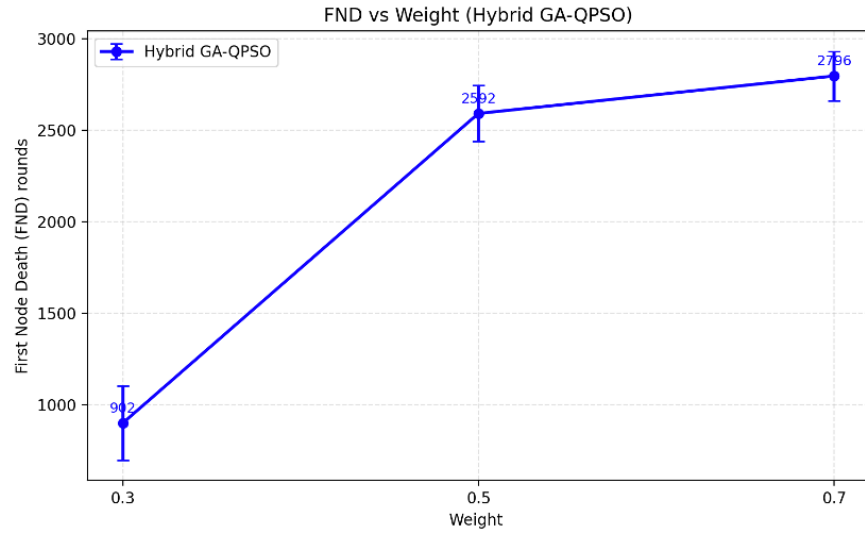


Figure 4.13: FND in weight settings scenario: proposed hybrid GA-QPSO

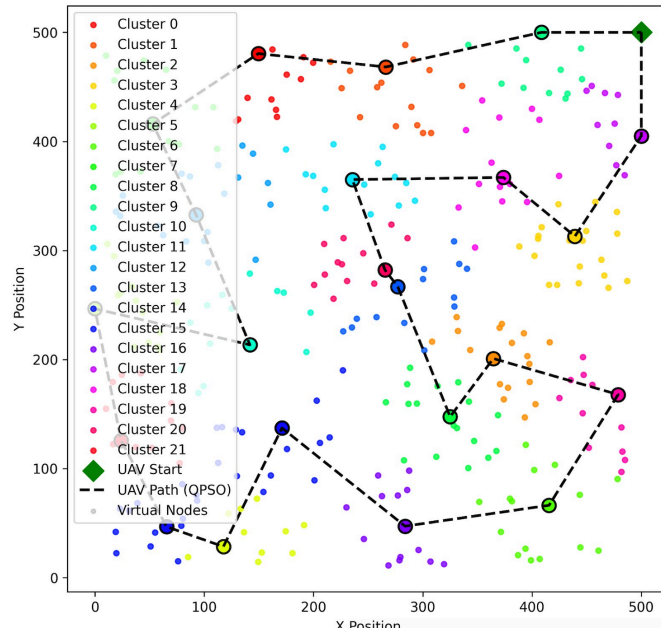


Figure 4.14: Lifetime-oriented Network

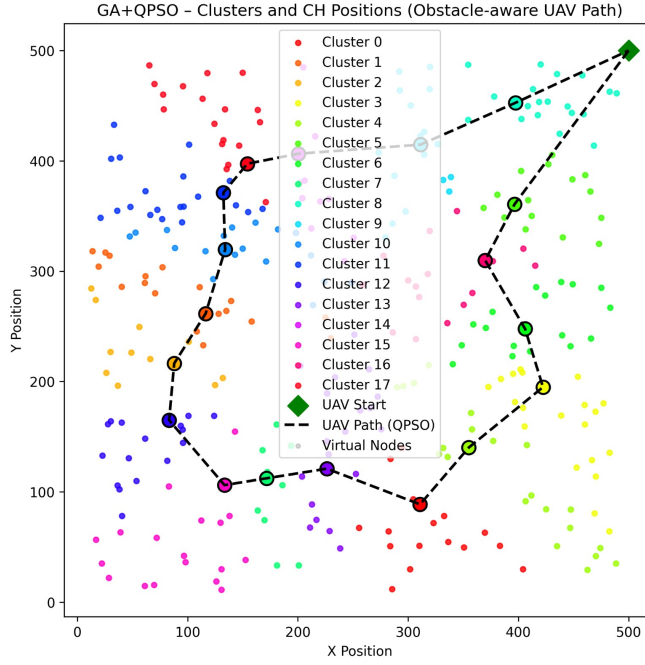


Figure 4.15: UAV-oriented Network

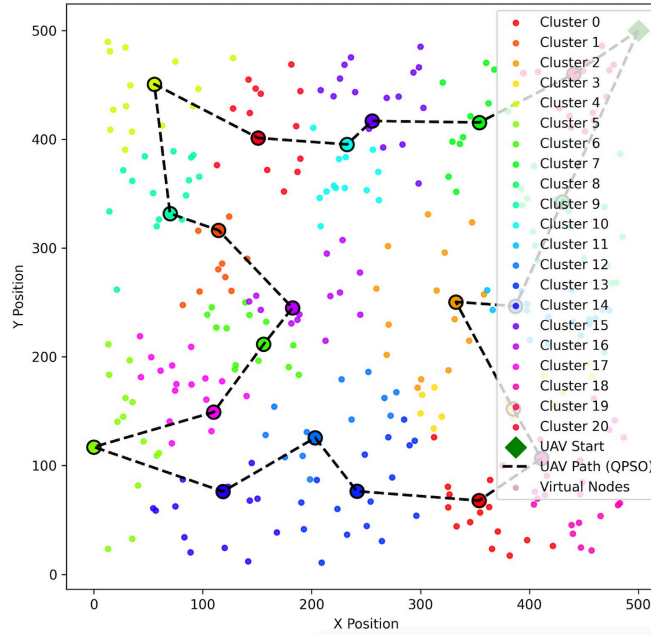


Figure 4.16: Balanced-oriented Network

Lifetime Performance: GA vs Hybrid GA–QPSO Comparison

Figure 4.17 illustrates the comparison between the GA baseline and hybrid GA–QPSO in terms of weighted configuration. Regarding the IoT node lifetime, it is observable that the lifetime-oriented configuration achieves the highest lifetime across all other settings, demonstrating the effectiveness of the optimizer to concentrate on what it is configured with. Therefore, the optimizer expands the distributions of CH to have better spacing with their cluster nodes to minimize energy usage. Although the GA has a high FND, the hybrid solution enhances it from 2271 rounds to 2796 rounds, which is around a 23.1% improvement. Furthermore, in the balanced weight configuration of the fitness function, it is noticeable that the hybrid algorithm contributes to increasing the lifetime of GA from an average of 1914 to around 2591, which is approximately a 35.4% increase.

However, in the UAV-oriented weight configuration, it is observable that the FND is the lowest compared to other weight settings, demonstrating the high focus of the optimizer in enhancing the UAV cost. However, it is noticeable that the hybrid optimizer provides better FND compared with GA, demonstrating its ability to provide better IoT lifetime even with a concentration of UAV energy minimization. The SE demonstrates the superiority of the hybrid algorithm to increase the IoT nodes' lifetime across all evaluated weighted settings compared with the baseline GA algorithm. However, it shows stability with some overlap with the GA in the balance and lifetime-oriented settings, indicating a statistically solid benefit.

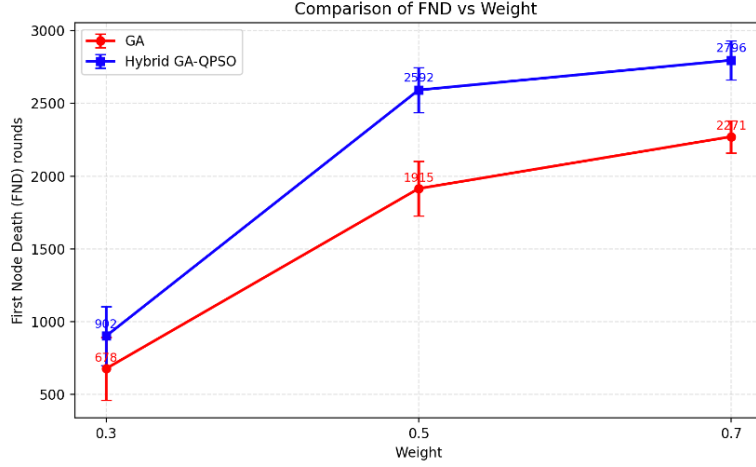


Figure 4.17: FND in weight settings scenario: GA vs proposed hybrid GA-QPSO

Figures at 4.18 demonstrate a comparison between the hybrid GA-QPSO and the GA baseline in terms of weight configuration. It is noticeable that it shows an upward shift in the hybrid curve, indicating its effectiveness in placing CHs in optimal locations to provide better lifetime performance.

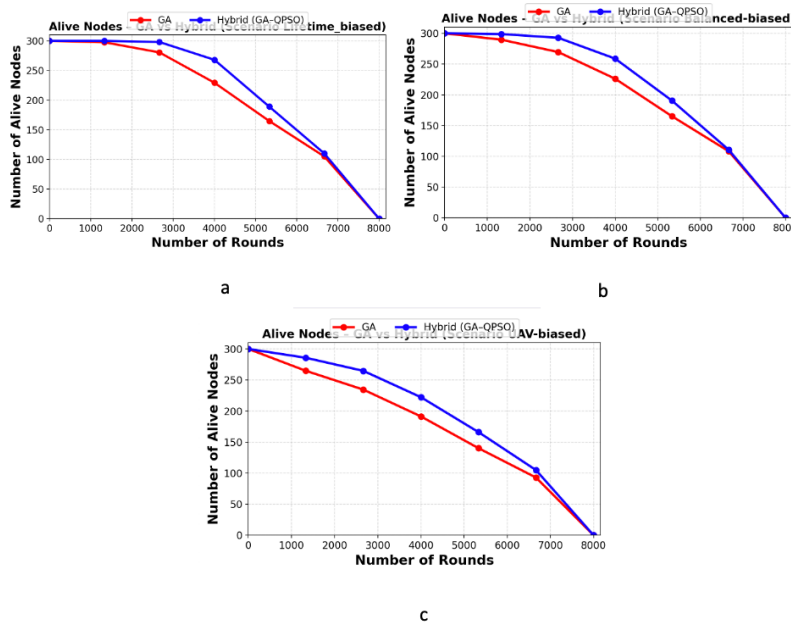


Figure 4.18: Alive-node curves for GA and hybrid GA-QPSO under (a) Lifetime_oriented, (b) Balanced_oriented, (c) UAV_oriented

Cluster Head Lifetime—Hybrid GA-QPSO

In terms of the cluster head lifetime, it is noticeable from bar chart 4.19 that the UAV-biased setting has the lowest FCHD of 4471 rounds. However, the FCHD in the balanced setting scenarios has the highest CH lifetime compared with lifetime-biased settings and the UAV-oriented string of 4929 rounds. This indicates that the balance weight provides a good load distribution across CHs. In contrast, the lifetime-biased setting has a CH lifetime at 4754 rounds, which is in the middle between the two other settings. In lifetime-biased, it has a slightly lower CH lifetime compared to the balanced weight, which indicates that the optimizer focuses on geometry to influence CH, which may lead to more load to the CH rather than increasing the count of CHs, as both the balance and lifetime-oriented settings have approximately the same average of the optimal number of CH of 21 [46]. Overall, the FCHD is considered high across all weight settings; that is due to the heterogeneity of our approach, as the CH has higher initial energy than the other IoT nodes in the system.

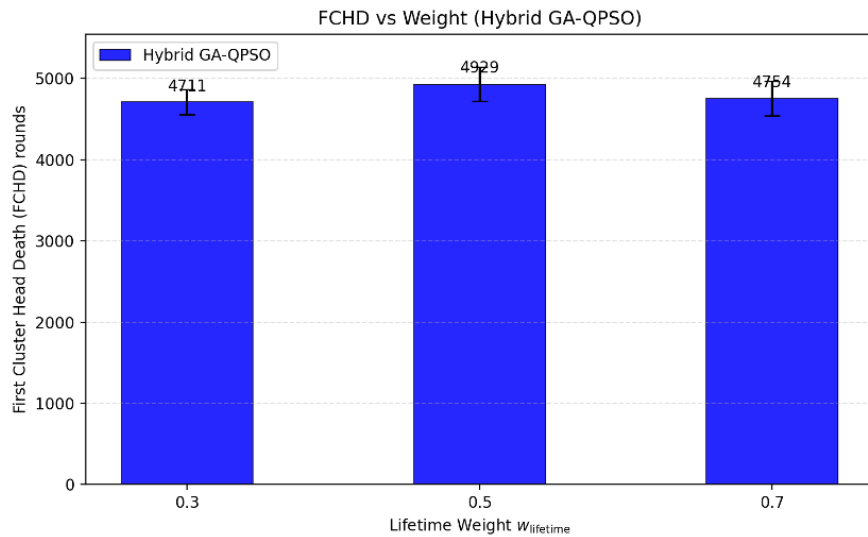


Figure 4.19: FCHD in weight settings scenario: proposed hybrid GA-QPSO

Cluster-Head Lifetime: GA vs Hybrid GA–QPSO Comparison

Focusing on FCHD metrics, it is clear from Figure 4.20 that the GA–QPSO contributes to enhancing the cluster head lifetime in all weight settings compared with the GA baseline. At the lift-oriented settings, the hybrid provides better FCHD with a 10% advantage compared with GA. Moreover, it has better narrow confidence intervals compared with GA, confirming its more reliable convergence [78]. At the balanced settings, the hybrid algorithm contributes to enhancing the FCHD to approximately 12–15% compared with the baseline algorithm, confirming its advantage of continuous refinement resulting in the elimination of overloaded CHs. In the UAV-oriented settings, the FCHD roughly improved by 8–10% with the hybrid algorithm, demonstrating its ability to enhance the GA’s irregular CH spacing even with lower lifetime priority. Overall, across all tested experiments with different weight settings, the optimizer proved that the formulation of the fitness function appropriately represents the trade-off between extending the IoT lifetime and reducing the UAV path length and energy usage.

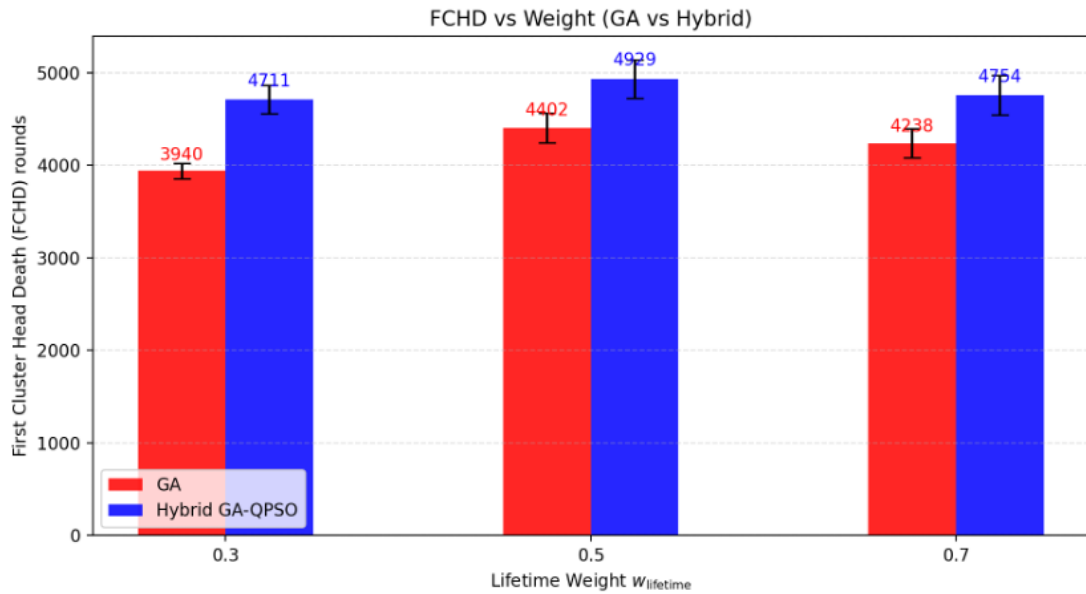


Figure 4.20: FCHD in weight settings scenario: GA vs proposed hybrid GA-QPSO

UAV Path Length and Energy - Hybrid GA-QPSO

Based on Figure 4.21 and Figure 4.22, it is clear that the UAV energy consumption and path length directly respond to the weight settings. Focusing on the lifetime-oriented leads to increased UAV energy of 2851 J and a path length of 2287 m. These figures directly reflect the trade-off between the IoT lifetime and the energy efficiency of the UAV. However, the balanced weight setting results in moderate energy consumption compared to other setting scenarios. While it is approximately 10% less than the lifetime-oriented in both UAV energy consumption and path length, and 29% higher than the UAV-oriented. In contrast, the UAV-biased scenario shows the UAV's highest energy efficiency. This is because the fitness function prioritizes the UAV energy efficiency; therefore, it reduces the geometric dispersion of the CH, thereby shortening the UAV path [14].

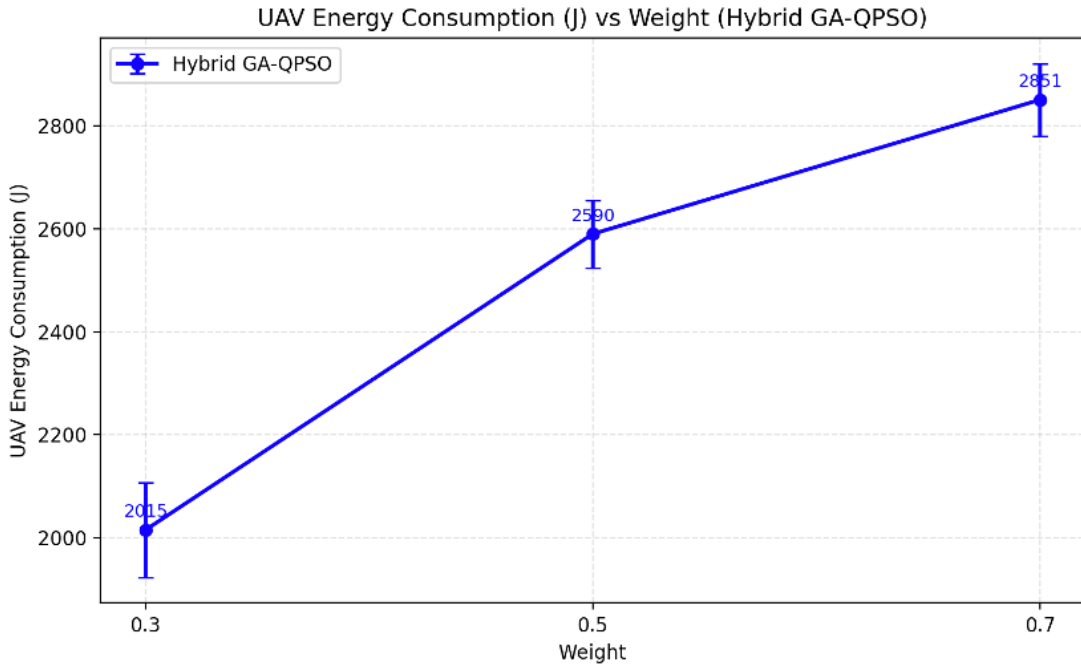


Figure 4.21: UAV energy consumption in weight settings scenario: proposed hybrid GA-QPSO

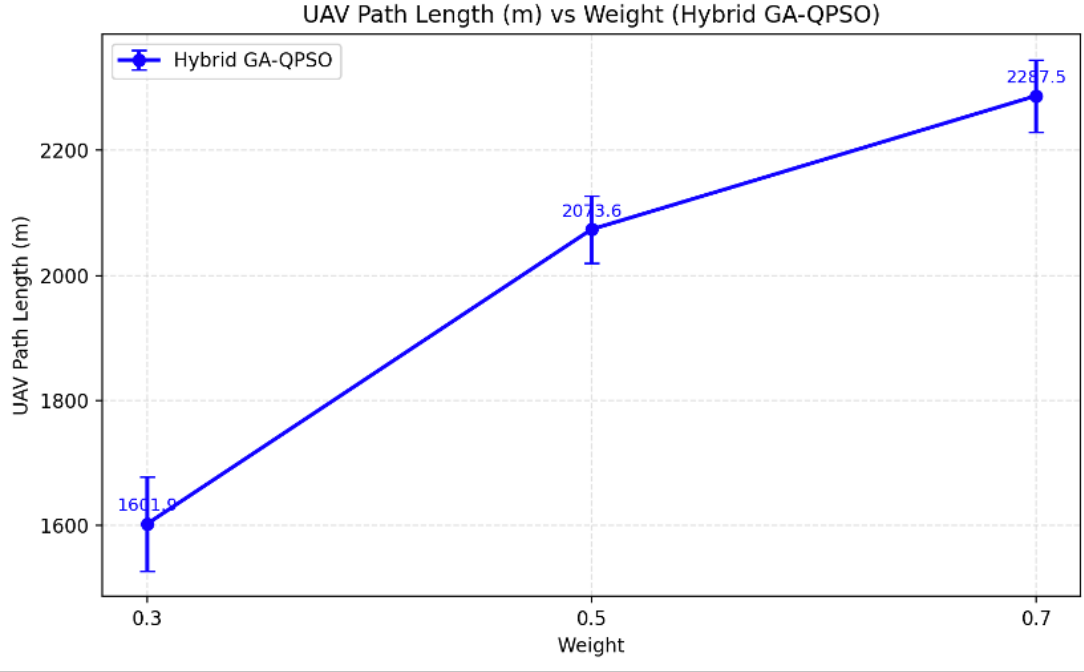


Figure 4.22: UAV path length in weight settings scenario: proposed hybrid GA-QPSO

UAV Path Length and Energy Consumption—GA vs Hybrid GA-QPSO

However, in terms of UAV energy efficiency and path length, we compare the baseline GA with our proposed hybrid GA-QPSO solution. Figures 4.23 and 4.24 below noticeably indicate that the proposed algorithm did not add a lot of overhead to the UAV while it enhanced the IoT lifetime. Although it noticeably increased the FND and FCHD, as discussed previously, the proposed approach demonstrated reduced energy consumption and path length in UAV-oriented settings with around 3%, compared to GA. This indicates that the UAV is energy efficient when the lifetime has less priority. Moreover, in balanced weight, both UAV energy consumption and the route length of the hybrid solution show approximately similar values of GA, indicating the stability in balanced settings. However, in a lifetime-oriented setting, the hybrid shows a slight increase in both energy and path of around 1–2%, compared to GA. Overall, the results confirm the high ability of the hybrid approach to preserve UAV efficiency across all weight settings while ensuring superior lifetime performance, leading to a strong

lifetime–energy trade-off.

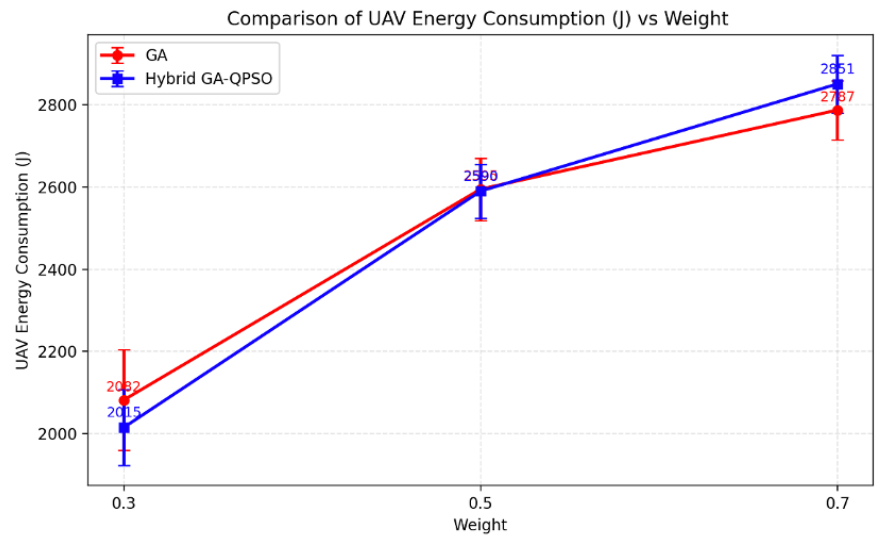


Figure 4.23: UAV energy consumption in weight settings scenario: GA vs proposed hybrid GA-QPSO

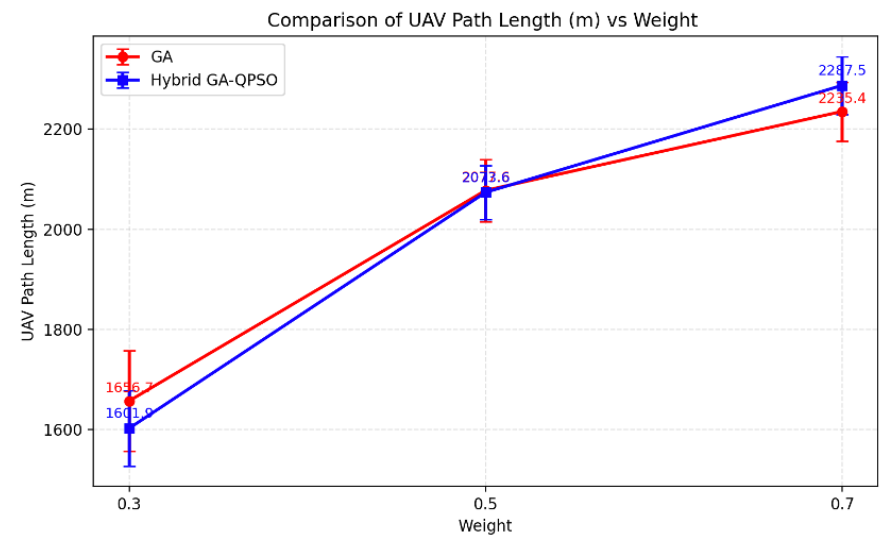


Figure 4.24: UAV path length in weight settings scenario: GA vs proposed hybrid GA-QPSO

Discussion of Impact of Weight Configurations Scenario

The results of the conducted experiments confirm the effectiveness of the proposed fitness function in guiding the optimization process toward lifetime–energy trade-off based on the weight configurations. However, it is noticeable that across all

Table 4.10: Summary of GA and Hybrid GA–QPSO Performance Across Lifetime Weights (300 Nodes)

Weight	FND (GA)	FND (Hybrid)	Energy (GA) [J]	Energy (Hybrid) [J]	Path (GA) [m]	Path (Hybrid) [m]
UAV-biased	618	902	2081.8	2014.9	1666.7	1601.9
Balanced-biased	1915	2592	2594.7	2590.0	2077.6	2073.6
Lifetime-biased	2271	2796	2787.1	2851.6	2255.4	2287.5

weight configurations, the proposed approach significantly enhances the lifetime, with careful consideration of UAV cost. In all configurations, it either shows approximately similar energy consumption and path length of the UAV or enhances its efficiency compared with the baseline GA.

In the UAV consideration, it significantly enhances the overall lifetime performance by approximately 33.0% with a slight decrease in overhead for the UAV, around a 3.2% decrease in energy consumption, and a 3.9% decrease in path length, indicating efficient clustering. However, in the balanced weight, it maintained approximately similar UAV route length and energy efficiency with slight decreases in both of 0.18% and 0.19%, respectively, with a noticeable improvement in FND of roughly 35.4%, indicating an excellent lifetime–energy trade-off. It was observed from the results discussed previously that in the balanced weight, it has the highest CH stability compared to other weights, indicating that it is distributing the energy load more balanced across CHs. In lifetime-oriented settings, the hybrid solution improves the FND by 23.1% with a minimal increase of UAV energy (0.47%) and path length (1.42%). However, the overall performance confirms that the proposed solution reacts to weight changes smoothly and predictably and remains stable in all circumstances, permitting the optimizer to adaptively prioritize either path or lifetime cost based on user-specified objectives. Overall, the results confirm that in all circumstances the hybrid GA–QPSO offers an excellent stable lifetime–energy trade-off, achieving significant enhancement in network longevity with minimal increase in UAV cost. Table 4.10 shows the summary of the weight scenario.

5.3 Obstacle-Avoidance Evaluation: GA vs Hybrid GA–QPSO

Designing an obstacle-free UAV represents a realistic challenge in deploying UAV-assisted IoT networks in urban cities [16]. In this section, we study the effectiveness of the proposed solution in optimizing the UAV route with an obstacle avoidance constraint. We applied several experiments with different configurations of the obstacle, first evaluating the framework without an obstacle, then with 2, 4, and 6 obstacles. All the experiments were repeated 10 times with independent seeds and evaluated in terms of the number of CHs, FND, FCHD, UAV energy consumption, and UAV path length. In this scenario, the obstacles are reflecting restricted zones or buildings in smart environments that UAVs or CHs may not enter. The routing module of the visibility graph is triggered only when an obstruction exists in the direct line of sight between two cluster heads. In this case, the virtual nodes will be considered waypoints that the UAV passes through to avoid collision.

Visual Examination of CH Layouts and UAV Paths

Figures 4.25 and 4.28 show the geometric impact of obstacles on cluster head placement and UAV path. The figures give an indication of several key behaviors:

Obstacle-free experiments study the nature of the behavior of the proposed algorithm. As shown in Figure 4.25, it illustrates the smooth distribution of cluster heads in the area. Moreover, the UAV path is smooth and clean without the existence of detours or abrupt changes in the way. This is a baseline evaluation that helps to study the effect of obstacles in the deployed environment.

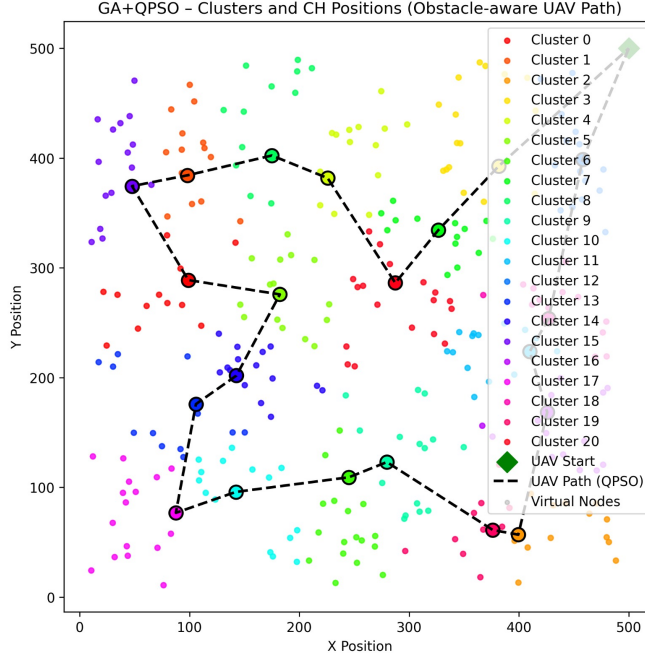


Figure 4.25: No obstacles hybrid GA-QPSO

In the case of two obstacles, as shown in Figure 4.26, it is clear that the optimizer places the CH outside the restricted zones and outside the obstacles' boundaries. However, the UAV route is structured and smooth; it does not pass through the virtual nodes, and the UAV detours around the obstacles. This indicates that the hybrid approach effectively combines the obstacle avoidance constraint by placing the CH outside the obstacle region, which leads to smoothing the UAV path with minimal distortion.

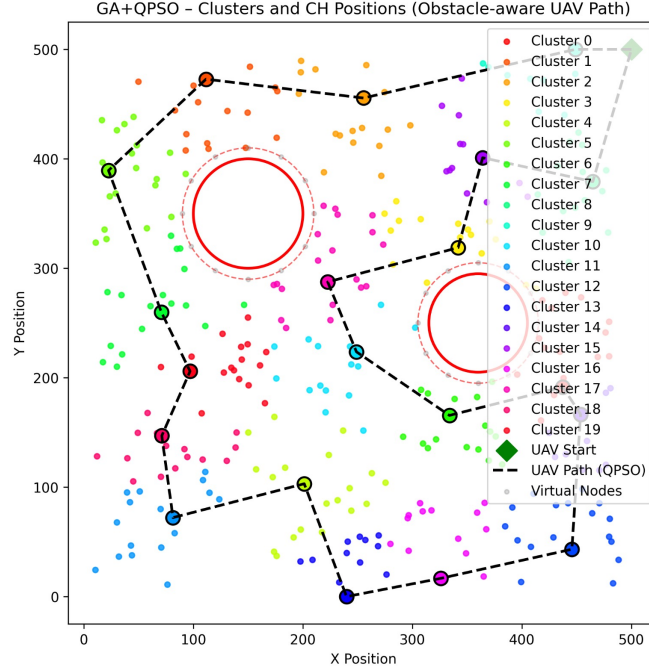


Figure 4.26: Two obstacles hybrid GA-QPSO

Figure 4.27 illustrates that the hybrid GA-QPSO approach is well adapted to the complex environments; specifically, in the case of four obstacles, the environment has less free space, yet the optimizer demonstrates its ability to provide balanced CHs and prevent extensive overspread and clustering. For the UAV path, there are moderate detours, but it displays smooth geometry, which is another confirmation of the ability of the optimizer to adapt to complex environments.

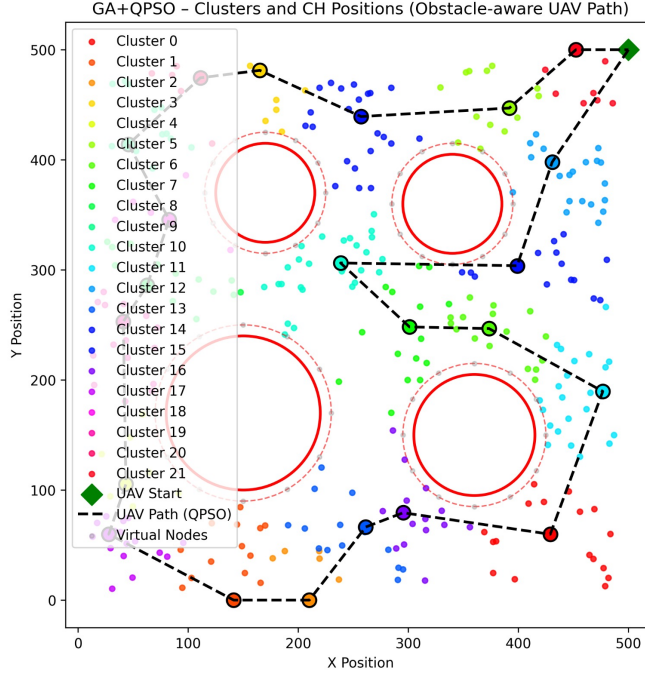


Figure 4.27: Four obstacles hybrid GA-QPSO

The scenario of six obstacles reflects an extremely cluttered environment. However, as shown in Figure 4.28, the experiments' results illustrate the ability of the proposed approach, with the advantage of the visibility graph and the virtual nodes, to optimize collision-free paths with smooth structures.

Among all conducted scenarios, it is noticeable that the optimizer distributes the CH in a way that avoids the line-of-sight obstructions. This results in reducing the need for virtual nodes in the majority of seeds. This demonstrates the strength of the optimizer in optimally placing cluster heads in locations that reduce the corrective detours, leading to a smoother path and better energy consumption. However, Figure 4.29 illustrates an example of avoiding an obstacle by passing through the virtual nodes.

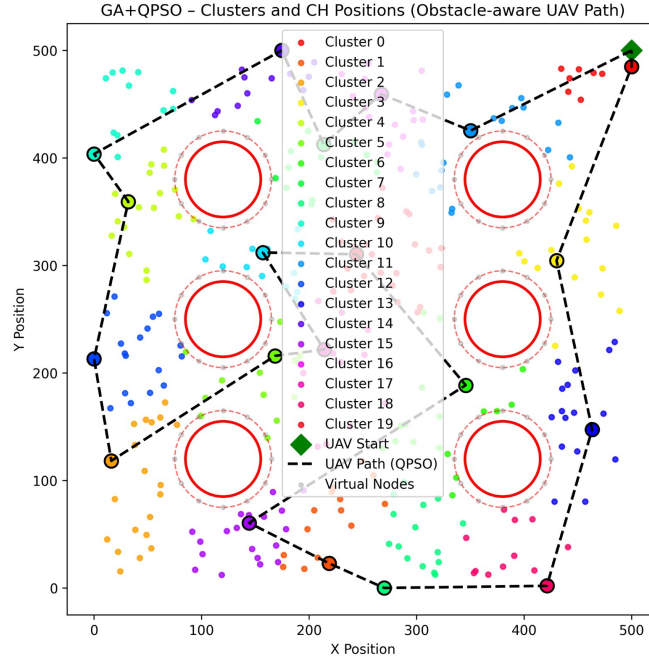


Figure 4.28: Six obstacles hybrid GA-QPSO

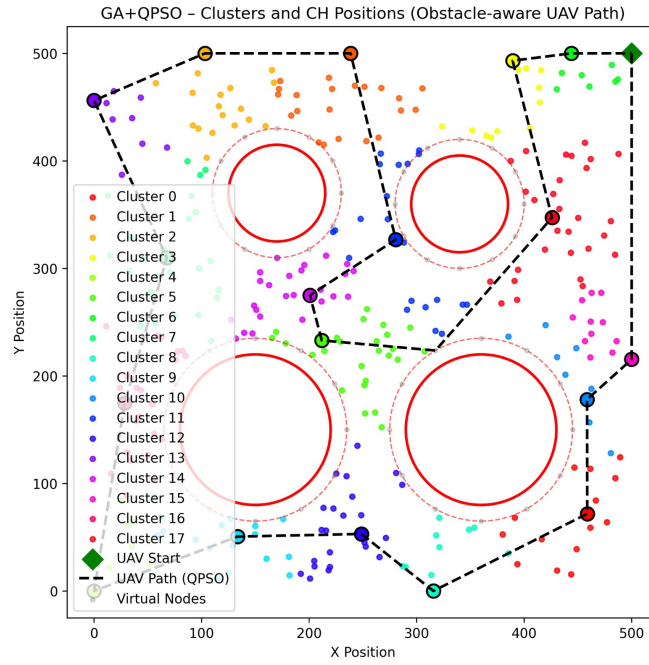


Figure 4.29: Sample of passing through virtual node

Optimal number of CH

Figure 4.30 illustrates the optimal number of cluster heads required in each obstacle scenario. We notice that the required count of CHs remains stable at 20 among different numbers of obstacles, with a slight increase at 6 obstacles to 21 CH. This is due to the restricted free zone, leading to maintained CH count inflation or clustering. Further, they indicate that the optimizer concentrates on optimizing the locations of CHs rather than increasing their number.

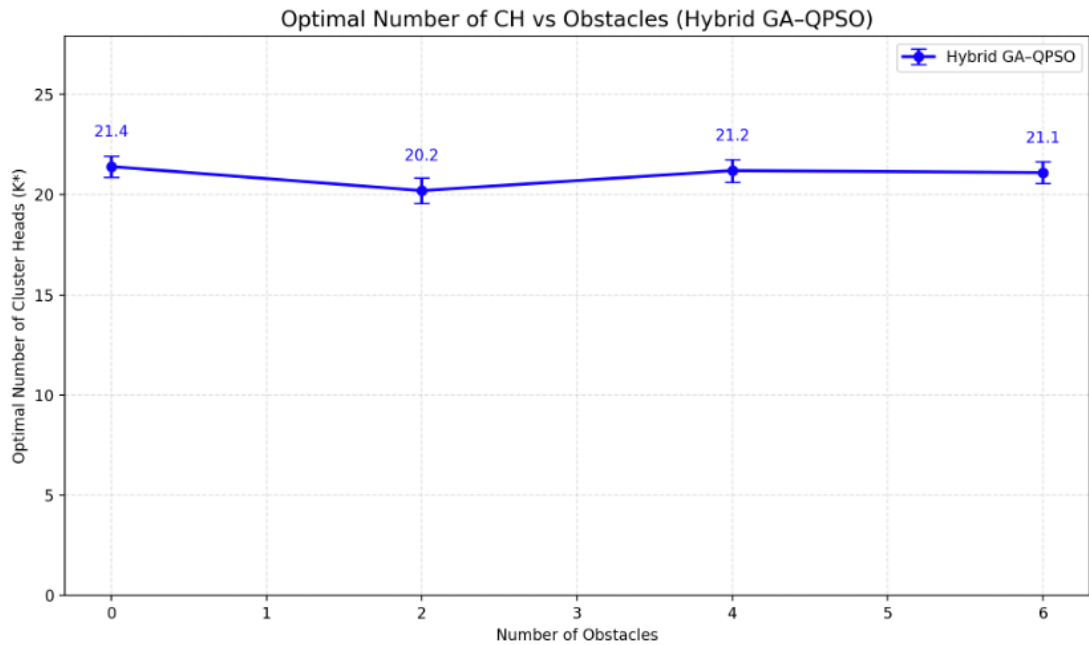


Figure 4.30: Six obstacles hybrid GA-QPSO

Network Lifetime —GA vs Hybrid GA-QPSO Comparison

Figures 4.31 compare the network lifetime between the base GA algorithm and the proposed hybrid GA-QPSO solution in terms of FND and FCHD across all tested obstacle scenarios. The data helps study the effectiveness of the algorithm to balance the energy efficiency of IoT nodes and CHs.

Figures 4.31 and 4.32 illustrate the comparison of FND and FCHD between the GA and hybrid algorithm. Focusing on the GA algorithm, it is observable that whenever the number of obstacles increases, both FND and FCHD decrease.

However, the degradation became very noticeable at six obstacles where the FND is around 692 rounds, indicating the early depletion of the nodes due to long intra-cluster communication distances and unbalanced clusters [112]. This result confirms that the GA collapses CHs into a small region without a strong consideration of load balancing. However, the hybrid approach achieved better performance than the baseline GA in terms of IoT node lifetime. Even with the reduced lifetime caused by obstacles compared with the obstacle-free baseline, the hybrid approach demonstrates its ability to increase the nodes' lifetime more than GA. In the obstacle-free case, it increases the FND by 35.4% compared to the GA alone. However, in the moderate number of obstacles, specifically two and four, the FND is improved by roughly 14–22%, respectively. The most noticeable increase occurs at the 6-obstacle case, where the GA-QPSO increases the FND to approximately 77%. Moreover, the hybrid GA-QPSO achieved better FCHD, as shown in Figure 4.32, with around 6.6–12.2% improvement compared to GA. These demonstrate the advantage of refining the CH placement at the proposed hybrid solution to provide better intra-communication distance, resulting in better place clusters and long node survival.

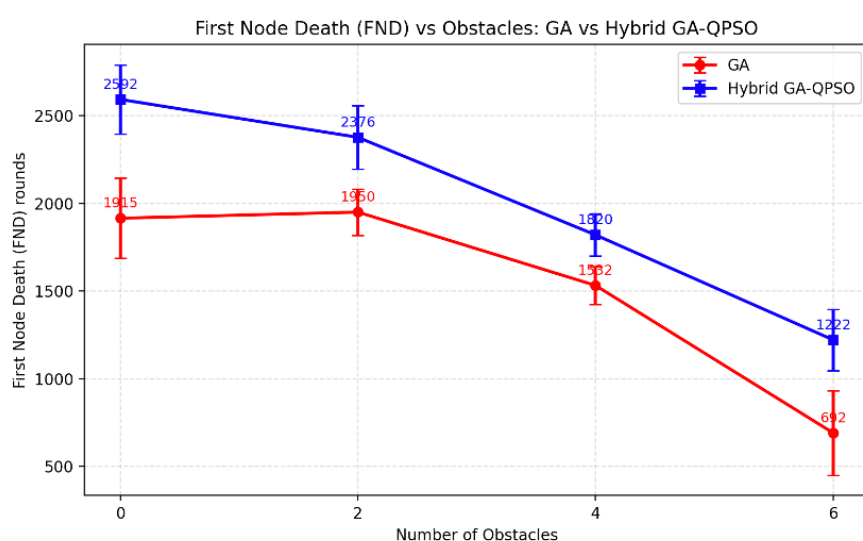


Figure 4.31: FND-GA vs. hybrid GA-QPSO

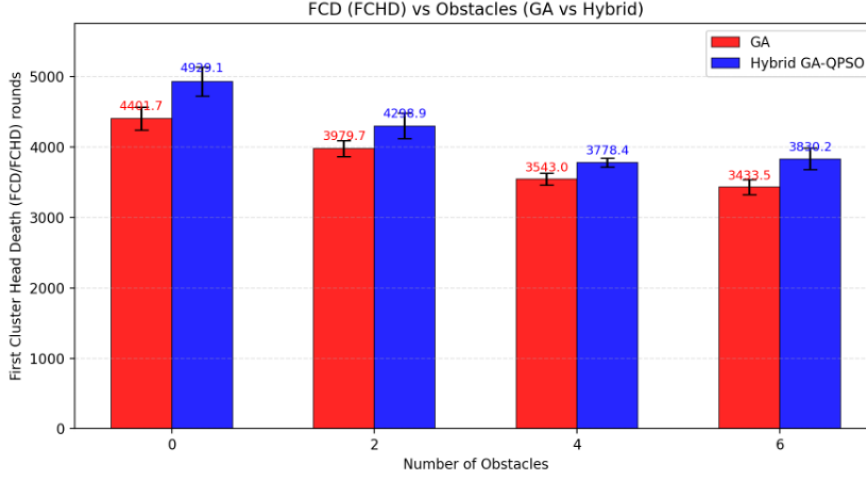


Figure 4.32: FCHD-GA vs. hybrid GA-QPSO

UAV Path Length and Energy Consumption—GA vs Hybrid GA-QPSO Comparison

The bar charts with SE in Figures 4.33 and 4.34 demonstrate the impact of obstacles on the energy efficiency of the UAV and its route length. In fact, the existence of obstacles leads to a distorted UAV trajectory, resulting in higher energy consumption [66]. However, in joint optimization approaches for CH coordination and UAV path planning, the relationship does not follow strict monotonicity. As is noticeable from the graph, the baseline algorithm achieved the lowest energy consumption at 6 obstacles. This indicates that the algorithm faced difficulties dealing with a dense number of obstacles. In a situation with a dense number of obstacles, the free space becomes small, and the GA faces difficulties in effectively distributing the CH to ensure balance and efficient clustering. Therefore, it tends to compress CHs into a small subregion. This reduces the distance between cluster head leads, which leads to long distances between IoT nodes and their CH, resulting in decreased lifetime performance and better UAV energy efficiency. The network lifetime discussion above supports this analysis, where the FND at 6 obstacles is around 622 rounds, demonstrating the long distance between IoT nodes and their CH. However, it is observable that the energy consumption at GA fluctuates irregularly across obstacle densities. This is due to the shortage of GA,

which deals with a discrete CH index space without refining the continuous search space [28]. Therefore, in the dense number of obstacles, it falls in placing the CH close to the obstacles region or compressing them in a small region, resulting in a non-monotonic energy pattern that indicates the instability of the algorithm rather than actual efficiency.

In contrast, it is noticeable that the proposed GA-QPSO approach averts such degenerate layouts. Whenever the number of obstacles increases, the UAV energy consumption and path length increase. The reason for this increase is that the optimizer navigates around the restricted region while preserving balance in CH spacing. This provides a smooth UAV path with increased energy consumption of the UAV. However, it is noticeable that the energy consumption and path length of the hybrid algorithm are slightly higher than the GA baseline algorithm, with a 3–10% increase, indicating the favorable distribution of CH rather than compressing them in a small area that leads to a shorter route but is considered inefficient in terms of network lifetime. This confirms the ability of the proposed algorithm to maintain better CH distribution and balanced clusters in cluttered environments. Therefore, this demonstrates that the GA-QPSO is willing to slightly increase the energy in order to have a better balance and distribution of CH to enhance the lifetime performance.

Therefore, the monotonic increase of energy consumption in the hybrid solution is an indication of the controlled optimization and robustness of the hybrid solution. While the reduced energy consumption of GA is an indication, it is short in spatial refinement [83]. The proposed solution provides balance in the lifetime of the network and UAV energy efficiency. The GA has lower energy usage of UAV, but it has high degradation in its lifetime.

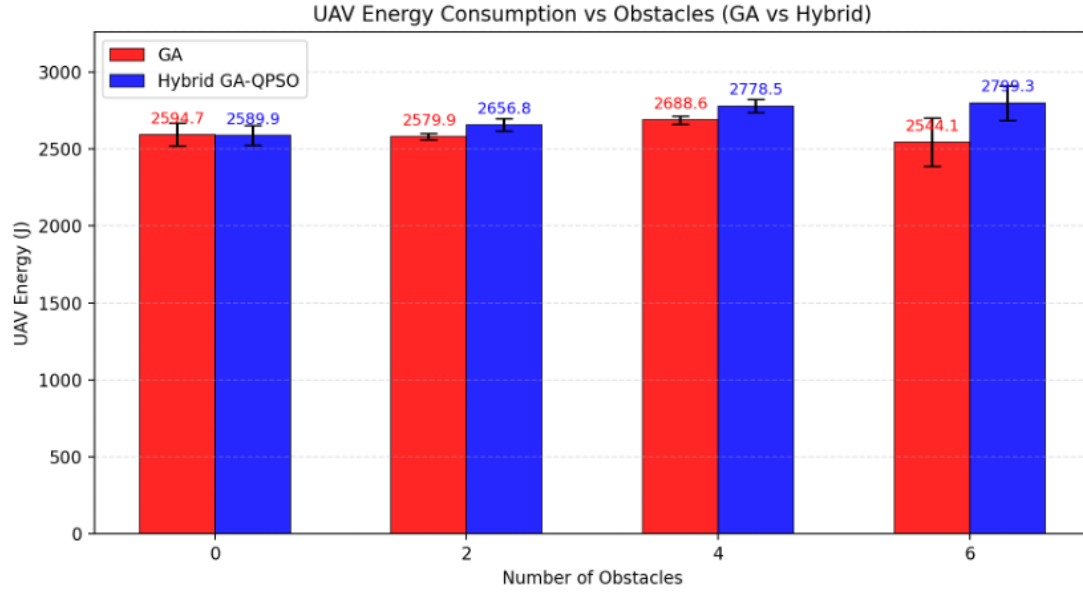


Figure 4.33: UAV energy consumption: GA vs hybrid GA-QPSO-obstacles scenario

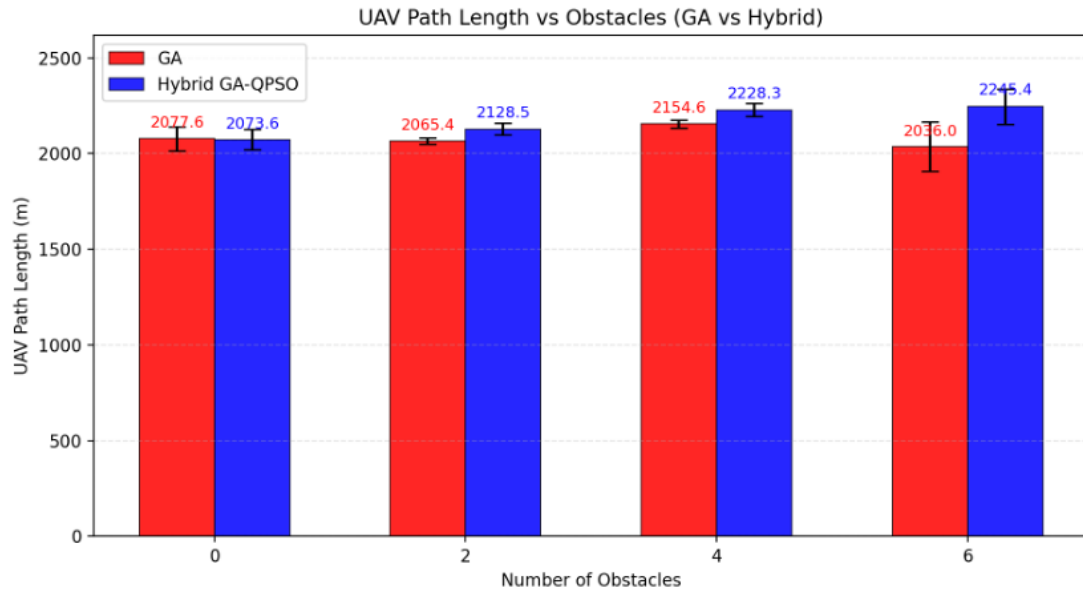


Figure 4.34: UAV path length: GA vs hybrid GA-QPSO-obstacles scenario

Discussion of Obstacles Avoidance Scenario

After evaluating our approach in different obstacle complexity scenarios and comparing it with the baseline GA, we found that spatial obstructions increase the route complexity as well as reduce network lifetime. However, our hybrid solution

Table 4.11: Summary of GA and Hybrid GA-QPSO Performance Across Obstacle Levels (300 Nodes)

Obs	GA FND	Hybrid FND	GA Energy (J)	Hybrid Energy (J)	GA Path (m)	Hybrid Path (m)
0	1915.3	2592.2	2594.7	2589.9	2077.6	2073.6
2	1950.0	2376.7	2579.9	2656.8	2065.4	2128.5
4	1552.0	1820.4	2688.6	2778.5	2154.6	2228.3
6	692.0	1222.3	2544.1	2799.3	2036.0	2245.5

demonstrates its ability to significantly provide better FND compared to GA. This demonstrates the advantage of QPSO to refine the CH placement effectively around the blocked area. The UAV cost, for both algorithms, increased whenever the number of obstacles increased. However, the GA-QPSO, even with six obstacles, which is the most challenging scenario, increases FND by over 557 rounds compared to GA with a slight increase in the UAV cost. Further, it is noticeable that the proposed algorithm provides a high lifetime with a slight overhead increase in the UAV in all scenarios. All these results confirm that the hybrid solution offers better lifetime-energy performance in complex environments and is clearly more robust to geometric constraints compared to the classical GA. Table 4.11 shows the summary of this scenario.

5.4 Baseline Algorithm Comparison

In this section, we compare our proposed hybrid GA-QPSO approach with three different metaheuristic algorithms, which are Genetic Algorithm [74], Particle Swarm Optimization (PSO) [75], and QPSO [105]. However, the GA and QPSO parameters were controlled as mentioned in Chapter 4, Section 2.5. Related to the PSO, the swarm size was set to 30, the inertia weight to 0.72, the cognitive factor to 1.49, and the social factor to 1.49 [75]. The comparison aims to evaluate how effective the proposed hybridization strategy is in providing an energy-efficient deployment of a UAV-assisted IoT network. To guarantee a fair and unbiased comparison, we evaluate all algorithms under the same configuration, considering a $200 \times 200 \text{ m}^2$ area, 200 nodes, and the initial energy of IoT nodes is 0.5J, while

the CH initial energy is 1 J. Also, a fixed number of CHs, which is 7% of the total number of IoT nodes, with a balanced weight of the weighted function, with a maximum number of iterations for each algorithm of 100 iterations and 5000 network simulation rounds. We run all algorithms ten times using independent seeds, and the average of the results is reported. The purpose of this comparison is not to replicate all the scenarios conducted in this study, which are designed to study the proposed approach; the main purpose is to evaluate the GA-QPSO under a representative and controlled configuration with baseline heuristics and study how it improved upon the compared algorithms, focusing on network lifetime and UAV energy cost criteria.

The curve of alive nodes in Figure 4.35 shows that the proposed hybrid GA-QPSO algorithm outperforms all other algorithms in terms of network lifetime. The GA-QPSO approach had the most survival nodes, where the first IoT node died at 2155 rounds, demonstrating observable improvement over GA, PSO, and QPSO. It achieved a roughly 26.1% to 51.6% increase compared to the baseline algorithms. Moreover, this improvement is clear in the mid-rounds, as it roughly increases the lifetime to approximately 16–21% compared with other algorithms. It is notable that these results confirm the advantage of integrating the GA’s global exploration with QPSO’s local exploitation. This integration provides better discovery for energy-balanced CH placement, leading to a noticeable enhancement in both IoT nodes and CH lifetime. However, in terms of UAV energy consumption and path length, it is observed from Figures 4.36 and 4.37 that the GA has the lowest energy consumption of 574 J and the shortest path length of 523.5 m, while the hybrid has slightly higher values. This proves the advantage of utilizing the GA elites to refine the CH’s placement and initiate the UAV route from the GA solutions with a local enhancement, resulting in controlled UAV overhead. These indications demonstrate that the lifetime enhancement does not result in excessive UAV overhead. Therefore, the hybrid approach shows the best balance between both IoT lifetime and UAV energy usage and validates reliability in joint optimization across tested algorithms. Therefore, we can sum up that the pro-

posed hybrid approach outperforms other algorithms in terms of the performance of UAV-assisted IoT networks.

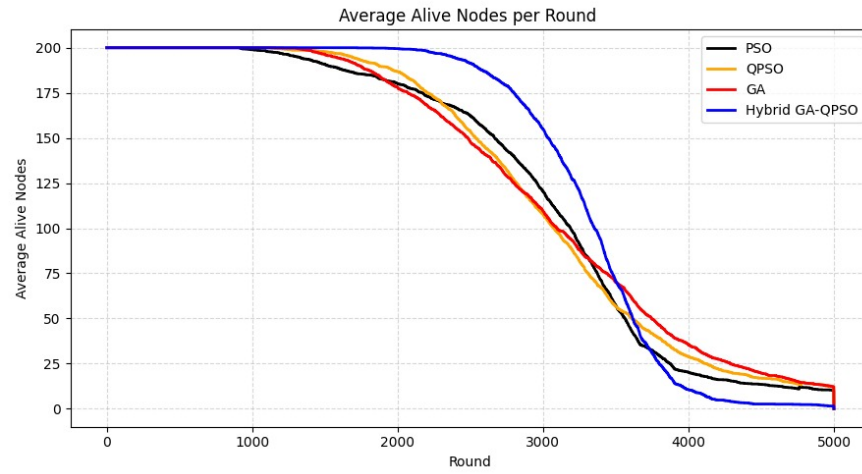


Figure 4.35: Alive nodes curve—comparison with baseline algorithms

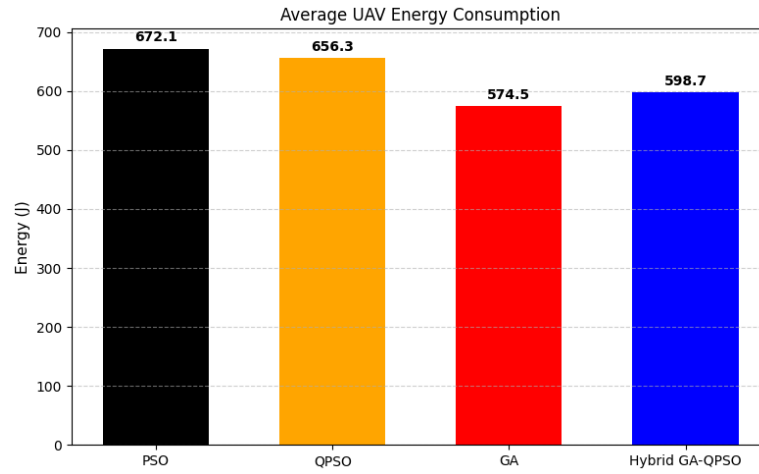


Figure 4.36: UAV energy consumption—comparison with baseline algorithms

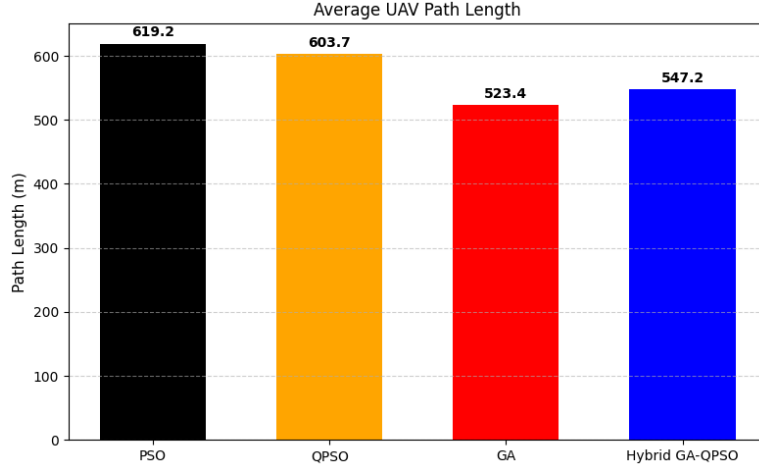


Figure 4.37: UAV path length—comparison with baseline algorithms

5.5 Comparison with the State of the Art

In this section, we compare our proposed framework with state-of-the-art approaches that focus on joint optimization in the UAV-assisted IoT network. Table 4.12 shows an overview of the comparison. We selected these papers, as they have approximately similar assumptions to our work, such as the offline optimization approach and the energy constraints.

However, based on the table, it is clear that the state-of-the-art approaches proposed sequential joint optimization strategies. Moreover, they considered a fixed and predefined number of CHs, and they did not study obstacle avoidance in the UAV trajectory.

In contrast, our proposed hybrid GA-QPSO approach provides a full joint optimization. It simultaneously optimizes three aspects together, which are the count of CHs, their placement, and a collision-free UAV route within a single unified fitness function. The advantage of the full optimization in our optimization approach is that it leads to a good interaction between clustering and UAV mobility in the optimization process, resulting in improved network stability and controlled energy overhead of the UAV.

Table 4.12: Comparison With Representative State-of-the-Art Joint Optimization Approaches

Work	Optimization Scope	CH Count	Obstacle-Aware
Zhu <i>et al.</i> [27]	Sequential	Fixed	No
Chai <i>et al.</i> [18]	Sequential	Fixed	No
This work	Full joint	Optimized	Yes

5.6 Discussion of the Results

After evaluating all conducted scenarios, the proposed hybrid GA-QPSO demonstrates its effectiveness in jointly optimizing the optimal count of CH, coordinating their optimal location, and designing a collision-free UAV path. It also considers the energy efficiency of the entire UAV-assisted IoT network. Compared to the baseline GA, the hybrid approach demonstrates noticeable enhancement in the network lifetime performance, confirming the advantage of QPSO refinement of the cluster head placement, resulting in better IoT survival. Moreover, it demonstrates the benefit of QPSO refinement that repairs the irregularities left by GA. This results in a more efficient clustering approach that ensures balanced and well-distributed clusters. Moreover, reducing the distance between the cluster head and its nodes, resulting in a short communication distance between them, leads to an extended lifetime [25].

Furthermore, it demonstrates its superiority in providing better optimization in density, weight, and obstacle variations. It is observed that the hybrid solution provides smoother UAV motion, stable cluster head survival, and more consistent performance patterns. Although the GA baseline algorithm designs a slightly shorter flight path in some cases, this enhancement comes from noticeable degradation in unbalanced cluster structures and quick cluster head depletion. On the other hand, the hybrid GA-QPSO demonstrates its ability to adhere more strictly to the objective weights, as it balances the trade-off between the lifetime and energy efficiency of the UAV, illustrating its superior adaptability. However, in

dense obstacle environments, it preserved better CH distribution and a collision-free path design while preserving the energy of the network devices, proving its suitability to deploy UAV-assisted IoT networks in urban cities. To sum up, the proposed approach validates its ability to generalize well, carefully responds to the priorities of the objective function, and offers an adaptable optimization for a variety of deployment scenarios.

Discuss The Tradeoffs Between Performance Gains and Computation Cost

In all the experiments conducted for this thesis, it was observed that the hybrid GA-QPSO provided a noticeable improvement in the lifetime of IoT nodes compared to the GA-alone algorithm. However, as the proposed approach is a hybrid, the implementation cost increased, as the QPSO is responsible for refining the cluster heads' placement for the best three elite solutions generated by the GA algorithm. After running both algorithms under the same conditions across most of the main scenarios, the GA required approximately 660 seconds to run, while the hybrid GA-QPSO required approximately 2340 seconds. However, even if there is a tradeoff between computational cost and optimization performance, it results in a noticeable improvement in the IoT lifetime of up to 77% while controlling the UAV overhead. Moreover, this thesis focuses on offline joint optimization prior to the network deployment, which means the computational cost does not affect the real-time network operation [19]. Consequently, the GA-QPSO framework effectively and practically balances the efficiency of the computation and the quality of the solution in UAV-assisted IoT networks.

5.7 Limitations of the Study

This study proposes a full joint optimization approach that jointly optimizes the clustering and UAV path to enhance the overall energy efficiency of UAV-assisted IoT. Despite the advantages of the proposed framework, there are some limitations

of this study. First, the study considers an offline optimization approach, where all the optimization occurs before the network deployment. Additionally, the study assumes a static 2D area and a fixed distribution of IoT nodes with a constant data rate, which simplifies the real-world scenario, which actually consists of a 3D area and a variable data rate. Moreover, consider one UAV model that used a simplified energy model, without considering multi-UAV coordination and dynamic flight altitude. Moreover, the obstacles are not represented in 3-D structures that exist in real scenarios. These limitations do not invalidate the findings; instead, they suggest future work directions to expand on the current study.

CHAPTER 5

CONCLUSION AND FUTURE WORK

This thesis explores the potentials and challenges in UAV-assisted IoT networks. It presents a preliminary review of recent research that focuses on optimizing IoT deployment and UAV trajectories to ensure their efficient energy consumption during data collection missions. Based on reviewing the state of the art, the study identifies research gaps and formulates a joint optimization problem aimed at improving the performance of UAV-assisted IoT networks. The primary objectives are to optimize the number and placement of CHs, focusing on placing them in optimal locations to maximize network lifetime, and optimize UAV trajectory planning while avoiding obstacles.

To overcome the current limitation in this field, this study proposes a full joint hybrid GA-QPSO optimization approach that simultaneously optimizes all three aspects of the research objective. We integrate the SOM-based initialization algorithm to design an initial coordination of cluster heads, followed by the GA algorithm that simultaneously optimizes the count of the CH and their placement, and designs a collision-free UAV route. In our approach, the GA serves as a global exploration, while the QPSO refines the best solutions generated by the GA to extend the network lifetime, taking UAV energy into account. However, the evaluation of the proposal demonstrates that it significantly enhances the

overall performance of a UAV-assisted IoT network when compared to the baseline algorithm and outperforms its performance in all conducted scenarios of node density, weight settings, and obstacle complexity. Compared with the baseline algorithm, the proposed approach illustrates more stable convergence and better intra-cluster energy consumption, leading to better network performance.

Despite these strengths, this study has some limitations due to the simplified assumptions of studying one UAV, a static environment, and a simplified first-order radio model. All of these limitations are considered future work to expand the proposed solution. Further, in our future work, we aim to study deploying UAV-assisted IoT in dynamic environments, considering multiple UAVs and dynamic routing. In conclusion, the studied hybrid GA-QPSO approach offers a reliable and obstacle-aware solution that contributes to UAV-assisted IoT data collection and builds a strong bias for more intelligent next-generation deployments.

REFERENCES

- [1] S. Bhuvaneswari, A. Abirami, R. P. Suvetha Sri, R. Srinithy, and R. Swathi, “A comprehensive review for optimizing the design of cluster head selection to enhance the network lifetime in wsn,” in *2022 OPJU International Technology Conference on Emerging Technologies for Sustainable Development (OTCON)*, 2023, pp. 1–6.
- [2] M. Abdel-Basset, R. Mohamed, I. Alrashdi, K. M. Sallam, and I. A. Hameed, “Evolution-based energy-efficient data collection system for uav-supported iot: Differential evolution with population size optimization mechanism,” *Expert Systems with Applications*, vol. 245, p. 123082, 2024.
- [3] C. Lin, G. Han, X. Qi, J. Du, T. Xu, and M. Martínez-García, “Energy-optimal data collection for unmanned aerial vehicle-aided industrial wireless sensor network-based agricultural monitoring system: A clustering compressed sampling approach,” *IEEE Transactions on Industrial Informatics*, vol. 17, no. 6, pp. 4411–4420, 2021.
- [4] H. Hu, K. Xiong, G. Qu, Q. Ni, P. Fan, and K. B. Letaief, “Aoi-minimal trajectory planning and data collection in uav-assisted wireless powered iot networks,” *IEEE Internet of Things Journal*, vol. 8, no. 2, pp. 1211–1223, 2021.
- [5] T. Qayyum, Z. Trabelsi, A. Malik, and K. Hayawi, “Trajectory design for uav-based data collection using clustering model in smart farming,” *Sensors*, vol. 22, 12 2021.

- [6] Z. Wang, R. Liu, Q. Liu, J. S. Thompson, and M. Kadoch, “Energy-efficient data collection and device positioning in uav-assisted iot,” *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1122–1139, 2020.
- [7] M. Li, G. Jia, X. Li, and H. Qiu, “Efficient trajectory planning for optimizing energy consumption and completion time in uav-assisted iot networks,” *Mathematics*, vol. 11, no. 20, 2023. [Online]. Available: <https://www.mdpi.com/2227-7390/11/20/4399>
- [8] R. Liu, M. Xie, A. Liu, and H. Song, “Joint optimization risk factor and energy consumption in iot networks with tinymml-enabled internet of uavs,” *IEEE Internet of Things Journal*, vol. 11, no. 12, pp. 20 983–20 994, 2024.
- [9] K. Shafique, B. A. Khawaja, F. Sabir, S. Qazi, and M. Mustaqim, “Internet of things (iot) for next-generation smart systems: A review of current challenges, future trends and prospects for emerging 5g-iot scenarios,” *IEEE Access*, vol. 8, pp. 23 022–23 040, 2020.
- [10] Q. Ni, Q. Pan, H. Du, C. Cao, and Y. Zhai, “A novel cluster head selection algorithm based on fuzzy clustering and particle swarm optimization,” *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 14, no. 1, pp. 76–84, 2017.
- [11] A. Panchal and R. Singh, “Eocgs: energy efficient optimum number of cluster head and grid head selection in wireless sensor networks,” *Telecommunication Systems*, vol. 78, pp. 1–13, 09 2021.
- [12] P. P. Raj, A. M. Khedr, and Z. A. Aghbari, “An enhanced evolutionary scheme for obstacle-aware data gathering in uav-assisted wsns,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 12, pp. 16 299–16 311, 2023.

- [13] P. P. V., A. Khedr, and Z. Al Aghbari, "Data gathering via mobile sink in wsns using game theory and enhanced ant colony optimization," *Wireless Networks*, vol. 26, 05 2020.
- [14] Z. Wei, M. Zhu, N. Zhang, L. Wang, Y. Zou, Z. Meng, H. Wu, and Z. Feng, "Uav-assisted data collection for internet of things: A survey," *IEEE Internet of Things Journal*, vol. 9, no. 17, pp. 15 460–15 483, 2022.
- [15] N. Cheng, S. Wu, X. Wang, Z. Yin, C. Li, W. Chen, and F. Chen, "Ai for uav-assisted iot applications: A comprehensive review," *IEEE Internet of Things Journal*, vol. 10, no. 16, pp. 14 438–14 461, 2023.
- [16] M. Su, H. Chai, C. Zhao, Y. Lyu, and J. Hu, "Lightweight obstacle avoidance for fixed-wing uavs using entropy-aware ppo," *Drones*, vol. 9, no. 9, 2025.
- [17] K. Soltani, F. Coro, and S. K. Das, "Optimizing uav-assisted data collection in iot sensor networks using dual cluster head strategy," in *2024 IEEE 21st International Conference on Mobile Ad-Hoc and Smart Systems (MASS)*, 2024, pp. 279–287.
- [18] R. Chai, Y. Gao, R. Sun, L. Zhao, and Q. Chen, "Time-oriented joint clustering and uav trajectory planning in uav-assisted wsns: Leveraging parallel transmission and variable velocity scheme," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 11, pp. 12 092–12 106, 2023.
- [19] O. Ghdiri, W. Jaafar, S. Alfattani, J. B. Abderrazak, and H. Yanikomeroğlu, "Offline and online uav-enabled data collection in time-constrained iot networks," *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 4, pp. 1918–1933, 2021.
- [20] K.-V. Nguyen, C.-H. Nguyen, T. V. Do, and C. Rotter, "Efficient multi-uav assisted data gathering schemes for maximizing the operation time of wireless sensor networks in precision farming," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 12, pp. 11 664–11 674, 2023.

- [21] S. A. Haider, K. M. Ahmad, and A. A. Khan, “Efficient unmanned aerial vehicle-based data collection for iot smart farming,” *Internet of Things*, vol. 26, p. 101184, 2024.
- [22] M. Alhafnawi, H. A. Bany Salameh, A. Masadeh, H. Al-Obiedollah, M. Ayyash, R. El-Khazali, and H. Elgala, “A survey of indoor and outdoor uav-based target tracking systems: Current status, challenges, technologies, and future directions,” *IEEE Access*, vol. 11, pp. 68 324–68 339, 2023.
- [23] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, “A tutorial on uavs for wireless networks: Applications, challenges, and open problems,” *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2334–2360, 2019.
- [24] Y. Wang, M. Chen, C. Pan, K. Wang, and Y. Pan, “Joint optimization of uav trajectory and sensor uploading powers for uav-assisted data collection in wireless sensor networks,” *IEEE Internet of Things Journal*, vol. 9, no. 13, pp. 11 214–11 226, 2022.
- [25] A. Shahraki, A. Taherkordi, . Haugen, and F. Eliassen, “A survey and future directions on clustering: From wsns to iot and modern networking paradigms,” *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 2242–2274, 2021.
- [26] J. Zhang, Y. An, J. Cao, S. Ouyang, and L. Wang, “Uav trajectory planning for complex open storage environments based on an improved rrt algorithm,” *IEEE Access*, vol. 11, pp. 23 189–23 204, 2023.
- [27] B. Zhu, E. Bedeer, H. H. Nguyen, R. Barton, and J. Henry, “Joint cluster head selection and trajectory planning in uav-aided iot networks by reinforcement learning with sequential model,” *IEEE Internet of Things Journal*, vol. 9, no. 14, pp. 12 071–12 084, 2022.

- [28] S. Katoch, S. S. Chauhan, and V. Kumar, “A review on genetic algorithm: past, present, and future,” *Multimedia Tools and Applications*, vol. 80, no. 5, pp. 8091–8126, 2021.
- [29] A. Nassef, M. Abdelkareem, H. Maghrabie, and A. Baroutaji, “Hybrid meta-heuristic algorithms: a recent comprehensive review with bibliometric analysis,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, p. 7022, 12 2024.
- [30] S. Krishnan, M. Nemati, S. W. Loke, J. Park, and J. Choi, “Energy-efficient uav-assisted iot data collection via tsp-based solution space reduction,” in *GLOBECOM 2023 - 2023 IEEE Global Communications Conference*, 2023, pp. 6189–6194.
- [31] L. Atzori, A. Iera, and G. Morabito, “The internet of things: A survey,” *Computer Networks*, pp. 2787–2805, 10 2010.
- [32] G. Jia, C. Li, and M. Li, “Energy-efficient trajectory planning for smart sensing in iot networks using quadrotor uavs,” *Sensors*, vol. 22, no. 22, 2022.
- [33] R. Singh, K. Sharma, and L. Awasthi, “A decade review of authentication and communication methods in iot environment,” *Wireless Personal Communications*, vol. 139, pp. 595–623, 11 2024.
- [34] S. Nižetić, P. Šolić, D. López-de-Ipiña González-de-Artaza, and L. Patrono, “Internet of things (iot): Opportunities, issues and challenges towards a smart and sustainable future,” *Journal of Cleaner Production*, vol. 274, p. 122877, 2020.
- [35] S. Moradi, A. Bokani, and J. Hassan, “Uav-based smart agriculture: a review of uav sensing and applications,” in *2022 32nd International Telecommunication Networks and Applications Conference (ITNAC)*, 2022, pp. 181–184.

- [36] M. Hassanalian and A. Abdelkefi, “Classifications, applications, and design challenges of drones: A review,” *Progress in Aerospace Sciences*, vol. 91, pp. 99–131, 2017.
- [37] A. Beishenalieva and S.-J. Yoo, “Uav path planning for data gathering in wireless sensor networks: Spatial and temporal substate-based q-learning,” *IEEE Internet of Things Journal*, vol. 11, no. 6, pp. 9572–9586, 2024.
- [38] T. R. Beegum, M. Y. I. Idris, M. N. B. Ayub, and H. A. Shehadeh, “Optimized routing of uavs using bio-inspired algorithm in fanet: A systematic review,” *IEEE Access*, vol. 11, pp. 15 588–15 622, 2023.
- [39] D. C. Tsouros, S. Bibi, and P. G. Sarigiannidis, “A review on uav-based applications for precision agriculture,” *Information*, vol. 10, no. 11, 2019.
- [40] A. Mairaj, A. Baba, and A. Javaid, “Application specific drone simulators: Recent advances and challenges,” *Simulation Modelling Practice and Theory*, vol. 94, 02 2019.
- [41] M. Deng, S. Peng, X. Xie, Z. Jiang, J. Hu, and Z. Qi, “A diffused mini-sniffing sensor for monitoring so2 emissions compliance of navigating ships,” *Sensors*, vol. 22, no. 14, 2022.
- [42] S. A. H. Mohsan, N. Othman, L. Yanlong, M. Alsharif, and M. Khan, “Unmanned aerial vehicles (uavs): Practical aspects, applications, open challenges, security issues, and future trends,” *Intelligent Service Robotics*, 01 2023.
- [43] A. A. Al-Habob, O. A. Dobre, S. Muhaidat, and H. Vincent Poor, “Energy-efficient data dissemination using a uav: An ant colony approach,” *IEEE Wireless Communications Letters*, vol. 10, no. 1, pp. 16–20, 2021.
- [44] M. Rouault, W. Ejaz, M. Naeem, and R. Masroor, “The role of uav-assisted iot networks in managing the impact of the pandemic,” *IEEE Communications Standards Magazine*, vol. 5, pp. 10–16, 12 2021.

- [45] W. Ejaz, M. A. Azam, S. Saadat, F. Iqbal, and A. Hanan, “Unmanned aerial vehicles enabled iot platform for disaster management,” *Energies*, vol. 12, no. 14, 2019.
- [46] R. Kumar and L. Ramasamy, “Optimal cluster head selection using modified rider assisted clustering for iot,” *IET Communications*, vol. 14, 08 2020.
- [47] M. Gamal, N. E. Mekky, H. H. Soliman, and N. A. Hikal, “Enhancing the lifetime of wireless sensor networks using fuzzy logic leach technique-based particle swarm optimization,” *IEEE Access*, vol. 10, pp. 36 935–36 948, 2022.
- [48] I. Dohare and K. Singh, “Pso-dec: Pso based deterministic energy efficient clustering protocol for iot,” *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 22, pp. 1463–1475, 11 2019.
- [49] S. Poudel, S. Moh, and J. Shen, “Residual energy-based clustering in uav-aided wireless sensor networks for surveillance and monitoring applications,” *Journal of Surveillance, Security and Safety*, vol. 2, no. 3, 2021.
- [50] I. Karim, H. Daud, N. Zainuddin, R. Sokkalingam, M. Farooq, E. Baig, G. Ayub, and M. Zafar, “Determining the optimal number of clusters by enhanced gap statistic in k-mean algorithm,” *Egyptian Informatics Journal*, vol. 27, p. 100504, 07 2024.
- [51] L. Shi and S. Xu, “Uav path planning with qos constraint in device-to-device 5g networks using particle swarm optimization,” *IEEE Access*, vol. 8, pp. 137 884–137 896, 2020.
- [52] Y. Wei, Y. Lu, P. Zhao, S. Leng, and K. Yang, “Minimizing age of information in uav-assisted data collection with limited charging facilities,” *IEEE Wireless Communications Letters*, vol. 13, no. 5, pp. 1463–1467, 2024.
- [53] S. Wan, J. Lu, P. Fan, and K. B. Letaief, “Toward big data processing in iot: Path planning and resource management of uav base stations in mobile-

- edge computing system,” *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 5995–6009, 2020.
- [54] A. Singh, S. Redhu, and R. M. Hegde, “Uav altitude optimization for efficient energy harvesting in iot networks,” in *2022 National Conference on Communications (NCC)*, 2022, pp. 350–355.
- [55] H. Hong, Y. Zhang, and Y. Xie, “Energy-limited uav visiting planning for age-aware wireless-powered sensor networks,” in *2023 IEEE 98th Vehicular Technology Conference (VTC2023-Fall)*, 2023, pp. 1–6.
- [56] X. Huang and X. Fu, “Fresh data collection for uav-assisted iot based on aerial collaborative relay,” *IEEE Sensors Journal*, vol. 23, no. 8, pp. 8810–8825, 2023.
- [57] S. Haider, A. Jiang, A. Almogren, A. Rehman, A. Ahmed, W. U. Khan, and H. Hamam, “Energy efficient uav flight path model for cluster head selection in next-generation wireless sensor networks,” *Sensors*, vol. 21, no. 12, pp. 1–12, 2021.
- [58] N. S. A. Ibrahim and F. A. Saporudin, “Resource-efficient coverage path planning for uav-based aerial iot gateway,” *J. Commun.*, vol. 18, no. 7, pp. 462–470, 2023.
- [59] O. M. Gul, A. M. Erkmen, and B. Kantarci, “Uav-driven sustainable and quality-aware data collection in robotic wireless sensor networks,” *IEEE Internet of Things Journal*, vol. 9, no. 24, pp. 25 150–25 164, 2022.
- [60] D. Li, S. Xu, C. Zhao, Y. Wang, R. Xu, and b. ai, “Data collection in laser-powered uav-assisted iot networks: Phased scheme design based on improved clustering algorithm,” *IEEE Transactions on Green Communications and Networking*, vol. PP, pp. 1–1, 01 2023.

- [61] S. Alfattani, W. Jaafar, H. Yanikomeroglu, and A. Yongacoglu, "Multi-uav data collection framework for wireless sensor networks," in *2019 IEEE Global Communications Conference (GLOBECOM)*, 2019, pp. 1–6.
- [62] Z. Ning, H. Ji, X. Wang, E. C. H. Ngai, L. Guo, and J. Liu, "Joint optimization of data acquisition and trajectory planning for uav-assisted wireless powered internet of things," *IEEE Transactions on Mobile Computing*, vol. 24, no. 2, pp. 1016–1030, 2025.
- [63] C. Wang, "A distributed particle-swarm-optimization-based fuzzy clustering protocol for wireless sensor networks," *Sensors*, vol. 23, no. 15, 2023.
- [64] H. Hu, X. Fan, and C. Wang, "Energy efficient clustering and routing protocol based on quantum particle swarm optimization and fuzzy logic for wireless sensor networks," *Scientific Reports*, vol. 14, 08 2024.
- [65] B. Ma, Y. Ji, and L. Fang, "A multi-uav formation obstacle avoidance method combined with improved simulated annealing and an adaptive artificial potential field," *Drones*, vol. 9, no. 6, 2025.
- [66] D. Debnath, F. Vanegas, J. Sandino, A. F. Hawary, and F. Gonzalez, "A review of uav path-planning algorithms and obstacle avoidance methods for remote sensing applications," *Remote Sensing*, vol. 16, no. 21, 2024.
- [67] J. Akshya, M. Sundarrajan, S. Amutha, R. K. Dhanaraj, A. O. Khadidos, A. O. Khadidos, and S. Selvarajan, "Geometric optimisation of unmanned aerial vehicle trajectories in uncertain environments," *Vehicular Communications*, vol. 54, p. 100938, 2025.
- [68] Z. Wang, Y. Li, and T. Chen, "Hybrid path planning based on adaptive visibility graph," *Engineering Applications of Artificial Intelligence*, vol. 126, p. 107095, 2023.
- [69] H. M. Hadi and I. M. Ibrahim, "A comprehensive review of shortest path algorithms for network routing," *Asian Journal of Research in*

Computer Science, vol. 18, no. 3, p. 152–175, Feb. 2025. [Online]. Available: <https://journalajrcos.com/index.php/AJRCOS/article/view/584>

- [70] A. Caruso, L. Galluccio, C. Grasso, M. Ignaccolo, G. Inturri, P. Leonardi, G. Schembra, and V. Torrì, “Advancing urban traffic monitoring in smart cities: A field experiment with uav-based system for transport planning and intelligent traffic management,” in *2025 Integrated Communications, Navigation and Surveillance Conference (ICNS)*, 2025, pp. 1–9.
- [71] M. Dai, N. Huang, Y. Wu, J. Gao, and Z. Su, “Unmanned-aerial-vehicle-assisted wireless networks: Advancements, challenges, and solutions,” *IEEE Internet of Things Journal*, vol. PP, pp. 1–1, 01 2022.
- [72] M. Gheisari, A. A. Abbasi, Z. Sayari, Q. Rizvi, A. Asheralieva, S. Banu, F. M. Awaysheh, S. B. H. Shah, and K. A. Raza, “A survey on clustering algorithms in wireless sensor networks: Challenges, research, and trends,” in *2020 International Computer Symposium (ICS)*, 2020, pp. 294–299.
- [73] S. Kaur, N. Arya, and S. Singh, “Optimizing uav-iot network integration: A scalable multi-objective communication framework,” *Engineering, Technology & Applied Science Research*, vol. 14, pp. 17 996–18 003, 12 2024.
- [74] M. M. Rahman, M. Al-Naeem, A. Banerjee, and A. Sufian, “Eeto-ga: Energy efficient trajectory optimization of uav-iot collaborative system using genetic algorithm,” *Applied Sciences*, vol. 13, p. 2535, 02 2023.
- [75] M. Haris and H. Nam, “Enhancing energy efficiency in iot-wsns through optimized pso cluster head selection,” *IEEE Access*, vol. 13, pp. 126 496–126 512, 2025.
- [76] X. Zhu, J. He, and M. Zhao, “Adaptive multi-objective optimization for uav-assisted wireless powered iot networks,” *Information*, vol. 16, p. 849, 10 2025.

- [77] M. L. Betalo, S. Leng, X. Chen, and L. Zhou, “Joint optimization for cluster head selection in uav-assisted wsn,” in *2021 International Conference on UK-China Emerging Technologies (UCET)*, 2021, pp. 31–36.
- [78] K. Kumar, A. Singh, and P. Gupta, “Metaheuristic algorithms for optimization: A brief review,” *Journal of Intelligent Systems*, 2024.
- [79] V. Prakash and S. Pandey, “Metaheuristic algorithm for energy efficient clustering scheme in wireless sensor networks,” *Microprocessors and Microsystems*, vol. 101, p. 104898, 2023.
- [80] K. Rajwar, K. Deep, and S. Das, “An exhaustive review of the metaheuristic algorithms for search and optimization: taxonomy, applications, and open challenges,” *Artificial Intelligence Review*, vol. 56, pp. 13 187–13 257, 04 2023.
- [81] M. Xu, J. Yang, and Z. Gao, “Parameters sensitive analyses for using genetic algorithm to solve continuous network design problems,” *Procedia - Social and Behavioral Sciences*, vol. 43, pp. 435–444, 2012.
- [82] O. Roeva, D. Zoteva, G. Roeva, M. Ignatova, and V. Lyubenova, “An effective hybrid metaheuristic approach based on the genetic algorithm,” *Mathematics*, vol. 12, no. 23, p. 3815, 2024.
- [83] C. Muniyappa and E. Kim, “Survey of genetic and differential evolutionary algorithm approaches to search documents based on semantic similarity,” *CoRR*, vol. abs/2507.11751, 2025.
- [84] S. Wenjuan, Q. Su, H. Yuan, and Y. Chen, “Optimization performance analysis for adaptive genetic algorithm with nonlinear probabilities,” *International Journal of Advanced Computer Science and Applications*, vol. 13, 01 2022.
- [85] Q. You, J. Sun, F. Pan, V. Palade, and B. Ahmad, “Dmo-qpso: A multi-objective quantum-behaved particle swarm optimization algorithm based on

- decomposition with diversity control,” *Mathematics*, vol. 9, no. 16, p. 1959, 2021.
- [86] M. O. Butt, N. Waheed, T. Q. Duong, and W. Ejaz, “Quantum-inspired resource optimization for 6g networks: A survey,” *IEEE Communications Surveys & Tutorials*, vol. 27, no. 5, pp. 2973–3019, 2025.
- [87] C. Li, J. Sun, W. Li, V. Palade, and X. Wu, “Analyzing and controlling diversity in quantum-behaved particle swarm optimization,” *arXiv preprint arXiv:2308.04840*, 2023.
- [88] Y. Mohammed, R. Hassan, M. K. Hasan, H. Abbas, M. Khan, J. Baili, and D. Gupta, “Optimizing uav-assisted iot sensor networks: A multi-objective approach to data collection and routing,” *Alexandria Engineering Journal*, vol. 115, pp. 47–56, 03 2025.
- [89] C. Ramirez Atencia, J. Del Ser, and D. Camacho, “Weighted strategies to guide a multi-objective evolutionary algorithm for multi-uav mission planning,” *Swarm and Evolutionary Computation*, vol. 44, p. 480–495, Feb. 2019.
- [90] S. Khan and A. B. Mailewa, “Discover botnets in iot sensor networks: A lightweight deep learning framework with hybrid self-organizing maps,” *Microprocessors and Microsystems*, vol. 97, p. 104753, 2023.
- [91] P. Gülüm and A. Taskin, “Clustering approach with self-organizing maps for unmanned aerial vehicle response to post-earthquake fires: An application for istanbul,” *Sigma Journal of Engineering and Natural Sciences – Sigma Mühendislik ve Fen Bilimleri Dergisi*, vol. 42, pp. 692–700, 02 2024.
- [92] V.-T. Le, R. De Leone, T. Hoang, D. Ong Mau, M. Kim, and N.-S. Vo, “Distance-, energy-, and density-aware som clustering-based routing in low-power iot-enabled wsns,” *IEEE Sensors Journal*, vol. 25, no. 22, pp. 42 231–42 242, 2025.

- [93] T. Kohonen, *Self-organizing maps*. Springer Science & Business Media, 2012, vol. 30.
- [94] J. Li, M. Noto, Y. Zhang, and J. Guo, “Joint optimization of wireless charging station location and operation scheduling for electric buses under uncertain demand,” *IEEE Access*, vol. 13, pp. 91 765–91 776, 2025.
- [95] F. Zitouni and S. Harous, “Integrating the opposition nelder–mead algorithm into the selection phase of the genetic algorithm for enhanced optimization,” *Applied System Innovation*, vol. 6, p. 80, 09 2023.
- [96] A. Nagpal and G. Gabrani, “Python for data analytics, scientific and technical applications,” in *2019 Amity International Conference on Artificial Intelligence (AICAI)*, 2019, pp. 140–145.
- [97] E. L. Platt, *Network science with Python and NetworkX quick start guide: explore and visualize network data effectively*. Packt Publishing Ltd, 2019.
- [98] S. Poudel and S. Moh, “Hybrid path planning for efficient data collection in uav-aided wsns for emergency applications,” *Sensors*, vol. 21, no. 8, 2021.
- [99] S. Wang, N. Qi, H. Jiang, M. Xiao, H. Liu, L. Jia, and D. Zhao, “Trajectory planning for uav-assisted data collection in iot network: A double deep q network approach,” *Electronics*, vol. 13, no. 8, 2024.
- [100] D. Debnath, F. Vanegas, J. Sandino, A. F. Hawary, and F. Gonzalez, “A review of uav path-planning algorithms and obstacle avoidance methods for remote sensing applications,” *Remote Sensing*, vol. 16, no. 21, 2024.
- [101] L. Lindemann, M. Cleaveland, Y. Kantaros, and G. J. Pappas, “Robust motion planning in the presence of estimation uncertainty,” in *2021 60th IEEE Conference on Decision and Control (CDC)*, 2021, pp. 5205–5212.
- [102] S. Sun, H. Wang, Y. Xu, T. Wang, R. Liu, and W. Chen, “A fusion approach for uav onboard flight trajectory management and decision making based

- on the combination of enhanced a* algorithm and quadratic programming,” *Drones*, vol. 8, p. 254, 06 2024.
- [103] C. Uthayakumar, R. Jayaraman, H. A. Raja, and K. Daniel, “Implementation and performance evaluation of quantum-inspired clustering scheme for energy-efficient wsns,” *Sensors*, vol. 25, no. 18, 2025.
 - [104] M. Farahani and A. Rahbar, “Double leveled unequal clustering with considering energy efficiency and load balancing in dense iot networks,” *Wireless Personal Communications*, vol. 106, 06 2019.
 - [105] A. Afridi, I. Hameed, and I. Koo, “Quantum pso-based optimization of secured irs-assisted wireless-powered iot networks,” *Applied Sciences*, vol. 14, no. 24, 2024.
 - [106] N. Merabtine, D. Djenouri, and D.-E. Zegour, “Towards energy efficient clustering in wireless sensor networks: A comprehensive review,” *IEEE Access*, vol. 9, pp. 92 688–92 705, 2021.
 - [107] A. Abadie, S. Athey, G. W. Imbens, and J. M. Wooldridge, “When should you adjust standard errors for clustering?” *The Quarterly Journal of Economics*, vol. 138, no. 1, pp. 1–35, 2023.
 - [108] D. Elmanakhly, A. Othman, R. Mohamed, and M. Abdel-Basset, “Robust metaheuristic algorithms with sequential replacement-improved dynamic population for optimizing energy consumption in a uav-empowered iot data collection system,” *Journal of Big Data*, vol. 12, 12 2025.
 - [109] A. Shahraki, A. Taherkordi, . Haugen, and F. Eliassen, “A survey and future directions on clustering: From wsns to iot and modern networking paradigms,” *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 2242–2274, 2021.

- [110] T. Liu, C. Sun, Y. Zhang, and W. Sun, “Energy-efficient end-to-end optimization for uav-assisted iot data collection and leo satellite offloading in sagin,” *Electronics*, vol. 15, no. 1, 2026.
- [111] H. Zafor, N. Mazumdar, and A. Nag, “An effective routing algorithm to minimize the uav routing time and extend the network lifetime in clustered iot network,” *Radioengineering*, vol. 34, pp. 342–352, 06 2025.
- [112] N. Merabtine, D. Djenouri, and D.-E. Zegour, “Towards energy efficient clustering in wireless sensor networks: A comprehensive review,” *IEEE Access*, vol. 9, pp. 92 688–92 705, 2021.
- [113] T. Ajewole, O. Olatunde, K. Hassan, A. Olawuyi, and O. Onarinde, “Comparative study of the performances of three metaheuristic algorithms in sizing hybrid-source power system,” *Turkish Journal of Electrical Power and Energy Systems*, vol. 2, 05 2022.
- [114] D. C. Montgomery and G. C. Runger, *Applied Statistics and Probability for Engineers*, 7th ed. Wiley, 2021.

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