Flying Ad-hoc Sensor Network Cluster Optimization using Bee Intelligence for Internet of Things

Ph.D. Thesis

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Declaration

I, Abdusalam, hereby declare that my Ph.D. thesis titled "***Flying Ad-hoc Sensor Network Cluster Optimization using Bee Intelligence for Internet of Things,***" is my work, neither as a whole nor as a part thereof has been copied out from any source except where due reference is made in the text. It is further declared that I have not previously submitted the work presented in the thesis report for partial or full credit for the award of degree at this or any other university.

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Dedication

To My:

Parents Babba, Aday, Wife,

Kids: Saad, Ammar, Hamna and Ayad,

Brothers & Sisters,

Teachers,

and

Friends

Abstract

Flying Ad-hoc Sensor Network (FASNET) for Internet of Things (IoT) consists of Unmanned Aerial Vehicles (UAVs) and Ground Segments (GS). During last decade, FASNET witnessed a high interest in academia and industries due to various applications such as remote sensing, monitoring, observing, tracking, etc. UAVs operate manually or automatically. The UAVs have a different nature than ordinary Mobile Ad-hoc Networks (MANET) and Wireless Sensor Networks (WSNs). UAVs' flying speed and diverse directions make it harder to route the information in the desired way. Data among the UAVs may be collected based on contract opportunities, and hence, timely delivery may not be guaranteed. To ensure the desired operation of FASNET, the data delivery among UAVs or UAVs to cluster head (CH) or the Base Station (BS), either deployed in the air or ground, should be in an efficient manner. Due to the UAVs constraints such as energy, mobility, a degree in FASNET, the procedure to select optimum CH, formation of the balanced cluster, accurate targets identification, and data aggregation needs careful consideration. The researchers tried to tackle the issue using a cluster-based routing approach, but this area is still in infancy.

To increase the Network lifetime first a novel bio-inspired approach is developed that optimizes energy, mobility, and degree parameters as a selection and evaluation criteria for UAVs-CH and balanced cluster formation. Second, we proposed clustering and localization of Multi-UAVs to accurately identify the Target Areas (TAs) in the field of precision agriculture. The TA (i.e., the affected crops area due to environmental factors) identification and delivery of timely information about diseases in the crops to the Ground Station (GS) are mandatory to make the preventive measurements. The accurate TAs by multi UAVs depends on the weights of environmental factors, i.e., relative humidity, temperature, light intensity, soil moisture, NPK (nitrogen (n), phosphorus (p), potassium (k)), and power of hydrogen (pH). Once clustering and localization are performed, the ordinary UAVs transmit data to their UAVs- CH. Third, a data aggregation scheme is proposed to save energy consumption and bandwidth. The data aggregation scheme is applied at the cluster level to minimize communication load on the CH and save bandwidth and energy. Next, the bio-inspired approach has experimented with many topologies in various flying ad-hoc sensor network scenarios. The results are compared with the existing swarm intelligence-based optimization schemes. The results are validated via a simulation that demonstrates the effectiveness of the proposed approach.

Keywords: *Flying sensor, Unmanned Aerial Vehicles, Bee intelligence, Clustering Optimization, IoT*

List of Acronyms

ACO	Ant Colony Optimization
BCO	Bee Colony Optimization
BIC	Bio-Inspired Clustering
BS	Base Station
BICSF	Bio-Inspired Clustering Scheme for FANET
BIMAC	Bio-inspired mobility aware clustering optimization
BICTID	Bio-Inspired Cluster based optimal Target Identification
BIMPC	Bio-Inspired Mobility Prediction Clustering
BOLD	Bio-Inspired Optimized Leader Election for Multiple Drones
CBLADSR	Cluster-Based Location-Aided Dynamic Source Routing
CM	Cluster Member
CH	Cluster Head
CCFGAIR	China Computer Federation Global AI & Robotics Summit
CH-UAV	Cluster Head-Unmanned Aerial Vehicle
DCPMO	Dynamic Clustering Protocol for Mission Oriented
EALC	Energy Aware Link-based Clustering
EE-UAV-DA	Energy Efficient UAV based Data Aggregation
EEDG	Energy Effective Data Gathering
ERSUAV	Efficient Routing Strategy for UAV
ESDA	Energy Saving Data Aggregation
FASNET	Flying Ad-hoc Sensor Network
FANET	Flying Ad-hoc Network
FA	Fireflies Algorithm
FOA	Fruit Flies Algorithm
GA	Genetic Algorithm
GMM	Gauss Markvo Mobility
GPS	Global Positioning System
GSO	Glowworm Swarm Optimization
GS	Ground Station
GSO	Glowworm Swarm Optimization
GWO	Grey Wolf Optimization
HBMO	Honey Bee Mating Optimization
IMU	Inertial Measurement Unit

LiDAR	Light Detection and Ranging
MACSI	Mobility Aware Clustering based on Swarm Intelligence
MANET	Mobile Ad-hoc Network
MLSC	Mobility and Location-aware Stable Clustering
MOUT	Military Operation in Urban Terrain
MPCR	Mobility Prediction Clustering Routing
MPCA	Mobility Prediction Clustering Algorithm
MPBC	Mobility Prediction-based Clustering
MTS	Minimum Time Search
Multi-UAVs	Multiple Unmanned Aerial Vehicles
NIR	Near-Infrared Radiation
NPK	Nitrogen (N), Phosphorus (P), Potassium (K)
OC-mUAV	Optimized communication for multi-UAV
OER	Onlooker Employed Ratio
OF	Objective Function
PDR	Packet Delivery Ratio
PH	Power of Hydrogen
PSO	Particle Swarm Optimization
PPO	Physarum Polycephalum Optimization
PPM	Path Planned Mobility
RPGM	Reference Point Group Mobility
RRGM	Reference Region Group Mobility
RWM	Random Waypoint Mobility
SIC	Swarm Intelligence Clustering
SMO	Spider Monkey Optimization
SOCS	Self-Organization based Cluster Scheme
SWIR	Short-Wave Infrared Radiation
SRCM	Semi-Random Circular Movement
TAs	Target Areas
TA-UAV-DA	Topology-Aware UAV Data Aggregation
TDM	Time Dependent Mobility
TSP	Traveling Salesman Problem
UAV	Unmanned Aerial Vehicle
UAV-DA	UAVs Assisted Data Aggregation
VANET	Vehicular Adhoc Network
WSN	Wireless Sensor Network

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Research Contribution

The following Research Papers related to this thesis are published in international conferences and journals during Ph.D. research.

International Conference Paper:

1. **A. Salam**, Q. Javaid, M Ahmad, G. Ali, F. Ahmed, I. Wahid "Flying Sensor Network Optimization Using Bee Intelligence for Internet of Things" *Intelligent Systems and Applications (SAI Intelligent Systems Conference) Springer*, Vol. 1252, pp. 331-339, 2020.

International Journal Publication:

1. **A. Salam**, Q. Javaid, M Ahmad., "Bioinspired Mobility-Aware Clustering Optimization in Flying Ad Hoc Sensor Network for Internet of Things: BIMAC-FASNET," *Complexity, Hindawi,* vol. 2020, pp. 1-20, 2020. **[IF: 2.833]**
2. **A. Salam**, Q. Javaid, M Ahmad., "Bio-Inspired Cluster-Based Optimal Target Identification (BICTID) Using Multi UAVs in Smart Precision Agriculture," *International Journal of Distributed Sensor Networks, Sage,* vol. 17, no. 7 pp. 1-17, 2021. **[IF:1.640]**

Chapter 1

Introduction

Internet of things (IoT) refers to the network of different computing devices embedded in everyday objects, including buildings, plants, animals, humans, vehicles, trains, unmanned aerial vehicles, etc. They share information over a wireless medium without the assistance of computer and human interaction [1]. These objects communicate with each other for a specific purpose. The objects can be positioned in the air or on the ground, which performs part of a router or a sensor, or both. The use of UAVs in the air in an ad-hoc manner is increasing day by day. Its role has changed into the 'Go-To' platform for many remote sensing applications.

1.1 General Background and Motivation

FASNET is a collection of multiple UAVs flying in the air connected, sensors, and GS with the ability to share information. Movement of these UAVs is very frequent compared to other ad-hoc networks [2]. The use of multi-UAVs improves the response time during searching, detecting, sensing, and monitoring operations. The sensing, communication, and computation cost can be decreased by using multiple small UAVs in terms of maintenance instead of costly and extensive ones. The addition of new UAVs in the existing UAVs network is easy to enhance scalability in critical situations. In case of failure of any single UAV, the mission will not be affected because of other UAVs that will continue the task to the desired end.

In FASNET, flying UAVs may perform as part of a router, sensor, or both. The role of the UAVs is varied from the nodes in an ad-hoc or conventional wireless sensor network [2]. The UAV's movement in the air consumes more energy. The energy-efficient communication among UAVs and UAVs to or from GS has several issues due to energy constraints, communication range, link expiration, high mobility, data aggregation, and frequent topology changes. These issues depend on the architecture of its clustering, localization of UAVs to accurate TAs identification, and data aggregation that needs to address the successful implantation of FASNET.

Clustering is the key aspect of improving UAVs network reliability and network lifetime. The development of a UAVs clustering scheme that routes the information efficiently is a critical issue. The UAVs are organized into clusters in clustering, each with its cluster head (CH) and cluster member (CM). The CM communicates with its CH. In cluster-based routing, routing of information updates locally, resulting in stability and efficiency at the cluster level. The member UAVs communicate only to its CH, which reduces routing overhead. The optimum CH selection and formation of the balanced cluster is a complex task. Still, it prolongs UAVs' network lifetime. Application of multiple UAVs in FASNET ties with the idea of swarm, which originates from nature, such as the organization of particles, bees, fireflies, ants, wolves, etc. The concept of clustering based on swarm approaches has attracted many researchers for the last one and a half decade.

The UAVs localization is used to locate Optimal Target Areas (OTAs) by considering communication range, topology, link expiration time, residual energy, and mobility. The localization and identification of TAs are based on the type of nodes. The nodes may be either GPS enabled or without it and in range or out of range. The range-based TAs identification scheme provides a more accurate and precise location than range-free based localization. Still, the methods may also vary based on error rate, accuracy, and computation cost [3-5].

Data aggregation approach reduces network capacity, communication cost, and bandwidth usage while obtaining aggregated information. After the cluster formation and localization, next step in FASNET is data aggregation, which aims to transmit data among UAVs, CHs, or GS. The concept of many-to-few is used in data aggregation. The data aggregation protocol defines how the UAVs gather information, how the aggregated information is routed to the destination, and when should send the aggregated information.

1.2 Applications of FASNET

The use of multi-UAVs in FASNET is not limited to destruction on the battlefield but is also applied for the betterment of human beings in different areas to reduce human encroachment and human labor. UAVs are commonly used for remote sensing, monitoring, tracking, and protecting [6]. There are numerous application scenarios to perform multiple tasks using flying UAVs. These UAVs communicate in ad-hoc modes to accomplish a specific mission in a distributed manner. The multi-UAVs technology has established a new era of applications due to the growing interests of users such as search and rescue operation, forest fire detection, traffic and urban monitoring, reconnaissance and patrolling, disaster management, and precision agriculture.

1.2.1 Search and Rescue Operations

Multi-UAVs quickly search or sense object or target on the ground in search and rescue missions. The multi-UAVs technology is used to find and detect the object in the unreachable area, which humans do not easily see. Different strategies are used for searching and detecting with minimum time, considering routing information, energy, and mobility of UAVs [7-9]. The critical issue is UAVs' mobility, which depends on their type and infrastructure. The TA and routes are predetermined at the beginning of the mission for quick response. The UAVs are continuously associated with BS for monitoring and transmitting data using aggregation approach. In emergency or rescue scenarios, real-time exchange of information is needed that guarantees reliable communication due to transmission impairments or obstacles.

1.2.2 Forest Fire Detection

Loss due to fire in the forest has a major impact on the environment. The fire may be on the ground surface or crown. The application of multi-UAV is to prevent the risk of fire or heat that may cause huge losses. Researchers tried to detect, measure, monitor, and control forest fires by using different approaches [10, 11]. These approaches are based on different mobility models and topology for the distinct scenario to keep the desired formation during monitoring. The UAV may be a stationary node that acts as a sensor or with mobility in the area of interest. The UAVs cooperate to detect fire and change the topology to move towards the affected area for monitoring purposes.

1.2.3 Traffic and Urban Monitoring

The numerous accidents and traffic jams in a complex infrastructure of metropolitan and urban areas can be monitored and resolved with the help of multi-UAVs. The UAVs easily and quickly identify and obtain statistics about the tracks, roads, or street junctions by capturing the real scenarios. There are different FASNET schemes proposed that observe the routes. The military operation in Urban Terrain (MOUT) monitors urban areas with military assets [12]. In FASNET, multi-hop communication [13] improves the range of observation tasks by establishing a link chain of flying nodes. The author in [14] proposed how flying UAVs are deployed in the street junctions. The UAVs coordinate and share evidence with BS due to long distance between the UAVs, targets, and BS. The optimization method is required to improve the performance with fewer UAVs. The optimization makes a system up to a specific number of targets because real-time communication is needed in this type of scenario.

1.2.4 Reconnaissance and Patrolling

The application of UAVs swarm is to detect the specific crime zone safe and free. During patrolling, the multi-UAVs capture the events, objects, and TAs. The UAVs visit in the area of interest to detect, examine or protect from suspicious or inexperienced movement. The UAVs notice and observe changes in the areas of interest such as drugs, crime, weapons, etc. [15]. During the mission, multi-UAVs patrol and reconnaissance the routs that are not expected. The random changes in their positions and routes are according to the situation [16]. The multi-UAVs communicate updated information and change the topology and routing method accordingly.

1.2.5 Environmental Sensing

The most challenging tasks are awareness, heterogeneity, secure communication, trust management, and cooperation among UAVs. The need for an intelligent environment is because the UAVs produce a massive amount of data incessantly; the gathered data needs to be transformed into intelligence to provide a smart environment. The smart environment plays a vital role in disseminating the network's data. The UAVs have low power batteries to examine environment temperature, humidity, pollution levels. The adaption of UAVs in FASNET with integration, mobility, and heterogeneity features can easily monitor and obtain information from the terrain [17].

1.2.6 Disaster Management

The application goals of multi-UAVs and sensors in disaster management are to forecast the incidence of disaster in advance [18]. The UAVs predict and monitor the early awareness of disaster with environmental factors. The awareness about the environmental factors is based on the sensing technologies that detect the matters and perform reliable data communication from sensor nodes. The main objective is to collect data from multiple sources to build a connection among various information technology during the assessment of information in disaster management. Different systems proposed by the authors such as mobile autonomous systems implemented in emergencies areas [19], heterogeneous vehicles controlled systems through FASNET to achieve complicated operations in automated humanitarian missions[20], and intelligent public safety systems using heterogeneous nodes such as flying nodes and ground components [21].

1.2.7 Agricultural Management

The application of FASNET in agriculture in which UAVs remotely sense crops and protect them from environmental factors. The UAVs provide required amount of fertilizer and chemicals for crops and soil at a specific time and location. The precise and accurate resolution for particular field management is necessary to monitor plants' health, status, soil properties, and water contents [22]. In precision agriculture, various multi-UAV schemes are used to monitor crop health status, soil properties, and water contents. The information in precision agriculture is obtained easily and quickly by multi-UAVs within a short time. These UAVs visit the given range periodically with predetermined paths. UAVs swarm with optimized flight paths manage water contents for plants and irrigation control [23, 24].

The application of multi-UAVs in precision agriculture for locating and identifying the affected area in crops has many issues. The FASNET platform in the precision agriculture domain plays a vital role in discovering the affected area and observing the crop field with excellent spatial and temporal resolution compared to the satellite platform. This platform first identifies the TAs and then captures the particularities of the plant's leaves, stems, roots, and fruits from a unique point of view that is not easily visible from the ground [25]. The UAVs with non-invasive sensors remotely sense/orthophoto the crops at tiny pixel sizes to improve the resolution. The reaction of the plants due to new pesticides, herbicides, fungicides, and fertilizers can be observed easily. The information obtained by UAVs help the farmers to decide on time, utilizing resources efficiently with low cost and saving time due to regular visits of UAVs [26].

1.3 Architecture of FASNET

The FASNET architecture has multiple UAVs and ground stations, as shown in Figure 1.1. A brief description of these components is presented in the following subsections.

1.3.1 Unmanned Aerial Vehicle

The UAV is an aircraft system commonly known as a drone operated automatically without human intervention. The role of UAV has changed into the "Go-To" platform for many remote sensing applications. In architecture, the multiple UAVs can fly

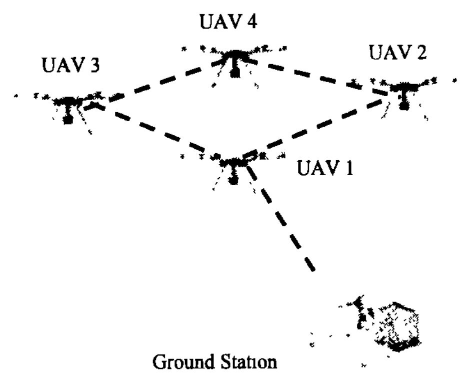


Figure 1.1: FASNET Architecture

remotely to detect, store, and communicate information to the GS. The inertial measurement unit (IMU) enable GPS embedded on the UAV board to provide precise and accurate location information. The GPS is used to locate the coordinates of UAVs and IMU for the effects of roll, pitch, and yaw [27]. The application program Polygon tool is used for flight planning with precise and accurate GPS points within which the UAV with sensors will operate. The wide variety of UAVs available with thermal, Light Detection and Ranging (LiDAR), multispectral and hyperspectral sensors in the market depend on the application scenario. These sensors use a non-invasive approach for sensing information from the fields.

1.3.1.1 Thermal Sensor

Thermal sensor provides aerial thermal imaging for analysis and reporting by measuring the relative surface temperature of land and objects. This sensor is used to gain insight into water use, heat stress, canopy temperature, etc. The application of thermal detectors is not limited only to precision agriculture. Still, it can also gather valuable information in a wide variety of industries like construction, energy, government, and insurance [28-32].

1.3.1.2 LiDAR Sensor

LiDAR sensor measures the ranges with reflected light. This sensor uses laser emitted light energy to produce maps, elevation data, and 3D models of natural and artificial objects with high resolution compared to other aerial survey methods. The applications of LiDAR are in various industries, like agriculture, construction, energy, and others, need clarity and exact results [33, 34].

1.3.1.3 Multispectral Sensor

Multispectral sensors capture Short-Wave Infrared Radiation (SWIR), Near-Infrared Radiation (NIR), and ultraviolet light beyond human vision. The multispectral sensor is used to capture information on the reflection of light energy off objects in the environment. The multispectral sensors are helpful in the identification of pest damage, assessing water quality, optimizing fertilization, and monitoring crop health [35-38].

1.3.1.4 Hyperspectral Sensor

Hyperspectral sensor is the most dominant among others to capture data. The UAVs-based hyperspectral sensor collects data with very narrow bands of spectral contents. The hyperspectral sensor is used to detect and identify minerals, vegetation, crop diseases, water quality, foliar chemistry, plant nutrients, and objects that are not easily identifiable by other sensors and human vision [39-45].

1.3.2 Ground Station

Ground station is a system controller that comprises of computers, software, and communication systems. The computer system receives the UAVs' information and applies processing tools to extract the desired information. The software tool interprets, analyzes, process, extracts information obtained from the UAVs, and provides precise and accurate results, e.g., in precision agriculture, the tools like Precision Analytics Agriculture, Hyperspec® III, and SpectralView®, etc. [46]. The software stores and manages the routing information of UAVs flights to avoid collision during flight. The flight path planning of UAVs remotely is very complex. The application program Polygon Tool is used for flight planning with precise and accurate GPS points within which the UAV will operate. It has storage space, saves battery life, and assures a more accurate data collection mission. The communication system provides an interface for communication among UAVs, GS, and ground segments.

1.4 Cluster-Based FASNET

FASNET is a developing area. It makes the connection of UAVs, BS, and GS, as shown in Figure 1.2. Routing information among flying UAVs is a thought-provoking task. It is a burning issue. It has taken the attention of researchers recently [47]. In FASNET, due to large number of UAVs, the network structure is divided into groups called clusters. Each cluster has multiple UAVs called Cluster Member (CM) and

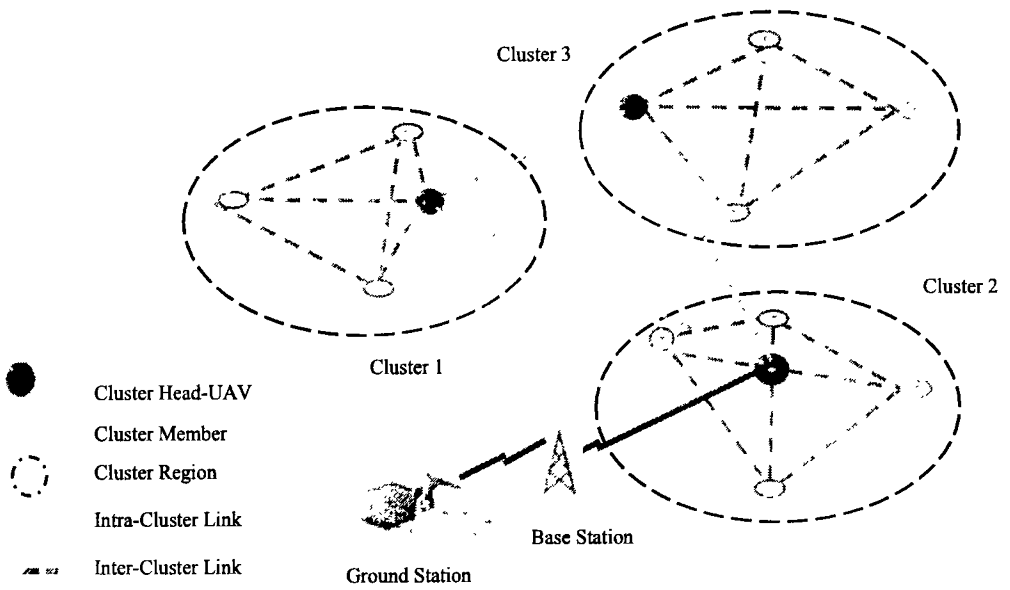


Figure 1.2: FASNET Cluster based Network Model

UAVs-CH. The member UAVs only communicate with its UAVs-CH. The UAVs-CH use a cumulative method to get information from member UAVs. The UAVs-CH in multi-hop networks results in low latency instead of flat routing. It fails due to high mobility, many UAVs, dynamic change in topology. Due to clustering the UAVs intra-cluster routing information update locally that shows consistency and effectiveness at UAVs-CH level. In the clustering process for communication, re-use of frequency avoids collision and non-overlapping clusters. The benefit is that unused bandwidth can be utilized for other purposes. The routing overhead is reduced because the member

UAVs only communicate with UAVs-CH. In FASNET, cluster formation is complex due to application priorities for UAVs placement, cluster degree, and CH selection to prolong the network lifetime. Besides this, the UAVs-CH is responsible for communicating inside and outside the cluster. The mobility of UAVs is very high, ranging from 10 to 30 m/s [48]. The TAs identification and path selection depend on the speed, direction, and range in most of the scenarios of FASNET. In some applications, information delay is not acceptable such as in precision agriculture, border supervision, search and destroy operations. The reliability of the communication link is required to provide real-time communication because the link may be down, the energy may be low, or the interference may occur. To overcome these issues, designing of cluster-based routing requires considering these issues to enhance FASNET lifetime.

1.4.1 Designing Goals

Designing efficient cluster-based routing for FASNET relies on several aspects that provide reliable inter-cluster and intra-cluster communication.

i. In FASNET, cluster formation is a complex task because different applications prioritize UAVs pre-arrangement, cluster size, and CH selection. In addition, how they communicate inside and outside the cluster is the responsibility of cluster head. Different parameters are considered during the process of clustering formation.

ii. CHs gather data from its cluster members using an aggregate manner. It is tedious to equally place the UAVs in the clusters without affecting the expected performance goals to balance the payload. The cluster with the same size extends network lifespan, decreases energy utilization, and avoids data delay.

iii. The UAV mobility is high comparatively. Due to its autonomous nature, path selection is primarily dependent on the earlier direction and speed. In FASENT application-dependent mobility models are used in which flexibility for paths selection are favored by flying UAVs.

iv. Most applications in FASNET need a quick response of data during the mission. They cannot compromise on data delay in precision agriculture, border supervision, rescue operation, search and destroy operation, surveillance, and reconnaissance. Hence, applications requirement are considered during designing cluster-based routing techniques.

v. In most applications, energy constraints directly impact the lifespan of the network. In cluster-based routing for FASNET architecture, the UAVs with resources such as high energy will be selected. The energy utilization of nodes can be reduced by placing the CHs in an inter-cluster in which all member nodes can easily communicate. The energy-efficient formation of clusters extends the network lifetime.

vi. During the mission, UAVs can die, the link can be down, and interference can occur in FASNET. The establishment of a reliable connection is required to provide real-time communication. To ensure reliable communication, there should be a cluster-based routing mechanism to recover the network from such a collapse.

vii. The essential factor in designing a clustering algorithm for FASNET is the quality of service. The division of networks in sub-networks (cluster) based on the clustering technique increases service quality. During inter-cluster or intra-cluster communication, congestion management and collision avoidance are easy compared to other ad-hoc network. Traffic monitoring, shaping, and link efficiency mechanisms also provide quality of service.

1.5 Swarm Intelligence-based Optimization

The multi UAVs clustering exploration and investigation is an evolving technology. The application of UAVs in a group matches with the idea of the swarm, which originates from nature like the organization of wolves, monkeys, fireflies, particles, ants, bees, frogs, etc. An intelligence of social creatures in a group is called Swarm intelligence [49]. Author proposed the UAVs swarm in 2000 and presented the 5S (Swarm, Safe, Smart, Small, and Speed) trend concept at China Computer Federation Global Artificial Intelligence & Robotics Summit (*CCFGAIR*) in august 2016. Due to this concept, the swarm clustering approach has attracted many researchers from both academia and defense. The swarm of UAVs functions can be performed resourcefully by using optimization algorithms. There are several optimization approaches such as Bee Colony Optimization (BCO) [50], Glow-warm Swarm Optimization (GSO) [51], Particle Swarm Optimization (PSO) [52], Ant Colony Optimization (ACO) [53], Grey Wolf Optimization (GWO) [54] and Genetic Algorithm (GA) [55] have used for finding optimal solutions. These optimization approaches are discussed in Chapter 3 in detail.

The cluster-based FASNET performance depends on the optimization algorithm for the optimal solution. In our research, bee-swarm intelligence-based clustering, localization for TAs identification, and data aggregation algorithms are proposed in the field of precision agriculture. The foraging properties of the honeybee are used to form clusters and select optimum CHs. Honey bees find food with more nectar efficiently. The honeybee's foraging behaviour is used to select suitable UAVs as CHs efficiently. This technique is simple, find local solutions, not costly, implementable, and resolve complex functionalities. The optimization schemes have been discussed thoroughly in the literature.

1.6 Challenges and Requirements

Despite numerous applications, multi-UAVs network still has many challenges; Each UAV in the FASNET commonly suffers from a limited lifetime of the battery issue. In most applications, energy constraint directly impacts the network lifetime. In FASNET, due to large number of UAVs, the network structure divides into groups called clusters to balance the load and reduce the energy consumption of each UAV. Identifying UAVs in a cluster and eliminating redundant data aggregation is a challenging task.

As identified in the literature, communication challenges arise due to limited energy, high mobility, UAVs density, communication load, etc. These challenges are:

i. Energy constraints
ii. Dynamic change in topology due to increased mobility
iii. Optimum CH selection
iv. Balance cluster formation
v. Localization of multi-UAVs
vi. Accurate target identification
vii. Redundant data aggregation Elimination

Designing localization and energy-efficient clustering schemes is the demand of today's multi-UAVs network. In FASNET, clustering of multi-UAVs is a dynamic problem. The clustering optimization scheme is required to solve the energy problems of UAVs. In this way, the optimal CHs will be selected. The size of the backbone network will be minimized, and the network lifetime will be increased.

The localization and clustering optimization scheme must have provisions for stable CH selection, balanced cluster formation, and maintenance to decrease the cost, time, bandwidth, battery, etc.

1.7 Aims and Objectives

In FASNET, due to large number of UAVs, network structure is divided into clusters to balance the load and reduce energy consumption. As previously discussed in this chapter, limited lifetime of UAVs batteries directly impacts the cluster lifetime. FASNET is operating in a dynamic environment. Therefore, this research aims to prolong the UAVs cluster lifetime by mapping the clustering problem into dynamic optimization. One of the primary objectives of this research is to identify the parameters for clustering optimization schemes that need to optimize clustering, localization, and data aggregation approaches for energy efficiency. The objectives of this research are to increase the FASNET lifetime as follow:

1. Exploring and analyzing various clustering optimization, localization, and data aggregation schemes based on different parameters, factors, and swarm intelligence that is required for energy efficiency.
2. Developing clustering-optimization-scheme based on the foraging behaviour of honeybees to select an optimum CH and formation of balanced clusters considering the parameters energy, mobility, and degree.
3. Designing of bio-inspired localization and clustering scheme for the identification of optimal TA based on environmental factors.
4. Designing a bio-inspired data aggregation algorithm for CH selection that detects and prevents duplicated data transmission to minimize message overhead and increases network lifetime.

Bio-inspired localization, clustering, and data aggregation schemes are designed to accomplish the aforementioned objectives. The performance of the proposed methods are compared with state of the art schemes in terms of different performance metrics and validated via a series of simulation experiments using MATLAB.

1.8 Scope of the Study

Scope of this research is broad; the UAVs of FASNET can be applied to many practical scenarios like precision agriculture, smart cities, intrusion detection, intelligent transportations, and smart buildings utilizing low-cost flying UAVs. This will help society by using advanced technology and working remotely with ease. In this research, our focus is on precision agriculture. For example, in smart agriculture using flying UAVs, the former will be informed about crops' diseases and irrigation requirements due to environmental factors on time. In other areas, such as in rescue operations, to detect the humans using UAVs in affected regions or find the unreachable place is not easy to see for human beings. In forest monitoring, to prevent the risk of fire, the UAVs can measure, monitor, and control forest fire with different mobility models of flying UAVs with a topology that keeps the desired formation during monitoring. In smart transportation, managing traffic jam situations and monitoring road or railway tracks incidents can be easily handled using multiple UAVs to reduce personnel costs. In border supervision, UAVs are used to protect from illegal immigrants, weapons smuggling, etc. Theoretically, this study's results and experiments can be extended to any scenario and can be implemented in a practical situation.

1.9 Research Contribution

The following novel contribution has been made in the field of FASENT during the research work carried out:

First, we propose Bio-inspired mobility-aware clustering optimization (BIMAC) scheme to increase the UAVs network lifetime. The UAVs network clustering issue is formulated as a dynamic optimization problem. An algorithm based on honeybee's foraging behavior is designed to select the optimum CH and form a balanced cluster by considering the UAVs energy, mobility, and degree to maximize the cluster lifetime.

Secondly, a Bio-Inspired Cluster-based optimal Target Identification (BICTID) scheme is proposed to localize the UAVs based on identified TAs in the tomato crop field with the help of optimization of environmental factors. The design and development of UAVs swarm algorithms for TAs identification are based on honeybee swarm intelligence. The TAs identification depends on the weights of environmental factors, i.e., relative humidity, soil moisture, temperature level, light intensity, NPK (nitrogen (n), phosphorus (p), potassium (k)), and power of hydrogen (pH). Environmental factors are modeled to an optimization function to obtain optimal TAs. The formation of the cluster is based on the requirements to avoid unnecessary computations. The proposed algorithm will provide accurate TAs identification as compared to other existing algorithms discussed in the literature.

Third, to minimize the load on multi-UAVs CH, a data aggregation approach named Flying Sensor Network Optimized-Communication and Data-Aggregation (FSNet-OC-DA) is proposed to save energy consumption and bandwidth utilization. The data-aggregation procedure is applied at the cluster level to minimize communication by avoiding duplicate data to the CHs and saving bandwidth and energy. The data aggregation approach is different in WSN and VANET from UAV networks. In WSN, the uses of the data aggregation approach are for decreasing energy consumption rather than minimizing network capacity usage. In VANET, due to high variation in the topology, the data aggregation is performed by many vehicles. Energy factors constrain the multi-UAVs system due to degree, mobility, density, and other parameters. It combines the requirement of sensor and vehicular ad-hoc networks. The UAVs also consume more energy to process and store more data like on-flight communication [56].

1.10 Structure of the Thesis

The structure of the thesis is organized as follow:

Chapter 1 Introduction describes general backround, applications, clustering overview, challenges, and objectives of the research.

Chapter 2 explains the basic parameters of the thesis and environmental factors used for target area identification in precision agriculture. These parameters and other factors are further used to evaluate localization and clustering schemes considered in this thesis. The mobility models considered for the proposed and existing systems in the literature are discussed in this chapter.

Chapter 3 present and summarize literature review, findings of the various state of art clustering, localization, and data aggregation schemes based on different parameters, factors, and swarm intelligence that is required for energy efficiency.

Chapter 4 describes the methodology to achieve the objectives of this research. The methodology consists of several inter-dependent sub-phases that show the working procedure in a figure of the research framework. Bee intelligence, fitness function, and performance metrics for the proposed schemes are added at the end of this chapter.

Chapter 5 presents the clustering optimization scheme based on honeybee foraging behaviour to select the optimum CH and form balanced clusters considering energy, mobility, and degree parameters.

Chapter 6 presents the bio-inspired localization and clustering scheme based on the optimum target area in precision agriculture. Furthermore, the measurement of environmental factors demonstrated the localization and cluster formation of multi-UAVs.

In chapter 7, to save energy and bandwidth, the Honey Bees-based Clustering and Data-Aggregation algorithm for CH selection is presented to detect and prevent duplicate data transmission that minimizes message overhead and increases network lifetime.

Chapter 8 presents the conclusion and summary of the research. The chapter concludes this research work with recommendations and suggestions for future directions.

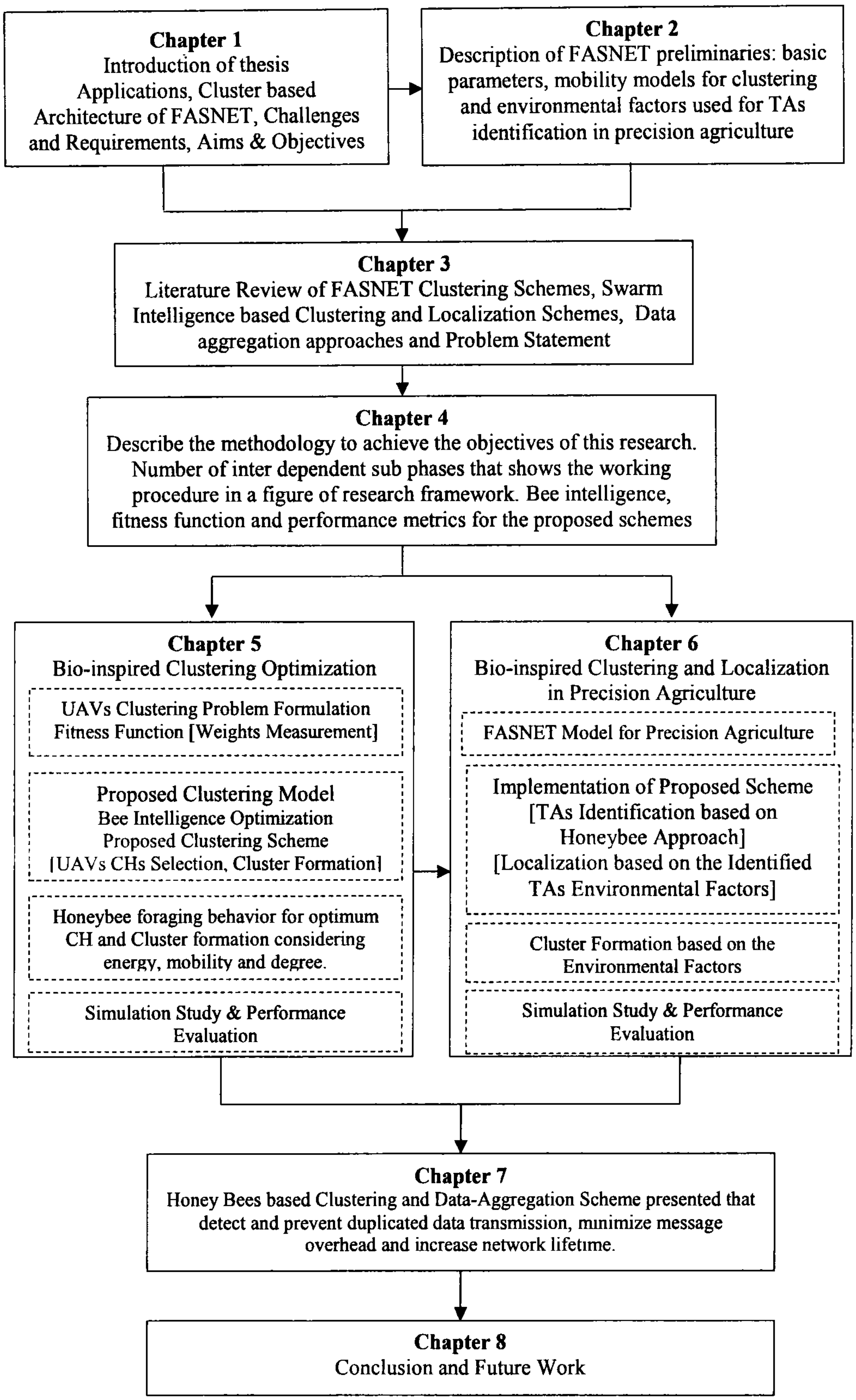


Figure 1.3: Chapter wise Structure and Workflow of Study

Chapter 2

Flying Adhoc Sensor Network Preliminaries

This chapter explains the importance of multi-UAVs in precision agriculture and the environmental factors used for localizing UAVs to identify the target areas. The basic parameters of this research are discussed, which are further used to evaluate clustering and localization schemes.

The scope of this research is broad; the UAVs in FASNET can be applied to many practical scenarios like smart agriculture, intrusion detection, smart cities, smart transportations, and smart buildings using low-cost flying sensors. Society will benefit by using advanced technology and working remotely with ease, e.g., in smart agriculture using flying UAVs; the former will be informed about the diseases in crops and their irrigation requirements in a timely manner.

2.1 Multi-UAVs Mobility Models

These mobility models give a full pattern based on UAVs' velocity, position, direction, speed, etc. These models are mandatory to be compared with the real-life pattern. This plays a key role during simulation, especially in the performance of clustering schemes. The UAVs move with high mobility, so the change in topology occurs frequently. The clustering schemes for the multi-UAVs network in the literature have commonly used the Random Waypoint (RWM) [57], Gauss Markov Mobility (GMM) [58], Reference Point Group Mobility (RPGM) [59], and Path Planned Mobility (PPM) [6] models. The proposed schemes in this research follow the RWP mobility model [60]. The mobility models are summarized in Table 2.1.

2.1.1 Random Waypoint Mobility Model

RWM model came in the pure randomized mobility model category and was proposed in 1996 for the first time by Johnson and Maltz [57]. Here, arbitrary movement of mobile UAVs is appended between its direction & speed interval. The interval is very short, which means a few seconds. The UAV selects an arbitrary destination. When it reaches, then it stops for a while. Again, it repeats this practice. The UAVs move openly, having no specified direction and limitation. It shows that UAVs find their speed, direction & destination independently. The application of this model is in the monitoring of urban areas, traffic, patrolling, environmental sensing, etc. Importantly, this model is also fit for aircraft networks. The reason behind this is its quick changes in direction and speed. Furthermore, it is based on previous movement and neighbour UAV [61].

2.1.2 Gauss Markov (GM) Mobility Model

This model comes under the category of time-dependent mobility (TDM). It uses different mathematical equations. It smoothly affects the speed and direction. This model is used for clustering protocols, especially in a wireless network [58]. Here, the direction and speed are adjusted first for each UAV. Further, the movement of the UAV is developed accordingly after each interval. More importantly, direction, previous speed & position are essential in this model. It is usually applied for simulating the swarm of UAVs' disposition in a different area. UAVs have high speed & mobility, due to which their position becomes dependent on the previous one, stored in the memory [59, 62]. Comparatively, this model decreases the abrupt stop and quick turn based on the related history of direction & speed. It is widely used in search, environmental sensing & rescue operation.

2.1.3 Reference point group (RPG) Mobility Model

This RPG model makes UAVs group for mobility in a specific area [59]. The UAVs used reference points (RP) to move openly at a distance. Each group's RP (i.e., CH and CM) is different. It is used to find member UAV positions. The RPG model is commonly used in the clustering approach. The CH movement describes the mobility behaviour of the whole group with a particular RP; each member UAV is assigned the mobility. A predetermined pattern followed for the UAVs group movement. In a range of communication, the member UAVs are located randomly [61]. The application of this category is into search, rescue operations, and environmental sensing. Some of the models of this category are CLMN, NC, and PRS.

2.1.3.1 Column Mobility Model

This model is made for multi-hops wireless networks. Here, with low-power transmission and medium, mobile UAVs exchange information. This model is applied to search a target in a particular region [63]. The UAVs move around an RP. It is placed in a predetermined way. The new place of every RP is estimated. The advance vector of the line is depicted at the interval time or based on the previous position of RP. Keeping the UAVs' movement around a particular point with a predetermined path and distance. This model hampers the collision and connection-oriented transmission established with constraints among the UAVs within the same group. In this model, the smooth turn of UAVs and random speed fluctuation are not present [6].

2.1.3.2 Nomadic Community (NC) Mobility Model

In this model, UAVs move randomly around a specific RP. The movement is random at each time interval. Here, UAVs share a common space. The flying space is divided and manages the distance among UAVs solely to escape from a collision. The unpredictable changes may occur due to direction, speed, reference points. Here, two things are absent: UAVs' smooth turn and speed fluctuation [6].

2.1.3.3 Pursue (PRS) Mobility Model

This model is closed to NCM. They have the same features. The UAVs pursuing the target use a random and straightforward relative motion. Later on, it follows a specific target. The specified direction is used for movement. It plays a role like a police officer chasing and catching criminals [6].

2.1.4 Path Planned (PP) Mobility Models

The PPM model works on a fixed pattern followed by UAVs during simulation. Every moment here is based on a particular pattern. It goes from one point to another. The pattern usually changes. Sometimes, it may be the same [6]. This model can be applied in agricultural management, traffic monitoring, and urban area. These models are SRCM and PPRM.

2.1.4.1 Semi-Random Circular Movement (SRCM) Mobility Model

SRCM mobility model is made for UAVs dependent ad-hoc networks. Here the movement of UAV is circular or curving [59]. The UAVs detect a specified region during simulation. It also acquires information about the area. This model fits where the movement is around of specific region. The UAVs progress towards the first desired target in the same area. UAVs wait for the pause time there and then move to another point. When it completes the round. It starts moving towards another circle randomly [6]. The flight destination of UAVs is not predetermined. But it looks for a target in a different location in the region.

2.1.4.2 Paparazzi (PPR) Mobility Model

PPRM depends on stochastic versatility. This copies features of paparazzi in the form of a UAV system [64]. It works in light of a static machine to carry a state based on a movement pattern, e.g., scan, oval, waypoint, eight, and stay-at. The movement type of each UAV is defined at the start. It has an initiating position. It has a specific speed at the beginning. Later, it exhibits a random attitude. The UAVs' positions are selected randomly. It is because of an absence of the management of the movement patterns. Further, it's based on the angle of rotation, completion first pattern of the UAV, and the beginning of the second [6].

Table 2.1: Summary of the Mobility Models and their Network Characteristics

Model	Category	Smooth Curve	Smooth Acceleration	Micro Variation	Conn. Awareness	Collison Avoid.
RWM [57]	Random Mobility	×	×	×	×	×
GMM [58]	Time Dependent Mobility	×	✓	✓	×	×
SRCM [59]	Path Planned Mobility	Partially	×	×	×	Partially
PPRM [64]	Path Planned Mobility	Partially	×	×	×	×
CLMNM [63]	Group Mobility	×	×	✓	✓	Partially
NCM [6]	Group Mobility	×	×	✓	✓	×
PRSM [6]	Group Mobility	×	×	✓	✓	×

2.2 Multi-UAVs in Precision Agriculture

The multi-UAV platform in the precision agriculture domain plays a vital role in observing the crop field with excellent spatial and temporal resolution compared to the satellite platform. This platform captures the particularities of a plant's leaves, stems, roots, and fruits from a unique point of view that is not easily visible from the ground [25]. Multi-UAVs with non-invasive sensors remotely sense/orthophoto the crops at petite pixel sizes to improve the resolution. The reaction of the plants can be observed quickly by sensors to new pesticides, herbicides, fungicides, and fertilizers. The information obtained by multi-UAVs can help the farmers to decide on the time, utilizing resources efficiently with low cost and saving time [26].

The use of information and modern technology in precision agriculture increased day-by-day with demands and challenges for diagnosing and detecting plant diseases. The temporal and spatial variation in crop and soil factors in the field need continuous monitoring of soil, crop, and environmental parameters to prepare the preventive measures. In conventional agriculture farming, the farmers assume that the parameters are homogeneous and use the same precautionary measures for different diseases unrelated to the entire existing disease situation. Due to the heterogeneous nature of diseases, precision agriculture farming methods are very beneficial to identify and diagnose the variability in crop diseases. In precision agricultural farming, the optical sensing non-invasive approach plays a vital role in diagnosing and detecting crop diseases at an early point in time [65]. The non-invasive techniques use thermal, LiDAR, multispectral and hyperspectral sensors.

2.2.1 Tomato Field Monitoring

Tomato is one of the most widely used vegetables in the world. The plant of tomato can be erected with short or long spreading stems with leaves and can grow from 0.7 to 2 m. The tomato is an appetizing fruit that belongs to the family of Solanaceae. The tomato fruit is rich in minerals, vitamins, sugar, and dietary fibers. It contains iron, phosphorous, vitamin *B*, and *C*. Yellow tomatoes have vitamin *A* content [66, 67]. The globe's annual production is around 37,489 thousand metric tons in 2019 [68]. The growing season is throughout the year in the world but depends on the production regions' intense heat, rain, and seasons. The tomato crop is sensitive to hot and cold seasons and susceptible to several diseases due to fungal, bacterial, and viral environmental factors. Fungal and bacterial causes leaf, fruit, stem, or root diseases in crops, resulting in enormous losses for the farmers and decreasing tomatoes' overall production [67]. The common diseases are summarized in Table 2.2.

Table 2.2: Tomatoes Crops Diseases, Symptoms and Causes [67]

Category	Disease Name	Symptoms	Infect				Cause
			Leaf	Stem	Fruit	Root	
Fungal	Anthracnose	Sunken & Lesions	✓	✓	✓	✓	Fungus
	Black Mold	Black or Brown Lesions	✓	✓	×	✓	Fungus
	Early Blight	Oval Shaped Yellow Lesions	✓	✓	✓	✓	Fungus
	Fusarium Wilt	Yellowing & Wilting Leaves	✓	✓	×	✓	Fungus
	Gray Mold	Fuzzy Gray-Brown Lesions	✓	✓	✓	✓	Fungus
	Leaf Mold	Leaves Greenish to Yellow Spot	✓	×	×	×	Fungus
	Leaf Spot	Water-soaked or greyish spot	✓	×	×	×	Fungus
	Target Spot	Necrotic Lesions	✓	✓	✓	✓	Fungus
	Verticillium Wilt	Yellow Blotches	✓	×	×	×	Fungus
Bacterial	Bacterial Canker	Unilateral Wilting of Plants	✓	✓	✓	×	Bacterium
	Bacterial Speck	Dark Specks on Leaves	✓	×	✓	×	Bacterium
	Bacterial Spot	Water Soaked Spot	✓	✓	✓	✓	Bacterium
	Bacterial Wilt	Wilting of the Youngest Leaves	✓	×	×	×	Bacterium
Viral	Mosaic	Leaves Dark Green Mottling or Mosaic	✓	✓	✓	✓	Virus
	Spotted Wilt	Bronzing or Purpling Young Leaves	✓	×	✓	×	Virus
	Yellow Leaf	Crumpled & Yellowing of Veins & Leaves	✓	×	×	×	Virus
Environ mental Factors and Others	Blossom-E- Rot	Light Tan, Water Soaked Area	×	×	✓	×	Physiological
	Catface	Large Holes or Corky Brown Scare	×	×	✓	×	Physiological
	Edema	Swellings or Blisters or Calluses on Leaves	✓	×	×	×	Physiological
	Fertilizer Burn	Slow Growth & Wilting, Leaf Tips Brown	✓	×	×	×	Nitr.Salts
	Magnesium	Interveinal Chlorosis of leaves	✓	×	×	×	Nutritional
	Water Stress	Green but Wilting, Moisture Stress Ring	×	×	✓	×	Physiological
	Late Blight	Water Soaked Green to Black on leaves	✓	✓	✓	✓	Oomycete
	Aphids	Yellow or Distorted Leaves	✓	×	×	×	Insects
	Beet Armyworm	Irregular Shaped Holes on Leaves	✓	×	×	×	Insects

2.2.2 Tomato Crops, Monitoring Environmental Factors

In precision agriculture, remote sensing techniques provide the required information timely to the farmers. Due to the increase in the population, crop production also requires the attention to increase for fulfilling today's requirements. The crop production growth depends on environmental factors such as humidity, temperature, moisture, light intensity, wind velocity, etc. The monitoring of these factors is possible with the help of environmental sensors that continuously monitor the crop field and provide accurate information. Based on the precise parameter's value of soil and air, the farmers decide the crop health, diseases, and any other requirement for increasing the crop production.

The accurate measurement of plant health is challenging without intelligent sensors. Wireless sensors improve greenhouse crops' production and prevent plant leaves from diseases. It requires the continuous process of sensing for the required information about the health of plants. The crop health is monitored by using a temperature sensor, humidity sensors, leaves temperature sensors, leaves humidity sensors [69]. There is a close relationship between tomato crop disease with environmental factors. The environmental factors measurement can control the diseases timely and increase tomatoes' quality production.

During the plantation of tomatoes, an ideal situation, the required temperature level daytime (65 to 85 °F), humidity (80-90%), and light intensity (350- 500 µmol m^{-2} s^{-1}). Soil nutrients (NPK) such as potassium (k), phosphorus (p), nitrogen (n), and pH level also play an essential role in the increase of crop production. Potassium directly impacts the crops' growth, strength, color, and fruit. Phosphorus deals with protection from diseases and improving fruit development. Nitrogen deals with the growth and colour of leaves. The pH level tries for stability in acidity and alkalinity [70].

The ideal measurement of environmental factors varies due to changes in the climate of different areas. The normal and favourable ranges are summarized in Table 2.3 [70-72].

Table 2.3: Environmental Factors Range Values for Tomato Crops Monitoring

Environmental Factors	Normal Range	Most Favorable Range
Relative Humidity	50-90 %	60-70 %
Soil Moisture	60-80%	65-70%
Temperature	12-35 °C	21-24 °C
Light Intensity	350- 500 µmol m^{-2} s^{-1}	400-450 µmol $m^{-2}\cdot s^{-1}$
NPK Ratio (NPK)	8-24-16 and 6-32-24	15-15-15
Power of Hydrogen (pH)	0.0-14.0	5.5-7.0

2.3 Parameters and Performance Metric for Clustering

Using swarm optimization algorithms, the researchers address the UAVs clustering issue differently with distinct objectives. The authors in the literature focus on partitioning UAVs network to form a balanced cluster while some focus on the UAV-CHs mobility, energy, etc. The balanced cluster formation & optimum CH selection needs the careful attention of the researchers. The researchers have considered different parameters and performance metrics but no significant standard available for performance evaluation. The parameters are selected on their own choices during a simulation. The parameters performance metrics considered for clustering and localization are discussed in this section, which is further used to evaluate clustering and localization schemes considered in this thesis.

2.3.1 UAV Energy

The power needed for the communication & movement during the mission is called UAVs' energy. The UAVs must have a sufficient amount of energy to complete the mission. During the selection of UAVs CH, the residual energy should be considered at the start to avoid any disconnectivity or loss during the mission.

2.3.2 UAV Mobility

The distance of a UAV's movement between two points during a specified interval is its mobility. The UAV with the same direction, speed, and movement towards the neighbour will be a more suitable candidate for a CH. The topological changes in the network can be minimized when the relative mobility of nodes is considered during the CH selection process. The UAVs with high and low mobility results in unstable CH selection.

2.3.3 UAV Distance and Position

The UAVs in a range of a cluster with minimum distance to a neighbour UAVs selected as a CH. The member UAVs join the nearest CH by sharing its relative position, energy, etc. The localization method measures the distance of UAVs to CH and the distance from one CH to another.

2.3.4 UAV Degree

The UAV degree is the number of neighbour UAVs in a range. The UAV with a larger number of neighbour UAVs will be a more suitable candidate as a CH. During cluster formation & CH selection, the UAVs' degree must be considered just to counter the load on each CH. The average node degree in the network will be the pivot value to obtain equal clusters concerning the size.

2.3.5 UAVs Neighbour Criteria

Neighbour criteria define the UAV position that may be a single-hop or multi-hop away based on the range and position of another UAV. The UAV whose neighbour stays for a long period will be a more suitable candidate for CH. The neighbour UAV criteria are defined with the help of weights, i.e., relative mobility, residual energy, distance, position, degree, etc.

2.3.6 Re-clustering

The frequent change in topology due to UAVs' high mobility and energy utilization results in the re-clustering process. The re-clustering process consumes more resources. Hence, the CH should be selected in such a manner so that the re-clustering procedure could be précised.

2.3.7 Clustering Parameters

Once the UAVs CH is selected, then cluster formation start. The UAVs join the cluster based on different parameters such as relative mobility, residual energy, distance, position, degree, etc.

2.3.8 Balanced Cluster

Balanced cluster formation means maintaining the UAV degree same in the cluster without affecting the expected performance goals to balance the communication load as the CHs gather data from its member nodes using an aggregate manner. The size of clusters should be nearly the same. It will count the load on each CH.

2.3.9 Simulation Metrics

The metric used for simulation such as number of UAVs, UAVs speed, simulation area, distance, initial energy, simulation time, etc.

2.4 Chapter Summary

A brief description of mobility models is added at the start of this chapter. The clustering schemes in the literature commonly used the RWM, RPGM, GMM, and PPM models. The basic concepts of multi-UAVs in precision agriculture are explained along with the environmental factors used to localize UAVs to identify the TAs. The basic parameters of this research are discussed, which are further used to evaluate clustering and localization schemes. The tomato crop is susceptible to hot and cold seasons and several diseases due to environmental factors like fungal, bacterial, and viral. Environmental factors such as humidity, temperature, moisture, light intensity, wind velocity, etc., are discussed in this chapter.

Chapter 3

Literature Review

Clustering of multiple UAVs is a challenging task compared to other ad-hoc networks (MANET, VANET) due to nature of UAVs, such as high-energy consumption, high mobility, and dynamic change topology. There are many cluster-based routing schemes. They are proposed for mobile and vehicular ad-hoc networks but not fulfilling the requirement of FASNET. The needs of schemes that provide flexible and reliable communication which are more appropriate for the situations and constraints of FASNET are discussed in detail. First, the multi-UAVs conventional and swarm intelligence-based clustering schemes are discussed in detail. Secondly, the localization

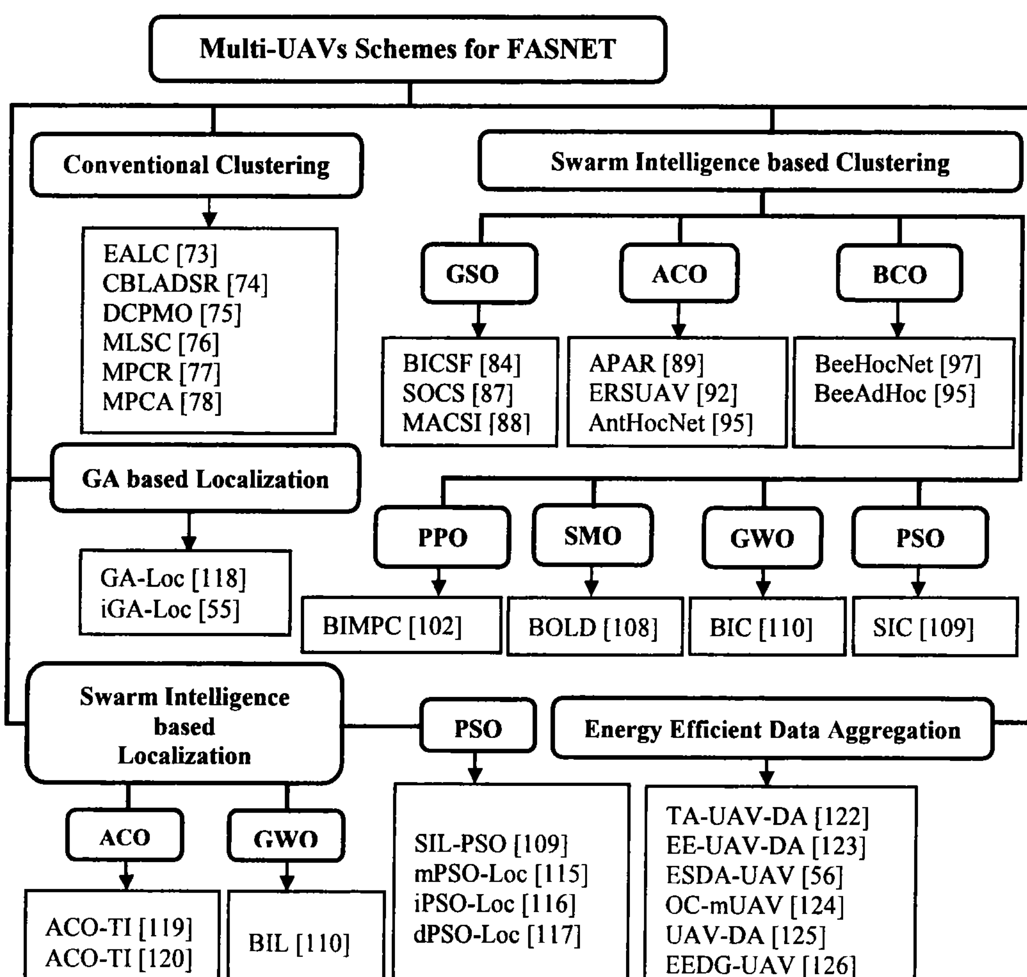


Figure 3.1: Organization of Multi-UAVs Schemes for FASNET

of UAVs in a cluster based on swarm intelligence for TA identification is presented with findings and a summary. In third second section swarm-intelligence-based data aggregation approaches discussed in detail. The organization of multi-UAVs schemes for FASNET is depicted in Figure 3.1. The problem statement is added based on the research gap/issues at the end of this chapter.

3.1 Conventional Cluster-based Routing Schemes

These routing protocols have different characteristics and issues. Due to problems in flat routing such as scalability, mobility, and topological changes, clustering-based routing protocols are proposed to resolve these issues. The conventional schemes provide reliable, scalable, and energy-efficient routing that reduces communication overhead and increases throughput in multiple UAVs networks. The cluster-based routing schemes divide the network into subgroups called clusters, each with CH. The number of UAVs may be the same in a cluster to form a balanced or unbalanced cluster. The communication among UAVs or to CH may be direct or indirect. CH selection is based on different metrics with different weights such as degree, energy, mobility, distance, and position of the UAVs. The conventional clustering schemes are analyzed, and compared rely on weighted metrics such as energy, degree, position, and distance of UAVs to one another or the CHs.

3.1.1 Energy-Aware Link-based Clustering (EALC)

Aadil *et al.* in [73] proposed the clustering model with an energy-aware link called EALC. EALC is based on multiple weights to manage energy, transmission terrain, and select the optimum CH for stability and increasing network lifetime. K-Means Sorted fitness algorithm used that grouped the UAVs to form a cluster. Dynamic weight assignment is used instead of static assignment of weights. CMs send their status (energy and position) to the CH. During the CH selection process, the fitness based on threshold level, if below the level, then all the UAVs of that cluster will be considered un-clustered, and clustering will be recalled. The responsibility of CH is to transfer data among UAVs inside, outside the cluster, or to BS. EALC has low computation complexity and easy search region implementation with an optimum solution.

Findings: (i) Mobility considered in EALC is moderated, but the UAVs mobility is very high and dynamic. (ii) The re-clustering process is frequently recalled due to the threshold level. (iii) Communication and computational overhead may increase with the frequent re-clustering process. (iv) Distance among UAVs considered is very short. (v) Speed of a UAV not mentioned in the study. (vi) Degree of the UAVs in a cluster varied result un-equal cluster size.

3.1.2 Cluster-Based Location-Aided Dynamic Source Routing (CBLADSR)

Nanxiang Shi in [74] presented a deterministic weight-based location-aided clustering algorithm called CBLADSR for FASNET. The location aided routing (LAR) defines the area in two zones to avoid the collision and minimize the route request, i.e., requested and expected zones. Slope-based forwarding strategy applied to select the neighbour UAV with minimum slope. CBLADSR provides location-aware routing and keeps the residual energy on high priority for the election of CH. The CH selection depends on mobility and energy. The role of CH assigned to lead UAV, which has high energy, minimum relative mobility, and broader coverage. In case of failure, the role is transferred to UAV, which has less energy, high mobility, and short-range transmission.

Findings: (i) UAVs random mobility is considered, which might cause failure and increase the clustering overhead. (ii) Distance among UAVs and flight time is not mentioned in the study. (iii) Only lead UAVs participate in the election of CH. (iv) No metric defined for re-selection of task UAV-CH in case of failure of first selected lead UAV-CH. (v) Delivery ratio and end-to-end delay are only considered performance metrics.

3.1.3 Dynamic Clustering Protocol for Mission-Oriented (DCPMO)

Park *et al.* [75] introduced a dynamic CH selection algorithm for flying ad-hoc networks called DCPMO in FANET). The author focuses on minimizing energy consumption with dynamic clustering for a mission-oriented FANET environment with the SOLAR mobility model. The UAVs movement uses a random waypoint mobility model for intra-hub communication and a point-to-point linear model for inter-hub communication. The ground system selects the CH randomly with high energy and short distance. In some scenarios, the clusters are formed randomly or with maximum energy or both. DCPMO may perform worst. The unknown UAVs may transmit other packets showing themselves as real ones.

Findings: (i) Neighbour criteria for joining the cluster are not defined. (ii) Cluster formation process is not mentioned in the study. (iii) UAV mobility plays a vital role in the CH selection and cluster formation, which is not considered. (iv) UAVs may not be equipped with the same battery power or not in the range of a hub that may cause dis-connectivity. (v) To form a balanced cluster, the degree of UAVs is not considered.

3.1.4 Mobility and Location-aware Stable Clustering (MLSC)

Bhandari *et al.* [76] presented an MLSC scheme in which the UAVs are randomly deployed to cover the area with the optimal number of CHs and minimum energy utilization. The UAVs-CH is located with the help of k-means clustering to determine the optimum number of UAVs-CH covering the circular geographical area. Once UAVs-CH is selected, the Euclidian distance formula calculates UAVs' distance to UAVs-CH. The UAVs-CH broadcast the advertisement message. The UAVs join the UAVs-CH having minimum distance and hop count to form the cluster. The UAVs-CH communicate with GS or sink UAVs. UAVs' relative mobility and position are considered for maintaining a stable cluster that improves stability, accuracy, and reliability. The localization technique and GPS are used to obtain UAVs' location and speed. The MLSC is compared with AODV in terms of network overhead. The performance of MLSC is compared with ACO and GWO and shows better performance in terms of delay and PDR.

Findings: (i) For increasing the transmission, the UAVs energy is the most crucial factor, which is not considered during the selection of CHs. (ii) Increase in transmission also requires a lot of time to find the optimum path for a high-speed UAV network. (iii) The route request flooding degrade the network performance in terms of end-to-end delay and delivery ratio. (iv) The degree of UAVs in a cluster not defined that may increase the load on each CH. (v) CH also has the responsibility of frequent route discovery that may degrade the efficiency of CH.

3.1.5 Mobility Prediction Clustering Routing (MPCR)

Shu *et al.* [77] proposed a Mobility Prediction Clustering Routing (MPCR) algorithm based on the association among UAVs distance and frequency of data transmission. In FANET, the UAVs have high mobility and frequent changes in topology. MPCR combines the group and ferry, mobility model. In the group mobility model, the group of UAVs has a stable thread for deciding the UAVs relation while the ferry model provides information timely about the entire UAVs. The ferry UAVs share data about the disconnected UAVs and move the data to the BS. Each UAV builds a neighbour table, and the UAV with maximum connectivity probability and minimum data transmission time is selected as UAVs-CH. The UAVs-CH maintains the speed and direction information about all the UAVs in a cluster. The speed and direction remain the same and independent for the specific time interval. The CH UAVs have the responsibilities of data exchange, position information, cluster maintenance, etc., and communicate with BS to report UAVs' location, speed, and direction. The MPCR compared with AFNC and SF (spray and focus) average hop count, delay, and PDR. The simulation result shows that MPCR has a high transmission success rate with minimum energy consumption and transmission delay.

Findings: (i) The UAV with the most effective connectivity was selected as a CH, but no neighbour criteria were defined for joining the CH to form the cluster. (ii) The re-clustering process is required due to high mobility and topological changes, which are not mentioned. (iii) Energy level of UAVs not considered during the election of CH and formation of clusters that may decrease the network's lifetime. (iv) Balance cluster formation required the same degree of UAVs in a cluster, which is not considered. (v) How to select the next UAV as a ferry node to store and forward data in case of failure did not mention in this study.

3.1.6 Mobility Prediction Clustering Algorithm (MPCA)

Zang *et al.* [78] proposed a deterministic weight-based clustering algorithm called Mobility Prediction Clustering Algorithm (MPCA) for FANET. The algorithm is based on prediction and link-expiration time mobility model: link expiration time and highest degree used to select CH. The cluster formation is based on the weights that consider parameters like neighbour UAVs, location, speed, and direction. Each UAV share its information with its CH, if the CH does not exist the larger link expiration time and highest weights UAV elected as a CH. MPCA is suitable for peer network communication with UAVs high mobility.

Findings: (i) Larger number of member UAVs increase the number of cluster-based only on UAVs connectivity and prediction while ignoring energy, degree, and distance (ii) Communication overhead increases due to rapid changes in topology. (iii) Focused on mobility while energy, load balancing, frequent topological change is not considered. (iv) Due to high mobility, the re-affiliation rate may be very high.

The existing conventional clustering schemes attributes are summarized as CH selection in Table 3.1, cluster formation in Table 3.2, performance metrics in Table 3.3, and simulation study in Table 3.4.

Table 3.1: Conventional Clustering Schemes [CH Selection Parameters]

Reference	Network	Energy	Mobility	Position Awareness	Node Degree	Distance
[73]	FANET	✓	--	✓	✓	✓
[74]	FANET	✓	✓	✓	✓	--
[75]	FANET	✓	--	✓	--	✓
[76]	FANET	--	✓	✓	--	✓
[77]	FANET	--	✓	✓	--	--
[78]	FANET	--	✓	✓	✓	--

Table 3.2: Conventional Clustering Schemes [Cluster Formation]

Ref	CH Election	Neighbour Criteria	Clustering Parameters	Re-Clustering	Balanced Cluster
[73]	Weighted Metric Based	M-hop	Energy, Degree, Distance	✓	✓
[74]	Weighted Metric Based	1-hop	Energy, Degree, Mobility	×	✓
[75]	Dynamic	1-hop	Energy, Distance	×	×
[76]	Dynamic	M-hop	Mobility, Distance	×	×
[77]	Dynamic	M-hop	Mobility, Location, Direction	×	×
[78]	Weighted Metric Based	M-hop	Degree, Mobility, Distance	✓	×

Table 3.3: Conventional Clustering Schemes [Performance Metrics]

Ref	Comparison Schemes	Routing Overhead	End to End Delay	Throughput	Delivery Ratio	Energy	Cluster Building Time	Cluster Lifetime
[73]	[79], [80]	✗	✗	✗	✗	✓	✓	✓
[74]	[81], [82]	✗	✓	✗	✓	✗	✗	✗
[75]	--	✗	✗	✗	✗	✓	✓	✗
[76]	ACO, GWO	✓	✓	✗	✓	✗	✗	✓
[77]	SF, AFNC	✗	✓	✗	✓	✗	✗	✗
[78]	LID, HD, WCA	✓	✗	✗	✗	✗	✓	✓

Table 3.4: Conventional Clustering Schemes [Simulation Study]

Ref.	Mobility Model	Technology	Simul. Tool	UAVs Speed	Simul. Area	Residual Energy	No. of UAVs	Simul. Time
[73]	RPGM	IEEE 802.11	MATLAB	--	2x2km^2, 3x3 km^2	80W/H	20, 30, 40, 50,60	120 s
[74]	RWP	IEEE 802.11	OPNET Modeler	30m/s	2x2km^2, 3x3 km^2, 4x4km^2, 5x5 km^2	150 to 300 J	10, 20, 30, 40, 50	600 s
[75]	RWP				1kmx1kmx1km	10 J	100	10 m
[76]	GMM	IEEE 802.11	MATLAB	10-30m/s	2kmx2kmx2km	--	20-140	--
[77]	Ferry Group	--	--	10-50m/s	10kmx10Km	--	90	--
[78]	LET	IEEE 802.11	NS2	0-60m/s	1000 * 1000 m	--	50,100,150,200, 250,300,350,400	1000s

In the literature, the authors aim to increase multi-UAVs network lifetime using a variety of conventional clustering schemes. Each clustering scheme has different criteria for UAVs-CH selection and cluster formation. Sustainable energy must be kept in mind during the selection of CH. The UAVs with more energy are suitable to become UAVs-CHs, but the authors in [76-78] ignored energy during the CH selection process.

Balanced cluster formation is a complex task because the applications have different priorities for UAVs pre-arrangement, cluster size, and selection of UAVs-CH. The UAV degree in each cluster needs to be considered to form stable clusters. The authors in [75-77] did not mention the UAV degree in each cluster. The large number of UAVs in a cluster increases the communication load on each UAV-CH. The frequent change in topology can be minimized by considering relative mobility. Still, all the authors in [73-78] ignored relative mobility.

The frequent change in topology due to other factors such as energy, degree, etc., also increases the re-clustering process. The stable cluster formation decreases the re-clustering process that will be called as minimum as possible. In this way, the benefits of clustering architecture will be achieved, but the authors did not mention the re-clustering in [74-77]. Due to its autonomous nature, the path selection commonly depends on the prior UAVs' direction and speed, which is considered only in [77, 78] while ignored in [73-76]. UAVs' distance and flight time did not mention except [73].

3.2 Swarm Intelligence Clustering Schemes

The clustering of multi-UAVs is a challenging task due to high mobility, limited energy, and frequent topology changes. The partition of many multi-UAVs into different non-intersecting clusters converts an optimization issue. Once the optimization based on the parameters is achieved, it can be utilized for different network scenarios. Swarm intelligence optimization schemes exhibited from nature are also known as bio-inspired solutions. These solutions are based on swarm intelligence that provides efficient algorithms. The algorithmic solutions deal with many desirable and attractive properties applied in the multi-UAVs network, such as clustering, multi-path cluster-based routing, clustering optimization, ensuring target coverage, etc.

In this section, multi-UAVs clustering schemes based on swarm intelligence optimization discussed how they select CH, how the cluster is formed, and how it performs cluster maintenance. As discussed in the following sub-sections, these schemes have different properties and limitations.

3.2.1 Clustering Schemes based on GSO

GSO algorithm [51] based on glow-worms swarm that perform random heuristics search. The glowworm work collectively in a swarm. The glow-worm contains luminescence, also known as luciferin. There are five steps of GSO: updation of luciferin value, neighbour selection, updation of movements, and radius decision [83]. The neighbour selection depends on the quantity of luciferin and the position of a glowworm. The optimum solution depends on the higher value of luciferin. The application of GSO is to solve the multicast routing problem and multi-constrained QoS. The problem in this optimization is the concession on the accuracy and speed of the fixed step size. Another problem is minimum precision in optimization and easy to drop into local optimum.

3.2.1.1 Bio-Inspired Clustering Scheme for FANET (BICSF)

Khan *et al.* [84] proposed a bio-inspired clustering scheme for FASNET (BICSF) based on GSO and Krill Herd (KH). The BICSF is based on the flashing behaviour of glowworms. Krill represent the CM. UAVs energy and luciferin value consider for cluster formation. The luciferin value is measured with fitness function. The highest weight of a UAV (i.e., high luciferin value and energy) elect as a UAVs-CH, and the rest becomes the member UAVs. The UAVs-CH were selected with minimum mobility. DURING THE MISSION, the KH manages and maintains the cluster and member UAVs movement. The path detection function (pdf) sets the best routes for routing information. The simulation results show better cluster formation, energy utilization, and network lifetime performance than GWO [85] and ACO [86].

Findings: (i) The selection of UAVs-CH performed with low mobility (ii) The distance among UAVs mentioned is very short. (iii) Due to the increase in CMs, frequent topology changes gradually shorten the cluster lifetime. (iv) In the cluster maintenance phase, only residual energy below the threshold value is considered for declaring the UAV as a dead node while ignoring the high mobility of UAVs. (v) Energy level of CH-UAVs may be below the threshold level, then the re-clustering performed, which is not mentioned in the study. (vi) The UAVs degree in a cluster not defined may create communication load on the CH.

3.2.1.2 Self-Organization based Cluster Scheme (SOCS)

Khan *et al.* [87] designed SOCS to enhance information communication between UAVs. The GSO features are considered to select optimized routes and topology maintenance. The luciferin value means residual energy and connection used to choose UAVs-CH and form a cluster. Each glow-worm has its luciferin value and range for neighbours. The residual energy and link connection weightage are considered in the fitness function for selecting UAVs-CH. The luciferin value plays a role in glow-warm position and objective function. The highest fitness value of a UAV is chosen as a UAV-CH, and the rest of them becomes the member UAVs. The UAVs position is updated with GSO properties for maintaining the topology. The routes between UAVs are selected based on UAVs position, neighbour distance, and residual energy. The performance of the SOCS in terms of cluster building time, cluster lifetime, and the delivery ratio is better than the GWO and ACO schemes.

Findings: (i) The election of CH based on highest fitness value and connectivity to GS. In case of CH failure, the UAV connected the next cluster and GS. The frequent re-clustering process affects the reliability of the multi-UAVs network (ii) The UAVs have low memory and computation power. More UAVs in a cluster may increase communication and computational overhead. (iii) The distance among UAVs considered is fixed and very short. (iv) UAVs mobility and flight time are not mentioned. (v) Due to UAVs limited resources and constraints, the network congestion affects the network performance.

3.2.1.3 Mobility-Aware-Clustering based on Swarm Intelligence (MACSI)

Wand [88] proposed a modified GSO-based mobility-aware and energy-efficient clustering protocol. The MACSI tried to resolve the issue of limited energy and frequent movement of UAVs. The Modified GSO (MGSO) with chaos strategy is used for cluster formation and CH selection. The UAV with the highest fitness function value plays a role of UAVs-CH, and the rest become the member UAVs. The energy, mobility, location, and luciferin level are considered to calculate the UAV fitness. The UAVs share information with their neighbour for stable formation of the cluster. The MGSO strategy is used for cluster management. The UAV-CH updates its member's positions, energy, and mobility. The CH will also update the UAVs that are not in a cluster range due to mobility. The performance is compared with ACO and GWO in cluster lifetime and energy utilization with changing the number of UAVs. The performance of MACSI considerably reduces the energy utilization compared to ACO and GWO.

Findings: (i) Frequent change in topology maximizes the maintaining cost and probability of errors, thereby reducing the cluster lifetime. (ii) The degree of UAVs in a cluster increases the energy consumption, which is not considered in the article. (iii) The large number of UAVs in a cluster maximize communication load on CH. (iv) The maintenance cost of many UAVs shortened the cluster lifetime. (v) The important parameter such as UAVs speed, flight, and simulation time is not mentioned in the simulation study.

3.2.2 Clustering based on ACO

The ACO is a swarm-based algorithm evaluating the ant colony foraging behaviour to determine the minimum distance to a destination. The ACO algorithm was proposed in 1991 for the first time [53]. Each ant in the colony forms a complete solution and assesses the solution with the help of fitness procedures. The ants use the stigmergy concept for communication. This optimization algorithm plays a key role in resolving optimization issues such as sequential ordering, routing among UAVs, traveling salesman problem (TSP), etc. Indeterminate time to convergence and complicated theoretical analysis is the main shortcoming of ACO. There is no specific clustering protocol based on ACO designed for clustering optimization and CH selection in multi-UAVs networks. Some of them, which are used for path optimization, are discussed in this section.

3.2.2.1 Polymorphism Aware Routing based on ACO (APAR)

Yu *et al.* [89] proposed a clustering protocol based on ACO to overcome the issues of packet loss, long delay, and increased routing overhead. APAR integrates the DSR with ACO to improve the performance of the network. Rout stability and supervision methods are considered that enhance the measurement accuracy. A reliable link supervision method is verified because the link may disconnect due to random movement of UAVs and variation in topology. The non-linear processing scheme with buffer occupancy and channel load is used to avoid and control congestion on the link. Sparse and concentrated formation strategies routing strategies were proposed that quickly discover the routes in the multi-UAVs network. The simulation was performed in NS 2.34. APAR, compared with HOPNET[90], Ant-DSR[91], and DSR[81], show significant improvement in performance in terms of delay, routing overhead, and packet loss.

Findings: (i) The authors' focus in this article is on UAVs routes discovery supervision mechanism by using different strategies. (ii) There is no clustering process performed for multi-UAVs. (iii) The routing strategies are based on the density of UAVs. (iv) ACO is used for path optimization instead of clustering optimization.

3.2.2.2 Efficient Routing Strategy for UAVs (ERSUAV)

ERSUAV proposed by Yang *et al.* in [92] is a probabilistic Energy-aware clustering scheme to find the best path for UAVs using ACO. Integration of UAVs and WSN efficiently monitor the farmland such as temperature, humidity, etc. The efficiency of data gathering in WSN is achieved with the help of UAVs, their position, and energy status. The network divides into clusters, each with cluster head, cluster members, and UAVs. The nodes are stationary with position-aware cluster heads; the CH will receive information from the UAVs flying around the cluster heads. ERSUAV network model has three stages. The first stage is to sense the data through UAVs from the ground segment about the event in the farmland. The second stage transmits UAVs' gathered data through CH to the data center. The data center contains a database and management information system in the last step. The proposed scheme compared with LCF [93] and AS [94] based on delay and path length.

Findings: (i) Cluster formation performed only on ground sensor flat network. (ii) Single UAV is considered for collecting data from the CH on the ground network. (iii) The UAV flying path optimized and ignored the UAVs-CH selection or clustering optimization.

3.2.2.3 AntHocNet

Leonov in [95] proposed a clustering scheme based on ant swarm intelligence to decrease delay, reduce communication overhead and increase reliability. The AntHocNet method incorporates ant's behavior to find the shortest path of the food source. The route decision comes from the source node instead of the middle. AntHocNet scheme compared with the existing mobile ad-hoc protocols AODV, DSDV, and DSR. The simulation result shows that swarm intelligence-clustering schemes are efficient for FANET.

Findings: (i) The multi-UAVs routes optimization performed based on ACO. (ii) UAV mobility is not mentioned in this study. (iii) The cluster formation and CH selection did not mention in the article.

3.2.3 Clustering Schemes based on BCO

The bees-colony-optimization algorithm is used to find the optimum food sources. They select the food source that has a maximum amount of nectar. The bees communicate the information about the food source with a waggle dance, which shows the direction, distance, and nectar amount of the food sources. The authors in [96] introduce the honey-bees mating optimization based on the breeding behaviour of bees. Artificial bees colony optimization is another famous scheme presented in [50]. This algorithm search for the best food sources with optimum solutions by communicating information among bees. They categorized bees into three groups; i.e., scout, onlooker, and employed bees. The representation for the feasible solution is the bees visit and find the food sources outside the colony. The optimum CH selection and balance cluster formation can be performed, but no specific work has been done for flying UAVs networks. Some of the authors proposed the bee optimization approach, which is discussed in this section.

3.2.3.1 BeeAdHoc clustering Protocol (BeeAdhoc)

Leonov [97] proposed a clustering protocol based on bee intelligence for flying ad-hoc networks. The author first performs a comparative study of ad-hoc networks, MANET, VANET, and FANET, based on mobility, topology, topology changes, energy constraint, and uses. FANET is an ad-hoc network, but it is different from MANET and VANET. Flying networks are UAVs with high mobility and dynamic change in topologies. The conventional routing schemes do not efficiently accommodate maximum mobility and topological changes. Secondly, the proposed BeeAdHoc compared with traditional routing protocols AODV [98], DSDV [99], and DSR [81] based on throughput, routing overhead, and end-to-end delay. Simulation performed in NS 2.35 shows better performance in the above performance metrics.

Findings: (i) How the CH is selected based on bee intelligence is not mentioned. (ii) How the clusters are formed using bee optimization also not added. (iii) The authors' focus is only on comparing other ad-hoc networks.

3.2.3.2 BeeHocNet

Leonov [95] introduced a clustering scheme based on bee swarm intelligence to decrease delay, reduce communication overhead and increase reliability. The BeeHocnet scheme incorporates the foraging behaviour of bee colonies in cluster formation with proper selection of CH and balance members in a cluster. BeeHocNet schemes compared with the existing mobile ad-hoc protocols based on topology are AODV, DSDV, and DSR. The simulation result shows the efficiency of swarm intelligence-based clustering schemes for flying ad-hoc networks. The simulation results of the proposed scheme perform well in terms of reliability, throughput, and communication overhead with existing conventional topology-based routing protocols. Multi-UAVs with multi-hop communication in FASNET and the proposed scheme is peer-to-peer communication.

Findings: (i) The proposed scheme is for peer-to-peer communication. (ii) No specific clustering formation and CH selection is discussed in the article. (iii) There are no criteria defined for the CH selection and cluster formation.

3.2.4 Physarum polycephalum Model (PPM)

This model was introduced in 1931 and is known as true Slime mold. It is a Physarales species with a small cell and gradually increases [100]. It consists of a tube and sponge to communicate chemical and physical information signals all over the organism [101]. During the exploration of the environment, it changes the topology. It uses the physarum foraging behaviour such as searching the minimum cost for delivering data to different UAVs, minimum risk problem, shortest pathfinding, connecting multiple UAVs in a short time, finding the UAVs with maximum weights, finding a large number of UAVs in neighbour, etc. This model suggests the network optimization problems based on physarum that improve the performance.

3.2.4.1 Bio-Inspired Mobility Prediction Clustering (BIMPC)

This protocol proposed in [102] is based on a physarum polycephalum foraging model with mobility prediction. This protocol integrates the feature of this model to reduce overhead, energy consumption, and frequent change in topology. The selection of UAVs-CH and formation of clusters start during UAVs-network establishment. The

HELLO packet broadcast to all the neighbour UAVs in the range of communication. The link quality and UAVs-CH availability measures at the start. The probability of each UAV in the cluster for UAVs-CH is calculated. Once UAVs-CH selection is performed, the member UAVs join the UAVs-CH on receiving the announcement. If the CM receives the announcement from UAVs-CH, then join based on the stability. If the CM receives the announcement from more than one UAV-CH, it will check and decide based on virtual communication fluxes. This protocol tries to resolve the issue of UAVs link failure and mobility. The maintenance of cluster in BIMPC increase the cluster structure stability. This protocol considers four actions are: to leave or join the cluster, movement of UAVs, integration of cluster, and separation of the cluster from one another. The performance of the BIMPC compared with MPBC [103], MOBIC [103], MPCR [104] and DDVC [105].

Findings: (i) The mobility considered of UAVs in BIMPC is reasonable, but UAVs in mission have high mobility reliable communication. (ii) The position of UAVs is essential, which is not considered for CH selection. (iii) The large number of UAVs directly impacts the overall performance, but the degree of UAVs is not considered for the clustering process. (iv) The distance among UAVs is not considered in the BIMPC for CH selection. (v) The simulation time and flight time is not mentioned.

3.2.5 Clustering based on SMO

This optimization is a population-based algorithm that exhibits the spider monkeys' social activities to resolve the optimization issues [106]. It uses a fission-fusion mechanism based on the spider monkeys' intelligent foraging behaviour. The grouping (fusion) and division (fission) are performed based on the availability and non-availability of food sources. The groups range from 40 to 50 individuals headed by a global leader (most senior female) to explore and locate the food sources. If the group leader fails to find, the group is divided into subgroups ranging from 3 to 8 individuals to explore the food sources. The small groups were also controlled by a female (local leader) to organize a foraging route each day. Local and distance communication is performed among regional and global groups with distinct sounds. The clustering formation is widely based on SMO [107]. The steps of optimization algorithm include local-global leader selection phase, learning by local-global leader phase, the decision by local and global leader phase.

3.2.5.1 Bio-Inspired Optimized Leader Election for Multiple Drones (BOLD)

Ganesan *et al.* [108] present a BOLD clustering scheme for multiple UAVs based on bio-inspired optimization. The UAVs move in random directions, and GPS is enabled for positioning the UAV location and distance. The same and nearest target is considered for all UAVs. BOLD used PSO for dynamic selection of UAVs-CH based on its energy, position, and velocity to UAVs or BS. The communication energy decreases with only a CH communication to BS and other UAVs. For cluster formation, the proposed BOLD scheme uses SMO based on UAVs' closeness to each other, RSSI, and the current energy of UAVs. The focus is on the dynamic CH election at different time intervals based on UAV constraints. The CH UAV will assign a task to other UAVs in case of failure of the current CH, then the re-election performed for the next suitable UAV as CH. This scheme is compared with the PSO-cluster head election (PSO-C) scheme, which performs better in energy consumption.

Findings: (i) The selection of UAVs-CH based on PSO and cluster formation is based on SMO. (ii) The cluster is formed based on UAVs' closeness, connection, and residual energy while ignoring the mobility and degree. (iii) The target of all UAVs is considered the same, but the UAVs find different targets in most scenarios. (iv) The transmission range and frequency are not considered during the selection of UAVs-CH and the formation of the cluster. (v) The communication overhead may improve with the increase in UAVs.

3.2.6 Clustering based on PSO

PSO was introduced by James and Eberhart in 1995 [52]. The swarm-based algorithm resolves the optimization problems based on the concept derived from bird flocking or fish schooling. The PSO explores the potential solutions based on population by implanting the social behaviour of fish or birds. The swarm contains several particles, each with its attributes and track. The solution space includes particles and has their position and velocity that represent a solution. In the search area, the birds move towards the optimal particles for the high-quality solution (fitness) it has reached so far.

The situation is known as an optimum solution. The fitness value kept known as *pbest*. The best solution attained so far by any other particle in the particle neighbour and value is *gbest*. The algorithm's objective is to speed up each particle towards its *pbest* and the *gbest* location with a random value each time to speed up. In the last decade, many researchers applied the PSO algorithm in applications such as Numerical function optimization, scheduling dynamic tasks, topology optimization, etc. The main issue with PSO is that it can be quickly down in local optimum in high dimension range, and the change rate of repeating practice is low.

3.2.6.1 Swarm Intelligence Clustering (SIC)

Arafat and Sangman [109] proposed a SIC approach that reduces energy consumption to increase the network lifetime. To explore the closest cluster pair, it uses a 3D node-pairing model based on PSO local sub-swarm. The UAVs join the nearest cluster to minimize energy utilization. The formation of clusters depends on UAVs' position, distance, range, and closeness. Particles' fitness function uses distance among inter and intra-cluster. To find the required location for the UAVs and balanced cluster size Euclidean distance formula was selected as the best. The number of UAVs is grouped into clusters, each with CH. The selection of CHs achieved with a fitness function that considers distance and energy. The SIC compared with other clustering schemes and better results in terms of packet delivery ratio and overhead.

Findings: (i) The movement of multi-UAVs in emergency scenario change the topology frequently. The selection of CH in such a scenario needs careful consideration, but the author ignored the high mobility of UAVs. (ii) The formation of clusters based on closeness, connection, and residual energy of UAVs while ignoring the mobility. (iii) The author did not mention the mobility model, but it plays a vital role how the UAVs' movement pattern in real-life scenarios. (iv) During simulation, the distance among UAVs is not mentioned.

3.2.7 Clustering based on GWO

This optimization algorithm was inspired by the grey wolves (GW). It is based on a meta-heuristic proposed by Mirjalili *et al.* [54]. GW lives in a pack with a strict hierarchy. The group size is 5 to 12 members on average and is led by males or females.

The four-level hierarchy of grey wolves consists of alpha (α), beta (β), delta (δ) and omega (δ). The most dominant wolves are α that decide to hunt with three principles; 1st searching, 2nd encircling, and 3rd attacking prey. The second hierarchy level is beta wolves (either male or female). These are the subordinate or advisor wolves of alpha. β wolves help α in hunting decisions on feasible time, wakeup time or sleeping place, etc. The third level in the hierarchy is a delta that is the subordinate of alpha and beta. The delta wolves may play the role of either scouts, sentinels, elders, hunters, or caretakers. Scouts are responsible for submitting information about any danger on the boundaries. The sentinels' wolves are accountable for the wolf's safety. The elders' wolves are the experience wolves. The hunters' wolves help in hunting prey. The caretaker helps all the weak wolves. The omega level in the hierarchy is the scapegoat in the group and succumbs to all other leading wolves. They are allowed to eat in the last. It maintains the internal structure to avoid violence and frustration. The GW optimizer provides optimal solutions for problems. This optimization is slow to practice specific problem solving, not good reputation in local search, and results take a long time in convergence.

3.2.7.1 Bio-Inspired Clustering (BIC) Scheme

Arafat and Sangman [110] proposed a BIC scheme for multi UAVs networks to detect and monitor wildfire. Hybrid GWO (HGWO) leadership hierarchy is used for energy-efficient clustering. The UAVs are categorized into alpha, beta, and delta to construct the tree hierarchy. The UAVs with high residual energy, maximum neighbour, and minimum distance are selected as CH. Compressive sensing GWO (CS-GWO) with a minimum-cost algorithm developed for connectivity among CHs and communication between BS and CHs. To reduce the load from CHs, the relay UAVs can also transfer data from CHs to BS. An analytical model with a 3D cubic region is considered for the optimal number of clusters. The BIC performance compared with SOCS, CBLADSR, MPCA, BICSF, and EALC in clusters, building time for the cluster, and energy consumption with different UAVs and rounds. The simulation result shows that the BIC reduces UAVs' energy utilization and enhances transmission efficiency and network reliability.

Findings: (i) The UAVs CHs selected with high residual energy, more neighbour and the minimum distance are considered and ignored UAVs' mobility. (ii) The re-clustering process consumes more resources, but there are no criteria defined that the re-clustering procedure is called as minimum time as possible. (iii) The authors did not mention the mobility model for simulation.

The existing clustering schemes based on optimization are summarized as CH selection in Table 3.5, cluster formation in Table 3.6, performance metrics in Table 3.7, and simulation study in Table 3.8.

Table 3.5: UAVs Swarm Intelligence Clustering Schemes [CH Selection Parameters]

SIO	Clustering Schemes	Network	Energy	Mobility	Location Awareness	UAVs Degree	Distance
GSO	SOCS [87]	FANET	✓	✗	✓	✓	✓
	BICSF[84]	FANET	✓	✓	✗	✓	✓
	MACSI [88]	FANET	✓	✓	✓	✗	✓
ACO	APAR [89]	FANET	✗	✗	✗	✗	✗
	ERSUAV [92]	FANET	✗	✗	✗	✗	✗
	AntHocNet [95]	FANET	✗	✗	✗	✗	✗
BCO	BeeAdhoc [97]	FANET	✗	✗	✗	✗	✗
	BeeHocNet [95]	FANET	✗	✗	✗	✗	✗
PPO	BIMPC [102]	FANET	✗	✓	✗	✗	✗
SMO	BOLD [108]	FANET	✓	✗	✗	✗	✓
PSO	SIC [109]	FANET	✓	✗	✓	✓	✓
GWO	BIC [110]	FANET	✓	✗	✗	✓	✓

Table 3.6: UAVs Swarm Intelligence Clustering Schemes [Cluster Formation]

SIO	Clustering Schemes	Neighbour Criteria	Clustering Parameters	Re-Clustering	Balanced Cluster
GSO	SOCS [87]	M-hop	Energy, Distance, Position, Distance	✗	✗
	BICSF [84]	M-hop	Energy, Mobility, Neighbors, Distance	✓	✗
	MACSI [88]	M-hop	Energy, Mobility, Position, Distance	✗	✗
ACO	APAR [89]	1-hop	✗	✗	✗
	ERSUAV [92]	1-hop	✗	✗	✗
	AntHocNet [95]	M-hop	✗	✗	✗
BCO	BeeAdhoc [97]	M-hop	✗	✗	✗
	BeeHocNet [95]	M-hop	✗	✗	✗
PPO	BIMPC [102]	1-hop	Mobility, Energy	✓	✗
SMO	BOLD [108]	M-hop	Energy, Distance, Position	✗	✗
PSO	SIC [109]	M-hop	Energy, Location, Distance, degree	✓	✓
GWO	BIC [110]	M-hop	Energy, Location, Distance	✗	✗

Table 3.7: Swarm Intelligence Clustering Schemes [Performance Metrics]

SIO	Clustering Scheme	Comparison Schemes	Routing Overhead	End to End Delay	Delivery Ratio	Residual Energy	Cluster Building Time	Cluster Lifetime
GSO	SOCS [87]	[92], [111], [86], [112]	✗	✗	✓	✓	✓	✓
	BICSF [84]	[85], [86]	✗	✗	✓	✓	✓	✓
	MACSI [88]	[80], [79]	✗	✗	✗	✓	✗	✓
ACO	APAR [89]	[81], [91], [90]	✓	✓	✓	✗	✗	✗
	ERSUAV [92]	[93], [94]	✗	✓	✗	✗	✗	✗
	AntHocNet [95]	[98], [99], [81]	✓	✓	✗	✗	✗	✗
BCO	BeeAdhoc [97]	[98], [99], [81]	✓	✓	✗	✗	✗	✗
	BeeHocNet [95]	[98], [99], [81]	✓	✓	✗	✗	✗	✗
PPO	BIMPC [102]	[103], [105], [113], [104]	✓	✗	✗	✗	✗	✓
SMO	BOLD [108]	[114]	✗	✗	✗	✓	✓	✓
PSO	SIC [109]	[73], [79], [74], [55], [97]	✓	✓	✓	✓	✓	✓
GWO	BIC [110]	[73], [74], [78], [87], [84],	✗	✗	✗	✓	✓	✓

Table 3.8: Swarm Intelligence Clustering Schemes [Simulation Study]

SIO	Clustering Scheme	Mobility Model	Simul. Tool	UAVs Speed	Simul. Area	Distance	Initial Energy	No. of UAVs	Simul. Time
GSO	SOCS [87]	RPM	MATLAB	✗	1x1, 2x2, 3x3 km^2	5m	80W/H	15, 20, 25, 30, 35	120s
	BICSF [84]	RPM	MATLAB	✗	$1.5x1.5km^2$ $2.5x2.5km^2$	5m	80W/H	15,20,25,30,35	120s
	MACSI [88]	RWP	✗	✗	1x1, 2x2 km^2	3m	10j	10, 20, 30, 40, 50	✗
ACO	APAR [89]	RWP	NS-2	20m/s	$1x1km^2$	✗	✗	30,200	10m
	ERSUAV [92]	✗	V.C++ 6.0	✗	$240\times240m^2$	✗	✗	25-200	10-30m
	AntHocNet [95]	RWP	NS-2	20-50m/s	$1.5x1.5km^2$	✗	✗	10, 20, 30, 40, 50	20s
BCO	BeeAdhoc [97]	RWP	NS-2	✗	$1.5x1.5km^2$	✗	✗	10, 20, 30, 40, 50	20s
	BeeHocNet [95]	RWP	NS-2	20-50m/s	$1.5x1.5km^2$	✗	✗	10, 20, 30, 40, 50	20s
PPO	BIMPC [102]	✗	NS-2	40-70m/s	50Km*50Km	✗	✗	100	✗
SMO	BOLD [108]	✗	MATLAB	50-70mph	$500x500m^2$	✗	28W/H	10,15,20,25,30,35	✗
PSO	SIC [109]	✗	MATLAB	10–30m/s	$1\times1km^2$	✗	2j	10–150	✗
GWO	BIC [110]	✗	MATLAB	10–30m/s	$1\times1km^2$	115m	5j	20-140	✗

The clustering of multi-UAV in FANET is a dynamic optimization problem. There is a need for a clustering optimization scheme to address the issues of UAVs' high-energy consumption, high mobility, degree, position, and distance. In the literature, the authors aim to improve the network lifetime of multi-UAVs using different schemes. Each scheme has different criteria for the optimum selection of CH and formation of balance clusters, but no standard mechanism is adopted to evaluate the performance of the proposed schemes. According to the author's understanding, sincere efforts have not been made to form stable and balanced clusters using bee intelligence.

In a multi-UAVs network, the UAVs' energy needs to keep in mind during the optimum CH selection to increase the network lifetime. The UAVs with more energy will be more suitable to become UAVs-CHs. Still, the authors in [89], [92], [95], [97] and [102] ignored energy during the CH selection process.

The frequent change in topology can be minimized by considering the relative mobility but the authors ignored the mobility in [87], [89], [92], [95], [97], [108], and [109]. The re-clustering process also increased with the frequent change in topology due to low energy, the larger number of UAVs, etc. That can be called less frequently if a stable cluster is formed. The re-clustering procedure did not mentioned in [87, 88], [89], [92], [95], [97], [108] and [110].

Forming the balanced cluster is a complex task due to the application requirement. Each application has different priorities for UAVs pre-arrangement, cluster size, and CH selection. The UAV degree in each cluster needs to be the same for balance cluster formation, but the authors in [88, 89, 92, 95, 97, 102, 108, 109] did not mention the number of UAVs in each cluster. The large number of UAVs in a cluster increases the communication load on each CH.

In most scenarios, the path selection is based on UAVs' relative direction and speed, which is considered only [87, 89, 95, 108, 109] while ignored in [84, 87, 88, 92, 97].

The mobility model is planned to provide a complete pattern based on UAVs' direction, position, speed, and velocity ignored in [92, 102, 108-110].

The riffle effect of re-clustering needs to be minimized to reduce the control message overhead, which is not considered in [87-89, 92, 95, 97, 108, 110].

In most of the proposed schemes [84], [87, 88], [89], [92], [95], [97], [102], [108], [109] and [110] the load on the link ignored which needs consideration to minimize the load and to reduce the energy consumption of cluster members.

3.3 Localization of UAV using Optimization Scheme

The accurate TAs identification with localizing multiple UAVs on the target spot is a complicated task because of the random mobility of UAVs. The researcher tried to find the accurate TAs in the field with or without prior knowledge about the position. They try to obtain information using the anchor node or range estimation technique. The existing TAs identification and UAVs localization schemes based on swarm intelligence are presented and discussed in the following sub-section and summarized in Table 3.9.

3.3.1 PSO based Localization

Arafat and Sangman in [109] proposed an energy-efficient clustering scheme based on particle swarm intelligence for an emergency scenario. Swarm intelligence-based localization (SIL) defines the search space using a boundary box to minimize computation energy. The placement of UAVs is randomly in the 3D search space. The grouping scheme measures the distance of the target UAVs. The distance of UAVs from CH measures with estimation model. Optimal path measures with PSO model. The number of localized target UAVs improves with the increase in the target UAVs because of SIL scalability. Furthermore, iterations were reduced to minimize the localization time per UAV. The proposed SIL method is compared with hybrid PSO (HPSO), PSO, Ant Colony Optimization (ACO), K-means, and Genetic Algorithm (GA) based localization algorithms that show better performance in terms of localization error and accuracy.

Findings: (i) The localization of UAVs is based on the target UAV instead of actual targets on the ground. (ii) The increase of target UAVs in the exact location results in a collision among UAVs. (iii) The computational cost will be increased because of the high degree of UAVs and decrease the convergence time. (iv) The topology changes due to UAVs' mobility based on particle position that needs to update frequently, which is not considered.

Ma'Sum *et al.* [115] proposed the modified-PSO scheme for military purposes in which a UAV performs tracking, localizing, and detecting the object. The UAV performs object detection depending on its colour, i.e., known as Blob. Fitness depends on Blob; if the size of the Blob is more significant than the threshold, the UAVs start the tracking process. The tracking algorithm Proportional Integral Differential (PID) control measures the object position error updates its current and previous position. Swarm of UAVs based on PSO is used to find the target with local and global perception. The

Odometry algorithm is used for updating information about the localization and mapping of UAVs. Three UAVs were selected to locate the static or mobile target in an indoor scenario. The proposed mPSO shows better tracking, localizing, and detecting the object in a small geographical area.

Findings: (i) The localization of UAVs is based on the ground targets in small-scale scenarios. (ii) The detection, tracking, and localization tested only for three UAVs for a single target. (iii) The convergence time increased in the proposed approach. (iv) The UAVs are placed at a specific point to detect the object. (v) The UAVs' movement and frequency are not defined.

Cheng *et al.* [116] developed the improved version of PSO for UAV path planning in real-time. The UAV may face obstacles during the mission in which the real-time path planning strategy is beneficial. The following steps are performed during path planning. First, Kalman filtering is applied to forecast and track the obstacles. Improved PSO used with chain structure for searching the target spot. Second, an adaptive approach is applied to enhance the searching capability that adjusts gbest dynamically, *l*best, and inertia parameters of PSO. Third, a search process depends on chaos optimization applied to enhance the ability to escape from local maxima. The results show that the iPSO performance is better in terms of real path planning than the other algorithms.

Findings: (i) In this research, a localization of a single UAV is considered. (ii) The number of targets is defined. (iii) UAVs' random movement and mobility are not defined in the study. (iv) The PSO-based localization has the issue of avoiding obstacles and collision.

Sánchez-García *et al.* [117] developed an algorithm named distributed and dynamic PSO-based algorithm (dPSO-U) for FANET to explore the disaster scenario for searching victims using a team of UAVs. This scheme uses a set of different values for neighbour best, local best, and inertia parameters to result in better performance. The victims are considered in a group known as victims cluster, each with static CH. The victims may be static and mobile, and the random mobility of victims is restricted to a cluster. A team of six UAVs is considered a multi-copter or a fixed-wing. The mobility of UAVs is assumed in 2D space, and a simplified collision avoidance mechanism is considered. The distributed scheme application produces flight information without any prior information about the destination, but the UAVs keep the information about the boundary's coordinates. Compared with optimal trajectory planning algorithms, the proposed algorithm was found faster in discovering victims' scenarios and efficient in the connection between victim and UAVs network.

Findings: (i) The parameter in dPSO is set to fixed values, but the parameter values are changed in a dynamic environment. (ii) The random values of parameters in d-PSO are not considered. (iii) The localization of UAVs not discussed.

3.3.2 GWO based Localization

Arafat and Sangman [110] proposed an energy-efficient and range-free-based localization algorithm (BIL) based on HGWO for a multi-UAVs network. The bounding cube technique is used for defining the initial search space. The BIL detects the target UAV position as the wolf leader estimates the prey's position and movement towards the target. The UAVs are categorized as normal, unknown, neighbour, and anchor UAVs deployed in the network. The UAVs in the sensing range are called neighbour UAVs. The position-aware UAVs are known as anchor UAVs that update their exact position information all the time. Unknown UAVs' location is estimated with initial, prediction, and filtering phases. There will be no location information about the target UAV at the start, but an anchor UAV position is considered to obtain information about the target UAVs. The anchor UAVs share their location with all the UAVs in a range. The performance of BIL compared with existing GWO and PSO-based algorithms in terms of localization accuracy, average localization error, and cost of convergence. The comparison result shows that the BIL decreases localization error and avoids Flip Ambiguity (FA) extended form.

Findings: (i) The UACs localization depends on the target UAV instead of actual targets on the ground. (ii) The increase of target UAVs in a similar location results in a collision among UAVs. (iii) The computational cost will be increased due to the large number of UAVs and decrease the convergence time. (iv) The topology changes due to UAVs' mobility based on particle position that needs to update frequently, which is not considered.

3.3.3 GA based Localization

Cheng *et al.* [55] presented a path planning algorithm for UAVs based on GA. Shortest path used and avoid all the obstacles during the mission for reaching the destination. The fitness function is based on the threat and path cost. The threat cost means to ignore all threats by the UAV during the mission safely, and path cost means to follow the shortest path to reach a target. The simulation result shows that IGA is taking advantage of the immune system approach to enhance the convergence speed by knowing the location and intensities of threats and flight constraints.

Findings: (i) The immune GA is used to find the shortest path, but the number of UAVs and targets is not mentioned. (ii) The simulation area and time not mentioned. (iii) Localization of multi-UAV not discussed to fined target.

Faelden *et al.* [118] proposed the scheme based on GA to localize UAVs position with the help of transceivers signals. In this scheme, the parameters, i.e., received signal, population size, and position of the transceiver utilized as an input to find the UAVs in the xyz axis. First, it measures the distance of each transceiver. Secondly, it calculates the received signal levels and compares both of them. This method requires multiple iterations and more computation for locating UAVs in a network.

Findings: (i) A single UAV is considered to find a single target. (ii) The simulation area and tools are not mentioned. (iii) The UAV relative mobility is essential for localization, which is not discussed. (iii) The localization accuracy was not measured in the study.

3.3.4 ACO based Target Identification (TI)

Perez-Carabaza *et al.* [119] proposed the ACO approach to optimize multiple UAVs' minimum time search (MTS) issue. The Time required parameter for the target identification is optimized. The scenario is formed as a grid representation in a cell. The target model is known in advance in which cell its probability is high. The updated information obtain quickly from the probability map (trajectories) about all the UAVs. The proposed approach is compared with other statistical techniques that show better performance.

Findings: (i) Minimum time search optimization is used based on probability in which the computation time is not defined in advance. (ii) The distance among UAVs may be large that increasing the computational cost and time. (iii) The localization error, iteration required, and computation cost are not discussed.

Hauert *et al.* [120] developed a swarm of micro-UAV (MAV) based ad-hoc wireless communication network systems for ground segments (GS) in the disaster area. The MAVs in the proposed approach are based on local communication with a neighbour and closest sensors that provide path information. The inspiration from the army ants is the ACO algorithm used to find the first target or responder in the disaster area. Reliable communication was established among the first responder and GS. Indoor and outdoor localization was performed with a k-means algorithm. The 3D simulation was performed in a scenario of two GS and 10 to 20 positionless MAVs with predefined trajectories.

Findings: (i) Minimum time search optimization is used based on probability in which the computation time is not defined in advance. (ii) The simulation area and tool are not mentioned. (iii) The simulation time and computational cost are not discussed.

3.3.5 K-means based FA for Localization

Liu and Chen [121] proposed a k-means firefly localization scheme to search the precise target location in the WSN. Initially, it calculates the distance between the nodes and the received signal strength identifier of a target. Secondly, with the help of the weighted k-means scheme, it establishes the improved fitness function. Finally, the FA was introduced to resolve the multi-objective optimization issue and accurate target location. The proposed algorithm decreases the significant distance error and enhances the estimation accuracy with the help of the fitness function. The proposed scheme's performance results better in terms of stability, convergence, and accurate localization.

Findings: (i) The number of UAVs for localization varies and is not discussed in the simulation. (ii) The computational cost will increase because of a high degree of UAVs and decrease the convergence time.

Table 3.9: Summary of the Existing Work on Localization

Ref.	Algorithm	Mission	Optimization	No. of Targets	No. of UAVs	Area	Scenario	UAV Speed	Comparison	Simulation Tool
[109]	SIL-PSO	Target localization	Localization accuracy	50	10-150	1*km* x 1*km*	3-D Outdoor	10-30 *m/s*	HPSO, PSO, *K*-means, ACO, and GA	MATLAB
[110]	GWO-BIL	Target localization	Localization accuracy		100	1000 m × 1000 m	3-D Outdoor	10-30 *m/s*	DV-Hop, GWOLPWSN, 3D-GAIDV-Hop, DECHDV-Hop, and HDPSO	MATLAB
[115]	mPSO-Loc	Target localization	Maximize target size	1	3	8 *m* x 6 *m*	3-D Indoor	×	×	ARDrone
[116]	iPSO-Loc	Real-time trajectory planning	Obstacle avoidance	×	1	100*100km²	2-D Outdoor	×	PSO, ICPSO	×
[117]	dPSO-Loc	Exploration and convergence	Discovering victims	200	6	5*km* x 5*km*	2-D	15 ms⁻¹	Lawn Mower	×
[55]	iGA-Loc	Path Planning	Shortest Path	×	×	×	2-D	×	GA	MATLAB
[118]	GA-Loc	Localization	Position	1	1	×	2-D	×	×	×
[119]	ACO-TI	Minimum time search of a target	Minimize the time of detection	1	1,2	×	2-D	×	CEO, BOA and GA	×
[120]	ACO-TI	Minimum time search of a target	×	2	15	×	3-D	10 m / s	×	×
[121]	K-Means Firefly	Localization of target	Searching accuracy	200	×	500 x 500 m^2	×	×	IPSO, IGA, FA	MATLAB

The existing localization methods average error rates from 10 to 30 meters [109]. The standard PSO-based localization avoids obstacles and a high risk of collision [115-117]. The UAV avoids all the threats and tries to follow the shortest path during the flight to reach the destination [55],[118]. The ACO-based target identification optimizes the minimum search time based on a probability approach in which the computational cost and time are not evident in advance [119, 120]. The PSO-based techniques try to resolve the localization issue in UAVs networks with the help of distance measurement methods. The distance-based localization method has a significant measurement error known as flip ambiguity (FA). FA is the difference between UAVs' actual and measured distance due to environmental factors such as external noise, etc. A multi-UAVs network requires a clustering scheme that provides high location accuracy with minimum difference. To develop the energy-efficient clustering protocol, the constraints such as limited energy, transmission range, and dynamic links need consideration. Localization aims to detect the target and measure the exact location of UAVs in a limited time. The clustering-based localization schemes [3, 109, 110, 116, 121] differ in terms of accuracy, error rate and computation cost. They categorized the localization method based on the UAVs characteristics such as range vs. range free, anchor vs. anchor free, static vs. mobile, indoor vs. outdoor and sparse vs. dense network. In literature, in most of the application scenario, the range free-based localization is preferred and compared with non-range free localization to achieve high accuracy and minimum localization rate.

3.4 UAVs based Data Aggregation

In a multi-UAVs network, collecting and transmitting information through multiple hops increase energy utilization. The data aggregation approach is used to reduce UAVs' energy utilization and minimize the load on UAVs-CH. It increases the multi-UAVs network lifetime. The data aggregation approaches reduce communication costs and energy consumption. The researchers proposed the following data aggregation approaches without redundant data elimination.

3.4.1 UAV-Assisted Topology Aware Data Aggregation

Wang *et al.* [122] introduced a UAV-assisted topology-aware data aggregation protocol (TA-UAV-DA). The data aggregation approach was inspired by the compressive sensing approach to reduce the errors rate in the data reconstruction process, extra overhead, and energy consumption. Balanced tree-based topology construction performs that minimize the scope and update matrix measurement. The cluster members send data to CH, and UAV gathers data from the CHs. The simulation results show that the approach performs better in the reconstruction of data, efficient in data aggregation and storage constraints as compared to a random walk (RW) and intelligent compressive sensing (ICS).

Findings: (i) In this research, the topology-aware data aggregation is performed in WSN. (ii) It is not mentioned how the UAVs will collect the data from the sink node. (iii) The sink node is only used to store the huge amount of data from sensors that need more computation and communication that will automatically affect the network's performance. (iv) The link transmission failure neglected that causes packet loss and decreases the performance of data aggregation. (v) The sink node can also receive redundant data, and there is no redundant data elimination scheme used for data aggregation.

3.4.2 Energy Efficient UAVs based Data Aggregation

Wu *et al.* [123] developed an energy-efficient UAV-based data aggregation protocol (EE-UAV-DA). The UAV gathers data as a data mule. The proposed scheme calculates the optimum link for the data mule through all CHs by using a genetic algorithm (GA), balancing the system throughput, and reducing the delivery delay from sensors to the sink node. The optimization scheme provided by heuristic search identifies optimum solutions for joint CH selection and optimal routes for the data mule to decrease the energy consumption. The objective function calculates and measures the quality of each solution for the optimum path. The optimum path is chosen with the high fitness value. The simulation result shows the increase in the network's lifetime in updating time, throughput, and energy consumption compared to the center-based, greedy-based, and cluster-based genetic algorithm.

Findings: (i) The data aggregation is used to minimize the energy utilization of sensor nodes and UAV. However, the number of UAVs and how these UAVs will collect data is not mentioned. (iii) The UAV collects data from CH of sensor nodes that also receive duplicate data, and there is no mechanism defined for duplicated data elimination.

3.4.3 Multi-UAVs Energy Saving Data Aggregation

Xiong *et al.* [56] proposed the data aggregation scheme which combines SCF and next-hop routing for multiple UAVs system to reduce energy utilization. The UAVs have low energy consumption during processing and storage compared to the flight and communication time; that is why the store-carry-forward (SCF) routing is better than next-hop routing. In the multi-UAVs system, Single and Coalition Formation Strategies (SCS & CFS) followed the CFG algorithm that reduces the energy utilization. All the UAVs that work under the individual decision are based on a hybrid model for forming a coalition aggregating the information to a UAV and then transferring information. In CFS, with the help of the CFG scheme, all the UAVs make a coalition format based on the size of data, position, and topology that collect information to a UAV that transfer in an optimized way. The SCS performs better for the limited number of UAVs and the CFS is recommended for many UAVs.

Findings: (i) The data aggregation scheme combined the store, carry, and forward mechanism to decrease energy consumption. (ii) The group of UAVs transmits data to a ferry UAV. There is no mechanism defined for eliminating or preventing the same data at ferry UAV. (iii) The sensing and communication of data from multi-UAVs will consume more energy.

3.4.4 Multi-UAVs Optimized Communication

Thammawichai *et al.* in [124] proposed Optimized communication and computation for multi-UAV (OC-mUAV). The multi-hop clustering incorporates data aggregation using a mixed-integer optimization formulation with MINLP. The optimal control problem was formulated for determining the UAVs' roles. The system framework tried to that the optimal number of UAVs communicate to BS. Each UAV acts as an aggregator and establishes the link to consume minimum energy during routing information. An adaptive energy consumption model is used to minimize energy consumption by considering sensing energy, aggregation energy, transmitting energy, and receiving the energy of multi-UAVs. Area mapping and target tracking applications are addressed during testing for reducing communication and communication energy. Target and sensor model is used to select the sensor UAV based on the subset of UAVs. The distance between UAVs is used for the mapping application. The data aggregation framework resulting in network flexibility and reliability due to self-organized network prolongs network lifetime due to multi-hop network. It provides better performance due to the clustering approach of heterogeneous UAVs.

Findings: (i) The mobile agent will collect data and send it to a UAV. (ii) A single UAV considered that would receive data from multiple agents. (iii) The optimization mechanism minimizes the energy and ignores duplicate data.

3.4.5 UAVs Assisted Data Aggregation

Dong *et al.* in [125] proposed an algorithm to collect and process data in WSN using UAVs and mobile agents (MAs) to search for victims in disaster sites. The mobile agents move around the area to collect data from sensor nodes and then share the desired information with UAVs. The UAV assigns the MAs to a group leader. The density of the sensor nodes in a group known by the group leader has high residual energy and optimum link to a UAV. The routing of MAs is based on information-driven static and dynamic mobile agent planning (ISMAP & IDMAP) algorithms for the dense and sparse network. The proposed scheme is efficient in energy and time for any dense network using MAs and UAVs.

Findings: (i) In this research, the data aggregation is performed in WSN. (ii) Mobile agent collects data from CH. There are no criteria defined for mobile agents. (iii) The duplicated data may be transmitted to a UAV, and there is no mechanism defined for prevention.

3.4.6 Energy Effective Data Gathering

Liu and Zhu [126] proposed the energy-efficient data collection approach to decrease the energy utilization within a stipulated time in UAV-aided WSN. The sensor nodes are placed randomly in the environment. The proposed approach uses three transmission modes to solve the issue of the short buffer size of sensor nodes to transmit data within the allotted time slots. The sensor node selects the modes, i.e., waiting, transmission to sink node, and uploading to a UAV in a given discrete time slot. Sleep and do not transmit the status of sensor node is selected in waiting mode. The sensor node uploads data to the sink node in the second mode. In the third mode, the sensor node delivers data to UAV based on the threshold value and distance condition during the UAV preplanned with trajectory visit. The fixed-wing UAV is deployed with a constant velocity. This article applies the first finite-horizon sequential Markov process and dynamic programming algorithm for the best transmission policy. Secondly, the optimization of the preplanned trajectory for UAVs using a recursive random search algorithm (RRS) is performed to fix the transmission policy. The results show efficient energy utilization among the existing benchmark schemes, i.e., optimal transmission, trajectory, and sink-SN transmission scheme.

Findings: (i) Preplanned trajectory for UAVs used to collect data from the sensor node. (ii) Fix transmission policy used to transmit and receive data but no mechanism defined for duplicate data. (iii) The optimum sensor node selected for transmission ignored redundant data transmission.

The performance of network lifetime depends on efficient energy utilization. The researchers tried to minimize the energy utilization in WSN, but in FASNET, energy utilization problem still exists. Due to the flying speed of UAVs, rapid variation in topology, terrain structure, and diverse directions make it difficult to collect and route information. The researchers proposed energy-efficient schemes by considering different parameters such as reducing the communication distance, computation cost, mobility, degree, etc. However, the data collection minimizes communication load to save bandwidth and energy [56], [122-125].

The data aggregation approaches are considered to be the best to minimize the load on multi-UAVs [56, 122-125]. It reduces UAVs' energy utilization and increases wireless networks' lifetime instead of multi-UAVs. The data aggregation approach is different in WSN and VANET from UAV networks. In WSN, uses of the data aggregation approaches are for decreasing energy consumption rather than minimizing network capacity usage, while in VANET, due to high variation in the topology, the data aggregation is performed by many vehicles. Energy factors constrain the multi-UAVs system due to degree, mobility, density, and other parameters that are why it combines the requirement of sensor and vehicular ad-hoc network. The UAVs also consume energy on processing and storing more data, just like on flight and communication.

3.5 Problem Statement and Research Questions

The detailed survey of the literature clarifies that FASNET has a set of communication challenges, which reduces the network lifetime. Researchers have proposed various clustering schemes to optimize the energy utilization in FASNET. In this study, exploration is performed on applying multiple concepts of clustering optimization, localizing of UAVs for accurate TAs identification, data aggregation, and its implementation on various scenarios of FASNET. The UAVs are operating in a dynamic environment. This research strives to identify mobility, degree, and energy parameters for designing bio-inspired energy-efficient and mobility-aware clustering. Considering the above parameters of FASNET in a dynamic environment for clustering, and becomes a dynamic optimization problem. The sub-problems in this research are:

The re-current change in the topology of FASNET introduces additional challenge of mobility. Re-affiliation rate of mobile UAVs reflects the change in topology with time. The UAVs-CHs should be selected in a fashion to minimize re-clustering.

The link-connection duration of a UAV to its CH depends on the UAVs communication range and remaining energy. The movement of a UAV outside its CH range reduces the link-connection duration that reduces the network's lifetime.

The fast movement of UAVs toward maximum limit increases the probability of escaping UAVs from the range of communication, and thus the UAVs degree will gradually decrease. For stable cluster formation, only those UAVs that accomplish the criteria to join or leave the cluster need to be considered.

Balance cluster formation in cluster-based architecture is the key optimization issue. Maintaining UAV degree in the clusters is tedious without affecting the expected performance goals to balance the communication load. The CHs gather data from its member UAVs using an aggregate manner. The size of each cluster should be approximately the same to reduce the burden on each UAV-CH.

Developing a UAV clustering scheme that routes the information efficiently is the key issue. Selection of optimum CH and cluster formation is a complex task. The CHs should be selected to minimize the cost of resources such as time, energy, and bandwidth. The localization of high mobile UAVs becomes more complicated in the cluster. The UAVs should be localized in such a way that more UAVs be localized with minimum iteration.

Another key issue is the redundant data transmission and control message overhead. The same data transmission to the CH by different UAVs in a cluster and control message overhead increases the CH load and maximizes delay. Data aggregation algorithm requires detecting and preventing duplicated data transmission to minimize the message overhead and communication load.

Benefits of clustering schemes are guaranteed when CHs are selected carefully. Furthermore, how will the clusters be formed once the CHs are chosen? However, to the best of the author's knowledge, based on the systematic literature review, none of the existing techniques utilize a combination of the above discussed designed consideration for the CHs selection, cluster formation, localization, accurate TAs identification, and data aggregation.

3.5.1 Research Questions

In FASNET, research questions are based on how to formulate a clustering problem to a dynamic optimization problem that prolongs the network life.

1. How to select optimum CHs for multi-UAVs to avoid un-stability?
2. How to select suitable CH to minimize re-clustering?
3. How should size of each cluster be approximately the same to balance the load on each CH?
4. How to localize the UAVs with minimum iteration to identify accurate TAs?
5. How to prevent transmission of duplicated data for reducing bandwidth utilization and communication delay?

Chapter 4

Research Methodology

This chapter highlights the research methodology to achieve the objectives. The methodology consists of several interdependent sub-phases, as shown in the proposed research methodology in Figure 4.1. The proposed bee intelligence optimization is included in how it works based on the foraging behavior approach. The metrics used by the proposed schemes for performance evaluation are explained in the subsection 4.4. The steps associated with the energy, degree and mobility of multi-UAV are discussed. This section further discusses the validation scheme for the validation and testing of the proposed schemes.

4.1 Proposed Research Methodology

In the proposed research methodology, the complete process comprises of the following steps.

4.1.1 Parameter Elicitation

The first step involves discovering different parameters that are considered during the UAVs CHs selection process based on objectives for clustering, localization, and data aggregation.

4.1.2 Parameter Specification

The second step involves the specification of parameters considered for the selection of CHs, formation of clusters, localization for TAs identification, and data aggregation to achieve the desired objectives.

4.1.3 Formulation of Clustering and Localization Problem

The third step involves modeling the network to a graph and formulating how it is partitioned to a subgraph if the graph is dynamic. Formulation of clustering problem to a dynamic optimization problem, based on the parameters, i.e., energy, degree, and mobility for clustering and environmental factors, i.e., relative humidity, soil moisture, temperature, light intensity, NPK (nitrogen (n), phosphorus (p), potassium (k)), power of hydrogen (pH) for localizing the UAVs for identification of optimal TAs.

4.1.4 Evaluation of Fitness Function

The fourth step deals with the experimental environment. Different scenarios are created, and then each scenario is evaluated based on the fitness function obtained in the previous step.

4.1.5 CH Selection

In this step, the algorithms for CH selection based on honeybees with foraging behaviour and fitness function is developed.

4.1.6 Cluster Formation

Once the CHs for UAVs are selected, ordinary UAVs will join the nearest CHs. In case of a tie, UAVs will join the CH randomly. The UAV CHs will communicate with other CHs for inter-cluster communication. The border UAVs will assist the CH UAV if direct contact is not possible. The border UAVs reside within the jurisdiction of more than one cluster.

4.1.7 UAVs Localization

Multi-UAVs' localization is based on the Identified TAs, i.e., environmental factors such as relative humidity, soil moisture, temperature, light intensity, NPK, and pH.

4.1.8 Data Aggregation

The multiple UAVs have the same information about an event in the network. The CHs aggregate the information and transmit it to the destination. Hence, redundant data elimination clustering approach prevents multiple transmissions of the same data packets to the BS.

4.1.9 Simulation of the Proposed Algorithm

In the last step, a simulation of the proposed algorithm is performed for different scenarios like changing network size, parameters, factors, and transmission range.

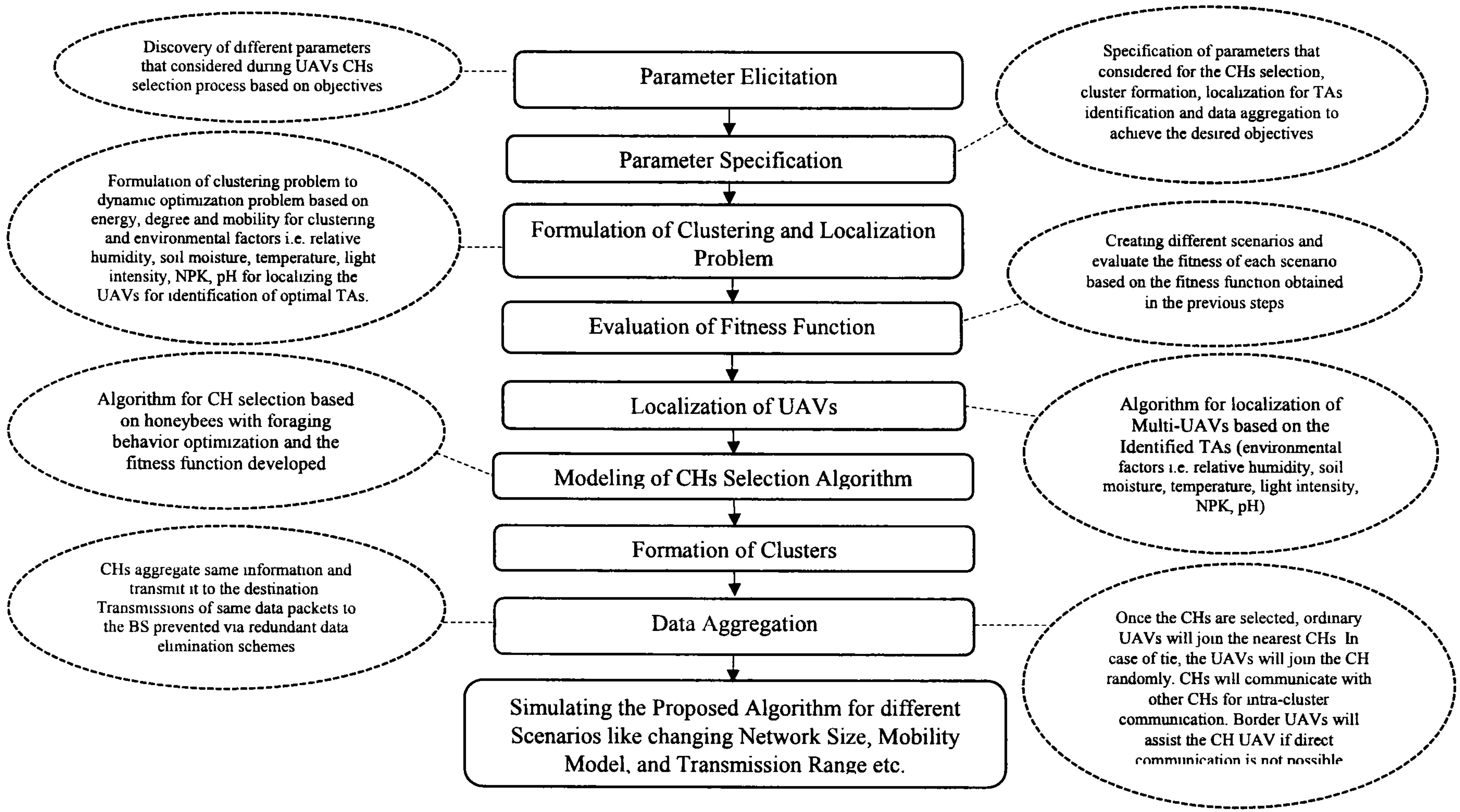


Figure 4.1: Proposed Research Methodology

4.2 Bee Intelligence

Honeybees live in big colonies (up to 50k) with a queen, female workers (from 20k to 40k), and male drones (from 200 to 300). The two common properties of honeybees are foraging and mating behaviour. Honeybees extend their range over a distance in a different direction for finding optimal food sources from all available sources. They visit in a group to the flower patches that contain a plentiful amount of nectar and less effort.

In this research, the clustering and localization of UAVs for accurate TAs identification problem in multi-UAVs network is formulated as a dynamic optimization problem. The UAVs-CH selection, cluster formation, and TAs identification algorithms are developed based on problem formulation and objective functions. The foraging property of bees algorithm used for the UAVs-CH selection. The honeybees efficiently select the sources of food with more nectar. The foraging behaviour is used to efficiently determine the suitable UAV as a CH. The cluster maintenance mechanism is established to keep the topological variation efficiently. The efficiency of bees optimization has been tested [127, 128] in similar areas like WSN, MANET, VANET, etc., and found efficient. The proposed bio-inspired schemes based on honeybees' foraging behaviour compared with the clustering schemes (i.e., based on GSO, PSO, and PPO), localization schemes (i.e., based on PSO, GA, and K-means), and data aggregation schemes (i.e., based on non-redundant data elimination aggregation). The benefits of bee optimization technique are flexibility, simplicity, managing objective cost, discovering local solutions, easy implementation, and solving complex functionalities.

4.3 Fitness Function

The fitness function for clustering optimization is based on the weights factor of UAVs residual energy, relative mobility, and the degree to select the UAVs-CH for multi-UAVs in FASNET. First, calculate the weight factor concerning residual energy to become the UAVs-CH. Second, to calculate the weight factor relating to UAVs degree to become the UAVs-CH. Similarly, third, the weight factor of a UAV concerning mobility is calculated as; the UAV with relative mobility (speed and direction) or static

UAVs are more suitable candidates. Fourth, the weight factor of a UAV concerning communication load by preventing the duplicate control messages will be as; the UAV with low communication overhead are suitable candidates. Fifth, the number of clusters should be calculated before the UAVs-CH selection. The fitness function for clustering and localization of UAVs identifies the TAs based on the weights of environmental factors, i.e., relative humidity, moisture, temperature, light intensity, NPK, and pH, which are calculated using the nectar amount for each UAV. Min-Max normalization is applied to balance the contribution of the parameters. The minimization or maximization function is used to calculate the fitness of UAVs-CH.

4.4 Performance Metrics

The performance of the proposed work is validated via a series of simulation experiments based on different performance metrics and compared with state-of-the-art clustering schemes based on PSO, GSO, and PPO to confirm that the proposed scheme extends the network lifetime.

The performance metrics considered in this research for BIMAC validation are link-connection time, CH lifetime, number of UAVs per cluster, re-association time, and formation time of cluster with varying UAVs speed and communication range. The average link connection time is the average time of connectivity among the UAVs to its CH. The Average UAV-CH lifetime is the average lifetime of a UAV on which it plays the role of CH. The average number of UAVs in a cluster is the average number of members per cluster. Average re-association time is the time of stability of a UAV to its CH instead of re-affiliation to a new cluster frequently. The time taken to form a cluster is called cluster formation time.

In the second contribution, standard performance metrics considered for validation of BICTID are packet delivery ratio (PDR), end-to-end delay, communication overhead energy consumption, and cluster lifetime with varying UAV degree and rounds. The packet delivery ratio is the ratio of packets received by the receiver UAVs versus the packet sent by the sender UAVs. Mean end-to-end delay is the average time taken by the UAVs for packets sending and receiving. It also measures the delay caused during routes discovery and waiting in a queue. Communication overhead means that the transmission of the same packets or the additional information to the UAVs- CH reduces communication speed and consumes energy. Energy consumption shows the total energy consumed by the UAVs for data transmission. The mean cluster life is the time of UAVs-CH fitness.

In the third contribution, FSNet optimized communication for data aggregation is proposed. The standard performance metrics considered for validation are PDR, end-to-end delay, packet drop ratio, communication overhead, energy consumption, bandwidth utilization with varying numbers of UAVs, and data rates. The packet delivery ratio is the ratio of packets received by the receiver UAVs versus the packet sent by the sender UAVs. End-to-end delay is the time taken by the UAVs for packets sending and receiving. It also measures the delay caused during routes discovery and waiting in a queue. Packets drop ratio means that the packets may be decreased during the transmission, and it counts the ratio of the total number of packets received and packets sent. Communication overhead means the transmission of duplicate packets or additional information to the UAVs- CH reduces communication speed and consumes energy. Energy consumption shows the average amount of energy consumed by the UAVs for data transmission. The bandwidth utilization means that the redundant data utilize the capacity of the transmission medium, which increases the bandwidth utilization.

Chapter 5

Bio-Inspired Mobility Aware Clustering

A single UAV is used to control, monitor, observe, and sense the field in the early stages. If a UAV fails, there are no alternatives to keep up the communication functionality. The application of multi-UAVs does not disturb the communication in case of a single UAV failure. The multi-UAVs re-configure and sustain the communication of UAVs and GS. The coordination and teamwork of multi-UAVs improve the overall performance of FASNET. The FASNET dynamic nature has the issues of degree, mobility, and energy that directly impact the network lifetime.

In clustering, structure of a multi-UAV network is divided into multiple clusters. The UAVs are grouped in a cluster, and each cluster has a head and members. The UAVs play a role of either a CH or a member or a gateway UAV. The member UAVs share their information to its CH. The CH has the responsibility to control and manage intra-cluster and inter-cluster communication. In clustering, the selection of optimum CH is a challenging task. The UAVs-CH has more residual energy and other characteristics to gather information from UAVs in the range. The CH selection constraints vary from scenario to scenario based on communication requirements. The CHs in FASNET have low latency in contrast with flat routing. The topological changes are adjusted locally at the CH level and do not affect the whole network.

UAVs-CH selection is accomplished by considering the UAVs' mobility, degree, and energy. In this fashion, the UAV network becomes more flexible, attain high routing efficiency, provides more stable and balanced networks. The objective is to provide a reliable exchange of information among UAVs and GS. This approach will dynamically update the topological changes that occur due to the high mobility of UAVs.

5.1 UAVs Clustering Problem Formulation

In FASNET, the modeling of clustering problem to a dynamic optimization problem, we assume the multi-UAVs network to a graph $G(VU, E)$ that desires to be clustered.

The VU is the number of UAVs, and E represents the number of communication links within a domain. The identification of CH sets in clustering problems is represented over several graphs. This research focuses on keeping the same degree of UAVs in each CH and least possible CH sets. The fitness function measures weights for selecting UAVs CH in FASNET as measured in [129] and [130]. The parameters considered to calculate the fitness values of UAVs are:

5.1.1 UAV Mobility (M_{UAV})

In our proposed BIMAC, the UAVs-CH role is allotted to a UAV based on combined weights. In BIMAC, the part of UAVs-CH assigned to a UAV depends on its weights, i.e., energy, mobility, and degree. Mobility is the key parameter to consider during the selection of UAVs-CH. The regular updation of links for UAVs due to mobility sometimes causes the formation of unstable clusters. Therefore, to attain stable clusters, UAVs' mobility needs special consideration. The UAVs transmit signals in a circular

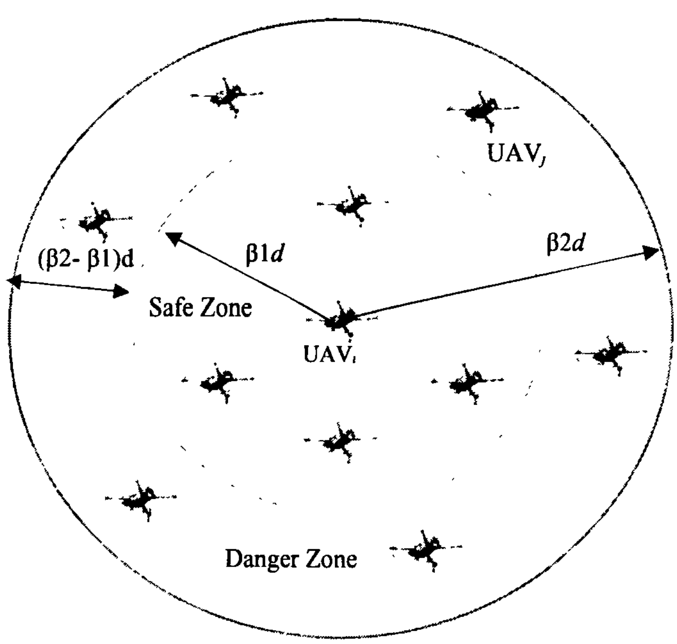


Figure 5.1: Transmission Zone

area with a radius r and comprise k UAVs. The UAVs may be close or far from the communication range.

The transmission zone of UAVs in the proposed BIMAC is divided into zones, i.e., safe and danger zones [131]. The inner-circle $\beta_1 d$ represent the distance from the safe zone, and the inner and outer circle $(\beta_2 - \beta_1)d$ represents the distance from the danger zone, as shown in Figure 5.1. The danger zone shows the UAVs' movement in a reverse direction. The member UAVs will be in a danger zone if the relative mobility is different from the UAVs-CH.

The mobility of UAVs is considered for the selection with co-efficient β_1 and β_2. The relative mobility is considered for the most suitable UAV selection to perform the responsibility of CH UAV. The relative mobility is calculated with UAVs signal strength. The distance between source UAV and destination UAV is determined by ping reply. Equation (5.1) is used to compute the relative mobility of UAV_i and UAV_j.

$$M_{UAV_i}(UAV_j) = 10\log_{10}\frac{\mathrm{R}_{ec}\,P_{wr}{}^{n}{}_{UAV_j\rightarrow UAV_i}}{\mathrm{R}_{ec}\,P_{wr}{}^{o}{}_{UAV_j\rightarrow UAV_i}} \tag{5.1}$$

The new receiving power (RP) of UAVs from UAV_j to UAV_i is $\mathrm{R}_{ec}\,P_{wr}{}^{n}{}_{UAV_j\rightarrow UAV_i}$, while the previous RP of the Hello packet from UAV_j to UAV_i is $\mathrm{R}_{ec}\,P_{wr}{}^{o}{}_{UAV_j\rightarrow UAV_i}$. If the result of equation (5.1) is negative, it means that UAV_j is run away from UAV_i and vice versa. For each nearbyUAV_j, of UAV_i, we discover its range predictor $R_{pre}(UAV_j,UAV_i)$ w.r.t UAV_i. The distance among UAVs and their mobility used to classify the UAVs as depicted in equation (5.2). If the UAV is lying in the danger zone and its relative mobility is less than "*0*"; it shows that the UAV movement is reverse. In the selection process of UAVs-CH, these UAVs will be moved out from the competition of UAVs-CH sets. The weight of these UAVs may be negative, i.e., "*-1*". Likewise, suppose the relative mobility value of the UAV is larger than zero and laying within the communication range. In that case, it shows that the UAV is getting closer, and its weight will be "*1*". If the UAV movement is in the opposite direction but lying in the safe zone, zero weight will be assigned to that UAV presented in equation (5.2).

$$R_{pre}(UAV_j,UAV_i) = \begin{cases} 0, if\,\beta 1d < dis(UAV_i,UAV_j) <= \beta 2d \wedge M_{UAV_i}(UAV_j) < 0 \\ 1, ifdis(UAV_i,UAV_j) <= d \wedge M_{UAV_i}(UAV_j) > 0 \\ 1+\dfrac{dis(UAV_i,UAV_j)-\beta 1d}{(\beta 2-\beta 1)d}, \\ ifdis(UAV_i,UAV_j) <= \beta 1d \wedge M_{UAV_i}(UAV_j) < 0. \end{cases} \tag{5.2}$$

5.1.2 UAV Degree (D_{UAV})

The parameters play a vital role in the cluster lifetime, load balancing, re-affiliation rate, etc. that is why in the BIMAC scheme, the choice of parameter is set with extra significance. The number of UAVs, i.e., the degree, has a key role in FASNET because it covers the region of interest with the least number of UAVs in a cluster. The projected area and transmission range are required to measure the least number of UAVs covering a particular region. This can be accomplished by dividing the total area by the area of the hexagon. The proposed BIMAC manages the issue of overlapping clusters by using a hexagon instead of a circle for easy computation.

$$A_{FASNET} = W \times L \left(\mathrm{m}^2\right) \tag{5.3}$$

A_{FASNET} is the targeted region, width, and length of the targeted field represented with W and L. To measure the coverage range of UAV, equation (5.3) is used.

$$A_{UAV} = 3\frac{\sqrt[3]{2}}{2}a^2 \tag{5.4}$$

The minimum number of UAVs (UAV_m) to cover the targeted region completely, can be achieved with the equation below:

$$UAV_m = \frac{A_{FASNET}}{A_{UAV}} \tag{5.5}$$

Here, the targeted area of the proposed network is A_{FASNET}, An area covered by a UAV is A_{UAV} in a regular hexagon. a is the side of the hexagon used to calculate the transmission range of a UAV. Suppose a=10 then how much area can be covered. Half the length of each diagonal is the distance of the centroid of the hexagon from the six vertices, and this distance will be the same as the side of the hexagon.

Equation (5.6) is used to compute the number of optimal UAVs in a cluster.

$$UAV_O = \frac{UAV_n}{UAV_m} \tag{5.6}$$

UAV_n is the number of UAVs in the equation (5.6), the least number of UAVs is UAV_m to cover the whole targeted region.

Hence, the projected number of neighbour UAVs in the FASNET can be obtained by:

$$UAV_p = \frac{UAV_c \bmod(UAV_o + 1)}{UAV_o} \tag{5.7}$$

Equation (5.7) UAV_c denotes the total number of current neighbour UAVs.

The UAV will have maximum neighbour UAVs to be the best candidate for UAVs-CH. The probability PD_i w.r.to UAVs degree is calculated by:

$$PD_i = C_p + \frac{UAV_p}{UAV_n} \tag{5.8}$$

In Equation (5.8), percentage of UAVs-CH is represented with C_p, UAV_p is the projected connectivity index of UAVs and total number of UAVs in the FASNET represented with UAV_n.

5.1.3 UAVs Energy (E_{UAV})

The UAVs-CH with more residual energy will be more suitable candidate for CH. The UAV has minimum chances to become UAV-CH that has low energy. In advance, the optimal number of UAVs-CH sets cannot be determined, so the UAVs CH percentage (C_p) is initially set to 10%. In the proposed BIMAC (C_p) is used to reduce the UAVs-CH announcements. There is no direct effect on the final UAVs-CH. The UAVs-CH probability concerning the energy of each UAV is measured before the execution of BIMAC.

$$EP_i = C_p + \frac{E_R}{E_M} \tag{5.9}$$

where the projected residual energy of UAV_i is represented with E_R and the maximum energy with E_M.

Furthermore, UAVs numbers in clusters are calculated before selecting UAVs CH. The minimization function used to calculate the fitness of UAVs-CH sets based on the UAVs weights and is discussed in detail in the next section.

5.1.4 Combined Weights

The equation (5.10) is used to calculate the weights of UAV_i that play the UAVs-CH role.

$$W_{UAV_i} = M_{UAV_i} + PD_{UAV_i} + EP_{UAV_i} \tag{5.10}$$

The number of UAVs clusters (k) must be calculated before selecting the UAVs-CH set by the equation (5.11). The value of k can be calculated as:

$$k = round(\frac{1}{n}\sum_{i=1}^{n} Deg_i) + 1 \tag{5.11}$$

The number of clusters in a multi-UAVs network is shown by k, where n is the number of UAVs and Deg_i represent the connectivity index with neighbour UAVs of UAV_i.

The CH set contains members not less than 3-hops distance. The minimization function is used to test the fitness of UAVs-CH after the computation of all UAVs weights.

5.2 Proposed Clustering Model

This section demonstrates the bee intelligence and proposed clustering model. The working process of the bio-inspired mobility-aware clustering scheme is described in detail in the following sub-section. The UAVs clusters structure in FASNET is shown in Figure 5.2. The UAVs are grouped in a cluster. There are three clusters, i.e., cluster 1, cluster 2, and cluster 3. Each cluster has a UAV-CH. Cluster 1 has four UAVs, cluster 2 has three UAVs, and cluster 3 has four.

5.2.1 Bee Intelligence Optimization

In the algorithm, for feasible solution representation, the bees are classified into three groups, i.e., scout, onlooker, and employed. The scout bees randomly search the high-quality food sources. The employed bees are also called worker bees. They collect the nectar amount and share the information with other bees. The selection of food sources depends on the type of dance. The employed bees start a waggle dance that shows the direction, track, distance to the food source, and nectar.

In the last one and a half-decade, different clustering algorithms have been designed based on honeybees' foraging and mating behaviour. These algorithms have been shown better performance in energy management, sidestepping the congestion, and providing a better solution for routing in FANET, MANET, and VANET.

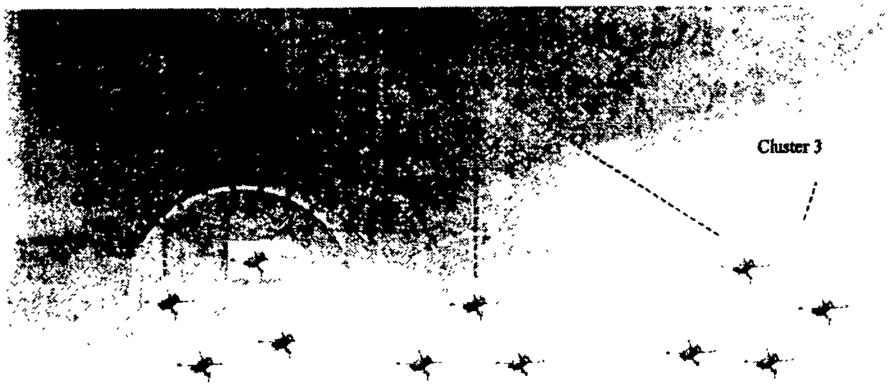


Figure 5.2: Structure of UAVs Cluster in FASNET

The UAVs are operating in a dynamic environment. This work identifies mobility, degree, and energy for the proposed mobility-aware clustering. The clustering issue becomes a dynamic optimization problem to consider these parameters of FASNET in a dynamic environment for clustering. The honeybees aggregation pattern or waggling dance is used to solve the optimization problem.

In FASNET, the clustering problem is formulated as a dynamic optimization problem. The algorithm designed for selecting UAVs-CH and the cluster formation is based upon the objective function (OF). OF is obtained from problem formulation. The selection of optimum CH is based on the foraging property of bees as the honeybees select food sources with more nectar. The topological changes are accommodated efficiently with a cluster maintenance mechanism. The bee optimization approach has been tested and found efficient in [95] and [97], but no proper procedure is defined for CH selection and cluster formation in the multi-UAVs network. The proposed bio-inspired mobility-aware clustering algorithm based on honeybee intelligence is compared with clustering protocols [84, 87, 102] based on GSO and PPO.

5.2.2 Proposed Mobility Aware Clustering Scheme

The proposed BIMAC is based on foraging property that refers to selecting the optimum CH among multi-UAVs and forming an optimal balance number of clusters. Due to UAVs large amount, the partition of these UAVs into diverse and non-overlapping clusters becomes an optimization problem [47].

This section emphasizes clustering based on optimization using the foraging property of bee that produces optimal cluster organization to form balanced clusters with dynamic UAVs degree, minimum energy, and high mobility. The notations used in algorithms are given in Table 5.1.

Table 5.1: Algorithm Notations

Symbols	Definition
n_{UAV}	Total UAVs in FASNET
C_{FANET}	Clusters in FASNET
UAV_p	Projected/average value of UAV degree
UAV[n]	Array of UAV IDs
$FV(W_{UAV}, AFV)$	Fitness value of CH set
SD_{UAV}	Sum of all UAVs degrees
SE_{UAV}	Sum of all UAVs energy
Deg_{UAV_i}	Degree of UAV i
CHs	Cluster heads
W_{UAV} [3][n_{UAV}]	Vector of UAV weights
SW_{UAV}	Sum of UAV weights
Eb	Employee bee
α_{ij}	Patch size
Z	random variable [z=-1 | 1]
$\Pr_i$	Probability of UAV i

The performance of the proposed solution compared with BICSF[84], SOCS [87], and BIMPC [102] clustering scheme based on PPO and GSO and validated via a series of simulation experiments. The advantages of optimization that depends on bee foraging property are: It is straightforward, flexible, efficient, easy to implement, explore local solutions at the cluster level, manage objective cost, and solve complex functions.

Algorithm 5.1: Psuedo Code of UAV Weight Computation

Procedure weight_computation ( )

Input: n_{UAV} , C_{FASNET}

Output: SW_{UAV} [n_{UAV}]

SD_{UAV}=0, SE_{UAV}=0

// initial values of UAV degrees and energies

for $\left(i = 1; i \leq n_{UAV}; i = i + 1\right)$ **do**

// summation of all UAVs remaining energy and degree

$SD_{UAV} = SD_{UAV} + Deg_{UAV_i}$

$SE_{UAV} = SE_{UAV} + Enr_{UAV_i}$

end for

$$ADeg_{UAV} = \frac{SD_{UAV}}{n_{UAV}}$$

// average UAV neighbors

$C_{FANET} = ADeg_{UAV}$

$AEnr_{UAV} = \frac{SE_{UAV}}{n_{UAV}}$ //Average of UAVs residual energy

for (i = 1; i ≤ n_{UAV} ; i + +) **do**

if $REnr_{UAV_i} > AEnr_{UAV_i}$ then

// compute weight of UAV w.r.t energy

W_{UAV} [1][i]=1

else if $REnr_{UAV_i} \approx AEnr_{UAV_i}$ **then**

W_{UAV} [1][i]=0

else

W_{UAV} [1][i]=-1

end if

if $Deg_{UAV_i} > ADeg_{UAV_i}$ **then**

// Compute weight of UAV w.r.t UAV degree

W_{UAV} [2][i]=1

else if $Deg_{UAV_i} \approx ADeg_{UAV_i}$ then

```
                    W_UAV [2][i]=0
                else
                    W_UAV [2][i]=-1
        end if
        if R_pre(UAV_j, UAV_i) > 0 then
    // compute weight of UAV w.r.t UAV mobility
                W_UAV [3][i]=1
        else
                W_UAV [3][i]=-1
        end if
    for (i = 1; i ≤ n_UAV; i + +) do
    // calculation of weighting factor values
        for (j = 1; j ≤ 3; j + +) do
            SW_UAV [i]= SW_UAV [i]+ W_UAV [i][j]
        end for
    end for
return SW_UAV [n_UAV], C_FASNET
// Return total clusters and UAVs weight values
end procedure
```

An additional challenge is the mobility of UAVs that brings a frequent change in the FASNET topology. The path selection depends on the prior speed and direction in most FASNET scenarios. The random waypoint mobility model used in FASNET favoured flexibility for path selection to multi-UAVs. The proposed BIMAC has a low re-affiliation rate compared to the other selected clustering scheme because of the consideration of relative mobility during the selection of CH and formation of the cluster.

Algorithm 5.2: Psuedo code of Bio – inspired Mobility based Clustering (BIMAC)

```
Procedure BIMAC_UAVs-CH_Selection()
Input: SW_UAV [n_UAV], C_FASNET
Output: UAVs-CHs
call procedure nectar_calculation(n_UAV)
    for (j = 1; i ≤ C_FASNET; j + +) do
// random UAVs- CH selection
```

UAVs-CH [j]=random (SW_{UAV})
end for
while (max!=true) **do**
for $\left(u = 1; i \leq n_{UAV}; u = u + 1\right)$ **do**
// Computer the fitness of solution
if (u in UAVs-CH) **then**
$FValue_{UAV} = FValue_{UAV} + 1(SW_{UAV}[u] + AFV_{UAV})$
end if
end for
if ($FValue_{UAV} < PFValue_{UAV}$) **then**
// $PFValue_{UAV}$ is the previous fitness value
replace $FValue_{UAV}$
end if
if (optimal_ UAVs-CH != true) **then**
while (eb! = 0) **do**
// visit all employee bees
$UAV_j(x+1) = UAV_j(x) + \alpha_{ij} * y$
// select new UAVs from neighbors
end while
$\Pr_i = \frac{W_{UAV_i}}{\sum_{j=1}^{k} W_{UAV_j}}$
// to fine the new UAVs probability $\Pr_i$
while (onlooker UAVs != null) **do**
subject to the probability $\Pr_i$, select a set of UAVs-CH
end while
Else
return UAVs-CH
end while
end procedure

5.2.2.1 UAVs-CH Selection

The multi-UAVs mobility in FASNET changes the topology frequently compared to other ad-hoc networks [48]. The minimum re-affiliate rate results in optimum CHs selection. The frequent change in topology is mainly due to the movement of UAVs. During the CH selection process, consideration of relative mobility directly impacts cluster stability. The re-clustering process will be called less frequently. The other two parameters, i.e., energy and degree, are also considered during the CHs selection process, increasing the cluster lifetime.

In the proposed BIMAC to select the UAVs-CH set, initially, UAVs-CHs are randomly chosen as presented in Figure 5.3.

The minimization equation (5.12) is used to evaluate the fitness of UAVs-CH as:

$$Minimize-Function(W_{UAV}, AFV) = \sum_{i=1}^{n}\sum_{j=1}^{k} RW_{UAV_{ij}}(W_{UAVi} - AFV_j)^2 \quad (5.12)$$

Subject to $\in RW_{UAV_j} = 1 \quad (j = 1,2,3,...,k)$

$$\in RW_{UAV_{i,j}} = 0 \ or \ 1 \ (i = 1,2,3,...,n \,/\, j = 1,2,3,...,k)$$

Here in the equation, total number of UAVs represent with n, k is total CH-UAVs set, the relationship of UAV_i to its cluster j represented with $RW_{UAV_{ij}}$, the weight of UAV_i is W_{UAVi} and AFV_j is the mean fitness of UAV at j^{th} cluster that play the role a UAVs-CH. Equation (5.13) can be used to calculate the value of AFV_j as:

$$AFV_j = \frac{1}{n_j}\sum_{j=1}^{k} RW_{UAV_{ij}} W_{UAV_i} \quad (5.13)$$

Here the total number of UAVs j^{th} cluster represented with n_j, $RW_{UAV_{ij}}$ represent the relation of UAV with this cluster j. If a UAV exists in a cluster range, then its value will be 1; otherwise, its value would be 0 if the condition is not met.

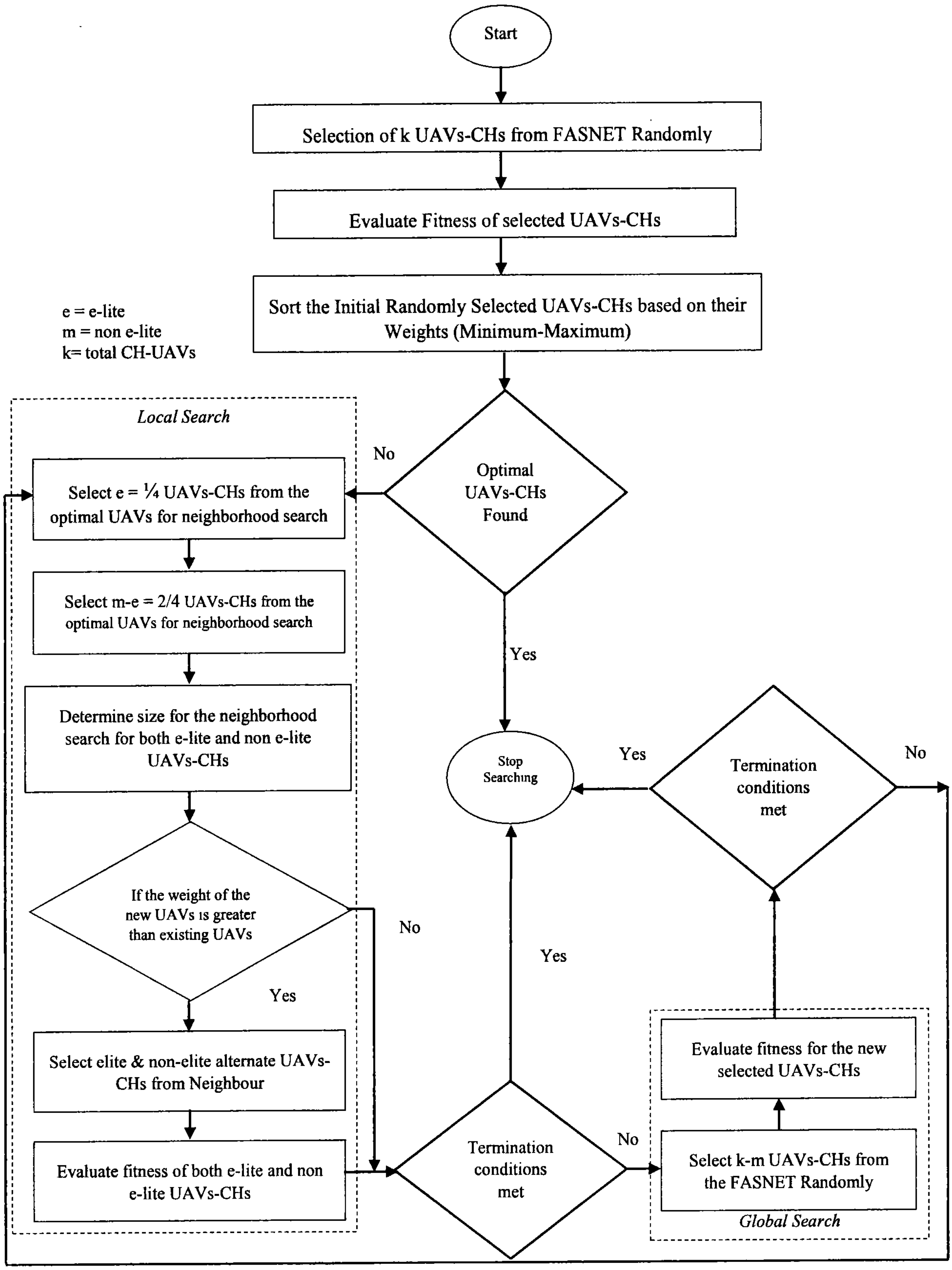


Figure 5.3: Proposed BIMAC Algorithms Flowchart

If optimum set of UAVs-CH has not been found in the first phase, the UAVs will initiate local search again. The scout UAVs are responsible for accomplishing the neighbourhood search and suggesting new searches. Hence, the employed-UAVs memory will be refreshed depending on available information. The old data will be overridden with further details of the memory of employed UAVs. The equation (5.10) is used for the memory updation, which is based on a calculation of nectar volume to get new solutions.

In the scenario, if the amount of nectar of previous UAVs-CH is more than the newly calculated nectar amount of UAVs-CH, then the information mentioned above will be maintained in the memory. If the new nectar amount is more significant than the old one, new one will be memorized and disremember the old one (stowed in the UAVs memory).

After completing the search process, the employed UAVs will arrive at the hive and perform a waggle dance on the dancing floor. The waggle dance communicates information about the nectar amount, distance, and direction. A distinct dance pattern shares different types of communication with other UAVs. The onlooker UAVs observe the dance floor to find the best route, direction, and nectar.

The new UAVs-CH will be picked based on their possibility of the nectar amount W_{UAV_i}. The onlooker UAVs observe the dance on the dancing floor and decide to visit $CH-UAV_j$ with probability pr_i by:

$$\Pr_i = \frac{W_{UAV_i}}{\sum_{j=1}^{k} W_{UAV_j}} \tag{5.14}$$

In equation (5.14), the nectar amount at UAV_i is represented with W_{UAV_i}; the onlooker UAV discovers the neighborhood spot or nectar location (CH-UAV) in the radius of UAV_j by using:

$$UAV_j(x+1) = UAV_j(x) + \alpha_{ij} * y \tag{5.15}$$

Here a_{ij} is the patch size to search neighbours and a uniform random variable represents with var the lies in the range $[-1,1]$.

5.2.2.2 UAVs Cluster Formation

The next step after the selection of UAVs CHs is cluster formation. The re-clustering process minimized that results in stable cluster formation. Other factors considered for the balanced and stable cluster are relative mobility, neighbour criteria, energy, and the degree of the UAVs.

Once the CH-UAV sets are selected, it broadcasts a message (ID, status, and location) in the multi-UAV network. UAVs that receive the message will become a member of a cluster. The CM shares this information with the nearest CH-UAV. If a UAV receives the membership message from more than one UAV-CH, the UAV will join the UAV-CH with minimum distance. The UAV will choose randomly to join a UAVs-CH in case of more than one UAVs-CH with the same distance.

5.3 Performance Evaluation and Simulation Study

The simulation study and performance evaluation of the proposed BIMAC scheme are compared for the first time with existing clustering schemes [84], [87], and [102].

The clustering scheme [102] is based on PPO and considers mobility for selecting UAVs-CHs. The clustering schemes [87] and [84] are based on GSO and choose the UAVs-CHs with high energy, location information, and connectivity. The proposed BIMAC uses foraging property of honeybees to select optimum CHs and form a balanced cluster. The clustering parameters considered are residual energy, mobility, and the degree to enhance cluster lifetime with the high mobility of UAVs. The performance metric used to evaluate the proposed BIMAC is average link-connection lifetime, UAVs-CH lifetime, UAVs degree, re-association time, and cluster formation time with varying UAVs speed and communication range. IEEE 802.11 and 802.16 are selected as standards for communication among UAVs and GS [132]. Rest of the simulation parameters are given in Table 5.2.

Table 5.2: Simulation Parameters

Parameters	Values
Field Size	500*500hm
No; of UAVs	100
Distance among UAVs	100 m

Parameters	Values
Communication Range	10km-15km
Standard with MAC	IEEE 802.11 & 802.16
Spectrum	2.3–2.5 GHz and 3.4–3.5 GHz
Mobility Model	RWP model in Section II
Speed of UAVs	40m/s-70m/s
UAVs Location Strategy	Random Placement

The link between UAVs and CH plays a key role due to their high mobility and varying communication range. The UAVs' fast movement inside the cluster and out-cluster change the topology structure frequently. The stability of link connections for an extended period enhances network lifetime and algorithm performance.

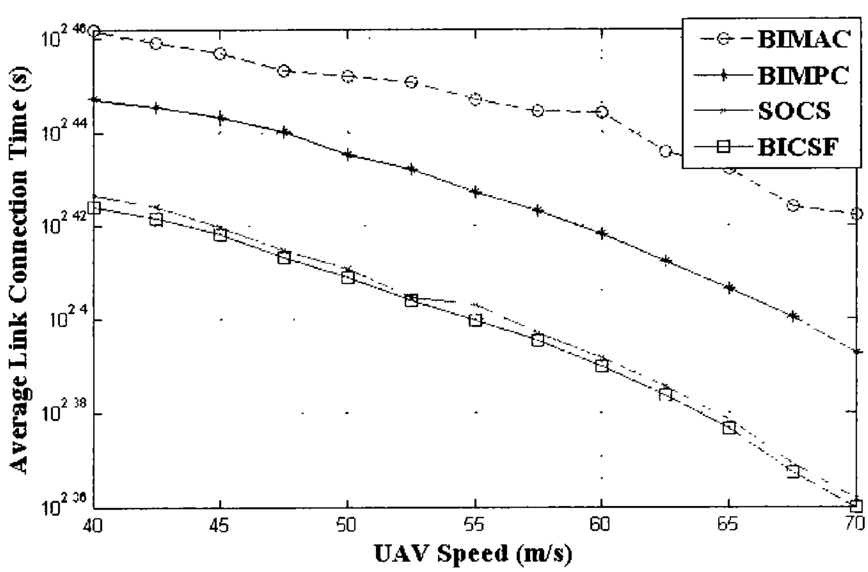


Figure 5.4: Average Link Connection Time vs. UAVs Speed

Figure 5.4 shows average link connection time with varying UAVs speed of the proposed BIMAC, [84], [87], and [102]. The speed rate considered for the UAVs is 55 m/s. The performance result shows member UAVs' established average connection time to its UAVs-CH. The proposed scheme, i.e., BIMAC duration in terms of average link connection, is higher than [84], [87], and [102], with varying speeds of UAVs towards the upper limit. The BIMAC algorithm is based on the constraints of forming a balanced cluster and enhancing CH-UAVs' stability and member UAVs. The simulation results show that BIMAC is more appropriate for dynamic networks. The clustering schemes [84], [87], and [102] performance falls with the change towards the UAVs' maximum speed. The increase of speed results in frequent changes in the structure of the multi-UAVs network. For that reason, in general, lifetime decreases gradually for average link connection. In the case of BIMPC [102], the simulation result shows that the average link connection lifetime decreases more gradually than [84] and [87] due to considering the mobility factor during CH-UAVs selection and cluster formation.

The link connection duration also depends on the communication range of UAVs. The probability of link-connection lifetime reduces to its UAVs-CH when UAVs move outside from the communication range of UAVs-CH.

In Figure 5.5, the simulation result shows an average link connection lifetime with a varying communication range of the proposed BIMAC and other clustering schemes i.e., [84], [87], and [102]. The communication range considered is 10 km. The proposed BIMAC scheme and other state-of-the-art schemes' average link-connection time increases with the movement of UAVs towards maximum communication range. The BIMAC scheme presents better results in average link-connection time among the selected schemes [84], [87], and [102].

In the proposed BIMAC, the selection of optimum CH depends on the foraging property of honeybees to optimize the UAVs' relative mobility, residual energy, and degree. Thus, the energy-efficient CH selection improves the cluster lifetime of high mobile UAVs. In the proposed BIMAC, CHs have more stability than other algorithms.

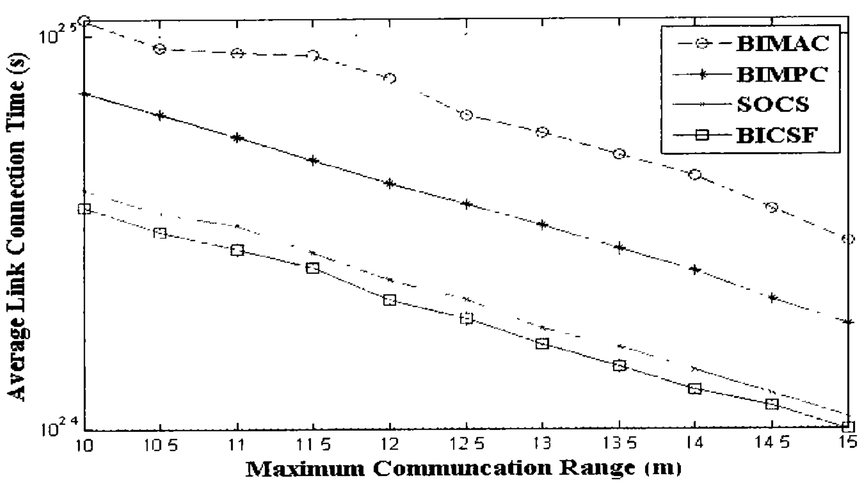


Figure 5.5: Average Link Connection Time vs. Maximum Communication Range

In Figure 5.6, simulation results represent the average CH lifetime with varying UAVs speed of the BIMAC and others clustering schemes [84], [87] [102]. The increase in speed towards the upper limit results in the frequent variation in the topological structure of the multi-UAVs network, and thus CH rotation is more affected. The simulation results show average CH lifetime reduces gradually with the increase of UAVs' speed for all the algorithms'.

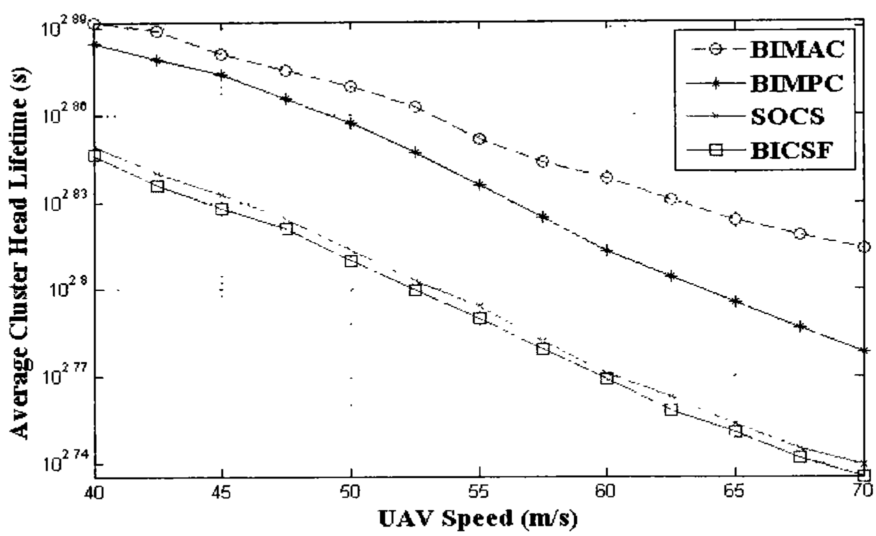


Figure 5.6: Average CH Lifetime vs. UAVs Speed

Figure 5.7 represents the average CH lifetime with a varying communication range of proposed BIMAC and others clustering schemes [84], [87], and [102]. All the

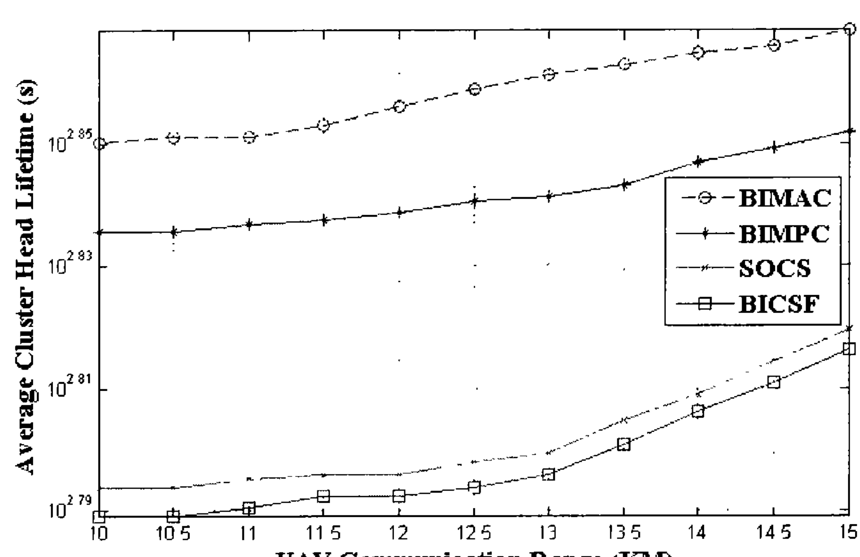


Figure 5.7: Average CH Lifetime vs. UAVs Communication Range

algorithms' average UAVs-CH lifetime rises with the movement of UAVs towards the upper limit of the range of communication.

The UAVs' movement towards upper limit of the communication range reduces average UAVs-CH duration. The high mobility of UAVs directly impacts the stability of UAVs-CH. In terms of average CH lifetime, the proposed BIMAC shows better performance among the selected schemes [84], [87], and [102].

To balance the load on each UAV-CH, UAVs number in a cluster should be least or approximately the same. The UAV degree plays a vital role in balance cluster formation.

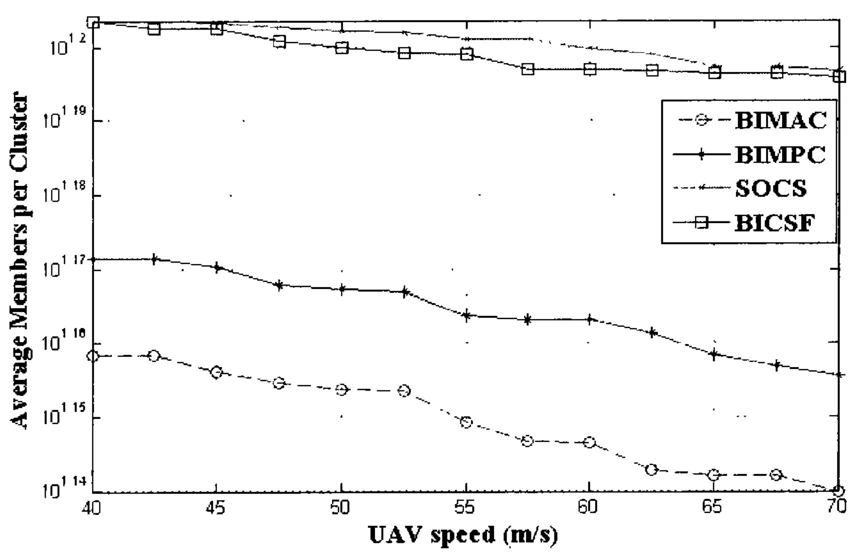


Figure 5.8: Average Members per Cluster vs. UAVs Speed

Figure 5.8 represents the average number of UAVs per cluster with varying UAVs speed for the proposed BIMAC and other clustering schemes [84], [87], [102]. The UAV degree in [84] and [87] is almost the same per cluster, increasing UAVs' speed accordingly. The movement of UAVs in the direction of upper limit increases the probability of UAVs escaping from the range of communication. Thus, the number of UAVs per cluster reduces slowly. The selected state of the art schemes and proposed BIMAC result in a negative association between the average number of UAVs per cluster and UAVs speed.

The proposed BIMAC has less UAVs degree per cluster than other selected algorithms. The main reason is that BIMAC considers the UAVs degree, mobility, and energy for cluster membership of UAVs. The UAVs that fulfill the criteria will be regarded as members to join or leave the cluster. The UAVs that satisfy the requirements will be considered members of the cluster to join or leave the cluster.

In the proposed BIMAC scheme, the member UAVs leave the current cluster update frequently and remove the status of member UAVs to result in cluster stability. In contrast, in [84], [87], [102], due to no frequent updation, the member UAVs still belong to that cluster. The BIMAC also reduces the re-clustering process that results in cluster stability.

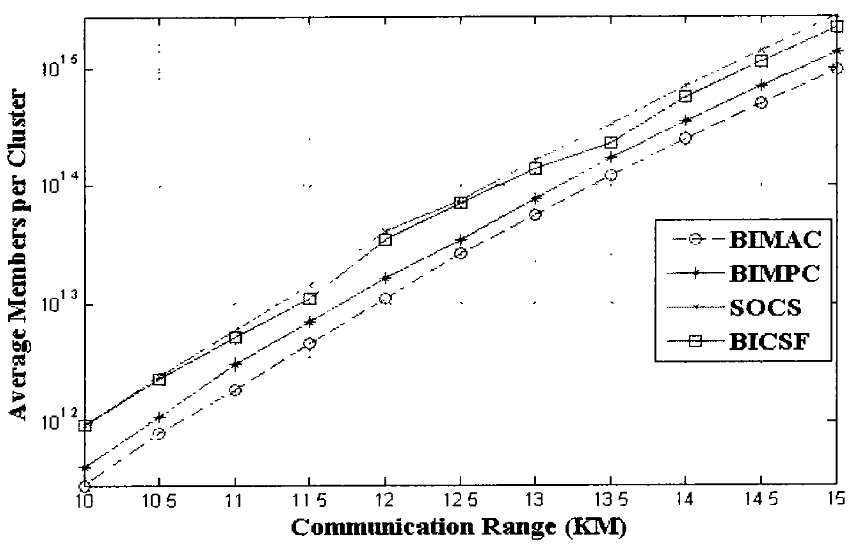


Figure 5.9: Average Members per Cluster vs. Communication Range

In simulation results, Figure 5.9 represents the average member UAVs per cluster with varying communication ranges for the proposed BIMAC and other clustering schemes [84], [87], [102]. The UAV degree in [84] and [87] is almost the same per cluster, increasing the communication range accordingly. The BIMAC and all the selected schemes [84], [87], [102] simulation results show that with the extension of communication range, the number of UAVs per cluster increases, but the BIMAC still indicates better efficiency.

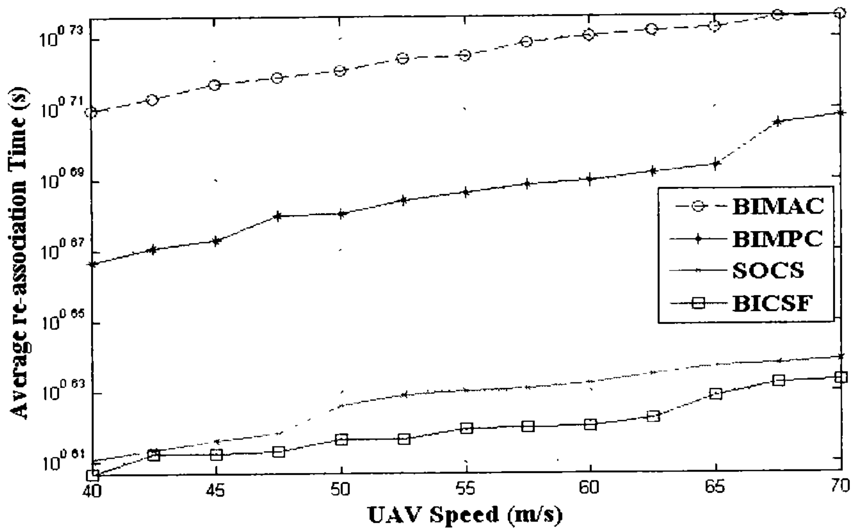


Figure 5.10: Average Re-association Time vs. UAVs Speed

The less re-affiliation rate plays a vital role in the optimal selection of UAVs CHs. The UAVs speed has direct changes in the topology structure. In Figure 5.10, the simulation result shows the average re-association time with varying UAVs speed for the proposed BIMAC and [84], [87], [102] clustering schemes. With the increase in the UAVs' speed towards the upper limit, the BIMAC algorithm takes maximum time and does not re-associate again and again than other clustering schemes [84], [87], [102]. The reason is mobility, degree, and energy in BIMAC.

In Figure 5.11, the results of simulation represent re-association time with varying communication ranges for the BIMAC and [84], [87], [102] clustering schemes.

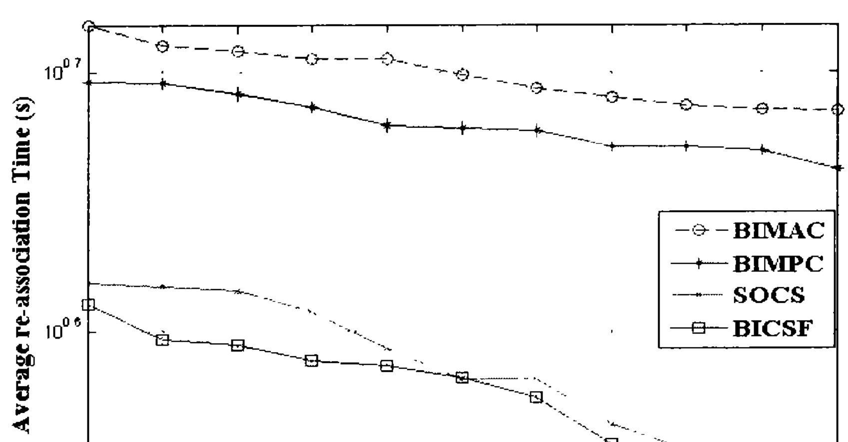


Figure 5.11: Average Re-association Time vs. Communication Range

The probability of re-association time of UAVs to its CH as a member decreases by increasing the range of communication. The proposed BIMAC algorithm still has a high average association time and gradually decreases among all clustering schemes in the simulation results.

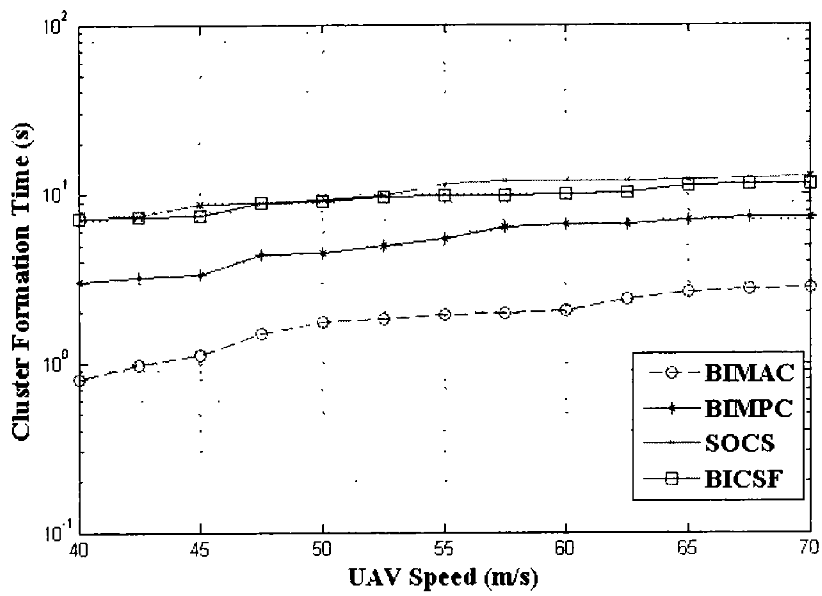


Figure 5.12: Average Cluster Formation Time vs. UAVs Speed

The cluster formation time is the time taken to form a cluster. In clustering the UAVs-CH selection and formation of cluster process, the proposed BIMAC scheme minimizes the cost in terms of time. Figure 5.12 represents cluster formation time with varying UAVs speed for the proposed BIMAC and clustering schemes [84], [87], [102]. The proposed BIMAC algorithm takes minimum cluster formation time with the increase in UAV speed as compared to clustering schemes in [84], [87], [102]. The reason is mobility, degree, and energy in BIMAC.

In Figure 5.13, the simulation results represent cluster formation time with varying UAVs communication range for the proposed BIMAC and other selected clustering schemes [84], [87], [102]. With the increase in the range of communication towards the upper limit, the proposed BIMAC scheme presents a minor variation in cluster formation time as compared to the other selected clustering schemes [84], [87], [102].

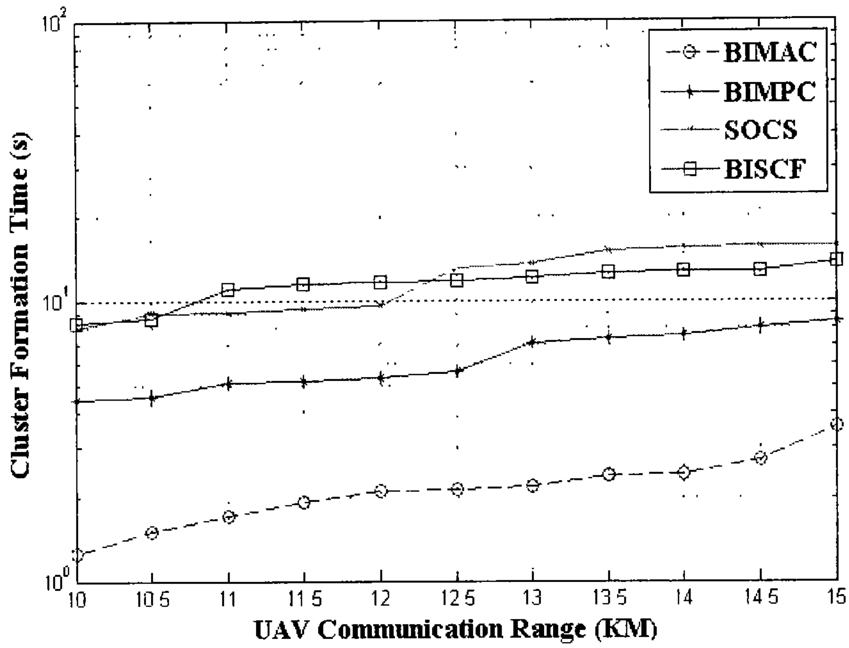


Figure 5.13: Average Cluster Formation Time vs. Communication Range

5.4 Chapter Summary

This chapter discusses the recent developments in the multi-UAVs network, focusing on clustering optimization using bee intelligence with foraging behaviour. The advantages of optimization based on bee foraging properties are: It is straightforward, flexible, efficient, easy to implement, to explore local solutions at the cluster level, manage objective cost, and solve complex functions. The multi-UAVs network structure is divided into multiple clusters. Each cluster has a CH and member UAVs. The selection of CH UAVs is accomplished in this work by considering the UAVs' relative mobility, degree, and residual energy. The proposed BIMAC based on foraging behaviour selects the optimum CH among multi-UAVs and forms a balanced optimal number of clusters. The proposed solution's simulation study and performance evaluation compared with BICSF, SOCS, and BIMPC clustering schemes. The performance metric used for the evaluation purposes is average link-connection lifetime, average CH-UAV lifetime, UAV degree, re-association time, and cluster formation time with varying UAVs speed and communication range. The simulation results show that our proposed BIMAC outperforms existing schemes regarding link-connection lifetime, re-affiliation rate, communication load, number of UAVs per cluster, CH lifetime, and cluster formation time.

Chapter 6

Target Area Identification based Localization and Clustering

FASNET is an emerging area that builds interconnection of multi UAVs, actuators, ground sensors, and Near Field Communication (NFC), which brings the revolution to everything by making it smart and intelligent [133]. There are numerous applications like agriculture management, observing borders, traffic monitoring, remotely tracking, surveillance, relief-search-destroy operation, automated protection of the homeland, etc., but precision agriculture farming system has emerging applications among all of them. Precision agricultural farming deals with farming management and monitoring. It includes remotely monitoring tomatoes' health condition, soil properties, measuring small-scale soil cultivation, sowing, fertilization, photogrammetry, spraying chemicals on crops and water contents. It is required with precise and high resolution to site-specific management [134]. Application of multi-UAVs in precision agriculture for localization and affected area identification in tomatoes crops has many issues. The researchers have tried to tackle it, but no proper implementation is currently available. The FASNET platform in the precision agriculture domain plays a vital role in locating the affected area and observing the crop field with excellent spatial and temporal resolution compared to the satellite platform. This platform first identifies the TAs and then captures the particularities of plants' leaves, stems, roots, and fruits from a unique point of view that is not easily visible from the ground [25]. UAVs with non-invasive sensors remotely sense/orthophoto the crops at small pixel sizes to improve the resolution. The plants' reaction can be observed quickly to new pesticides, herbicides, fungicides, and fertilizers. The information obtained by UAVs can help the farmers to decide on time, utilizing resources efficiently with low cost and saving time due to regular visits of UAVs [26].

Energy-efficient communication among UAVs, UAVs to Ground Station (GS), and GS to UAVs have several issues due to energy constraints, communication range, frequent change in topology, link expiration, and high mobility. Critical point is accurate target identification using UAVs without localization errors. Researchers proposed several localization schemes to resolve the issue of target spots localization accurately but could not provide precise target spots without localization error [3-5]. Most of them consider distance, localization time, and signal strength to measure the localization error. UAVs' routing protocols are used to locate the optimal TAs by considering communication range, topology, link expiration time, residual energy, and mobility. The localization and identification of TAs are categorized based on the type of nodes. The nodes may be mobile or static, GPS enabled or without GPS, indoor or outdoor, in range or out of range. The range-based TAs identification scheme provides more accurate and precise location than range-free based localization. Still, the methods may also vary based on error rate, accuracy, and computation [3].

The multi-UAVs network divides the network structure into groups called clusters. The UAVs-CH use an aggregation approach to obtain information from the member UAVs. Due to clustering UAVs intra-cluster routing information is updated locally that shows stability and efficiency at UAVs-CH level. Routing overhead is reduced because the member UAVs only communicate with UAVs-CH. In FASNET, cluster formation is complex due to application priorities for UAVs placement, cluster degree, and CH selection to prolong the network lifetime. Besides this, the UAVs-CH is responsible for communicating inside and outside the cluster. The mobility of UAVs is very high, ranging from 10 to 30 m/s [48]. Due to the autonomous system in most scenarios, the TAs identification and path selection are based on the range, speed, and direction. In some applications, information delay is not acceptable such as in precision agriculture, border supervision, search and destroy operations. The reliability of the communication link is required to provide real-time communication because the link may be down, the energy may be low, or the interference may occur. To overcome these issues, designing cluster-based routing required considering these issues to enhance FASNET lifetime.

The application of multiple UAVs in FASNET matches with the idea of the swarm, which comes from nature, such as the organization of particles, bees, ants, fireflies, wolves, etc. The concept of clustering based on swarm approaches attracted many researchers for the last one and a half decade. There are several optimization schemes based on the swarm intelligence for TAs identification, such as ACO, PSO, GSO, GA, etc. The cluster-based FASNET performance depends on the optimization algorithm for an optimal solution. In this chapter, bee-swarm intelligence-based TAs identification algorithms are proposed for precision agriculture.

The main contribution of the proposed scheme is to localize the UAVs and identify TAs in the tomato crop field based on the optimization of environmental factors. The UAVs swarm design and development for TAs identification are based on honeybee optimization. The TAs identification depends on the weights of environmental factors, i.e., relative humidity, soil moisture, temperature, light intensity, NPK (nitrogen (n), phosphorus (p), potassium (k)), and power of hydrogen (pH). The environmental factors are modeled to an optimization function to obtain optimal TAs. Formation of the cluster is based on the requirements to avoid unnecessary computations. The accurate TAs identification will be enriched with the proposed algorithms compared to other existing algorithms.

6.1 Proposed FASNET Model for Precision Agriculture

The research on localization and cluster formation of multi-UAVs to identify the TAs in precision agriculture is still confined to a lab, and no specific application implementation is currently available. However, in this section, we describe the FASNET model and workflow for multi-UAVs localization based on the environmental factors of TAs, as shown in Figure 6.1. The proposed system provides information about the affected areas in the tomato crops field. The numbers of ground sensor nodes are randomly placed in the field to measure the environmental factors. Field is divided into zones. The zone is represented with clusters, and each cluster has a CH, as shown in Figure 6.1. The selection of CH will be in a distributed fashion. Role of CH will be rotated among all sensors. The data aggregation approach collects environmental factors information from the sensor nodes. Multi-UAVs are configured to identify the affected TAs. The localization of multi-UAVs depends on the weights of environmental factors of the TAs. The UAVs will randomly search the affected TAs using honeybee optimization approach. UAVs visiting the field will communicate with CH UAVs on the ground network. Once a UAV identifies a target area, the next step is to form a cluster (cluster 1, cluster 2). The honey bee clustering algorithm is applied for the optimal UAVs-CHs as in [135]. UAVs-CHs communicate the information to the GS for further processing.

Due to wide varieties of UAVs in the market, rotary-wing UAVs are used in our proposed architecture, which can fly remotely with thermal and hyperspectral sensing,

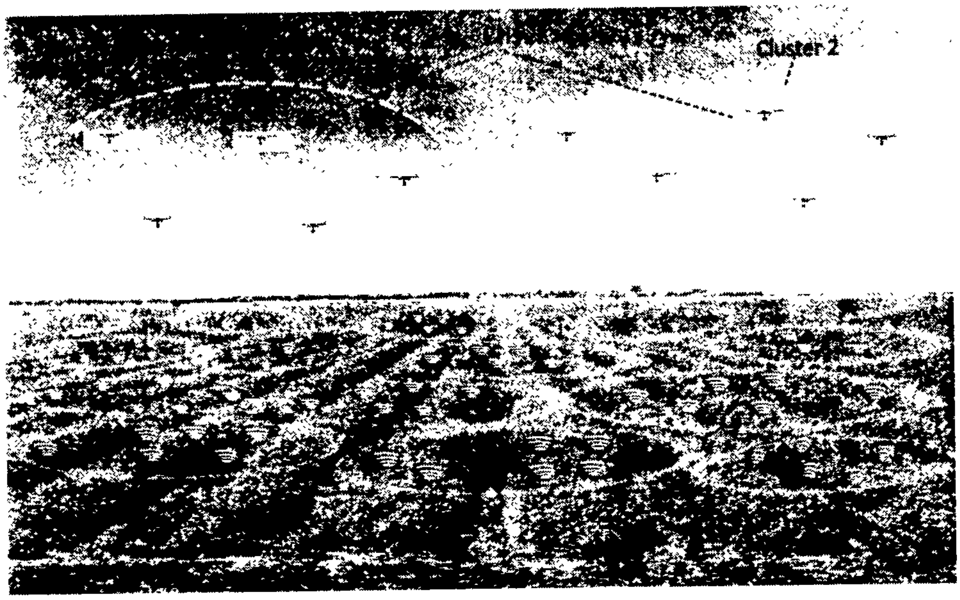


Figure 6.1: Proposed Scheme for Clustering and Localization

detecting, storing, and communicating information in the precision agriculture domain. The rotary-wing UAVs operate at 3 to 45m heights and cover the area up to several kilometers (Km). The GPS is embedded in the UAVs, enabling precise hyperspectral data acquisition. Global Positioning System (GPS) locate the coordinates of UAVs. Flight planning of hyperspectral sensor UAVs remotely is very complex. The application program Polygon Tool is used for flight planning with precise and accurate GPS points within which the UAVs will operate. The UAVs use pre-planned path strategies to cover the specific crop field without interfering with obstacles. The multi UAVs avoid collisions based on localization accuracy and identified TAs.

6.2 TA Identification based on Honey Bee Approach

The honey bees live in a colony (ranges up to 50k), with a queen, female workers (ranges from 20k to 40k), and male drones (ranges from 200 to 300). The algorithm based on a honeybee identifies targets with an ideal solution by sharing the information and cooperation among the bees of a colony. In the algorithm for feasible solution representation, the bees are classified, i.e., onlooker and employed. The onlooker bees randomly search for locating food sources and share the information with employed bees. The employed bees visit to get the nectar amount. They collect nectar and share information with other bees. The food source selection depends on the type of dance; that's why the onlooker bees wait for the type of employed bees dance.

The employed bees start a waggle dance that shows the track, distance to the food source, and nectar. In the proposed approach, multi-UAVs' localization and cluster formation is based on the honey foraging behaviour to identify TAs. The nectar amount

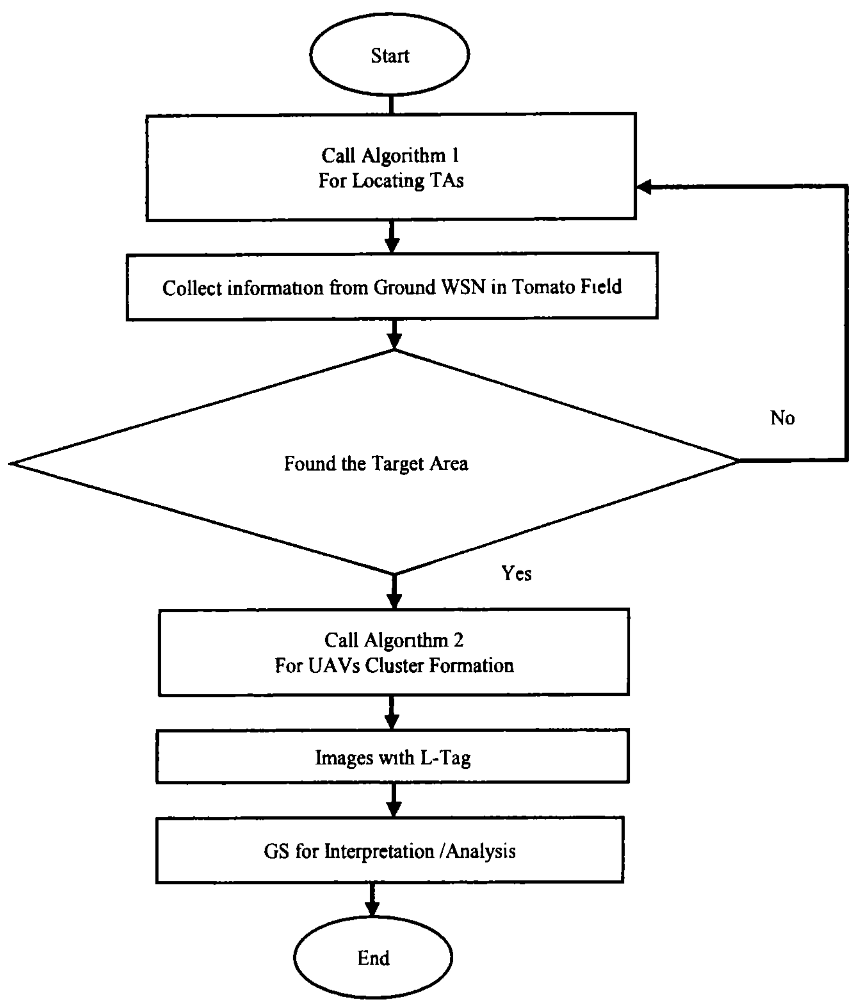


Figure 6.2: Proposed Scheme Implementation Workflow

of TAs is based on environmental factors. The workflow of the proposed scheme implementation is shown in Figure 6.2.

6.3 Localization of Multi UAVs based on the Identified TAs

The bee colony, i.e., the multi UAVs network, is divided into two sets of UAVs in this work. The first ninety percent are employed UAVs, while the remaining ten percent are labeled as onlooker UAVs. The grouping of UAVs in a network is performed with a clustering algorithm based on the honey bee [135]. The flowchart in Figure 6.3 shows the process of optimal TAs identification based on the honey bee algorithm.

Table 6.1: List of Notations used in Algorithms

Notations	Description
AV	Aerial Vehicle
O-UAVs	onlooker UAVs
E-UAVs	Employed UAVs
TA	Targeted Problem Area
AV-CH	Aerial Vehicles-Cluster Head
Q(NEC)	Quantity of Nectar
TDMA	Time Division Multiple Access
EPV	Environmental Parameter Values

The algorithm starts with initiating investigational trail points, i.e., initial TAs in the search space, i.e., multi UAVs network from where the foraging of honey bees starts. The working procedure of the setup phase is explained in *Algorithm 6.1*. The notations used in algorithms and flowchart is described in Table 6.1.

Algorithm 6.1: Target Area Identification

```
Procedure Target_area_identification ()
Input: EPV from ground WSN
Output: TAs
Starting population initialization (target areas)
AVs extract the nectar from ground WSN based on EPV using Eq. 6.7
Calculate fitness of the TAs using Eq. 6.8
    if (fitness of the TAs using Eq.6.8 not satisfied) then
        while (set of AVs equipped with geo-tag
        camera ≠ null) then
                Generate new TAs using Eq. 6.11
                Compute the value Q (Nec_i)
        Search for the neglected TAs (food sources)
            if (a new TA found) then
                Substitute the new TA with existing
                TA based on nectar quantity
            end if
        end while
```

16.	*end if*
17.	*end procedure*

The parameters that are ideal for measuring environmental factors vary with climate change. The parameters such as relative humidity, moisture, temperature, light intensity, NPK, and power of hydrogen level are considered to measure the nectar amount in an unmanned Aerial Vehicle AV_i. Min-Max normalization is used to balance the contribution of the parameters.

6.3.1 Humidity Level: H_l

Relative soil humidity level is too favorable when it is $(60-70\ \%)$, normal $(50-90\ \%)$ and bad $(<50,\ >90)$. The value can be calculated as:

$$H_l = \frac{H_i - \min_H}{\max_H - \min_H}(new\_\max_H - new\_\min_H) + new\_\min_H \tag{6.1}$$

Where H_l is the humidity level of location i, $\min_M$ is the minimum humidity level, and $\max_M$ is the maximum humidity level of a location. The values of new_max_x *and* new_min_x are set to 1 and 0 respectively in all parameters.

6.3.2 Moisture Level: M_l

The moisture level is said to be normal $(60-80\%)$, favourable $(65-70\%)$, and unfavourable $(<60\%$ and $>80\%)$ can be calculated as:

$$M_l = \frac{M_i - \min_M}{\max_M - \min_M}(new\_\max_M - new\_\min_M) + new\_\min_M \tag{6.2}$$

Where M_i is the moisture level of location *i*, $\min_M$ is the minimum moisture level, and $\max_M$ is the maximum moisture level of a location.

6.3.3 Temperature Value: T_v

The soil and air temperature measured from the sensor deployed are categorized as favourable $(21-24\ °C)$, normal $(12-35\ °C)$, and unfavourable $(below\ 12°C\ and\ above\ 35°C)$, and can be calculated as:

$$T_v = \frac{T_i - \min_T}{\max_T - \min_T}(new\_\max_T - new\_\min_T) + new\_\min_T \quad (6.3)$$

6.3.4 Light Intensity: L_i

The light intensity measured from the sensor deployed are categorized as normal $(350-\ 500\ \mu mol\ m^{-2}s^{-1})$, favourable $(400-450\ \mu mol \cdot m^{-2} \cdot s^{-1})$, and unfavourable $(<300\ and\ >500)$. The value can be calculated as:

$$L_i = \frac{L_{in} - \min_L}{\max_L - \min_L}(new\_\max_L - new\_\min_L) + new\_\min_L \quad (6.4)$$

6.3.5 NPK: NPK_r

The NPK ratio measured from the sensors deployed in the tomato field categorized as normal and favourable $(8-32-16\ \text{and}\ 6-24-24)$ and above or below this limit is known as unfavourable The value can be calculated as:

$$NPK_r = \frac{NPK_t - \min_{NPK}}{\max_{NPK} - \min_{NPK}}(new\_\max_{NPK} - new\_\min_{NPK}) + new\_\min_{NPK} \quad (6.5)$$

6.3.6 Power of Hydrogen: pH_v

The soil pH values (in water and soil solution) are normal $(0.0-14.0)$, favourable $(6.0-7.0)$, and unfavourable $(<0\ \text{and}\ >14)$ are denoted by zero, positive and negative. The value can be obtained as:

$$pH_v = \frac{pH_t - \min_{pH}}{\max_{pH} - \min_{pH}}(new\_\max_{pH} - new\_\min_{pH}) + new\_\min_{pH} \quad (6.6)$$

The TAs in the tomato crop field is optimized so that the Euclidian Distance should be approximately equal from one problem area to another.

$$TA_i = H_l + M_l + T_v + L_i + pH_r + NPK_r \quad (6.7)$$

The following equations express the problem by measuring and considering the grouping of N sensor nodes into K the number of non-overlapping TAs.

$$Minimize F(W_{TA}, AN) = \sum_{i=1}^{n} \sum_{j=1}^{k} Nw_{ij} (W_{TA_i} - AN_j)^2 \quad (6.8)$$

$$Subject\ to \in Nw_{ij} = 1 \quad (i = 1,2,3,...,n, j = 1,2,3,...,k)$$

$$Nw_{ij} = 0$$

In equation (6.8), the degree of sensor nodes is represented with n in the UAVs enabled WSN. W_{TA} is the weight factor of TAs and AN is the average fitness of TAs that perform the role of Cluster Head (CH). k is the total number of targeted areas (food sources) to be identified, $TA_i \in l_n$ $(i = 1,........,n)$ is the location of sensor nodes i, $AN_j \in l_n (j = 1,.....,k)$ is the average nectar value of sensor nodes to mark it target sensor nodes and can be calculated by the equation:

$$AN_j = \frac{1}{k} \sum_{j=1}^{k} Nw_{ij} TA_i \quad (6.9)$$

In equation (6.9), the degree of sensor nodes in the j^{th} cluster (TAs) is depicted by k , Nw_{ij} the sensor node i association with the target area j . If the sensor node i is marked as the target sensor node j , value of Nw_{ij} will be either one or zero. After completing this practice, to generate a new population of the TAs, the search process is repeated with onlookers and employed UAVs. The stored TAs in employed UAVs' memory are updated depending on the information. Equation 6.12 (used to compute the amount of nectar) obtain the result of the tests for the new TAs. In the results, if the new TAs nectar amount is more than the existing stored nectar amount of TAs, the UAV updates the new quantity of nectar and discards the old one. If not, then no change occurs in the location of TAs. The employed UAVs come back to the ground station after the completion of the process of exploration. Then they start to dance on the dancing floor and communicate different TAs nectar amount, track, distance, and direction with other UAVs in the form of a beacon. The onlooker UAVs wait and observe the beacon type and analyze the quantity of nectar of the next TAs. The selection of the next TAs depends on the probability of nectar quantity denoted with $Q(Nec_i)$ where the nectar amount is represented at the source i. The probability of p_i for TA_i computed as:

$$p_i = \frac{Q(Nec_i)}{\sum_{k=1}^{fs} Q(Nec_i)} \tag{6.10}$$

In equation (6.12), fs is the total TAs, $Q(Nec_i)$ is the nectar amount at source i, the onlooker UAVs discover the TAs in the neighbour or the candidate solution in the region of TA_i with the following equation:

$$TA_{(i+1)} = TA_i + r_{ij} \times ruv \tag{6.11}$$

The region size r_{ij} in equation (6.11), for j^{th} target position in the neighbourhood, the ruv is the random uniform variable with values between (-1, 1) and then compute the fitness value. The new solutions must be in the range and measure the nectar amount.

The employed UAVs visit the new candidate position and measure the nectar amount. Based on the fitness of a candidate position, it stores the new location and discards already stored previous position. If the value of the nectar amount is higher than the old one, then the new candidate position will be qualitative.

Equation (6.12) is used to find the potential problem area as the nectar location's position and its fitness that shows its associated quality to the possible results.

$$Q(Nec_i) = \frac{1}{1 + cf_i} \tag{6.12}$$

The following equation represents the maximum cost function as:

$$cf_i = \frac{1}{k} \sum_{i=1}^{k} i(TA_i, N_i) \tag{6.13}$$

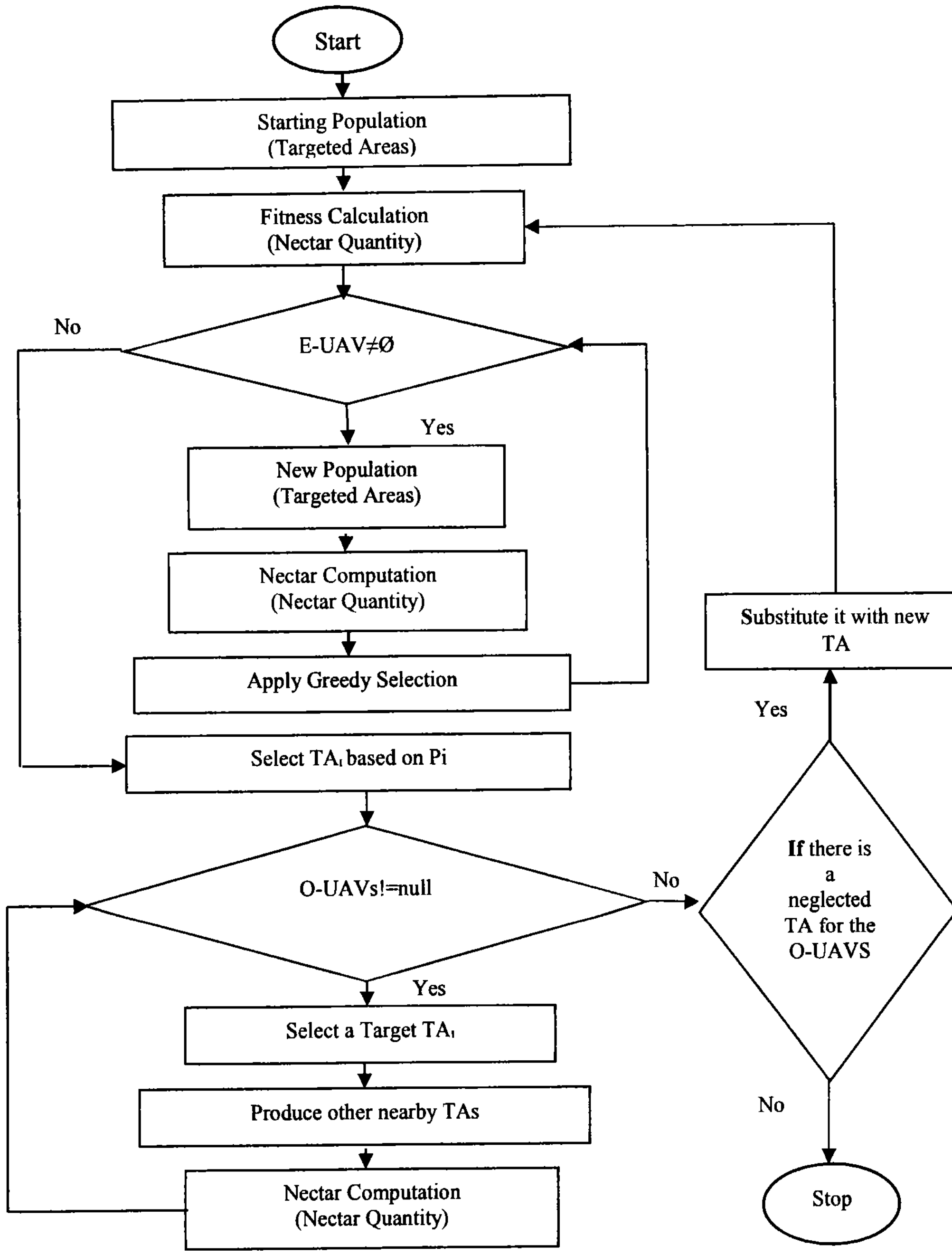


Figure 6.3: Flowchart of Honey Bee Algorithm based Target Area Identification

After locating the candidate target locations TA_{ij} and evaluation by onlooker UAVs, the existing position is compared with the candidate positions. The existing position will be replaced with the new one if the nectar amount is more significant than the previous one; otherwise, old one is retained. This selection of positions is based on the greedy mechanism, which is further based on the maximum round and number of TAs using control parameters.

The honeybees' exploitation and exploration search process can be achieved together. In this work, the onlooker and employed UAVs together attained the exploitation process of the search space, and the onlooker UAVs also performe the exploration task. The greedy selection approach is adopted in which the onlooker and employed UAVs performance are better for local neighbourhood search and global search. The onlooker UAVs also perform a random search in the search space. The TAs, in this approach are based on the greater quantity of nectar.

6.4 Cluster Formation

The UAVs visiting the field will communicate with cluster head nodes on the ground segment of the network. Once a UAV/onlooker bee identifies a target area based on the environmental factors transmitted via the ground segment, the next step is to form a cluster. The onlooker bee broadcasts a message to the employed bees in the neighbourhood about a TA. The employed bees sent their residual energy information to the onlooker bee. The onlooker bee calculates the CH node based on energy and degree. The information is communicated to all the employed bees in the vicinity. The CH nodes broadcast a message to all nearby nodes and ask them to join. In this way, the clusters are formed. Once the cluster formation is completed, the data collection process begins. All the employed bees collect and communicate data to the CHs. Once the data collection is complete, the search is initiated for a new TA. The CH selection, cluster formation, and data collection process is depicted in *Algorithm 6.2*.

Algorithm 6.2: CH selection based on TAs and data gathering

```
Procedure CH_selection_gathering()
Input: TAs calculated on the basis of EFV, E-UAVs: Energy and Degree
Output: Cluster Headset of UAVs
The onlooker UAVs announce TAs
            //The employed UAVs near to a TA will start monitoring/capturing
Do
            //Employed UAVs communicate with their neighbors in the TAs and
              ask for their residual energy and number of neighbors
      if (E-UAV_i energy & degree=max) then
```

```
                //A UAV having maximum residual energy and degree announce its
                  role as CH-UAV
            Broadcast CH-UAV message to neighbors
                //The employed UAVs join the nearest CH-UAV
            Send join message to CH-UAV
                // the collected data communicated to the CH-UAV
            Transmit data to CH-UAV based on TDMA schedule
        end if
    while (flight time < threshold or residual energy > avg-energy)
    end while
end procedure CH_selection_gathering ()
```

6.5 Performance Evaluation and Simulation Results

Performance of the proposed Bio-Inspired Cluster-based optimal Target IDentification (BICTID) is evaluated and compared with the SIL-PSO, Loc-GA, and Loc- KMeans for localization of UAVs on TAs. The TAs identification is based on the optimization metrics, i.e., relative humidity, moisture level, temperature value, light intensity, NPK, and power of hydrogen level.

The simulation area for the proposed system is selected for 2x2 km^2, where UAVs (10 - 60) are distributed randomly. These UAVs are equipped with high residual energy, and the speed limit ranges from 5 to 20 m/s. IEEE 802.11b,n standards are selected for inter and intra-cluster communication. To avoid interference among UAVs, we choose the IEEE 802.11b with 2.4GHz and 802.11n with 5GHz frequency bands. The rest of the parameters are summarized in Table 6.2.

Table 6.2: Simulation Parameters

Parameter	Value
Area	2 x 2 Km^2
UAV Operating Height	3 – 45 m
Range for UAVs Transmission	200 to 300 m
UAV Coverage range	Several Kilometers (Km)
UAVs Sensor Type	Thermal and Hyperspectral
Number of UAVs	10 to 60

IEEE Standard	IEEE 802.11b,n with 2.4 and 5GHz
BS at ground	One
Traffic Type and Data Rate	CBR - 2Mbps
Number of Rounds	2000
Number of Iteration	50
Initial Energy	2 – 5 j
Transmission Power of UAV	5w

The localization of UAVs in BICTID is based on the honeybee's optimization. The UAVs' localization accuracy, error rate, and the cost of convergence are considered performance metrics as done in [109].

$$\text{Localization Error } Ei = \sqrt{(x_i^{est} - x_i^{act})^2 + (y_i^{est} - y_i^{act})^2 + (z_i^{est} - z_i^{act})^2} \tag{6.14}$$

Table 6.3: Summary of Localization Error in Target Identification [Total UAVs = 40]

Scheme	Total UAVs	E-UAVs	O-UAVs	Max-Loc Error	Min-Loc Error	Mean Loc Error	Req. Iteration	Req. Time (ms)	Success Rate	Cost (Min)	Cost (Max)	Avg. Cost
BICTID	40	36	4	0.0	0.0	0.0	6	17.440	100	5.820	19.176	12.498
SIL-PSO	40	36	4	0.276	0.144	0.210	9	24.410	85	8.136	26.856	17.496
Loc-GA	40	36	4	1.428	0.432	0.930	18	57.200	69	18.312	34.056	26.184
Loc-KMeans	40	36	4	2.244	0.864	1.554	21	66.960	57	23.604	39.588	31.596

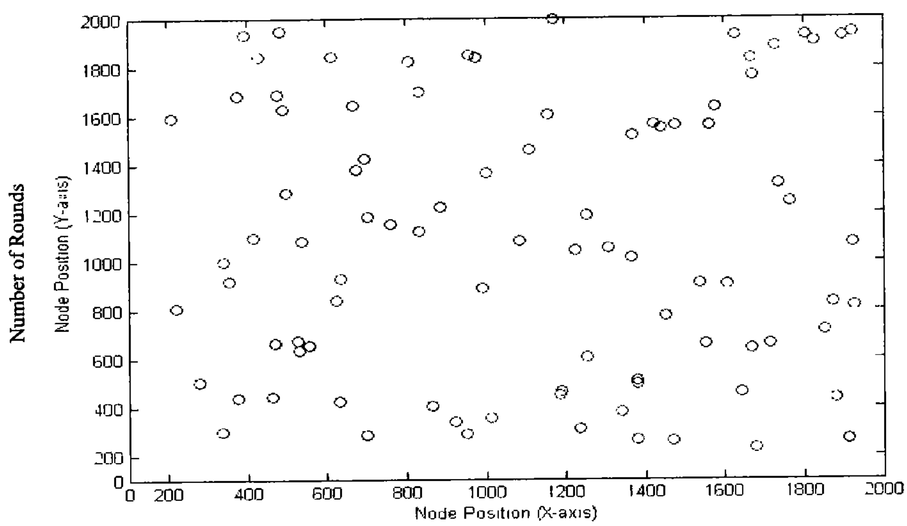
Minimum, maximum and mean localization errors are shown in Table 6.3. For a ratio of E-UAVs over O-UAVs (EOR) is 10 (i.e., EOR=10) and the network size is 40. Our proposed BICTID shows better results as compared to the existing algorithms.

Table 6.4: Summary of Localization Error in Target Identification [Total UAVs = 60]

Scheme	Total UAVs	E-UAVs	O-UAVs	Max-Loc Error	Min-Loc Error	Mean Loc Error	Req. Iteration	Req. Time (ms)	Success Rate	Cost (Min)	Cost (Max)	Mean Cost
BICTID	60	54	6	0.0	0.0	0.0	10	26.150	100.0	8.724	28.776	18.750
SIL-PSO	60	54	6	0.420	0.216	0.318	14	36.620	85.380	12.216	40.284	26.250
Loc-GA	60	54	6	2.148	0.648	1.398	28	85.810	69.550	27.468	51.084	39.276
Loc-KMeans	60	54	6	3.372	1.296	2.334	32	100.440	57.780	35.412	59.376	47.394

Figure 6.4 and Figure 6.5 represent the placement of nodes in the UAV network. The employed UAVs (E-UAVs) are represented with (×), and onlooker UAVs (O-UAVs) are represented with (o).

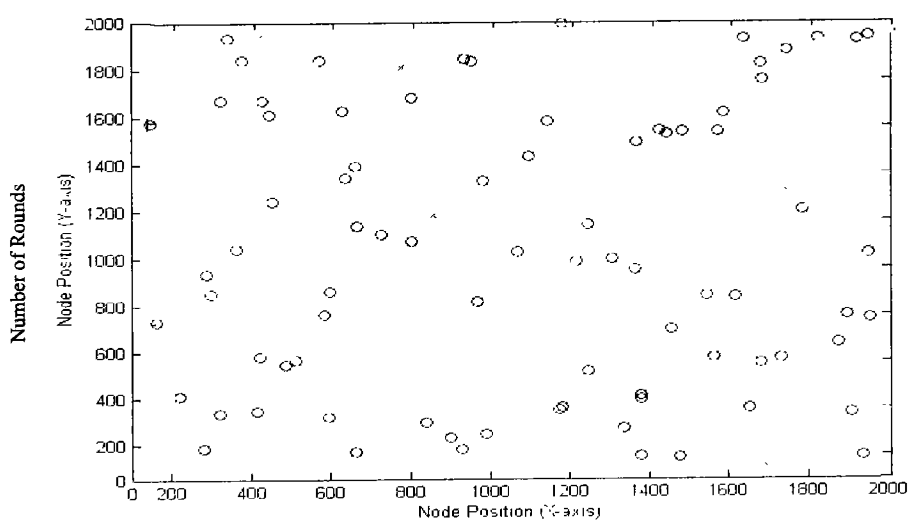
The BICTID shows better results with the increase of E-UAVs and O-UAVs, which means that O-UAVs localize E-UAVs is efficiently.



Number of Rounds

Figure 6.4: Random Deployment of UAVs

The error rate with the required iteration and proposed BICTID is minimal compared to the existing algorithms. The honeybee approach reduces the search space, so the computation time and the number of iterations automatically decrease.



Number of Rounds

Figure 6.5: Initial E-UAVs and O-UAVs Deployment

The localization success rate is higher of the proposed algorithm BICTID among all other algorithms. The minimum, maximum and mean cost of each bee shows that our proposed BICTID is efficient compared with the existing schemes. The minimum, maximum, and average of localization error are shown in Table 6.4 When the ratio of E-UAVs over O-UAVs (EOR) is 10 (i.e., EOR=10) and the network size is 60.

The proposed algorithm also shows efficient results as compared to the existing algorithms. With the increase of UAVs, the localization of UAVs also increases. The error rate with required iteration and time decreased in our proposed algorithm compared to the existing algorithms. The computation time and number of iterations automatically shows decrease by using neighbour search criteria in the defined search space. The BICTID localization success rate is higher among all other algorithms. The minimum, maximum and mean cost of each bee with the increase of UAVs shows that BICTID is more efficient than the existing schemes. The number of localization errors increases without the honey bee algorithm (neighbour search method), as shown in Figure 6.6. The localization error in the distance is represented with a line, i.e., O-UAV actual position to E-UAV position. The number of localization errors decreases with the honey bee algorithm, as shown in Figure 6.7.

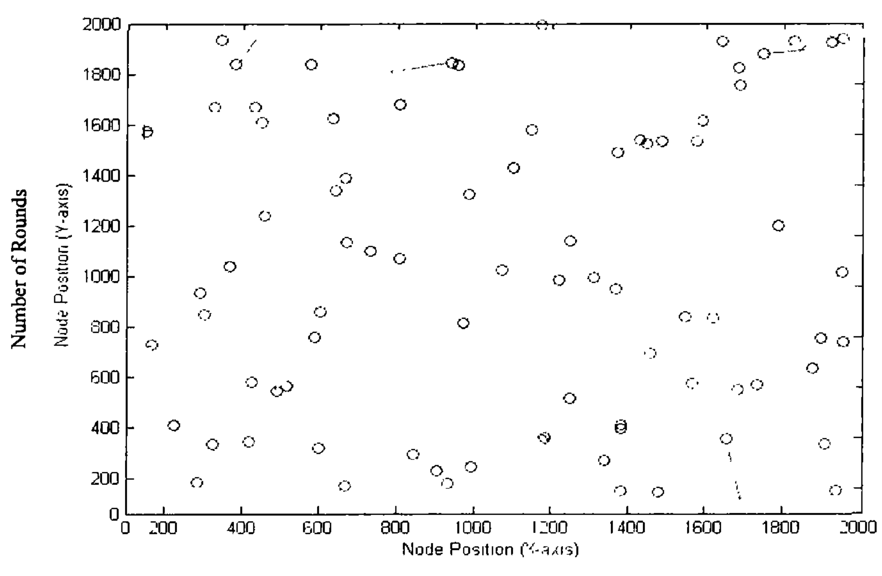


Figure 6.6: Localization Error without Neighbour Search Method

The O-UAVs communicate with E-UAVs. Figur 6.7 shows the connectivity of O-UAVs to E-UAVs using neighbour search criteria. The performance of the BICTID clustering is also evaluated and compared with SIC, EALC, BICSF, and SOCS. In this work for optimal TAs identification, we consider the optimization metrics, i.e., relative humidity, moisture level, temperature value, light intensity, NPK, and power of

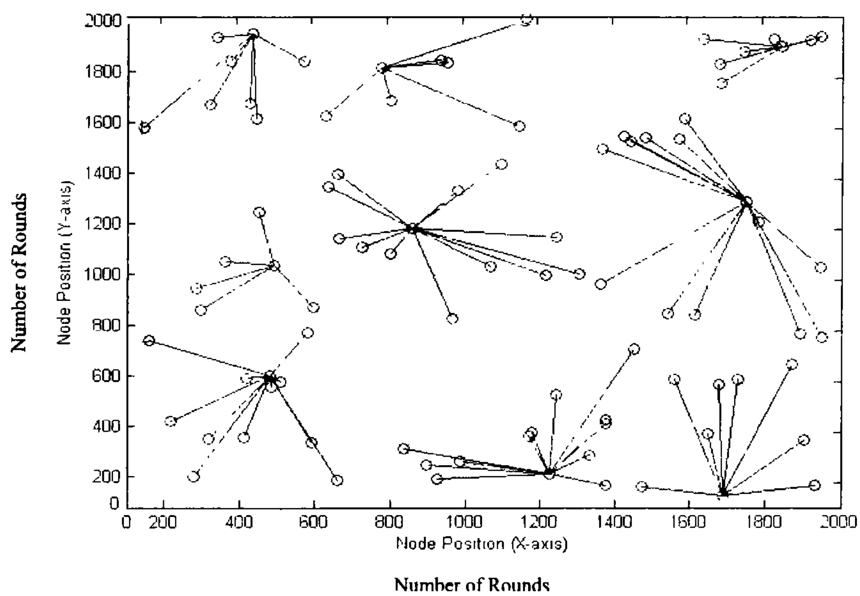


Figure 6.7: Localization and Connectivity of O-UAVs with E-UAVs

hydrogen level. The performance metrics for the BICTID evaluation are communication overhead, packet delivery ratio (PDR), mean end-to-end delay, and energy consumption. The communication overhead between source and destination is the redundant data for the payload transmission. PDR is the ratio of successfully received data by the target that was sent. The mean end-to-end delay is the time to transmit data from source to destination. Energy consumption is the utilization of energy on sending, receiving, processing of data by source or destination.

The simulation result shown in Figure 6.8 compares UAVs degree vs. PDR in the multi-UAVs network for the BICTID, SIC, EALC, BICSF, and SOCS. The BICTID in Figure 6.8 presents its effectiveness in delivering above 95% of data. The BICTID demonstrates the best performance as compared to the selected clustering protocols while increasing the number of UAVs.

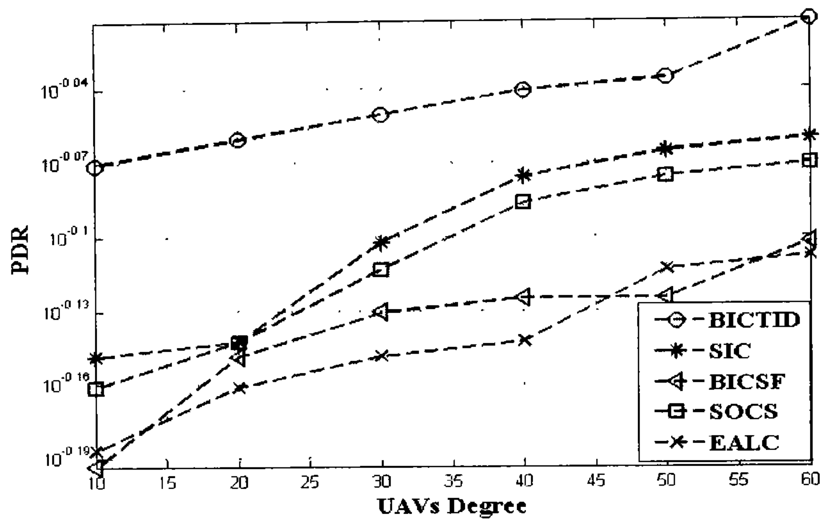


Figure 6.8: UAVs Degree vs. PDR

The speed of UAVs varies from 5 to 20 m/s. The delay may occur due to UAVs' high mobility to find the TAs. The OTAs identification is performed based on the bee's concept, forming the clusters for reliable communication among UAVs.

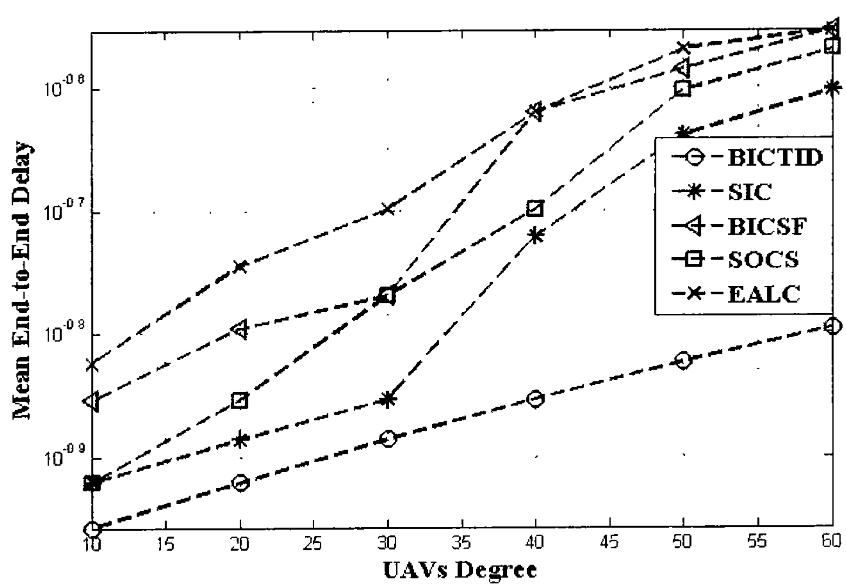


Figure 6.9: UAVs Degree vs. Mean End-to-End Delay

Figure 6.9 shows UAVs degree and mean end-to-end delay of BICTID and other selected protocols. Due to the reliable communication among UAVs, the mean end-to-end delay of the proposed BICTID is considerably less than SIC, EALC, BICSF, and SOCS.

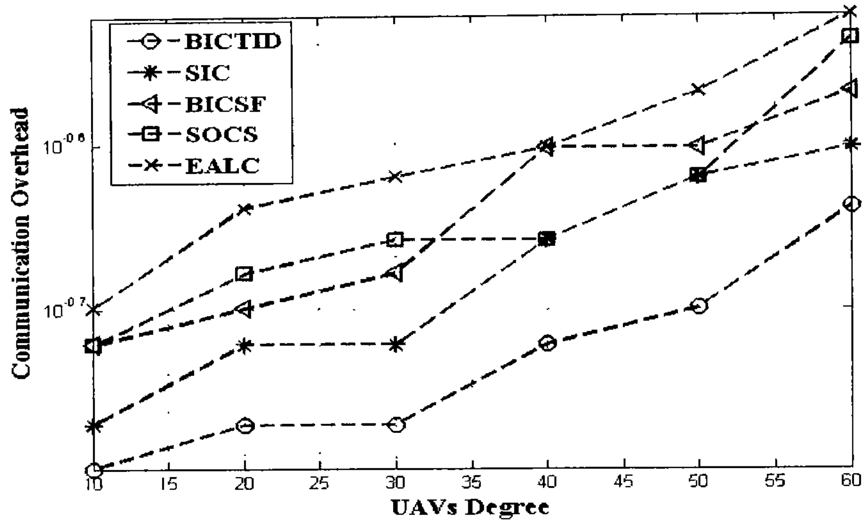


Figure 6.10: UAVs Degree vs. Communication Overhead

The increase in UAVs also increases the communication overhead. The bio-inspired clustering approach form balanced clusters that reduce the communication overhead, as shown in Figure 6.10. In the simulation results, the increase in the UAV degree

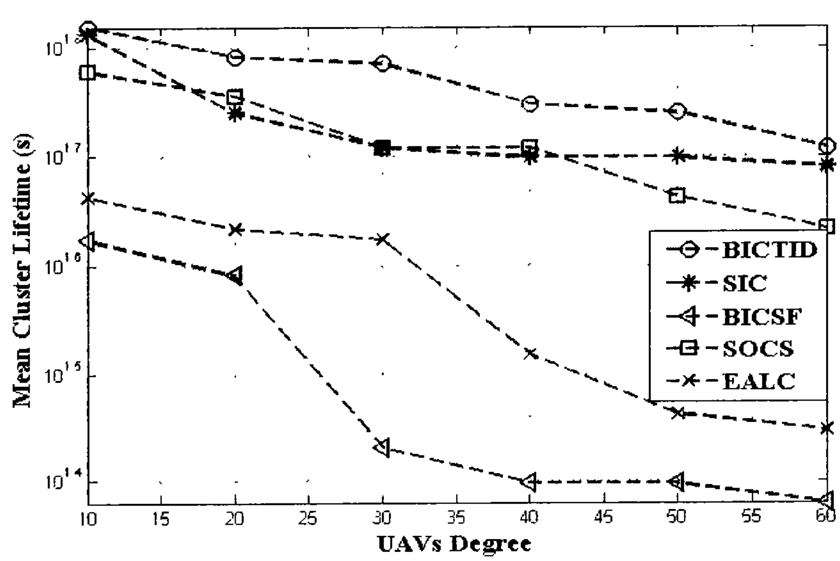


Figure 6.11: UAVs Degree vs. Mean Cluster Lifetime

indicates that the proposed BICTID has less communication overhead among all other schemes.

Time for the formation of the cluster is called cluster lifetime. Once the clusters are formed, the CH is selected, responsible for managing its member UAVs. With time, the CH fitness value reduces because of different constraints. Due to mobility and topological changes frequently, re-clustering is performed to select the next UAV for the role of CH. The proposed BICTID minimizes the re-clustering to prolong the cluster lifetime. The simulation result in Figure 6.11 presents that the mean cluster lifetime decreases with the increase in UAV degree. The BICTID, SIC, and SOCS cluster lifetime are much better than the EALC and BICSF.

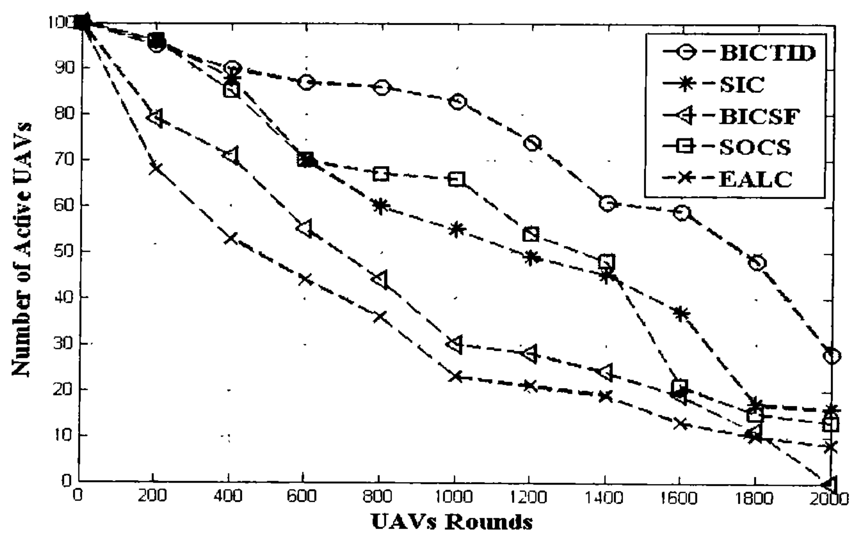


Figure 6.12: Number of Active Nodes vs. Number of Rounds

UAVs continuously monitor the field to identify the TAs. During the visit at each round, UAVs' energy reduces while some UAVs may die due to high energy consumption or drainage. Figure 6.12 presents the number of active nodes at each round. The proposed BICTID shows better energy utilization to prolong the lifetime and minimize the ratio of die UAVs compared to SIC, EALC, BICSF, and SOCS.

Due to energy constraints, the proposed BICTID form balance clusters with optimum CHs, and minimize re-clustering that reduces energy utilization. Figure 6.13 present the total number of UAVs and energy consumption of all the selected protocols. The SIC, BICSF, and EALC consume more energy when increasing the number of UAVs compared to BICTID and SCOS.

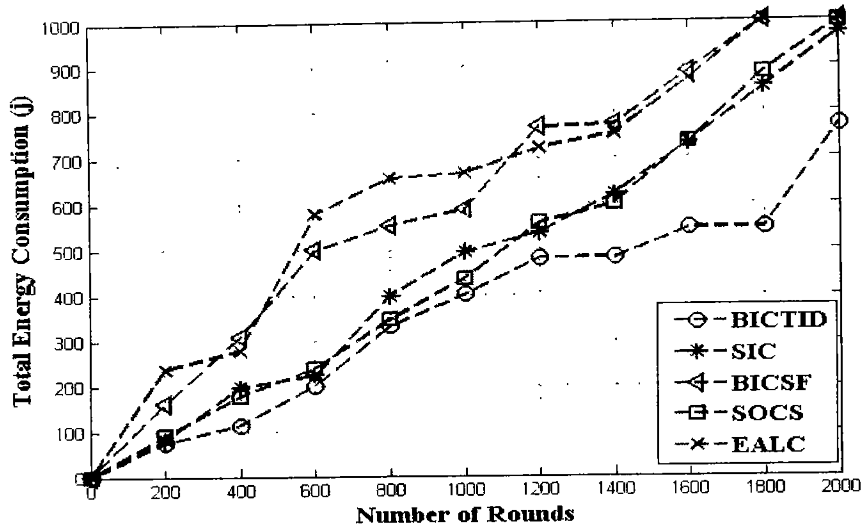


Figure 6.13: Total Energy Consumption vs. Number of Rounds

Figure 6.13 presents the total energy consumption and the number of rounds of the BICTID, SIC, EALC, BICSF, and SOCS. The energy utilization of BICTID is better among all other selected schemes.

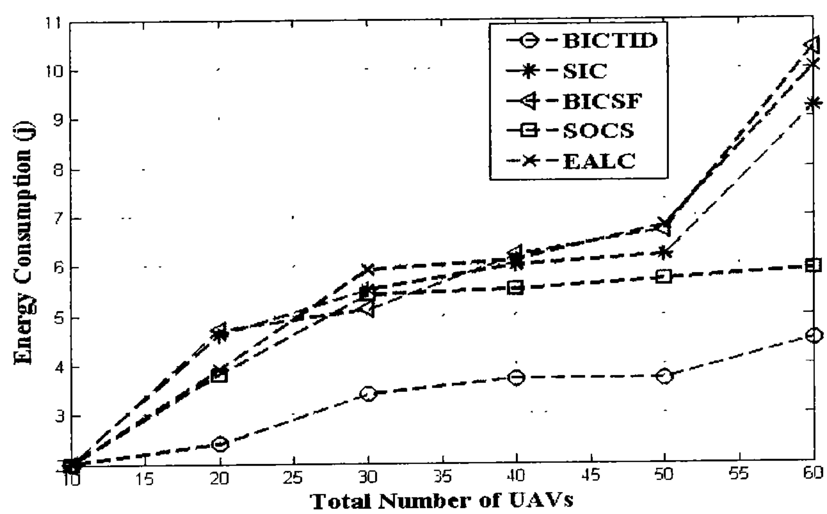


Figure 6.14: Total Number of UAVs vs. Energy Consumption

Figure 6.14 shows that the total energy consumption also increases with the increase in the number of rounds. Still, the BICTID, SIC, and SOCS offer more stability in energy utilization than EALC and BICSF.

6.6 Chapter Summary

In this chapter, the proposed BICTID clustering and localization scheme for FASNET is presented to identify the TAs in precision agriculture accurately. The FASNET platform in the precision agriculture domain plays a vital role in locating the affected area and observing the crop field with excellent spatial and temporal resolution. The localization and clustering of multi UAVs for TAs identification is a challenging task. BICTID first identifies the affected TAs in the tomato crop field. The TAs identification was performed based on environmental factors weights, i.e., relative humidity, soil moisture, temperature, light intensity, and NPK. The honeybees foraging approach is applied that shows better performance than GSO and PSO-based intelligence approaches. The performance metrics considered in the BICTID are UAVs localization accuracy, error rate, and convergence cost. In the BICTID scheme, the localization of multi-UAVs for TAs identification achieved very high accuracy compared to the localization schemes (i.e., SIL-PSO, Loc-GA, Loc- KMeans). The BICTID is compared with the existing clustering schemes (i.e., SIC, EALC, BICSF, and SOCS). The performance of the BICTID clustering significantly improved in terms of packet delivery ratio, communication overhead, mean end-to-end delay, and energy consumption. The simulation results show that the BICTID prolongs the network lifetime efficiently. BICTID will increase tomatoes' productivity, reduce wastage due to diseases, and make it cost-effective.

Chapter 7

Honey Bees based Clustering and Data-Aggregation

Multi-UAVs in FSNet are constrained by different energy factors such as limited energy, computation, memory, and communication. The energy consumption on sensing and computation is less than energy utilization on communication among the UAVs or the ground station (GS). Available energy resources are sometimes insufficient for transmission and calculation during the mission, but collected data needs to be communicated to the destination for further processing. Performance of network lifetime depends on efficient energy utilization. The researchers tried to minimize energy utilization in other networks such as MANET, VANET, and WSN, but in FSNET, energy efficient utilization problem still exists. Due to the flying speed of UAVs, rapid variation in topology, terrain structure, and diverse directions make the collection and routing of information difficult. The researchers proposed energy-efficient schemes by considering different parameters such as reducing the communication distance, computation cost, mobility, degree, etc. However, the data collection minimizes communication load to save bandwidth and energy [109].

In order to minimize the load on multi-UAVs, a data aggregation approach is used that reduces UAVs' energy utilization and increases the lifetime of networks. Data aggregation approach is different in WSN and VANET from UAV networks. In WSN, the uses of the data aggregation approaches are for decreasing energy consumption rather than minimizing network capacity usage, while in VANET, due to high variation in the topology, data aggregation is performed by many vehicles. Energy factors constrain the multi-UAVs system due to degree, mobility, density, and other parameters; that's why it combines sensor and vehicular ad-hoc network requirements. The UAVs have also consumed energy on processing and storing more data, just like on flight and communication [56].

Fundamental operation in the flying ad-hoc sensor network is data aggregation, which aims to transmit data among UAVs or GS. The data aggregation approach reduces the communication cost usage of network capacity while obtaining aggregated information.

The concept of many-to-few is used in data aggregation. The data aggregation protocol defines how the data is gathered, how the aggregated data is routed to the destination and schedule of when the aggregated data should be sent.

This section describes our developed cluster-based data aggregation scheme for UAV-based FSNet. The contributions of this research are:

- Design of an effective mechanism for selecting optimal UAVs- CH based on the honeybee algorithm.
- Formation of balance and stable clusters to reduces the re-affiliation rate.
- A data aggregation algorithm is proposed to limit duplicated data to the BS.
- Avoid communication of unwanted packets to the BS and save the bandwidth of FSNet.

In FSNets, collecting and transmitting information through multiple hops increases energy utilization. A data aggregation approach reduces energy utilization and increases the FSNets lifetime by minimizing UAVs-Ch load. Data aggregation approaches reduce communication cost and energy consumption. The researchers developed aggregation approaches for FSNet without redundant data elimination.

7.1 FSNet Cluster Optimization and Data aggregation

In cluster-based flying networks, the selection of cluster heads (CHs) and cluster formation require special attention to decrease the re-affiliation rate and save FSNet resources. The parameters such as remaining energy, mobility, and degree are considered to select the CH with optimal clusters. These parameters are optimized to distribute the load among all clusters. Our previous approaches are adopted to balance and optimal CHs selection [135, 136]. The data aggregation procedure is initiated once the clusters are formed.

In cluster-based routing for flying sensor networks, the CHs may receive multiple copies of the same data set from different sensors located in the vicinity. The communication of data requires more resources as compared to computation. Hence, a method is required to discard the duplicated packets when sending data to the base station at the cluster level. In this way, the network resources: battery and bandwidth will be used for other useful operations. The lifetime of the network will increase. Our proposed algorithm works in two phases: cluster setup and data aggregation.

7.1.1 Cluster Setup

In the cluster setup phase, honey bee algorithm is applied to select the optimal CHs as in our previous research [135]. The CH selection based on the honeybee clustering algorithm results in the formation of balanced cluster. The relative UAVs mobility, neighbour criteria, and other clustering parameters such as energy, degree are considered when selecting CHs that minimize the re-clustering and form stable clusters. In FSNet, once the UAVs' CHs set, the CHs broadcast a message containing ID, position, and status. All the UAVs in the range of CH-UAVs will receive the broadcast message and join the cluster. Once the UAVs join a cluster, they become the cluster member (CM) and share their information with CH-UAV. In case of receiving membership messages from multiple CH-UAVs, the joining will be based on the distance to a CH-UAV. If the distance is the same, then the random mechanism for the CH-UAV selection will take place. The working of the cluster setup phase is shown in *Algorithm 7.1.*

Algorithm 7.1: Psuedo code of UAVs enabled CH selection

Procedure CH-Selection-MUAVs()
Input: SW_{UAV} $[n_{UAV}]$, C_{FSNet}
Output: CH-UAVs
call function calculate-UAVs-Nectar(n_{UAV})
    for $(v = 1; v \leq C_{FSNet}; v++)$ **do**
// selection of CHUAVs in a random way
        CHUAVs[v]=functionRand (SW_{UAV})
    end for
while (highest-value!=yes) **do**
    for $(v1 = 1; v1 \leq n_{UAV}; v1 = v1 + 1)$ **do**
// the suitability of current selection is computed
        if (v1 in CHUAVs) **then**
            $FValue_{UAV} = FValue_{UAV} + 1(SW_{UAV}[u] + AFV_{UAV})$
        end if
    end for
    if ($FValue_{UAV} < PFValue_{UAV}$) **then**
// $PFValue_{UAV}$ is the suitable value in the existing solution
        swap $FValue_{UAV}$
    end if
    if (CHUAVs-optimum != yes) **then**
        while (empb! = 0) **do**

// visiting of bees employed till empty

$$UAV_j(x+1) = UAV_j(x) + \alpha_{ij} * y$$

// selection of different UAVs from a fellow citizen

end while

$$\Pr_i = \frac{W_{UAV_i}}{\sum_{j=1}^{k} W_{UAV_j}}$$

// the new UAVs probability $\Pr_i$ will be calculated

while (the Obees $\neq$ €) **do**

Selection of another set of CHUAVs will be carried out subject to the probability $\Pr_i$

end while

Else

return CHUAVs

end while

end procedure

Once the clusters are formed, the data aggregation and communication phase are initiated to transmit the data to BS.

7.1.2 Data Aggregation and Communication

We collect data from flying UAVs and match the data to discard similar data sent by multiple UAV sensors in the data aggregation process. Data is collected using a TDMA schedule when multiple sensors simultaneously communicate data.

This similarity among data X and Y is known as data match with moves (DMM) and designated as $d(X,Y)$. In computational biology, there are various applications where partial data match is considered a primeval in multiple situations where moving a larger sub-sequence is similar to insert or delete operation; during the text processing, moving a large array together might be assumed like reordering to deleting or inserting typescripts. Keep in mind that the nontrivial placements are still a challenge for DMM. Hence, $d(X,Y)$ is the size of the smaller structure of edit procedures, which convert Y to X, the allowable process affects a data stated below:

- The deletion of a character at location loc transform X to $X[1]...X[loc-1], X[loc+1]...X[n]$.
- The insertion of a character $"c"$ at a location $"loc"$ gives in $X[1]...X[loc-1], c, X[loc]...X[n]$

- The substitution of a character at a location "loc" with character"c"results $X[1]...X[loc-1], c, X[loc+1]...X[n]$
- The partial data movement with parameters $1 \le loc \le loc_2 \le k \le n$ transforms $X[1]...X[n]$ into $X[1]...X[loc-1], X[loc_2]...X[loc_3-1], X[loc]...X[loc_2-1], X[loc_3]...X[n]$.

The data will be identical when the edit distance between two data is "0". The metric represents its measure. The transformation is performed in several operations. The cost of each operation is equal to even in the inverse case. Hence, $d(X,Y) = d(Y,X)$; then every distance resulting from transforming one data to another must follow the triangular inequity. The restrictions of the interaction of edit operations are none. These restrictions may be like, it is relatively conceivable for a fractional data move to take a fractional data to a different position and then for a successive data move to function on a fractional data that overlays the relocated fractional information neighbouring typescripts.

The deterministic algorithm results in the DMM problem and the running time complexity is $O(n \log n)$. The algorithm returns the equivalent array "Ar" where each $Ar[loc]$ is estimated to nearly $O(\log n \log^* n)$ factor. The proposed methodology depends on inserting data to a vector of arrays below L_1 metric. L_1 size among these arrays is $O(\log n \log^* n)$ an estimate of DMM between the two original data.

The proposed scheme focus on the vital components. Firstly, we parse data into a hierarchy of partial data. We use a simple hierarchical mechanism for parsing named Edit Sensitive Parsing (ESP), which generates a tree having three degrees. ESP may not be an innovative parsing method; though, an effort to make straightforward the procedural details of relating predefined coin throwing to get classified data fragmentation. It is expected that the ease of ESP assist exposes more uses of classified data decays. The next module of this research is the approximate distance preservative data inserting to array spaces based on hierarchical parsing.

In *Algorithm 7.1*, the data coming from different sensors in the locality are matched with each other. The algorithm receives input in the form of long strings X and Y. Once data duplication is found, the algorithm results true and false in other cases. The algorithm starts initialization by assigning the length of vector *X* to X_{len} and the length of vector *Y* to Y_{len} in the first step. In step 2, a two-dimensional array of two rows and $Y_{len} + 1$ columns store the results of previous solutions. The initial value is assigned zero to all the cells of array *V*. Assigning an integer value to all cells of array *V* in row *0*. When X is blank, it is the base criteria; then, we must add each remaining *Y* symbol.

Algorithm 7.1: Data Aggregation Algorithm to Find the Duplicated Data in Two Data Set X and Y

Procedure Data_Match_with_Moves (DMM)

Input: Data sets X and Y

Output: True/False // Duplication Found or Not Found

1. Initializations
   i. $X_{len} \leftarrow$ X.length()
   ii. $Y_{len} \leftarrow$ Y.length ()
2. Allocate vector space V[0 : m, 0 : n] ▷ V[i, j] will contain the length of X[1 : i] and Y[1 : j].
3. V[0, j] ← 0 for all 0 ≤ j ≤ n and V[i, 0] ← 0 for all 0 ≤ i ≤ m. ▷ Base Cases
4. **for** (i ← 1 to Xlen) **then**
5. **for** (j ← 0 to Ylen) **then** // matching the symbols from X with Y symbols
6. **if** (j = 0) **then** // if Y is blank then eliminate all X symbols
   // if symbol from both data set is matching then no operation is required
7. V[i % 2][j] ← i;
8. **else if** (X[j - 1] = Y[i - 1]) **then**
9. V[i % 2][j] ← V[(i - 1) % 2][j - 1];
10. **end else if**
   // if symbols from both datasets do not match, then we take the smallest from 3 operations.
   // i.e. insert, delete and substitute
11. **else then**
12. V[i % 2][j] ← 1 + min(V[(i - 1) % 2][j],
13. min(V[i % 2][j - 1],
14. V[(i - 1) % 2][j - 1]));
15. **end if**

```
16.       end for
17.     end for
          // after filling the V vector, if the size of Xlen is even, then
         //we end up in the 0th row else
        //we end up in the 1st row, so we take Xlen % 2 to get row

18.     P←V[Xlen % 2][Ylen] // the final value after matching two data sets
19.     L←max (Xlen, Ylen)
20.   if (P<L/2) then
21.       return 1 // true value will return i.e. duplication found
22.       else then
23.       return 0 // false value will return i.e. duplication not found
24.   end if
25.   end procedure DMM
```

For Loop in step 4, they are executed for each symbol of dataset X to perform the matching operation with symbol dataset Y. The inner loop in step 5 performs the matching function of both datasets X and Y. The conditional statement in step 6 heck whether dataset Y is empty or not. If the condition satisfies, all the symbols of dataset X will eliminate. The data match operation "no operation" result if the symbols of datasets X and Y match. The conditional statement in step 8 performs the least expensive operation. If symbols from both datasets do not match, we take the smallest from 3 operations, i.e., insert, delete, and substitute. After filling the V vector, if the size of Xlen is even, then we end up in the 0th row; else, we end up in the 1st row, so we take Xlen % 2 to get a row. The matching values are assigned to variables P and L in step 18 and step 19, respectively. The algorithm results in the value "1" for true in step 21 if the values of datasets X and Y match. The value "0" false returns when the datasets X and Y are not identical.

Based on the output of *Algorithm 7.1*, the data are coming from sensors discarded when the algorithm returns true or "1". The BS communicates the data via multi-UAVs when the algorithm returns false or "0". The complexity of the algorithm is O (m*n). Where *m* represents the length of dataset *X* and n represents dataset Y's length. The initialization in step 1 and step 2, 3 takes constant O (1) time. The loop in step 3 takes O (n+1) and O (n) time, respectively. Step 4 and step 5 contain the inner-loop of size m, size n, and will take O [(m+1)*(n+1)] time. The remaining statements in the preceding steps will also take constant time O (1). Hence, by adding the time complexity of all statements in *Algorithm 7.1*, we get overall complexity O (m*n).

7.2 Performance Evaluation and Simulation Study

The performance metrics for evaluating the proposed scheme are measured with packet delivery ratio, energy consumption, end-to-end delay, packets drop ratio, communication overhead, and bandwidth utilization. The packet delivery ratio is the ratio of packets received by the receiver UAVs versus the packets sent by the sender UAVs. The higher percentage means that the proposed approach performance is better. The energy consumption shows the mean amount of energy consumed by the UAVs for data transmission. The end-to-end delay means the time taken by the UAVs for packets sending and receiving. It also measures the delay caused during routes discovery and waiting in a queue. The packet drop ratio means that the packets dropped during the transmission, and it counts the total number of packets received and packets sent. Sometimes the duplicate packets or the additional information communicated to the CH-UAVs reduce the communication speed and consume energy.

The performance of the proposed redundant data elimination aggregation approach, i.e., Flying Ad-hoc Sensor Network Optimized-Communication Data Aggregation (FSNet-OC-DA) compared with non-redundant data elimination aggregation approaches, i.e., EE-UAV-DA, OC-mUAV, and TA-UAV-DA in terms of End-to-end delay, packet

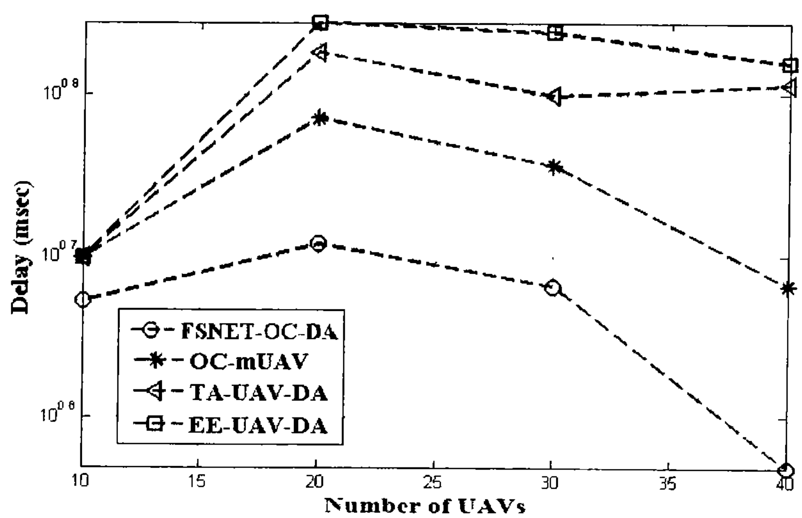


Figure 7.1: Number of UAVs vs. End-to-End Delay

delivery ratio, packet drop ratio, residual energy, communication/message overhead, bandwidth occupancy With the varying number of UAVs, data rate and redundancy rate.

The data rate is fixed (i.e., 250kbps) in the simulation, and the number of UAVs varies from 10 to 40. Figure 7.1 shows the number of UAVs and the end-to-end delay. It is observed that with the increase of UAVs, the proposed scheme has a minor average

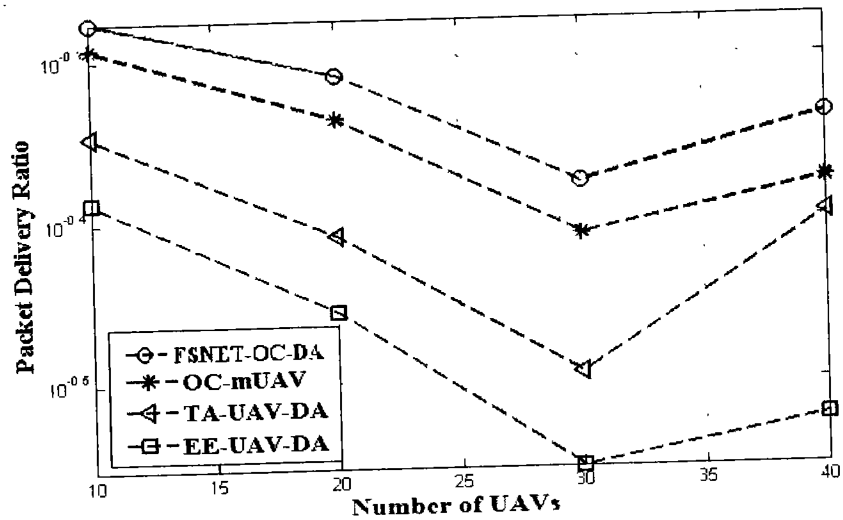


Figure 7.2: Number of UAV vs. Packet Delivery Ratio

delay as compared to the EE-UAV-DA, OC-mUAV, and TA-UAV-DA.

Figure 7.2 present the number of UAVs vs. PDR. The simulation results show that with the increase of UAVs and decreased PDR. The PDR of the proposed scheme falls, while

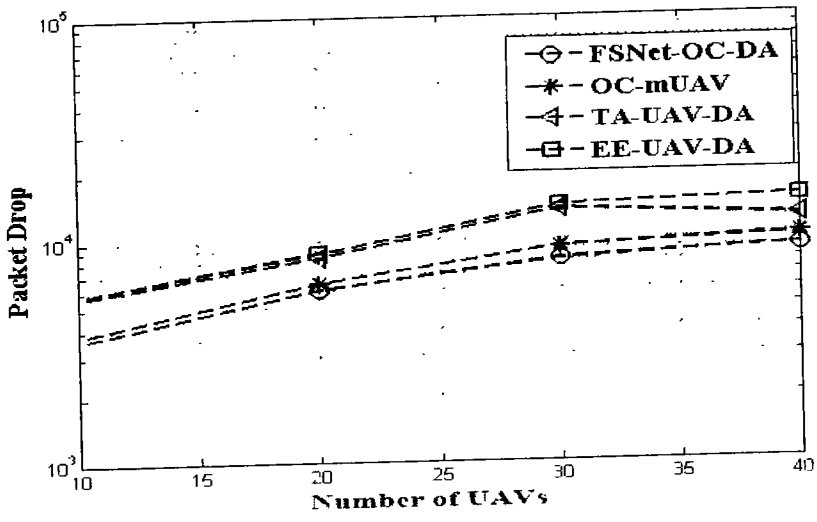


Figure 7.3: Number of UAVs vs. Packet Drop Ratio

the EE-UAV-DA, OC-mUAV, and TA-UAV-DA have more decrease as compared to our proposed one.

Figure 7.3 present the number of UAVs and packet drop ratio of the proposed scheme and other selected approaches. The simulation result shows that the drop ratio has increased in the existing methods with increasing UAVs.

The increase of UAVs has a direct impact on the residual energy. Figure 7.4 shows that the FSNet-OC-DA residual energy is better among all the existing approaches.

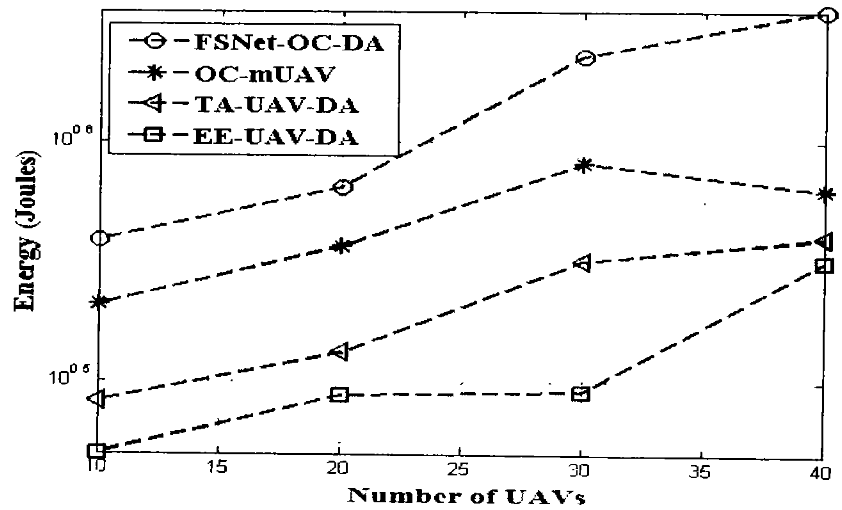


Figure 7.4: Number of UAVs vs. Energy

The proposed scheme eliminates the duplicate data transmission to the CH-UAV by using a near-linear time algorithm. Figure 7.5 shows that the communication overhead

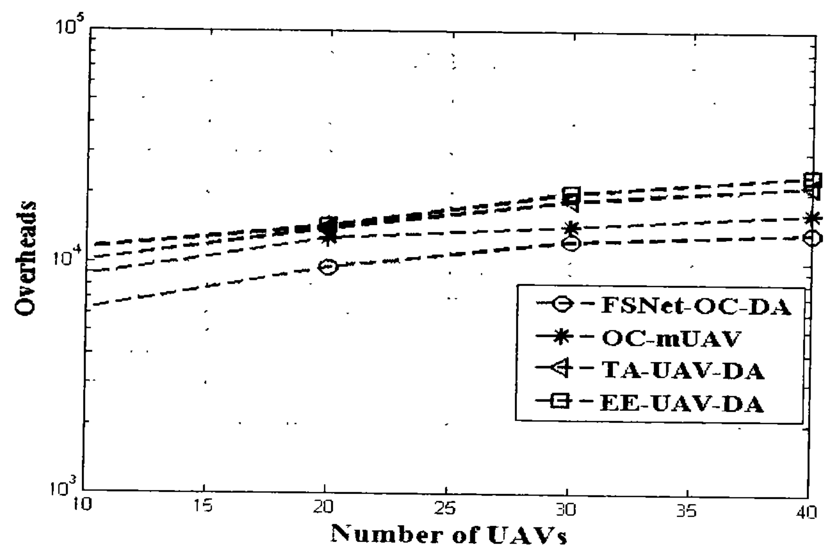


Figure 7.5: Number of UAVs vs. Communication Overhead

increases with the increase of UAVs, but the FSNet-OC-DA has significantly less message overhead.

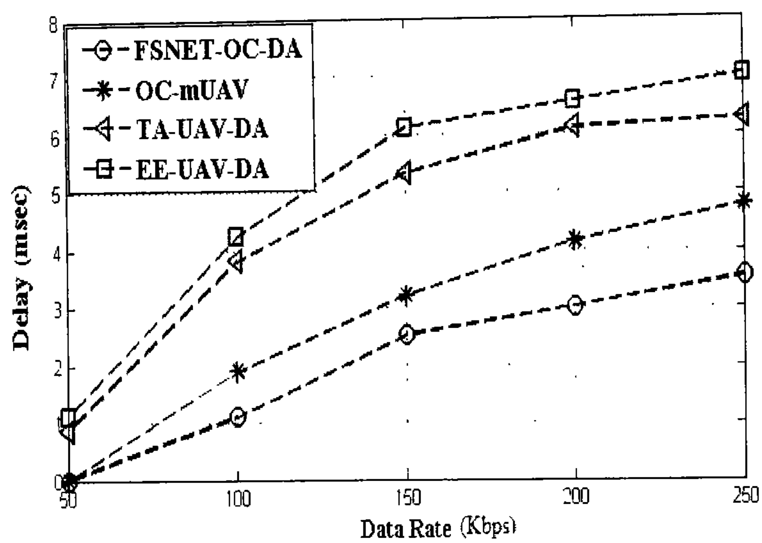


Figure 7.6: UAVs Data Rate vs. End to End Delay

In the simulation, the number of UAVs is 40, and the data rate varies from 50 to 250 Kbps. Figure 7.6 represents the UAVs' data rate and end-to-end delay. The simulation result shows that the end-to-end delay increases with 50 to 250 Kbps data rates. It is observed that the FSNet-OC-DA has a minor end-to-end delay than the existing approaches.

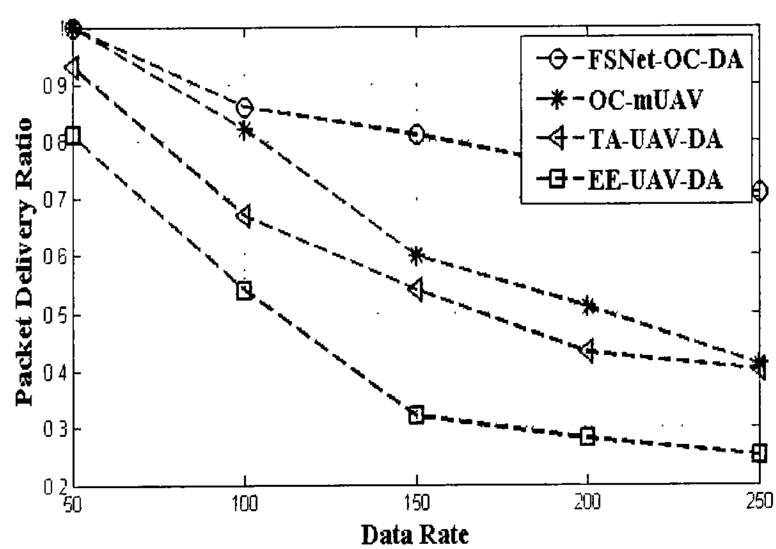


Figure 7.7: UAVs Data Rate vs Packet Delivery Ratio

Figure 7.7 presents the packet delivery ratio for different data rates (50 to 250 Kbps). Initially, when the data rate is 50 Kbps, the PDR is very high, but the delivery ratio gradually decreases with the increase in data rate.

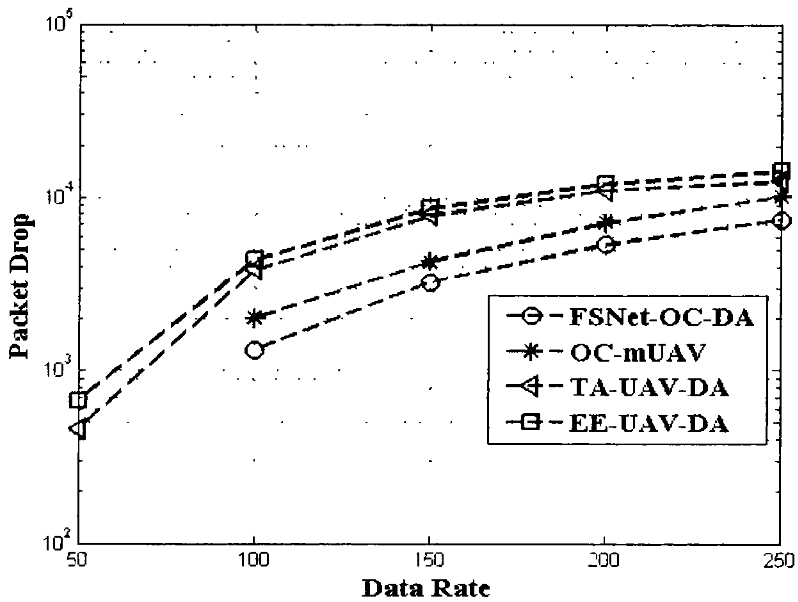


Figure 7.8: UAVs Data Rate vs. Packet Drop Ratio

In Figure 7.8, initially, the UAVs data rate is 50, and the packet drop ratio is very minimum. Still, with the increase in UAVs data rate, the packet drop ratio increases up to the highest level. The FSNet-OC-DA packet drop ratio is always less when the data rate varies from 50 to 250 Kbps.

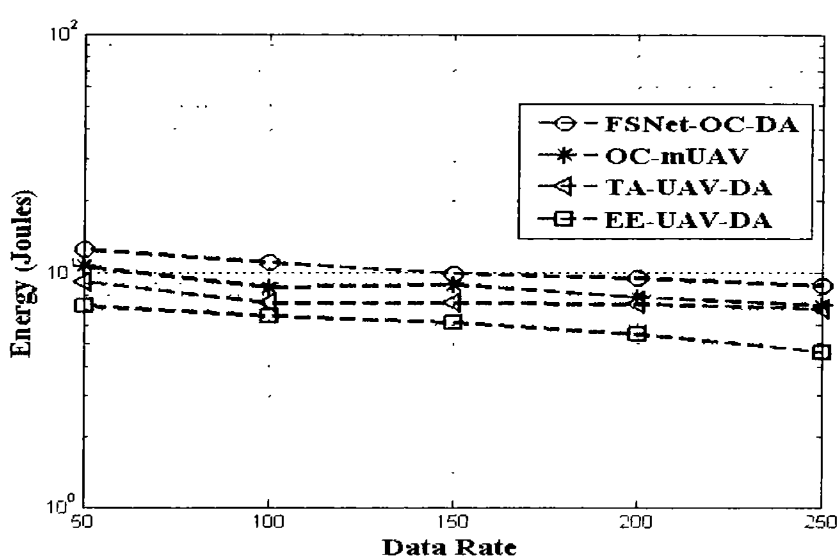


Figure 7.9: UAVs Data Rate vs. Residual Energy

Figure 7.9 represents the data rate and residual energy of UAVs. The residual energy decreases with the increase in the data rate of UAVs. The remaining residual energy of the FSNet-OC-DA is still better among other existing approaches.

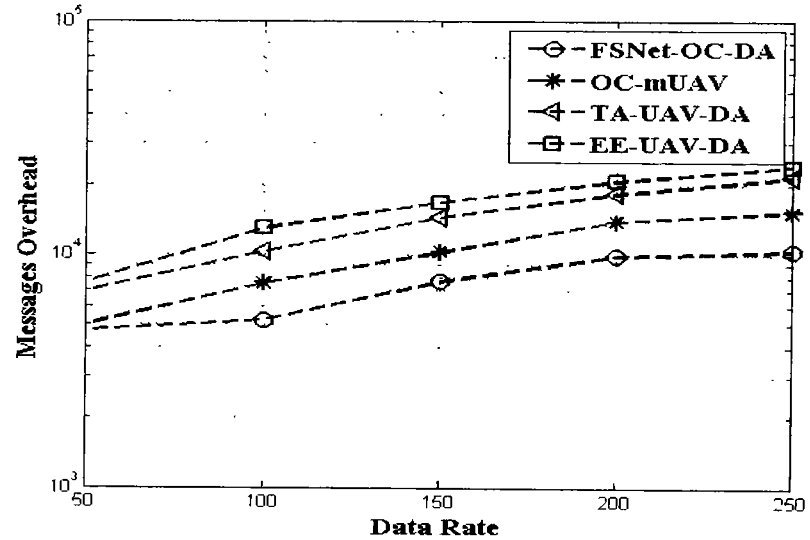


Figure 7.10: UAVs Data Rate vs. Message Overhead Ratio

Figure 7.10 represents the UAVs' data rate and the ratio of the message overhead. The non-redundant data elimination approaches' communication overhead is higher than the proposed redundant data elimination schemes.

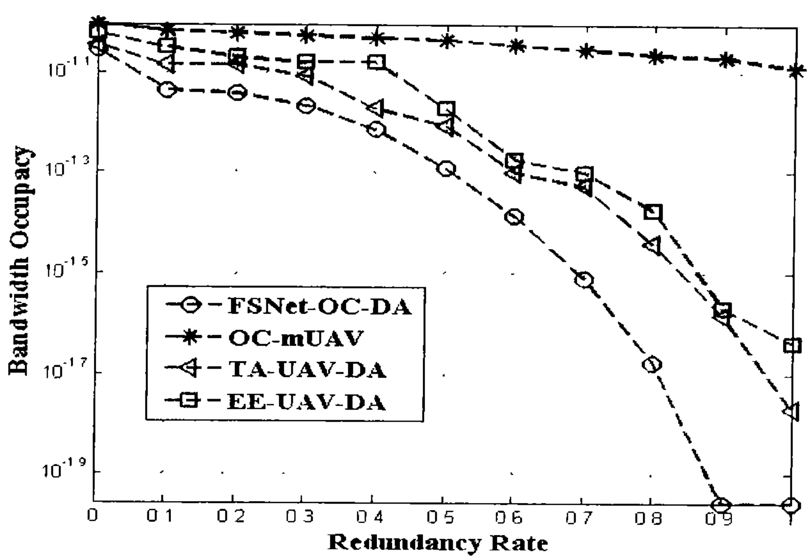


Figure 7.11: UAV Redundancy Rate vs. Bandwidth Occupancy Rate

The capacity of the transmission channel is called bandwidth. The bandwidth occupancy rate is the ratio of the bandwidth used by the redundant and non-redundant aggregation approaches. Figure 7.11 represents each UAV bandwidth occupancy and redundancy rate. The bandwidth occupancy of the FSNet-OC-DA is moving towards close to zero compared to the existing methods. In FSNet-OC-DA, the UAVs avoid redundant data and transmit only actual data to a CH-UAV. At the same time, the conventional data aggregation approaches utilize 50 percent bandwidth of the total available bandwidth.

7.3 Chapter Summary

This chapter proposes a honeybee algorithm to select an optimal CH UAV set and form stable and balanced clusters. The modified version of the honeybee algorithm determines the UAVs-CH based on residual energy, UAV degree, and relative mobility. The UAV joins the nearest UAVs-CH to transmit/share data. Ordinary UAVs with the same distance to two or more UAVs-CH randomly join a UAV-CH. The re-affiliation rate will decrease with the proposed stable clustering procedure. Once the clusters are formed, the ordinary UAVs transmit data to their UAVs-CH. An aggregation method is proposed based on dynamic programming to save energy consumption and bandwidth. The data aggregation procedure is applied at the cluster level to minimize communication and save bandwidth and energy. A series of simulation experiments validate the proposed FSNet-OC-DA. FSNet-OC-DA compared with non-redundant data elimination aggregation approaches, i.e., EE-UAV-DA, OC-mUAV, and TA-UAV-DA in terms of End-to-end delay, packet delivery ratio, packet drop ratio, residual energy, communication/message overhead, bandwidth occupancy with varying number of UAVs, data rate and redundancy rate. Simulation results show that our proposed FSNet-OC-DA outperforms state-of-the-art cluster-based data aggregation schemes.

Chapter 8

Conclusion and Future Work

In this research work, the problem is concerned with energy-efficient clustering in flying ad-hoc sensor networks. An investigation is performed on applying various concepts of multiple UAVs clustering optimizations, localization, data aggregation, and its implementation on multiple scenarios of FASNET. The findings were analyzed, and the reasons for their deficiency were identified. It is observed that UAVs operate in a dynamic environment and consume more energy. In this research, the focus is on energy-efficient clustering to optimize the energy utilization and prolong the network lifetime. Clustering parameters such as UAVs energy, mobility, and degree are identified for designing energy-efficient clustering. The clustering issue becomes a dynamic optimization problem to consider these parameters for UAVs clustering in a dynamic environment. Honeybee foraging optimization optimizes the energy utilization by considering these parameters to resolve the clustering problem.

Clustering is the key aspect of improving reliability and UAVs' network lifetime. This research proposes a bio-inspired clustering optimization scheme. First, the clustering problem in the UAV network is formulated to the dynamic optimization problem. Secondly, the clustering parameters, i.e., mobility, degree, and energy, are identified and considered during the CH selection process. Third, the weight computation algorithm is designed that compute the weight of different parameters based on the foraging behaviour of honeybees. Fourth, an algorithm is presented for optimum CH selection and balance cluster formation. The optimum CH selection and balanced cluster formation prolong the UAVs network lifetime. The proposed clustering scheme increases the lifetime of link connection, re-association, CH, and cluster formation with varying UAVs speed and communication range compared to the selected existing schemes. It also balances the load on CH-UAVs and the number of UAVs per cluster.

The FASNETs platform in the precision agriculture domain plays a vital role in locating the affected area and observing the crop field with excellent spatial and temporal resolution. The localization and clustering of multi UAVs for TAs identification is a challenging task. In this research, bio-inspired clustering and localization scheme is proposed to identify the TAs in precision agriculture accurately. The proposed scheme first identifies the affected TAs in the tomato crop field. The TAs identification was performed based on environmental factors weights, i.e., relative humidity, soil moisture, temperature, light intensity, NPK (nitrogen (n), phosphorus (p), potassium (k)), and power of hydrogen (pH). The honeybees foraging algorithm-based optimization approach shows better performance than other swam intelligence approaches. In the proposed scheme, localization of multi UAVs for TAs identification achieved very high accuracy compared to the existing selected localization schemes. The performance of the proposed scheme in clustering is significantly improved in terms of packet delivery ratio, communication overhead, mean end-to-end delay, and energy consumption with varying UAV degrees and rounds. The simulation results show that the proposed scheme prolongs the network lifetime with efficient energy utilization.

In this research, after clustering and localization of multi-UAVs in FASNET, Data aggregation is applied to transmit data among UAVs or to CH or the GS. The data aggregation approach reduces the communication cost usage of network capacity while obtaining aggregated information. In data aggregation, the concept of many-to-few is used to gather data. The data aggregation protocol defines how data is collected, how aggregated data is sent to the destination, and when the aggregated data should be sent. It reduces UAVs' energy utilization and increases the lifetime of networks by minimizing the load on multi-UAVs. It is different in WSN and VANET from UAV networks. Energy factors constrain the multi-UAVs system due to degree, mobility, density, and other parameters; that's why it combines sensor and vehicular ad-hoc network requirements. The UAVs have also consumed more energy on processing and storing data, just like on flight and communication. A data aggregation scheme is proposed to save energy consumption and bandwidth applied at the cluster level. The proposed method minimizes the load on CH and saves bandwidth by avoiding the communication of unwanted or redundant packets to the CH.

The research will help academia to explore new research areas. This research work may attract more researchers to unfold and solve the issues in precision agriculture, smart cities, intrusion detection, smart transportation, and smart buildings utilizing low-cost flying UAVs. Moreover it will help society by using advanced technology and working remotely efficiently. The suggestions for future directions are:

The selection of UAVs-CH based on more than one parameter is a multi-objective optimization problem. The researcher can use any multi-objective optimization scheme for cluster formation and CH selection using different parameters in the future.

Multi-UAVs path optimization is another critical issue to avoid obstacles such as building, trees, wind, etc. Paths can be optimized using different optimization techniques.

The localization and clustering of multi-UAVs based on the target spots can be performed in other networks such as VANETs.

The researcher can apply machine learning methods to identify the diseases in tomatoes plants. The reaction of plants' can be observed easily and quickly to new pesticides, herbicides, fungicides, and fertilizers. The BICTID scheme can be applied with slight modification to other plants

References

[1] L. Atzori, A. Iera, and G. Morabito, "Understanding the Internet of Things: definition, potentials, and societal role of a fast-evolving paradigm," *Ad Hoc Networks, Elsevier*, vol. 56, pp. 122-140, 2017.

[2] W. Qi, Q. Song, X. Kong, and L. Guo, "A traffic-differentiated routing algorithm in Flying Ad Hoc Sensor Networks with SDN cluster controllers," *Journal of the Franklin Institute, Elsevier*, vol. 356, no. 2, pp. 766-790, 2019.

[3] Q. Guo, Y. Zhang, J. Lloret, B. Kantarci, and W. K. Seah, "A localization method avoiding flip ambiguities for micro-UAVs with bounded distance measurement errors," *IEEE Transactions on Mobile Computing, IEEE*, vol. 18, no. 8, pp. 1718-1730, 2018.

[4] P. DeLima, G. York, and D. Pack, "Localization of ground targets using a flying sensor network," in *IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing (SUT-'06), IEEE*, pp. 194–199, 2006.

[5] G. J. Toussaint, P. De Lima, and D. J. Pack, "Localizing RF targets with cooperative unmanned aerial vehicles," in *2007 American Control Conference (ACC-07), IEEE*, pp. 5928-5933, 2007.

[6] A. Bujari, C. T. Calafate, J.-C. Cano, P. Manzoni, C. E. Palazzi, and D. Ronzani, "Flying ad-hoc network application scenarios and mobility models," *International Journal of Distributed Sensor Networks, SAGE*, vol. 13, no. 10, pp. 1–17, 2017.

[7] Y.-H. Ho, Y.-R. Chen, and L.-J. Chen, "Krypto: assisting search and rescue operations using Wi-Fi signal with UAV," in *Proceedings of the First Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use, ACM*, pp. 3-8, 2015.

[8] S. Waharte and N. Trigoni, "Supporting search and rescue operations with UAVs," in *2010 International Conference on Emerging Security Technologies (EST '10), IEEE Computer Society*, pp. 142-147, 2010.

[9] J. Scherer, S. Yahyanejad, S. Hayat, E. Yanmaz, T. Andre, A. Khan, *et al.*, "An autonomous multi-UAV system for search and rescue," in *Proceedings of the First Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use, ACM*, pp. 33-38, 2015.

[10] K. A. Ghamry and Y. Zhang, "Fault-tolerant cooperative control of multiple UAVs for forest fire detection and tracking mission," in *2016 3rd conference on control and fault-tolerant systems (SysTol '16), IEEE*, pp. 133-138, 2016.

[11] L. Merino, F. Caballero, J. R. Martínez-de Dios, J. Ferruz, and A. Ollero, "A cooperative perception system for multiple UAVs: Application to automatic detection of forest fires," *Journal of Field Robotics, Wiley Periodicals, Inc.* vol. 23, pp. 165-184, 2006.

[12] T. Samad, J. S. Bay, and D. Godbole, "Network-centric systems for military operations in urban terrain: The role of UAVs," *Proceedings of the IEEE, IEEE,* vol. 95, pp. 92-107, 2007.

[13] P.-M. Olsson, J. Kvarnström, P. Doherty, O. Burdakov, and K. Holmberg, "Generating UAV communication networks for monitoring and surveillance," in *2010 11th International Conference on Control Automation Robotics & Vision, IEEE* pp. 1070-1077, 2010.

[14] R. Reshma, T. Ramesh, and P. Sathishkumar, "Security situational aware intelligent road traffic monitoring using UAVs," in *2016 international conference on VLSI systems, architectures, technology and applications (VLSI-SATA '16), IEEE*, pp. 1-6, 2016.

[15] W. Zafar and B. M. Khan, "Flying ad-hoc networks: Technological and social implications," *IEEE Technology and Society Magazine, IEEE,* vol. 35, pp. 67-74, 2016.

[16] E. Kuiper and S. Nadjm-Tehrani, "Mobility models for UAV group reconnaissance applications," in *2006 International Conference on Wireless and Mobile Communications (ICWMC'06), IEEE*, pp. 33-34, 2006.

[17] O. Alvear, C. T. Calafate, E. Hernández, J.-C. Cano, and P. Manzoni, "Mobile pollution data sensing using UAVs," in *Proceedings of the 13th International Conference on Advances in Mobile Computing and Multimedia, (AMCM '15), ACM*, pp. 393-397, 2015.

[18] M. Erdelj and E. Natalizio, "UAV-assisted disaster management: Applications and open issues," in *2016 international conference on computing, networking and communications (ICNC '16), IEEE*, pp. 1-5, 2016.

[19] V. Kumar, D. Rus, and S. Singh, "Robot and sensor networks for first responders," *IEEE Pervasive computing, , IEEE,* vol. 3, no. 4, pp. 24-33, 2004.

[20] P. J. Mosterman, D. E. Sanabria, E. Bilgin, K. Zhang, and J. Zander, "A heterogeneous fleet of vehicles for automated humanitarian missions," *Computing in Science & Engineering, IEEE,* vol. 16, pp. 90-95, 2014.

[21] B. Grocholsky, J. Keller, V. Kumar, and G. Pappas, "Cooperative air and ground surveillance," *IEEE Robotics & Automation Magazine, IEEE,* vol. 13, pp. 16-25, 2006.

[22] J. Torres-Sánchez, F. López-Granados, A. I. De Castro, and J. M. Peña-Barragán, "Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management," *PloS one,* vol. 8, pp. 809-816 , 2013.

[23] H. Chao, M. Baumann, A. Jensen, Y. Chen, Y. Cao, W. Ren, *et al.*, "Band-reconfigurable multi-UAV-based cooperative remote sensing for real-time water management and distributed irrigation control," *IFAC Proceedings, Elsevier* vol. 41, pp. 11744-11749, 2008.

[24] X. Li, Y. Zhao, J. Zhang, and Y. Dong, "A hybrid PSO algorithm based flight path optimization for multiple agricultural UAVs," in *2016 IEEE 28th international conference on tools with artificial intelligence (ICTAI '16), IEEE,* pp. 691-697, 2016.

[25] S. Candiago, F. Remondino, M. De Giglio, M. Dubbini, and M. Gattelli, "Evaluating multispectral images and vegetation indices for precision farming applications from UAV images," *Remote sensing* vol. 7, pp. 4026-4047, 2015.

[26] S. Nebiker, A. Annen, M. Scherrer, and D. Oesch, "A light-weight multispectral sensor for micro UAV—Opportunities for very high resolution airborne remote sensing," *The international archives of the photogrammetry, remote sensing and spatial information sciences,* vol. 37, pp. 1193-1199, 2008.

[27] P. Horstrand, R. Guerra, A. Rodríguez, M. Díaz, S. López, and J. F. López, "A UAV platform based on a hyperspectral sensor for image capturing and on-board processing," *IEEE Access, IEEE,* vol. 7, pp. 66919-66938, 2019.

[28] S. Khan, M. Narvekar, M. Hasan, A. Charolia, and A. Khan, "Image Processing based application of Thermal Imaging for Monitoring Stress Detection in Tomato Plants," in *2019 International Conference on Smart Systems and Inventive Technology (ICSSIT '19), IEEE,* pp. 1111-1116, 2019.

[29] W. Zhu, H. Chen, I. Ciechanowska, and D. Spaner, "Application of infrared thermal imaging for the rapid diagnosis of crop disease," *IFAC-PapersOnLine,* vol. 51, pp. 424-430, 2018.

[30] G. Prince, J. P. Clarkson, and N. M. Rajpoot, "Automatic detection of diseased tomato plants using thermal and stereo visible light images," *PloS one,* vol. 10, pp. 1-20, 2015.

[31] X. Xu, H. Jiang, and Y. Hang, "Study on detection of tomato mosaic disease at an early stage based on infrared thermal imaging," *Transactions of the Chinese Society of Agricultural Engineering,* vol. 28, pp. 145-149, 2012.

[32] K. Chiwaki, S. Nagamori, and Y. Inoue, "Predicting bacterial wilt disease of tomato plants using remotely sensed thermal imagery," *Journal of Agricultural Meteorology (Japan),* vol. 63, no. 3, pp. 153-163, 2005.

[33] J. Llop, E. Gil, J. Llorens, A. Miranda-Fuentes, and M. Gallart, "Testing the suitability of a terrestrial 2D LiDAR scanner for canopy characterization of greenhouse tomato crops," *Sensors,* vol. 16, pp. 1-14, 2016.

[34] K. Omasa, F. Hosoi, and A. Konishi, "3D lidar imaging for detecting and understanding plant responses and canopy structure," *Journal of experimental botany, Oxford,* vol. 58, pp. 881-898, 2007.

[35] S. Oh, A. Ashapure, T. G. Marconi, J. Jung, and J. Landivar, "UAS based Tomato Yellow Leaf Curl Virus (TYLCV) disease detection system," in *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IV,* pp. 1-7, 2019.

[36] J. Fahrentrapp, F. Ria, M. Geilhausen, and B. Panassiti, "Detection of gray mold leaf infections prior to visual symptom appearance using a five-band multispectral sensor," *Frontiers in plant science,* vol. 10, pp. 628-642, 2019.

[37] N. Schor, A. Bechar, T. Ignat, A. Dombrovsky, Y. Elad, and S. Berman, "Robotic disease detection in greenhouses: combined detection of powdery mildew and tomato spotted wilt virus," *IEEE Robotics and Automation Letters, IEEE,* vol. 1, pp. 354-360, 2016.

[38] M. Zhang, Z. Qin, and X. Liu, "Remote sensed spectral imagery to detect late blight in field tomatoes," *Precision Agriculture, Springer,* vol. 6, pp. 489-508, 2005.

[39] U. Žibrat, N. Susič, M. Knapič, S. Širca, P. Strajnar, J. Razinger, *et al.*, "Pipeline for imaging, extraction, pre-processing, and processing of time-series hyperspectral data for discriminating drought stress origin in tomatoes," *MethodsX, Elsevier,* vol. 6, pp. 399-408, 2019.

[40] J. Abdulridha, Y. Ampatzidis, S. C. Kakarla, and P. Roberts, "Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based

hyperspectral imaging techniques," *Precision Agriculture, Springer,* vol. 21, pp. 955-978, 2020.

[41] J. Lu, M. Zhou, Y. Gao, and H. Jiang, "Using hyperspectral imaging to discriminate yellow leaf curl disease in tomato leaves," *Precision agriculture, Springer,* vol. 19, pp. 379-394, 2018.

[42] J. Lu, R. Ehsani, Y. Shi, A. I. de Castro, and S. Wang, "Detection of multi-tomato leaf diseases (late blight, target and bacterial spots) in different stages by using a spectral-based sensor," *Scientific reports, Springer,* vol. 8, pp. 1-11, 2018.

[43] C. Xie, C. Yang, and Y. He, "Hyperspectral imaging for classification of healthy and gray mold diseased tomato leaves with different infection severities," *Computers and electronics in agriculture, Elsevier,* vol. 135, pp. 154-162, 2017.

[44] C. Xie, Y. Shao, X. Li, and Y. He, "Detection of early blight and late blight diseases on tomato leaves using hyperspectral imaging," *Scientific reports,* vol. 5, pp. 1-11, 2015.

[45] M. Zhang, Z. Qin, X. Liu, and S. L. Ustin, "Detection of stress in tomatoes induced by late blight disease in California, USA, using hyperspectral remote sensing," *International Journal of Applied Earth Observation and Geoinformation, Elsevier,* vol. 4, pp. 295-310, 2003.

[46] S. K. a. P. B. T. Sanjay Kumar Gupta, *Drones for Future Agriculture Agriculture & Food e-Newsletter, Balurghat,* vol. 4, pp. 16-19, 2019.

[47] M. Y. Arafat and S. Moh, "A survey on cluster-based routing protocols for unmanned aerial vehicle networks," *IEEE Access, IEEE,* vol. 7, pp. 498-516, 2019.

[48] Z. Han, A. L. Swindlehurst, and K. R. Liu, "Optimization of MANET connectivity via smart deployment/movement of unmanned air vehicles," *IEEE Transactions on Vehicular Technology, IEEE,* vol. 58, pp. 3533-3546, 2009.

[49] F. Yang, P. Wang, Y. Zhang, L. Zheng, and J. Lu, "Survey of swarm intelligence optimization algorithms," in *2017 IEEE International Conference on Unmanned Systems (ICUS '17), IEEE,* pp. 544-549, 2017.

[50] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Technical report-tr06, *Erciyes university, engineering faculty, computer engineering Department* 2005.

[51] K. Krishnanand and D. Ghose, "Glowworm swarm optimization: a new method for optimizing multi-modal functions," *International Journal of Computational Intelligence Studies, Inderscience,* vol. 1, pp. 93-119, 2009.

[52] R. Eberhart and J. Kennedy, "Particle swarm optimization," in *Proceedings of the IEEE international conference on neural networks, IEEE* pp. 1942-1948, 1995.

[53] A. Colorni, M. Dorigo, and V. Maniezzo, "Distributed optimization by ant colonies," in *Proceedings of the first European conference on artificial life, (ECAL '92),* pp. 134-142, 1992.

[54] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software,* vol. 69, pp. 46-61, 2014.

[55] Z. Cheng, Y. Sun, and Y. Liu, "Path planning based on immune genetic algorithm for UAV," in *2011 International Conference on Electric Information and Control Engineering, (ICEICE '11), IEEE,* pp. 590-593, 2011.

[56] F. Xiong, H. Zheng, L. Ruan, H. Wang, L. Tang, X. Dong, *et al.*, "Energy-Saving Data Aggregation for Multi-UAV System," *IEEE Transactions on Vehicular Technology, IEEE,* vol. 69, no. 8, pp. 9002-9016, 2020.

[57] D. B. Johnson and D. A. Maltz, "Dynamic source routing in ad hoc wireless networks," in *Mobile computing, Springer,* pp. 153-181, 1996.

[58] B. Liang and Z. J. Haas, "Predictive distance-based mobility management for PCS networks," in *IEEE INFOCOM'99. Conference on Computer Communications. Proceedings. Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies. The Future is Now (Cat. No. 99CH36320), IEEE,* pp. 1377-1384, 1999.

[59] K. Kumari, B. Sah, and S. Maakar, "A survey: different mobility model for FANET," *International Journal of Advanced Research in Computer Science and Software Engineering,* vol. 5, pp. 1170-1173, 2015.

[60] F. Bai and A. Helmy, "A survey of mobility models in wireless adhoc networks," in Book chapter in Wireless Ad Hoc and Sensor Networks, *Kluwer academic Publishers*, pp. 1-30, 2004.

[61] R. R. Roy, "Mobility model characteristics," in *Handbook of Mobile Ad Hoc Networks for Mobility Models*, ed: *Springer*, pp. 23-32, 2011.

[62] T. Camp, J. Boleng, and V. Davies, "A survey of mobility models for ad hoc network research," *Wireless communications and mobile computing,* vol. 2, pp. 483-502, 2002.

[63] M. Sánchez and P. Manzoni, "ANEJOS: a java based simulator for ad hoc networks," *Future generation computer systems, Elsevier,* vol. 17, pp. 573-583, 2001.

[64] O. Bouachir, A. Abrassart, F. Garcia, and N. Larrieu, "A mobility model for UAV ad hoc network," in *2014 international conference on unmanned aircraft systems (ICUAS '14), IEEE,* pp. 383-388, 2014.

[65] A.-K. Mahlein, "Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping," *Plant Disease, APS,* vol. 100, pp. 241-251, 2016.

[66] K. M. Khokhar and N. HRI, "Present status and prospects of tomatoes in Pakistan," *Report* 2013. http://www agricorner.com/present-status-and-prospects-of-tomatoes-in-pakistan/

[67] Mayor. (2020, 12 April 2020). *Tomato Plant Common Pests and Diseases, [Plantvillage]*. Available: https://www.plantvillage.psu edu/topics/tomato/infos

[68] S. Colvine. (2020, 12-Apr-2020). *AMITOM & WPTC : Crop situation as of 28 June 2019.* Available: http://www.tomatonews com/en/amitom-&-wptc-crop-situation-as-of-28-june-2019_2_748.html

[69] D.-H. Park, B.-J. Kang, K.-R. Cho, C.-S. Shin, S.-E. Cho, J.-W. Park, *et al.*, "A study on greenhouse automatic control system based on wireless sensor network," *Wireless Personal Communications, Springer,* vol. 56, pp. 117-130, 2011.

[70] S. Manickam, "IoT-Based Soil Condition Monitoring Framework," *Elseiver,* pp.1-6, 2020, https://ssrn.com/abstract=3711616

[71] A. Bah, S. Balasundram, and M. Husni, "Sensor technologies for precision soil nutrient management and monitoring," *American Journal of Agricultural and Biological Sciences,* vol. 7, pp. 43-49, 2012.

[72] H.-J. Kim, K. A. Sudduth, and J. W. Hummel, "Soil macronutrient sensing for precision agriculture," *Journal of Environmental Monitoring,* vol. 11, pp. 1810-1824, 2009.

[73] F. Aadil, A. Raza, M. Khan, M. Maqsood, I. Mehmood, and S. Rho, "Energy aware cluster-based routing in flying ad-hoc networks," *Sensors, MDPI,* vol. 18, pp. 1-16, 2018.

[74] X. L. Nanxiang Shi, " A novel cluster-based location-aided routing protocol for UAV fleet networks," *International Journal of Digital Content Technology and its Applications(JDCTA),* vol. 6, no. 18, pp. 376-383, 2012.

[75] J.-H. Park, S.-C. Choi, H. R. Hussen, and J. Kim, "Analysis of dynamic cluster head selection for mission-oriented flying Ad hoc network," in *2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN '17), IEEE,* pp. 21-23, 2017.

[76] S. Bhandari, X. Wang, and R. Lee, "Mobility and location-aware stable clustering scheme for UAV networks," *IEEE Access, IEEE,* vol. 8, pp. 106364-106372, 2020.

[77] J. Shu, Y. Ge, L. Liu, and L. Sun, "Mobility prediciton clustering routing in UAVs," in *Proceedings of 2011 International Conference on Computer Science and Network Technology(ICCSNT '11), IEEE,* pp. 1983-1987, 2011.

[78] C. Z. a. S. Zang, "Mobility prediction clustering algorithm for UAV networking," *011 IEEE GLOBECOM Workshops (GC Wkshps),* pp. 1158-1161, 2011.

[79] F. Aadil, K. B. Bajwa, S. Khan, N. M. Chaudary, and A. Akram, "CACONET: Ant colony optimization (ACO) based clustering algorithm for VANET," *PloS one,* vol. 11, pp. 1-21, 2016.

[80] M. Fahad, F. Aadil, S. Khan, P. A. Shah, K. Muhammad, J. Lloret, *et al.*, "Grey wolf optimization based clustering algorithm for vehicular ad-hoc networks," *Computers & Electrical Engineering, Elsevier,* vol. 70, pp. 853-870, 2018.

[81] V. R. Khare, F. Z. Wang, S. Wu, Y. Deng, and C. Thompson, "Ad-hoc network of unmanned aerial vehicle swarms for search & destroy tasks," in *2008 4th International IEEE Conference Intelligent Systems, (IS '08), IEEE,* pp. 665-672, 2008.

[82] R. Shirani, M. St-Hilaire, T. Kunz, Y. Zhou, J. Li, and L. Lamont, "The performance of greedy geographic forwarding in unmanned aeronautical ad-hoc networks," in *2011 Ninth Annual Communication Networks and Services Research Conference, (CNSR '11), IEEE,* pp. 161-166, 2011.

[83] Z. Li and X. Huang, "Glowworm swarm optimization and its application to blind signal separation," *Mathematical Problems in Engineering, Hindawi,* vol. 2016, pp. 1-8, 2016.

[84] A. Khan, F. Aftab, and Z. Zhang, "BICSF: Bio-inspired clustering scheme for FANETs," *IEEE Access, IEEE,* vol. 7, pp. 31446-31456, 2019.

[85] N. Al-Aboody and H. Al-Raweshidy, "Grey wolf optimization-based energy-efficient routing protocol for heterogeneous wireless sensor networks," in *2016 4th International Symposium on Computational and Business Intelligence (ISCBI '16), IEEE,* pp. 101-107, 2016.

[86] V. A. Maistrenko, L. V. Alexey, and V. A. Danil, "Experimental estimate of using the ant colony optimization algorithm to solve the routing problem in FANET," in *2016 International Siberian Conference on Control and Communications (SIBCON '16), IEEE*, pp. 1-10, 2016.

[87] A. Khan, F. Aftab, and Z. Zhang, "Self-organization based clustering scheme for FANETs using Glowworm Swarm Optimization," *Physical Communication, Elsevier*, vol. 36, pp. 1-8, 2019.

[88] M. Wang, "A Mobility Aware Clustering Scheme Based on Swarm Intelligence in FANETs," in *2020 IEEE/CIC International Conference on Communications in China (ICCC '20), IEEE*, pp. 747-752, 2020.

[89] Y. Yu, L. Ru, W. Chi, Y. Liu, Q. Yu, and K. Fang, "Ant colony optimization based polymorphism-aware routing algorithm for ad hoc UAV network," *Multimedia Tools and Applications, Springer*, vol. 75, pp. 14451-14476, 2016.

[90] J. Wang, E. Osagie, P. Thulasiraman, and R. K. Thulasiram, "HOPNET: A hybrid ant colony optimization routing algorithm for mobile ad hoc network," *Ad Hoc Networks, Elsevier*, vol. 7, pp. 690-705, 2009.

[91] M. Aissani, M. Fenouche, H. Sadour, and A. Mellouk, "Ant-DSR: cache maintenance based routing protocol for mobile ad-hoc networks," in *The Third Advanced International Conference on Telecommunications (AICT '07), IEEE*, pp. 35-35, 2007.

[92] J. Yang, X. Wang, Z. Li, P. Yang, X. Luo, K. Zhang, *et al.*, "Path planning of unmanned aerial vehicles for farmland information monitoring based on WSN," in *2016 12th World Congress on Intelligent Control and Automation (WCICA '16)*, pp. 2834-2838, 2016.

[93] M. Chen, V. Leung, S. Mao, T. Kwon, and M. Li, "Energy-efficient itinerary planning for mobile agents in wireless sensor networks," in *2009 IEEE International Conference on Communications, (IC '09), IEEE*, pp. 1-5, 2009.

[94] Y. Zhou, X. Yang, X. Guo, M. Zhou, and L. Wang, "A design of greenhouse monitoring & control system based on ZigBee wireless sensor network," in *2007 International Conference on Wireless Communications, Networking and Mobile Computing(WCNMC '07), IEEE*, pp. 2563-2567, 2007.

[95] A. V. Leonov, "Modeling of bio-inspired algorithms AntHocNet and BeeAdHoc for flying ad hoc networks (FANETS)," in *2016 13th International Scientific-Technical Conference on Actual Problems of Electronics Instrument Engineering (APEIE '16), IEEE*, pp. 90-99, 2016.

[96] H. A. Abbass, "MBO: Marriage in honey bees optimization-A haplometrosis polygynous swarming approach," in *Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No. 01TH8546), IEEE*, pp. 207-214, 2001.

[97] A. V. Leonov, "Application of bee colony algorithm for FANET routing," in *2016 17th International Conference of Young Specialists on Micro/Nanotechnologies and Electron Devices (EDM '16), IEEE*, pp. 124-132, 2016.

[98] S. Murthy and J. J. Garcia-Luna-Aceves, "An efficient routing protocol for wireless networks," *Mobile Networks and applications, Springer*, vol. 1, pp. 183-197, 1996.

[99] C. E. Perkins and P. Bhagwat, "Highly dynamic destination-sequenced distance-vector routing (DSDV) for mobile computers," in *ACM SIGCOMM computer communication review, ACM*, pp. 234-244, 1994.

[100] F. L. Howard, "The life history of Physarum polycephalum," *American journal of botany, JSTOR*, pp. 116-133, 1931.

[101] Y. Sun, "Physarum-inspired network optimization: A review," *arXiv preprint arXiv:1712.02910*, 2017.

[102] Y. Yu, L. Ru, and K. Fang, "Bio-Inspired Mobility Prediction Clustering Algorithm for Ad Hoc UAV Networks," *Engineering Letters*, vol. 24, pp. 1-10, 2016.

[103] Q. Yu, N. Zhang, W. Meng, and F. Adachi, "A novel stability weighted clustering algorithm for multi-hop packet radio virtual cellular network," in *2010 IEEE Wireless Communication and Networking Conference, (WCNC '10), IEEE*, pp. 1-6, 2010.

[104] K. Liu, J. Zhang, and T. Zhang, "The clustering algorithm of UAV networking in near-space," in *2008 8th International Symposium on Antennas, Propagation and EM Theory, (ISAPE '08), IEEE*, pp. 1550-1553, 2008.

[105] W. Zheng and J. Shu, "An Improved Artificial Bee Colony-Based Relocation Algorithm in Mobile Sensor Network," *Information Engineering Letters*, vol. 2, pp. 1-10, 2012.

[106] J. C. Bansal, H. Sharma, S. S. Jadon, and M. Clerc, "Spider monkey optimization algorithm for numerical optimization," *Memetic computing, Springer*, vol. 6, pp. 31-47, 2014.

[107] V. Agrawal, R. Rastogi, and D. Tiwari, "Spider monkey optimization: a survey," *International Journal of System Assurance Engineering and Management, Springer*, vol. 9, pp. 929-941, 2018.

[108] R. Ganesan, X. M. Raajini, A. Nayyar, P. Sanjeevikumar, E. Hossain, and A. H. Ertas, "BOLD: Bio-Inspired Optimized Leader Election for Multiple Drones," *Sensors, MDPI,* vol. 20, no.11, pp. 1-20, 2020.

[109] M. Y. Arafat and S. Moh, "Localization and Clustering Based on Swarm Intelligence in UAV Networks for Emergency Communications," *IEEE Internet of Things Journal, IEEE,* vol. 6, pp. 8958-8976, 2019.

[110] M. Y. Arafat and S. Moh, "Bio-Inspired Approaches for Energy-Efficient Localization and Clustering in UAV Networks for Monitoring Wildfires in Remote Areas," *IEEE Access, IEEE,* vol. 9, pp. 18649 - 18669, 2021.

[111] N. E. H. Bahloul, S. Boudjit, M. Abdennebi, and D. E. Boubiche, "A flocking-based on demand routing protocol for unmanned aerial vehicles," *Journal of Computer Science and Technology, Springer,* vol. 33, pp. 263-276, 2018.

[112] J. Wang, Y.-Q. Cao, B. Li, S.-Y. Lee, and J.-U. Kim, "A glowworm swarm optimization based clustering algorithm with mobile sink support for wireless sensor networks," *Journal of Internet Technology (JIT),* vol. 16, pp. 825-832, 2015.

[113] M. Abd-El-Barr, "Ant Colony Heuristic Algorithm for Multi-Level Synthesis of Multiple-Valued Logic Functions," *IAENG International Journal of Computer Science,* vol. 37, pp. 1-7, 2010.

[114] N. A. Latiff, C. C. Tsimenidis, and B. S. Sharif, "Energy-aware clustering for wireless sensor networks using particle swarm optimization," *18th international symposium on personal, indoor and mobile radio communications, IEEE,* pp. 1-5, 2007.

[115] M. A. Ma'Sum, G. Jati, M. K. Arrofi, A. Wibowo, P. Mursanto, and W. Jatmiko, "Autonomous quadcopter swarm robots for object localization and tracking," *(MHS '13), IEEE,* pp. 1-6, 2013.

[116] Z. Cheng, E. Wang, Y. Tang, and Y. Wang, "Real-time Path Planning Strategy for UAV Based on Improved Particle Swarm Optimization," *Journal of Computers (JCP),* vol. 9, pp. 209-214, 2014.

[117] J. Sánchez-García, D. Reina, and S. Toral, "A distributed PSO-based exploration algorithm for a UAV network assisting a disaster scenario," *Future Generation Computer Systems, Elsevier,* vol. 90, pp. 129-148, 2019.

[118] G. E. U. Faelden, J. M. Z. Maningo, R. C. S. Nakano, A. A. Bandala, and E. P. Dadios, "Blind localization method for quadrotor-unmanned aerial vehicle (QUAV) utilizing genetic algortihm," in *2014 International Conference on Humanoid, Nanotechnology,*

Information Technology, Communication and Control, Environment and Management (HNICEM '14), IEEE, pp. 1-5, 2014.

[119] S. Perez-Carabaza, E. Besada-Portas, J. A. Lopez-Orozco, and M. Jesus, "Ant colony optimization for multi-UAV minimum time search in uncertain domains," *Applied Soft Computing, Elsevier,* vol. 62, pp. 789-806, 2018.

[120] S. Hauert, L. Winkler, J.-C. Zufferey, and D. Floreano, "Ant-based swarming with positionless micro air vehicles for communication relay," *Swarm Intelligence, Springer,* vol. 2, pp. 167-188, 2008.

[121] Y. Liu and J. Chen, "AK-means based firefly algorithm for localization in sensor networks," *International Journal of Parallel, Emergent and Distributed Systems, Taylor & Francis,* vol. 34, pp. 364-379, 2019.

[122] X. Wang, Q. Zhou, and C.-T. Cheng, "A UAV-assisted topology-aware data aggregation protocol in WSN," *Physical Communication, Elsevier,* vol. 34, pp. 48-57, 2019.

[123] Q. Wu, P. Sun, and A. Boukerche, "An energy-efficient uav-based data aggregation protocol in wireless sensor networks," in *Proceedings of the 8th ACM Symposium on Design and Analysis of Intelligent Vehicular Networks and Applications, ACM,* pp. 34-40, 2018.

[124] M. Thammawichai, S. P. Baliyarasimhuni, E. C. Kerrigan, and J. B. Sousa, "Optimizing communication and computation for multi-UAV information gathering applications," *IEEE Transactions on Aerospace and Electronic Systems, IEEE,* vol. 54, pp. 601-615, 2017.

[125] M. Dong, K. Ota, M. Lin, Z. Tang, S. Du, and H. Zhu, "UAV-assisted data gathering in wireless sensor networks," *The Journal of Supercomputing, Springer,* vol. 70, pp. 1142-1155, 2014.

[126] B. Liu and H. Zhu, "Energy-effective data gathering for uav-aided Wireless Sensor Networks," *Sensors, MDPI,* vol. 19, pp. 1-12, 2019.

[127] A. V. Leonov, *Application of bee colony algorithm for FANET routing, 17th International Conference of Young Specialists on Micro/Nanotechnologies and Electron Devices (EDM '16), IEEE,* pp. 124-132, 2016.

[128] H. F. Wedde, M. Farooq, T. Pannenbaecker, B. Vogel, C. Mueller, J. Meth, *et al.*, "BeeAdHoc: an energy efficient routing algorithm for mobile ad hoc networks inspired

by bee behavior," in *Proceedings of the 7th annual conference on Genetic and evolutionary computation, ACM,* pp. 153-160, 2005.

[129] M. Ahmad, A. Hameed, F. Ullah, I. Wahid, S. U. Rehman, and H. A. Khattak, "A bio-inspired clustering in mobile adhoc networks for internet of things based on honey bee and genetic algorithm," *Journal of Ambient Intelligence and Humanized Computing, Springer,* vol. 11, pp. 1-15, 2020.

[130] M. Ahmad, A. A. Ikram, I. Wahid, M. Inam, N. Ayub, and S. Ali, "A bio-inspired clustering scheme in wireless sensor networks: BeeWSN," *Procedia computer science, Elsevier,* vol. 130, pp. 206-213, 2018.

[131] N. Khatoon, "Mobility aware energy efficient clustering for MANET: a bio-inspired approach with particle swarm optimization," *Wireless Communications and Mobile Computing, Hindawi,* vol. 2017, pp. 1-13, 2017.

[132] A. M. S. Abdelgader, L. Wu, and M. M. M. Nasr, "A simplified mobile ad hoc network structure for helicopter communication," *International Journal of Aerospace Engineering, Hindawi,* vol. 2016, pp. 1-16, 2016.

[133] A. Salam, Q. Javaid, G. Ali, F. Ahmad, M. Ahmad, and I. Wahid, "Flying Sensor Network Optimization Using Bee Intelligence for Internet of Things," in *Proceedings of SAI Intelligent Systems Conference, Springer,* pp. 331-339, 2020.

[134] F. G. Costa, J. Ueyama, T. Braun, G. Pessin, F. S. Osório, and P. A. Vargas, "The use of unmanned aerial vehicles and wireless sensor network in agricultural applications," in *2012 IEEE International Geoscience and Remote Sensing Symposium, IEEE,* pp. 5045-5048, 2012.

[135] A. Salam, Q. Javaid, and M. Ahmad, "Bioinspired Mobility-Aware Clustering Optimization in Flying Ad Hoc Sensor Network for Internet of Things: BIMAC-FASNET," *Complexity, Hindawi,* vol. 2020, pp. 1-20, 2020.

[136] A. Salam, Q. Javaid, and M. Ahmad, "Bio-inspired cluster-based optimal target identification using multiple unmanned aerial vehicles in smart precision agriculture," *International Journal of Distributed Sensor Networks, Sage,* vol. 17, pp. 1-17, 2021.