GODWIN ANUORK ASAAMONING

WIRELESS NETWORKING FOR AUTONOMOUS MOBILE SMART CAMERA DRONES

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To my Grandmother, my mother, wife and sons

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DECLARATION OF AUTHORSHIP

I, Godwin Anuork Asaamoning, declare that this thesis titled, “WIRELESS NETWORKING FOR AUTONOMOUS MOBILE SMART CAMERA DRONES” and the work presented in it was carried out and developed by me.

I also confirm that:

- The work was done wholly while in candidature for a research degree at Universidade Lusófona de Humanidades e Tecnologias.
- I have previously stated all the submission either for the degree or any other qualification at Universidade Lusófona de Humanidades e Tecnologias or any other institution.
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- I have always given source for the work I might have quoted. Otherwise, if no such quotations exist, the thesis work is entirely my own work.
- I have acknowledged all sources of help and funding.
- I have clearly differentiated what was done by others and what I have contributed myself, where it applies.

Signed:______________________________

(Godwin Anuork Asaamoning)

Date: 25 / 11 / 2022

Resumo

Dispositivos voadores em rede, tais como veículos aéreos não tripulados (UAV), também chamados drones, equipados com câmaras inteligentes estão cada vez mais a serem utilizados para formar sistemas autónomos cooperativos para realizar tarefas de fotogrametria e detecção, incluindo a captação de dados de vídeo e imagem em tempo real de alta qualidade para monitorização no terreno, vigilância e serviços de gestão de desastres. O aumento dos UAV tem sido principalmente atribuído a sua maleabilidade e oferta de grande autonomia no estabelecimento de uma rápida ligação sem fios, permitindo esforços coordenados na recuperação de informação crítica e sensível ao tempo a partir de vários locais, incluindo locais em perigo para reduzir os factores de risco humano. Embora tenham sido desenvolvidos drones de câmara inteligente em rede para produzir enormes quantidades de dados críticos de locais atingidos por catástrofes que precisam de ser transferidos e analisados em tempo real, o funcionamento em rede e relacionado com a comunicação, abrangendo o sistema de UAV único a uma grande rede ad hoc de UAVs (UAV-FANET) capaz de fornecer uma coordenação rápida de agentes para uma recuperação e disseminação adequadas de dados de vídeo e imagem, vem com desafios significativos, nomeadamente topologia dinâmica e mobilidade rápida dos nós. Além disso, as UAV-FANETs enfrentam desconexões intermitentes e nós disponíveis intermitentemente, em grande parte devido a sua estrutura 3D, impactando assim a qualidade dos pacotes disseminados. Determinada a enfrentar estes desafios, o principal objectivo desta tese é investigar novos sistemas de redes de câmaras inteligentes voadoras capazes de capturar e transmitir imagens e vídeo de alta qualidade em grandes áreas geográficas, concentrando-se não na reprodução de vídeo, mas na investigação de abordagens avançadas de redes sem fios para a transmissão de pacotes. Para este fim, o objetivo desta tese surge no seguinte: analisar o estudo de aplicabilidade de enxames de drones para rede e requisitos de computação necessários para o funcionamento eficiente de um sistema de enxame como um sistema de controlo em rede; investigar escolhas fiáveis de desenho de comunicações sem fios capazes de fornecer apoio suficiente para a captura e disseminação adequadas de pacotes de vídeo e imagem em grandes UAV-FANETs; conceber e implementar um novo esquema baseado em clusters chamado Mecanismo de Clustering Dinâmico com Balanceamento de Carga para realizar o clustering devido à mobilidade dos nós e à estrutura 3D, ao mesmo tempo que se abordam as restrições causadas por alterações topológicas, e em sincronia com uma função de entropia para lidar com a tolerância a falhas de cluster e sobrecargas de tráfego para uma disseminação adequada dos pacotes de dados FANETs; e finalmente, para investigar o encaminhamento híbrido interoperável baseado na posição, onde o encaminhamento intra-cluster é capaz de evitar caminhos de encaminhamento inadequados com base num método de classificação simples, enquanto o encaminhamento entre cluster baseado em abordagens gananciosas e de regras de mão direita para reduzir a sobrecarga de mensagens e para escapar a situações de nós vazios, para resolver desconexões intermitentes e limitações de escalabilidade em FANETs agrupadas. A avaliação experimental realizada utilizando a ferramenta de simulação NS-3 provam que as nossas novas estruturas de comunicação são capazes de fornecer uma disseminação adequada de pacotes de dados em comparação com outros mecanismos de última geração. Em suma, as estruturas teóricas e lógicas investigadas neste estudo fornecem a base para a concepção e implementação de sistemas sem fios adequados capazes de fornecer uma disseminação adequada de pacotes de vídeo e imagem em grandes FANETs de UAV.

Palavras-chave: Veículos Aéreos Não Tripulados, Redes sem fios, Redes Ad Hoc Voadoras, Cluster-Redes, Encaminhamento baseado na posição.

Abstract

Networked flying devices such as unmanned aerial vehicles (UAVs), also called drones, equipped with smart cameras are increasingly being deployed to form cooperative autonomous systems to perform photogrammetry and sensing tasks, including the capture of high-quality real-time video and image data for field monitoring, surveillance and disaster management services. The rise of UAVs has been mainly attributed to their malleability and offer of great autonomy in establishing links, allowing for coordinated efforts in retrieving critical and time-sensitive information from various locations, including endangered sites to reduce human risk factors. While networked intelligent camera drones have been developed to produce huge amounts of critical data from disaster-stricken locations that need to be transferred and analyzed in real time, the networking and communication-related operation, spanning the single UAV system to a large flying (UAV-FANET) capable of providing rapid agent coordination for proper retrieval and dissemination of video and image data, comes with significant challenges, namely dynamic topology and rapid node mobility. Moreover, UAV-FANETs face intermittent wireless disconnections and intermittent available nodes, largely due to their 3D structure, thus impacting the quality of disseminated packets. Determined to address these challenges, the main objective of this thesis is to investigate novel flying smart camera networked systems capable of capturing and transmitting high quality images and video over large geographical areas, focusing not on video rendering, but on investigating advanced wireless networking approaches for packets transmission. To this end, the core of this thesis arises in the following: analyze applicability study of drone swarms for networking and computing requirements needed for efficient operation of a swarm system as a networked control system; investigate reliable wireless communications design choices capable of providing sufficient support for proper capture and dissemination of video and image packets in large UAV-FANETs; design and implement a novel cluster-based scheme called Dynamic Clustering Mechanism with Load Balancing to perform clustering based on node mobility and 3D structure while addressing constraints caused by topological changes, and in sync with an entropy function to handle cluster fault tolerance and traffic overloads for proper dissemination of data packets in FANETs; and finally, design and implement an interoperable Position-based Hybrid routing protocol, where intra-cluster routing is capable of avoiding unsuitable forwarding paths based on a simple ranking method, while inter-cluster routing based on greedy and right-hand rule approaches to reduce message overheads and to escape void node situations, to address intermittent wireless disconnections and scalability limitations in clustered FANETs. Experimental evaluations performed using the NS-3 simulation tool prove that our new communication structures are able to provide adequate data packets dissemination compared to other state-of-the-art mechanisms. In summary, the theoretical and logical frameworks investigated in this study provides the basis for the design and implementation of suitable wireless systems capable of providing adequate video and image packets dissemination in large UAV-FANETs.

Keywords: Unmanned Aerial Vehicles, Wireless Networking, Flying Ad Hoc Networks, Cluster, Position-based Routing.

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List of Symbols

B	Represents buffer state of the current cluster head
c	Represents the group of all the constituencies
c_j^i	The i^{th} party representative in the j^{th} constituency
c_j	Represents the j^{th} constituency
c^*	Represents Constituencies leader
c_j^*	Represents winner of the j^{th} constituency
D_n	Destination node
$f(p)$	Calculates the fitness value of the input parameters
$f(p_i^j)$	Calculates the fitness
L	Represents the current load of the node
n	Represents the number of political parties, constituencies, and members in each party
N_b	Represents the buffer state the node
N_c	Represents distance towards representatives of other constituencies
N_e	Represent energy level of the node
N_d	Represents distance of node towards a base station
N_l	Represents link quality of node
ρ	Population of entire members of all political parties
p_i^*	Denotes the leader of the i^{th} party
ρ_i	Represents the i^{th} party
ρ^*	Represents Party leader
p_i^j	Represents the j^{th} member in the i^{th} party
$\rho_{i,k}^j$	The k^{th} dimension of the j^{th} member in the i^{th} party
r	Represents a random variable number
S	Represents a measure of choice
s^*	Holds the two values of the Constituency and Party leaders
S_n	Source node
U_d	Moving direction
U_h	Height variation
U_L	Link quality
U_p	Position of the node

U_s	Speed of node
γ	Represents party switching rate

List of Acronyms

AGPSR	Advanced Greedy Perimeter stateless Routing
ACO	Ant Colony Optimization
BCO	Bee Colony Optimization
C2G	Cluster Head-to-Ground communication
CH	Cluster Head
CM	Cluster members
DA	Destination Address
DCM	Dynamic Clustering Mechanism
3D	Tree dimensional
DL	Downlink
EEOR	Energy-Efficient Opportunistic Routing
FANET	Flying Ad hoc Network
FoV	Field of View
G	Ground controller
GB	GigaByte
Gbps	GigaByte per second
GBS	Ground Base Station
GHz	Gigahertz
3G	Third Generation
3GPP	Third Generation Partnership Project
GPSR	Geographic Perimeter Stateless Routing
GPS	Global Positioning System
GSM	Global System for Mobile Communications
GWO	Grey Wolf Optimizer
Hdr Ext Len	Header Extension Length
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IP	Internet Protocol
IPv6	Internet Protocol version six
ITU	International Telecommunications Union

J	Joules
Kbps	Kilobyte per second
Km	Kilometers
Kg	Kilogram
LPWAN	Low Power Wide-Area Network
LoRaWAN	Long Range Wide Area Network
LoS	Line-of-sight
LTE	Long-Term Evolution
LTS	Long-term support
m	Meters
MANET	Mobile Ad hoc Network
Mbps	Megabyte per seconds
MCDM	Multiple Criteria Decision-Making
MHz	Megahertz
ms	Milliseconds
NCS	Networked Control System
NDN	Named Data Networking
NFN	Named Function Networking
NIEEOR	Nature Inspired Energy Efficient Routing
NS-3	Network Simulator 3
OS	Operating System
PO	Political Optimizer
PSO	Particle Swarm Optimization
QoE	Quality of Experience
QoS	Quality of Service
RAM	Random Access Memory
RLS	Reactive Location Services
RT	Routing Type
RWP	Random waypoint
SCF	Store-carry-and-forward
SCH	Substitute Cluster Heads
SCS	Stable Clustering Scheme
SDN	Software-Defined Networking
SDN-WISE	Software Defined Networking for WIreless SEnsor Networks
SID	Segment Identifiers
SIR	Superiority and Inferiority Ranking
SL	Segment List
Soft-RAN	Software Defined Radio Access Network
SR	Segment Routing

SRH	Segment Routing Header
TLV	Type Length Value
UAV	Unmanned Aerial Vehicle
U2G	UAV-to-Ground communication
UL	Uplink
U2U	UAV-to-UAV communication
VTOL	Vertical Take-Off & Landing
WSN	Wireless Sensor Network

Chapter 1

Introduction

1.1 Unmanned Aerial Vehicles-(Drones)

Unmanned aerial vehicles (UAVs), also known as drones, are pilot-less flying aircrafts installed with various sensors such as smart cameras and remotely operated to perform functions encompassing civic and military works [1]. Due to their diversity, they have varying platforms and are classified based on their size, design, how long they fly as well as based on usage [2]. However, their generalized categorization stems from the weight of the drone, thus they come as Micro drones with less than 2 kilograms (Kg) of weight; Mini drones with more than 2 Kg of weight, Small drones with weight factors ranging from between 20 to 150 Kg, and Large drones with weight factors greater than 150 Kg [3]. On the other hand, they can also be classified based on aerial platform namely Fixed wing drones; Multi-rotor drones; Single-rotor helicopter drones; and the Fixed-wing hybrid drones which are also known as the Vertical Take-Off & Landing (VTOL) drones [1]. Drones can be controlled using two techniques, namely semi-autonomous control and fully autonomous control [2]. Semi-autonomous control is the utilization of a wireless remote controller for its operations, while autonomous drones have on-board controller and depending on the task various algorithms are installed to propel their operations in terms of decision-making without explicit human command. This thus makes the autonomous operated type of smart camera drone a kind of complex system which could be explored for critical tasks operations especially with regards to gathering data from disaster-hit locations for crisis management as well as emergency responses [4]. To this, for the drones to autonomously perform their tasks, they are usually connected to a ground base station (GBS), allowing for their coordination to fly while keeping track with their telemetry data. The telemetry data for drone operation may include metrics such as speed, height of drone, warnings and residual power signals. Generally, the unique attributes of drones include their collaborative, versatile, autonomic and malleable attributes [5].

Recently, research interest in UAV drones especially with regards to drones equipped with smart cameras has intensified due to technological advancements in computer vision [1] and photogrammetry technology [6]. Notably, these embedded sophisticated vision technologies empower the smart camera drone with agile capabilities to capture, analyze and to extract application-specific information from captured data, alongside generating event descriptions such as object classifications or identifiers for decision-making in intelligent and automated systems [5]. To this, much to the research motivation can be traced to the identified drones' exceptional collaborative, re-configurable, versatile, autonomic and malleable characteristics [5], as well as to the advancements in wireless technologies allowing for their coupling effects in establishing self-organizing and adaptive flying ad hoc networks (FANETs), encompassing the single smart camera UAV system to a collaborative autonomous flying drone system capable of performing all kinds of applications such as emergency and disaster support services [7], [8], public surveillance [9], sports streaming [10], and wireless coverage extensions [11]. The self-organizing, re-configurable and collaborative properties of such a system allows for the networked drones to synchronize by way of adoption in their individual actions in order to quickly adjust in response to changing situations in the network [5]. To this end, the design of collaborative autonomous drone camera FANETs bring significant benefits such as addressing the limited field of view (FoV) attribute of the single drone camera system and provision of large area coverage of disaster-hit locations in real-time [12]. In this regard, some studies in the literature have pointed to the significance that UAV-FANETs may bring, one of such can be referenced to the recent studies of Zhou et al. [7], where they did not only highlight the significant role that UAV-FANET systems are most likely to play by way of seamless and flexible emergency communication coverage, and information service provision for disaster support services and management in future generation mobile networks and beyond, but pointed to ways to examine such locations, as available provisions could be leveraged to assist set up communication links for use by rescue teams [13]. This thus brings to the fore the advantages of such systems, particularly in ensuring for the design of suitable smart camera drone FANET architectures capable of providing scaling and stable factors for their efficient operation. On that basis, we argue that the impact that large autonomous smart camera drone FANETs may have is much more important than the challenges in their design and implementation [5].

Subsequently, we can draw attention to several attempts in the literature seeking to devise autonomous smart camera drone FANET systems for real-time image and video gathering and dissemination. For example, authors in [14] proposed a multi-UAV FANET framework to provide reliable communication and traffic load-balancing in support for stable and scalable communication in an emergency communication situation. The composed mechanism encompasses aerial nodes and designated relay nodes, for gathering and transmitting information from remote locations to a ground station while also allowing for exchange of operational commands. Popescu et al. [15] proposed the use of a team of UAV systems to provide aerial imagery of flood hit location for evaluation and to provide rescue support. Another approach suggested by M. Erdelj et al. [13] proposed for the deployment of ad hoc UAV network system to provide aerial disaster information acquisition and dissemination for assessment by rescue teams for quick support services to victims as well as ways to safeguard property. Similarly, a flood monitoring system based on high quality image acquisition from a swarm of UAV network system is also proposed [16]. The main objective being to perform pre-processing, implement feature selection analysis and to perform image classification to assist in the detection, zoning and flagging of flooding regions. Alternatively, a scheme for tracking and delivery of video footage from flood hit location for hindsight evaluation and support services by rescue team is offered [17].

The motivation lies in the large applicability of such autonomous flying camera drone systems, namely in the extraction and analysis of high-quality augmented video and image data. The networking and coordination related communication of self-organizing cooperative tasks performance and autonomous decision-making in FANETs, especially with regards to the capture and proper dissemination of image and video data in support for their operation over large geographic areas, come with several research challenges many of which were highlighted alongside proposals to address their effects in the extended abstract of Asaamoning et. al [18]. In the adjoining subsections, we introduce and discuss the ensuing impacts of various challenges encountered in large UAV-FANET setup, propose analytical methods towards mitigating their effects and present our contributions.

1.2 Research Challenges

The major objective of this thesis is to investigate novel flying smart camera drone networked communication systems capable of capturing and transmitting high quality image and video data over large geographic areas. The focus not being on video rendering, but on investigating advanced wireless networking and communication approaches allowing for high quality video and image acquisition by the smart camera drones, for real-time coordination and transmission between the drones as well as to the ground station, while being able to receive control commands under sustained network connectivity. The associated significant challenges encountered in the existing UAV-FANET approaches include the following:

- **Intermittent Wireless disconnections:** Image and video packet transmissions in large FANETs between aerial nodes and between the nodes and the base station are challenged with constant network partitioning resulting in wireless disconnections leading to packet retransmissions, which impacts on transmission reliability, network resilience and bandwidth usage. The existing approaches fail to address these challenges.

- **Frequent topology changes:** UAV nodes in FANETs are faced with constant topology changes especially when faced with an increasing number of deployed unmanned aerial vehicles, leading to transmission challenges such as increased routing overheads and network instability. The existing approaches fail to address the topological dynamics.

- **Fast mobility nature of UAVs:** UAV nodes have fast mobility attributes which contribute to frequent wireless disconnections and impacts on the reliability of communication in large UAV-FANETs. The existing approaches fail to address the fast mobility nature of UAV-FANETs.

- **3-dimensional (3D) structures of FANET nodes:** UAV nodes in FANETs are 3D structure in nature and may impact on the reliability of routing if the 3D movement factors of the aerial nodes are not taken as part of the metrics for the discovery of routing paths. The existing approaches fail to address the 3D movement attributes of UAV-FANETs.

- **FANETs scalability and fault-tolerant challenges:** FANET nodes are challenged with network scalability and stability challenges for large area coverage mainly when facing increased number of nodes due to network partitioning arising from inefficient network clustering thus causing packet retransmissions, network reliability and instability challenges. The existing solutions do not adequately address FANET scalability and fault tolerance concerns.

1.3 Research Objectives

In order to achieve our research objectives, we implement the following research investigations:

- **FANET design choices for stable transmission reliability:** To investigate applicability study for drone swarm deployment by proposing cluster-based design choices for their deployment in large FANETs, where intra-cluster routing is facilitated by beaconless rank-based approach to avoid unsuitable forwarding paths to address wireless disconnection and bandwidth wastage, while inter-cluster routing performed using a combination of greedy and right-hand rule approaches to escape void node situation to address wireless resilience concerns in FANETs.
- **Frequent topology, node mobility and scalability challenges:** To design algorithmic models capable of minimizing effects of topology and node mobility challenges in FANET environments when facing increasing number of cooperative unmanned aerial vehicles, by proposing the implementation of position-based routing to periodically update the network with current positions, moving direction, height variation and link quality of nodes to ensure for good image and video routing process to address topology challenges for transmission reliability. While stability and scaling challenges, addressed by considering node mobility factors of residual energy, buffer occupancy, distances and link quality for cluster formation.
- **3D attributes of FANET nodes:** To investigate the design of algorithms capable of addressing impact's caused by 3D attributes of nodes in large FANETs, by proposing the placement of nodes in 3D spaces in FANET based on node movement factors of position, moving direction, height variation and speed to ensure for effective route discovery for good routing performance to address transmission reliability, lower number of re-transmissions, low delay and latency requirement challenges.
- **Mobility aware clustering and optimum load-balancing:** To investigate models to address network scalability, reliability and robustness challenges in FANET, by proposing cluster formation to be based on node movement awareness for stable cluster formation and scaling, and subsequently cluster head (CH) and a substitute cluster head (SCH's) election to allow for implementing load-balancing mechanisms within and between selected CH and SCH's to address FANET transmission reliability, potential congestion and fault tolerant challenges.
- **Position-based Hybrid routing in clustered FANETs:** To investigate a robust and inter-operable hybrid-based clustered network solution which utilizes a rank-based scheme to be used inside of

clusters to ensure for transmission reliability while inter-cluster routing which encompasses several CHs performed using a combination of greedy position-based and the right-hand rule approaches for benefit of efficient network scaling and fault tolerance.

1.4 Research Contributions

The main contributions of this dissertation are summarized as follows:

- Study of related work on the development and deployment of autonomous camera UAV swarm FANETs.
- An analysis of Named Data Networking (NDN) and Named Function Networking (NFN) paradigms in support for the coordination function of networked control system nodes.
- Analysis of placement of computation functions in networked control systems.
- Analysis of the applicability study of UAV drone swarms as a networked control system, networking and computing requirements and their coupling effect.
- Proposed design choices for cooperative networking and deployment of large UAV camera drone FANETs, namely non-interactive and interactive design strategies.
- A new mobility aware Dynamic Clustering Mechanism based on a socio-inspired meta-heuristic optimization algorithm aiming to support a stable and reliable operation of large scale FANETs, namely in what concerns data packet dissemination.
- An entropy-based optimal load-balancing mechanism to provide fault-tolerant data dissemination inside and between clusters.
- An inter-operable Position-based Hybrid routing protocol for clustered FANETs which support use of a rank-based routing method inside of clusters while inter-cluster routing which encompasses several CHs performed in sync with a greedy position-based and the right-hand rule approaches for benefit of packet transmission reliability, high throughput and network scaling.

1.5 Thesis Outline

The remainder of this thesis is organized in the following:

In Chapter 2, we start with an overview of autonomous systems, architectures and best methods for their deployment. We describe autonomous smart camera drone systems and existing approaches to stream video and image data in FANETs. In Section 2.4 we provide review of existing cluster and load-balancing based approaches and their limitations. In Section 2.5 we establish most significant challenges faced in bringing good routing performance in FANETs, and investigate the characteristics of position-based routing, existing solutions and limitations, and made assumptions for the design and implementation of an inter-operable routing solutions for UAV-FANET environments.

Chapter 3 presents an analysis of the applicability study of drone swarms as networking and computing system together with their coupling effect. In Section 3.3, we describe how drone swarms look like as a networked control system and analyze two different deployment strategies for UAV swarms. In Section 3.4, we analyze the basic functionalities expected of the networking and computational systems. While in Section 3.5, we investigate how the networking and computational system should be integrated to realize a networked control system. We end-up showing that by relying on a networking system capable of resolving on-demand computation expressions composed from named data and functions in a transparent fashion to each drone, contributes to the self-organization properties of drone swarm, and present in section 3.6 the summary of the chapter.

In Chapter 4, we introduce a new Dynamic Clustering Mechanism with Load-Balancing which is able to support large scale fault-tolerant FANETs. In Section 4.2, we give the background of the models used to build our proposed solution, while in Section 4.3, we describe different components of our proposed solution and how end-to-end connectivity can be achieved. In Section 4.4, we present the experimental setup and conduct the performance evaluation of our solution. Finally, Section 4.5 summarizes the findings of this chapter.

The Chapter 5 of this thesis presents an inter-operable Position-based Hybrid routing protocol for clustered FANET. Section 5.2 provides a background of concepts and mechanisms used for developing our new protocol. Section 5.3 describes our proposed solution and how end-to-end communication can be performed. Section 5.4 presents the simulation and the performance evaluation of our new routing approach, while section 5.5 presents the summary of this chapter.

Chapter 6 draws inferences from the research investigations preformed in chapters 3, 4 and 5, followed by the summary of the Scientific Contributions of this dissertation by way of Journal, Conference and Extended Abstract Publications. Finally, while acknowledging the research limitations of this dissertation, we point to open research challenges that merit attention in the direction of our future research.

Chapter 2

State-of-the-Art

2.1 Introduction

In Chapter 1, we introduced the UAV drone system, mainly taking into consideration the autonomous drone equipped with smart cameras, drone classifications, attributes, benefits and applicability scope especially when organized into FANET aiming to cover large areas for video and image data. We also revealed the motivation behind this thesis and end by highlighting the key challenges faced in large UAV-FANETs operations. In this Chapter, we present background study to allow the reader to get acquainted with the autonomous drone system and introduce the relevance of autonomous drone systems equipped with smart cameras compared with the traditional fixed camera system, as well as a presentation of existing solutions to stream video and image data packets. Further, we discuss research relevant to the development of cluster-based and load-balancing mechanisms for UAV-FANETs, characteristics and requirements for the design of position-based routing strategies and existing solutions implemented in FANET environments.

2.2 Background Autonomous Drone System

An autonomous drone system is a UAV drone capable of navigating across a set of designated flight routes to execute a designated task with or without human intervention. In fact, due to wireless advances, research attention has greatly tilted towards exploiting the reported collaborative properties of the single autonomous UAV drone system to establishing distributed networked drone FANET system capable of providing on-demand aerial tasks accomplishment over large geographic areas under time constraints [19]. To this end, the deployment of such distributed system of autonomous drones are mostly organized in centralized or decentralized fashion, where in the former case, a central controller manages and merges all tasks related operations and commands of the entire system. However, the central controller is observed to be a single point of failure, hence a disadvantage to such network arrangement [20].

On the other hand, when deployed as a decentralized system, the distributed networked drone system is empowered with coordinated and self-configurable factors to act autonomously in decision-making towards an overall system wide goal, thus making the overall system more efficient and resilient in its operations [21]. Aside the aforementioned benefits, such a system is also noted to have malleable, easy to deploy attributes, low cost in nature and have large applicability scenarios [9]. As indicated, they have decentralized control and most often the interaction between multi-agents leads to the emergence of collaborative and self-organizing properties capable of solving complex problems [22]. They also have inherent adaptive attributes; hence, the aerial nodes are able to harmonize their actions while providing quick response to changing network dynamics [23]. A typical reference could be made to a distributed and collaborative data processing and occupancy reasoning algorithms put together, to assist in autonomous vision analysis of targeted tracked scenes, so as to perform distributed and collaborative processing [24]. This system obtains and estimates ground points for tracked objects from the multiple views captured by the distributed networked cameras so as to adjust in order to construct a topological work-tree. This combined work-tree forms the basis for performing distributed and collaborative processing whilst the reasoning algorithm allows for scaling up the network.

In that regard, several approaches exist for which coordinated flying ad hoc network of UAVs (i.e., drone swarms) could be organized to allow for effective communication in exchange of gathered information between the aerial nodes and the ground base station. One such case, could be organizing FANET into cluster-based and load-balancing approaches for data gathering and communication, as such arrangement have the potential to provide reliable, scalable and fault-tolerant factors in the network. Hence, in Section 2.4, we point to cluster and traffic load-balancing solutions in the literature while also highlighting their encountered challenges.

The remainder of the Chapter is organized in the following. In Section 2.3, we introduce the relevance of smart camera equipped autonomous drone systems and present some existing solutions to stream video and image data. Then, in section 2.4 we present state-of-art research relevant to UAV swarm FANET deployment based on clustering and load-balancing approaches, while in the section 2.5, we analyze prior art regarding position-based routing requirements and solutions in FANET environments.

2.3 Autonomous Mobile Smart Camera Drone Systems

Traditional fixed camera network systems have limitations for large area coverage, quality of image and video resolution as well as ability to perform on-board analytical processing, extraction and communication, hence the introduction of smart camera equipped autonomous mobile UAVs has been very critical to the advancement and application of time constraint real life scenarios such as disaster response services, distributed drone cooperative public safety monitoring and analyzing to detect and report abnormal crowd behaviors. This thus has brought additional functionalities allowing for network self-organization, reconfiguration and adaption properties to be incorporated so as to assist respond to changing network situations as well as optimizing for expanded coverage [25]. It is on this basis that L. Esterle et al. [12] suggested that since autonomous coordinated smart cameras have knowledge of their own selves and neighbors, the design and implementation of such flexible and re-configurable autonomous camera networks shall greatly enhance remote support for updating the application parameters of nodes at run time while still facilitating dynamic communication between the aerial networked nodes as well as bi-directional communication with a remote control entity [26].

In that regard, the deployment and application of UAV smart camera FANETs is an increasingly common attractive option to allow for real-time quality of services (QoS) information provisioning from remote locations, for assessment of damages, checking for survivors as well as provision of onsite views to assist rescue teams, mainly, due to their agility to move to hostile and endangered locations to gather and propagate information with great precision under reduced time period, while safeguarding risks factors on humans lives. To this end, many solutions have been implemented in the literature seeking to stream image and video data with great QoS and quality of experience (QoE) factors over large geographic areas, using a set of coordinated autonomous smart camera drone FANET. For instance, Liu et al. [27] proposed the implementation of a cooperative transmission framework for video streaming in small cell networks to minimize the challenge of video freezing and to improve the video QoS and QoE delivery. While the approach leads to a boost in system performance, a greedy-based scheme is utilized to facilitate in transmitting the video files in segments via distributed caching. Bousbaa et al. in [28], also proposed a routing approach in which node dynamic factors of 3D movement, topology changes and node mobility are the considered metrics for establishing routing paths in order to perform a routing process between source and destination nodes in FANET environment. The main objective of the approach is to ensure for packet delivery reliability to specific UAVs in the network using their geographical locations, to address the FANET dynamic constraints, with particular focus on reducing the number of packet retransmissions while also improving transmission throughput and network delay.

Similarly, Wang et al. [10] proposed a fog-based distributed network model for UAV smart camera FANET deployment. The model aimed at automating coordination between the distributed nodes for video capturing and streaming of sport events over a large field. The system is enabled to specifically provide optimization for coverage extension as well as aerial diversity to capture critical scenes of interest to be streamed to remote locations for access by end users. The work of Cumino et al. in [29] presented a cooperative scheme capable of augmenting video transmission quality in an UAV-FANET environment while tackling the anticipated energy limitations in the nodes to ensure for sustained tasks performance. Overall, in spite of all these contributions, researchers are still confronted with several associated challenges needing to be adequately addressed to ensure for proper data packet dissemination in UAV-FANETs.

On that account, having thoroughly scrutinized the literature, we believe that the most challenging factors to guarantee proper routing performance in FANETs while scaling, covers the network ability to handle topology and node mobility dynamics, 3D attributes and above all ability to provide accurate node position information for updating, shall lead to good routing performance in FANETs. Therefore, in the forgone, we examine critically the core challenges faced by researchers together with suggested methods in the literature seeking to provide proper, scalable and fault-tolerant routing performance in FANETs while examining existing prior art solutions based on position-based routing approaches in

Section 2.5.

2.4 Cluster-based and Load-balancing approaches in FANETs

Routing of data packets in cluster-based FANETs is confronted with several challenges mainly due to wireless intermittent links, 3D structure, and node and topology dynamics. Here, we focus on reviewing available clustering and traffic-load balancing solutions and their identified challenges in FANET environments so as to investigate methods towards addressing the limitations.

Over the past decade, there has been many attempts towards the proper integration of clustering and optimization techniques to improve routing efficiency in FANETs. For example, L. Ye et al. [30] proposed a mechanism to reduce end-to-end delay and to increased throughput, but at the expense of high communication overheads. Most of similar solutions fail to achieve high performance with low costs due to the clustering mechanisms that are not aware of the network and traffic dynamics. To this end, other cluster-based routing solutions have also been proposed aiming to address the dynamics found in FANETs. For example, Ali Khan et al. offered a bio-inspired clustering scheme aiming to provide efficient energy consumption and stable routing based on swarm optimization and a krill herd scheme to split the network nodes into several clusters [31]. In this proposal, the choice of CHs is done based on the residual energy levels of the nodes. The dynamics of the network is considered by providing coherent alignment of cluster nodes based on the social behavior of insects, such as change and movement. Nevertheless, results show that the cluster lifespan is short-changed due to the constant topology changes, which affect the overall performance. You et al. [32] proposed a UAV clustering scheme that optimizes both coverage areas and mobile edge computing for FANET. The scheme provides coverage extension, prompt computation, and low transmission delay, but fail to account on how the clusters and overall network reacts to the frequent topology changes and node mobility.

While trying to cope with network scaling, a mobility prediction clustering algorithm for managing network stability is proposed [33]. This algorithm explores the dictionary trie structure prediction scheme in sync with the link expiration time mobility model to manage the network cluster stability seamlessly. However, cluster formation is short lived causing more overheads mainly due to the frequent node dynamics and topology changes. S. Bhandari et al. [34] also proposed a mobility and location aware stable clustering scheme that estimate transmission efficiency by considering coverage probability and the size of clusters to cope with network scaling. In this case, the number of CHs is determined using a K-means clustering formation scheme, and the maintenance of clusters is performed by considering the relative speed and distance of UAVs. But, this approach leads to buffer overflows and high overheads on energy and bandwidth spending, thus this protocol may be unsuited for time-critical and prolonged application scenarios.

To react to network topological changes, a self-organizing clustering algorithm is proposed in [35] seeking to efficiently manage UAV-FANET communication. This model utilizes Glowworm swarm optimization factors to select routes aiming for good routing performance while also tackling topology changes. Nodes with highest fitness values are calculated based on residual energy, relative mobility and luciferin values are selected as CH while link selection between UAVs is based on neighbor nodes distance and position of UAVs. However, the basic assumption of fixed distances among the UAVs and CH's is erroneous due to the inherent dynamic attributes of FANET thus impacting on routing performance. A similar instance of a self-organizing based clustering algorithm is proposed for mobile ad hoc network (MANET) with aim to aggregate node mobility based on zones, in order to enhance network expansion and resilience [36]. The formation and maintenance of clusters is motivated by bird flocking behavior. CHs are elected and oversees the overall performances of cluster members. Communication between cluster members of different clusters is via a gateway node, which is responsible for facilitating communication between clusters. This study shows that the usage of self-organised methods aiming to reduce energy expenses in order to prolong network lifespan comes with an increase of communication overheads, a drawback that we aim to tackle with our new proposed Dynamic Clustering Mechanism with Load-Balancing routing approach presented in chapter 4.

Having as an objective to reduce energy spending, an energy-aware clustering mechanism was proposed to address limitations of high energy consumption and unreliable routing in FANETs [37]. In this approach, transmissions are adjusted to ensure optimal end-to-end packet transmissions resulting in reduced energy overheads. For this, a K-means density clustering scheme is used to assist in selecting optimal CHs, thus increasing the lifespan of the CH while reducing operational overheads. However, the node mobility and link instability attributes of FANETs are not considered during the cluster formation process, hence adversely affecting the reliability of the proposed solution. A load-balancing and energy efficient clustering scheme which is based on swarm intelligence and meant to provide communication needs during emergency communication is introduced in [14]. The scheme relies on metrics such as UAV residual energy, geo-location and distances of inter-cluster and intra-clusters to decide on the CH selection. Limitations of energy expending, traffic loads, coverage and network lifespan are tackled but the scheme accrues excessive communication overheads.

In recent times, the utilization of meta-heuristic optimization inspired by nature, social and biological behaviors, have variously been implemented for energy efficient clustering in wireless sensor networks (WSN). For instance, Mann et al. [38] proposed an improved meta-heuristic-based energy-efficient clustering scheme aiming to enhance the resolution exploration equation on its exploitation abilities together with an increase in its global convergence rates. The scheme thus retains a good optimal load balance between intra-cluster member as well as inter-cluster heads for sustained communication while utilizing less memory and energy overheads and high throughput. Here, CH is responsible for the management of cluster members as well as serving as a gateway to enable communication between a cluster member and a different cluster group member in the network. Similar meta-heuristic clustering approaches implemented in [39] and [40] also aimed at resolving load balancing concerns by creating effective inter-cluster routing to extend the network lifespan, improve throughput as well as minimize the traffic loads on gateways. Nonetheless, these techniques have mostly been utilized in WSN.

Also, several efforts have also been proposed towards providing efficient routing solutions to mitigate the challenges faced by FANETs. To that end, opportunistic-based routing approaches [41] implemented store-carry-and-forwarding schemes aiming to exploit nodes mobility to overcome the challenges imposed by intermittent wireless links in delay-tolerant networks as is the case of FANETs. However, since UAVs may follow a mobility pattern that might not be correlated with the social encounters assumed by opportunistic routing solutions, the efficiency of such routing protocols may be inconsistent [42]. Other approaches try to reduce the dependencies from mobility models by implementing a movement-aware routing approach [43], but with a surge on computation and latency overheads.

Independently of the overall performance of routing optimization solutions, their complexity and the time needed to take decisions, may not be suitable for FANETs, which are constraints in terms of energy and communication opportunities. Hence, the hypothesis that we seek to investigate in chapter 4 of this thesis is that an efficient Dynamic Clustering Mechanism with Load-balancing allows the usage of standard routing protocols within and between clusters.

2.5 Position-based routing demands and approaches in FANETs

The design of routing approaches for highly dynamic networks such as UAV-FANETs needs to deal with the core research challenges of frequent link disconnections, topology and node dynamics and challenge of inaccurate node location information provisioning which impacts on the reliability, stability, scalability and fault-tolerant factors of the network [41]. Generally, routing protocols designed for UAV-FANETs are classified according to their deployed strategies namely topology-based, position-based, hybrid and bio-inspired routing strategies [44]. That being the case, topology-based routing approach requires obtaining the topological information of nodes in the network, only after which packet transmission is performed. Position-based routing approach involves forwarding data packets from a source to a destination node based on the geographic position information of nodes. Hybrid routing approach on the one hand, combines both position and topology-based routing to facilitate in packet forwarding in the network, while bio-inspired routing is driven by the social behaviours of insects to precede with packet forwarding.

Overall, the survey of Gupta et al. [45] investigated various metric factors on these routing approaches especially with focus on analysing their applicability in UAV networks. Static routing was examined not to be suitable for dynamic networks together with traits in bandwidth wastage and scaling challenges, while proactive routing is observed with slow to countering topology changes resulting in network delays. Reactive routing approaches were remarked with none scaling factors and high communication overheads. Hybrid routing was observed as being complex to implement. Position-based routing approach noted to have resilient factors capable at handling network attributes and require only accurate node location information to proceed with data forwarding. Similarly, Lakew et al. [44] also conducted a study into the capabilities of position-based routing approach to provide support for FANET operations with guaranteed packet forwarding reliability. The authors analysed and compared the routing approaches by considering some important benchmark factors to account in the selection of routes or next hop forwarders. This involved an analysis based on an application scenario and metric requirements such as memory and bandwidth usage, signalling overheads, energy consumption, latency, and network size. The evaluated outcome showed that position-based routing approach provided significant gains on the mentioned benchmark factors with regards to deployment in highly dynamic scenarios when compared with other routing categories.

Further, it was observed in the study of Oubbati et al. [46] that a Position-based routing approach utilizes both reactive and greedy-based forwarding strategies to establish several forwarding paths for packets forwarding reliability, compared with other routing protocols. Moreover, with regards to scalability factors anticipated from high node mobility, topology, and environmental dynamics especially when facing increasing numbers of UAVs, Bujari et al. [47] performed a comparative analysis on position-based routing algorithms for FANETs. They showed that deterministic forwarding strategies implemented using a greedy-based approach offers exceptional network scaling properties in highly dynamic network scenarios and are suitable for cluster-based UAV-FANET deployment. For instance, the cluster-based networking approach implemented in Asaamoning et al. [48] may allow for the creation of large scale FANETs able to sustain end-to-end efficient communications over different clusters, while allowing the overall network to adapt to variable UAV mobility and wireless conditions, which may differ from cluster to cluster.

Nonetheless, position-based routing protocols are challenged by the need for location information about nodes in order to estimate the shortest distance to the destination, and to enable a decision about the next hop for packet forwarding. But, in that regard, GPS on-board the UAV drone can be leveraged to provide node location information to assist in packet forwarding decisions [49]. To that effect, several position-based routing approaches have been proposed in support for the requirements of different FANETs scenarios. For instances, a geo-position based routing protocol for UAV networks is proposed in [50]. The protocol is a variant of both position-based and hopless protocols and so exploits both features for benefit of utilizing all communication opportunities within the network irrespective of hop distances and link qualities. In addition, each node uses its location information to compute its forwarding precedence in a distributed manner to reduce communication overheads. Another geographic-based protocol is suggested where the location of nodes are exploited for the purpose of estimating link quality stability and node mobility [51]. In order to ensure for effective route discoveries and forwarding, the protocol selects only paths with sufficient connection with other nodes in the network while overlooking all disjointed paths.

In addition, a genetic algorithm based on the optimization of throughput in FANET is proposed [52] where the positions of the UAVs are optimized to maximize transmission throughput. The authors considered the numbering area, correlation matrix, adjacency matrix, and movement of UAV position to significantly improve throughput performance. Yin et al. [53] proposed the design of a Fountain-code routing protocol for flying UAV networks by considering the geographical location information of nodes. In this protocol, impacts arising from packet backlogs are mitigated using a power allocation and routing strategy to reduce transmission delays while achieving reliable end-to-end packets transmissions and low latency. Recently, Hussen et al. [54] proposed a novel stateless and predictive geographic multicast routing algorithm for FANETs. The algorithm reactively predicts neighbor nodes' positions to allow for selecting the neighbor relay nodes capable of advancing packets towards multicast location with the main aim to ensure for high throughput rates to multiple destinations. In a similar way, Bousbaa et al.

[28] introduced a new geocast routing protocol for a swarm of UAVs. The protocol seeks to improve end-to-end packets delivery ratio under low delay to a set of specific nodes by taking into account the geographic locations and 3D movement of nodes to enhance throughput rates.

Aiming to conserve network connection robustness and resilience among aerial UAVs and between the UAVs and the ground base station, a geolocation-based multi-hop routing protocol is proposed for FANETs [55]. In this protocol, at time intervals each UAV broadcasts its position, direction, and speed. Based on this information, each UAV in the network selects next hop forwarders, and perform routing using the greedy forwarding approach to reduce impacts ensuing from topology dynamics, while ensuring the reliability of packet delivery. Alternatively, a geographical position mobility oriented routing protocol is proposed in [56]. The algorithm seeks to reduce the number of hops towards the destination by using the Gauss-Markov mobility model to predict the future location of nodes in FANETs. The main objective is to improve routing performance. The protocol thus utilizes the predicted future location of nodes to facilitate in the delivery of packets to the destination while also influencing the reduction of network end-to-end latency. Another protocol proposed by Sang et al. [57] seeks to predict node positions to facilitate in packet forwarding delivery while aiming to reduce packet re-transmissions and energy spending. Other protocols such as that proposed in [58] seeks the establishment of an energy stabilizing limit. To this, the algorithm thus selects only nodes with higher energy levels than the threshold to facilitate in the greedy forwarding of packets for sustained network performance.

Overall, it is evidently clear that there are a lot of solutions in the literature utilizing Position-based routing approaches in FANETs. Nonetheless, these solutions are more generic and are unable to provide the required methods to tackle the core research challenges faced in FANETs. Again, having thoroughly searched the literature and found barely any specific solution seeking to implement Position-based hybrid routing in clustered FANETs to improve network robustness and scaling factors. We argue that the best approach to ensure a scalable and inter-operable solution for FANETs is to consider clustered networks. Hence, in chapter 5, we proposed a new Position-base Hybrid routing protocol, which apart from optimizing the network for efficient energy and communication spending, different routing protocols are utilized inside each cluster while inter-cluster routing performed using position-based routing between CHs aiming for benefit of network scaling, resilience and sustained data packets delivery.

Chapter 3

UAV-FANETs, Swarms and Applicability Study

3.1 Introduction

In the previous chapter, we presented background information on autonomous drone systems, benefits of drone equipped camera systems, and reviewed solutions based on clustering and traffic load-balancing approaches, and position-based routing approaches in FANET environments. In this chapter, we shall introduce the background and concepts of FANETs and their purpose, as well as their development from the single UAV system to drone swarm systems, especially with regards to autonomous camera swarms. Next, we present and investigate networking design considerations necessary for the efficient deployment of drone swarm systems, while analyzing an applicability study on how drone swarms should be modeled as a networked control system (NCS). The basic networking and computing system components and requirements are thoroughly discussed, while analyzing how to integrate the networking and computing system to realize a NCS. Further, it is essential to point out that, this chapter is composed of several studies which were performed as preliminaries to the realization of the applicability study of drone swarms as an NCS and its implications. In that regard, the analysis on NDN as a potential solution for the coordination of functions between the nodes of a networked control system was investigated and reported in Asaamoning et al. [59]. Similarly, the investigation to extract sensing data from the environment together with the decision to communicate the data to a location for processing, which required a decision on where to place the computation function, which in our context is ideally inside of the drone swarm, is regarded as a fog computing system, was studied and reported in [60]. Additionally, the analysis to show the dependence on a networking system capable of resolving on-demand computation expressions composed from named data and functions in a transparent fashion to each drone, contributes to the self-organization properties of drone swarms is the outcome of the research conducted in Asaamoning et al. [61].

3.2 Background and concepts of FANET and Drone Swarms

A flying ad-hoc network (FANET) is mirrored as a sub-set of mobile ad-hoc networks (MANETs) which before was used to establish temporal ground communication system for information gathering in the absence of a fixed network infrastructure [62]. From a networking point of view, the concept of FANET was particularly coined by Micheal Muller as reported by Singh et al. [62], and used for the design of an efficient network to provide seamless communication capabilities among UAVs, which are fixed with technologies such as smart cameras, GPS and sensors. This thus grant the UAVs with the potential to navigate to unreachable locations to remotely gather and transfer critical information to known ground base station(s) without fixed network infrastructure [63]. In that sense, in the extreme occurrence of calamities such as earthquakes, fires and floods, ground access by the MANET system is challenged, hence, a FANET is indispensable to establish communication links between a base station and the flying UAV to allow for aerial information gathering and transfer. Nonetheless, situations of calamities require swift information gathering and transfer in real-time from such locations for decision-making and quick response by emergency support teams. Consequently, the single UAV-FANET system may be incapacitated to provide large area coverage in real-time due to processing and energy limitations. As a result, it is necessary to expand it by using a team of drones (i.e., drone swarms) to form a FANET system, regarded as a collaborative system of UAVs capable of allowing distributed processing of tasks performance among the networked nodes to overcome the challenges of the single UAV-FANET system [64]. On that accord, the concept of FANET did not only overcome the challenges of the single FANET system (i.e., in what concerns synergy for real-time large area coverage), but also defeated the disadvantages of the ground MANET systems' inability to reach land-hit disaster locations for information gathering and sharing.

On that account, this Chapter is dedicated to investigating the design and implementation of an autonomous drone FANET system to be modeled as a NCS. This shall bring the full benefit of the operational chain, beginning with the sensing act to gather data from the environment into the swarm system while the networking system is responsible for ensuring that the captured data get to that points on the network swarm, or remote locations where the data computation is performed, as well as ensuring that the computational results are conveyed to the UAVs that require the information to take actions necessary to adapt to the overall behavior of the swarm system. On that basis, we begin by devising network design strategies to be considered for drone swarm FANET deployment, and a study of methods capable of building consensus for mission oriented tasks performance. Finally, we pass by analyzing the applicability study of how to model drone swarms as a NCS.

The remainder of this chapter is structured in the following. We start by providing in section 3.3, the characterization of how drone swarms look like as NCSs, and provide an analysis of two different deployment strategies namely non-interactive and Interactive deployment strategies. In section 3.4, we provide an analysis of the basic functionalities expected from the networking and computational systems. Section 3.5 provides an analysis of how the networking and computational system should be integrated to realize a networked control system. Finally, section 3.6 provides the summary of this chapter.

3.3 Drone Swarms as Networked Control Systems

Drone swarms are mission-oriented systems and in most cases can be of different scales and complexities, requiring the deployment of networks with different strategies ranging from small to large scale. For example, for a simple, low-scale mission, a drone system may encompass a single drone or a group of non-interactive drones connected to a ground control center, while for larger-scale missions, the system may encompass multiple interactive drones (i.e., a swarm of drones) performing tasks through consensus and swarm intelligence. This means that a large drone system may encompass several drone swarms connected via a ground or satellite platform, through which they can share information. Hence, both cases may be modelled as an NCS [65], as analyzed in the adjoining sections.

3.3.1 Networked Control System Model

A drone swarm can be modelled as a NCS encompassing a set of computational systems (i.e., the drones) connected via a communication network, and controlled in a closed loop. Specifically, the control and feedback messages are exchanged among the system computational units, or agents, in the form of information packet transmitted through a network. The functionality of a typical NCS is established using two basic elements: (i) a computational system able to gather data via sensors to reach decisions and to perform commands via actuators; (ii) a network, based on communication modules, standards and protocols (e.g., medium access control and routing) to enable the exchange of information.

Drones are equipped with on-board computers responsible for data processing, each of them can include several micro-services to perform specific tasks, such as sensing, image or video streaming, decision-making (e.g., about the flight control), and actuation on the environment or on the swarm itself [66]. By evaluating and reacting, the effectiveness of the action of each drone is leveraged allowing them to behave as a group of multiple agents that work together aiming to produce a common goal; A swarm system exhibits emergent behaviors, where simple behaviors are shared across many agents giving rise to a collective behavior capable of solving complex problems [67]. The deployment of drone swarms largely depends on the wireless and networking technologies for transmitting specific data and control commands among drones or between drones and the ground control, leading to the deployment of drone swarms based on two approaches, namely non-interactive and interactive strategies.

3.3.2 Non-Interactive Network Deployment Strategy

In a non-interactive deployment strategy, each drone is directly connected to a ground control station, which is used to monitor their status (e.g., location, condition of sensors, networking configurations), take decisions and send out new commands, such as new waypoints.

A non-interactive deployment strategy leads to a simple example of a network that cannot be further divided. This kind of strategy may be regarded as a single NCS considering that each drone can build a controlling closed loop to optimize its operation. The capability to communicate is also indispensable since the drone still needs to interact with the ground control to complete its system operation of perceiving, communicating, computing, and controlling. Hence, in the network topology of a non-interactive deployment strategy, drones are controlled by the ground controller, meaning that this strategy relies on the existence of efficient uplinks and downlinks, as shown in Figure 3.1, allowing the ground controlled to transfer flight status to the drones and to collect data from them. In scenarios with multiple drones, drones are not capable of communicating directly nor even through the ground controller. Figure 3.1 illustrates a case with multiple drones.

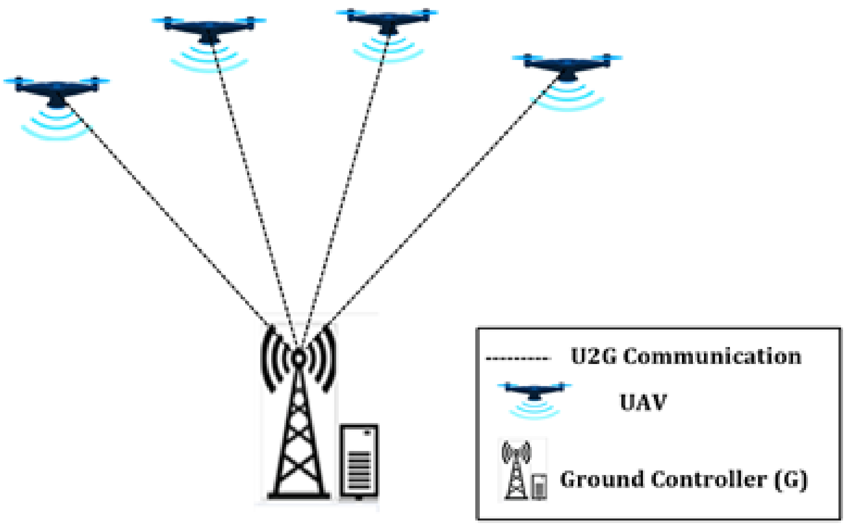

Figure 3.1: Non-interactive deployment.

In this type of simple deployment strategy, there is a bidirectional communication link from each drone to the ground control system allowing for direct transmission of application specific data and control commands. This strategy is suitable for small size applicability scenarios with lower coverage range. The main limitation of this strategy is that the ground control station is a single point of failure on which the entire network can have a shutdown, together with transmission delays culminating from the long wireless links aiming to cover a wider area. From a communication point of view, a non-interactive deployment strategy relies on a precise air-to-ground channel model, antenna design, and mobility model.

According to a non-interactive deployment strategy, drones gather relevant information from themselves and from the environment. The collected data needs to be processed, for which the drone needs to communicate with a ground control station. The result of the computational system in the ground station is communicated back to the drones, being used by the relevant local actuators.

To that end, major technologies to provide communication requirements include cellular technologies, such as long-term evolution (LTE), can be used to provide improved system capacity, coverage, high data rates, and reduced latency deployment [68]. For instance, LTE provides data rates delivery range between 0.07 to 1 Gbps with coverage range of up to 350 km on flexible spectrum. On the other hand, Low Power Wide-Area Network (LPWAN), such as LoRaWAN, provides broad area connectivity operating on unlicensed frequency bands with low data rate, power consumption, and throughput [69].

For instance, LoRaWAN provides data rates that vary from 0.3 kbps to 50 kbps [70].

In what concerns the computational system, this deployment strategy may rely simply on accurate mobility models or path planning functions based on intelligent algorithms, such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Bee Colony Optimization (BCO).

3.3.3 Interactive Network Deployment Strategy

In an interactive deployment strategy, drone swarms can be deployed in an autonomous manner, making their own decisions (e.g., about path adjustment) based on their perception of the environment including neighbor drones. In an interactive deployment strategy, the drone swarm will be able to coordinate their operation based on a cooperative approach towards sensing, monitoring as well as information sharing, allowing them to get to a consensus about the best way to execute a mission while facing detected obstacles. In what concerns the exchange of information, an autonomous drone swarm must rely on a networking system that does not depend on the operation of a ground controller, with the exception of emergency situations.

In a full autonomous drone system, swarms rely on airborne networks with potentially strong line of sight attributes, which facilitate data transmissions, as well as with the capability to generate suitable routing tables allowing drones to take decisions based on a good understanding of the nearby neighbor. This localized operation, typical of self-organized systems, does not require a networking system capable of creating a full image of the complete drone swarm, which is an advantage in dynamic settings.

Independently of the considered network topology for the airborne network, the design of a reliable wireless communication system allowing for autonomous drone interaction under dynamic propagation conditions is essential for achieving efficient swarm operations [22].

Hence, an interactive deployment strategy leads to a more flexible swarm with higher density and range than a non-interactive strategy. In that regard, the network topology of the interactive deployment strategy requires drones to communicate with each other directly or through multi-hop links [71]. For that reason, the topology can be done with different levels of complexity from a network based on ground communication to several networks relying on air-to-air communication. In the latter case, the network can be simple, encompassing a single cluster, or more complex including multiple clusters or a large flat ad hoc network.

An infrastructure-based network follows the same topology as the non-interactive deployment (c.f. Figure 3.1), where all drones connect directly with a ground control station. The difference is that in an interactive deployment the drones can communicate among themselves via the ground station, which is responsible for relaying all communications. However, by relaying all control information via the ground controller, makes this arrangement a low robust system due to the existence of a single point of failure. In what concerns the decision-making process, this can be done in a centralized or decentralized manner. In the former case, all decisions are taken by the ground controller based on information provided by all drones. In the latter case, each drone should be able to take their own decisions based on information that the drones share among themselves via the ground controller, which in this case act only as relay.

In the case of a cluster-based network, every single drone is connected to another drone that is set as configuration parameter during the deployment of the system or selected during operation based on the status of the swarm. Such drone is selected to operate as head of a cluster of neighbor drones, meaning that every communication generated or terminated in such neighbors are sent via the CH [72]. In this situation, the CH may become a bottleneck within the drone swarm causing link blockage and high latency. This system can be extended to include several clusters, each one with its own CH. In both cases (i.e., single or multiple clusters), the CHs are responsible to establish communication among the clusters and between each cluster and the ground control. The decision-making process can be done by the drones themselves in a distributed manner: based on individual decisions or in a consensus-based manner. This is possible due to drones being able to communicate with each other via CH, and not only via the ground control. Figure 3.2 provides an illustration of a set of single clusters that forms a multi-cluster network.

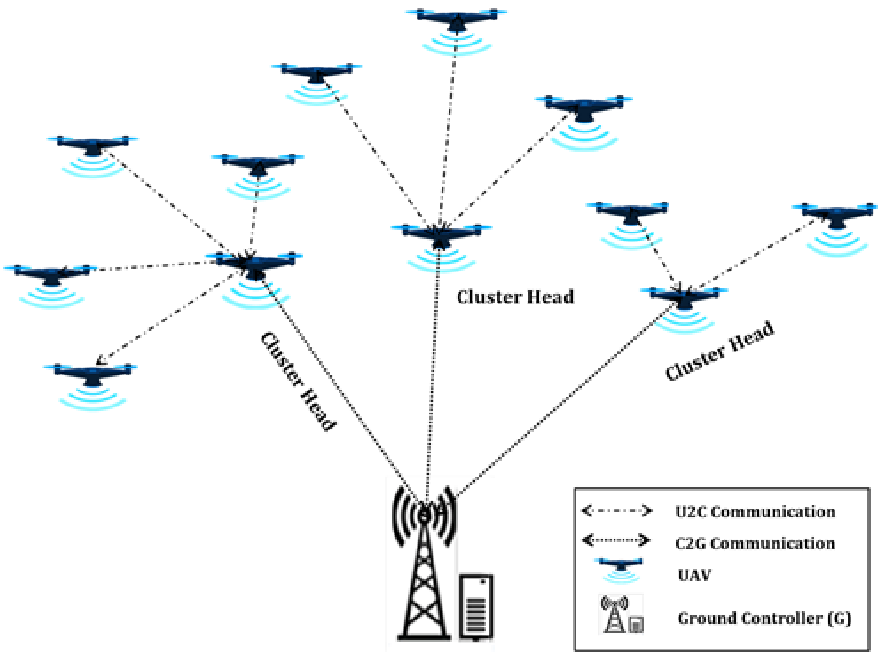

Figure 3.2: Multiple cluster interactive deployment.

On the other hand, in an ad hoc-based network drones can communicate via one-hop or multi-hop wireless network that normally has a flat organization, and relies not solitarily on CH [73]. Consequently, single node failures have little impact on the whole system. This deployment strategy brings reduced downlink bandwidth and latency requirements because of shorter links among drones. The advantages of an ad hoc-based network deployment strategy include network scale-up, fault tolerance, device autonomy, flexible and less expensive to setup [8].

In an ad hoc network setup, the coverage of the drone swarm can be bigger than in a cluster-based network due to the possibility to route packets over multiple hops [74]. However, since routing may not scale in a flat organization, an ad hoc network may be organized into many separate clusters, and each of them operating as a single ad hoc network. In this case, each ad hoc network will need to have one or several CHs, which will function as gateways. Figure 3.3 shows the overall topology of a set of ad hoc networks, which together might form a cluster-based ad hoc network.

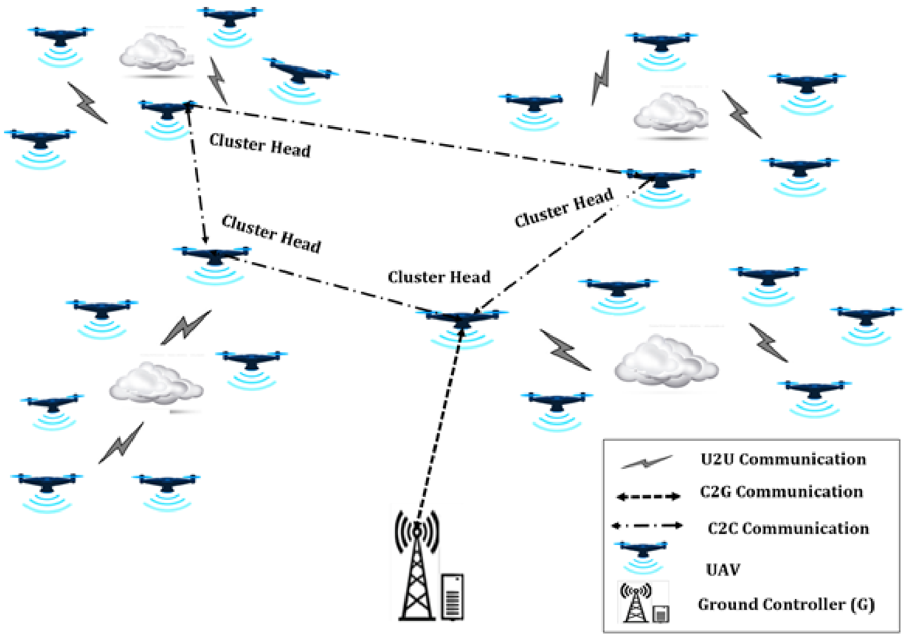

Figure 3.3: Cluster-based ad hoc interactive deployment.

To model a drone swarm as NCS, it is necessary to address the communication requirements capable of guaranteeing maximum system performance over an airborne wireless network. From a networking point of view, challenges of transmission failures, delays and message errors may lead to degradation of the overall system performance.

It is essential to rely on wireless technologies capable of connecting all drones together through effective mechanisms to allow for an effective interaction between drones [75]. Several technologies can be used to deploy an interactive strategy, including IEEE 802.11 [76], 3G/LTE [77], and satellite communications [78]. However, an alternative networking solution should be further investigated since due to the mobility and power limitation of drones, the networking system needs to be able to operate even in the presence of irregular connection and device challenges, while still providing the needed delay and throughput requirements of several services. Moreover, wireless reliability and stability are key for the operation of swarms, but notably the communication protocols designed for close-loop control systems are challenged in providing the needed guarantees.

Such an alternative networking system should rely on routing protocols capable of providing secure data transmission routes from source to destination. In this context, literature already provides several studies about the different families of routing protocols suitable for drone effective communications. These protocols include Swarm Intelligence-based protocols, Position-based routing protocols, and Topology-based routing protocols [8].

In an interactive deployment strategy, computational resources are dispersed in different drones, as well as in the ground control station. This means that several computing tasks need to be designated to create a suitable decision-making process, namely to decide where and how the decisions are made. First, the coordination of computational tasks depends on the requirements of each one of them. For example, while simple flight control can be guaranteed by the controller on-board on each drone, more computing intensive tasks such as image recognition may need to be transferred to the ground control or to a set of drones that together may provide the needed resources. Moreover, the coordination of computational tasks may be done based on the exchanged information between drones, while avoiding links that may impact on the effective performance of the drone swarm.

3.4 System Components

Drone swarms encompass the integration of networking and computational systems, which together contribute to the closed-loop operation of the NCS. Looking into the full operational chain, sensing acts to gather data from the environment into the swarm system while the networking system ensures that such data gets to the points on the network where computation should be done, as well as ensuring that computational results are delivered to the drones that require that information to take actions needed to adapt to the overall behavior of the swarm. The remaining sections of this Chapter analyzes the properties (basics, demands and challenges) of the two fundamental elements of a drone swarm: networking system and computational system.

3.4.1 Networking System

The networking system builds a communication graph for data to be exchanged between drones, as well as between drones and a ground infrastructure. The networking system should guarantee the closed loop by driving the data flow between sensing, decision-making and actuation. This is achieved by considering that those three elements (i.e., sensing, decision-making and actuation) may reside in different drones providing a cooperative sensing. For instance, a drone may sense a new obstacle that does not interfere with its own position, but it may have an impact on the overall swarm. This information is made available to another drone able to compute an action, which may be executed by a set of other drones that are in the way of such obstacle.

In a drone swarm, communication is not only imperative for disseminating observations, tasks and control information, but can also assist in coordinating the drones more effectively and safely. The communication demands vary significantly in different applications. However, it is a particularly challenging task to provide robust networking, due to the energy limitation of drones and to external factors such as wireless shadowing and intermittent available links.

In that regard, we analyze the networking requirements of the data traffic related to the system operation which is classified into two major types, namely command and control traffic and coordination traffic [79]. The former allows the ground control to monitor and influence the behavior of drones as well as monitor messages with information about the drone's status. The coordination of traffic encompasses information related to cooperation and collision avoidance. In addition to the mentioned system traffic, drone communication can also include payload data related to services implemented on-board such as data generated by observations of the physical environment (e.g., video cameras) and data generated and consumed by passengers.

In what concerns the air-to-ground communication links, the International Telecommunications Union (ITU), under The 3rd Generation Partnership Project (3GPP), classified command and control communication as well as payload communication for drone safe operations in terms of throughput, reliability and latency [80], as detailed in Table 3.1. These performance requirements aim to guarantee timely communication, processing, and coordinated movement in real time. Although the information provided by 3GPP refers to air-to-ground links in a centralized scenario (c.f. Figure 3.1) the same quality requirements should be expected to any air-to-air links between drones.

Table 3.1: Communication requirements for drone operations as specified by 3GPP

	Data type	**Throughput**	**Reliability**	**Latency**
DL (Ground station to UAV)	Command and control	60-100 Kbps	10^{-3} Packet error rate	50 ms
UL (UAV to Ground station)	Command and control	60-100 Kbps	10^{-3} Packet error rate	-
UL (UAV to Ground station)	Application Data	Up to 50 Mbps	-	Similar to Terrestrial user

Communication over air-to-air links is expected to have increased importance in autonomous drone systems since drones require exchanged information among themselves to be able to take local decisions. Drone swarms require reliable wireless for real-time distributed coordination and processing to achieve system wide-goals [81]. Hence, for swarms to attain a wide-area communication in support for coordinated and distributed real-time processing, the networking system needs to have network performance specifications embracing reliability, high throughput and low delays to offer greater cooperation and synchronization for effective control of aerial nodes [45].

3.4.2 Computing System

Computation within a drone swarm relies in a process similar to an NCS in which the simple data may lead to complicated decision-making. Hence, the development of a suitable computational system relies on the investigation of the best strategies for decision-making depending upon the used deployment strategy and intelligence algorithms. Hence, due to the distinctive attributes of UAV swarm FANETs, it is required to consider decision factors such as self-organizing decision-making and swam intelligence properties for swarms as analyzed below.

1. **Self-Organized decision-making**

   In general, all drones have computation ability to achieve the basic flight control, but only the drones with high autonomy level can make decisions by themselves in a distributed manner to fulfil their missions. However, swarms with low autonomy are aided in decision-making by a centralized control entity to accomplish their tasks obligations.

   A centralized decision-making process offers simple solutions in terms of the overall system design, while contributing to reduce the energy consumption of each drone. On the other hand, a distributed decision-making approach may lead to a more robust and scalable drone swarm. With this in mind, our focus is on distributed decision-making processes that may lead to more autonomous, robust, and scalable drone swarm.

Table 3.2: Self-Organizing distributed algorithms

Ref.	Performed Function	Technique Deployed
[82]	Deployed to perform distributed cooperative search in Multi-UAV system	Implements the distributed decision-making based on receding horizon techniques
[83]	Resolve slot access problem for neighbor UAV swarm network co-operation	Implements a collision discovery method to ensure slot access is not delayed by topology information exchanges
[84]	Implements self-organized collision avoidance in autonomous UAVs	Algorithm Computes safe reaction distance on which UAVs begin collision avoidance movement
[85]	Tackles sensing coverage constraints in multi-UAV swarm operations	Reciprocal decision-based approach performed between neighbor UAVs to reduce trajectory oscillations
[86]	Provides formation control for UAV and Mobile Robots communication networks	Distributed asymmetric control to implement formation control based on 'mergeable nervous systems' approach
[87]	Plays the role of implementing distributed control laws in swarm indexing and position-free density control	Pseudo-localization method used to localize agents to a new coordination frame with distributed control policies for desired coverage extensions
[88]	Solves limitations in transmission extensions in UAV wireless networks	Deploys relay selection techniques to improve coverage transmission constraints
[89]	Provides solution for slot access transmission problem in UAV Swarms	Makes use of game model as collision detection method to derive feedback in a common control channel for access slots
[90]	Performs flock distribution for UAVs to fly and coordinate as a unit	UAVs coordinates without a leader and on constant basis broadcast and as well receive movement information in order to share their common goal
[91]	Deployed to perform formation control in multi-UAV system	Formulates formation solution based on circle and arbitrary polygon formations techniques

In more challenging applicability scenarios, it is expected that drone swarms can operate in a self-organized manner. This means that drones need to collaborate, while facing fluctuating network conditions to maintain the network connectivity [45]. The self-organized nature of a drone swarm aims to assist distributed agents in each drone in order to act by sharing the environment data to observe conditions and to autonomously decide on actions that will fulfil the system wide goals [92]. We present self-organizing distributed algorithms in Table 3.2 taking into consideration the reference to the algorithm, function it performs and deployed technique.

From the list of self-organizing distributed algorithms presented in Table 3.2, we reference one of the algorithms [85] to enable us explain control procedures used for implementing self-organizing decision-making controls for multi-UAV systems, as shown in Figure 3.4.

The control architecture is decentralized and decision-making by each individual UAV is autonomous, but their local interactions bring out their emergent global behavior. Network scale or removing a

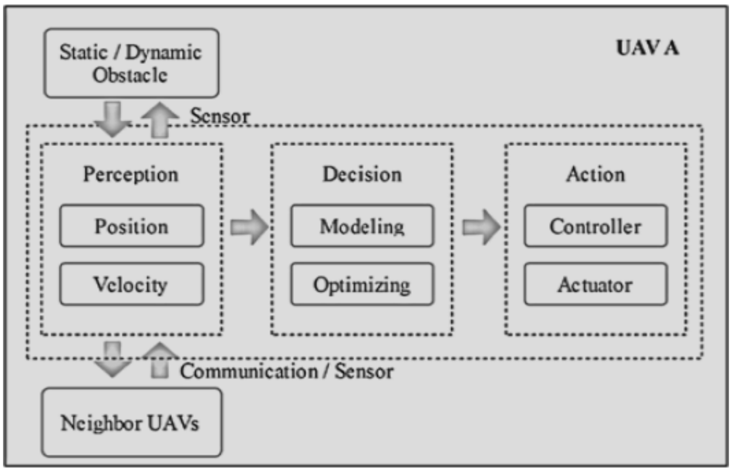

Figure 3.4: Self-Organizing Decision-Making Procedures.

node does not impact network performance. For cooperation and function of each UAV, the self-organizing decision support procedures are put into three stages namely Perception, Decision and Action, as shown in the Figure 3.4. Information on position and velocity of UAVs and neighbors are acquired by considering stationary and mobile obstacles after which processes decision-making-based on modelling and optimization are performed to improve outcomes. The actuator then processes the penultimate best possible decisions, and the processes iterate again.

To share system observations allowing for the emergence of a collective behavior, drone operation's need to also be synchronized. Synchronization allows for the coordination of events among individual agents in different drones to support their harmonious swarm operation [93]. It helps the distributed processors to have a common notion of time through the exchange of beacon messages to allow for effective fault diagnosis and recovery. Synchronization facilitates to merge data from the different distributed nodes into a single meaningful information through what is called data fusion.

There are several techniques proposed in the literature aiming to provide various levels of synchronization functions in distributed systems. Mention can be made to decentralized techniques that exploit the resources of visible light communication to facilitate effective video streaming synchronization in coordinated digital cameras [94]. In what concerns systems that require a tight clock synchronization, an adaptive synchronization method has been proposed based on time slotted channel hopping technique to empower devices needing to synchronize the ability to track and predict its own clock trickling relative to neighbors [95]. Other approaches related to clock synchronization for the coordination of multi-robot models have been exploited, namely the theory of swamalators in space and time to form a coupling block for swarms [96].

Synchronization allows self-organized systems to be managed and coordinated aiming to respond swiftly to internal and environmental influences on the system with regards to failing nodes, resource variability and other factors contributing towards the overall system objective. This demand is termed system adaptability, which mainly contribute for making drone swarms robust. Adaptability models are required to be instantiated at run-time to allow an effective system control while responding to varying mission demands, and topology changes due to mobility of drones [93].

The self-adaptation property of a swarm system relies on an efficient propagation of information within the swarms. This requires an efficient set of network functions capable of maintaining the global knowledge of the network while localizing the interactions between drones to ensure that they do not rely on global knowledge to operate. Such networking functions (e.g., routing) should support system scalability, allowing for the expansion of the network without hampering performance [93].

2. **Swarm Intelligence**

The goal of swarm intelligence is to leverage the operation of drone systems to exhibit advanced and complex swarm behaviors through their cooperation, organization and information exchange. A swarm intelligence systems is made of a set of simple agents (drones in this case) interacting locally among themselves and with the environment. The operation of swarm intelligence systems aims to mimic some biological systems, where agents (e.g., ants, bees) follow simple rules which are not dictated by any central entity. In these systems the interactions among the agents give way to the emergence of global behaviors. In this context, swarm intelligence algorithms aim to control drone swarms in what concerns their behaviors based on two approaches namely optimization and consensus. Hence, in this section we aim to analyze optimization approaches such as PSO, ACO and BCO [97], as well as consensus approaches mainly Paxos and Raft algorithms [98].

The PSO approach proposed by Kennedy and Eberhart in 1995 is inspired by the flocking behavior of birds [97]. PSO can be used to allow drones to cooperate in searching for the best solution to solve an identified problem, such as avoiding an obstacle. For this purpose, the PSO algorithm continuously updates velocities and positions of the drones in the solution space. By sharing this information, the algorithm allows different drones to move towards best positions relative to their neighbors to maintain strong bonds for collective sailing in attaining optimum performance [99]. We shall present in the adjoining tables swarm intelligence algorithms implemented based on the two approaches. Table 3.3 references are made to optimization-based implemented algorithms considering their optimization approach, solution provided in terms of function and deployed technique.

The ACO algorithm is devised to assist in finding optimal paths based on the travelling behavior of ants in search for food sources while releasing pheromones on their paths [97]. As ants pursue food sources, the release of more pheromones on a path is a likely indication of a food source. The algorithm has strong cooperative behaviors and so has strong global optimal abilities as well as it is flexible to implement. It is applied in combinatorial optimization problems, job scheduling problems and network optimization routing [110].

The BCO algorithm was also devised to find optimal solutions to distributed control system problems such as scheduling, clustering and engineering designs taking inspiration from the collective

Table 3.3: Optimization-based Algorithms

Ref.	Optimization	Performed Function	Technique Deployed
[100]	PSO	Implemented path planning for swarms	Deploys jump-out and revisit methods to avert both null search attempts and local optimum
[101]	PSO	Implemented for finding moving targets using UAVs	Employs the Bayesian theory to convert a search problem to optimized cost function which will represent the probability of discovering targets
[102]	PSO	Implements cooperate path planning for Multi-UAV operations	Deploys time stamp model to manage UAV coordination expenses
[103]	PSO	Used to create exploratory trajectories for UAV networks	Delay tolerant networking approach is used for the team of UAV to follow
[104]	BCO	Implements UAV formation, obstacle avoidance control and target tracking	Deploys metaheuristic optimization approach exploited from the intelligent behaviour of honeybee swarm
[105]	BCO	Implements flight planning solution for Multi-UAVs networks	Executed based on RNA coding procedure and so creates a coding technique pool to improve global search capability
[106]	BCO	Implements to achieve efficient Node localization process in UAV networks	Deploys UAV anchors to reduce localization oversights
[107]	ACO	Optimizes energy consumption and efficient path planning for UAV collision avoidance	Uses pheromone enhancement technique to implement a gain function for efficient path planning
[108]	ACO	Implements cooperative mission planning for UAV swarm target attack	Deploys time-sensitive target probability map for determining targets
[109]	ACO	Resolves cooperative search attacks mission planning in Multi-UAV networks	Uses distributed control architecture to separates the global optimization problem into separate sets to implement

intelligence of bee's behavior in food search [111]. The difference towards other algorithms such as PSO and ACO is that the BCO algorithm relies on different roles that bees have in a colony. Hence, this algorithm may have a good applicability to the optimization of swarms encompassing drones with different roles.

In what concerns consensus algorithms, the goal is to allow the drone swarm to work as a logical group capable of withstanding the failures of some of its members [98]. Within the consensus algorithms, Paxos [98] remains the foundation frontier of consensus building in distributed networked devices. Paxos performs optimization process by defining peer-to-peer consensus based on single majority decision and ensuring that only one result is agreed upon. Peer nodes can suggest, lead and share equal responsibilities to achieve a resolution. Paxos is also deployed as trade-off to fault tolerance in distributed systems.

As an alternative to provide harmonization in distributed systems, the Raft algorithm [98] aims to decompose the consensus problem through sub-groupings. The number of sub-groups to considered are clarified through determinism thus limiting inconsistent incidences between logs. In these sub-groups, elected leaders take responsibility to manage replicated logs, accept log entries from clients and replicate to other servers together with a notification of when to apply the log entries to their machines. In Table 3.4, we detail sample consensus algorithms implemented based on Paxos and Ralf models to provide harmonization in distributed systems.

Table 3.4: Consensus-based

Ref.	Consensus	Performed Function	Technique Deployed
[112]	Paxos	Implemented to provide guaranteed consensus solution in distributed systems	Applies technique of flexible Paxos to reach consensus
[113]	Paxos	Provides a resolution to operational bottlenecks in consensus algorithms	Executes programmable network hardware to attain consensus service for requests
[114]	Raft	Solves inefficiencies and leader load balance issues, to enhance the stability of the algorithm	Uses Kbucket formed in the Kademlia protocol to influence the leader election process in the Raft algorithm, an approach seeking to improve the algorithm
[115]	Raft	Resolves message replication inconsistencies in blockchain networks	The Raft algorithm is enhanced through use of the Blockchain Hyperledger Fabric framework

3.5 Computing and Networking Integration

In drone swarms, the need to create a closed loop requires a tight coupling between the computational systems (i.e., drones) and networking system, which implies mutual influences and dependencies. Therefore, understanding such consolidated system effects is important to be able to make the best usage of the scarce resources that each drone may have to tackle with regards to sensing, computational, and networking tasks. Hence, below we discuss the dependencies on their integration and implications that both systems have on each other with regards to overall system performance.

3.5.1 Networking Supporting Computing

Intuitively, networking contributes to the computational system by setting up a network topology able to support the required data exchange between all drones in the swarm. The data required by the computational system is transported using the networking system, while the outcome of the computational system of each drone is usually shared with others through the networking system, in order to allow the overall system to reach consensus. Hence, the performance of the networking system may have a significant impact on the computational capability of the drone swarm, especially for tasks that require real-time data.

Based on a pure IP networking solution (e.g., typologies created and maintained by mobile ad hoc routing protocols), all drones need to know with which other drone they need to communicate in the process of a computational function (e.g., collision avoidance). This approach leads to a scalability and performance problem, due to the amount of state that each drone needs to store, and the time needed to update that state. Hence, one potential solution passes by using a networking system based NDN [116]. NDN relies on broadcasting of Interest packets to construct end-to-end connectivity between the networked drones that need the data and the nodes that have the data. However, a broadcast approach is not suitable for packet forwarding since it leads to resource wastage and scalability challenges. To this end, NFN proposed in [117], which is based on NDN, may be a good candidate to support swarms as an NCS system. In that case, since NDN is named-based, we form a basic premise with the assumption of an existing Name translation system capable of translating from name of data object to geo-coordinates of data holders to allow for routing Interest packets to specific destinations instead of flooding the entire network. Also, NFN has the capability to resolve computational functions while allowing the requester to be agnostic about the status of the drone swarm, which contributes to the self-organization properties of a swarm, since drones will only need to store local information. However, the usage of a networking system based on NFN would treat the drone swarm as a fully trusted entity, which may not be the case. Hence, an NFN-based drone swarm should be capable of transparently evaluating the results of every computational function [118].

3.5.2 Computing Supporting Networking

The computational system may enhance the networking system in several situations; for instance, several environmental information, such as altitude or terrain changes may lead to changes in the used channel models, which will have an impact in the performance of the networking system. In this scenario, the networking performance can be improved by the computational system since it can measure and model the wireless channel and classify that channel according to predefined rules.

Several research attempts have been conducted in an attempt to embed computation into a networking system aiming to improve the overall system performance. Instances of such intelligence algorithms (e.g., through P4-assisted constraint operations) [119] helps to mitigate the limitations brought by high latency and low transmission rates. These computational functions are normally focused on data plane operations such as aggregation of acknowledgement messages, better support for multicast, improved routing decision, scalability of forwarding depending on current conditions (e.g., link quality, drone mobility), reduction of the communication overhead in the whole system considering communication costs constraints.

In a drone swarm, and due to the potential hazards brought by the usage of wireless channels, communication security and data protection are significant for a successful deployment of drone swarms. Misbehavior and information leakage can lead to physical damage and endanger the operation of the swarm. In this context embedding computing in the swarm would allow the processing of traffic and data directly in the network and at line-rate. Hence, an integration of computational and networking systems creates the needed support for providing the needed security and privacy mechanisms, namely: first by supporting a mechanism for preventing attacks and intrusion; second for detecting intrusion and undesired behavior when it has already taken place; third, embedding computing in the network augments the swarm capacity for analyzing potential incidents, preventing future attacks.

By introducing a computational system, the decision-making process can help drones to better control their networking considering their own properties as well as the status of the environment.

3.6 Summary

Under this chapter, we presented applicability study of drone swarms, particularly drone swarms as an NCS. Developing drone swarms as NCSs is anticipated to assist in improving their performance when facing operational and environmental challenges. Hence, in that perspective this chapter seeks to contribute to a better understanding of the operation of drone swarms as NCSs. We started by providing an analysis of the topologies and technologies needed to implement two types of drone deployment strategies. Next, we provided a description of the two building blocks of any drone swarm, i.e., the networking and computational systems, and a thorough analysis of how to integrate them to achieve a self-organized swarm system. We ended up showing that building a networking system that does not rely on identifying hosts (e.g., drones) but rather computational functions, which can be deployed in any drone provides the baseline to tackle the major challenges identified for the development of drone swarms as networked control systems. Finally, by relying on a networking system able to resolve on-demand computation expressions composed of named data and functions in a transparent fashion to each drone contributes to the self-organization properties of a swarm.

Chapter 4

A Dynamic Clustering Mechanism With Load-Balancing for Flying Ad Hoc Networks

4.1 Introduction

In chapter 3, we presented background concepts on UAV-FANETs and their advancement into drone swarms, and highlighted two design considerations for drone swarm deployment. Then, we considered an applicability study on how to model drone swarms as a networked control system. In this chapter, we propose a new Dynamic Clustering Mechanism with Load-Balancing capable of providing sufficient support for large scale fault-tolerant routing performance in UAV-FANETs. While we maintain that UAV swarms have many applicability scenarios, it is obvious that the number of UAVs encompassed in a swarm network, as well as the way they are organized, have a direct impact on the usefulness of the FANET to deliver data with high probability, low latency, and low power consumption over large areas. Moreover, independently of the number of UAVs, the operation of FANETs come with significant challenges due to the dynamic topology, three-dimensional movement of UAVs, and intermittent wireless links [120], which previous studies have shown that these challenges lead to network instability and high energy and communication overheads [30]. To that effect, recent proposals aimed to tackle some of these challenges in isolation, such as trying to reduce energy consumption by predicting the trajectory of UAVs, or implementing bio-inspired routing protocols to improve the efficiency of data transmission [121]. Yet, such approaches fail to address the overall challenge of ensuring efficient data transmission in large scale FANETs, while ensuring low levels of delay, packet loss, and power consumption.

In such scenarios a cluster-based approach may allow the creation of large scale FANETs while reducing power and communication overheads, if such approach is able to adapt to the mobility patterns of UAVs and to properly balance traffic among suitable CHs. This is because such a clustering based approach may ensure a good end-to-end performance when associated with standard routing protocols

[61]. Though, some cluster-based solutions were proposed where CHs are selected based on Euclidean distance to ensure for efficient management of clusters [122], research findings show that selection of CHs using Euclidean distance produces poor routing performance mostly due to the noise associated with such measurements. Therefore, while keeping in mind the drawbacks of the existing methods, we argue in this chapter that the most suitable method to route packets with high performance and low cost in FANETs is based on a novel clustering and load balancing mechanisms between selected cluster nodes. Following that, we propose a new Dynamic Clustering Mechanism with Load-Balancing which is able to support large scale fault-tolerant FANETs by: (i) dynamically grouping nodes into clusters taking into account their mobility patterns, and (ii) balancing traffic between CHs and substitute cluster heads (SCHs) by taking into account buffer occupancy. The aim is to support standard routing protocols, within and between clusters, to achieve a high packet delivery probability, low end-to-end delay, and low power consumption via a clustering mechanism that can support large sums of successful transmissions between a large number of UAVs. The outcome of this proposal is the publication reported in Asaamoning et al. [48].

The remainder of this chapter is organized as follows. In section 4.2, we provide a description of the optimization algorithms that are used to devise the proposed solution. Section 4.3 provides a description of the different components of the proposed Dynamic Clustering Mechanism with Load-Balancing, namely the mobility aware dynamic clustering, and the entropy-based load balancing. In addition, section 4.3 also provides a brief description of the standard routing protocols that are used in this study to ensure end-to-end connectivity within and between clusters. In section 4.4, we describe the experimental setup and conducts a performance evaluation of the proposed mechanism. Finally, section 4.5 summarizes the findings of this chapter.

4.2 System Background

In this section, we introduce our new proposal for a dynamic clustering mechanism with load balancing based on two models namely a meta-heuristic optimization technique known as political optimizer used to solve optimization problems and a concept from Shannon entropy information theory used to provide insights as well as inferences into arbitrariness, particularly in complex networks.

Generally speaking, meta-heuristic optimization procedures may be split into four groups: swarm-based, evolution-based, social-based, and physics-based algorithms [123]. Recently, Askari et al. [124] proposed a new meta-heuristic method called Political Optimizer (PO) that was inspired by the multi-staged process of politics and described a model to solve global optimization problems. The PO algorithm is the mathematical mapping of all major stages of politics such as constituency allocation, party switching, election campaign, inter-party election, and parliamentary affairs. It has been shown that the PO algorithm can solve classical engineering design problems, such as welded beam and speed reducer design [124]. Furthermore, the algorithm has an outstanding convergence speed performance, and a good exploration proficiency in early iterations, which makes it suitable for the coordination of clustered networks.

The experimental evaluations of the PO algorithm [124] demonstrated that it outperformed the particle swarm optimization (PSO) [125] and Grey Wolf Optimizer (GWO) [126] algorithms in what concerns agents exploitative, and exploration and convergence capabilities. The PO algorithm is known to stimulate agents search discovery and utilization by offering the agents with multiple options to update their search positions by splitting the population into parties and constituencies, where each member has the privilege to hold double roles. In this sense, search agents can improve their positions while interacting with the two best constituency and party candidates. Secondly, most algorithms utilize global best position to update the outcome of search agents whereas it is proven that the PO algorithm employs two best solutions to explore for any possible update of the position of agents. Further, a distinctive property of the PO algorithm is that the best positions of the individual search agents are always saved and referenced for future position updating, allowing the utilization of the most recent positions of each agent to uncover the best search space regions. Additionally, the experimental results also prove that PO has strong convergence to its global optima, as it retains its excellent routines when function shifting is applied in high dimensional functions.

Table 4.1: Comparison of position updating mechanisms and metric appraisals

Position updating mechanism	PO	PSO	GWO
Use of subgroup best	Yes	No	No
Use of global best position	No	Yes	Yes
Use of randomly selected solution	Yes	No	No
Preservation of solution records	Yes	Yes	No
Collaboration of better solutions for further improvement	Yes	No	No
Metric Appraisal	PO	PSO	GWO
Exploration ability	Good	Normal	Good
Exploitative ability	Good	Normal	Weak
Ability to avoid premature convergence	Normal	Weak	Average
Convergence speed	Fast	Slow	Slow
Capacity to converge on global best	Strong	Weak	Weak

In Table 4.1, presents the comparison of position updating mechanisms and metric appraisals by Askari et al. [124], which illustrate the advantages of the PO algorithm over other meta-heuristic methods.

In that regard, our dynamic clustering mechanism is based on the PO algorithm. The PO process assumes that politicians always seek to optimize two different approaches: (i) each candidate aims to optimize its goodwill to win the election; (ii) each party aims to garner enough parliamentary seats. The algorithm consists of five stages: party formation and constituency allocation, election campaign, party switching, inter-party election, and parliamentary affairs. Such five phases are further divided in the following eight steps: (1) Population initialization, with the creation of different political parties and different constituencies; (2) Members of different political parties conduct activities within their constituency; (3) Party leaders and constituency winners are determined; (4) The positions of party members is updated according to the constituency winners; (5) The positions of party members is updated according to the party leaders; (6) The resultant positions are synthesized according to the position of the constituency winners and the party leaders; (7) Switching of parties between constituencies; (8) Election phase and reassign party leaders and constituency winners.

In a FANET scenario, the representatives of each constituency or otherwise the cluster, (i.e., CHs and SCHs) will divide the traffic load of their cluster. In the proposed solution, load balancing between CHs and SCHs is achieved by using a Shannon entropy algorithm.

The Shannon entropy is a widely known information theory concept used for providing insights into inferences of arbitrariness particularly in complex networks, physics, statistics, and dynamic systems [127]. Entropy is projected as a measure of diversity, disorder and uncertainty. Its probability distribution can be realized as a measure of uncertainty or randomness. For instance, to decide on differences or variations in the population of a given entity, entropy defines and incorporates diversity information, which allows for a study to be conducted to filter out the differences in the multi-paired elements, on which foundation a trade off on collaboration can be reached.

4.3 System Description

This section details the two building blocks used to defined the Dynamic Clustering Mechanism with Load Balancing, namely the mobility aware dynamic clustering mechanism and the entropy-based load-balancing mechanism. Towards the end of this section, we provide a brief description of the two standard routing algorithms that are considered in this study to drive the intra-and inter-cluster communication.

The overall goal is to keep the FANET network structured in a way that it allows an efficient routing of data packets between any pair of UAVs, or between UAVs and a base station on the ground, while improving performance parameters such as delivery probability, delay as well as power consumption. It is assumed that each UAV knows its position by means of a GPS and is able to communicate by means of an omni-directional radio frequency system.

Figure 4.1 illustrates the architecture of our proposed solution, in which UAVs deployed in a certain geographical area are grouped into clusters. Each cluster has two representatives that are elected by means of a PO algorithm. Such representatives, CHs and SCHs share the traffic load in their cluster(s) by means of a Shannon entropy function while serving as cluster gateways. The selected set of gateways (i.e., CHs) are able to communicate between them and with a set of base station(s) deployed on the ground and with the UAVs in their own clusters by means of an inter- and intra-cluster routing protocols, respectively.

4.3.1 Mobility Aware Dynamic Clustering

The proposed clustering mechanism aims to divide the network into separate groups of UAVs. In the current implementation, this algorithm is executed in a ground station based on information collected from each UAV, namely position (U_p), speed (U_s), moving direction (U_d), height variation (U_h), and link quality (U_L). Each deployed UAV is configured with the information about the geo-position of the ground station. Hence, throughout the lifespan of the network, the UAVs utilize a geo-position routing protocol to

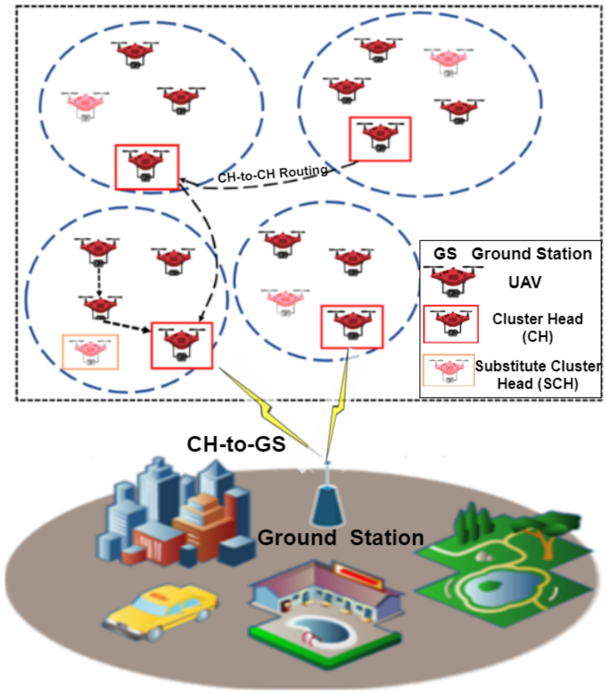

Figure 4.1: Architecture of proposed solution

periodically update the ground station with information on their current position, speed, direction, height variation, and link quality. The usage of the proposed routing mechanism allows us to minimize used bandwidth, in comparison to using a simpler broadcast communication method. After providing this information, every individual UAV participates in the election process and a fitness value is computed for each UAV based on the number of votes that it gets by running the PO-based mobility aware dynamic clustering algorithm. The election process results in the election of a CH and an SCH per cluster as shown in Figure 4.2.

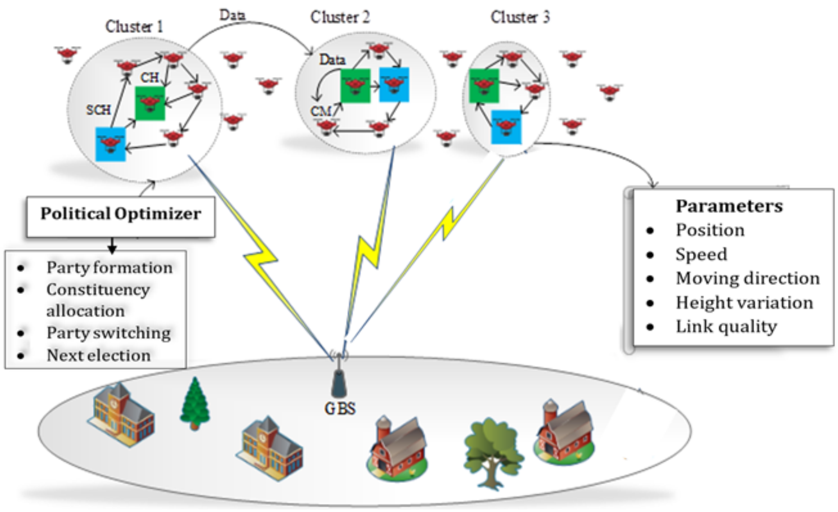

Figure 4.2: Mobility Aware Dynamic Clustering

The Mobility Aware Dynamic Clustering mechanism periodically starts by collecting updated information from each UAV, as previously stated. To this, the collected information is used to divide the UAV population ρ into n different parties based on similarities, which can be represented as Eq (4.1),

$$\rho = \{\rho_1, \rho_2, ..., \rho_n\} \tag{4.1}$$

Each party ρ_i comprise of m_i members (i.e., UAVs) as shown in Eq. (4.2),

$$\rho_i = \{p_i^1, p_i^2, ..., p_i^n\} \tag{4.2}$$

Each j^{th} party member denoted as p_i^j is considered as a potential solution consisting of a d-dimensional vector, where d is the number of input variables of the problem to be solved as expressed in Eq. (4.3),

$$p_i^j = [p_{i,1}^j, p_{i,2}^j, ..., p_{i,d}^j]^T \tag{4.3}$$

After this, the position information of each UAV is used to collocate the different parties in a set of 3D dimensional spaces, which correspond to the number of constituencies in the PO process as expressed in Eq (4.4),

$$c = \{c_1, c_2, ..., c_n\} \tag{4.4}$$

Every party member plays dual roles: being a member and a potential candidate for an election. Thus, if the j^{th} member of each party in the j^{th} constituency (c_j) participates in an election, then the winner is expressed as,

$$c_j = \{p_1^j, p_2^j, ..., p_n^j\} \tag{4.5}$$

After the election, the fittest member of a party is selected as the party leader, as is expressed in Eq. (4.6), where p_i^* designates the leader of the i^{th} party and $f(p_i^j)$ calculates the fitness of p_i^j expressed as,

$$p_i^* = p_i^q \quad \text{where} \quad q = \underset{1 \leq j \leq n}{\operatorname{argmin}} f(p_i^j), \;\; \forall i \in \{1, ..., n\} \tag{4.6}$$

The collection of the group of all party leaders denoted by ρ^* is as presented in Eq. (4.7),

$$\rho^* = \{p_1^*, p_2^*, ..., p_n^*\} \tag{4.7}$$

The winners from all constituencies are known as parliamentarians. Hence, the group of all parliamentarians from the various constituencies is denoted by c^* and expressed as,

$$c^* = \{c_1^*, c_2^*, ...c_n^*\} \tag{4.8}$$

At this stage, denoted as election campaign phase, the party and constituency leaders seek to influence their performance in the next election by using Eq. (4.9) and Eq. (4.10), which are mathematically modeled based on a position updating strategy to give insights on the previously held election from which candidates can harness to further improve the positions of party and constituency leaders. These equations are interchangeably used by assessing current and previous fitness values of a candidate. For instance, if the current fitness of the candidate is $f(p_i^j(t))$ represents an improvement and its past fitness was $f(p_i^j(t-1))$ represents a decline, first the position of the candidate is updated with reference to the party leader p_i^* and next with reference to the constituency winner c_j^*. Please note that Eq. (4.9) and Eq. (4.10) are used to compute the gain and lose of fitness, respectively. In these equations, t denotes iteration, k denotes dimension (i.e., location described in orthogonal axes), whereas r is a random number in the range [0,1] and s^* denotes the position of either the party leader $p_{i,k}^*$ or the constituency winner $c_{j,k}^*$ in k^{th} dimension.

Therefore, to begin the process of updating positions on p_i^* and c_j^*, the current fitness of p_i^j is evaluated with respect to its previous fitness based on the following condition: $f(p_i^j(t)) \geq f(p_i^j(t-1))$. If the last condition holds, Eq. (4.9) is initially used to update the position with respect to the party leader p_i^* of the i^{th} party, in which case we substitute $p_{i,k}^j$ into s^*, inputs for k and r effected, and then substitute $p_{i,k}^j(t)$ into $p_{i,k}^j$ to compute the position update on party leader. After that, Eq. (4.9) is used to update the position with respect to winner of the j^{th} constituency c_j^* expressed based on Eq. (4.12) where the winner of the j^{th} constituency is the representative of the i^{th} party. Hence, $c_{j,k}^i$ is substituted into s^* and values of r and k respectively updated and the substitution of $p_{i,k}^j$ into $p_{i,k}^j(t+1)$ accordingly made to compute position update on constituency winner. However, if the above mentioned condition of the evaluation with respect to the current and previous fitness values is false, Eq. (4.10) is used for the computation, following a similar set of considerations.

$$p_{i,k}^j(t+1) = \begin{cases} s^* + r(s^* - p_{i,k}^j(t)), \text{ if } p_{i,k}^j(t-1) \leq p_{i,k}^j(t) \leq s^* \; or \; p_{i,k}^j(t-1) \geq p_{i,k}^j(t) \geq s^*; \\ s^* + (2r-1)|s^* - p_{i,k}^j(t)|, \text{ if } p_{i,k}^j(t-1) \leq s^* \leq p_{i,j}^j(t) \; or \; p_{i,k}^j(t-1) \geq s^* \geq p_{i,k}^j(t); \\ s^* + (2r-1)|s^* - p_{i,j}^j(t-1)|, \text{ if } s^* \leq p_{i,k}^j(t-1) \leq p_{i,k}^j(t) \; or \; s^* \geq p_{i,k}^j(t-1) \geq p_{i,k}^j(t); \end{cases} \tag{4.9}$$

$$p_{i,k}^j(t+1) = \begin{cases} s^* + (2r-1)|s^* - p_{i,k}^j(t)|, \text{ if } p_{i,k}^j(t-1) \leq p_{i,k}^j(t) \leq s^* \; or \; p_{i,k}^j(t-1) \geq p_{i,k}^j(t) \geq s^*; \\ p_{i,k}^j(t-1) + r(p_{i,k}^j(t) - p_{i,k}^j(t-1)), \text{ if } p_{i,k}^j(t-1) \leq s^* \leq p_{i,k}^j(t) \; or \; p_{i,k}^j(t-1) \geq s^* \geq p_{i,k}^j(t); \\ s^* + (2r-1)|s^* - p_{i,j}^j(t-1)|, \text{ if } s^* \leq p_{i,k}^j(t-1) \leq p_{i,k}^j(t) \; or \; s^* \geq p_{i,k}^j(t-1) \geq p_{i,k}^j(t); \end{cases} \tag{4.10}$$

To form clusters for the election of stable and reliable CH and SCHs, a fitness evaluation value $f(p)$ is computed based on metrics on each UAV which is used to divide them into clusters (constituencies). For dynamic scenarios such as UAV-based FANET, the fitness value is calculated based on the characteristic input parameters of each UAV's position (U_p), speed (U_s), moving direction (U_d), height variation (U_h) and the link quality (U_L) towards the base station as shown in Eq. (4.11),

$$f(p) = \{U_p, U_s, U_d, U_h, U_L\} \tag{4.11}$$

The next step is party switching also known as balancing, exploring and exploitation. Here, an adaptive parameter γ is used, which is linearly decreasing from one to zero during the entire iterative process.

This parameter is termed as the party switching rate, allowing every UAV selected with probability γ to exchange with the member of a randomly selected party.

In the election phase, the fitness of all constituency candidates participating in an election is evaluated. For instance, the fitness of all candidates participating in the j^{th} constituency is evaluated, and the fitness value of the winner expressed as,

$$c_j^* = p_q^j, \qquad \text{where} \quad q = \underset{1 \leq i \leq n}{\operatorname{argmin}} f(p_i^j) \tag{4.12}$$

The party leader and constituency winner are respectively expressed based on Eq. (4.6) and Eq. (4.12).

Based on the winners of each of the constituencies, i.e., the representatives called members of parliament in the PO algorithm, clusters are formed and the first two winners in each constituency are selected as CH and SCH for each cluster. This election process is done based on several properties of each UAV, such as energy level (N_e), buffer state (N_b), distance towards a base station (N_d), distance towards representatives of other constituencies (N_c), and link quality (N_l), as expressed in Eq. (4.13). The distance from an UAV towards a base station can be obtained by using a probe mechanism, such as pinging the IP address of known base station(s),

$$CH = \{N_e, N_b, N_d, N_c, N_l\} \tag{4.13}$$

After the election, the selected SCHs are used to balance traffic load in their clusters in cooperation with the local CHs, using an entropy-based mechanism described in the next section. At the end of the election process, the base station broadcasts the election result to all network members. Algorithm 1, presents the pseudo-code for the mobility-aware clustering mechanism.

4.3.2 Entropy-Based Stable Load Balancing

Cluster members (CM) communicate with nodes outside the cluster through the CH. Each CH aggregates packets from member nodes and routes them to the CH of the cluster where the destination node is located. In situations in which the cluster has a large number of nodes or when the existing nodes generate a large amount of traffic, there is the possibility of overloading the buffer of the CH, resulting in increased latency and unwanted re-transmission of packets. In order to avoid such situation, a load balancing mechanism is implemented to split the traffic between the CH and the SCH, as illustrated in Figure 4.3. The proposed load balancing mechanism is based on the Shannon entropy function.

Shannon entropy gives the concept of information loss that is convex-linear and continuous. The function of entropy equation in Eq. (4.14), has S which denotes a measure of choice in a probability density function $S(l)$, c denotes a constant random variable that is a measure of uncertainty associated with a random variable l whose value l_i is p_i, where i is assumed to be in the range $(1, 2, ...n)$. Whereas, L represents the current load of the node, p_i denotes the probability of l_i. Hence, entropy S of l can be expressed as follows,

Algorithm 1: Mobility Aware dynamic clustering

```
Input: (U_p, U_s, U_d, U_h, U_L), Population (ρ)
Output: Clusters
Initialize ← U_p, U_s, U_d, U_h, U_L, and ρ based on Eq. (4.1) to Eq. (4.5)
for every UAV do
    Compute U_p, U_s, U_d, U_h, U_L, based on Eq. (4.11)
    Compute fitness of each member p_i^j based on Eq. (4.6)
    Calculate the set of party leaders ρ* based on Eq. (4.7)
    Calculate the set of constituency winners c* based
    on Eq. (4.12) and Eq. (4.8)
    t = 1;
    ρ(t − 1) = ρ;
    f(ρ(t − 1)) = f(ρ);
    γ = γ_max;
    while t ≤ T_max, do
        ρ_temp = ρ;
        f(ρ_temp) = f(ρ);
        for each ρ_i ∈ ρ do
            for each p_i^j ∈ ρ_i, do
                p_i^j =ElectionCampaign(p_i^j, p_i^j(t − 1), p_i^*, c_j^*);
        Party Switching (ρ, γ);
        Evaluate and save fitness values for each member
        Calculate the set of constituency representatives c*
           based on Eq. (4.12) and Eq. (4.8)
        Parliamentary Affairs (c*, ρ);
        ρ(t − 1) = ρ_temp;
        f(ρ(t − 1)) = f(ρ_temp);
        γ = γ − γ_max/T_max;
        t = t + 1;
    //Cluster head selection
    Initialize clusters ← N_e, N_b, N_d, N_c, N_l
    for each cluster member, do
        Compute N_e, N_b, N_d, N_c and N_l,
        based on Eq. (4.13)
        Select CH
        Select SCH // substitute cluster head
```

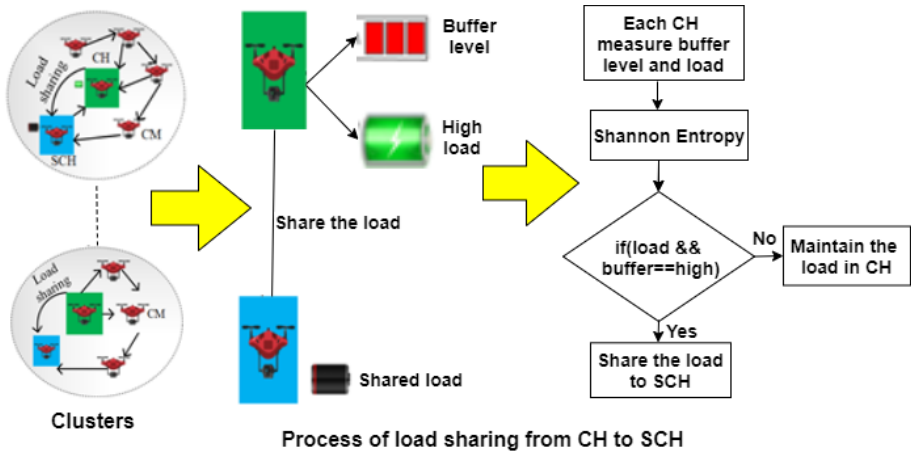

Figure 4.3: Entropy based Load Balancing

$$S(l) = -c\Sigma_{l\epsilon L} P_{i-Th}(l) log P_{i-Th}(l) \tag{4.14}$$

Eq. (4.15) represents the improved form of the Shannon entropy to a random variable, where B represents the buffer state of the current CH. The Shannon entropy function generates the threshold value based on the current load and buffer state of the CH. Suppose the load and buffer exceed the threshold value. In this case, the extra load is shared with the SCH. This decision is broadcast in the cluster, allowing sources to diverted traffic and start sending packets to SCH, resulting in stable load balancing and reducing the overhead caused due to the buffer overload.

$$S(l,b) = -c \sum_{l\epsilon L} \sum_{b\epsilon B} P_{i-Th}(l,b) log P_{i-Th}(l,b) \tag{4.15}$$

The overall pseudo-code process to balance traffic load of a cluster between the CH and the SCH is as shown in Algorithm 2.

Algorithm 2: Load Balancing

Input: No. of cluster heads $(CH_1, CH_2, ...CH_n), L, B$
Output: Balancing load
Initialize $\leftarrow (CH_1, CH_2, \ldots CH_n), L, B$
for *each node* **do**
  Get L, B
  Compute threshold based on Eq. (4.15)
  if *($L \&\& B >$ Threshold)* **then**
    Load is shared with SCH

4.3.3 Routing

As previously stated, this work investigates the hypothesis that the proposed Dynamic Clustering Mechanism with Load Balancing can be used with standard routing protocols within and between clusters. Here, we provide a brief description on how to route packets within and between clusters following a position-based routing approach.

The basic assumption is that UAVs know their own geographical position and periodically exchange information with their neighbors. Elected CHs and SCHs identify themselves as such in these periodic broadcasts. In our study, it is also assumed that nodes have updated information about the geographic position of destination nodes. Please note that this is a basic assumption of position based routing protocols where a system is usually defined to keep the geo-position information up to date [128].

In our implementation, intra-cluster routing is facilitated by a simple rank-based algorithm used to allow nodes to broadcast data packets towards a destination node. Such data packets include the position of the destination node. After receiving data packets, nodes calculate their ranking based on the length of their packet queue Q_l, their speed N_s, location N_l, direction N_d, the minimum of their distance towards the CH/SCH D_c and the destination D_d. The computed rank is used to configure a random time slot duration equal to the length of the packet required for transmitting the packet by the overheard node. This process helps to reduce the bandwidth usage. Higher reliability is easily achieved by allowing a certain number of nodes to transmit packets even after overhearing a configured number of transmissions.

If the destination is in another cluster (i.e., the destination is faraway from the closest CH), packets are sent to the CH or SCH. At this point a position-based routing protocol is used to forward packets between CHs until they reach the CH that is closest from the destination node. In this work, we consider a Geographic Perimeter Stateless Routing (GPSR) based protocol, since it is widely adopted for vehicular networks [129]. In the operation of this protocol, every node maintains the knowledge of its one-hop neighbors. Each node (i.e., CHs and SCHs) participating in the routing process selects as next-hop, the CH or SCH that is nearest to the destination. The locations of neighbors are obtained by exchanging periodic messages among nodes, as mentioned before.

When packets reach the CH or SCH that is closest to the destination, as a results of the inter-cluster routing process, they are routed inside the destination cluster towards the position of the destination based on the ranking algorithm.

4.4 Performance Evaluation

In this section, we perform an evaluation of the proposed Dynamic Clustering Mechanism with Load-Balancing (DCM with Load-Balancing) aiming to demonstrate its effectiveness in terms of increasing the percentage of covered UAVs as well as the number of end-to-end transmissions over a set of created clusters. The performance of the proposed mechanism is compared with the Stable Clustering Scheme (SCS) algorithm [34], which is a location-based K-means clustering mechanism integrated with the mobility and relative locations of UAVs to enhance performance. First, the location and mobility of UAVs are used to optimize deployment for maximum coverage performance by ensuring no UAV fields are overlapped with another while making sure that each UAV is attached to an identified CH. Cluster creation and maintenance is performed using K-means clustering approach followed by election of CHs. The overall goal is to strengthen the network performance and reliability.

Even if a clustering mechanism is able to cover a large percentage of deployed UAVs, the characteristic of the created clusters (e.g., diameter, density, and the average distance between UAVs) has a significant impact on data transmission in the FANET. Hence, besides evaluating the performance of the proposed mechanism, our aim is also to assess the usefulness of the created clusters, i.e., the elected CHs and SCHs, in supporting a successful routing in terms of packet delivery probability, end-to-end delay and power consumption.

To analyze how efficient clusters are created and maintained by the proposed mechanism in support of the process of routing packets end-to-end, we compare the performance of an intra- and inter-cluster position-based routing scheme (c.f. Section 4.3.3) with state-of-the-art routing solutions, namely the Energy-Efficient Opportunistic Routing (EEOR) protocol [57] and the Smart IoT Control-Based Nature Inspired Energy Efficient Routing (NIEEOR) protocol [58]. Whereas, the EEOR algorithm considers the prediction of UAV location based on node trajectory metrics before performing routing aiming to reduce packets' re-transmissions and energy spending, the NIEEOR algorithm introduced an energy stabilizing limit with the goal to select only nodes with higher energy levels than the identified threshold as relay nodes aiming to improve network QoS.

The performance evaluation is done based on simulations carried out on the NS-3 simulator[1] to analyze various performance metrics. Communications were performed using the 2.4 GHz frequency range of the IEEE 802.11n standard [130] under the Rayleigh channel model, used to calculate the channel fading characteristics. The simulation area is set to $1000m \times 1000m \times 880m$ with one ground base station for bi-direction communication, while UAVs are placed in 3D spaces. Their mobility is based on random way point (RWP) movement model. To get the most realistic setting for nodes progressive speed variations and direction, the JAVA code for RWP model was imported to enable the setting of moving parameters on the UAVs [57]. The simulation area was chosen to reflect the performed scenario of an increasing number of UAVs between 10 and 100. Our assumption is that the benefits of clustering are not so evident for smaller networks. The packet size is set to 600 bytes with an overall simulation time of 100 seconds. We provide a summary of the system configuration, as well as the parameters used in the simulations in Table 4.2 and Table 4.3, respectively.

Table 4.2: System Configuration

Hardware Specification	Processor	Pentium Dual Core and Above
	RAM	8GB
	Hard Disk	60GB
Software Specification	Simulation Tool	NS-3 (version 3.26)
	Operating System	32-bit Ubuntu 14.4 LTS

4.4.1 Percentage of covered UAVs

The percentage of covered UAVs is an important metric for measuring the efficiency of a clustering process, since it is influenced by the parameters considered for the formation of clusters. In this context

[1] https://www.nsnam.org/

Table 4.3: Simulation parameters

Parameters	Description
Simulation area	$1000m \times 1000m \times 880m$
Number of UAVs	10-100
Number of ground base station	1
Data rate	36 Mbps
Size of a message packet	600 bytes
Time to live	3h
Mobility	Random waypoint
Speed	30-50 m/s
Channel model	Rayleigh model
Transmission radius	1000m
Simulation time	100s
Transmission latency	20ms
Bandwidth	1MHz
GPS file	Route1.gps, route3.gps
Maximum energy	20250 J
Message interval	20ms-30ms

Figure 4.4 shows the results of a comparison of DCM with Load-Balancing and SCS with respect to the number of clusters that are created when facing an increasing number of UAVs.

As showed in Figure 4.4 the proposed mechanism covers a higher number of UAVs than SCS, being able to cover all deployed UAVs with twenty clusters, while with SCS the same number of clusters only cover 80$\%$ of all UAVs. The better performance of the DCM with Load-Balancing scheme is due to its mobility awareness based on factors such as position, speed, moving direction, height variation, and link quality.

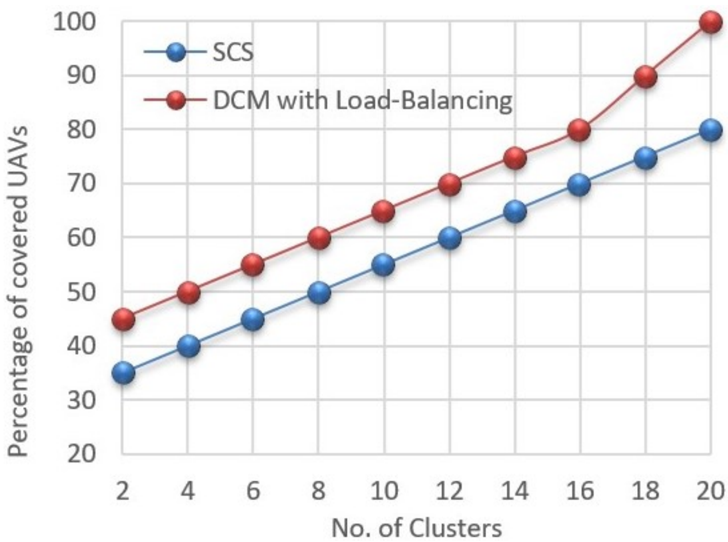

Figure 4.4: Number of clusters vs. Percentage of covered UAVs

Table 4.4 presents the numerical comparison between the DCM with Load-Balancing and the SCS clustering mechanism in what regards the percentage of UAVs that are covered by the formed clusters. Our approach covers an average of 70% of UAVs, whereas the SCS approach covers only 57% of UAVs. The main reason for this difference is the fact that the SCS approach implements a K-means clustering approach in which the number of clusters needs to be determined a priori. This makes SCS unable to react swiftly to the dynamic topology of UAVs resulting in inefficient clustering.

Table 4.4: Analysis of Percentage of covered UAVs

Technique	Average percentage of covered UAVs
SCS	57.5±3
DCM with Load-Balancing	70.2±1

4.4.2 Number of end-to-end transmissions

The number of supported end-to-end transmissions is an essential metric used to determine the efficiency of a clustering process. A higher number of end-to-end transmissions reflects the efficiency of the clustering process in supporting the forwarding of data packets from source to destination, in what concerns potential bottlenecks between clusters.

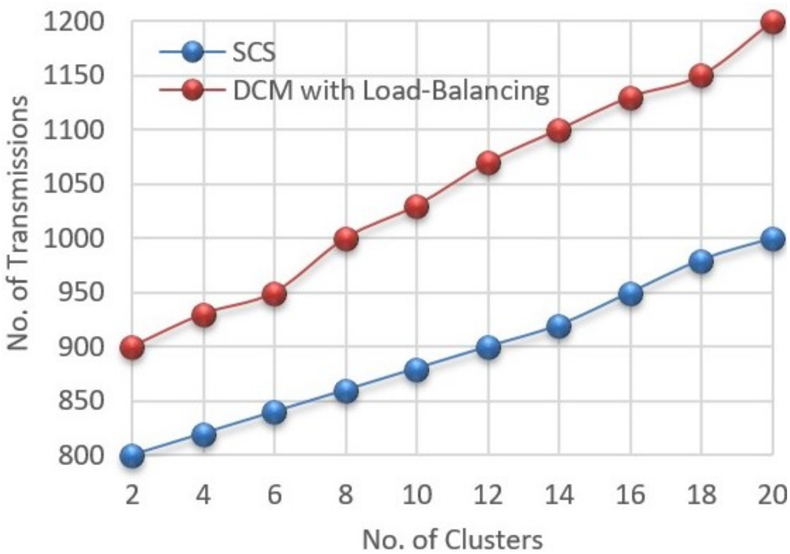

Figure 4.5: Number of clusters vs. Number of transmissions

As illustrated in Figure 4.5 a higher number of end-to-end transmissions are achieved when clustering the network based on the DCM with Load-Balancing approach when compared to SCS. This higher number of transmissions is due not only to the PO clustering process, but mostly to the election of CHs and the usage of the entropy-based scheme to balance the load between the elected CH and SCH. The proposed entropy-based load balancing mechanism helps to ease the limitations brought by network instability and by the potential congestion of CHs. On the other hand, the SCS approach performed K-means clustering, which does not address the dynamic topology of flying networks, resulting in congestion, which further reduces the number of transmissions.

Table 4.5 provides the numerical comparison of the number of transmissions achieved when the DCM

Table 4.5: Analysis of Number of transmissions

Technique	Number of transmissions
SCS	895.2±3
DCM with Load-Balancing	1046.8±1

with Load-Balancing and SCS approaches are used. The former is capable of supporting an increased number of transmissions up to an average of 1046 transmissions, whereas the SCS approach is able to sustain only an average of 895 transmissions mostly due to its incapability of balancing loads between clusters. The higher number of successful end-to-end transmissions supported by the DCM with Load-Balancing approach contributes to the efficiency of the routing process as shown in the analysis of packet delivery ratio, end-to-end delay and power expending performed in the following subsections.

4.4.3 Packet delivery ratio

The packet delivery ratio is the ratio between the total number of packets received by the destinations and the total number of packets transmitted by the sources. A higher packet delivery ratio denotes a good routing performance.

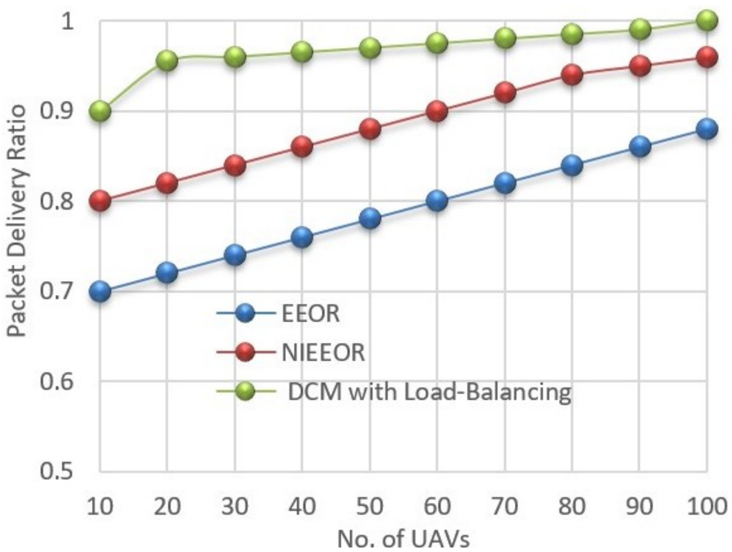

Figure 4.6: Number of UAVs vs. Packet delivery ratio

In this sense, Figure 4.6 illustrates the efficiency of the position-based routing strategy supported by the DCM with Load-Balancing mechanism in comparison with the EEOR and NIEEOR routing protocols. Figure 4.6 shows that while the EEOR and NIEEOR routing protocols have a similar performance when facing an increasing number of UAVs (with a differential of circa 10%), routing packets with the DCM with Load-Balancing mechanism is capable of achieving a higher percentage of delivered packets even with a small number of deployed UAVs: from 90% with only 10 UAVs to close to 100% with 70 UAVs. These results show that an efficient clustering and load balancing procedure can support a good performance of simple routing protocols such as the ranking intra-cluster and the geographical inter-cluster routing considered in this study. On the other hand, performing routing over the complete network by using the EEOR and NIEEOR routing protocols results in a reduced packet delivery ratio mostly due to the inefficient convergence, which implies a scalability issue that is shown to be mitigated by clustering the network.

Table 4.6: Analysis of Packet delivery ratio

Technique	Average packet delivery ratio
EEOR	0.79 ± 0.05
NIEEOR	0.887 ± 0.03
DCM with Load-Balancing	0.968 ± 0.02

Table 4.6 provides the numerical comparison of the average packet delivery ratio when the routing process is based on the proposed DCM with Load-Balancing mechanism, as well as when the EEOR and NIEEOR routing protocols are used to route packets, in respect to number of UAVs. Table 4.6 shows that with a network varying from 10 to 100 UAVs, routing based on the proposed DCM with Load-Balancing mechanism achieves an average packet delivery ratio of 97%, which is 9% and 18% higher than using the NIEEOR and the EEOR routing protocols, respectively.

4.4.4 End-to-end delay

The end-to-end delay corresponds to the total time needed to transmit a packet between a source and a destination. Figure 4.7 illustrates the average end-to-end delay achieved when routing packets based on our proposed mechanism, as well as the NIEEOR and the EEOR routing protocols. As shown, the average end-to-end delay increases linearly with the number of UAVs when the NIEEOR and the EEOR routing protocols are used. This is mostly due to the fact that such approaches perform routing by considering only the energy and speed without considering hop count, resulting in increased end-to-end delay.

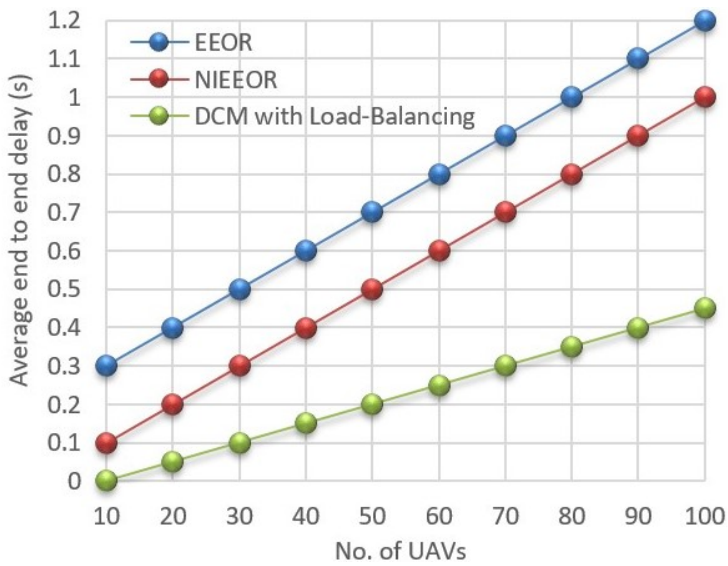

Figure 4.7: Number of UAVs vs. Average end-to-end delay

When using the proposed mechanism, the average end-to-end delay increases with the number of deployed UAVs, but with a smaller factor than when the NIEEOR and the EEOR routing protocols are used. On the one hand, this is due to the execution of a mobility-aware clustering and the selection of CHs based on link quality. On the other hand, the good performance of routing based on the proposed DCM with Load-Balancing mechanism is due to the usage of an inter-cluster routing protocol only between a reduced number of UAVs (CHs and SCHs), thereby contributing to the reduced end-to-end delay.

Table 4.7: Analysis of Average end-to-end delay

Technique	Average end-to-end delay in seconds
EEOR	0.75$\pm$ 0.3
NIEEOR	0.55$\pm$ 0.2
DCM with Load-Balancing	0.225$\pm$ 0.1

The numerical comparison of the end-to-end delay obtained with a routing protocol incorporated with the proposed mechanism, as well as the NIEEOR and EEOR routing protocols is presented in Table 4.7. The average end-to-end delay of our approach is as low as 0.225 seconds, whereas the NIEEOR and EEOR protocols may reach average end-to-end delays exceeding 0.55 seconds.

4.4.5 Power consumption

The power consumption of UAVs is an important metric to be considered to validate the energy efficiency of a clustering approach. Therefore, an efficient clustering approach should be capable of creating clusters that allow UAVs to communicate without spending a lot of energy, for instance, by grouping UAVs that are at a close distance from the CH.

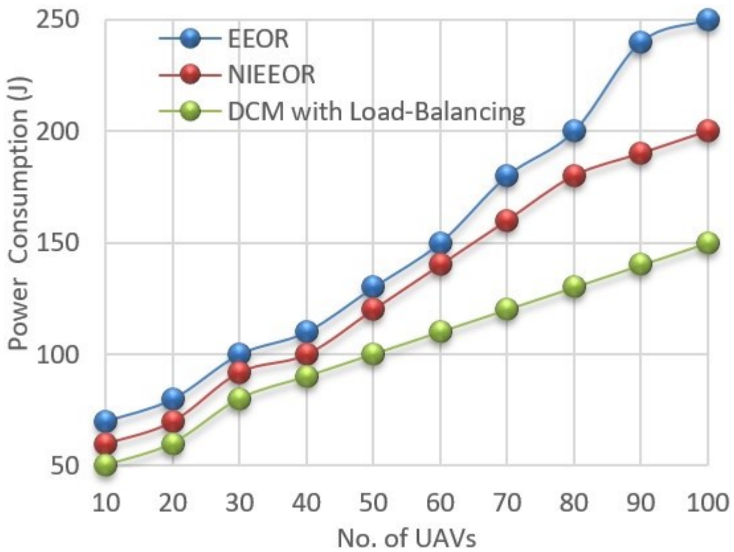

Figure 4.8: Number of UAVs vs. Power consumption

In this context, Figure 4.8 shows the power consumption encompassed in data transmission activities with an increasing number of UAVs. Here, the position-based routing scheme incorporated with the proposed DCM with Load-Balancing mechanism is also compared with the EEOR and NIEEOR routing protocols.

The power consumption involved in data transmissions in a network clustered with the DCM with Load-Balancing mechanism is much lower than when using the the EEOR and NIEEOR routing protocols. The major reason for the higher power consumption of the EEOR and NIEEOR protocols is related to the high number of re-transmissions due to a low packet delivery ratio and a high packet drop count. On the other hand, the DCM with Load-Balancing mechanism supports routing with a lower number of re-transmissions due to its awareness of UAV's mobility. Moreover, the increased power consumption of EEOR and NIEEOR protocols reduces the network lifetime, hence its usefulness.

Table 4.8: Analysis of Power consumption

Technique	Average power consumption in Joules
EEOR	151$\pm$5
NIEEOR	131.2$\pm$3
DCM with Load-Balancing	103$\pm$ 2

Table 4.8 presents the numerical comparison of the average power consumption of our approach, and the EEOR and NIEEOR routing protocols. The average power consumption when the DCM with Load-Balancing mechanism is used is of about 103 J. In contrast, the EEOR and NIEEOR routing protocols consume an average of 151J and 131J, respectively. These findings show that our approach can support data transmission in FANETs with a higher energy-efficiency than just applying existing routing protocols over the complete network.

4.5 Summary

In this chapter, we presented a new Dynamic Clustering Mechanism with Load-Balancing aiming to tackle the challenges faced by UAV-FANETs, namely frequent wireless disconnections, intermittent available nodes, and dynamic topologies, mostly when facing an increasing number of deployed UAVs. To address these challenges our proposed solution ensures efficient dissemination of data packets in FANETs by dynamically grouping UAVs into clusters using a Political Optimizer algorithm to address topology and UAV mobility challenges while an entropy-based function implemented to balance traffic loads between cluster heads and secondary cluster heads to address overall network fault tolerance and traffic overload concerns. To that end, by combining our solution with standard position-based routing protocols our model is capable of providing sufficient support for efficient dissemination of data packets in large FANETs while ensuring exceptional wireless reliability and scalability factors. Through simulation results, we showed that our proposed Dynamic Clustering Mechanism with Load-Balancing ensures an efficient clustering process by covering in average 70% of UAVs, while at the same time recording an average packet delivery ratio of 97%, which is 9% and 18% higher than the compared state-of-art mechanisms namely the NIEEOR and the EEOR routing protocols, respectively.

Chapter 5

A Position-based Hybrid Routing Protocol for Clustered Flying Ad Hoc Networks

5.1 Introduction

In chapter 4, we implemented a new dynamic clustering and load-balancing mechanism to address FANET's clustering and traffic load-balancing challenges. Nonetheless, due to technological advances and the increasing research interest in UAV-FANET use-case scenarios, their applicability scope keeps expanding. This trend thus, require further investigation of methods capable of handling the diverse unique characteristics of UAV-FANETs so as to ensure for their successful utilization [131]. To this end, having deeply conducted a thorough research analysis and comparison of the performances and requirements of the existing routing strategies in FANETs together with exploring methods in the literature for FANETs efficient operation in section 2.5, it was observed in the analyzed studies [44]—[47] that position-based routing strategies poses exceptional factors capable of providing adequate support in addressing the most significant challenges of reliability, stability, scaling and fault-tolerant factors faced in UAV-FANETs. Further, the study conducted by S. Rosati et al. [49] revealed that position-based routing protocol's require information provisioning about the location of network nodes in order to estimate the shortest distance to the destination node, which helps in choosing the next hop-node to facilitate in packet forwarding. In that regard, GPS technology equipped on-board each UAV could be utilized to provide the location information. Thus, based on the outcome of the analyzed factors, we believe that the design and implementation of routing strategies utilizing position-based methods shall provide the requirements necessary to support the proper operation of cluster-based UAV-FANETs. Hence, we hypothesize in this chapter that the best approach to ensure scalable and inter-operable solution in clustered FANETs is to exploit different routing protocols to be used within clusters while inter-cluster routing which encompasses several CHs performed using a combination of greedy position-based and the right-hand rule approaches for the benefit of a robust and scalable network. Our proposed solution is independent of any cluster mechanism and so can be implemented in any cluster-based FANET. We believe that our solution is novel because, to the best of our knowledge, this is the first attempt seeking to tackle the intrinsic FANET challenges through the implementation of a Position-based Hybrid routing solution for clustered FANETs, which work has been submitted to a journal.

The rest of this chapter is organized in the following: Section 5.2 introduces the concepts and technology used for developing our new protocol. Section 5.3 presents the description of the proposed Position-based Hybrid routing protocol and how end-to-end communication can be achieved. Section 5.4 presents the simulation and the performance evaluation of the proposed routing approach. Finally, section 5.5 presents the summary of this chapter.

5.2 System Background

In this section, we introduce the relevant concepts utilized in the implementation of our proposed approach, which is based on segment-by-segment routing (SR) [132] and the Superiority and Inferiority ranking (SIR) method [133].

The segment routing concept concerns a mechanism to allow for encoding a routing packet with a header extension known as segment routing header (SRH). This encoding is termed SR policy and can be instantiated in the Internet Protocol version 6 (IPv6) planes [134]. The encoded information in each segment list contains the forwarding tables and segment identifier (SID) information which together are used to steer a packet through to specific topological routes for information to be extracted for performing routing at the end of each segment list until the packet reaches the destination address (DA). The studies of A. Abdelsalam et al. [135] showed that SRH provides sufficient support for various forwarding engines including routers. To that end, packet forwarding in an SR policy can be instantiated as an ordered list of IPv6 SIDs in the SR extension header encoded at the source node. This means that the SRH which contains the ordered list of segments together with the intermediate routes is used to facilitate packet forwarding to the DA [134].

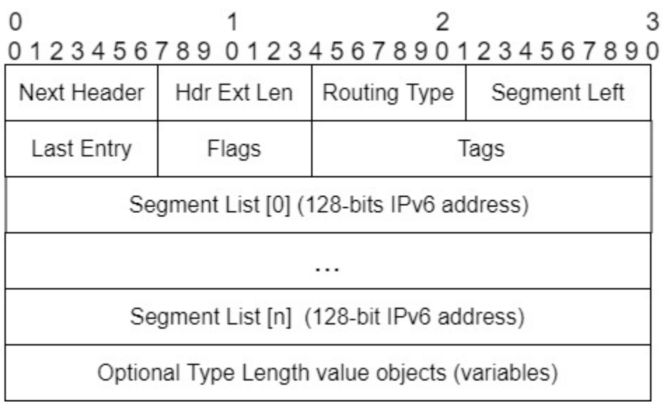

Figure 5.1: Segment Routing Extension Header

As embodied in Figure 5.1, it can be observed that SRH compared to the traditional IPv6 header contains extra field attributes which we shall briefly discuss. The first field is the Next header which is an 8-bit selector which performs the function to identifying the type of header that comes after the routing header. The adjoining field is the header extension length (Hdr Ext Len), which is an 8-bit unsigned integer with a routing header length in octet units. Next is the routing type which is an 8-bit attribute field used to specify the routing variant to execute. The segment left field is also an 8-bit unsigned integer which contains the precise number of segments remaining to be traversed by the packet till the DA is reached. The Last Entry field holds index zero and points to the last element on the segment list. The Flags are used to create a registry to define new flags such as unused or for future use and assigned zero value to be ignored during transmission. Segment List (SL) is assigned 128-bit and holds definite pointer SIDs up till the last segment of the SR policy (i.e., the DA). The segment list are encoded in the reverse starting from the first segment list to be processed (i.e., segment list (n)) while the next holds segment list (n-1) [136]. Finally, the Type Length Value (TLV) is responsible for providing the metadata used for the segment routing procedures. Many TLVs can be encoded in an SRH and defines the format and the semantic of the information contained in each. Two bits (0 and 1) are used to specify whether data encoded in the TLV can be modified while in motion to a destination. Data assigned with 0 implies cannot be modified while data assigned 1 can be modified.

Therefore, to use the IPv6 SRH in our scenario (i.e., cluster-based), studies show that the use of IPv6 segment-based routing provide support for dynamic use-case scenarios. Please note that as defined in Figure 5.1, the information to encode in each segment list should be IP addresses. However, in our scenario, we require GPS position information of nodes. To that, since each packet segment list contains IPv6 addressing space of 128 bits, which has attributes to explicitly encode routes together with functions to be executed such as associated routing type at the end of a segment list, it is necessary to encode the routing paths together with an aligning intra or inter-cluster routing function to each segment list and in the process extracted at the end of each segment list and used to facilitate in packet forwarding to the destination. To that end, we define and inversely encode three types of information namely; segment list (2) assigned as position of the source node; segment list (1) assigned as position of source CH; and segment list (0) assigned as position of destination CH. The encoded information at the end of each segment list is extracted from the packet as earlier indicated and based on the content used for performing an intra or inter-cluster routing. In our assumption, since a segment list contains 128-bit addressing space and the studies of J.C. Navas et al. [137] show that eight bytes of floating point number addressing space is capable of optimally holding GPS positioning information, we can confidently state that the utilization of the 128-bit addressing space of each segment list is sufficient to code the GPS position information of nodes required for performing position-based routing between CHs using the Advanced Greedy Perimeter stateless Routing (AGPSR) protocol [138].

We exploit the use of SIR method [133], which is a multiple criteria decision-making method (MCDM) implemented with aim to analyze diverse factors in neighbor nodes towards the choice of an ideal node for the purpose of facilitating an intra-cluster routing process. This means that the process leads to the best ranked node being selected to facilitate in the intra-cluster packet forwarding so as to ensure for transmission reliability. It is on this basis that we hypothesize in this chapter that the implementation of an inter-operable cluster-based hybrid routing approach, where intra-cluster routing performed using a rank-based algorithm shall ensure for transmission reliability while the execution of a greedy position-based inter-cluster routing in sync with the right-hand rule approach tackles void node situation and network scalability concerns.

5.3 System Description

In this section, we provide the foundation and detailed description of our proposed position-based hybrid routing protocol together with how end-to-end communication can be performed.

Due to the evolution of technology such as GPS [49] embedded on the UAVs the geographic position location of nodes could be obtained to facilitate in packet forwarding, thus making it an obligation for researchers to work towards obtaining energy efficient and scalable factors in UAV-FANETs. In that regard, the application of position-based routing has become necessary to facilitate in the design and implementation of robust and scalable FANETs [139]. As revealed in the experimental studies conducted in [140] and [141], routing strategies that do not utilize geo-location information of nodes for forwarding decisions are potentially unreliable and do not scale well.

Notably, recent studies have shown that ad hoc network deployments especially those for FANETs are mostly mission oriented and are challenged with dynamic topology, intermittent network disconnections and high node mobility. However, position-based routing has proven to have sufficient resilience to mitigating these challenges [129]. Similarly, the survey of Oubbati et al. [46] indicates that the improvisation of routing strategies using the location of the nodes' position shall allow for ease of network coverage extension and interfacing based on an imagery of the geographic locations of nodes. On that basis, we argue in this Chapter that the design of FANET protocols based on Position-based Hybrid routing, especially in what concerns inter-CH routing, is most suitable to assist in gluing the overall network together in mitigating the frequent network partitioning, high node mobility and topology issues in cluster-based FANETs. In addition to that, the target of CH-to-CH position-based routing is to harmonize the forwarded packet in a resilient manner to ensure for increased delivery ratios.

To that end, in order to support end-to-end communications between nodes in different clusters, the proposed routing protocol follows a segment-by-segment routing approach including: i) intra-cluster routing within the cluster of the sender node, ii) inter-cluster routing between the CH's of packet destination node; and iii) intra-cluster routing from the CH of the destination cluster to the destination node. In the proposed solution, the rank-based scheme and position-based approaches are considered mainly to ensure that the FANET's mobility and 3D structure attributes are taken care of to improve transmission reliability and scalability factors.

In the initial setup, all deployed nodes are configured with the geographic information of the base station, hence, allowing for the UAVs to update their positions, speed and direction using position-based routing. The flowchart in Figure 5.2 describes how a packet traverses from a source node by performing an intra-cluster forwarding to inter-cluster routing and back to intra-cluster forwarding until the packet reaches the destination node. In our implementation, as earlier indicated, each segment list is encoded with GPS positioning information together with associating the segment with an intra or inter-cluster routing function. Hence, at the end of each segment list such information is extracted and used for the purpose of routing.

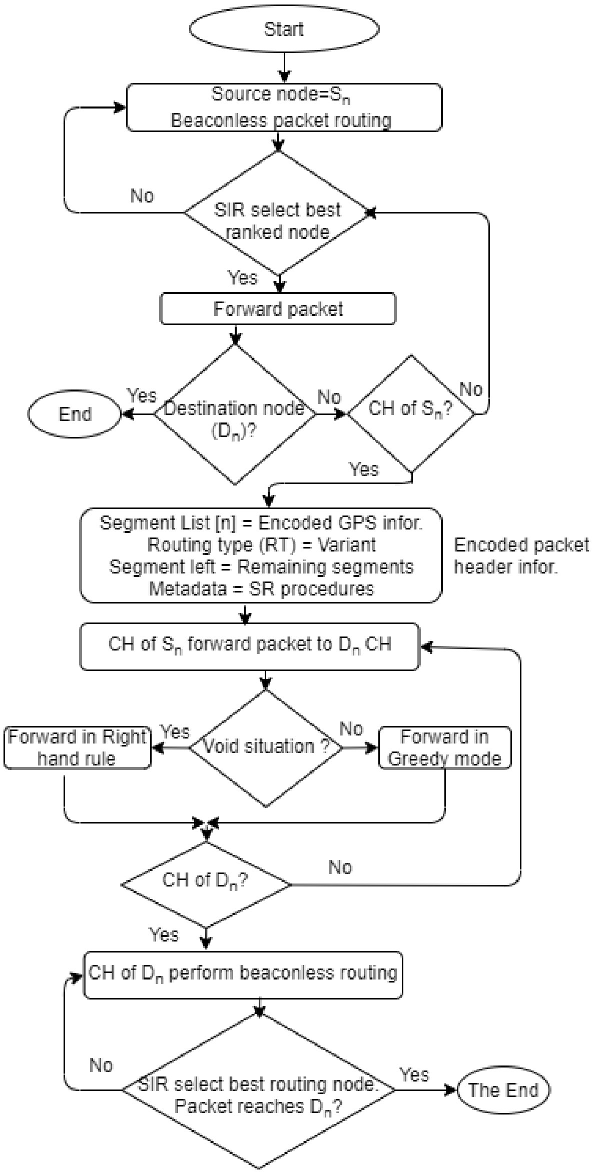

Figure 5.2: Intra-and Inter-cluster forwarding flowchart

5.3.1 Intra-and Inter-Cluster Routing

As previously indicated, the intra-cluster beaconless routing of packets is facilitated by the SIR-based method allowing for the MCDM to analyze for diverse conditions towards the choice of an ideal node capable of forwarding packets.

Consequently, to facilitate the process of generating and performing intra-cluster routing, the source node utilizes the beaconless SIR procedure to broadcast the packet to be sent. All neighbor nodes receive the packet, and each node calculates a rank based on the link quality l_q, distance d_i, speed s_i, queue length Q_l, location loc and direction dir in relation with the destination node. All nodes are configured to the sliding windows of the transmission protocol to delay their transmission based on the calculated rank thereby permitting only the highest ranked nodes to transmit the packet while low ranked nodes stop their transmission after overhearing the transmission of the highest ranked node, which helps to reduce bandwidth wastage.

On the other hand, the inter-cluster forwarding between CH-to-CH is performed using AGPSR protocol, which is based on two techniques, namely greedy forwarding and right-hand rule approach. Greedy forwarding is utilized at any feasible location to discovery paths to facilitate in packet forwarding, but fails only when a void situation is reached. Hence, to facilitate in greedy forwarding using Figure 5.3 as an example, we assume that nodes B, C, D and E are elected CH's of a group of clusters in a FANET scenario. The transmission radius of CH D does not encompass any other CH. However, transmission radius of CH E encompasses CH D as illustrated with the arc dotted lines. Also, transmission radius of node B encompasses C and E. It is also assumed that coverage radius for C encompasses B and E, meaning that E can only receive from C but cannot perform the reverse to C. On the other hand, B radius encompasses both C and E as shown with the thick circle. Therefore, in such a scenario, if node A that is a cluster member of CH B intends to forward a packet to node F which is a member in CH E, beaconless rank-based intra-cluster routing is performed by node A to node B. Node B extracts the encoded GPS position information and function to perform at the end of segment list A, and switches to the greedy mode to perform an inter-cluster routing to the CH closest to the destination node, which is CH E. The packet upon reaching node E is extracted and based on the information at the end of segment list B switches to perform beaconless rank-based intra-cluster routing to facilitate the packet to the destination node F which is a cluster member of CH E as illustrated in Figure 5.3.

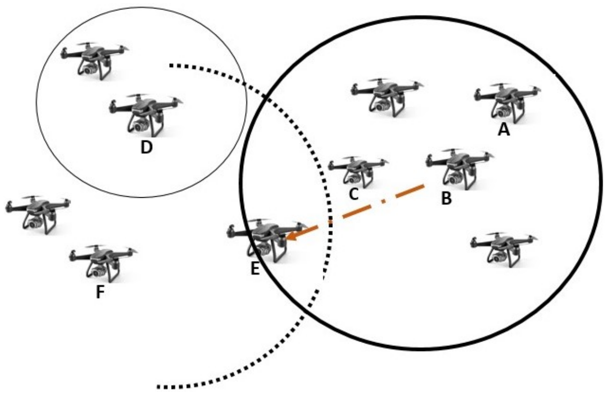

Figure 5.3: Greedy forwarding example

However, when faced with a void situation where the node carrying the packet is the closest to the destination, but unable to reach the destination, greedy forwarding is switched to the right-hand rule approach to traverse to the edges of the void regions to search for paths to facilitate in packet forwarding to the destination CH. However, in the unlikely event that a route is not found, the packet is dropped.

5.3.2 End-to-end Segment Routing Operation

In our implementation, the basic assumption is that a packet is expected to be sent and received by cluster members in separate clusters in a FANET scenario. Hence, to ensure for efficient end-to-end communication, we explore our novel Position-based Hybrid routing protocol in which a rank-based routing technique is utilized to perform the intra-cluster routing while a greedy-based routing in sync with the right-hand rule approach is utilized to perform the inter-cluster CH-to-CH routing. This solution is platform agnostic and so can be implemented in any clustering approach to improve performance metrics such as routing overhead, dropped packets, average waiting times, energy consumption and throughput. Therefore, in the adjoining section, we provide a description of how a packet is composed by a source node to allow for performing routing within and between clusters using the concept of segment-by-segment routing until the packet reaches its destination.

The novelty of our proposed solution is that it is platform independent and so can be implemented in any clustered FANET, hence, we state in this case that our network is clustered into separate clusters with each having a known elected CH and a group of cluster members. Given that the GPS location of the base station is known, position-based routing is utilized by the nodes to periodically update their position information. To facilitate the end-to-end communication as indicated, we use the concept of segment-by-segment routing whose background was introduced in 5.2. In that sense, the source node composes the packet to send by assigning each segment list with the updated position information of the expected routing routes necessary to steer the packet to the destination node. For this, similar to the packet encoding in Figure 5.1 the position of the source node is assigned to segment list (2) and its addressing space encoded with the GPS position of the source CH. To that effect, beaconless intra-cluster routing of packet is performed and the SIR-based method implemented to select the best node to forward the packet to the source node CH. When the packet reaches the position of the source CH (i.e., segment list (1)), the information encoded into the end of segment list (2) is extracted for routing type information and based on that switches to perform inter-cluster routing using AGPSR approach to route the packet to the destination node CH (i.e., the position of segment list (0)). However, if during the CH-to-CH AGPSR routing process a void node situation is reached, where the CH carrying the packet is the closest to the destination CH but unable to reach it, the right-hand rule is used to facilitate in packet forwarding to the destination CH. Finally, at the CH of the destination node (i.e., segment list (0)) the GPS position of the destination node is extracted from the end of segment list (1) together with information on the routing type to perform, and based on the information switches to beaconless intra-cluster routing while implementing the SIR-based method to select the best ranked node to route the packet to the destination node.

5.4 Performance Evaluation

This section presents the performance evaluation of our proposed Position-based Hybrid routing for clustered FANET. We begin by providing a description of our system configuration and the used simulation parameters. Next, we introduce the considered metrics and the compared models. Finally, we discuss the performance evaluation of our proposed approach compared with other state-of-the-art routing protocols.

Our performance evaluation was done using the NS-3 simulator[1], in which various performance metrics were evaluated. The 2.4 GHz frequency range of the IEEE 802.11n standard [34] was used to perform the communication. The Rayleigh channel model was used with the aim to allow for calculating channel fading characteristics. Our simulation environment is set to $1000m \times 1000m \times 880m$. UAVs are placed in 3D spaces and have bi-direction communication capability to a ground base station. Their mobility is based on random way point (RWP) movement model. The packet size is set to 600 bytes while simulation duration is 100 seconds. In Table 5.1 and Table 5.2, we further provide the summaries of the system configurations and the simulation parameters.

Table 5.1: System Configuration

Hardware Specification	Processor	Pentium Dual Core and Above
	RAM	8GB
	Hard Disk	60GB
Software Specification	Simulation Tool	NS-3
	Operating System	Ubuntu

Table 5.2: Simulation parameters

Parameters	Description
Network Parameters	
Simulation area	$1000m \times 1000m \times 880m$
Number of UAVs	100
Number of ground base station	1
Data rate	36 Mbps
Size of a message packet	600 bytes
Time to live	3h
Mobility	Random waypoint
speed	30-50 m/s
Channel model	Rayleigh model
Transmission range	1000m
Simulation time	100s
Transmission latency	20ms
bandwidth	1MHz
Maximum energy	20250 J
Message interval	20ms-30ms

For us to effectively appraise the end-to-end routing efficiency of our proposed mechanism, we compared it to other state-of-the-art routing protocols such as the Energy-Efficient Opportunistic Routing

[1] https://www.nsnam.org/

(EEOR) protocol [57], a position-based routing protocol that utilizes the positions of nodes to predict their trajectories and to address packet re-transmission and energy consumption constraints in FANETs, and the Smart IoT Control-Based Nature Inspired Energy Efficient Routing (NIEEOR) protocol [58], which presented an energy stabilizing limit for FANET with the goal of selecting only nodes with higher energy than the threshold for packet forwarding to ensure for transmission reliability.

5.4.1 Impact of Average Waiting Time

The evaluation of our solution is carried out by comparing its waiting time with the existing approaches in what concerns the number of UAVs. The waiting time represents the time taken for the packet to be in queue until the source node receives an acknowledgment to start transmitting. Our approach had a superior performance with a time retention of 0.199 seconds of waiting time compared to the existing approaches of 0.28 seconds waiting time as shown in Table 5.3.

Table 5.3: Analysis of Average Waiting Time

Technique	Average Waiting Time (s)
EEOR	0.375± 0.05
NIEEOR	0.28± 0.03
Position-based hybrid routing	0.199± 0.2

Figure 5.4 presents a comparison of the waiting time of the proposed Position-based Hybrid routing in FANETs and the existing approaches based on the number of UAVs. As shown, the average waiting time increases when the number of UAVs increase. The average waiting time of our approach is minimal due to use of intra-cluster highest rank forwarding strategy to facilitate in the quick discovery and selection of the best rank node as the next-hop node for packet forwarding. Thus, this contributes in mitigating delays in the network to ensure for fast routing processes.

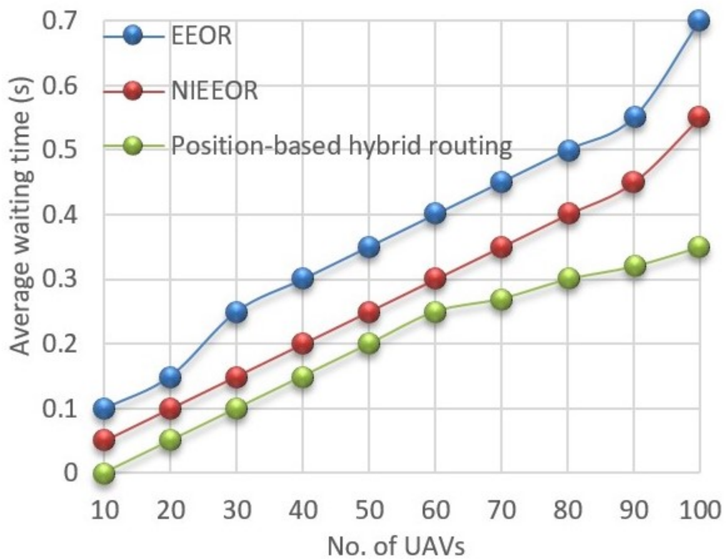

Figure 5.4: Number of UAVs vs. Average Waiting Time

5.4.2 Impact of Packet Drop Count

The packet drop count represents the total number of unsuccessful packet deliveries due to incorrect or unavailable routes to facilitate in packets forwarding from a source to a destination node. The following factors could contribute to packets being dropped in FANETs namely topology changes, network traffic overload and fast node mobility attributes. The network size and the the average packets dropped are illustrated in Figure 5.5, to show how reliable our approach is in comparison to other existing protocols. As shown, packet drop count in our proposed approach is lower mainly due to implementing both bea-

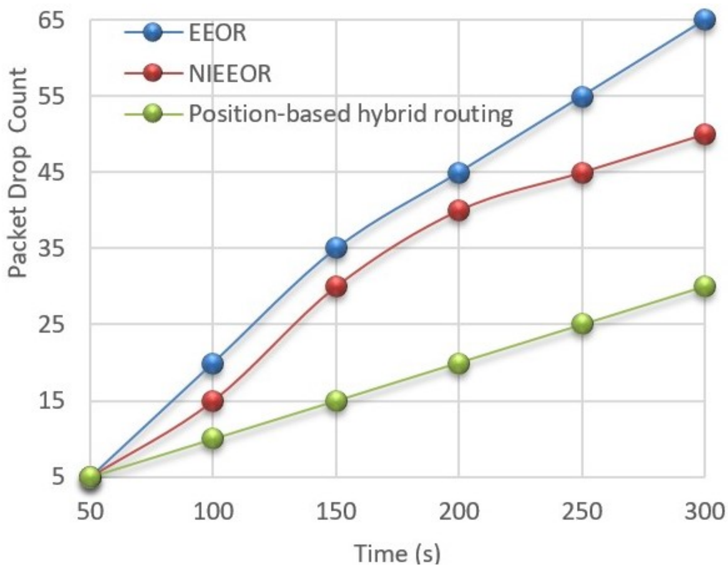

Figure 5.5: Packet Drop Count vs. Time

conless rank-based intra-cluster routing aiming to ensure for selecting the best ranked node to facilitate in packet forwarding under reduced traffic flooding while executing an AGPSR inter-cluster routing to utilize the positions of node locations to facilitate in accurate route discovery for a reliable CH-to-CH packet forwarding.

Table 5.4: Analysis of Packet Drop Count

Technique	Packet Drop Count
EEOR	37.5 ± 5
NIEEOR	30.87 ± 3
Position-based hybrid routing	17.5 ± 2

Hence, the results presented in Table 5.4 shows that average packet dropped count in our solution is 17.5, which is far lower than the average packet dropped count of 37.5 attained by existing approaches. These results show that the use of beaconless ranked-based intra-cluster routing and position-based inter-cluster routing in our approach led to good routing performance. While the increased packet drop count in the existing protocols could be attributed to inefficient convergence due to scalability challenges leading to several re-transmissions and network congestion.

5.4.3 Impact of Routing Overhead

Routing overhead constitute the ratio of all generated messages including the control packets transmitted by the routing protocol. Control messages comprise of the Hello packets as well as the node location information inserted in packet headers for topology construction and routing decisions. The Figure 5.6 illustrates the comparison of our approach to the existing approaches concerning the effect of routing overheads as a function of network density. Notice that, as number of nodes expands, the overhead also increases as a result of large numbers of exchanged control messages.

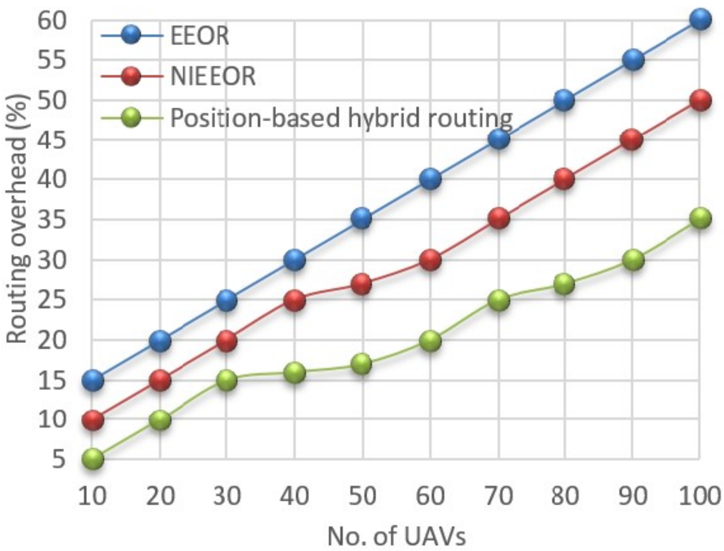

Figure 5.6: Number of UAVs vs. Routing Overhead

The routing overhead on our proposed approach is lower than the existing approaches due to the performance of beaconless intra-cluster routing which helps to reduce network flooding with control messages. Also, use of GPS on-board the UAVs facilitated in obtaining node location information for reliable inter-cluster routing hence, contributed in reducing routing overhead in our approach.

Table 5.5: Analysis of Routing Overhead

Technique	Routing Overhead in percentage
EEOR	37.5±0.3
NIEEOR	29.7±0.2
Position-based hybrid routing	20±3

Table 5.5 provides the analysis of the routing overhead of our approach and existing approaches concerning the number of UAVs. Our solution attains a routing overhead of 20, whereas the existing approaches attained as high as 37.5 routing overhead. The cause being that the existing protocols generated huge topology control and HELLO packets to manage their routing table which resulted into packet flooding and congestion’s. Hence, the increased routing overhead.

5.4.4 Impact of Power Consumption

Energy utilization by nodes is a critical measure to describe the performance of the FANET as the UAV device has energy limitations. We have considered cumulative energy consumption for packets to be transmitted against increasing UAVs consumption in the network. The Figure 5.7 shows that our proposed approach consumes less amount of energy compared to the existing protocols.

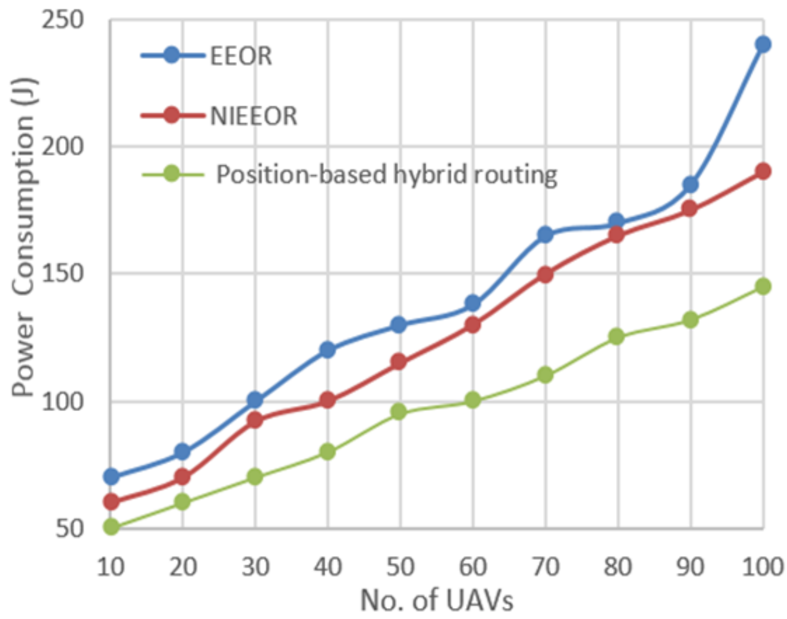

Figure 5.7: Number of UAVs vs. Power Consumption

The efficient execution of ranked-based beaconless intra-cluster routing and AGPSR inter-cluster routing ensures the reliability of packet transmission in our proposed approach. In contrast, the EEOR and NIEEOR protocols are based on beacon routing which floods the network with control and HELLO messages in their quest to discover routing routes. This leads to bandwidth wastage and network congestion, thus, since the nodes persist in re-transmitting the dropped packets, it places excessive processing and communication demands on the UAVs, which translates into high power consumption in these protocols as shown.

Table 5.6: Analysis of Power Consumption

Technique	Average power consumption (J)
EEOR	139$\pm$6
NIEEOR	124$\pm$3
Position-based hybrid routing	96$\pm$ 7

Table 5.6 presents the numerical comparison of the average energy consumed by our proposed routing protocol and the existing approaches. As observed, when the number of nodes increases, the cumulative energy consumption of UAVs also increases. However, comparatively, the average cumulative energy consumption of our proposed Position-based hybrid routing protocol is 96.7J, which is lower than the 124.3J and 139.6J energies consumed by the existing protocols.

5.4.5 Impact of Throughput

Throughput is the measure of the quantity of data packets successfully transmitted from source to destination node. The comparison of throughput between our solution and the existing approaches with respect to the number of UAVs is presented in Figure 5.8.

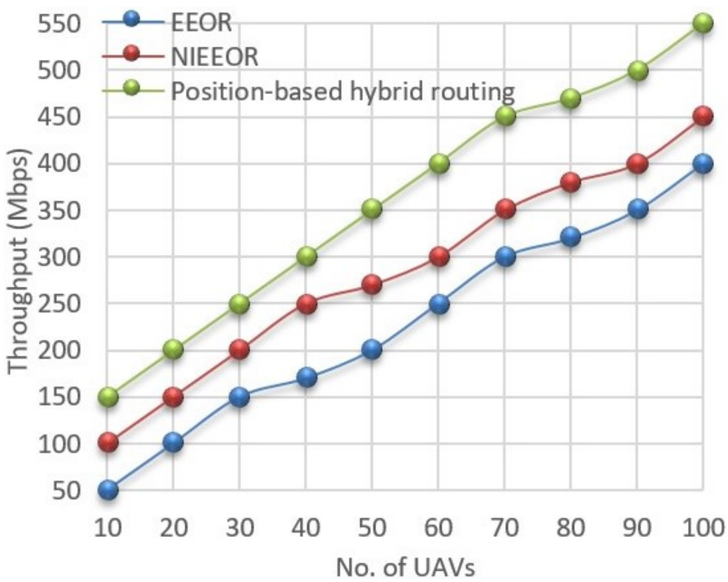

Figure 5.8: Number of UAVs vs. Throughput

The throughput of our proposed approach is higher due to efficient hybrid intra-and inter-cluster routing of packets in the network to overcome the bandwidth wastage, delays and packet retransmissions caused by congestion. Hence, our approach facilitated fast and reliable packet transmission from source to destination to achieve the high throughput.

Table 5.7: Analysis of Throughput

Technique	Throughput (Mbps)
EEOR	229$\pm$3
NIEEOR	285$\pm$2
Position-based hybrid routing	362$\pm$1

The analysis of throughput rates on our solution and the existing approaches is provided in Table 5.7. Our approach attained a transmission throughput rates of 362 Mbps, whereas the existing approaches attained 229 Mbps throughput.

Based on the analysis of the compared results above, which clearly shows that our mechanism outperforms the selected state-of-the-art schemes in dynamic FANETs as at every instance our solution selects potential forwarders using rank-based intra-cluster routing, and a combination of greedy position-based and the right-hand rule approaches for inter-cluster routing with the aim to ensure for transmission reliability while reducing delay in discovering next forwarder nodes, to decrease transmission delay, packet drop count and to increase transmission throughput.

5.5 Summary

In this Chapter, we implemented Position-based Hybrid routing in FANET with the aim to improve routing efficiency while scaling in cluster-based UAV-FANETs. We believe that our mechanism is novel as it is platform independent and could be implemented with any clustering approach, to tackle network reliability, void node situations and scalability concerns in large UAV-FANETs. To this end, our mechanism achieves this by utilizing different routing protocols inside of clusters based on ranking to avoid unsuitable forwarding paths to ensure for reliable transmissions and low delays while inter-cluster routing which encompasses several CHs performed in sync with a greedy position-based and the right-hand rule approaches with aim to escape from void node situation to improve routing and scalability factors. Simulation results manifest that our mechanism outperformed other state-of-the art routing approaches with a desirable performance while scaling as it notably achieved a packet transmission rate of 362 Mbps and a superior average retention time of 0.199 seconds compared to a transmission rate of 229 Mbps and a retention time of 0.28 seconds by the existing approaches.

Chapter 6

Conclusion

Largely, the evolution of UAV-FANETs has a significant benefit to future generation of mobile networks and beyond in many use-cases scenarios especially under emergency communication situations. Therefore, to fully utilize these promising potentials of UAV cooperation as swarm FANETs, we argue for the design and implementation of efficient routing protocols capable of mitigating the networking and communication related challenges with regards to proper data packet dissemination in UAV-FANETs. In that regard, throughout the various chapters of this thesis, we made several contributions and drew inferences in support of our assertion. To that end, we round off the main objectives of this thesis and its validation here below.

In Chapter 2, we started by presenting a background to familiarize the reader with autonomous drone systems, the importance of autonomous drone systems equipped with smart cameras and showed existing solutions to stream video and image data. State-of-the-art studies relevant to the development of cluster and load-balancing mechanisms, as well as position-based routing approaches in FANET environments were appraised. Further, in advancing for methods to address the identified challenges in FANETs, various hypotheses were argued to justify our proposals to design dynamic clustering and load-balancing, and Position-based hybrid routing methods to address node mobility, 3D structure, fault-tolerance and scalability concerns in FANET environments.

In Chapter 3, we presented background and concept study of FANET and drone swarm developments, especially with regards to autonomous camera swarms in a networking perspective. Then, we investigated networking design considerations necessary for drone swarm deployment, while analyzing an applicability study on how drone swarms could be modeled as a NCS. The networking and computing system components and requirements were discussed, methods on integrating the networking and computing system to realize a networked control system were studied. Finally, we end-up showing that relying on a networking system capable of resolving requested computation expressions composed from named data and functions in a transparent fashion to each node, contributes to the self-organization properties of drone swarms.

In Chapter 4, we presented our novel Dynamic Clustering Mechanism with Load-Balancing and showed that our solution is able to tackle the limitations encountered in FANETs by providing a stable and reliable routing performance within and between clusters, to achieve a high packet delivery probability. To validate our solution, we showed through simulation results that our solution supports an average packet delivery ratio of 97%, end-to-end delay of 0.225 seconds, and power consumption 37% lower than other state-of-the-art clustering mechanisms. Moreover, to augment our routing mechanism offered in Chapter 4, we presented in Chapter 5, an inter-operable Position-based Hybrid routing protocol for clustered FANETs where different routing protocols are used within clusters while inter-cluster routing which encompasses several CHs performed using a combination of greedy position-based and the right-hand rule approaches for the purpose of tackling network robustness, scalability, throughput and delay concerns. Our protocol which is platform independent can be implemented in any clustering approach to tackle the FANET intrinsic challenges, and to provide performance improvement in metrics such as routing cost and overheads, dropped packets, and average waiting times. We showed through simulation results that our model achieved a lower packet drop count of 17.5%, a higher throughput of 36.7%, and a lower waiting time of 8.1% when compared with other state-of-the-art routing approaches.

Overall, in this thesis we introduced two essential conceptual design choices necessary for the networking deployment of swarm FANETs and presented two separate routing approaches namely Dynamic Clustering and Load-balancing Mechanism and Position-based Hybrid routing approaches implemented to mitigate wireless challenges and to satisfactorily provide for proper data packet dissemination in large UAV-FANETs.

6.1 Scientific Contributions

The major achievements of this thesis includes the following catalogued publications:

6.1.1 Journal Publications

- G. Asaamoning, P. Mendes and N. Magaia. “A Position-based Hybrid Routing Protocol for Clustered Flying Ad Hoc Networks”, (**Submitted to an International Journal**).

- [48] G. Asaamoning, P. Mendes and N. Magaia. ”A Dynamic Clustering Mechanism with Load-Balancing for Flying Ad Hoc Networks,” in IEEE Access, vol. 9, pp. 158574-158586, November 2021. https://doi.org/10.1109/ACCESS.2021.3130417

- [61] G. Asaamoning, P. Mendes, D. Rosário and E. Cerqueira. “Drone Swarms as Networked Control Systems by Integration of Networking and Computing”. Sensors 2021, 21(8), 2642. https://doi.org/10.3390/s21082642

6.1.2 Conference Publications

- [60] D.M.A. Silva, G. Asaamoning, H. Orrillo, R.C. Sofia and P.M. Mendes. “An Analysis of Fog Computing Data Placement Algorithms”. In 16th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous), November 12–14, 2019, Houston, TX, USA, pp. 527-534. https://doi.org/10.1145/3360774.3368201

- [59] G. Asaamoning and P. Mendes. "A Study for a Name-based Coordination of Autonomic IoT Functions". In 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob): WiMob 2018, October 15-17, 2018, Limassol, Cyprus, pp. 296-302. https://doi:10.1109/WiMOB.2018.8589182

6.1.3 Extended Abstract

- [18] G. Asaamoning and P. Mendes. "Wireless networking for autonomous mobile smart cameras". Extended abstract, In Proceedings of the 2019 International Networked Systems Conference and PhD forum (NetSys-2019), March 18-21, 2019, Garching b. München, Germany. URL: $http://netsys2019.org/proceedings/public/hotcrp-final29.pdf$

6.2 Future Work

Despite having to address a considerable number of the networking and communication challenges faced in large UAV-FANETs, we believe that further direct and indirect investigations on our solutions may lead to more improvements. In that regard, in addition to seeking improvement in our solutions we look forward to investigating research challenges in the following direction.

Resource Constraint Nature of UAVs

While the operation of UAVs are very important in many use-case scenarios such as disaster communication scenarios, the flight duration and processing capabilities of UAV's are dependent on several factors including energy and computational power. Hence, it is essential for the design of routing solution capable of consuming less energy as well as synergy to ensure for coordinated and sustained tasks performance. Related resource challenges of drones when facing services that require high computational power such as pattern recognition, image and video processing, could be addressed through computation offloading using novel technologies such as mobile edge computing and fog computing paradigms. For instance, game theory could be used together with resource scheduling and task allocation schemes to achieve a trade-off between computing time and energy consumption while offloading part of the computing task to a nearby ground infrastructure.

Resource Management in Multi-UAV FANETs

Resource management in UAV-based FANETS has been a challenging task due to the UAV's resource constraints in bandwidth and transmission power leading to limited flight durations. The problem is due to the high mobility nature of the nodes and the dynamics of the operating environment. To that end, there is need to provide mechanisms capable of managing these dynamic attributes and to provide for regulating the number of UAVs encompass in the network, the transmission power and nodes movement patterns leading to an efficient management of the multi-UAV system for sustained tasks operations. This thus, calls for research into dynamic frameworks capable of offering joint optimization of real-time deployment and resource allocations in what concerns analysis of impacts; on mobility, node flight location, traffic distribution among the UAVs and also transmission to the ground base controller as well as LoS interference. Based on these analysis, the requisite adjustable bandwidths, transmission power and node motility patterns may be provisioned to allow for LoS communication capable of mitigating such impacts on operational efficiency.

UAV Security Concerns

A major concern to be addressed in multi-UAV assisted networks is security. Due to vulnerabilities in wireless, UAV-FANETs are largely faced with various malicious attacks ranging from eavesdropping, hijacking and other forms of cyber-attacks. This therefore requires the development of secure mechanisms to counter these malicious attacks. To this end, Gupta et al. [142] in their study highlighted several security issues and suggested potential solutions that could be studied and implemented to mitigate their effects. They revealed that machine learning and physical layer security mechanisms could significantly contribute to the protection of UAV-assisted networks, which is therefore worthy of investigating.

Node Location Information Provisioning

UAV-FANET routing protocols mainly require location information of nodes using positioning services to perform packet forwarding. This makes the performance of the protocols dependent on these positioning systems. This implies that providing inaccurate node position information impacts network performance. The commonly used positioning service is GPS in many protocols. However, this system also depends on environmental conditions to operate accurately. For example, in the study conducted by Lansky et al. [143], it was revealed that GPS services in open space and in good weather are accurate, but in contrast, its use in indoor environment and cloudy weather provides weak signals and hence impact on network performance. To this end, investigations into free infrastructure location methods to help calculate node location information are of interest for future research.

Blockchain in Multi-UAV Systems

Network and communication management of the multi-UAV system is quite challenging due to the requirement of a distributed model instead of a centralised control system which has a major drawback of single point of failure. Blockchain, in contrast, is a decentralized network model with sequences of blocks that is safe and stores all transaction-related information in an automated manner, while providing authentication. Moreover, this technology enables the synchronization of all transaction-related work. This means that consensus is required for all discharges to eliminate security, fraudulent or duplication-related concerns as revealed in the survey conducted by Indhuja et al. [144]. To this, the use of blockchain technology in multi-UAV systems shall allow for data encryption for secure processing, storage and secure transmission over the network while scaling. Therefore, further research towards the in cooperation of blockchain technology into multi-UAV systems shall bring about a decentralized, distributive and secure processing and sharing, as well as eliminate the single point of failure feature in the multi-UAV system.

Standardization of Suitable Frequency Bands for UAV Operations

As with regards to wireless coverage concerns in UAV-FANETs, we expect future research target to be geared towards the design of innovation antenna array designs to be implemented under 5G and beyond mobile networks to address coverage and communication related challenges. This is because the use of the ultra-high frequency bands of between 300 MHz to 3 GHz used by satellite and GSM communication networks and that of the unlicensed bands of 0.9 GHz and 2.4 GHz are apparently unsuited for UAV-based communication due to congestion and interference related issues [145]. In that regard, this calls for painstaking research into the standardization of suitable frequency bands capable of providing support for dynamic spectrum sharing leading to minimal congestion and interference related concerns in the multi-UAV systems operation.

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