Model-based Clustering Methodologies with Drones Integration in Multi-Agent Critical Infrastructures

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Abstract

Routing protocols are fundamental in networks because they define how data is transferred from one device to another, ensuring that information finds the most efficient or appropriate path across the network. Routing protocols are essential for the efficient, reliable, and scalable operation of networks. They automate path selection, improve network fault tolerance, adapt to changes in topology, and enhance security. Clustering protocols are widely used for organizing and managing the structure of networks, especially in scenarios like wireless sensor networks, ad hoc networks, and mobile networks. Clustering is a technique of grouping nodes in a network into clusters based on specific criteria, such as proximity, communication range, or energy levels. A cluster head is often selected within each group, and the nodes in the cluster communicate with the cluster head rather than directly with each other or with distant nodes. The cluster head plays a crucial role in managing communication within a cluster. If a cluster head becomes non-functional due to failure, it introduces communication breakdown with loss of data aggregation and a disconnected cluster. In critical scenarios such as natural disasters or security threats, the importance of data cannot be overstated, as it plays a pivotal role in making informed decisions, responding swiftly to emergencies, and ensuring the safety and well-being of individuals, communities, and even entire societies. The ability to collect, analyze, and act on data in real time is crucial for responding swiftly and effectively to emergencies, predicting risks, and managing recovery in complex and rapidly changing environments. The integration of Unmanned Aerial Vehicles, also known as drones, into data transfer processes during critical cases has proven to be a game-changer in improving the speed, efficiency, and reliability of communication and information flow. UAVs, with their ability to access difficult-to-reach areas, provide real-time data, and act as relays or platforms for data collection and transfer, play a crucial role in enhancing response capabilities in critical situations. In this regard, this research provides a comprehensive approach to clustering methodologies in critical infrastructure. The target of this research is to suggest a clustering methodology with the integration of drones and other agents to ensure data transmission in critical infrastructure. The following are the research innovative contributions and effects on clustering methodologies and practice:

Keywords: Ad-Hoc Networks, Cluster-Based Routing, Cluster Head Failure, Crisis Scenarios, Dynamic Network Topology, Energy-Efficient Communication, Fault Tolerance, Multi-Agent Systems, Network Resilience, Redundant Cluster Head Selection, Swarm Unmanned Aerial Vehicles (S-UAVs), UAV-Assisted Networking

Dedication

This thesis is dedicated to my beloved husband and my children, who have been my constant source of strength, love, and inspiration throughout this journey. To my husband, thank you for your endless patience, understanding, and unwavering support during the many sacrifices, long nights, and moments of exhaustion that this work required. Your belief in me never faltered, even when the path felt overwhelming.

To my children, thank you for your love, smiles, and gentle reminders of what truly matters. You gave meaning to every effort and motivated me to keep moving forward, even during the most challenging moments. This achievement is as much yours as it is mine.

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Publications

Book Chapters (Refereed)

BC5. Grace Khayat, Constandinos X. Mavromoustakis, Evangelos K. Markakis, Athina Bourdena, and George Mastorakis, "The Next Generation for Multi-Redundant Weighted Clustered Reliable Data Transmission Scheme in Critical S-UAV Networks," Intelligent Transformative Technologies, 2025.

BC4. Grace Khayat, Constandinos X. Mavromoustakis, George Mastorakis, Evangelos Pallis, Evangelos K. Markakis, and Athina Bourdena, "S-UAV Multiple Redundant Routing Scheme for Crisis Scenario," in *Intelligent Technologies for Healthcare Business Applications*, series *Internet of Things*, 2023.

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BC2. Grace Khayat, Constandinos X. Mavromoustakis, George Mastorakis, Jordi Mongay Batalla, Hoda Maalouf, Evangelos Pallis, Imran Khan, and Naerco Magaia, "Damaged Critical Infrastructure for VANETs," in *Intelligent Wireless Communications*, The Institution of Engineering and Technology (IET), June 2021.

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Journal Publications

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J4. Grace Khayat, Constandinos X. Mavromoustakis, Jordi Mongay Batalla, George Mastorakis, and Evangelos K. Markakis, "An IoT-Driven Redundant Clustering Framework for Reliable E-Health Communication in Emergencies," under review in *IEEE Internet of Things Journal*.

Conference Publications

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tional Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD 2025).

C16. Grace Khayat, Constandinos X. Mavromoustakis, Andreas Pitsillides, and Jordi Mongay Batalla, "Redundant Weighted Clustering Scheme for Critical S-UAV Infrastructures," *IEEE International Conference on Communications (ICC 2025)*.

C15. Grace Khayat, Constandinos X. Mavromoustakis, Andreas Pitsillides, and Jordi Mongay Batalla, "Multi-Agent Redundant Clustering Scheme for E-Health Reliable Data Transmission in Crisis Scenarios," *IEEE International Conference on Communications (ICC 2025), E-Health Track*.

C14. Grace Khayat, Constandinos X. Mavromoustakis, Jordi Mongay Batalla, and Andreas Pitsillides, "Multiple Redundant Weighted Clustered Scheme with Dynamic Weight Adjustment for Damaged S-UAVs," *IEEE International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD 2024)*.

C13. Grace Khayat, Constandinos X. Mavromoustakis, Andreas Pitsillides, Jordi Mongay Batalla, and Evangelos K. Markakis, "Redundant Weighted Clustered Scheme with Dynamic Weight Adjustment for Damaged S-UAVs," *IEEE International Conference on Communications (ICC 2024)*.

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C5. Grace Khayat, Constandinos X. Mavromoustakis, George Mastorakis, Jordi Mongay Batalla, Evangelos Pallis, and Evangelos K. Markakis, "Transfer Time Calculation in FANET and WSN Networks in Crisis Scenarios," in *IEEE Global Communications Conference (GLOBECOM2021)*.

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Declaration

I hereby declare that this thesis is my own original work and has been written independently. All sources of information and material used in this thesis have been properly acknowledged and cited in accordance with academic standards. This thesis has not been submitted, either in whole or in part, for the award of any other degree or qualification at this or any other academic institution. Parts of the work presented in this thesis have been published or submitted for publication in peer-reviewed journals and conference proceedings. These publications are clearly identified and appropriately referenced throughout the thesis. The contribution of co-authors, where applicable, is explicitly stated. I confirm that this thesis complies with the rules and regulations of the university regarding originality, academic integrity, and ethical conduct.

Signed .... Date ....

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Abbreviation	Definition
$\Delta\phi$	Difference in latitude
$\Delta\chi$	Difference in longitude
$\Delta E(k)$	Energy consumed during interval $[k, k+1]$
δt_{k_i}	Segment duration (s)
ψ	Weight of the distance component
κ	Weight of the rewarding index component
ζ	Weight of the velocity component
ω	Tolerance parameter for packet forwarding
ρ	Air density (kg/m^3)
ϕ	Latitude (in radians)
χ	Longitude (in radians)
$(x_k(t) - x_k(t-1))$	Direction of motion of UAV k along x–axis
$(x_l(t) - x_l(t-1))$	Direction of motion of UAV l along x–axis
η_{elec}	Electrical subsystem efficiency
η_p	Propulsive efficiency
η_{rot}	Rotor efficiency
A_{tot}	Total rotor disk area (m^2)
BatteryCapacity	Nominal usable traction battery capacity
$C_{\max}$	Maximum number of CMs per cluster
$C_{(k,l)}$	Cluster index for UAV k relative to UAV l
C_{D0}	Zero-lift drag coefficient
$d_{\max}$	Maximum communication range
$D_{(k,l)}$	Inter-node distance between UAV k and UAV l
$d_{(k,l)}$	Geodesic distance between UAV k and UAV l
$\tilde{d}_{(k,l)}$	Normalized distance between nodes k and l

$D_0(k,l)$	Reference distance between nodes k and l
Dir	Direction indicator (+1 same direction, −1 opposite direction)
$E(k)$	Remaining energy of vehicle k
E_{k_i}	Segment-wise energy consumption (Wh)
$E_{k_{\text{total}}}$	Total mission energy (Wh)
$f_{(k,l)}$	The total number of forwarded packets from UAV k to UAV l
k	Induced drag factor
$\mathcal{N}$	The set of neighbouring UAVs within the S-UAV network
p	Path-loss exponent
P_{air}	Total aerodynamic power (W)
P_{climb}	Climb/descent power (W)
P_{elec}	Electrical power drawn from the onboard battery (W)
P_{ind}	Induced power in hover for multirotor UAVs (W)
P_{induced}	Induced drag power (W)
P_{k_i}	Segment-wise electrical power (W)
P_{parasite}	Parasite drag power (W)
$P_{\text{prof-frac}}$	Profile power fraction accounting for profile and mechanical losses
P_{shaft}	Shaft power required after accounting for propulsive losses (W)
R	Earth radius (typically $R \approx 6371$ km)
$R_{(k,l)}$	Cooperation-based rewarding index between UAV k and UAV l
$R_{D(k,l)}$	Direct Rewarding index between UAV k and UAV l
$R_{I(k,l)}$	Indirect Rewarding index between UAV k and UAV l
ROC	Rate of climb (m/s), negative for descent
$\text{RSSI}(D(k,l))$	Received Signal Strength at distance $D(k,l)$
$\text{RSSI}(D_0(k,l))$	Received Signal Strength at reference distance $D_0(k,l)$
S	Wing area (m^2)
$S_{(k,l)}$	Link-stability metric between nodes k and l
S_{ref}	Reference area for parasite drag (m^2)
$\text{SOC}(k)$	State of Charge of vehicle k (normalized $[0,1]$)
$\text{SOC}(k+1)$	State of Charge at next time step
$t_{(k,l)}$	The forwarding delay of packets from UAV k to UAV l
t_{avg}	The average forwarding delay observed in the network
t_{loop}	cluster update period

V	Flight speed (m/s)
$v_{\max}$	Maximum expected relative velocity
$V_{(k,l)}$	Relative velocity between UAV k and UAV l
$\tilde{v}_{(k,l)}$	Normalized relative velocity between nodes k and l
$v_a(k,l)$	Angular velocity metric between nodes k and l
$v_s(k,l)$	Scalar relative velocity between nodes k and l
W	Aircraft weight (N)
$w_D(t)$	Distance weight coefficient
$w_E(t)$	Residual energy weight coefficient
$w_R(t)$	Trust (reward) weight coefficient
$w_V(t)$	Relative velocity weight coefficient
x_ϕ	Gaussian random noise term with standard deviation ϕ
$x_k(t)$	x–coordinate of UAV k at time t
$x_k(t-1)$	Previous x–coordinate of UAV k at time $t-1$
$x_l(t)$	x–coordinate of UAV l at time t
$x_l(t-1)$	Previous x–coordinate of UAV l at time $t-1$
$y_{(k,l)}$	The total number of received packets from UAV k to UAV l
$\lvert\Delta v_{(k,l)}\rvert$	Magnitude of relative velocity between nodes k and l
$\Delta E(k)$	Energy variation of node k
Δt	Discrete simulation step size
ε	Small stability constant (prevents division by zero)
δ	Stability tolerance threshold
λ	Consistency threshold
ε	Small constant preventing division by zero
$\Delta^+(t)$	Allowable weight increment
ϵ_{amp}	Transmit amplifier coefficient
$\Delta_j^-(t)$	Weight reduction for metric j
c_1	Minimum stability threshold
c_2	Adaptation control constant
$C_S(t)$	Delay Stability Coefficient at time t
$C_{S,\text{threshold}}$	Stability threshold for triggering adaptation
$\text{clip}(\cdot, 80, 140)$	Saturation operator constraining altitude to $[80, 140]$
$d[n]$	One-way routing delay sample at discrete index n

d	Transmission distance
$\bar{d}_{\text{cur}}(t)$	Current window-averaged delay
$D_{\text{norm}}(t)$	Normalized Distance
$\bar{d}_{\text{prev}}(t)$	Previous window-averaged delay
E_{min}	Minimum energy threshold
E_{agg}	Data aggregation energy per bit
E_{comm}	Communication energy
E_{elec}	Electronic circuitry energy per bit
$E_{\text{norm}}(t)$	Normalized Energy
$E_{\text{oh}}(k)$	Cluster head overhead energy
E_{oh}	Overhead energy
E_{proc}	Processing energy per bit
E_{rx}	Reception energy
E_{tx}	Transmission energy
L	Packet size (bits)
m	Integer decision step index ($m \in \mathbb{N}$)
m_{min}	Minimum permissible bound
m_{max}	Maximum permissible bound
$m_i(t)$	Metric value at time t
$m_i(t-1)$	Metric value at the previous time step
m_i	Metric value
$\bar{m}_{\text{nbr}}$	Neighborhood average
$\mathcal{N}(0,1)$	Zero-mean, unit-variance Gaussian random variable
n	Path-loss exponent
$\mathbf{p}_i(t)$	Position of node i at time t
r_c	Cluster communication radius
$R_{\text{norm}}(t)$	Normalized Reward
$s_j(t)$	Removable slack of metric j
t	Discrete time index
t^+	Post-update time instant
T_{max}	Freshness threshold
t_{current}	Current time
$\mathcal{T}_{\text{DMRWP}}$	Set of DMRWP decision instants

T_{DMRWP}	Window duration
$t_{\text{last-update}}$	Last update time
$\mathcal{T}_{\text{upd}}$	Set of update instants
$\mathcal{V}(t)$	Set of valid metrics
$\mathbf{v}_i(t)$	Velocity vector of node i at time t
$V_{\text{norm}}(t)$	Normalized Velocity
W	Window length in samples
w_{min}	Minimum allowable metric weight
$w_i(t)$	Metric weight at time t
$w_i(t^+)$	Post-update metric weight
$z_i(t)$	Altitude of UAV i at time t
BS	Base Station
CBR	Cluster-Based Routing
CH	Cluster Head
CM	Cluster Member
DMRWP	Dynamic Multi-Redundant Weighted Cluster Protocol
EV	Electric Vehicles
FANET	Flying Ad-hoc Network
GS	Ground Stattion
IoT	Internet of Things
MADMRWP	Multi-Agent Dynamic Multi-Redundant Weighted Cluster Protocol
MANET	Mobile Ad-hoc Network
MN	Metric Normalization
MRWP	Multi-Redundant Weighted Cluster Protocol
PDR	Packet Delivery Ratio
PDR	Packet Delivery Ratio
QoS	Quality of Service
RCH	Redundant Cluster Head
RWP	Redundant Weighted Cluster Protocol
S-UAV	Swarm Unmanned Aerial Vehicle
TBS	Terrestrial Base Station
TUE	Terrestrial User Equipment
UAV	Unmanned Aerial Vehicle

UE	User Equipment
VTOL	Vertical Take-Off and Landing
WSN	Wireless Sensor Network

Chapter 1

Introduction

A Vision of UAVs

Unmanned Aerial Vehicles (UAVs), also known as drones, are autonomous aerial platforms used for real-time data collection and analysis [?]. In recent years, UAVs have begun to play an increasingly significant role across a wide range of civilian and industrial domains. In the military field, drones are employed for tasks including weapon delivery, missile guidance, artillery coordination, and target identification [?]. Additionally, UAVs are widely employed across multiple industries. These include emergency response during natural disasters such as landslides, earthquakes, and floods, as well as applications in safety, entertainment, traffic monitoring, and agriculture [?, ?]. During emergencies, UAVs are often used to support search-and-rescue operations [?, ?].

A swarm of unmanned aerial vehicles (S-UAVs) denotes a coordinated group of UAVs executing a shared mission [?]. Routing systems in S-UAVs pose significant challenges due to highly dynamic network topologies. Ad-hoc communication, which relies on neighboring nodes to relay packets without fixed infrastructure, provides a reliable communication method for S-UAVs [?,?]. Clustering is an established routing strategy for improving the performance of ad-hoc networks. This technique reduces overhead and improves performance, making it widely used in S-UAVs. Clustering algorithms group UAVs into clusters based on metrics such as residual energynergy, separation distance, direction, velocity, and routing speed [?, ?]. Each cluster consists of a Cluster Head (CH) and Cluster Members (CMs). The CH coordinates intra- and inter-cluster communication and aggregates packets from CMs before forwarding them to the base station (BS) [?]. The BS forwards the received packets for analysis by the control station. Depending on the interpretation of the data, the control station may trigger actions or simply use the data for informational purposes [?]. As the key communication component, CH selection is crucial for optimal cluster performance. Different routing protocols adopt different CH selection methods [?, ?].

In crisis situations, S-UAVs support emergency response tasks including situational analysis, survivor search, and status monitoring. However, any UAV can become non-functional or be destroyed during a mission for various reasons. Since clustering is widely used in S-UAV routing schemes, a non-functional CH may disconnect the cluster. This can result in the loss of critical and potentially life-saving data [?].

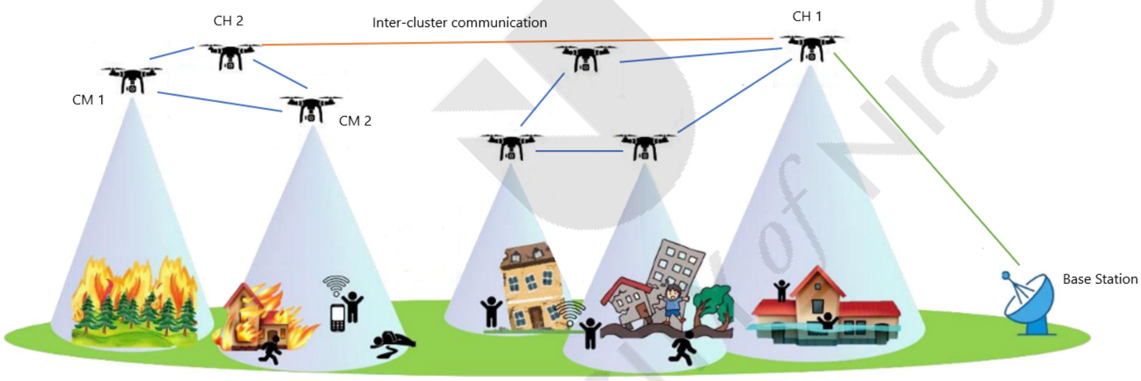

Figure 1.1: Clustered S-UAV network in a crisis scenario

A clustered S-UAV network in a crisis scenario is shown in Figure ??. Several UAVs are arranged into clusters in the figure, each of which has a CH and a number of CMs. To transmit sensed information or event-related data, the CMs in each cluster communicate with their corresponding CH directly. Depending on network connectivity and proximity, CHs forward aggregated data either directly to the BS or through inter-cluster links with neighboring CHs. A multi-hazard crisis environment, including forest fires, urban fires, infrastructure failure, and flood-affected areas, is highlighted in the scenario. S-UAVs assist situational awareness, emergency response, and disaster assessment by flying over these regions. Short-range connections show communication ties between CMs and CHs, whereas CH-to-CH interconnections show mid-range inter-cluster communication [?, ?].

The effects of a non-functioning CH in a clustered S-UAV network are shown in Figure ??. The cluster can no longer aggregate and send data to the BS when the CH on the left side of the network stops working. Because of this, the CMs beneath the failing CH are unable to transmit sensed data and are momentarily cut off from the BS. This causes data loss and interferes with the network's entire communication chain [?]. In contrast, the right side of the figure shows a functioning cluster where the CH successfully gathers and forwards sensed data from devices and ground users to the BS. As a result, the BS still handles crisis management, coordination, and data processing for that portion of the network.

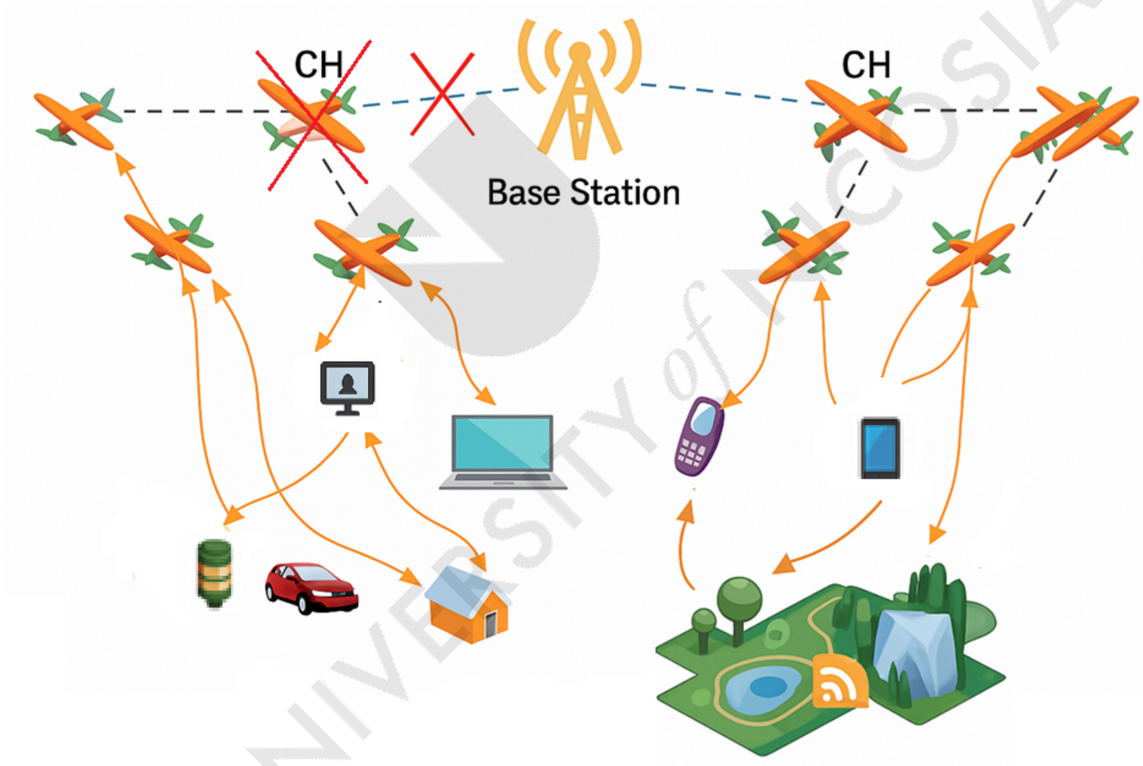

Figure 1.2: Clustered S-UAV network in a crisis scenario with non-functional CH

To address the issues mentioned above, this thesis focuses on the problem of non-functional CHs and the associated data loss. The goal of this research is to propose a new cluster routing scheme for S-UAVs that ensures reliable end-to-end communication and data upload to the BS, even in the presence of non-functional UAVs. The remainder of this chapter is organized as follows. Section 1.1 defines the scope and boundaries of the research. Section 1.2 sets out the main assumptions.

Section 1.3 introduces the crisis scenario taxonomy, while Section 1.4 defines the performance metrics used for evaluation. Section 1.5 presents the research problems and the proposed solutions. Section 1.6 outlines the research methodology adopted in this thesis. Section 1.7 summarizes the main research contributions. Finally, Section 1.8 provides an overview of the thesis organization.

1.1 Scope and Boundaries

This thesis focuses on cluster-based ad-hoc communication schemes for S-UAVs operating in crisis scenarios. This thesis is primarily concerned with the design and evaluation of a routing mechanism that ensures reliable end-to-end data transmission from UAVs to the BS under failure conditions. This research is limited to the networking and communication aspects of S-UAV systems. It does not address flight control, path planning, sensing hardware, payload delivery, or mission planning.

The crisis scenarios considered involve the non-functionality of agents such as drones and vehicles due to environmental, operational, or infrastructural disruptions. The operational scope assumes a multi-agent infrastructure in which UAVs act as airborne communication relays, while other ground-based agents may provide additional sensing or communication support. The performance evaluation focuses on communication reliability, delay, and operational resilience under crisis conditions, and does not address mission success rate, autonomy, or energy optimization beyond communication overhead.

1.2 Assumptions

The proposed approach is developed based on the following assumptions:

- All UAVs are equipped with GPS modules and are aware of their spatial positions.

- The UAVs operate within a three-dimensional airborne environment and maintain ad-hoc multi-hop communication links.

- CHs are responsible for coordinating intra- and inter-cluster communication and forwarding data to the BS.

- The BS remains reachable as long as at least one functional CH exists within the network.

- UAVs are initially assumed to have homogeneous capabilities in terms of communication range and operational characteristics.

- Failures arise from crisis-induced non-functionality rather than malicious attacks.

- Energy consumption is modeled through communication costs and routing overhead, and the energy required for flight is taken into account, while detailed physical battery models are not considered.

- Ground vehicles possess sensing and/or communication modules sufficient for data exchange with nearby UAVs.

- The mobility patterns of ground vehicles are not explicitly optimized and follow predefined or scenario-based movement.

- Ground vehicles are assumed to have sufficient energy for sensing and short-range communication.

- Ground vehicles may experience crisis-induced immobilization or sensor failure depending on the underlying scenario.

These assumptions serve to constrain the system model and to enable analytical and simulation-based evaluation within a realistic but manageable crisis context.

1.3 Crisis Scenario Taxonomy

Crisis scenarios in which S-UAV networks operate may vary in origin, scale, and impact. For the purposes of this thesis, crisis scenarios are categorized as follows:

1. **Natural disasters:** Flooding, earthquakes, storms, landslides, and similar events that disrupt infrastructure and may destroy or immobilize agents.

2. **Electronic non-functionality:** Electronic equipment becoming non-operational due to environmental stress, overload, or physical damage.

3. **Multi-agent instability:** Simultaneous failure of multiple agent types, such as UAVs being unable to fly during storms while vehicles become immobilized during flooding.

These scenarios motivate the need for routing schemes that can adapt to heterogeneous agent failures and provide continuous communication under crisis-induced uncertainty.

1.4 Performance Metrics

To evaluate the performance of the proposed routing scheme under crisis scenarios, the following metrics are considered:

- **Latency (delay):** Time taken for packets to reach the destination node from source node.
- **Packet Delivery Ratio (PDR):** Proportion of successfully delivered packets relative to the total number of generated packets.
- **Cluster stability:** Robustness of the clustering structure under mobility and crisis-induced disruptions.
- **CH recovery capability:** Effectiveness with which the system compensates for CH failures through redundancy and reconfiguration.

These metrics enable an objective comparison of the proposed scheme against existing cluster routing techniques and highlight its performance in crisis conditions.

1.5 Research Problems and Solutions

This thesis addresses the research challenges associated with clustering schemes for multi-agent infrastructures, including drones and vehicles, in crisis scenarios. Specifically, the following research problems and questions are investigated:

1. The need for reliable data transmission from various equipment to the BS using UAVs.

2. The high risk of electronic equipment becoming non-functional in a crisis scenario. In such situations, a CH, which is responsible for all inter-cluster communication, may become non-functional, resulting in the loss of data within its cluster.

3. The need for a cluster routing scheme that provides a robust solution for a non-functional CH.

4. The risk that a redundant CH (RCH), which is also vulnerable to failure in a crisis, could still result in data loss within the cluster.

5. The limitations of a weighted cluster routing scheme with fixed predefined weights, which may lead to high latency or low throughput depending on the network's dynamic status.

6. The possibility that, in a crisis scenario, certain types of agents may be at high risk of simultaneous failure. For example, during a storm, all UAVs may become non-functional or unable to fly properly, while during a flood or earthquake, all vehicles could become immobilized or damaged.

To address these challenges, the following solutions are proposed:

1. Examine and categorize existing cluster routing schemes used in S-UAVs to gain a systematic understanding of the key factors influencing current systems.

2. Analyze available cluster routing schemes that propose solutions for a non-functional CH.

3. Propose a new weighted cluster routing scheme for S-UAVs with a RCH to address the issue of non-functional CHs.

4. Optimize the newly proposed weighted cluster routing scheme for S-UAVs with multiple RCHs to mitigate the risk of non-functionality.

5. Optimize the newly proposed multi-redundant weighted cluster routing scheme for S-UAVs with dynamic weight adjustment that accommodates changes in the network in real time.

6. Further optimize the newly proposed multi-redundant weighted cluster routing scheme for S-UAVs to incorporate multi-agent coordination, including drones and vehicles.

1.6 Research Methodology

The following sequential steps describe the research path and progress:

1. **Problem identification:** A survey of the literature on cluster routing schemes in crisis scenarios with UAV integration is conducted to identify unresolved challenges and limitations.

2. **Research motivation:** A notable research gap exists in cluster-based routing for crisis-oriented communication networks with UAV integration. Current schemes tend to overlook key crisis-induced conditions, particularly the potential non-functionality or fail-stop behavior of CHs, and they provide limited mechanisms for rapid reconfiguration or redundancy under disaster dynamics. At the same time, UAV-assisted networking research predominantly treats UAVs as data ferries, relays, or temporary BSs rather than cooperative agents within clustering hierarchies. As a result, the coordinated integration of UAVs with ground infrastructure to support, replace, or supervise CHs remains insufficiently explored, especially in heterogeneous crisis environments.

3. **Solution definition:** The objective is to develop a new multi-agent cluster routing scheme with UAV integration for crisis scenarios to ensure reliable end-to-end data transmission despite any agent non-functionality, while targeting minimal delay, as data lifespan may expire and thus become non-useful in some cases.

4. **Model and algorithm design:** The proposed new cluster routing scheme is carefully designed, implemented, and analyzed to address the challenges associated with non-functional CHs in S-UAV networks, particularly in crisis scenarios. The goal of this scheme is to ensure continuous, reliable data communication across the network, even in the event of CH failure, which is crucial in scenarios where timely information can be life-saving.

5. **Evaluation and refinement:** The performance of the proposed scheme is evaluated under a range of crisis-related scenarios. Any remaining gaps or limitations identified during this phase are used to refine the model and algorithms.

6. **Synthesis and conclusion:** This thesis concludes by synthesizing the findings,

reflecting on the scope and limitations of the work, and outlining directions for future research.

A flowchart illustrating the research methodology followed in this thesis is shown in Figure **??**.

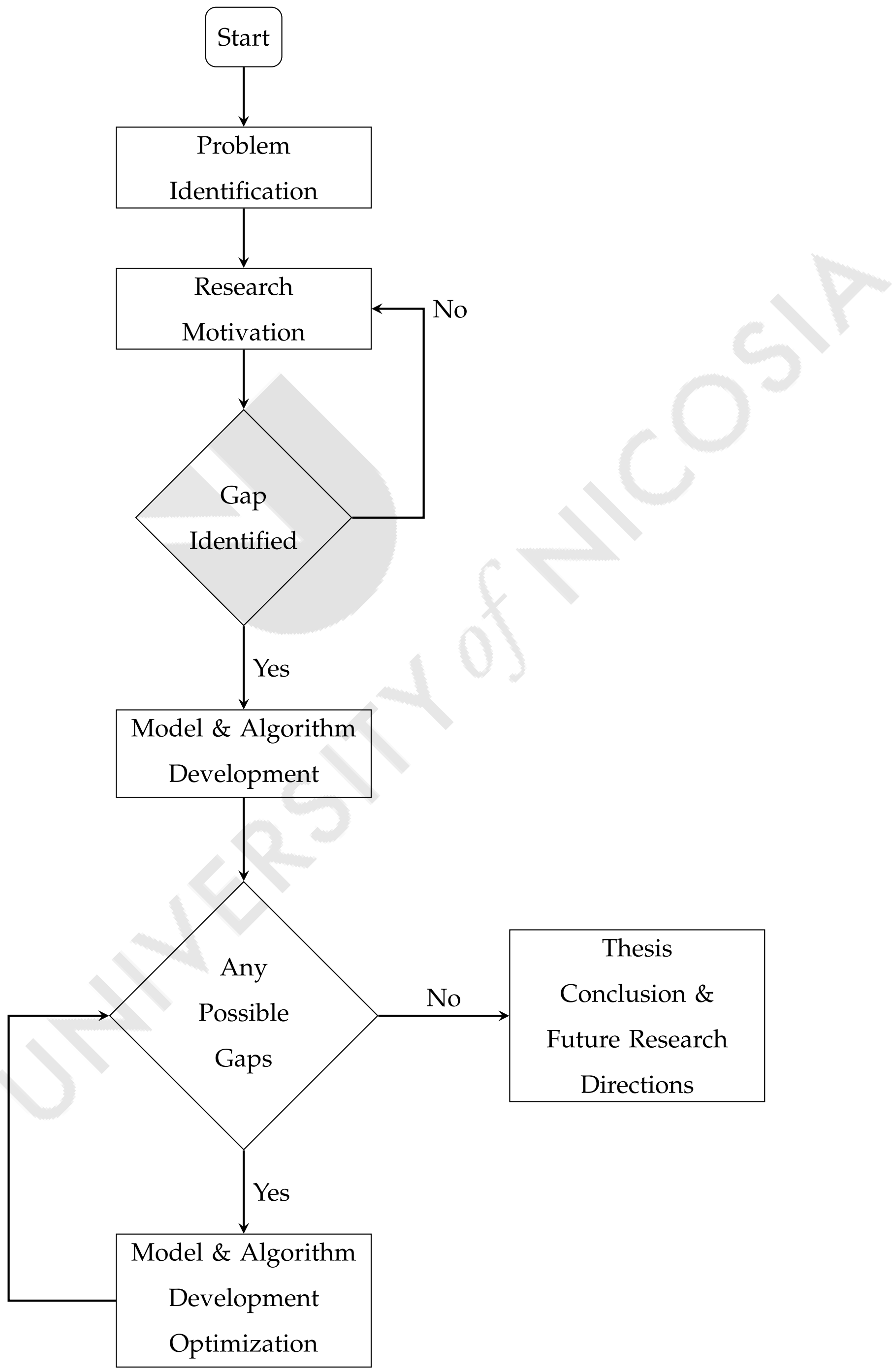

Figure 1.3: Research methodology flowchart

1.7 Thesis Organization

The chapters of this doctoral thesis are structured as shown in Figure **??**. Chapter 2 outlines the scope of the research and development project, its place within the field of study, and presents an up-to-date literature review of cluster routing schemes with UAV integration in crisis scenarios. Chapter 3 addresses the first identified gap, namely the non-functionality of the CH in cluster routing schemes, which is likely to occur in crisis situations. Chapter 4 introduces a novel multi-redundant cluster routing scheme with drone integration, focusing on ensuring reliable data transfer from UAVs to the BS, even in the event of CH non-functionality. Chapter 5 explores the challenges posed by the dynamic nature of S-UAV networks. Since the proposed scheme up to that point relies on predefined weights, this chapter resolves issues arising from network dynamics by incorporating a dynamic weight adjustment protocol. Finally, Chapter 6 examines the high likelihood of agent non-functionality in crisis scenarios. It proposes a multi-agent enhancement to increase reliability and ensure end-to-end communication with minimal delay.

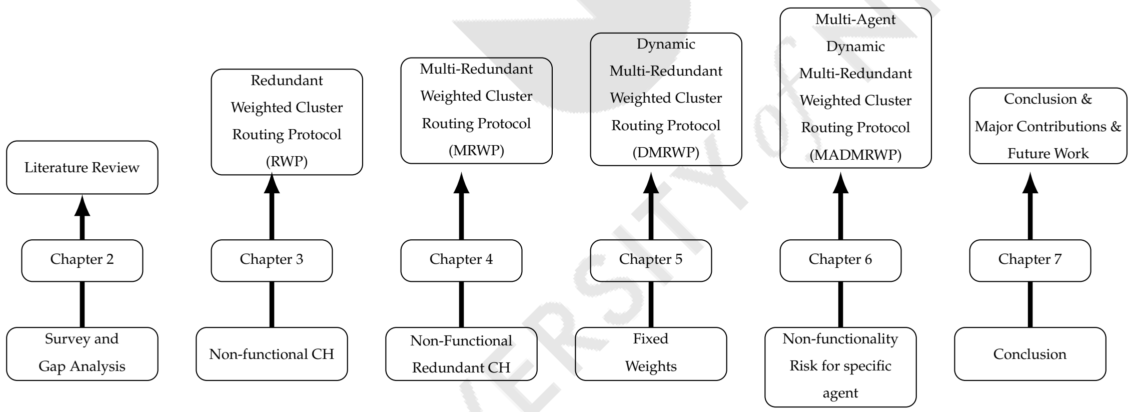

Figure 1.4: Thesis organization

1.8 Conclusion

In conclusion, this thesis proposes a cluster routing scheme that provides an effective solution to the challenges faced by S-UAV networks in crisis scenarios. Through its adaptive and fault-tolerant mechanisms, it ensures that data communication remains reliable and efficient, even when UAVs fail. The implementation and analysis of the scheme confirm its potential to enhance the performance and resilience of UAV-based systems, making it a valuable tool for emergency response and other mission-critical applications.

This chapter presented the scope and context of the research and introduced the topic under investigation. It provided a general introduction to the research problem and the proposed solutions. Additionally, the methodology employed in the study was discussed in detail, accompanied by a flowchart for clarity. The key contributions arising from this research were outlined thoroughly. The chapter concluded with an overview of the thesis structure and organization.

Chapter 2

Survey of Cluster Routing Schemes in Crisis Scenarios

2.1 Introduction

UAVs have drawn significant interest in recent years for a variety of uses, such as communication relaying, environmental monitoring, search and rescue, and surveillance. S-UAVs offer a novel way to improve the functionality and efficiency of UAVs. In this setting, several UAVs cooperate to perform tasks that would be challenging or inefficient for a single UAV. This collaborative approach allows S-UAVs to cover larger areas, perform parallel operations, and dynamically adapt to environmental changes [?].

Cluster routing techniques are essential for S-UAVs because they enhance coordination and communication between UAVs in the swarm [?]. In a decentralized and dynamic setting, these schemes seek to increase the effectiveness of resource management, data transfer, and decision-making procedures. By grouping UAVs into clusters, each responsible for specific tasks or regions, cluster routing techniques enable improved communication traffic management and reduced energy usage [?].

In crisis scenarios, such as natural disasters, search and rescue operations, or emergency response situations, efficient communication and coordination among multiple UAVs are critical for successful mission execution. S-UAVs offer a promising solution in these scenarios by enabling a fleet of UAVs to work collaboratively, covering larger areas and performing parallel tasks in real time. However, to ensure that the S-UAV network operates efficiently and reliably under high-stress conditions, effective cluster routing schemes are essential [?].

In cluster routing schemes, the CH is a critical component. It manages intra-cluster communication, collects data from member nodes, and forwards information to other clusters or to the BS. However, in certain scenarios, there is a significant risk associated with CH non-functionality, which can severely impact the performance and efficiency of the entire system, especially in dynamic or crisis environments. The failure of a CH can introduce several challenges to the network. These include communication disruption, increased energy consumption, loss of coordination, routing inefficiency, delayed reconfiguration, reduced fault tolerance, and overall performance degradation [?].
The remainder of this chapter is organized as follows. Section 2.2 introduces the organizational forms of S-UAV networks. Section 2.3 describes the survey methodology and scope. Section 2.4 presents a taxonomy of S-UAV routing schemes. Section 2.5 discusses generic cluster-based routing schemes and clustering approaches.

Sections 2.6 and 2.7 provide a comparative analysis and detailed review of representative cluster routing schemes. Sections 2.8 and 2.9 summarize the main weaknesses of existing schemes and identify the resulting research gaps. Sections 2.10 and 2.11 formalize the problem statement and trace the evolution of the proposed protocols, respectively, and finally, Section 2.12 brings the chapter to a conclusion.

2.2 Organizational Forms of S-UAV Networks

Three different forms in which UAVs can be organized and coordinated within an ad-hoc network are shown in Figure ??. These forms refer to the structure of the network, how communication occurs, and how UAVs interact within their swarm.

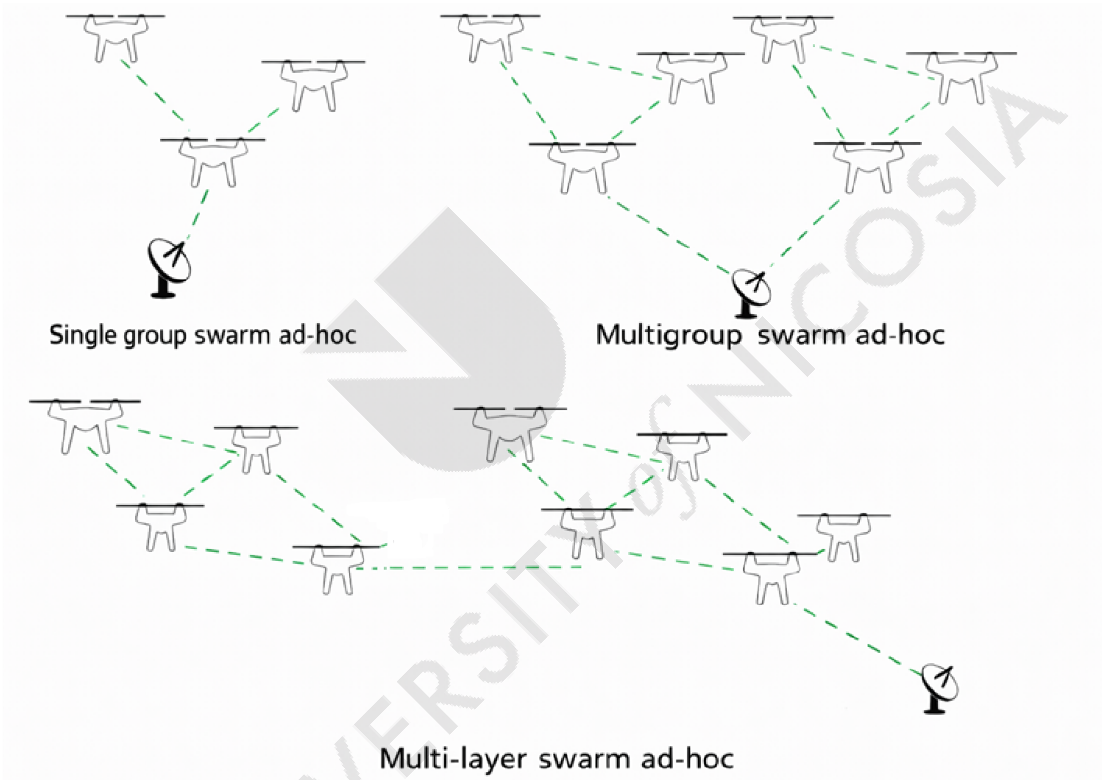

Figure 2.1: Ad-hoc Communication Structures in UAV Swarms

Single-group Swarm Ad-Hoc Network

A single-group swarm ad-hoc network is independent of infrastructure. One of the swarm's UAVs, the gateway UAV, is responsible for interacting with the infrastructure. All UAVs in the group are typically in close proximity and communicate directly with one another to share information and coordinate actions [?]. In this type of network, the UAVs form a single interconnected ad-hoc network where each UAV may act as both a node and a relay within the swarm, facilitating multi-hop communication when necessary [?].

Multi-group Swarm Ad-Hoc Network

In a multi-group swarm ad-hoc network, multiple groups of UAVs operate independently but may collaborate and communicate with each other through inter-group links. Each group has its own internal coordination, and communication within a group is typically ad-hoc, while inter-group communication may use specialized protocols to manage information exchange. This structure is suitable for large-scale missions where several subgroups of UAVs need to perform distinct tasks but still share data and work toward a common goal [?].

Multi-layer Swarm Ad-Hoc Network

A multi-layer swarm ad-hoc network involves a more complex organizational structure, where the swarm is divided into multiple layers, with each layer having its own specific function or role within the overall mission. These layers may be based on UAV types, mission requirements, or roles within the swarm. Each layer can operate independently to some extent, but they communicate and work together to achieve the overall objective. The layers may be organized based on functionality, communication needs, or the physical altitude of UAVs [?].

2.3 Survey Methodology and Scope

This chapter surveys routing schemes and clustering techniques that are relevant to S-UAV networks operating in crisis scenarios. The focus is on protocols that either employ clustering as a core mechanism for organizing communication, or can be adapted to cluster-based S-UAV deployments in dynamic and infrastructure-limited environments.

The survey is structured along two main dimensions [?]:

- **Network architecture:** including single-group, multi-group, and multi-layer swarm ad-hoc networks [?, ?].
- **Routing strategy:** including classifications based on communication model, network topology, and data routing paradigm [?, ?].

The protocols included in this chapter have been selected because they:

1. Incorporate clustering or can support cluster-based organization.
2. Address mobility, scalability, or energy constraints relevant to S-UAVs.
3. Provide insights or design patterns that are useful for crisis scenarios, even if they were originally proposed for other domains (e.g., vehicular networks or wireless sensor networks).

This survey does not attempt to provide an exhaustive catalog of all existing routing protocols. Instead, it concentrates on those schemes that expose specific weaknesses related to CH non-functionality, lack of redundancy, static weighting, or limited multi-agent support. These weaknesses directly motivate the routing protocols proposed later in this thesis.

2.4 S-UAV Routing Schemes

For UAVs to communicate effectively and dependably with one another, S-UAV routing schemes are essential. By reducing energy consumption, preserving network connectivity, and enhancing overall performance, these approaches seek to optimize data routing between UAVs and their communication infrastructure. S-UAV routing algorithms address the unique challenges of UAV networks, including mobility, energy limitations, and communication reliability. The size and mobility of the UAV network, energy requirements, and application type all influence the choice of routing scheme, and each scheme offers specific benefits [?].

2.4.1 S-UAV Routing Schemes Classification Based on Communication

S-UAVs can use either centralized or decentralized communication [?, ?, ?] as shown in Figure **??**.

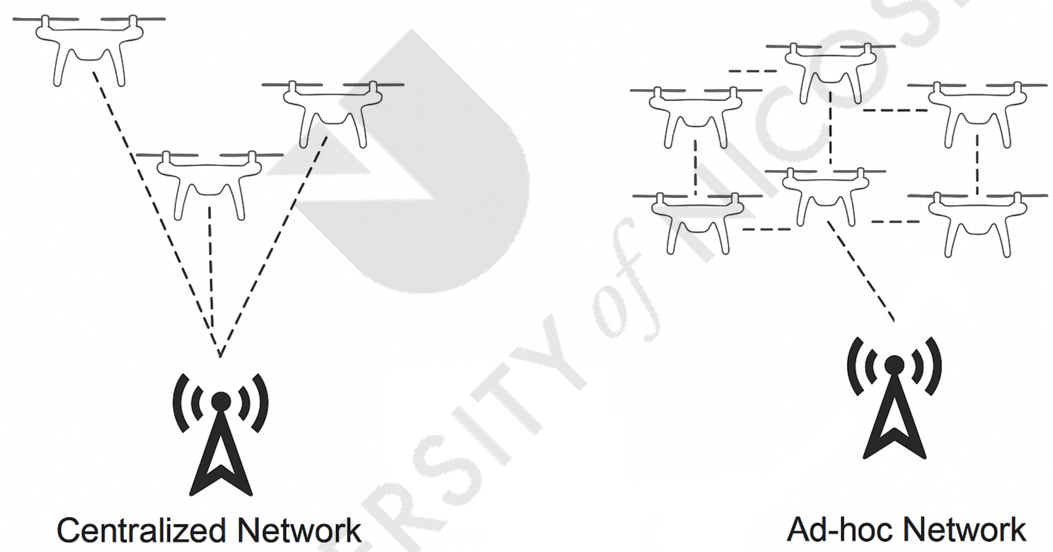

Figure 2.2: Hierarchical Cluster for S-UAVs

Centralized Communication

In centralized communication, the central entity can make global decisions by considering the entire system's data, ensuring coordinated behavior and efficiency. For a small network or specific mission, centralized communication can simplify control, reduce the complexity of coordination, and be easier to design and deploy. However, centralized communication has several disadvantages. As the number of UAVs grows, so do the bandwidth and processing requirements of the central controller [?]. A failure in the central controller can lead to a breakdown of the entire network, which is a significant risk for mission-critical operations and is a core concern of this thesis. In addition, transmitting all data to a central hub for processing introduces delays, especially when UAVs are far from the control station or when communication links are poor. This potential increase in delay is one of the main issues that the proposed scheme seeks to mitigate [?, ?].

Decentralized Communication

Decentralized communication, also known as ad-hoc communication, eliminates fixed communication range restrictions by relying on neighboring nodes, where each UAV operates independently without a central control unit [?]. To share information, UAVs communicate directly with each other, which is known as peer-to-peer communication. Decentralized communication improves autonomy, scalability, dependability, and adaptability. Through dynamic routing, peer-to-peer communication, and self-organisation, UAVs can function as a network capable of performing complex tasks autonomously and with resilience to failures. However, to maximize the performance of decentralized systems in practical situations, issues such as interference, limited communication range, and the need for efficient coordination must be addressed [?].

The communication channels utilized by UAVs are generally divided into air-to-air (A2A) and air-to-ground (A2G). To ensure secure and reliable communication, an appropriate channel model is essential, typically based on geometric, or deterministic approaches. The main types of UAV communication are UAV-to-UAV, UAV-to-BS, and UAV to Ground Station (GS) or User Equipment (UE) (UAV-to-GS/UE) [?, ?, ?]:

1. **UAV-to-UAV:** In many routing schemes, UAVs communicate with one another, which is challenging due to their three-dimensional flight paths and mobility [?].

2. **UAV-to-BS:** UAVs act as aerial users for terrestrial base stations (TBS) to maintain reliable beyond-line-of-sight communication links over long distances. TBS differs from ground stations or user equipment in that it is fixed at a certain height and uses down-tilt directional sector antennas [?].

3. **UAV-to-GS/UE:** In this configuration, a UAV functions as an aerial BS for terrestrial UE (TBS), serving as an auxiliary or alternative to TBS. The International Telecommunication Union recommends using L-band for control and non-payload communication and C-band for payload communication. Therefore, the operating frequency range for this link spans from hundreds of megahertz to the millimetre-wave band [?].

2.4.2 S-UAV Routing Schemes Classification Based on Network Topology

Based on the network structure, routing techniques are commonly separated into two categories: flat and hierarchical [?].

Flat Routing

Where UAVs are not subject to stringent energy constraints or extremely high mobility, flat routing schemes can operate effectively in small, straightforward networks [?]. In flat routing, all UAVs are treated equally and share similar responsibilities for routing data [?]. Peer-to-peer communication takes place without hierarchy; each UAV functions autonomously and makes its own routing decisions, as illustrated in Figure ??.

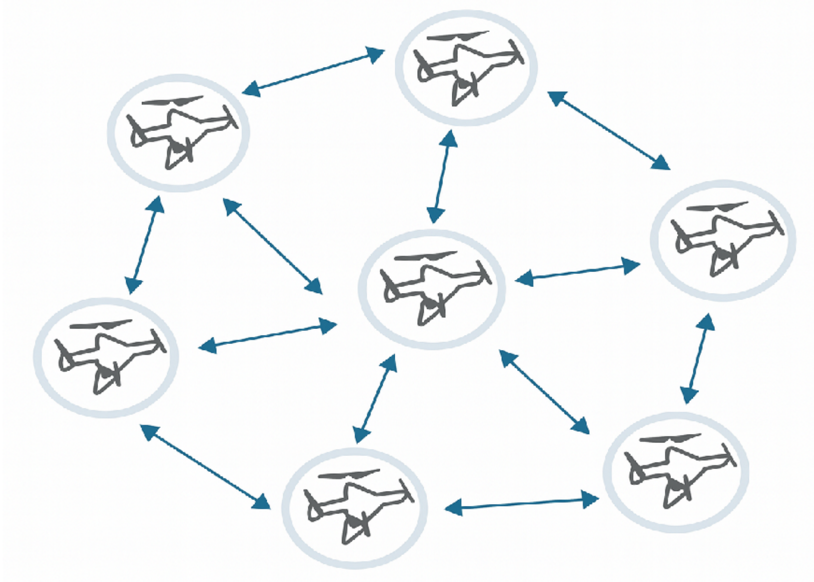

Figure 2.3: Flat Topology for S-UAVs

Hierarchical Routing

Hierarchical routing is employed in large-scale UAV networks where scalability and energy efficiency are crucial. For S-UAVs, hierarchical routing techniques are essential for improving efficiency, scalability, and communication in large UAV networks [?]. These protocols attempt to address the dynamic, decentralized, and potentially large-scale nature of UAV systems [?, ?]. To maximize performance and improve resource management, including energy usage, bandwidth, and computational load, hierarchical routing divides the network into layers or clusters, as shown in Figure **??**.

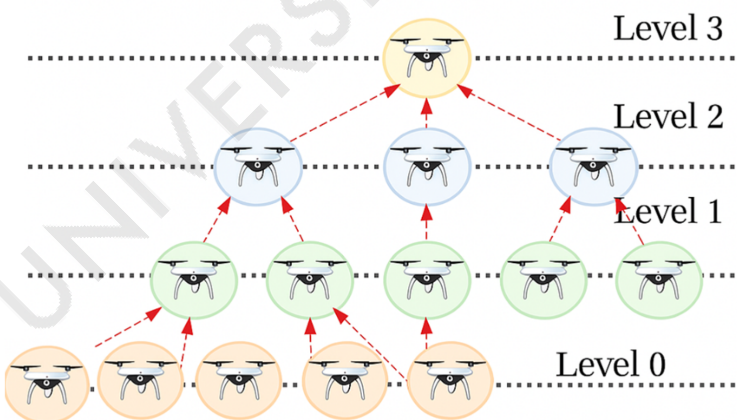

Figure 2.4: Hierarchical Cluster for S-UAVs

Clusters are created within the UAV network using hierarchical routing. As per Figure **??** every cluster has a CH which manages internal communication and coordinates with other clusters. By reducing the communication load on individual UAVs, this type of routing lowers energy usage and improves network scalability. CH selection is therefore a crucial component of the routing strategy and remains an active area of research [?, ?].

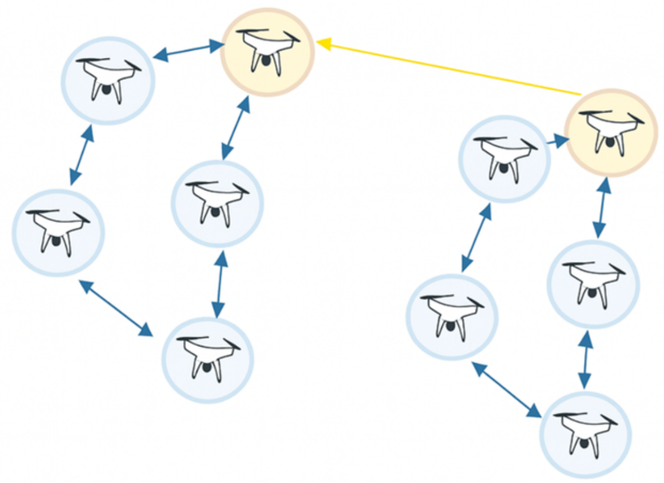

Figure 2.5: Clustered S-UAV Network

2.4.3 S-UAV Routing Schemes Classification Based on Data Routing

Based on the data routing technique, routing strategies can be separated into four groups [?, ?].

Geographic Routing

Geographic routing is a scalable and energy-efficient technique used in highly dynamic mobile networks or large S-UAV systems. It determines the path for data transmission based on the positions, usually GPS coordinates, of UAVs. UAVs forward data according to the relative positions of the source, intermediate UAVs, and destination [?].

Multi-hop Routing

Multi-hop routing is intended for networks with sparse UAVs and long-range communication requirements. Data is sent via intermediary UAVs that serve as relays. A packet is routed from one UAV to another until it reaches its destination. This method is particularly useful when there are obstacles preventing direct connections between UAVs or when they are located far apart [?].

Cluster-based Routing

Cluster-based routing is used in networks where multiple UAVs operate cooperatively within a region, enabling efficient communication and coordination. Under this strategy, UAVs in a cluster aggregate data locally before sending it to the BS or other clusters. This reduces the amount of data transmitted, lowers communication overhead, reduces network congestion, and improves energy efficiency [?].

Delay-Tolerant Routing

Delay-tolerant routing is designed for networks with intermittent connectivity. Data is temporarily stored at UAVs and forwarded when a feasible communication link becomes available. UAVs employ a store-and-forward strategy, which is appropriate for settings such as rural areas or wide-area surveillance where UAVs have poor connectivity or cover very large regions [?].

Figure **??** summarizes the main routing categories for S-UAV networks and highlights how different schemes fit within communication, routing, and topology perspectives.

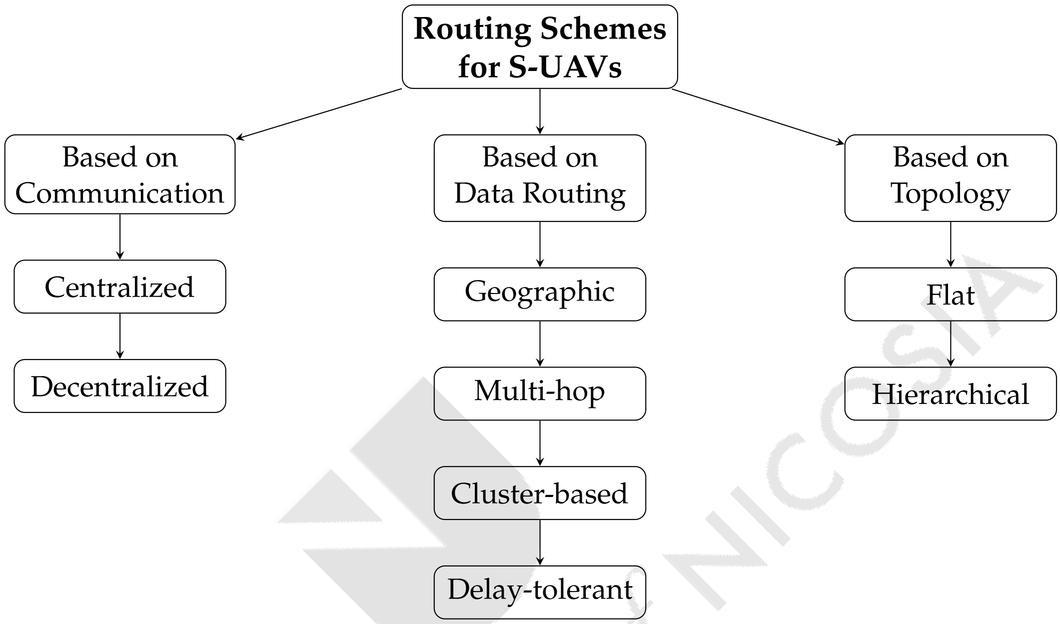

Figure 2.6: Taxonomy of routing schemes for S-UAV networks

2.5 Cluster-Based Routing Schemes

Cluster-Based Routing (CBR) protocols are widely used in wireless ad-hoc networks, including S-UAV networks, to improve network efficiency, scalability, and energy management [?]. In these schemes, the network is divided into smaller manageable groups called clusters, based on factors such as residual energy, distance, speed, and direction [?]. Each cluster consists of a CH and CMs. The CH plays a vital role in controlling communication within and between clusters, as well as handling tasks such as data aggregation, routing, and coordination with the BSs.

Since CH selection significantly affects the performance of CBR schemes, it has been a key focus of research. Each cluster routing scheme defines its own method for selecting CHs to optimize routing efficiency.

Applying clustering techniques to enhance coordination, efficiency, and communication is central to CBR. The main goal is to organize communication effectively inside these networks. Maintaining efficient communication, data transfer, and resource usage in such networks is complicated by dynamic communication patterns and mobility. Different types of clustering approaches are applied in CBR [?]:

1. **Proximity-Based Clustering:** The objective is to minimize intra-cluster communication distances by forming clusters of nodes that are physically close to

one another. The CH is chosen from among these nodes based on centrality or higher node connectivity and link reliability [?].

2. **Geographical Clustering:** Nodes are clustered according to geographical proximity in order to preserve consistent and localized communication patterns. This strategy capitalizes on the likelihood that nodes in the same vicinity will have similar network characteristics [?].

3. **Mobility-Based Clustering:** Mobility-based clustering groups nodes according to their speed and direction. Clusters of nodes travelling in similar directions and at comparable speeds can lessen disruptions caused by relative motion. Nodes with low mobility are favored as CHs to maintain cluster stability [?].

4. **Energy-Based Clustering:** Clusters are created using the remaining energy levels of nodes. Higher-energy nodes are chosen to lead the cluster because they can bear the burden of cluster management for extended periods. To avoid rapid energy depletion and to ensure that clusters operate for longer, nodes with higher battery levels are selected as CHs [?].

5. **Connectivity-Based Clustering:** Connectivity between nodes determines cluster formation. A cluster is made up of nodes that can communicate directly with one another. CHs are selected from among nodes with the highest connectivity such as those with the greatest number of neighbors [?].

6. **Density-Based Clustering:** Density-based clustering creates clusters according to the number of nodes in a region. High-density regions create smaller clusters, whereas low-density regions may create larger clusters. Because they are more connected and have more neighbors, nodes in high-density areas are more likely to become CHs [?].

7. **Distance-Based Clustering:** A predetermined distance threshold is used to construct clusters. A cluster is made up of nodes that are close to one another. The CH is chosen from among the nodes with the highest centrality or most favorable relative position within the cluster [?].

8. **Hybrid Clustering:** Hybrid clustering integrates several clustering criteria, including mobility, energy, proximity, and connectivity, to produce a more flexible and effective clustering method. The optimal CH candidate is chosen based on a combination of metrics such as mobility, distance to other nodes, and energy levels [?].

9. **Leadership-Based Clustering:** The concept of leadership is used to build clusters, with nodes possessing specific capabilities such as greater processing power or improved communication performance serving as CHs. Leadership traits, such as processing capacity, data forwarding capability, or network role, are used to elect the CH [?].

2.6 Cluster Routing Schemes – Literature Review

2.6.1 Cluster-based Directional Routing Protocol (CBDRP)

The Cluster-based Directional Routing Protocol (CBDRP) splits the network into clusters based on movement direction. A vehicle that has the shortest distance to the cluster's center is selected as the CH. The protocol is divided into an initialization phase and a data transmission phase. During the initialization phase, cluster formation and CH selection take place. Following the initialization phase, the data transmission phase begins, composed of four sub-phases: routing request, routing establishment, routing maintenance, and link disconnection. A request packet is flooded whenever a source node requests a route. The request only passes among CHs to reduce traffic overhead. The packet is delivered by the CH to the destination when it reaches the CH of the cluster containing the destination node. However, in highly crowded clusters, the packet size, overhead, and transmission delay increase due to the additional node information processed and stored in routing messages [?, ?].

2.6.2 Location-Aware Dynamic Traffic Routing (LADTR)

The Location-Aware Dynamic Traffic Routing (LADTR) scheme is a dynamic routing strategy used in transportation or networking systems where routing decisions are based on the location or current condition of traffic. Vehicles are outfitted with systems that supply real-time location information. The system uses this information to make intelligent routing decisions based on the proximity of traffic or packets to specific nodes. Depending on factors such as traffic, available bandwidth, and road conditions, the system modifies the route in real time. Because the routing strategy is flexible, it can adapt continuously to new circumstances, such as variations in network load, traffic volume, or environmental influences. The objective is to increase overall system efficiency, either by improving traffic flow in transportation systems or by reducing data transmission latency [?]. While LADTR can greatly improve traffic management, it has weaknesses and challenges, such as dependence on accurate and reliable position data, potential overloading of alternative routes, reliance on connectivity, complexity of data integration, scalability issues, and limited coverage in rural areas. Continuous advancements in infrastructure, security protocols, data collection, and system flexibility are necessary to address these limitations.

2.6.3 Low Energy Adaptive Cluster Hierarchical (LEACH)

Low Energy Adaptive Cluster Hierarchical (LEACH) is a well-known energy-efficient routing technique originally proposed for wireless sensor networks and applicable to S-UAV networks. By lowering node energy consumption and maintaining efficient communication, it is designed to increase the network's lifespan. In LEACH, nodes are arranged into clusters with a leader, known as a CH, and multiple CMs. The CH coordinates communication within the cluster and sends aggregated data to the BS or sink. LEACH employs data aggregation to eliminate duplicated data and reduce the energy usage of nodes. However, because of random CH selection, CHs may be poorly distributed, resulting in uneven energy use. Some clusters may be overloaded while others remain underutilized, leading to shortened network lifetime, increased transmission delay, and higher energy consumption [?].

2.6.4 Temporal-Clustered Routing Protocol (TCRP)

The Temporal-Clustered Routing Protocol (TCRP) dynamically groups the network into clusters while taking into account temporal aspects of communication patterns, such as time-based requirements, fluctuating network conditions, or energy constraints. TCRP is designed to manage routing tasks efficiently by combining clustering with temporal information. Although TCRP employs temporal elements to aid CH selection, it may still suffer from issues such as unequal CH distribution and overhead associated with frequent clustering operations. TCRP aims to minimize communication overhead, guarantee energy-efficient operation, and adapt to shifting network conditions by exploiting both clustering and temporal characteristics. Its main benefits include scalability, energy economy, and extended network longevity. However, TCRP may incur additional latency and increased coordination overhead in very large or highly dynamic networks [**?**].

2.6.5 Probabilistic and Position-based Clustered Routing (PPS)

Similar to LEACH, the Probabilistic and Position-based Clustered Routing (PPS) scheme groups nodes into clusters, with CHs responsible for aggregating data and sending it to the BS or other CHs. Cluster formation in PPS depends on both node positions and probabilistic selection, which improves scalability and flexibility. CH responsibilities in PPS are assigned using both probabilistic and positional criteria. To improve fairness and load balance throughout the network, CH selection is based on a probability function rather than a fixed pattern. This probabilistic nature enhances network longevity and energy efficiency by preventing any single node from being overburdened with data routing. Position information, such as GPS coordinates or estimated positions based on signal strength, is also used to guide packet forwarding and manage cluster head assignments, improving routing efficiency in large-scale and mobile environments [**?**]. PPS depends on precise location data and probabilistic CH selection, which could result in overhead and frequent re-clustering under mobility. Its lack of redundancy for CH failure and disregard for node failures and energy variations restrict its resilience in crisis situations.

2.6.6 Density and Distance-Based Cluster Head Selection (DD-CHS)

The Density and Distance-Based Cluster Head Selection (DDCHS) protocol selects CHs based on the distance and density of neighboring nodes. Every node in the network determines its distance from other nodes, typically using Euclidean distance or another topology-aware method. CHs may be chosen from nodes that are farther apart to improve coverage and reduce the communication distance between CMs and their CH. This helps avoid situations where CHs are too close to one another, which may result in redundant communication or inefficient energy usage. Data aggregation from CMs and transmission to the BS are the responsibilities of CHs. Effective CH placement should reduce communication distance to the BS and further minimize energy consumption. However, accurately calculating distance can be challenging, particularly in dynamic or large-scale networks where GPS or other positioning technologies might not be accessible or sufficiently precise. While DDCHS optimizes energy consumption by considering distance, it may need to incorporate additional factors, such as node battery levels and communication range, to be fully effective [?].

2.6.7 Cluster-Based Energy Efficient Routing Protocol (CEERP)

The Cluster-Based Energy Efficient Routing Protocol (CEERP) is designed to optimize energy consumption and prolong the operational life of UAV networks. By grouping UAVs into clusters with carefully chosen CHs, CEERP minimizes communication costs, lowers energy consumption, and ensures that the network can scale with additional nodes. Nodes initially determine their energy levels and positions when the UAV network is established. To facilitate CH selection, each node broadcasts this information to its neighbors. CHs are then chosen based on local information, including neighbor distance and energy levels. Nodes with higher energy levels and/or more favorable positions are more likely to be selected as CHs [?]. Although CEERP offers clear advantages, such as extended network lifetime and improved energy efficiency, it also has drawbacks. For example, some nodes may be chosen as CHs more frequently than others, leading to energy imbalance and faster depletion of certain nodes. Dynamic network conditions may also complicate CH administration.

2.6.8 Distributed Swarm Clustering and Routing (DSCR)

Distributed Swarm Clustering and Routing (DSCR) employs swarm intelligence to perform distributed clustering and routing tasks in networked or multi-agent systems. It is inspired by natural phenomena such as the behavior of ant colonies, bees, and bird flocks, which solve complex problems through local interactions and simple rules. Clustering in DSCR can be used to form groups of nodes that are geographically adjacent or share similar attributes. The swarm-based approach enables nodes to dynamically adjust their cluster membership based on local information, enhancing scalability and adaptability. For routing, swarm intelligence is used to efficiently and fault-tolerantly forward information through the network. The routing mechanism is decentralized, meaning that each node makes its own decisions about forwarding data to the next node. The absence of a central authority makes DSCR attractive for large-scale and dynamic systems where global knowledge may not be available or practical [?]. However, DSCR still depends on the correct operation of CHs and intermediary nodes, and failures at these points can degrade performance.

2.6.9 Weighted Clustering Algorithm (WCA)

A representative example of multi-parameter weighted clustering is the Weighted Clustering Algorithm (WCA), which selects CHs using a composite weight function that jointly accounts for node degree, transmission power, mobility, and residual energy. By aggregating these metrics, WCA aims to minimize re-clustering overhead and improve stability in highly dynamic mobile ad hoc networks. The work demonstrated that clustering decisions based on multiple parameters outperform single-metric selection strategies, particularly under conditions of node mobility and heterogeneous resource constraints [?]. However, WCA assumes relatively homogeneous node capabilities and does not incorporate redundancy or failure-awareness, limiting its applicability to crisis-oriented or infrastructure-degraded environments.

2.6.10 Hybrid Energy-Efficient Distributed Clustering (HEED)

The Hybrid Energy-Efficient Distributed Clustering (HEED) protocol is a distributed clustering approach developed for wireless sensor networks to enhance energy efficiency and prolong network lifetime. HEED selects CHs based primarily on residual energy, ensuring that nodes with higher available power are more likely to assume leadership roles. A secondary parameter, such as communication cost measured through node proximity or intra-cluster transmission power, is used to refine the selection process and promote well-distributed clusters. The protocol operates in iterative phases, during which nodes probabilistically elect themselves as tentative CHs and broadcast their status to neighboring nodes. After several iterations, final CHs are determined, and regular nodes join the cluster offering the lowest communication cost. HEED achieves balanced energy consumption and avoids the random CH selection found in earlier protocols, resulting in improved scalability and network stability. However, the periodic re-clustering process introduces additional control overhead and energy expenditure, particularly in large-scale or highly dynamic deployments [**?**].

2.6.11 Mobility-Aware Clustering Protocol for UAV Networks (MAC)

The Mobility-Aware Clustering (MAC) protocol is designed to enhance network stability in S-UAV networks by considering node mobility during cluster formation. Unlike conventional clustering methods that primarily rely on static metrics, MAC evaluates parameters such as relative velocity, link duration, and spatial proximity to select stable CHs. UAVs with lower mobility variation are preferred as CHs to reduce the frequency of re-clustering and improve communication reliability. The protocol operates through dynamic cluster formation, maintenance, and reconfiguration phases, ensuring that clusters adapt efficiently to topology changes caused by UAV movement. Additionally, MAC incorporates predictive mechanisms to estimate link stability, enabling more robust routing decisions and minimizing packet loss. Although the protocol significantly improves cluster longevity and network performance, the computation required for mobility prediction and continuous monitoring may increase control overhead in highly dynamic aerial environments [**?**].

2.6.12 Unequal Clustering Algorithm (UCA)

The Unequal Clustering Algorithm (UCA) is a distributed clustering approach developed to enhance energy efficiency and mitigate the hotspot problem in heterogeneous wireless sensor networks. Unlike conventional clustering protocols that create clusters of similar sizes, UCA forms clusters with unequal radii based on their distance from the base station. CHs located closer to the base station are assigned smaller clusters to reduce their relay burden, as they are responsible for forwarding data from farther clusters in multi-hop communication. The algorithm enables nodes to self-organize into clusters using local information, promoting scalability and balanced energy consumption across the network. Data collected from member nodes are aggregated at the CH before being transmitted toward the base station, thereby reducing redundant transmissions. Although UCA effectively prolongs network lifetime by distributing energy usage more evenly, the process of determining optimal cluster sizes may introduce additional control overhead, particularly in dense network deployments [**?**].

2.6.13 Threshold Sensitive Energy Efficient Network (TEEN)

The Threshold Sensitive Energy Efficient Network (TEEN) is a hierarchical routing protocol designed for time-critical wireless sensor network applications. TEEN organizes nodes into clusters, where CHs aggregate data from member nodes and forward the information to the base station. Unlike proactive protocols that transmit data continuously, TEEN adopts a reactive approach by introducing two threshold values: a hard threshold and a soft threshold. The hard threshold defines the minimum sensed value that triggers data transmission, while the soft threshold specifies the minimum change in the sensed attribute required for subsequent transmissions. This mechanism significantly reduces the number of transmissions, thereby conserving energy and extending network lifetime. The protocol is particularly suitable for environments that require immediate reporting of sudden changes, such as temperature spikes or hazardous events. However, TEEN may not be ideal for applications requiring regular data updates, as the absence of threshold-triggered events can result in limited communication and reduced network visibility [**?**].

2.6.14 Fuzzy Logic-Based Clustering (FLC)

Fuzzy Logic-Based Clustering (FLC) is an intelligent clustering approach that enhances CH selection in wireless sensor networks by incorporating fuzzy logic principles. Instead of relying solely on deterministic metrics, the protocol evaluates multiple parameters such as residual energy, node proximity, and communication cost to determine the suitability of nodes for the CH role. These inputs are processed through a fuzzy inference system that assigns each node a probability of becoming a CH, resulting in more balanced cluster formation and improved energy utilization. By considering uncertainty and dynamic network conditions, FLC reduces the likelihood of selecting poorly positioned or energy-depleted nodes as cluster heads. Consequently, the method contributes to prolonged network lifetime and improved overall stability. However, the implementation of fuzzy logic introduces additional computational complexity and may require parameter tuning to achieve optimal performance in diverse deployment scenarios [**?**, **?**].

2.6.15 Particle Swarm Optimization-Based Clustering (PSO-C)

Particle Swarm Optimization-Based Clustering (PSO-C) is an energy-aware clustering technique that applies particle swarm optimization to determine optimal CH placement in wireless sensor networks. The protocol models each potential clustering configuration as a particle within the search space, where particles iteratively adjust their positions based on individual and collective experience to minimize energy consumption. Key factors such as intra-cluster communication distance and transmission energy are considered during the optimization process to achieve balanced clusters and reduce overall power usage. Once the optimal CHs are identified, sensor nodes associate with the nearest cluster head for data transmission, enabling efficient aggregation and forwarding to the base station. This approach enhances network lifetime by preventing uneven energy depletion among nodes. However, the iterative optimization process may introduce computational overhead and increased set

2.6.16 Stable Election Protocol (SEP)

The Stable Election Protocol (SEP) is a clustering-based routing protocol developed to improve the stability and energy efficiency of heterogeneous wireless sensor networks. SEP extends traditional clustering schemes by introducing nodes with different energy levels, commonly classified as normal and advanced nodes. Advanced nodes possess higher initial energy and are assigned a greater probability of becoming CHs, thereby distributing energy consumption more effectively across the network. The protocol operates in rounds similar to LEACH, where CHs are elected based on weighted probabilities that reflect node energy heterogeneity. This strategy prolongs the stability period, defined as the time until the first node depletes its energy, and enhances overall network lifetime. Additionally, SEP maintains low computational complexity while supporting scalable cluster formation. However, since the protocol relies on predetermined energy differences and does not dynamically adjust to residual energy during operation, it may lead to suboptimal CH selection in later network stages [**?**].

2.6.17 Distributed Energy-Efficient Clustering (DEEC)

The Distributed Energy-Efficient Clustering (DEEC) protocol is designed to enhance energy utilization in heterogeneous wireless sensor networks by dynamically selecting CHs based on the residual energy of nodes. Unlike conventional clustering approaches that assign equal CH election probability, DEEC calculates the average network energy and adjusts each node's probability of becoming a CH according to its remaining energy relative to this average. As a result, nodes with higher energy are more frequently chosen as cluster heads, leading to balanced energy dissipation and prolonged network lifetime. The protocol operates in rounds that include cluster formation, CH selection, and data transmission phases, where aggregated data are forwarded to the base station to reduce redundant communication. DEEC improves network stability and scalability while minimizing premature node failures. However, advanced nodes may experience faster energy depletion due to their increased participation in CH duties, which can affect long-term performance if not properly managed [**?**].

2.6.18 Developed Distributed Energy-Efficient Clustering (DDEEC)

The Developed Distributed Energy-Efficient Clustering (DDEEC) protocol is an enhancement of the DEEC scheme, designed to further optimize energy consumption in heterogeneous wireless sensor networks. DDEEC improves CH selection by introducing a threshold residual energy level that prevents advanced nodes from being overburdened with CH responsibilities. In traditional DEEC, high-energy nodes are repeatedly selected as CHs, leading to their premature depletion. To address this issue, DDEEC adjusts the CH election probability once the energy of advanced nodes approaches that of normal nodes, ensuring a more balanced distribution of energy usage. Similar to its predecessor, the protocol operates in rounds involving cluster formation, CH election, and data transmission, with data aggregation performed to minimize communication overhead. This balanced approach enhances network stability and extends overall lifetime. However, the protocol still relies on accurate energy estimation and may incur additional computational overhead in dynamically heterogeneous environments [**?**].

2.6.19 Distributed Clustering Algorithm (DCA)

The Distributed Clustering Algorithm (DCA) is a pioneering clustering approach developed for mobile ad hoc networks to support scalable and efficient network organization. In DCA, each node is assigned a weight based on predefined metrics such as node degree, transmission power, mobility, or battery capacity. Nodes with the highest weight within their local neighborhood are elected as CHs, while neighboring nodes join the cluster as members. The algorithm operates in a fully distributed manner, allowing nodes to make clustering decisions using local information without requiring centralized coordination. This structure helps reduce routing complexity and improves channel utilization by enabling hierarchical communication. Additionally, DCA adapts to topology changes by allowing re-clustering when significant network variations occur. Despite its advantages in scalability and simplicity, frequent topology changes in highly mobile environments may trigger repeated cluster reformation, leading to increased control overhead and potential network instability [?].

2.6.20 Genetic Algorithm-Based Clustering (GA-C)

The Genetic Algorithm-Based Clustering (GA-C) scheme employs evolutionary optimization techniques to improve cluster formation and energy efficiency in wireless sensor networks. The approach models clustering as an optimization problem, where candidate solutions represent different CH configurations. Through genetic operations such as selection, crossover, and mutation, the algorithm iteratively refines these configurations to minimize communication distance and balance energy consumption among nodes. Fitness functions typically consider parameters such as residual energy, node distribution, and intra-cluster communication cost to identify near-optimal clustering structures. Once the optimal CH set is determined, sensor nodes associate with the most suitable cluster head for data aggregation and transmission to the base station. This strategy enhances network lifetime and scalability by preventing uneven energy depletion. However, the computational complexity and convergence time of genetic algorithms may limit their applicability in real-time or resource-constrained sensor network environments [?].

2.6.21 Ant-Based Routing Algorithm (ARA)

The Ant-Based Routing Algorithm (ARA) is an energy-efficient routing approach inspired by the foraging behavior of ant colonies, designed to improve data transmission in wireless sensor networks. The protocol utilizes artificial ants that explore multiple paths between source nodes and the BS, depositing virtual pheromones to indicate path quality. Over time, routes with higher pheromone concentrations are preferred, enabling the network to adaptive select paths with lower energy consumption and reduced transmission cost. The algorithm supports both route discovery and maintenance through continuous path evaluation, allowing it to respond effectively to topology changes. Additionally, probabilistic forwarding helps distribute traffic across multiple routes, preventing excessive energy depletion along a single path. While ARA enhances network reliability and extends operational lifetime, the generation of control packets and pheromone updates may introduce additional communication overhead, particularly in dense network deployments [?].

2.6.22 Hierarchical Clustering Scheme (HCS)

The Hierarchical Clustering Scheme (HCS) is a structured clustering approach developed to improve scalability and resource management in multi-hop wireless networks. The scheme organizes nodes into clusters governed by CHs, which coordinate communication within their clusters and facilitate inter-cluster routing. HCS focuses on constructing a hierarchical control architecture that reduces routing complexity and enhances network efficiency by limiting the scope of control messages. Cluster formation is typically based on network topology and node proximity, ensuring that communication paths remain relatively short and manageable. Additionally, the hierarchical structure supports efficient bandwidth utilization and helps maintain network organization as it grows in size. However, the reliance on cluster heads may introduce potential bottlenecks, and maintaining the hierarchy in highly dynamic environments can result in additional control overhead [?]

2.6.23 Energy Efficient Clustering Scheme (EECS)

The Energy Efficient Clustering Scheme (EECS) is a clustering protocol designed to improve energy distribution and extend the lifetime of wireless sensor networks. EECS enhances CH selection by considering the residual energy of nodes, allowing those with higher energy levels to assume leadership roles more frequently. Unlike traditional schemes with fixed cluster sizes, EECS introduces a distance-based competition mechanism that produces clusters of varying sizes depending on their proximity to the base station. Nodes closer to the base station form smaller clusters to compensate for their higher communication burden, thereby promoting balanced energy consumption across the network. After CH election, non-cluster-head nodes select their CH based on a cost function that accounts for both communication distance and cluster load. This strategy reduces intra-cluster transmission energy and improves overall network efficiency. However, the competitive CH selection process may generate additional control messages, potentially increasing overhead in dense deployments [?].

2.6.24 Algorithm for Cluster Establishment (ACE)

The Algorithm for Cluster Establishment (ACE) is a distributed clustering protocol designed to produce highly uniform cluster formations in wireless sensor networks. ACE operates through localized interactions, allowing nodes to self-organize into clusters without requiring global network knowledge. The protocol relies on an emergent behavior mechanism in which nodes periodically evaluate their neighborhood and decide whether to become CHs based on predefined spawning and migration rules. This process promotes even cluster distribution and prevents the formation of overly dense or sparse clusters, thereby improving communication efficiency. Additionally, ACE minimizes control overhead by limiting message exchanges to nearby nodes, making it suitable for large-scale deployments. The algorithm also adapts to topology changes by allowing clusters to reorganize when necessary. However, repeated cluster adjustments may increase energy consumption, particularly in networks with frequent node mobility or dynamic conditions [?].

2.6.25 Stable Election Protocol (SEP)

The Stable Election Protocol (SEP) is a clustering-based routing protocol proposed to enhance stability and energy efficiency in heterogeneous wireless sensor networks. SEP introduces energy heterogeneity by classifying nodes into normal and advanced categories, where advanced nodes possess higher initial energy. To leverage this difference, the protocol assigns weighted probabilities for CH election, increasing the likelihood that higher-energy nodes assume the CH role. This strategy balances energy consumption and prolongs the stability period, defined as the time interval before the first node exhausts its energy. Similar to LEACH, SEP operates in rounds consisting of cluster formation and data transmission phases, with CHs responsible for aggregating data and forwarding it to the base station. Although SEP improves network lifetime and reduces premature node failures, its reliance on predefined energy levels and lack of dynamic residual en

2.6.26 Enhanced Distributed Energy-Efficient Clustering (EDEEC)

The Enhanced Distributed Energy-Efficient Clustering (EDEEC) protocol is an extension of DEEC designed to further improve energy efficiency and network lifetime in heterogeneous wireless sensor networks. EDEEC introduces three levels of node heterogeneity—normal, advanced, and super nodes—each characterized by different initial energy capacities. CH selection is performed based on the ratio of a node's residual energy to the average network energy, ensuring that higher-energy nodes are more frequently elected as CHs. This probabilistic approach promotes balanced energy dissipation and delays premature node failures. Similar to other distributed clustering schemes, the protocol operates in rounds that include CH election, cluster formation, and data transmission with aggregation to minimize redundant communication. By leveraging multi-level heterogeneity, EDEEC enhances network stability and throughput. However, nodes with greater energy reserves may experience faster depletion due to their repeated selection as CHs, potentially affecting long-term energy balance if not carefully managed [?].

2.6.27 Mobility-Based Clustering (MOBIC)

The Mobility-Based Clustering (MOBIC) algorithm is a clustering technique developed for mobile ad hoc networks that emphasizes node mobility as the primary criterion for CH selection. The protocol evaluates the relative mobility of nodes by estimating variations in received signal strength, enabling the identification of nodes with more stable movement patterns. Nodes exhibiting lower mobility relative to their neighbors are preferred as CHs, as they are less likely to cause frequent topology changes. This strategy enhances cluster stability and reduces the need for repeated re-clustering, thereby lowering control overhead. MOBIC operates in a distributed manner, allowing nodes to independently compute mobility metrics using local information. While the algorithm improves network reliability by forming longer-lasting clusters, its reliance on signal strength measurements may lead to inaccuracies in environments with interference or fluctuating channel conditions [?].

2.6.28 Distributed Mobility-Adaptive Clustering (DMAC)

The Distributed Mobility-Adaptive Clustering (DMAC) algorithm is designed to enhance cluster stability in mobile ad hoc networks by incorporating node mobility into the CH selection process. DMAC assigns weights to nodes based on mobility-related metrics, favoring nodes with relatively stable movement patterns to serve as CHs. This approach reduces the frequency of cluster reconfiguration caused by rapid topology changes. The algorithm operates in a fully distributed manner, allowing nodes to make clustering decisions using locally available information without centralized control. Additionally, DMAC supports adaptive cluster maintenance by enabling nodes to switch clusters when significant mobility variations are detected, thereby preserving network connectivity. By prioritizing stability, the protocol improves routing efficiency and lowers control overhead. However, continuous mobility evaluation may increase computational and communication costs, particularly in highly dynamic network environments [**?**].

2.7 Weaknesses of Existing Cluster Routing Schemes

Below is a summary of the weaknesses identified in the literature review, which formed the foundation of this research. These weaknesses were specifically considered when developing the new routing scheme.

- **CBDRP:** Inefficient CH selection, as the algorithm ignores variables such as node mobility, energy levels, and geographic dispersion. This leads to weaknesses related to dynamic behavior, control overhead, energy consumption, and adaptability to network changes.

- **LADTR:** Inefficient routing in environments where accurate position data (e.g., GPS) is unavailable or unreliable. Errors in location information can degrade routing performance, particularly in challenging environments.

- **LEACH:** Load imbalance and shortened network lifetime due to random CH selection, which can cause transmission delays, higher energy usage, and uneven energy depletion.

- **TCRP:** Increased overhead of node coordination and communication, since dynamic clustering according to temporal activity patterns may consume significant energy and bandwidth.

- **PPS:** Frequent restructuring of clusters, as it depends on the precision and availability of position data, typically via GPS. This can result in packet forwarding delays and instability in highly dynamic networks.

- **DDCHS:** CH selection based solely on node density and position can lead to rapid energy depletion and imbalance, as some nodes may be overused while others remain underutilized.

- **CEERP:** Potential energy imbalance, as nodes with favorable energy and distance characteristics may be chosen as CHs more frequently than others, leading to uneven energy consumption and possible node overloading.

- **DSCR:** Vulnerability to failures at CHs or intermediary nodes, since DSCR relies on these nodes operating correctly to transmit data. This can introduce bottlenecks or points of failure in crisis environments.
- **WCA:** WCA provides no CH fault-tolerance and incurs high re-clustering overhead in dynamic environments, limiting its resilience during crisis-related disruptions.
- **HEED:** Periodic re-clustering and iterative cluster-head election introduce additional control overhead and energy consumption, reducing efficiency in large-scale or highly dynamic networks.
- **MAC:** Continuous mobility monitoring and prediction increase computational and signaling overhead, particularly in fast-changing UAV environments.
- **UCA:** The determination and maintenance of unequal cluster sizes require additional control messaging, which may increase overhead in dense or frequently changing deployments.
- **TEEN:** Event-driven communication can result in prolonged inactivity when threshold conditions are unmet, limiting network observability for periodic monitoring applications.
- **FLC:** Increased computational complexity and the need for careful tuning of fuzzy membership functions and rule sets reduce suitability for resource-constrained and highly dynamic networks.
- **PSO-C:** Iterative optimization introduces significant computational cost and convergence delay, limiting applicability in real-time or highly dynamic deployments.
- **SEP:** Reliance on predefined energy heterogeneity without adapting to residual energy variations can lead to suboptimal cluster-head selection in later network stages.
- **DEEC:** Frequent selection of high-energy nodes as cluster heads may cause premature energy depletion and long-term imbalance if not properly managed.
- **DDEEC:** Dependence on accurate residual energy estimation and adaptive probability adjustment introduces additional computation and may be less effective in rapidly changing environments.
- **DCA:** Frequent topology changes in mobile networks can trigger repeated re-clustering, increasing control overhead and reducing network stability.
- **GA-C:** Genetic algorithm operations incur high computational complexity and convergence latency, limiting suitability for real-time and resource-constrained networks.
- **ARA:** Pheromone updates and control packet generation introduce additional communication overhead, particularly in dense networks.
- **HCS:** Dependence on cluster heads may create bottlenecks and single points of failure, while maintaining the hierarchy incurs extra overhead in dynamic networks.

- **EECS:** Competitive cluster-head election and distance-based clustering increase control message exchanges, raising overhead in large-scale deployments.
- **ACE:** Repeated cluster adjustments driven by local interactions may increase energy consumption in highly dynamic or mobile networks.
- **EDEEC:** Nodes with higher initial energy may experience accelerated depletion due to repeated cluster-head selection, affecting long-term energy balance.
- **MOBIC:** Mobility estimation based on received signal strength is sensitive to channel fluctuations, leading to potentially inaccurate cluster-head selection.
- **DMAC:** Continuous mobility evaluation and adaptive maintenance increase computational and communication costs in highly dynamic environments.

It is evident that most existing schemes were not originally designed with crisis scenarios as their primary target environment. While they provide valuable mechanisms for clustering, energy management, and scalable routing, they often lack:

- Explicit handling of CH non-functionality and its impact on data delivery.
- Redundant or multi-level CH structures capable of tolerating multiple failures.
- Dynamic adjustment of routing weights in response to rapidly changing network conditions.
- Support for heterogeneous multi-agent infrastructures that combine UAVs with vehicles and sensors.

These observations highlight the need for a cluster routing scheme that explicitly incorporates redundancy, dynamic weight adjustment, and multi-agent coordination while maintaining acceptable latency and reliability under crisis conditions. The next sections formalize these weaknesses and translate them into the problem statement addressed by this thesis.

2.8 Identified Research Gaps

Based on the comparative analysis and the weaknesses identified in existing CBR schemes, several research gaps can be clearly articulated. These gaps directly motivate the routing protocols proposed in this thesis:

1. **Limited support for CH non-functionality in crisis scenarios.** Most existing schemes assume that CHs remain functional or can be replaced without significant disruption. They do not explicitly model or mitigate the impact of CH failures on end-to-end data delivery in highly dynamic crisis environments.
2. **Lack of systematic CH redundancy and multi-level protection.** While some protocols improve CH selection or rotation, very few introduce structured redundancy (e.g., primary and multiple backup CHs) capable of tolerating simultaneous failures without compromising cluster connectivity and data forwarding.

3. **Static weighting of routing and clustering parameters.** Many schemes use fixed weights for metrics such as distance, energy, mobility, or reward. These static configurations are not well suited to crisis scenarios, where network conditions can change rapidly, and routing decisions must adapt in real time.

4. **Insufficient integration of heterogeneous multi-agent infrastructures.** Existing cluster routing protocols generally focus on a single class of nodes such as vehicles or UAVs. They do not fully exploit the complementary capabilities of heterogeneous agents such as UAVs, vehicles, and ground sensors in a unified cluster routing framework.

5. **Incomplete consideration of crisis-induced failure patterns.** Although many protocols address mobility, energy, or topology changes, they rarely consider correlated failures caused by crisis events such as when all vehicles are immobilized in floods, or UAVs grounded in storms, which can significantly alter the effective topology and reliability of the network.

The subsequent chapters address these gaps through the design of multi-redundant weighted cluster routing schemes with dynamic weight adjustment and explicit multi-agent coordination tailored to crisis scenarios.

2.9 Problem Statement

S-UAVs can act as efficient communication relays to help transmit packets from a source node to a destination node in situations where traditional communication infrastructure is unavailable, such as during emergencies, crises, or natural disasters.

Routing is a crucial component of S-UAV networks to guarantee effective communication between UAVs and other devices, especially in emergency or disaster situations where infrastructure is lacking. The structure of the network, communication requirements, UAV mobility, and the operating environment all influence the optimal routing strategy. An effective routing method should maximize network dependability, data delivery, and resource efficiency.

The scalability, energy efficiency, and lower communication overhead of clustering-based routing make it one of the most suitable routing paradigms for S-UAV networks. This is essential for missions in time-sensitive applications such as search and rescue and disaster recovery. Clustering-based methods simplify routing, guarantee reliable communication even in dynamic environments, and extend the operational life of UAVs by grouping them into clusters and assigning CHs. The CH is in charge of overseeing communication inside the cluster and serving as a conduit for information sent to other clusters and to the BS.

Figure **??** illustrates a crisis-induced disconnection scenario in which CH2 is nonfunctional, leading to the loss of its inter-cluster forwarding role. As a result, the communication path between the two adjacent clusters is disconnected, creating network fragmentation and isolation of nodes that rely on CH2 for data relay toward the BS. This highlights the vulnerability of single-CH structures to individual failures and the need for redundant and resilient clustering mechanisms.

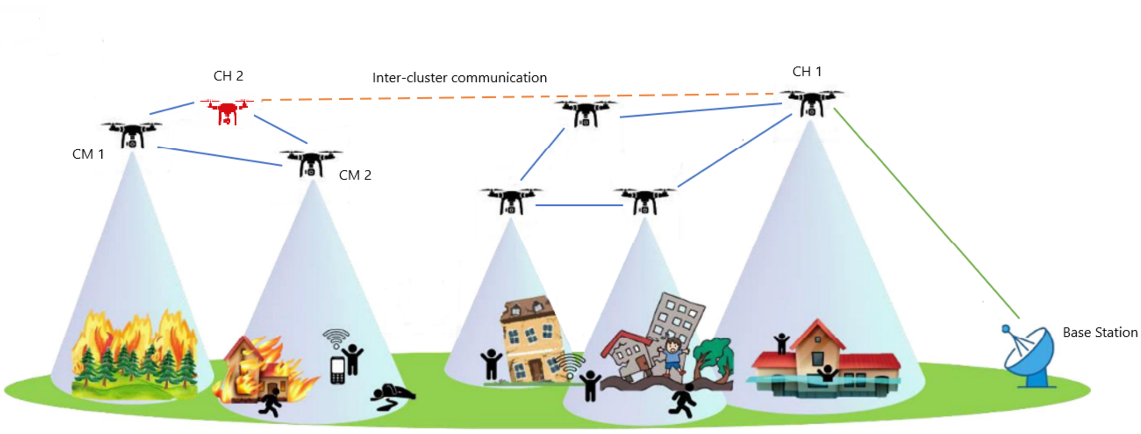

Figure 2.7: UAV clustering in crisis-induced disconnection scenarios.

2.10 Evolution of the Proposed Protocols

One of the most widely adopted technologies in intelligent aerial systems is the S-UAV network. S-UAVs offer numerous benefits, including enhanced communication efficiency, improved coordination, environmental monitoring, and greater operational flexibility. Clustering is employed to increase communication efficiency by aggregating messages and sending them to the BS, leveraging the network's scalability and resilience. When selecting the CH for stable cluster formation in S-UAV networks, factors such as mobility dynamics and distance between UAVs must be carefully considered [?, ?].

To evaluate the likelihood of selecting a CH, we proposed a novel clustering technique based on a weighted formula [?]. Four main components are included in this formula: reward, distance, energy, and velocity. A new metric introduced in our approach, reward, measures how reliably a UAV transmits data with minimal delay. Each node should ideally connect to the closest CH to optimize energy consumption; this is ensured by considering both distance and velocity during the clustering process. Monitoring the energy levels of UAVs is crucial to guarantee efficiency, performance, and safety. Because UAVs are powered by batteries, it is essential to control energy consumption. Flying in different conditions results in different energy usage; therefore, our protocol in [?] explicitly considers energy as a parameter in the weighted calculation.

One consequence of infrastructure failure caused by the direct effects of natural disasters is disconnected communication. We optimized our proposed protocol in [?] to address packet transmission failures in S-UAV networks under disaster conditions where UAVs experience disrupted connectivity. In clustering protocols, the node responsible for data transmission to the infrastructure is the CH. The issue that arises when a CH fails and cannot successfully send packets to the infrastructure is addressed in [?, ?]. Any node is at risk of being damaged in a crisis scenario, including the redundant CH. In [?], our proposed approach selects a redundant CH for each node to ensure that data is uploaded even if the CH is damaged. As a result, regardless of how many UAVs are inactive, a CH is chosen to maintain inter-cluster communication. Up to this stage, the weighted parameters were set to predefined constant values. To reflect the network's dynamic nature, a dynamic weight adjustment protocol was introduced in [?, ?]. Following the initial clustering phase, the proposed approach dynamically and autonomously adjusts the weights to optimize UAV role selection.

Our final contribution adds a multi-agent dimension to the clustering protocol, giving the system greater flexibility and adaptability—particularly in emergency situations. In such scenarios, various agent types—such as vehicles and UAVs—may face different levels of risk and operational constraints. UAVs are less vulnerable to ground-level obstacles since they operate in the air and can often maintain communication even in challenging circumstances. However, during natural catastrophes like earthquakes or floods, vehicles are more likely to be obstructed or destroyed by debris or environmental conditions, making them less reliable for communication and data transfer. Because of this dynamic variation in risk and usefulness across different node types, we optimized our protocol to take into account the distinct characteristics and limitations of both vehicles and UAVs. By incorporating the multi-agent aspect, which captures the varying risks and capabilities of different node types in crisis scenarios, our proposed protocol guarantees more reliable, resilient, and energy-efficient clustering. This method maximizes resource use, enhances overall network stability, and lowers the probability of communication failures by leveraging the distinct advantages of each node type. Vehicles and UAVs within the same cluster ultimately improve the network's fault tolerance and decrease the need for frequent reformation, ensuring more effective operation in disaster response scenarios.

The proposed study aims to create a novel routing method for S-UAV clusters in emergency scenarios focusing on the following key aspects: multi-agent coordination, end-to-end data communication, handling network scalability, and real-time adaptability.

Figure 2.8: Ad-hoc multi-agent communication scenario involving UAVs, vehicles, and terrestrial infrastructure.

Figure **??** depicts a heterogeneous multi-agent communication environment where terrestrial infrastructure, ground vehicles, and UAVs work together to share data in real time. UAVs facilitate communication between stationary BS and mobile ground agents by acting as airborne communication relays. Vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), UAV-to-infrastructure (U2I), and multi-hop UAV-assisted relaying are among the various wireless communication links that coexist. The overlapping communication zones show that line-of-sight availability, signal quality, and dynamic spatial interactions all affect coverage and connectivity. In areas with high urban traffic, where traditional infrastructure may experience congestion, blockages, or limited coverage, such architectures are especially pertinent. The network benefits from increased flexibility, better coverage, and lower data delivery delay when UAVs are incorporated into the communication loop. Research into adaptive protocols for dependable and effective multi-agent communication is prompted by the scenario, which also highlights issues with interference, resource allocation, routing coordination, and mobility management among diverse nodes.

2.11 Conclusion

In this chapter, S-UAV routing protocols have been reviewed with an emphasis on their design principles and challenges. S-UAVs, which provide high flexibility, robustness, and scalability in a variety of real-time applications, represent a rapidly expanding field in networked autonomous systems. Routing protocols designed for S-UAV networks must account for the difficulties arising from their dynamic characteristics, including mobility, topology changes, and crisis-induced failures.

The reviewed literature highlights the diversity and complexity of routing protocols created for S-UAVs, focusing particularly on routing mechanisms and clustering protocols. Although S-UAV routing protocol development has attracted significant interest in recent years, several aspects remain unresolved. For example, many protocols do not adequately address dynamic environmental changes that occur in real time during crisis scenarios.

In crisis scenarios such as natural disasters, the need for reliable, real-time communication, monitoring, and decision-making is critical. However, traditional communication infrastructure may be damaged, destroyed, or unavailable. S-UAV networks, with their ability to deploy quickly and operate independently of ground-based infrastructure, offer unique advantages in such situations. Although many S-UAV routing protocols employ CHs, they rarely address CH non-functionality caused by energy depletion, malfunction, or loss of connectivity. This can result in ineffective routing, communication failures, and overall degradation of network performance.

In the subsequent chapters, we propose innovative routing methods to address the identified gaps. These protocols aim to increase the scalability, efficiency, and reliability of S-UAV networks by incorporating dynamic techniques for detecting CH failures, reassigning CH roles, and maintaining network stability even in the presence of node failures. In particular, the next chapter introduces the baseline clustered routing scheme that forms the foundation for the four parameters weighted, multi-redundant, dynamically weighted, and multi-agent enhancements developed later in this thesis.

Chapter 3

Weighted Cluster Routing Protocol (RWP)

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Introduction

S-UAV networks represent a highly dynamic category of airborne wireless systems that enable real-time data exchange, sensing, and coordination among multiple UAVs. These networks support critical services such as situational awareness, emergency communications, surveillance, and data transmissison in environments lacking terrestrial infrastructure [?].

Clustering is one of the most widely adopted networking mechanisms for organizing communication within such swarm-based systems. By partitioning UAVs into subgroups (clusters), the approach enhances scalability, increases communication efficiency, and improves routing resilience. Within each cluster, data aggregation mitigates redundant transmissions and reduces interference, while hierarchical organization enables orderly communication toward decision-making nodes such as BS [?].

Despite its advantages, cluster-based networking faces significant challenges due to the high mobility of UAV nodes. Stable formation and maintenance of clusters is particularly difficult in S-UAV environments, where frequent topological changes disrupt routing links. CHs are central to the functionality of clustering protocols, as they coordinate intra-cluster routing and facilitate inter-cluster data forwarding [?]. The literature indicates that UAV velocity and inter-node separation distance considerably impact the stability and suitability of CH candidates. In most clustering schemes, nodes with shorter separation distances and moderate velocities—positioned approximately central to neighboring nodes—are preferred for CH selection [?, ?, ?]. Beyond mobility-induced factors, node reliability and cooperation also influence routing performance. To address this aspect, a rewarding index is introduced in this research to quantify cooperative packet forwarding behavior. Nodes that deliver packets with minimal delay receive higher rewards relative to non-cooperative nodes that contribute to increased latency or packet drops [?].

To address the limitations of existing schemes, this chapter proposes a novel weighted clustering protocol for CH selection that integrates three key metrics: distance, velocity, and rewarding index. The objective is to minimize routing delay and network overhead while ensuring reliable end-to-end data delivery under high-mobility conditions. The proposed protocol computes a weighted cluster index and selects the CH with the optimal score, thereby improving throughput and reducing both packet loss rate and end-to-end delay. Furthermore, RCHs are introduced to enhance robustness against node failure and improve survivability in dynamic swarm scenarios. By maintaining a backup CH within each cluster, the network can rapidly reconfigure when the primary CH becomes non-functional, ensuring sustained connectivity and minimizing control overhead during re-clustering events.

The remainder of this chapter is structured as follows:

- Section 3.1 formulates the problem of CH vulnerability and its effect on routing.
- Section 3.2 presents the proposed redundant weighted clustering protocol and CH selection mechanism.
- Section 3.3 evaluates the protocol through simulation and discusses performance results.
- Section 3.4 summarizes limitations of the proposed method.
- Section 3.5 concludes the chapter and motivates the multi RCH extensions introduced in the next chapter.

3.1 Problem Statement

Consider two UAV nodes, k and l, belonging to the same S-UAV network. In cluster-based routing, nodes may reside within the same cluster or across different clusters. If k and l share the same cluster, direct communication is typically feasible. However, if they reside in different clusters, data exchange must be relayed through their respective CHs, which are responsible for inter-cluster forwarding.

In crisis-oriented scenarios, CHs are subject to elevated operational risk due to factors such as physical damage, energy depletion, sensing overload, or temporary loss of connectivity. When a CH becomes non-functional, packets generated by its CMs fail to reach their intended destinations [?, ?]. This failure results in inter-cluster communication disruption, increased data loss, and degradation of situational awareness—effects that are particularly detrimental in time-critical environments [?].

These considerations motivate the need for CH selection mechanisms that minimize forwarding delay and improve routing efficiency, while also motivating redundancy-based strategies that preserve packet delivery continuity in the event of CH failures.

Figure ?? illustrates representative communication in S-UAV network operating under clustered topologies. UAVs are organized into clusters composed of CHs and CMs, where intra-cluster links are established through V2V communication, and inter-domain connectivity is supported through V2I links to ground infrastructure or BS. Under fault-free operation, CHs coordinate local forwarding and relay aggregated data toward the BS. However, failure of a CH disrupts both intra- and inter-cluster communication, as indicated by the damaged CH on the right, demonstrating how localized disruptions can induce wider network degradation [?]. This scenario highlights the sensitivity of non-redundant clustering schemes to CH failures and motivates the need for resilient, redundancy-aware S-UAV communication architectures [?].

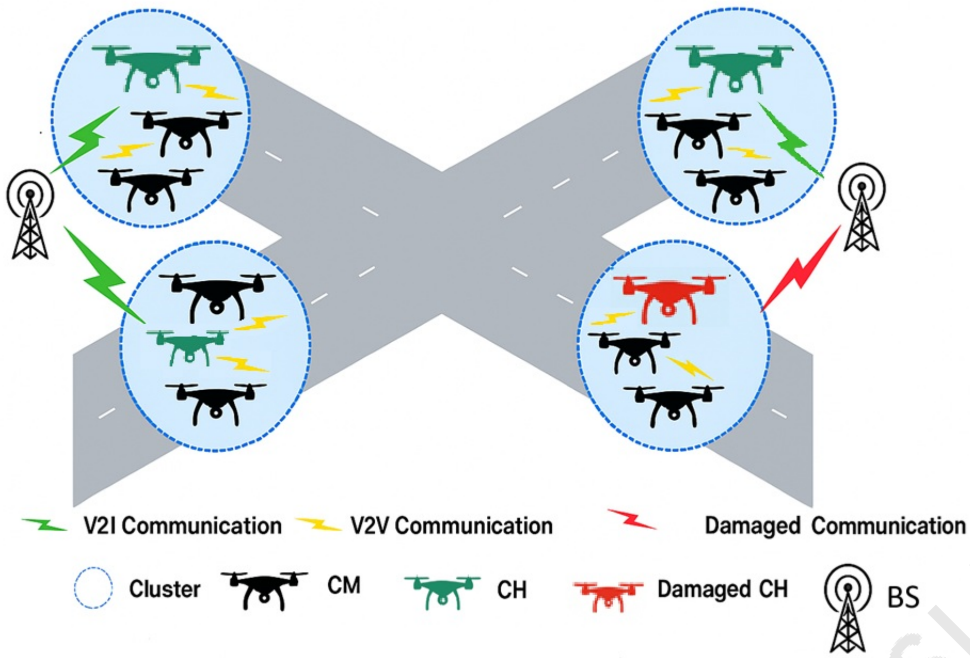

Figure 3.1: Cluster-based S-UAV networking forms in crisis conditions.

3.2 Proposed Protocol

Figure **??** illustrates a clustered S-UAV network composed of multiple clusters, each managed by a CH. Cluster 1 and Cluster 3 are controlled by fully functional CHs, which coordinate intra-cluster communication and relay information externally. In contrast, Cluster 2 contains a non-functional CH, which disrupts local forwarding and inter-cluster communication pathways. To maintain connectivity and avoid cluster isolation, a RCH assumes the forwarding role and restores communication continuity. This redundancy mechanism prevents fragmentation, mitigates the impact of CH failures, and highlights the importance of fault-tolerant cluster management in crisis-oriented S-UAV networks.

The primary objective of the proposed protocol is to select optimal CHs within an S-UAV network. To this end, each UAV computes a weighted cluster index based on separation distance, rewarding index, and relative velocity [**?**]. The weighted characteristic index for UAV pair (k, l) is expressed as:

$$C_{(k,l)} = -\psi D_{(k,l)} + \kappa R_{(k,l)} - \zeta V_{(k,l)}, \tag{3.1}$$

where:

- $C_{(k,l)}$ denotes the cluster index for UAV k relative to UAV l;
- $D_{(k,l)}$ denotes the inter-node distance between UAV k and UAV l;
- $R_{(k,l)}$ denotes the cooperation-based rewarding index between UAV k and UAV l;
- $V_{(k,l)}$ denotes the relative velocity between UAV k and UAV l;

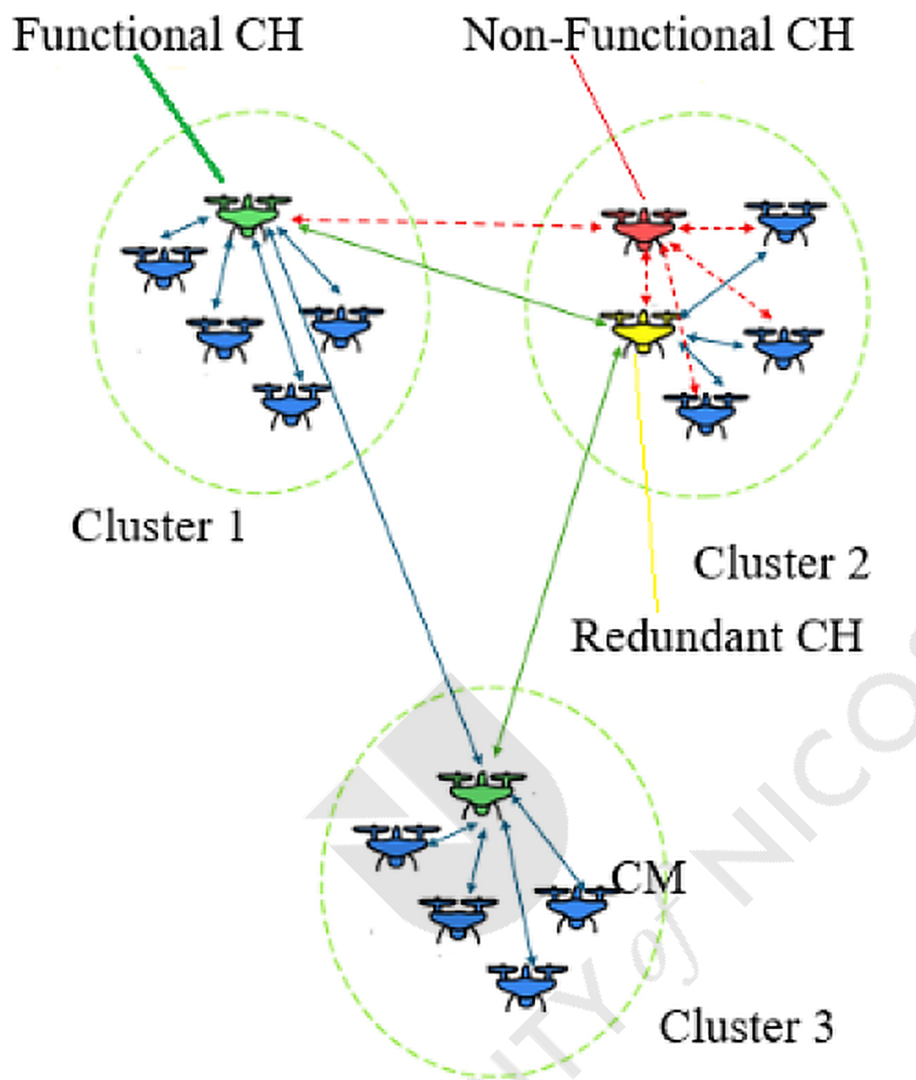

Figure 3.2: Redundant CH support in clustered S-UAV networks in crisis conditions.

- ψ corresponds to the weight of the distance component.
- κ corresponds to the weight of the rewarding index component.
- ζ corresponds to the weight of the velocity component.

3.2.1 Separation Distance

All UAVs are assumed to possess GPS modules that provide real-time positional coordinates. Let UAVs k and l have positions (x_k, y_k, z_k) and (x_l, y_l, z_l), respectively [?]. Their mutual separation distance is computed as:

$$D_{(k,l)} = \sqrt{(x_k - x_l)^2 + (y_k - y_l)^2 + (z_k - z_l)^2}, \tag{3.2}$$

The parameter $D_{(k,l)}$ quantifies spatial proximity between nodes and is used to evaluate local topology density and cluster cohesion. Smaller values of $D_{(k,l)}$ indicate tighter spatial grouping and a higher likelihood of maintaining stable intra-cluster links, while larger separations may result in communication degradation or cluster fragmentation, especially under high mobility [?]. In UAV swarms, separation distance additionally reflects the dynamic interplay between trajectory, mission constraints, and inter-node coordination. By continuously monitoring $D_{(k,l)}$, nodes can make informed decisions regarding cluster membership and role assignment, thus promoting more reliable multi-hop forwarding and reducing re-clustering overhead during rapid topology changes.

3.2.2 Rewarding Index

The rewarding index reflects packet forwarding cooperation and consists of direct and indirect rewarding components [?].

Let $t_{(k,l)}$ denote the forwarding delay of packets from UAV k to UAV l, and let t_{avg} denote the average forwarding delay observed in the network. A packet is forwarded or discarded based on the following condition, which compares the instantaneous forwarding delay against the average forwarding delay observed in the network [?].

$$\text{Packet} = \begin{cases} \text{forwarded}, & \text{if } t_{(k,l)} \leq \omega\, t_{\text{avg}}, \\ \text{discarded}, & \text{if } t_{(k,l)} > \omega\, t_{\text{avg}}, \end{cases} \tag{3.3}$$

Where ω is a dimensionless tolerance parameter that accounts for delay variability in the network and regulates the strictness of the forwarding criterion. Typically, ω is selected as a real-valued scalar in the range $\omega < 1$, allowing the mechanism to differentiate acceptable forwarding delays from excessive ones. By tuning ω, the network can reward cooperative forwarding behavior and suppress latency-inducing transmissions; smaller values of ω enforce stricter delay constraints, while larger values relax the condition to accommodate higher mobility or transient congestion.

The direct rewarding index $R_{D(k,l)}$ is defined as [?]:

$$R_{D,(k,l)} = \frac{f_{(k,l)}}{y_{(k,l)}}, \tag{3.4}$$

where:

- $f_{(k,l)}$ denotes the total number of forwarded packets
- $y_{(k,l)}$ denotes the total number of received packets from UAV k.

The indirect rewarding index $R_{I(k,l)}$ reflects cooperative reports broadcasted by neighboring UAVs and is computed as :

$$R_{I,(k,l)} = \sum_{n \in \mathcal{N}} R_{D,(n,l)}, \tag{3.5}$$

Where: $\mathcal{N}$ denotes the set of neighboring UAVs.

The overall rewarding index is given as a weighted sum [?]:

$$R_{(k,l)} = \lambda R_{D,(k,l)} + (1 - \lambda) R_{I,(k,l)} \tag{3.6}$$

Where $0 \leq \lambda \leq 1$ is a weighting parameter that determines the relative contribution of direct and indirect rewarding components. The term $R_{D,(k,l)}$ captures direct cooperation behavior, which is derived from the forwarding performance observed between UAVs k and l, while $R_{I,(k,l)}$ represents indirect cooperation inferred through neighboring observations or secondary interactions within the swarm.

By tuning λ, the network can prioritize the most relevant source of cooperation evidence. Values of λ closer to 1 emphasize direct interactions and are suitable in environments where nodes frequently exchange packets and have reliable direct observations. Conversely, smaller values of λ increase the influence of indirect rewarding, which becomes beneficial in sparse topologies or highly dynamic mobility scenarios where direct interactions are intermittent.

The resulting cooperation score $R_{(k,l)}$ is then used as a composite measure of packet forwarding behavior and serves as an input to higher-level decision-making processes such as cluster head selection or routing role assignment.

3.2.3 Relative Velocity

The final weighted metric is the scalar relative velocity. Let UAV k travel at speed v_k with azimuth and elevation angles (α_k, θ_k). The azimuth angle α_k represents the horizontal bearing of the UAV relative to a reference axis (typically the positive x-axis) when projected onto the x-y plane, while the elevation angle θ_k specifies the vertical inclination of the UAV with respect to the horizontal plane as shown in Figure **??** [**?**].

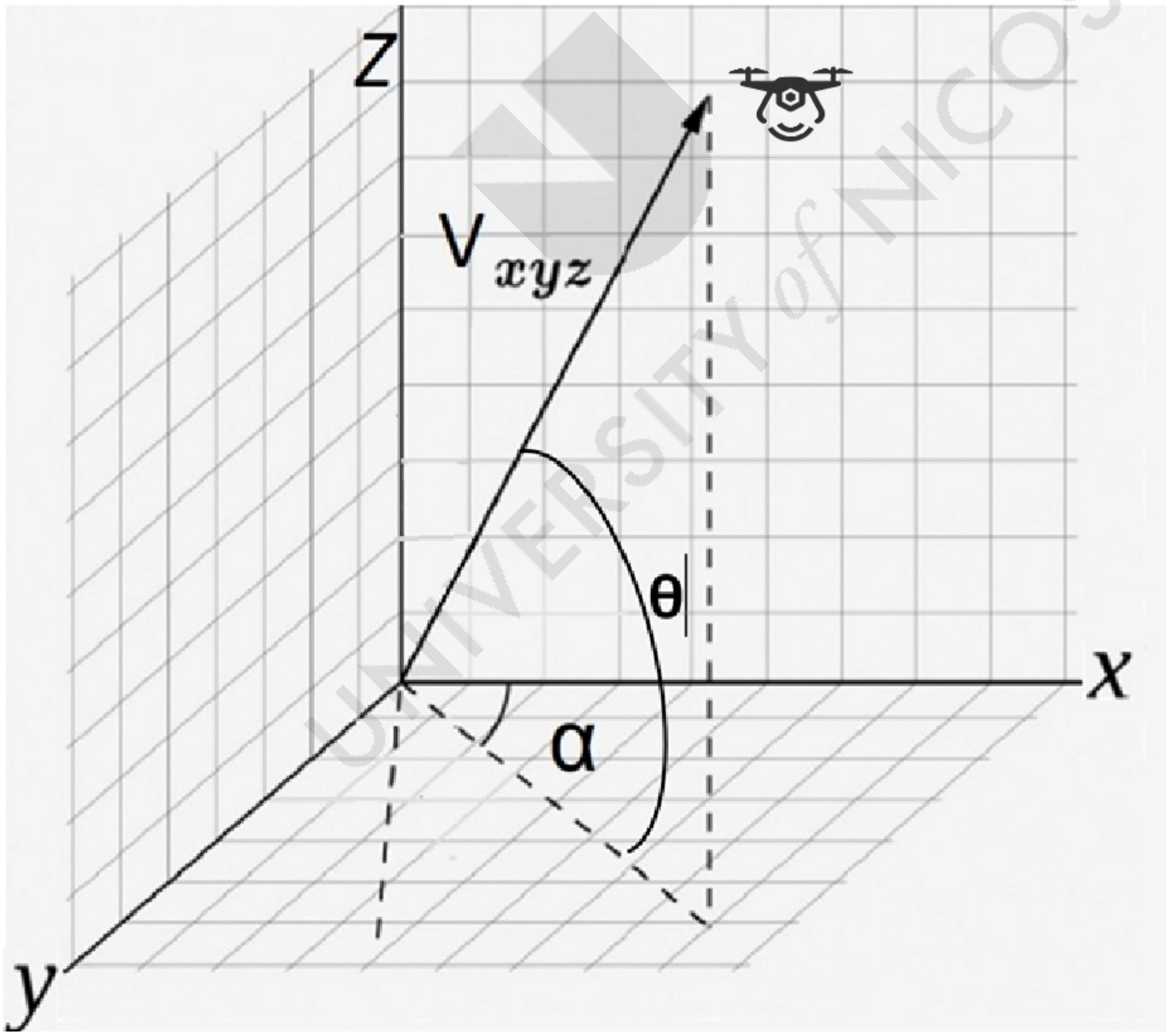

Figure 3.3: Drone position angles in 3D.

Its velocity components in 3D space are [**?**]:

$$
\begin{aligned}
v_x &= v\cos(\alpha),\\
v_y &= v\sin(\alpha),\\
v_z &= v\sin(\theta).
\end{aligned} \tag{3.7}
$$

The relative velocity of UAV k with respect to UAV l is given by:

$$
\begin{aligned}
v_{x,(k,l)} &= v_k\cos(\alpha_k) - v_l\cos(\alpha_l),\\
v_{y,(k,l)} &= v_k\sin(\alpha_k) - v_l\sin(\alpha_l),\\
v_{z,(k,l)} &= v_k\sin(\theta_k) - v_l\sin(\theta_l),
\end{aligned} \tag{3.8}
$$

and the resulting scalar relative velocity is computed as:

$$
V_{(k,l)} = \sqrt{v_{x,(k,l)}^2 + v_{y,(k,l)}^2 + v_{z,(k,l)}^2}. \tag{3.9}
$$

Thus

$$
V_{(k,l)} = \sqrt{(v_k\cos(\alpha_k) - v_l\cos(\alpha_l))^2 + (v_k\sin(\alpha_k) - v_l\sin(\alpha_l))^2 + (v_k\sin(\theta_k) - v_l\sin(\theta_l))^2}. \tag{3.10}
$$

3.2.4 Cluster Formation and CH Selection

Using (**??**), each UAV computes its cluster index, which reflects its likelihood of being selected as a CH. The UAV with the highest cluster index is elected as the CH. Once elected, the CH selects the nearest UAV with the next highest index as a CM [**?**]. To enhance resilience, the first CM is designated as a RCH, acting as a backup leadership node in case the primary CH becomes non-functional during operation. This RCH acts as a standby leadership node and automatically assumes CH responsibilities if the primary CH becomes non-functional during operation. This redundancy mechanism ensures leadership continuity and prevents disruption in cluster management and routing [**?**]. This iterative process continues until all UAVs are assigned either as CH or CM. Cluster formation operates continuously, with all UAVs recalculating their indices every t_{loop} milliseconds to account for network mobility and topology changes [**?**].

Figure **??** illustrates the proposed weighted clustering and CH selection procedure. The protocol first initializes network parameters and begins random packet routing. Next, each UAV computes its relative velocity and separation distance, capturing the mobility and spatial characteristics that affect cluster stability. Each UAV also computes its rewarding index to quantify forwarding behavior.

From these metrics, each UAV calculates a cluster index representing its leadership suitability. This value is broadcast to neighboring UAVs, enabling a distributed comparison. The average cluster index is then computed, allowing each UAV to determine whether it should act as a CH or CM. UAVs are assigned in descending order of cluster index. During assignment, a UAV joins a cluster as a CM if the cluster is currently being populated and if its number of CMs is below the maximum threshold $C_{\max}$. Otherwise, it initiates a new cluster and resets $C_{\max}$ [**?**, **?**].

This process continuously repeats, ensuring that cluster roles adapt dynamically as UAV motion and cooperation behavior change over time.

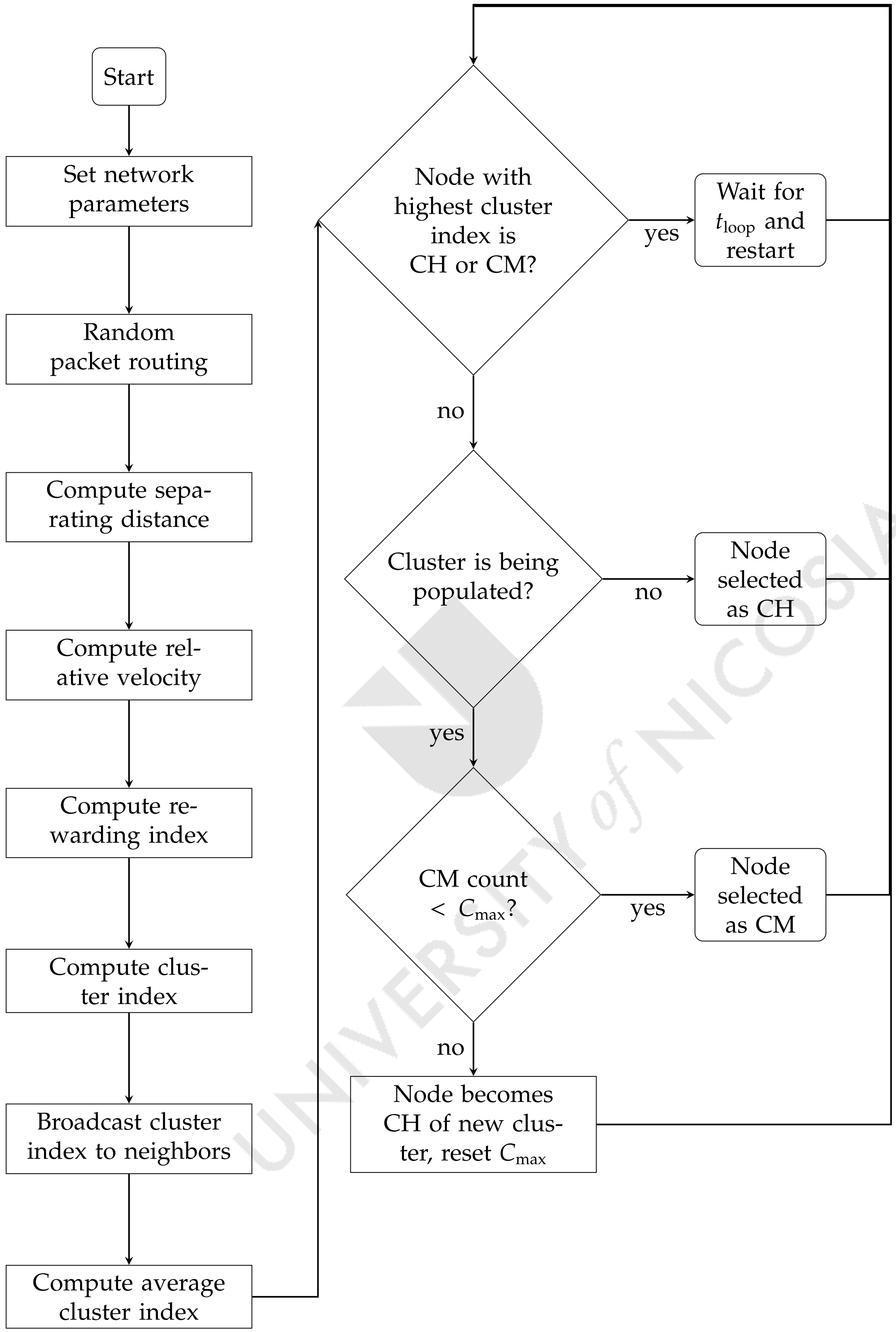

Figure 3.4: Flowchart of the proposed weighted CH selection and clustering scheme.

Topology Maintenance Procedures

In dynamic S–UAV environments, node mobility, energy depletion, and operational failures continually alter the connectivity structure of the network [?]. To preserve stable communication and cluster integrity under such conditions, the proposed scheme implements a lightweight set of topology-maintenance procedures. These procedures ensure that clusters can evolve in response to node arrivals, node departures, and CH malfunction without resorting to costly global reclustering [?]. The topology of the S-UAV network evolves continuously due to the high mobility of UAVs and the dynamic nature of their operating environment [?, ?]. Consequently, the proposed scheme must preserve network connectivity while ensuring timely information transmissison across nodes. To this end, the protocol defines a set of procedures to handle various topological events, including the arrival of new vehicles or UAVs, the departure of existing nodes, and the reassignment of CH. Together, these mechanisms enable robustness and adaptability in scenarios where network partitions and frequent link disruptions are likely to occur. The following subsections describe the key events and the associated protocol behavior.

1. New Vehicle or UAV Joining the S–UAV Network

When a new UAV joins the S-UAV network, it initially lacks knowledge regarding surrounding nodes and the existing cluster structure. To facilitate network discovery, the new node periodically broadcasts `HELLO` messages to neighboring nodes within communication range. If a `HELLO` message is received by a CH, the CH may respond with a join-request, indicating that the node satisfies admission criteria and can be incorporated into the cluster. Upon reception of such a request, the new node joins the cluster and ceases further `HELLO` broadcasting. If no join-request is received prior to the next clustering round, the node remains unclustered until reclustering occurs.

The `HELLO` message format contains both structural and operational fields, enabling distributed decision-making, as shown in Table **??**.

Table 3.1: HELLO Message Format

Node ID	Cluster ID	CH ID	Role	Position	Speed	Energy

Each field conveys key information for the clustering process:

- **Node ID:** uniquely identifies the node within the network.
- **Cluster ID:** denotes the cluster to which the node belongs (set to N/A if the node is not yet assigned to a cluster).
- **CH ID:** denotes the cluster-head to which the node should route its packets (set to N/A if no cluster association exists).
- **Role:** indicates whether the node operates as a CH or CM.
- **Position:** provides geographic location information for network discovery and clustering.
- **Speed:** provides mobility information used for link estimation and cluster stability decisions.
- **Energy:** indicates residual energy, supporting energy-aware cluster formation and CH eligibility.

After receiving a HELLO message from a newly arrived UAV, a CH evaluates whether the node satisfies the cluster admission criteria, including communication range, cluster capacity, and residual energy requirements. If the conditions are met, the CH transmits a JOIN-REQUEST message inviting the UAV to become a CM. Upon reception of the JOIN-REQUEST, the UAV confirms its acceptance by replying with an acknowledgment (ACK) message. This acknowledgment serves as a commitment to the association and allows the CH to update its membership table accordingly. This two-step exchange establishes a lightweight admission handshake that ensures reliable cluster formation while preventing duplicate or incomplete associations. If the CH does not receive the ACK within a predefined timeout interval, the admission attempt is considered unsuccessful, and the reserved cluster slot is released to maintain clustering efficiency.

Table 3.2: JOIN-REQUEST Message Format

JOIN-REQUEST	CH ID	Cluster ID	Assigned Role	Validity Timer

Each field conveys essential information for the cluster admission procedure:

- **JOIN-REQUEST:** Identifies the packet as a cluster admission invitation transmitted by the CH.
- **CH ID:** Specifies the identifier of the CH issuing the request.
- **Cluster ID:** Indicates the cluster that the UAV is invited to join.
- **Assigned Role:** Defines the operational role granted to the joining UAV, typically as a CM.
- **Validity Timer (T_{join}):** Represents the time interval within which the UAV must respond with an acknowledgment before the request expires.

Table 3.3: ACK Message Format

ACK	Node ID	CH ID	Status

Each field conveys essential information required to confirm successful cluster admission:

- **ACK:** Identifies the packet as an acknowledgment message transmitted in response to a JOIN-REQUEST.
- **Node ID:** Specifies the identifier of the UAV confirming its acceptance of cluster membership.
- **CH ID:** Indicates the cluster head responsible for the admission and subsequent coordination.
- **Status:** Reflects the outcome of the admission process, typically set to *Accepted* to confirm successful association.

If no JOIN-REQUEST is received within the current admission interval set equal to the interval time of reclustering, the UAV remains unclustered and waits for the next clustering round.

2. CM Departure Handling

Due to high mobility, nodes may leave the communication range of their CH, resulting in temporary or permanent disconnections. To detect such events, the CH employs a timer-based mechanism [**?**]. If three consecutive periodic `HELLO` messages from a CM are missed, the CM is deemed to have departed or become unreachable. The CH subsequently removes the CM from its routing table and ceases forwarding packets to the departed node, thus preventing unnecessary retransmissions and ensuring consistency in the routing state.

3. CH Substitution

Failure of a CH poses significant risk to cluster stability, as CHs are responsible for coordination and intra-cluster routing [**?**]. To provide resilience, each cluster maintains RCH. If the RCH does not receive three consecutive periodic `HELLO` messages from the primary CH, the primary CH is declared inactive. The RCH then broadcasts a CH-replacement message to all CMs, informing them of the role transition. Upon receiving this message, each CM updates its local cluster information and acknowledges the replacement via an `ACK CH Replacement` message. After acknowledgments are collected, the RCH assumes the primary CH role and updates its routing table accordingly, ensuring cluster continuity without requiring a global reclustering event.

Table 3.4: Replacement Broadcast Message Format

0	Old Node ID	New Node ID

The first field specifies the message type, while the *Old Node ID* and *New Node ID* denote the CH transition. To confirm that the replacement was successfully received and processed, each CM responds with an acknowledgment message. The acknowledgment (ACK) ensures synchronization between the newly appointed CH and its CMs and prevents ambiguous or conflicting CH roles.

Table 3.5: ACK CH Replacement Message Format

Ack	CM Node ID	Old Node ID	New Node ID

In this format, the first field indicates the message type (ACK), while the second field identifies the CM confirming receipt of the replacement broadcast. To ensure reliable leadership transition, the newly elected CH requires acknowledgments from at least half of the CMs, i.e., minimum responses of $C_{\max}/2$. This quorum-based confirmation prevents premature role activation and reduces the likelihood of operating with incomplete cluster awareness. Once the required acknowledgments are received the new CH finalizes the role transition and resumes cluster coordination duties. This mechanism enhances fault tolerance by ensuring that the leadership handover is validated by a sufficient portion of the cluster, thereby maintaining operational continuity even under dynamic network conditions. If the quorum condition is not satisfied before the timeout expires, the leadership transition is aborted, and a new CH is selected during the next clustering cycle.

4. Reclustering

A new clustering cycle is initiated periodically to maintain network connectivity and adapt to topology variations caused by UAV mobility, node failures, or energy depletion. At the beginning of each cycle, all UAVs reassess their local neighborhood information, update relevant clustering metrics, and recompute their cluster indices. During this process, CH eligibility is recalculated, enabling the network to elect new CHs when necessary and to restructure clusters in response to evolving operational conditions. This periodic reclustering mechanism ensures that the network maintains balanced load distribution, preserves link reliability, and prevents prolonged dependence on suboptimal cluster configurations. Consequently, the clustering cycle acts as a self-stabilizing procedure that enhances scalability, robustness, and overall routing efficiency in dynamic S-UAV environments.

Each UAV periodically disseminates its position, velocity, and reward metrics at intervals of t_{loop} - $t_{\text{loop}}/10$, enabling accurate neighborhood awareness and supporting stable clustering decisions. This periodic state advertisement allows neighboring nodes to continuously monitor relative mobility, estimate link persistence, and evaluate cooperative behavior, all of which are essential for reliable cluster-head selection. By maintaining up-to-date metric information, the protocol reduces the likelihood of outdated data influencing clustering outcomes, thereby minimizing unnecessary re-clustering events and improving overall network stability. The broadcast interval t_{loop} is selected to balance responsiveness and control overhead: shorter intervals enhance topology awareness but increase channel utilization and energy consumption, whereas longer intervals conserve resources at the potential cost of delayed adaptation to network changes. Consequently, periodic metric update serves as a foundational mechanism for distributed decision-making, allowing the network to react promptly to mobility-induced topology variations while preserving scalability and routing efficiency in highly dynamic S-UAV environments.

Table 3.6: Periodic Information Broadcast Message Format

INFO-BROADCAST	Node ID	Position	Velocity	Reward

Each field conveys critical state information required for distributed clustering and routing decisions:

- **Node ID:** Specifies the unique identifier of the UAV transmitting the broadcast.
- **Position:** Provides the current spatial coordinates of the UAV, enabling accurate distance estimation and neighborhood awareness.
- **Velocity (V_k):** Indicates the instantaneous speed of the UAV, supporting mobility prediction and link-stability evaluation.
- **Reward (R_k):** Represents the cooperative behavior or forwarding reliability of the UAV, assisting in leadership assessment during cluster-head election.

Table 3.7: Cluster Index Broadcast Message Format

CI-BROADCAST	Node ID	Cluster Index

Each field conveys essential information required for distributed cluster-head election:

- **CI-BROADCAST:** Identifies the packet as a cluster index broadcast message used to advertise leadership suitability.
- **Node ID:** Specifies the identifier of the UAV transmitting the broadcast.
- **Cluster Index:** Represents the computed leadership score that reflects the UAV's suitability for CH selection based on the weighted clustering metrics.

3.3 Simulation and Analysis

Table **??** lists the simulation parameters used to evaluate the proposed clustering and routing schemes.

Table 3.8: Network and Cluster Simulation Parameters

Parameter	Symbol / Variable	Value
Number of UAVs	N	50
Communication radius	r_c	700
Maximum cluster size	$C_{\max}$	4
Area side length	L	$2r_c$
Reward factor	γ	0.90
Decay parameter	λ	0.50
Metric weight (distance)	π	0.33
Metric weight (velocity)	ψ	0.33
Metric weight (reward)	ω	0.33
Packets simulated	numPkts	100
Minimum UAV speed	$v_{\min}$	5
Maximum UAV speed	$v_{\max}$	15
Weight of the distance component	ψ	1/3
Weight of the rewarding index component	κ	1/3
Weight of the velocity component	ζ	1/3

Figures **??** to **??** illustrate the resulting cluster structures produced by four clustering strategies applied to the same S-UAV topology.

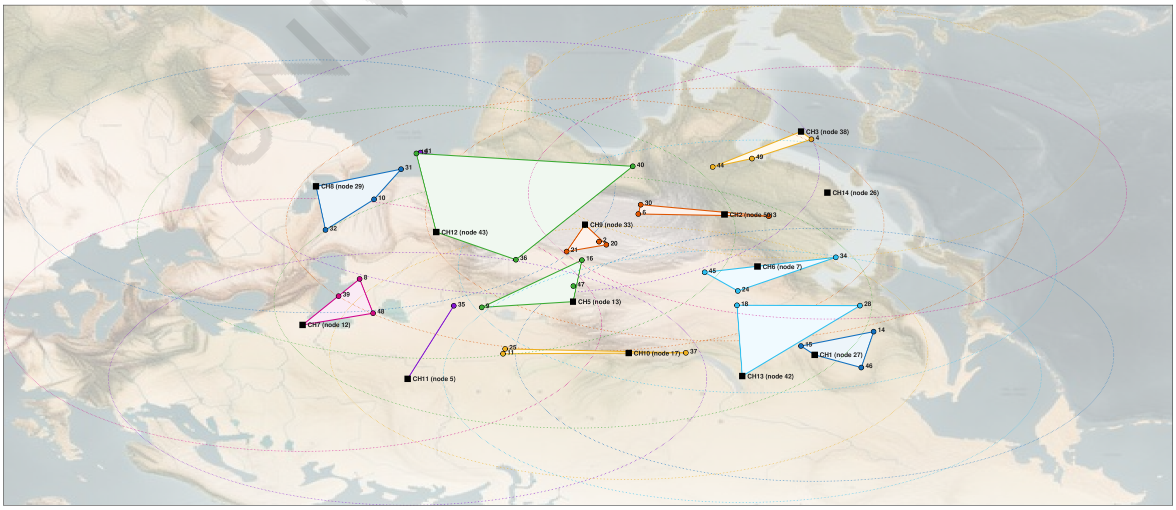

Figure 3.5: Distance-Based Clustering

The distance-based protocol forms geographically compact clusters with short CM–CH links as shown in Figure ??. CHs tend to occupy geometric centers, although excessive CH separation can lead to fragmentation in the CH backbone.

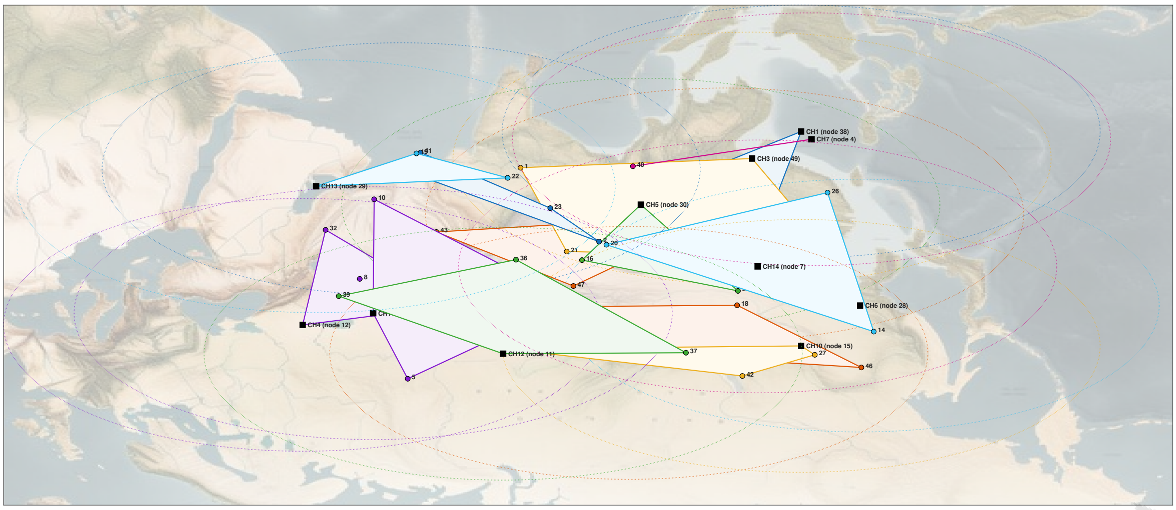

Figure 3.6: Velocity-Based Clustering

The velocity-based protocol yields elongated clusters aligned with motion vectors as in Figure ??. This favors temporal coherence, allowing groups of co-moving UAVs to remain clustered despite longer CM–CH distances.

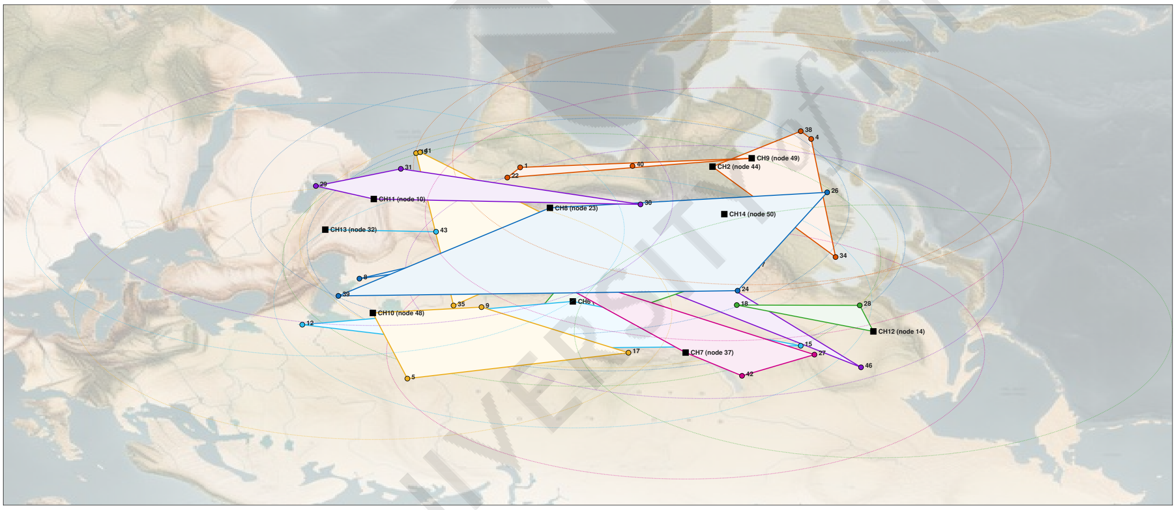

Figure 3.7: Reward-Based Clustering

The reward-based protocol as in Figure **??** allows non-local memberships when beneficial for reliability, enhancing robustness but also increasing spatial spread and potential hop counts.

The weighted combined protocol presented in Figure **??** balances spatial compactness, temporal coherence, and reliability. Compared with the other schemes, it avoids the extreme compactness of distance-only clustering and the elongated structures of velocity- or reward-only strategies. The resulting CH backbone exhibits improved connectivity and moderate cluster sizes, reflecting an effective trade-off across metrics.

Figure **??** shows the average hop count for 100 UAVs routing 100 packets. The weighted combined (C) protocol achieves the smallest mean hop count (≈ 2.36),

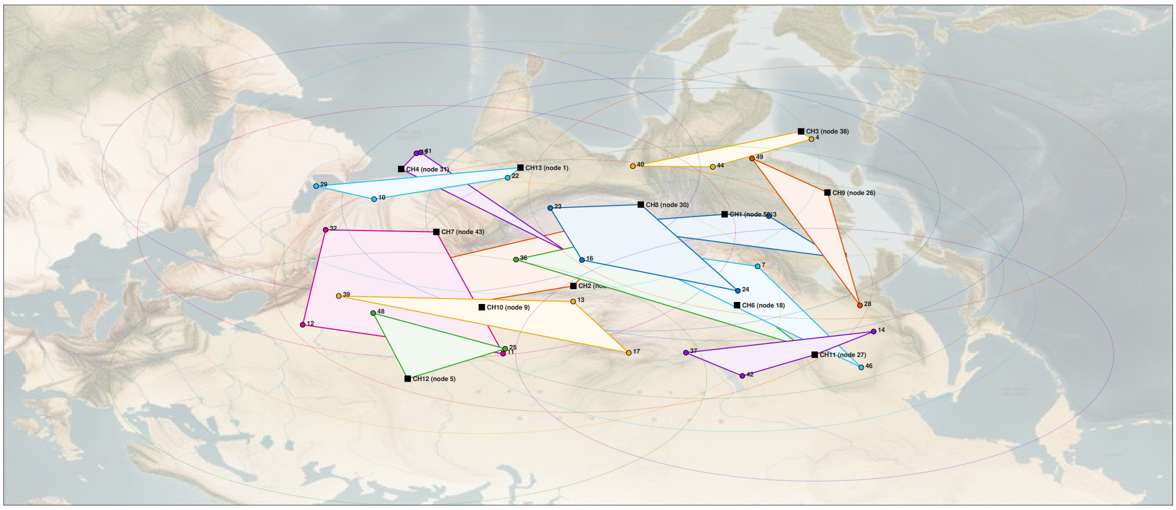

Figure 3.8: Weighted Combined Clustering

followed closely by the velocity-based protocol ($\approx$ 2.37). Distance- and reward-based protocols exhibit higher mean hop counts ($\approx$ 2.51 and $\approx$ 2.52, respectively). This corresponds to a $\sim$ 6% reduction relative to distance and reward.

These results indicate that minimizing hop count correlates with motion coherence and balanced metric selection. As each hop introduces additional transmission and processing delay, reduced hop counts imply improved end-to-end performance.

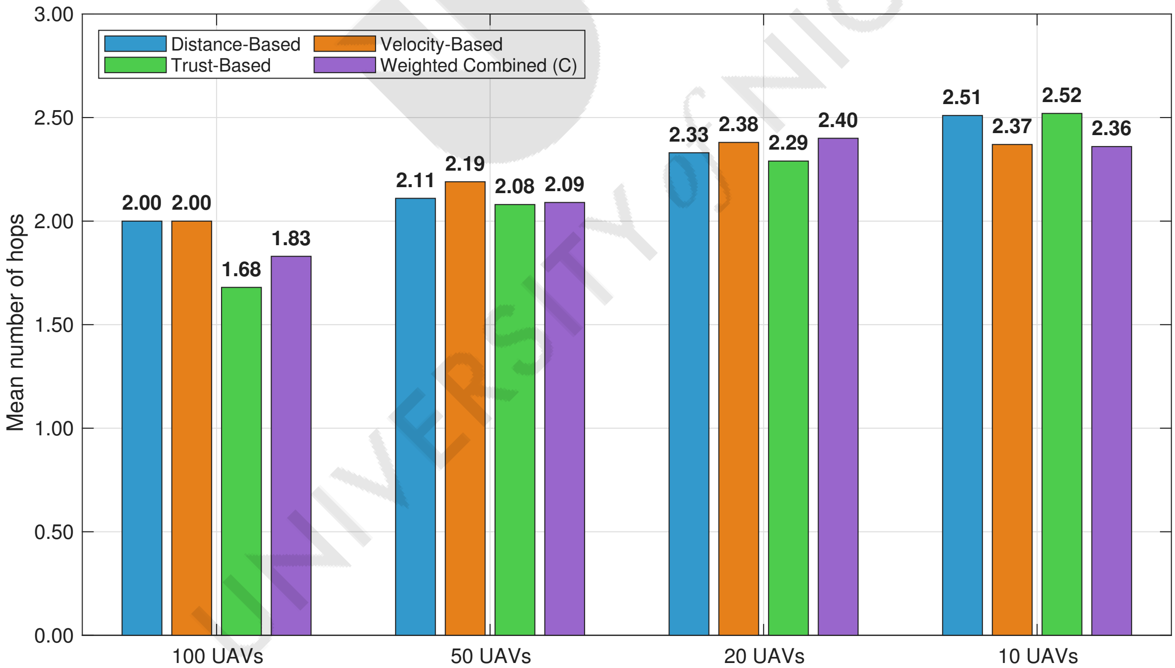

Figure 3.9: Mean Hop Count versus Routing Method

Figure **??** presents the total end-to-end delay as a function of UAV count. All methods exhibit a sharp increase around $N = 200$, after which delay stabilizes as N increases from 200 to 1000 UAVs. The distance-based method achieves the lowest delay at high densities, demonstrating superior scalability. Conversely, the velocity-based method incurs the highest delay due to additional processing overhead associated with velocity prediction and route adjustments. The weighted combined method provides a balanced trade-off, maintaining moderate latency across network sizes. The reward-based method incurs higher delays as network density increases due to the additional packet evaluation and routing time. Overall, distance-based and weighted combined strategies prove more effective for large-scale UAV networks with regard to delay minimization.

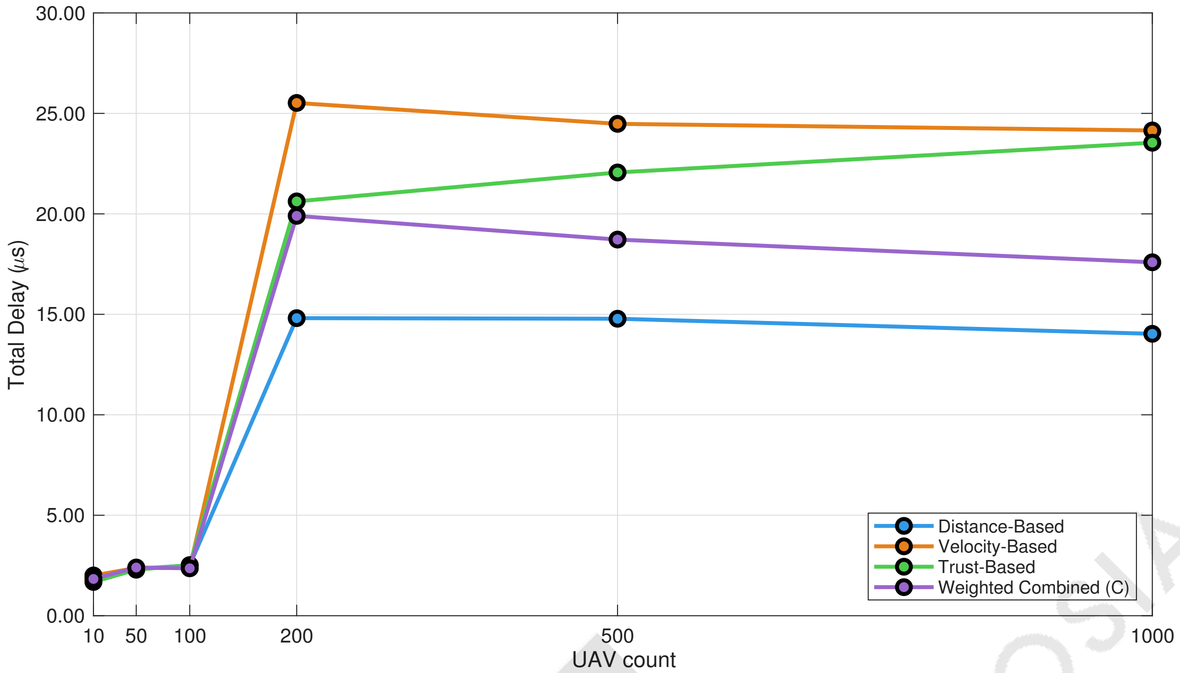

Figure 3.10: Total Delay versus UAV Count

Figure ?? compares Packet Delivery Ratio (PDR) at 100 and 1000 UAVs. As expected, PDR decreases with network density due to increased interference and routing contention. Distance-based clustering achieves the highest PDR which is 57% at 100 UAVs and 47% at 1000 UAVs with the weighted combined method performing similarly. Velocity- and reward-based strategies exhibit lower PDR values (~44–53%), reflecting weaker resilience at scale. These results indicate that combining distance, velocity, and reward enhances routing robustness, particularly under dense conditions.

Figure ?? reports re-clustering frequency for distance-based and weighted combined clustering. Cluster changes increase with N, indicating reduced temporal stability in dense networks. For small networks ($N \leq 100$), both methods remain stable with less than 55% changes. At larger scales ($N = 1000$), distance-based clustering approaches nearly 100% re-clustering, while the weighted combined method stabilizes around 94%. Although both degrade with scale, the weighted combined protocol maintains comparatively higher stability, making it more suitable for large-scale UAV swarms where minimizing re-clustering overhead is crucial.

Figure ?? illustrates the hop count distribution for 100 successfully delivered packets under three mobility-aware routing strategies: WCA, RWP, and CEERP. For each packet index, the number of hops reflects the length of the selected routing path from the source to the destination.

While all three schemes exhibit some degree of hop variability, the RWP-based scheme consistently generates shorter end-to-end paths, resulting in the lowest average hop count of 2.17. This suggests that RWP is able to form efficient transient routes during packet transmission, possibly due to favorable node movement characteristics that temporarily reduce path length.

CEERP presents an average hop count of 2.51, slightly higher than RWP, but demonstrates a tighter clustering around that mean, implying more stable and pre-

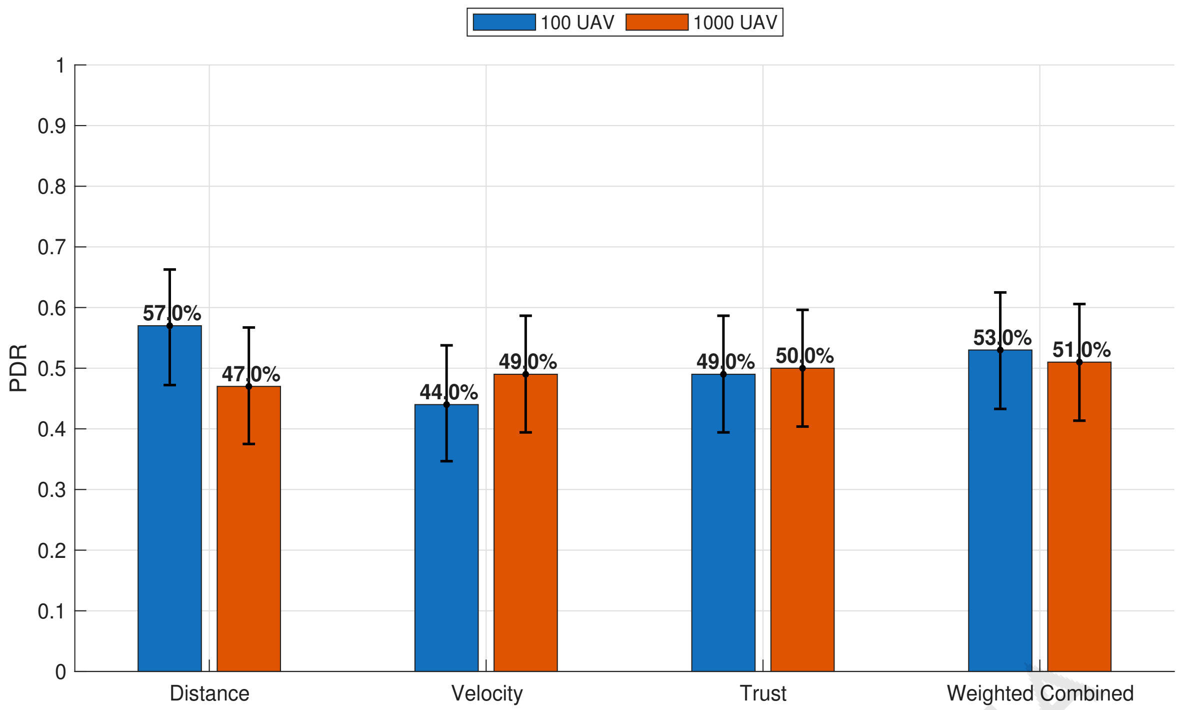

Figure 3.11: PDR by Method and UAV Count

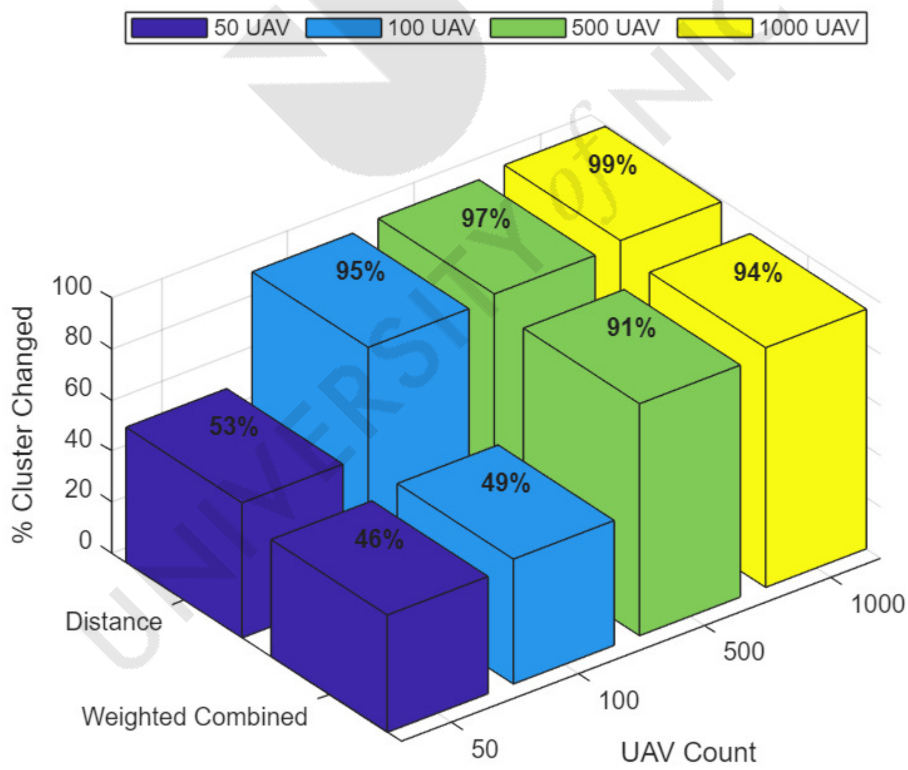

Figure 3.12: Re-Clustering Percentage vs. UAV Count

dictable route formation despite mobility. The reduced spread of hop values indicates that CEERP tends to preserve route lengths even under dynamic topology changes.

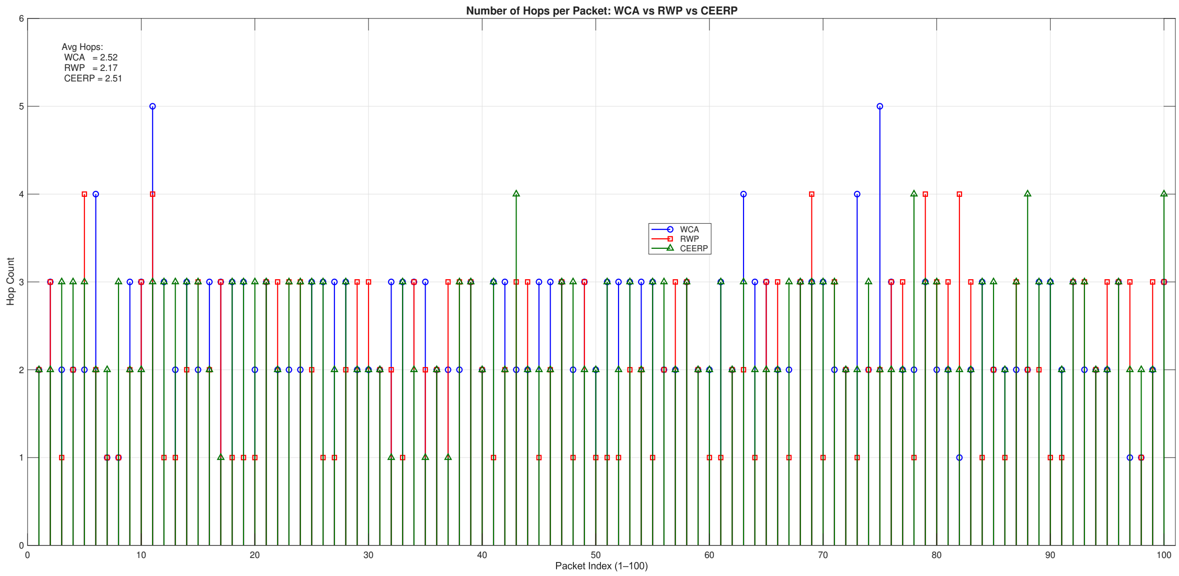

Figure 3.13: Hops per packet for WCA, RWP, and CEERP over 100 transmissions

WCA achieves an average hop count of 2.52, comparable to CEERP, but displays more frequent higher-hop events reaching 4 or 5 hops. These elevated values suggest occasional route detours or temporary reductions in connectivity, likely arising from WCA's impact on spatial node distribution.

Taken together, the results show that although RWP produces the shortest average routes, CEERP provides more uniform path behavior, with fewer extreme hop values. WCA, by contrast, offers similar mean performance but with greater variability, reflecting less consistent routing efficiency. These differences highlight a trade-off between minimizing average hop count and maintaining stable route characteristics in mobility-centric wireless sensor environments.

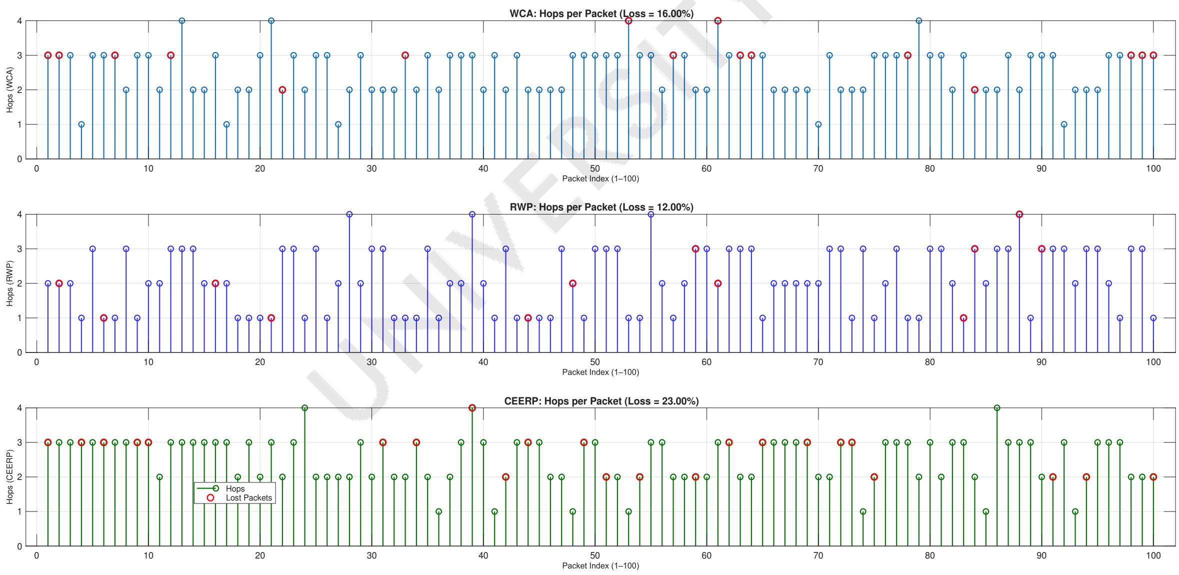

Figure 3.14: Hops per packet for WCA, RWP, and CEERP with 5 non-functional nodes

Figure **??** illustrates per-packet hop counts for three distinct clustered routing schemes within a wireless sensor network simulation environment. Each subplot corresponds to one scheme and displays the hop count required for successful packet delivery, as well as instances of packet loss due to non-functional nodes, which are highlighted with red markers.

In WCA hop counts are highly variable across the 100 transmitted packets, indicating inconsistent routing performance. This variability is accompanied by a relatively high packet loss rate of 26%, suggesting that the network frequently fails to establish or maintain reliable routes under WCA mobility dynamics.

CEERP presents a more uniform hop distribution, with hop counts clustering around a narrower range. Although packet losses still occur around 20%, they are generally less disruptive to the overall distribution, indicating that CEERP supports more stable routing paths. The relative consistency in hop counts suggests that CEERP yields predictable route lengths even under mobility.

Our suggested protocol RWP shows a moderate reduction in hop variability. While hop counts still fluctuate, the degree of fluctuation is less pronounced than in WCA, and packet losses are notably fewer, totaling 14%. This suggests that incorporating RCH improves routing stability and reliability.

Collectively, these results indicate that CEERP offers the most stable hop behavior, while RWP achieves the lowest packet loss rate. These observations highlight the trade-off between route stability and delivery reliability when comparing the three mobility-aware routing schemes.

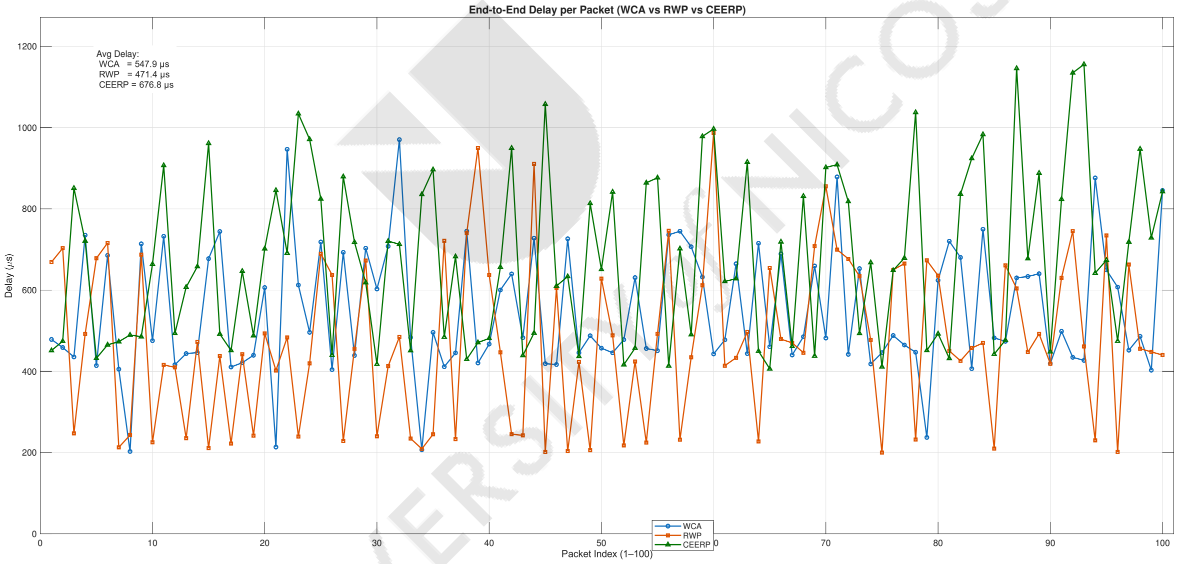

Figure 3.15: End-to-end delay per delivered packet for WCA, RWP, and CEERP over 100 transmissions.

Figure **??** depicts the end-to-end delay for 100 successfully delivered packets under the three mobility-aware routing schemes: WCA, RWP, and CEERP. Packet delays vary significantly within each scheme due to topological changes and dynamic route establishment. On average, RWP achieves the lowest delay (458.4 μs), followed by WCA (568.4 μs). CEERP exhibits the highest average delay (697.1 μs), along with more pronounced fluctuations and occasional large delay spikes. These results indicate that RWP provides faster packet delivery, while CEERP prioritizes stability and reliability at the cost of increased latency.

Based on the hop-count, packet loss, and end-to-end delay results, the proposed RWP protocol outperforms both WCA and CEERP in the evaluated scenarios. Specifically, RWP achieves the shortest average routing paths and the smallest delays, indicating efficient route formation and reduced transmission overhead under node mobility. In addition, RWP yields the lowest packet loss rate, demonstrating improved delivery reliability even in the presence of non-functional nodes within the network. These characteristics collectively highlight the effectiveness of the RCH-based redundancy strategy in sustaining connectivity and adapting to topology changes.

3.4 Weaknesses of the Proposed Protocol

The proposed weighted clustering protocol introduces a new approach for reducing packet delivery delay in S-UAV networks. The preceding analysis highlights fundamental trade-offs among stability, scalability, and performance, and identifies the advantages and limitations of various clustering strategies.

Due to its emphasis on spatial proximity, the Distance-Based protocol is effective at preserving low latency and forming compact clusters. However, its strong dependence on geographic closeness leads to frequent re-clustering as network density increases, resulting in instability and elevated control overhead. Small variations in node positions can trigger cluster reformation, limiting scalability in large swarms.

The Velocity-Based approach provides temporal stability by grouping UAVs moving with similar velocities. While this reduces cluster fragmentation, it often yields elongated clusters with longer CM–CH communication links. Additionally, continuous velocity updates introduce computational overhead and may increase packet losses and delay during abrupt mobility changes.

The reward-Based protocol improves reliability by incorporating forwarding behavior and cooperative packet delivery. Nevertheless, it requires continuous reward evaluation and periodic message exchange, increasing energy consumption and latency. Because reward evolves gradually, this method may react slowly to sudden topology changes or malicious behavior.

By jointly incorporating distance, velocity, and reward, the Weighted Combined protocol provides a more balanced solution that enhances cluster stability, reduces packet delay, and maintains consistent PDR across different UAV densities. However, this method still requires careful weight calibration for its constituent metrics, and its control complexity increases with network size, potentially challenging large-scale deployments. As a future enhancement, introducing multi-redundancy within clusters—where multiple standby CMs are capable of assuming CH responsibilities—could further improve robustness to node non-functionality and transient link disruptions. Such redundancy would enable seamless CH handover and preserve connectivity during mobility, though it may require additional coordination mechanisms to remain scalable.

3.5 Conclusion

The comparative analysis demonstrates that while each clustering strategy contributes desirable properties, none individually satisfies all performance requirements for dynamic S-UAV networks. Distance-based clustering offers spatial compactness and reduced delay but becomes unstable at scale due to frequent re-clustering. Velocity- and reward-based methods improve temporal and behavioral robustness, respectively, but incur higher latency, computational overhead, and reduced routing performance under rapid mobility.

The proposed weighted combined protocol mitigates many of these limitations by integrating physical proximity, motion coherence, and cooperative forwarding behavior. Simulation results indicate improved PDR, reduced hop count, and higher cluster stability relative to conventional clustering methods, making it a more scalable and dependable option for dense UAV deployments.

Despite these advantages, the protocol lacks resilience to CH non-functionality—an issue that becomes critical in crisis scenarios where CH failures result in inter-cluster routing disruption and packet loss. These limitations motivate the development of enhanced weighted clustering schemes capable of incorporating redundancy and explicit failure awareness. The next chapter introduces a multi RCH-based routing extension designed to ensure end-to-end data delivery even under CH disruption.

Chapter 4

Multi-Redundant Weighted Cluster Routing Protocol (MRWP)

Introduction

The previous chapter introduced a redundant weighted cluster routing scheme for S-UAV networks. Its main objective was to optimize the CH selection process using three weighted parameters—trust, velocity, and distance—in line with earlier cluster-based and energy-aware routing designs for WSNs and UAV/FANETs [?, ?, ?]. The proposed protocol improved clustering stability, communication efficiency, and data delivery. However, reliance on a single CH and a single RCH introduces a serious vulnerability in crisis scenarios. If both nodes become non-functional due to damage, energy depletion, or loss of connectivity, all data generated by the cluster members is lost, as also reported in FANET reliability surveys [?, ?].

To address this issue, this chapter introduces a multi-redundant clustering scheme. Each cluster contains a primary RCH responsible for coordination, and one or more backup CHs capable of immediately taking over communication and routing duties. The goal is to eliminate single points of failure and ensure continuous end-to-end data transmission in the presence of CH disruption, similar to recent delay/energy-aware and trust-based approaches [?, ?, ?, ?, ?]. Redundancy is achieved through an optimization process that selects multiple CHs rather than random backups. This improves fault tolerance, network stability, and PDR under the dynamic and unpredictable conditions typical of crisis environments.

A second limitation observed in the previous scheme concerns energy imbalance between UAVs, particularly those serving as CHs. This is a well-known challenge in energy-aware clustering for aerial and ground wireless networks [?, ?, ?, ?]. Because CHs perform data aggregation, packet forwarding, and inter-cluster communication, they consume significantly more energy than ordinary CMs. As a result, their operational lifetime decreases at a faster rate, reducing network availability. If several CHs deplete their energy simultaneously, the network may experience coverage gaps, re-clustering events, and mission degradation [?]. Addressing this imbalance is therefore essential for achieving a more stable and resilient cluster-based communication architecture in crisis-oriented S-UAV missions.

This chapter is structured as follows:

1. Section 4.1 discusses the drawbacks of single-RCH clustering and the lack of explicit energy-awareness in the previous weighted scheme, relating these issues to existing clustering-based designs [?, ?].

2. Section 4.2 presents the proposed S-UAV Multi-Redundant Weighted Clustering Scheme and describes its algorithmic operation (MRWP).

3. Section 4.3 evaluates the improved scheme through performance analysis and simulation results, comparing it with the previously proposed method.

4. Section 4.4 highlights that while multi-redundancy improves resilience and continuity, it adds coordination overhead and leaves mobility challenges for future work.

5. Section 4.4 concludes the chapter and discusses remaining limitations of the multi-redundant approach.

4.1 Drawbacks of WRP

Clustering is widely used to enhance scalability and efficiency in S-UAV networks [?, ?]. In the conventional single-CH structure, one CH manages intra-cluster coordination, aggregates sensed data, and forwards information either to neighboring clusters or directly to the BS [?]. While this reduces communication overhead and simplifies routing, it introduces several limitations that significantly compromise network performance in crisis scenarios.

The most critical weakness of single-CH clustering is its dependency on a single node for cluster operation. If the CH becomes non-functional due to energy depletion, link failure, or physical damage, the entire cluster loses connectivity, leading to data loss and interrupted forwarding services [?]. This is particularly detrimental in crisis environments where time-sensitive information is required for environmental sensing, hazard assessment, and survivor detection.

When a CH fails, the network must initiate a re-clustering process to elect a new CH. In highly mobile S-UAV environments, repeated re-clustering increases control overhead, reduces effective throughput, and delays the restoration of normal operation [?, ?]. Without redundancy, the network cannot maintain service continuity; disruptions propagate across dependent clusters, causing packet loss and increased end-to-end delays. This degradation in quality of service is unacceptable for real-time, mission-critical S-UAV applications [?, ?].

Single-CH clustering also introduces substantial energy imbalance. The CH consumes significantly more energy than ordinary CMs due to data aggregation, routing, and inter-cluster transmission tasks [?]. Once the CH energy drops below a functional threshold, the cluster disconnects and re-clustering is triggered, further increasing control overhead. In crisis-oriented S-UAV missions, where UAVs operate for extended durations without the possibility of recharging or replacement, such imbalance accelerates failure propagation and reduces network availability [?, ?].

Figure **??** illustrates the operation of WRP with non-functional CH and non-functional RCH. Three distinct clusters are depicted, each bounded by a dashed circular region representing its communication range. In Clusters 1 and 3, the CHs are functional and continue to coordinate normal intra-cluster communication with their respective CMs. In contrast, Cluster 2 experiences a failure scenario in which the primary CH is non-functional, as denoted by the red UAV. This failure disrupts direct intra-cluster coordination and impairs local data aggregation. Although a RCH is designated to provide backup leadership, the RCH in this cluster—highlighted in yellow—is also non-functional, preventing immediate CH takeover and further exacerbating communication disruption within the cluster. Due to the simultaneous failure of both the CH and RCH in Cluster 2, the affected CMs are unable to rely on local leadership. As a result, packets originating from CMs of Cluster 2 are lost due to the lack of a functional CH or RCH, despite the presence of neighboring clusters.

Overall, the figure highlights the impact of concurrent CH and RCH failures on cluster stability and connectivity. It underscores the importance of redundancy, fault tolerance, and cooperative inter-cluster communication in sustaining network operation in dynamic UAV environments subject to node failures.

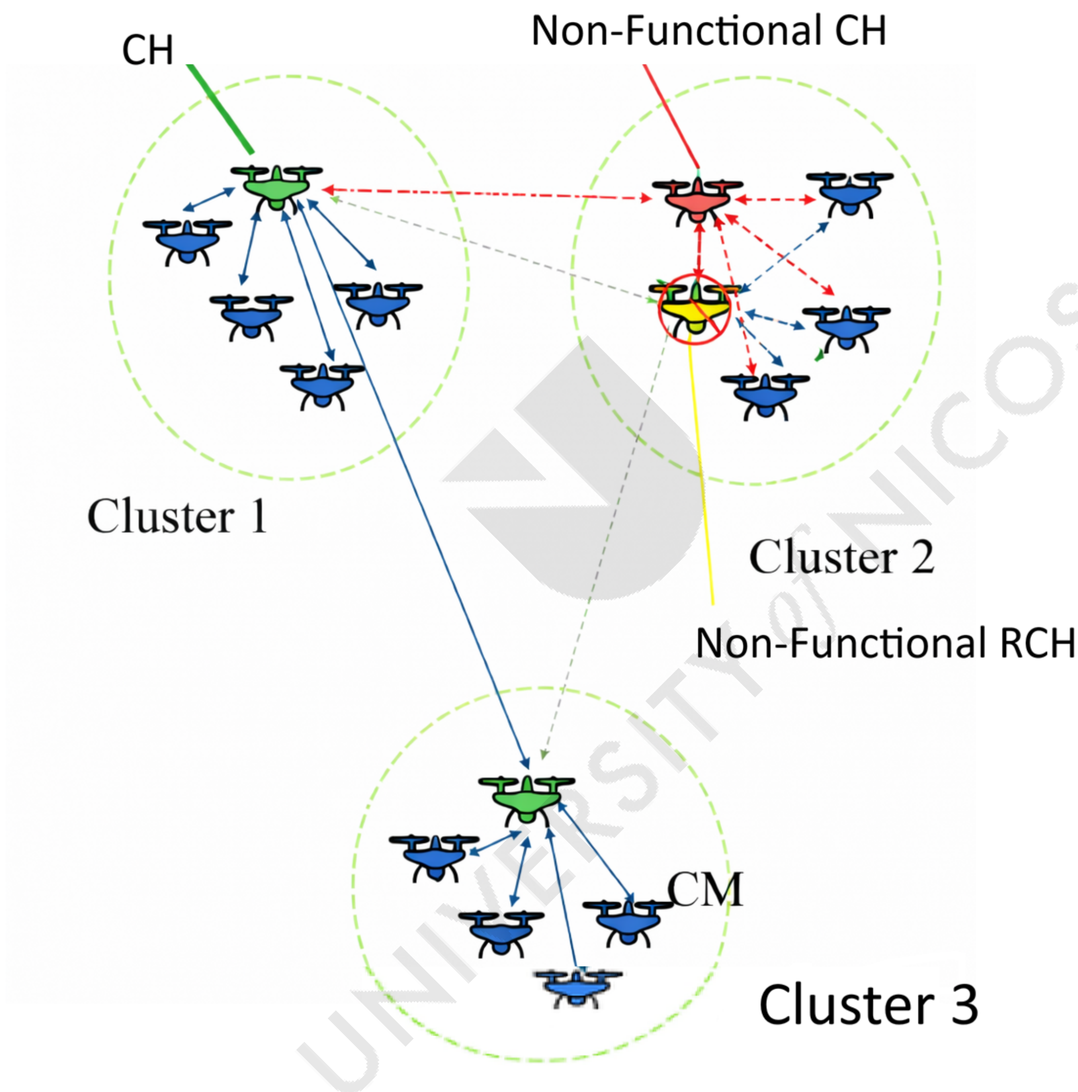

Figure 4.1: Cluster operation with non-functional CH and RCH.

4.2 Proposed Protocol

The UAV energy model used in this work follows a segment-based mission formulation consistent with recent studies on UAV power consumption and endurance [?, ?, ?, ?, ?]. The overall mission profile of UAV k is discretized into flight segments (e.g., hover, cruise, ascent, descent), enabling different aerodynamic loads, speeds, and climb rates to be represented within a single scenario. For each segment, the aerodynamic and propulsive power demand is first estimated and then converted into electrical energy consumption [?]. The energy drawn from the battery during segment i is computed as

$$E_{k_i} = \frac{P_{k_i} \delta t_{k_i}}{3600}, \tag{4.1}$$

where:

- P_{k_i} denotes the segment-wise electrical power in Watts
- δt_{k_i} denotes the segment duration in seconds
- the factor 1/3600 converts watt-seconds to watt-hours (Wh).

The total mission energy for UAV k is then obtained by summing the contributions of all segments:

$$E_{k_{\text{total}}} = \sum_i E_{k_i}. \tag{4.2}$$

This segment-based methodology provides a flexible framework capable of capturing multirotor hover-intensive profiles as well as fixed-wing cruise-efficient profiles. Figure **??** illustrates the fundamental differences between fixed-wing and multirotor platforms, where fixed-wing UAVs generally favor forward flight for aerodynamic efficiency while multirotors specialize in hover and low-speed maneuvering, leading to distinct power consumption characteristics [?].

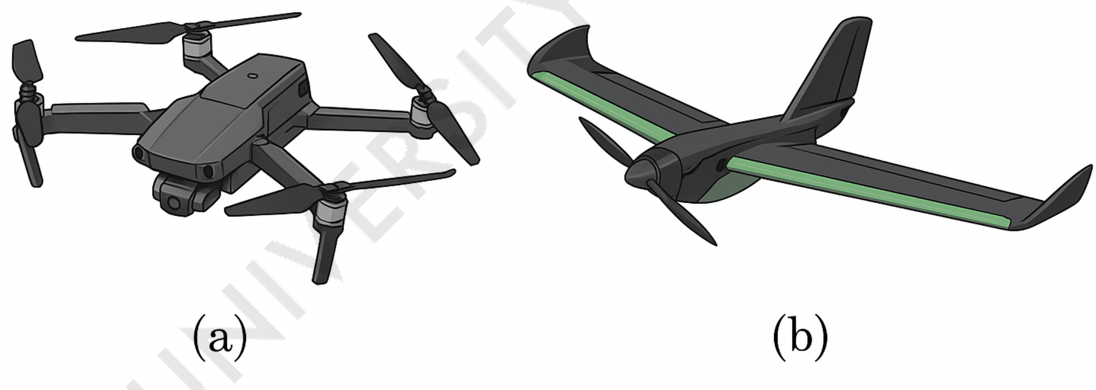

Figure 4.2: Comparison between multirotor (a) and fixed-wing (b) UAV

For fixed-wing UAVs, the aerodynamic power is modelled as the sum of parasite drag power and induced drag power [?]. These components are given by :

$$P_{\text{parasite}} = \frac{1}{2}\rho V^3 S C_{D0}, \qquad P_{\text{induced}} = \frac{2kW^2}{\rho V S}, \tag{4.3}$$

where:

- ρ is the air density
- V is the flight speed
- S is the wing area
- C_{D0} is the zero-lift drag coefficient
- k is the induced drag factor
- W denotes the aircraft weight.

Parasite drag power accounts for the energy required to overcome form drag, skin friction, and other aerodynamic losses as the aircraft moves through the air. This component grows approximately with the cube of the flight speed, since drag scales quadratically with velocity while the power depends on the product of drag and airspeed. In contrast, induced drag power captures the energy associated with lift generation and decreases with increasing airspeed, reflecting the fact that lower speeds require higher lift coefficients and therefore higher induced drag [**?**].

The total aerodynamic power is

$$P_{\text{air}} = P_{\text{parasite}} + P_{\text{induced}}.$$

To account for propulsion losses, the aerodynamic power is corrected by the propulsive efficiency η_p, yielding the required shaft power [**?**]:

$$P_{\text{shaft}} = \frac{P_{\text{air}}}{\eta_p}. \tag{4.4}$$

Finally, electrical power draw from the onboard battery is obtained by considering electrical subsystem efficiency η_{elec} as [**?**]:

$$P_{\text{elec}} = \frac{P_{\text{shaft}}}{\eta_{\text{elec}}}. \tag{4.5}$$

This representation distinguishes aerodynamic, propulsive, and electrical losses and allows endurance and energy estimates to be computed directly from segment-level aerodynamic loading [**?**].

For multirotor UAVs, the energy model is based on momentum theory, which relates total rotor disk area to the power required to generate thrust in hover [**?**,**?**,**?**,**?**]. The induced power component in hover is expressed as

$$P_{\text{ind}} = \frac{W^{3/2}}{\sqrt{2\rho A_{\text{tot}}}}, \tag{4.6}$$

where:

- W denotes aircraft weight
- ρ is the air density
- A_{tot} is the combined rotor disk area.

The $W^{3/2}$ dependence reflects the nonlinear growth of induced power with mass, implying that a doubling of weight increases P_{ind} by approximately 2.83×.

To account for profile and mechanical losses, a profile fraction $P_{\text{prof-frac}} \in [0.1, 0.3]$ is introduced, and rotor efficiency η_{rot} is considered [?]. The total shaft power becomes

$$P_{\text{shaft}} = \frac{P_{\text{ind}}\left(1 + P_{\text{prof-frac}}\right)}{\eta_{\text{rot}}}. \tag{4.7}$$

Forward flight introduces an additional parasite drag power component of the form $\frac{1}{2}\rho V^3 S_{\text{ref}} C_{D0}$, which arises from the velocity-dependent aerodynamic drag acting on the airframe, where S_{ref} denotes the reference aerodynamic area, typically corresponding to the projected frontal area of the UAV in forward motion [?]. Since drag force scales with V^2 and power is the product of force and velocity, the resulting power demand increases with V^3.

The climb/descent power term is then [?, ?]:

$$P_{\text{climb}} = \frac{W\,\text{ROC}}{\eta_p}, \tag{4.8}$$

where:

- ROC is the rate of climb (negative for descent)
- η_p is propulsive efficiency.

Electrical power draw is finally obtained by dividing by electrical efficiency, analogous to the fixed-wing case [?, ?].

The complete energy is evaluated by integrating electrical power over segment durations, enabling estimation of endurance under different flight regimes and environmental conditions [?, ?, ?].

To enhance clustering performance, an energy term E_k is incorporated into the CH selection metric. The rationale is to prevent premature depletion of CH candidates and extend operational lifetime under crisis-driven workloads. By favoring UAVs with higher residual energy, the method maintains connectivity, balances routing cost, and reduces the likelihood of cluster collapse due to energy-exhausted CHs. Similar concepts have been utilized in recent energy-aware clustering and routing approaches for FANETs and WSNs [?, ?, ?, ?].

Assuming equal contribution from spatial, behavioral, mobility, and energy domains, fixed and uniform weights of 0.25 are applied, yielding the following cluster index:

$$C_{(k,l)} = -0.25\, D_{(k,l)} + 0.25\, R_{(k,l)} - 0.25\, V_{(k,l)} + 0.25\, E_k \tag{4.9}$$

Where the weighting choice reflects a balanced policy that provides robustness without bias toward any single attribute. This weighting ensures scalability and fairness in scenarios where S-UAVs operate under heterogeneous mobility and crisis-induced operational constraints.

To further enhance cluster resilience with node non-functionality, MRWP supports a multi-redundant CH mechanism in which backup CHs are assigned during cluster formation. Specifically, once the primary CH is selected based on the highest cluster index, the UAV with the next highest cluster index within the same cluster is designated as the RCH. This UAV is initially assigned the role of a CM but maintains an elevated priority to assume CH responsibilities if the primary CH becomes non-functional. By selecting the RCH as the next-ranked CM, leadership redundancy is achieved without introducing additional control overhead or separate election procedures. This approach ensures that backup CH candidates possess comparable spatial suitability, mobility characteristics, behavioral reliability, and residual energy levels to the primary CH. In the event of CH failure, the RCH can immediately take over cluster coordination, preserving intra-cluster communication and minimizing service disruption. Such redundancy is particularly beneficial in highly dynamic or crisis-driven environments where simultaneous node failures may occur due to energy depletion, mobility-induced disconnections, or adversarial conditions. While the introduction of multi-redundant CHs improves fault tolerance and cluster longevity, it also introduces additional state awareness among CMs. However, since redundancy is derived directly from the existing cluster index computation, the added complexity remains minimal and scales naturally with network size. This design choice balances robustness and efficiency, enabling rapid leadership recovery while maintaining energy-aware and mobility-adaptive clustering behavior.

Algorithm **??** outlines the operation of the proposed MRWP. The protocol operates in a periodic and fully distributed manner, where each UAV independently computes a cluster index based on spatial, mobility, behavioral, and energy-related metrics. These indices are exchanged locally among neighboring UAVs and averaged to reflect relative leadership suitability within the surrounding topology. UAVs are then sorted in descending order of their average cluster index, enabling the formation of clusters through a priority-based assignment process. During cluster formation, UAVs are either assigned as CMs to existing clusters, subject to capacity constraints, or elected as CHs when no suitable cluster is available. To enhance fault tolerance, MRWP introduces multi-redundant CHs by ranking CMs according to their cluster index and maintaining an ordered list of backup CH candidates within each cluster. The highest-ranked CM is designated as the first RCH, followed by additional backup candidates as needed [**?**, **?**]. In the event of CH non-functionality, leadership is seamlessly transferred to the highest-priority RCH without requiring a new election process. This mechanism ensures rapid recovery from node failures and minimizes packet forwarding disruption. If no redundant CH is available, the cluster is declared disconnected and packets originating from that cluster are dropped. By continuously repeating this process at each loop interval, MRWP dynamically adapts to mobility, energy depletion, and node failures, providing improved routing reliability and robustness in highly dynamic UAV network environments.

4.3 Simulation and Analysis

The primary mission parameters and flight segments used in the MRWP simulation are summarized in Tables 4.1 and 4.2. Table 4.1 lists the physical and aerodynamic characteristics of the fixed-wing and multirotor UAV models, including drag coefficients, efficiency factors, rotor disk area, and air density. These parameter values follow commonly adopted ranges in recent UAV endurance and power-modelling studies [**?**, **?**, **?**]. The representative mission profile used for energy evaluation is decomposed into discrete segments—climb, cruise, descent, and hover—with their respective durations and velocity transitions shown in Table 4.2. These segments serve as the basis for computing instantaneous power demand and cumulative energy consumption across the mission envelope.

The cumulative energy consumption profiles for fixed-wing and multirotor UAVs over their respective mission segments can be compared using the cumulative energy

Algorithm 1: Multi-Redundant Weighted Cluster Routing Protocol (MRWP)

Input : Set $\mathcal{U}$ of UAVs; neighbor sets $\mathcal{N}(k)$; loop period t_{loop}; max CMs per cluster $C_{\max}$

Output: Clusters with CH and multi-RCHs; CM assignments

while *network is active* **do**
- **foreach** $k \in \mathcal{U}$ **do**
  - Compute mobility and spatial metrics (e.g., relative velocity, separation distance)
  - Compute reward index
  - Estimate residual energy E_k
  - Compute cluster index $C_{(k,l)}$ using (4.9); Broadcast $C_{(k,l)}$ to neighbors $\mathcal{N}(k)$
- **foreach** $k \in \mathcal{U}$ **do**
  - Receive neighbors' cluster indices and compute local average $\overline{C}_k$
- Sort UAVs in descending order based on $\overline{C}_k$ Initialize all UAV roles to `UNASSIGNED`;
- **foreach** $u \in \mathcal{U}_s$ **do**
  - **if** *u is* `UNASSIGNED` **then**
    - **if** *there exists a cluster* $c \in C$ *with* #CM(c) $< C_{\max}$ *and u is within range of* CH(c) **then**
      - Assign u as CM of c
    - **else**
      - Create new cluster c
      - Assign u as CH(c)
      - Add c to C
- `// Multi-redundancy assignment: the next highest-ranked CMs become backups`
- **foreach** *cluster* $c \in C$ **do**
  - Sort CMs of c by descending index; Set RCHList(c) $\leftarrow$ CMs$_c$ `// ordered backups:` RCH$_1$, RCH$_2$, ...
- `// Failure handling (executed upon detection of non-functionality)`
- **foreach** *cluster* $c \in C$ **do**
  - **if** CH(c) *becomes non-functional* **then**
    - **if** RCHList(c) $\neq \emptyset$ **then**
      - Promote the first available RCH in RCHList(c) to CH(c)
      - Remove promoted node from RCHList(c)
      - Broadcast CH update to members of c
    - **else**
      - Declare cluster c disconnected; packets originating from c are dropped
- Wait t_{loop} ms and repeat

Table 4.1: UAV Parameters Used in Energy Simulation

Parameter	Symbol	Fixed-Wing	Multirotor
Weight	W	≈ 5.1 kg	≈ 5.1 kg
Wing Area	S	0.8 m^2	—
Rotor Disk Area	A_{tot}	—	0.5 m^2
Frontal Area	S_{ref}	—	0.05 m^2
Zero-lift Drag Coeff.	C_{D0}	0.020	1.0
Induced Drag Factor	k	0.050	—
Propeller Efficiency	η_p	0.75	0.75
Rotor Efficiency	η_{rot}	—	0.70
Electrical Efficiency	η_{elec}	0.90	0.90
Profile Power Fraction	$P_{\text{prof-frac}}$	—	0.20
Air Density	ρ	1.225 kg/m^3	1.225 kg/m^3
Reference Speed	V	1.0 m/s	—

Table 4.2: Mission Flight Segments Used in Energy Simulation

Segment	Duration	Start Speed	End Speed
Climb	300 s	25 m/s	+3 m/s
Cruise	900 s	30 m/s	0 m/s
Descent	200 s	22 m/s	−2 m/s
Hover	60 s	—	—
Climb	120 s	+2 m/s	—
Cruise	600 s	12 m/s	—
Descent	120 s	−2 m/s	—
Hover	60 s	—	—

versus time plot. As shown in Figure **??** the multirotor UAV exhibits a significantly steeper slope, indicating a higher rate of energy expenditure, whereas the fixed-wing UAV shows a more gradual cumulative increase consistent with empirical and analytical results reported in [**?**, **?**, **?**]. This disparity primarily arises from their different lift-generation mechanisms. Once the fixed-wing UAV reaches cruise speed, aerodynamic lift produced by forward motion allows sustained flight at relatively low power. In contrast, the multirotor must continuously generate lift via its rotors, even during low-speed or stationary flight, resulting in substantial power draw during hover and climb phases.

Despite having a slightly shorter total mission duration, the multirotor consumes approximately 175 Wh by the end of the simulation, compared to roughly 140 Wh for the fixed-wing. The multirotor's initial climb and hover segments dominate its energy profile, reflecting the high power demand required to operate continuously against gravity. The fixed-wing's cruise segment, by comparison, produces a nearly linear cumulative profile indicative of stable power usage. These behaviors confirm the superior endurance of fixed-wing configurations and highlight the mission-dependent trade-off between mobility and energy efficiency [**?**, **?**]. In general, fixed-wing UAVs are suited for long-range or endurance-critical scenarios due to lower energy expenditure per unit distance, whereas multirotors excel in short-duration or spatially constrained missions requiring vertical take-off and landing (VTOL) and precise hovering. Hybrid configurations that combine VTOL capability with efficient fixed-wing cruise therefore present an attractive compromise for many real-world

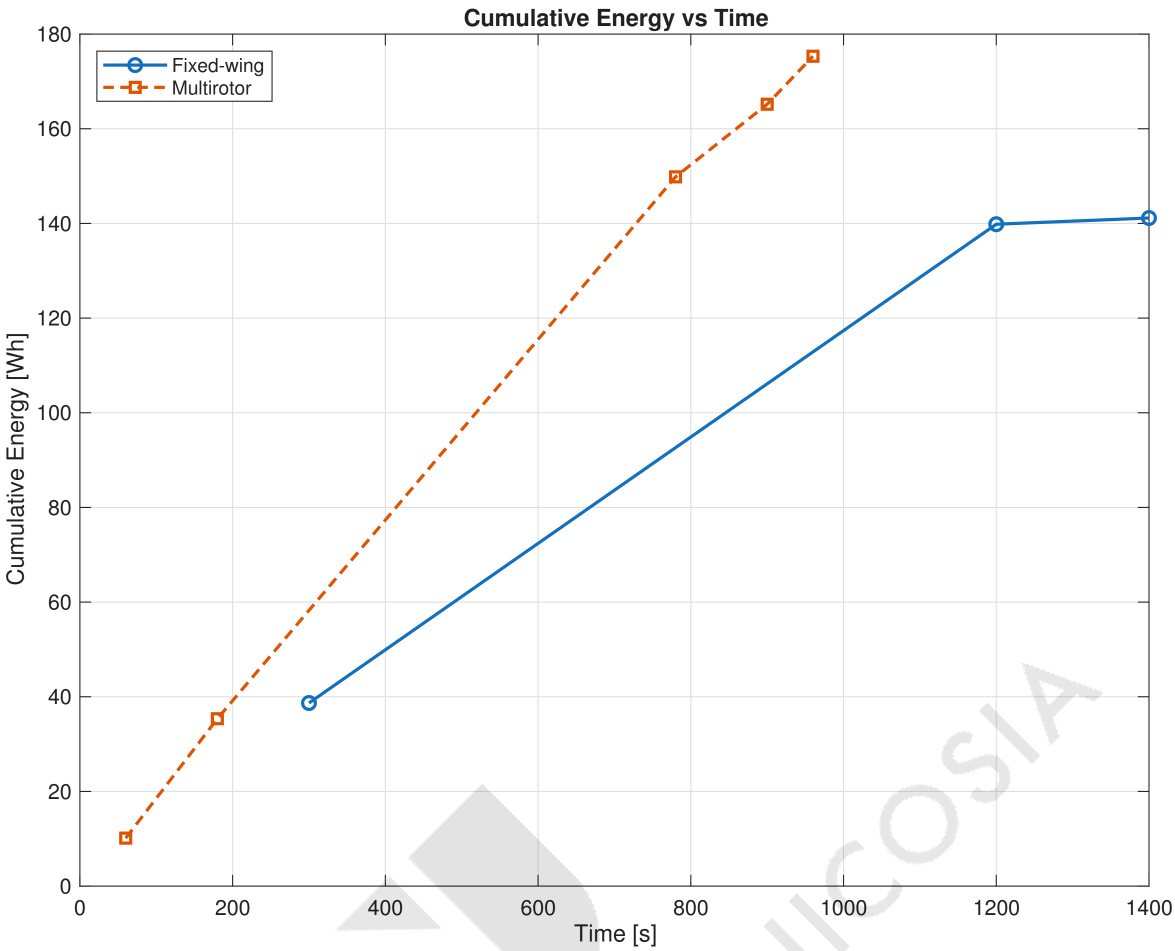

Figure 4.3: Energy consumption comparison between fixed-wing and multirotor UAVs for the simulated mission profile

S-UAV applications. Overall, the results verify that mission profile, propulsion efficiency, and aerodynamic characteristics are major determinants of UAV energy consumption [?, ?].

The average electrical power consumption for fixed-wing and multirotor UAVs across common mission phases—climb, cruise, descent, and hover—is shown in Figure **??**. The multirotor (orange bars) consistently exhibits higher electrical power demand across all phases, whereas the fixed-wing (blue bars) maintains considerably lower power levels. Both platforms experience their highest power usage during the climb phase due to the need to overcome gravity. However, the multirotor's climb power is significantly greater, further demonstrating the inefficiency of rotor-based lift under high thrust. During cruise, the fixed-wing benefits from aerodynamic lift and displays modest electrical power requirements, while the multirotor incurs simultaneous lift and propulsion costs. The descent phase shows the lowest power levels for both vehicles due to gravitational assistance. Finally, the hover segment highlights the multirotor's principal drawback: a sustained high power requirement to maintain lift in the absence of forward motion.

Overall, the power-distribution comparison reinforces that fixed-wing UAVs are substantially more energy-efficient during sustained flight, while multirotors sacrifice endurance to achieve maneuverability and operational flexibility. Mission objectives therefore become the primary determinant in platform selection: multirotors for agility and VTOL capability, fixed-wing UAVs for long-range or time-extended operations [?, ?].

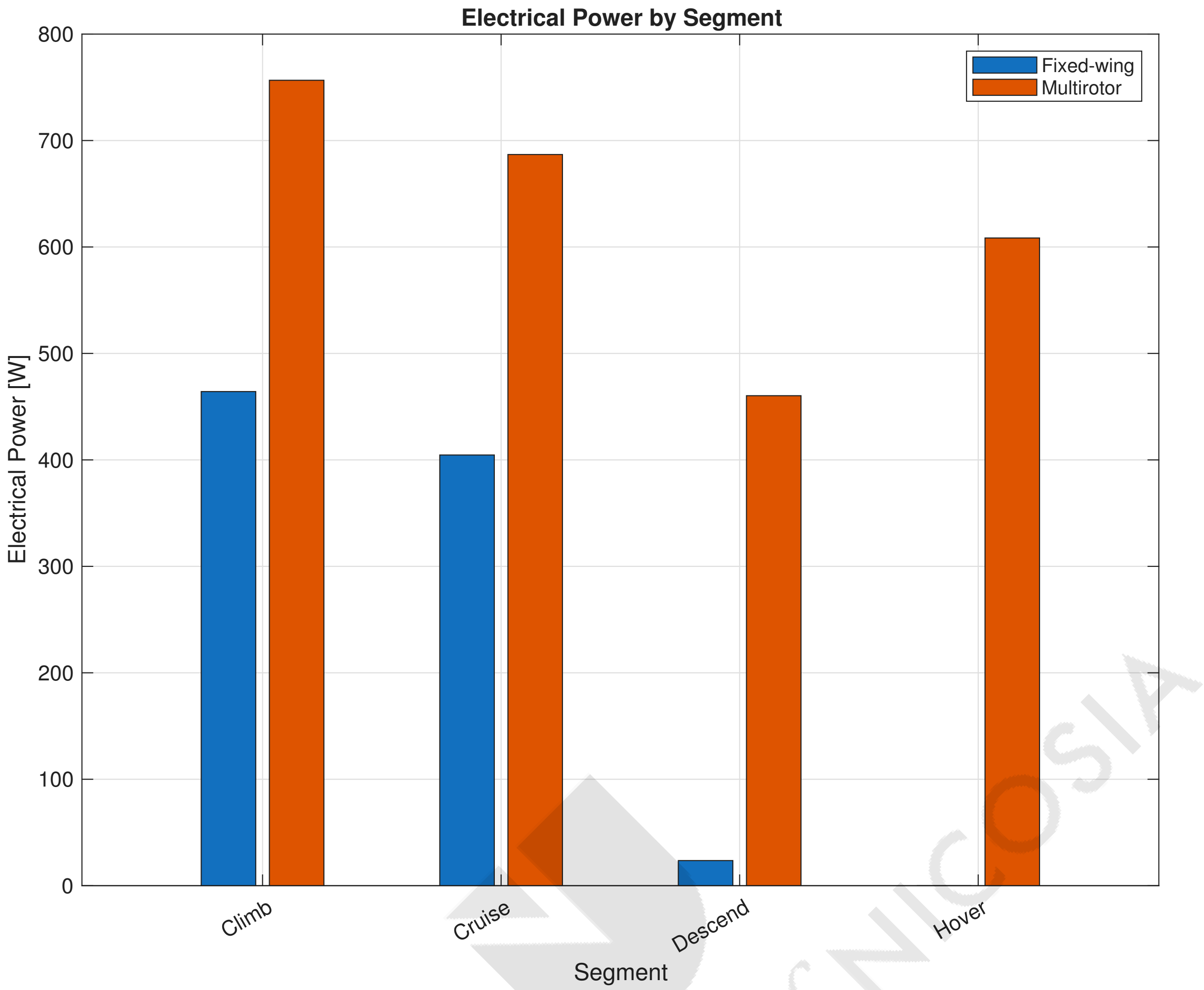

Figure 4.4: Energy for Fixed Wing UAV and Multirotor UAV

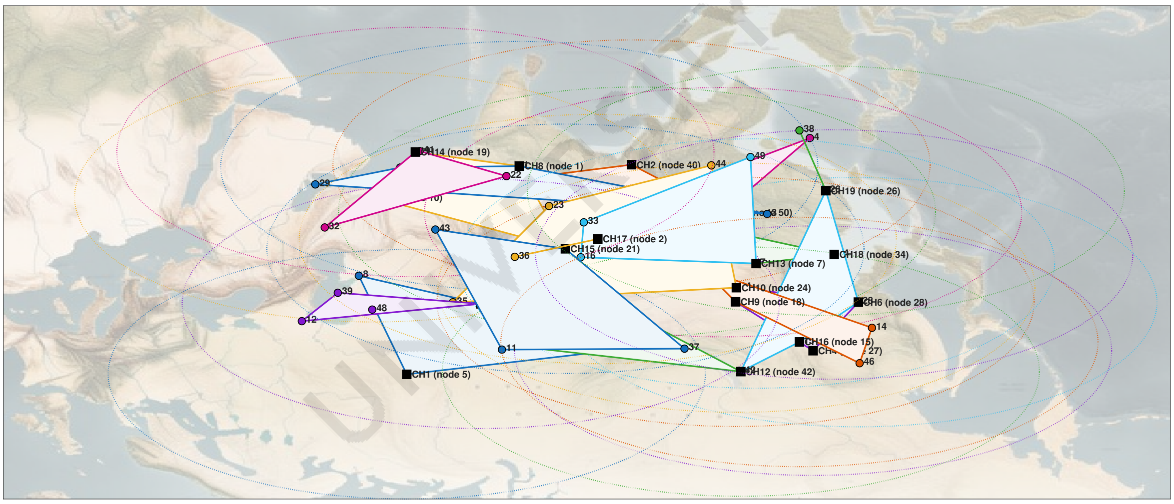

Figure 4.5: Clusters Formed Based on Energy for Fixedwing UAVs

The clusters formed solely on the basis of residual energy as shown in Figure **??** exhibit compact intra-cluster structure, as most UAVs are positioned near their respective CHs. However, certain CHs appear spatially separated, generating longer inter-CH links that may weaken the CH backbone and degrade routing stability. Thus, although energy-based selection balances energy expenditure, it may produce uneven cluster layouts and reduced global connectivity, a behaviour also noted in

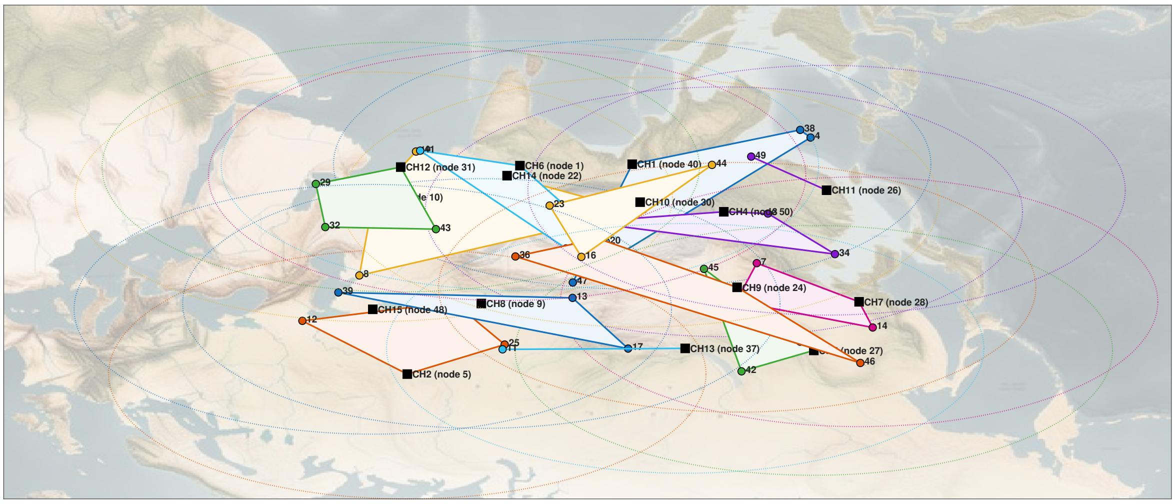

Figure 4.6: Clusters Formed Based on MRWP for Fixedwing UAVs

purely energy-centric FANET clustering approaches [?, ?].

In contrast, the weighted approach as in Figure **??** yields a more balanced and spatially uniform topology. By considering distance, rewarding index, velocity, and energy simultaneously, CH placement achieves improved coverage and reduced spatial isolation, resulting in a stronger backbone and more reliable inter-cluster communication. This demonstrates a better trade-off between connectivity, link stability, and energy management, making it more suitable for dynamic S-UAV scenarios [?, ?].

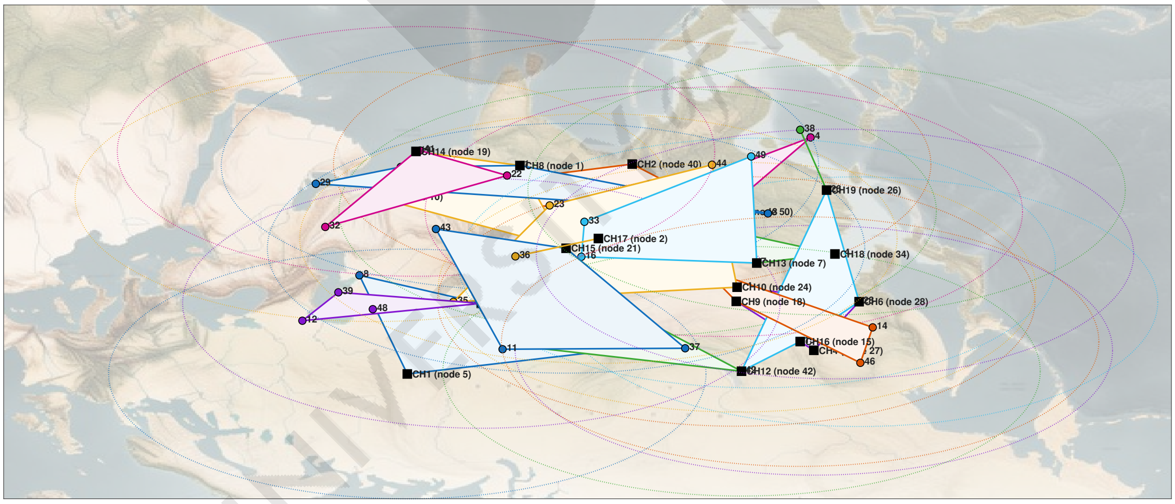

Figure 4.7: Clusters Formed Based on Energy for Multirotor UAVs

Figure **??** and Figure **??** show analogous results for multirotor UAVs. Due to limited operational range and reduced cruise endurance, multirotor clusters tend to be denser and more compact, resulting in shorter CM–CH links and reduced intra-cluster communication energy. This agrees with observations reported in multirotor FANET deployments [?, ?]. However, excessive density may increase interference or redundancy under high-overlap conditions. Weighted clustering further strengthens local connectivity while maintaining backbone continuity, adapting effectively to platform-specific flight characteristics: multirotors emphasize energy and communication reliability, whereas fixed-wing UAVs emphasize coverage and spatial reach [?, ?].

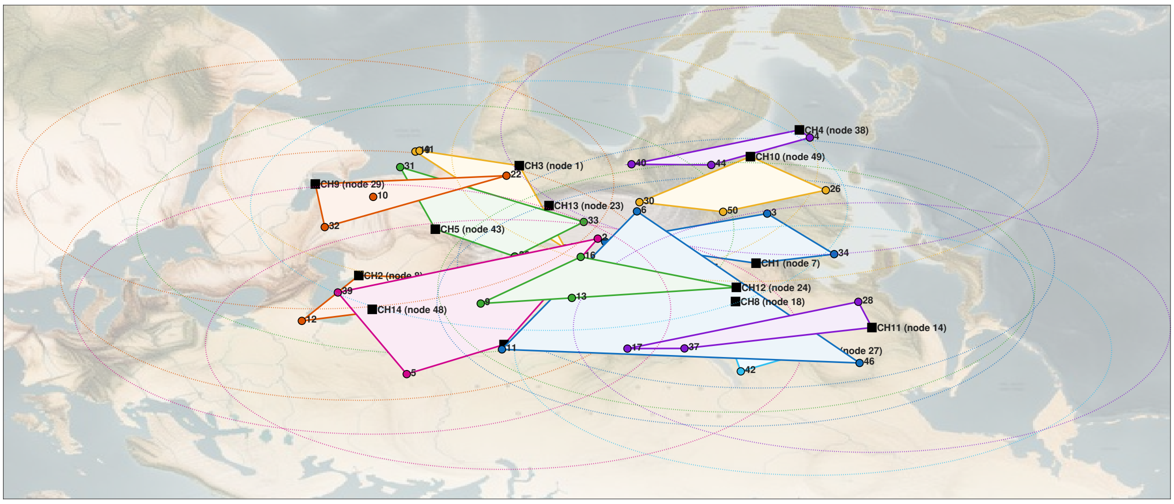

Figure 4.8: Clusters Formed Based on MRWP for Multirotor UAVs

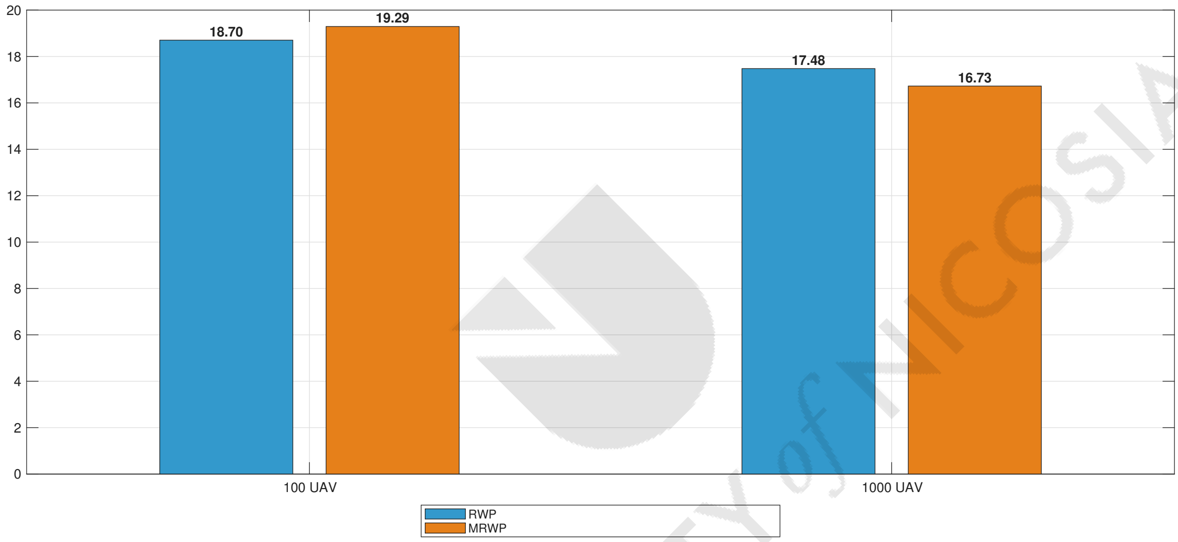

Figure 4.9: Total delay comparison

Figure ?? evaluates the effect of adding the energy metric to the weighted clustering protocol. For the 100-UAV scenario, the 3-parameter method achieves a total delay of 18.70 μs, while the 4-parameter model increases delay slightly to 19.29 μs. The additional constraint during CH selection can elongate routing paths or introduce processing overhead in smaller networks, consistent with delay/energy-aware strategies [?, ?]. However, for the 1000-UAV scenario, the behaviour reverses: the 4-parameter model reduces delay to 16.73 μs compared to 17.48 μs for the 3-parameter approach. In dense networks, energy improves CH suitability and cluster stability, reducing re-clustering and improving routing efficiency. The results confirm that the influence of energy scaling depends on network size: minor delay penalties in smaller networks and clear gains in denser deployments.

The Packet Delivery Ratio results in Figure ?? show similar behavior. For 100 UAVs, the 3-parameter model achieves a PDR of 0.53, while the 4-parameter model attains 0.50, again suggesting slightly stricter CH selection in sparse networks. In the 1000-UAV case, the two strategies converge (0.51 versus 0.50), indicating that energy becomes less influential when node proximity and mobility dominate cluster stability. Overall, adding energy introduces a modest performance trade-off in small networks but yields clear stability benefits in large-scale deployments where

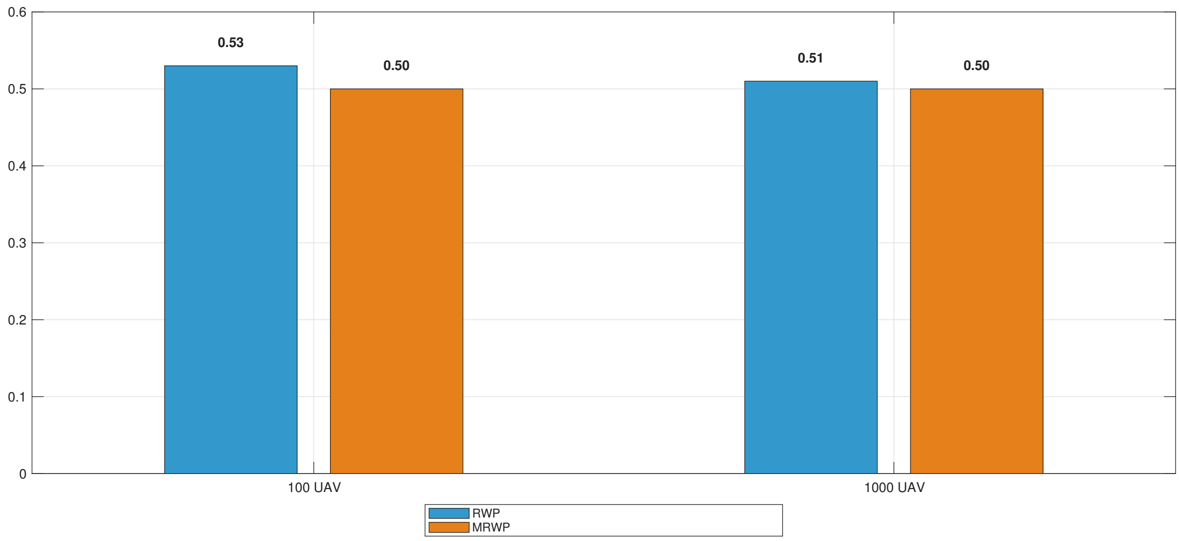

Figure 4.10: PDR comparison

node endurance heterogeneity plays a greater role in cluster longevity and routing performance [?, ?].

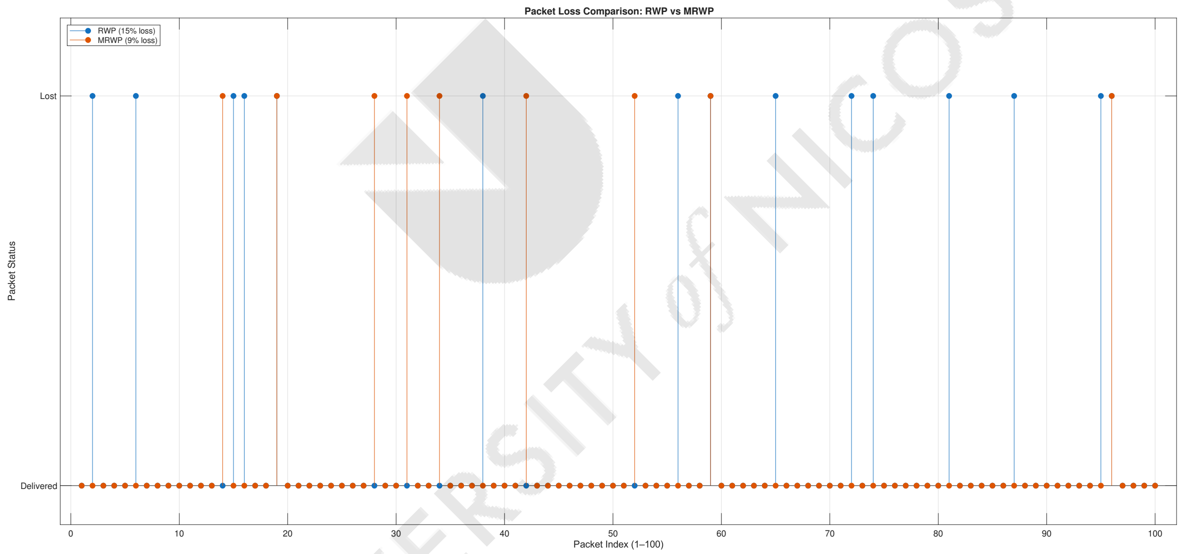

Figure 4.11: Packet loss comparison between RWP and MRWP over 100 packet transmissions.

Figure **??** illustrates packet delivery outcomes for the RWP and MRWP routing schemes for 100 transmitted packets. Each marker represents the status of an individual packet, where packets successfully delivered are indicated at the lower level, and lost packets are shown at the upper level. The RWP scheme exhibits a packet loss rate of 15%, with losses occurring intermittently throughout the transmission sequence. In contrast, MRWP reduces packet loss to 9%, demonstrating improved delivery reliability. The reduced number of loss events under MRWP highlights the effectiveness of the multi-redundant CH mechanism. By designating backup CHs from the highest-ranked CMs, MRWP enables rapid leadership recovery when the primary CH becomes non-functional, preventing packet forwarding interruptions. This redundancy mitigates the impact of node failures and energy depletion, reducing route breakage and packet drops. Consequently, MRWP achieves improved packet delivery reliability compared to RWP, which lacks multi-redundancy and is more susceptible to packet loss under CH and RCH failure conditions.

4.4 Proposed Protocol's Weakness

Although the proposed MRWP reduces single points of failure and improves robustness, several performance trade-offs remain. Key limitations include potential inefficiency in CH selection when energy is overemphasized, increased computational complexity, elevated control-message overhead, and minor delay penalties in smaller networks. Furthermore, improvements in PDR remain modest in dense deployments, reflecting challenges commonly reported in energy- and delay-aware FANET clustering and routing designs [?,?,?]. These weaknesses indicate that further optimization is required to adapt the scheme effectively across diverse S-UAV scenarios. In particular, adaptive weighting mechanisms could better balance mobility, energy, and reward metrics to match mission conditions.

4.5 Conclusion

This chapter presented MRWP, an enhanced clustering framework developed to overcome the limitations of conventional RWP. By incorporating redundancy and extending the weighted CH selection mechanism to include residual energy, the scheme aims to improve network resilience, extend operational lifetime, and maintain continuous communication in mission-critical scenarios. The design integrates concepts from energy-aware, reward-based, and bio-inspired clustering frameworks [?,?,?,?].

A unified energy model for both fixed-wing and multirotor UAVs enabled realistic estimation of mission energy consumption across typical flight segments. Simulation results confirmed that multirotor platforms naturally incur higher power consumption, reinforcing the importance of incorporating energy awareness to prevent premature CH depletion [?, ?, ?]. Performance analysis further demonstrated that the impact of the energy parameter depends on network scale. For small networks (100 UAVs), adding energy slightly reduced PDR and increased delay due to more restrictive CH selection that altered cluster geometry. In contrast, in dense networks (1000 UAVs), the energy-aware scheme reduced end-to-end delay and maintained comparable PDR to the three-parameter model. These findings suggest that energy becomes increasingly relevant as network density increases and CH fatigue becomes more likely.

Despite these advantages, the redundancy mechanism introduces new limitations, including additional energy consumption for backup CHs, activation latency during failover, increased control overhead, and potential CH misselection when energy is weighted too strongly. Improvements in PDR remain limited, indicating that predictive mobility models, redundancy scheduling, or adaptive weighting could further enhance performance [?, ?]. Overall, MRWP offers substantial benefits over RWP, particularly in large-scale S-UAV deployments where reliability and continuity of service are critical [?, ?]. However, the identified limitations highlight the need for additional optimization mechanisms, such as dynamic weight adjustment, to adapt clustering decisions to evolving network conditions. In highly dynamic S-UAV environments, factors such as residual energy, link stability, mobility intensity, and mission urgency fluctuate over time. Relying on static weights prevents the clustering process from responding to these changes, resulting in premature node failures, inefficient role assignment, and increased re-clustering overhead. Adaptive weighting enables the clustering scheme to continually re-balance decision criteria according to current operating conditions, thereby improving robustness, prolonging network lifetime, and maintaining service continuity during mission execution. These considerations motivate the enhancements explored in the next chapter.

Chapter 5

Dynamic Multi-Redundant Weighted Cluster Routing Protocol (DMRWP)

Introduction

By integrating multiple backup CHs and incorporating residual energy into WRP, MWRP introduced in the previous chapter enhances network robustness and mitigates single points of failure. However, this method continues to rely on predetermined, fixed weights for all clustering parameters. These static weights remain unchanged during the entire clustering process and are not sensitive to changes in network density, mobility patterns, failure dynamics, or traffic conditions. In highly dynamic crisis scenarios, where S-UAV topologies fluctuate rapidly and link quality may degrade unpredictably, fixed-weight assignment can lead to suboptimal cluster structures, increased latency, or reduced PDR [?, ?].

In practice, the relative importance of clustering parameters is context-dependent and varies with operational conditions. For example, in sparse networks with high-mobility UAVs, distance may weigh more heavily than energy to preserve connectivity and reduce re-clustering frequency. Conversely, in dense deployments, energy concerns become dominant as CHs may deplete their batteries rapidly due to higher coordination and forwarding loads. Similarly, during mission phases where data is time-sensitive such as search or hazard mapping, minimizing delay and improving link reliability may temporarily outweigh other factors. Static weighting cannot capture these evolving trade-offs and may force the clustering process into a configuration that is only optimal for a narrow set of operating scenarios [?, ?, ?] .

To address these limitations, this chapter introduces a Dynamic Multi-Redundant Weighted Cluster Routing Protocol (DMRWP). Instead of predefining weight values, the proposed approach continuously monitors key network metrics—including average latency, PDR, and re-clustering frequency—and adjusts the contribution of each clustering parameter accordingly. When latency exceeds a configurable threshold, the protocol increases the influence of distance, velocity, energy, or reward to encourage the selection of more stable and better-connected CHs [?]. The adjustment mechanism maintains normalized weights to prevent oscillations and to avoid excessive structural fluctuations. Moreover, DMRWP remains compatible with the redundancy mechanisms introduced in Chapter 4, ensuring that primary and backup CH selection jointly optimize performance without compromising robustness.

DMRWP is evaluated via simulation under multiple operating conditions, including varied mobility levels, failure intensities, and network sizes. Results indicate that dynamic weighting can further reduce end-to-end delay, and optimize CH selection, particularly in highly dynamic or long-duration missions. At the same time, the findings highlight trade-offs introduced by the adaptive process, such as increased control overhead and performance sensitivity to the selection of thresholds and adaptation rules [?, ?].

The remainder of this chapter is structured as follows:

- Section 5.1 formalizes the motivation for adaptive weighting and revisits the limitations of fixed-weight CH selection in dynamic S-UAV environments.
- Section 5.2 presents the proposed Dynamic Multi-Redundant Weighted Cluster Routing Protocol (DMRWP), including monitored metrics, adaptation rules, and integration with the multi-redundant weighted clustering mechanism.
- Section 5.3 describes the simulation setup and performance evaluation comparing DMRWP against the fixed-weight baseline across multiple scenarios.
- Section 5.4 discusses performance trade-offs and limitations of the proposed protocol and prepares for Chapter 6, where multi-agent coordination is incorporated into the overall clustering architecture.

5.1 Proposed Protocol's Weakness

Conventional clustering techniques widely used in WSNs, MANETs, and FANETs rely on fixed thresholds or static parameter weighting, which cannot adapt to rapidly changing network conditions such as mobility, residual energy, link variability, or UAV density. Early clustering mechanisms adopt probabilistic or threshold-based CH selection, where weights remain constant throughout the network lifetime [?]. These methods perform adequately in static terrestrial environments but degrade significantly in UAV-based networks characterized by high link dynamics and continuous topological variation, as highlighted in major research surveys [?, ?]. Mobility-aware clustering protocols in MANETs and FANETs [?, ?] introduce link-stability weighting in which node velocity influences CH selection; however, the associated weights are predefined and do not adjust based on network state.

Adaptive clustering strategies based on performance metrics have also been explored. Delay-aware routing schemes dynamically modify routing behavior in response to congestion or mobility conditions, yet they do not modify clustering weights directly [?]. Similarly, trust-based and reliability-centric clustering schemes [?] incorporate trust ratings using static weighting, restricting responsiveness to sudden variations in UAV behavior, link reliability, or energy dissipation.

More advanced adaptive mechanisms have been proposed in IoT networks, including fuzzy logic-based metric weighting, reinforcement learning-based CH selection, and bio-inspired optimization using evolutionary or swarm heuristics. These approaches demonstrate improved cluster stability and network longevity; however, they are typically computationally complex and therefore unsuitable for time-sensitive S-UAV networks with strict latency and energy constraints. Parallel work in energy-efficient UAV routing highlights the importance of energy-aware decision-making [?, ?, ?], yet these models do not introduce mechanisms for dynamically adjusting CH selection weights. Redundancy-based clustering schemes further improve robustness by employing backup CHs [?], but they still rely on static criteria and do not adapt as the network evolves.

Collectively, these studies indicate that dynamic adaptation can significantly enhance cluster stability, energy balance, and routing performance. However, a critical gap remains in the literature: the absence of lightweight, distributed, and dynamic weighting algorithms specifically tailored to S-UAV environments. DMRWP proposed in this chapter addresses this gap by offering a computationally efficient and redundancy-compatible mechanism. The protocol adjusts CH parameter weights in real time to optimize clustering performance under diverse and evolving operational conditions.

5.2 Proposed Protocol

The purpose of the proposed clustering framework, DMRWP, is to enhance MRWP mechanism by enabling clustering weights to adapt dynamically to current network conditions. Instead of relying on fixed and predetermined coefficients, DMRWP updates the relative contribution of distance, reward, velocity, and residual energy over time citeKhayat2023SUAV. In Chapter 4, the cluster index for a UAV k with respect to UAV l was computed using four equally weighted parameters:

$$C(k,l) = -0.25\,D(k,l) + 0.25\,R(k,l) - 0.25\,V(k,l) + 0.25\,E_k. \tag{5.1}$$

To incorporate dynamic behavior, this formulation is extended by introducing time-varying weights that satisfy a normalization constraint [**?**]:

$$w_D(t) + w_R(t) + w_V(t) + w_E(t) = 1, \qquad w_i(t) \in [0,1]. \tag{5.2}$$

The dynamic cluster index at time t is thus defined as:

$$C_{(k,l)}(t) = -\,w_D(t)\,D(k,l) + w_R(t)\,R(k,l) - w_V(t)\,V(k,l) + w_E(t)\,E_k. \tag{5.3}$$

Initially, at network deployment or after a reset triggered by large-scale topology changes, all weights are initialized equally:

$$w_D(0) = w_R(0) = w_V(0) = w_E(0) = 0.25. \tag{5.4}$$

Cluster formation proceeds identically to the MRWP: the UAV with the largest cluster index becomes the primary CH, while the next $C_{\max}$ nodes with the highest indices become backup CHs and subsequently cluster members until all nodes are assigned.

Discrete Adaptation Events.

To avoid sensitivity to short-lived fluctuations [**?**, **?**, **?**], DMRWP operates at discrete decision instants:

$$\mathcal{T}_{\text{DMRWP}} = \{t \mid t = m\,T_{\text{DMRWP}},\ t > 2T_{\text{DMRWP}},\ m \in \mathbb{N}\}\,. \tag{5.5}$$

Delay-Based Stability Coefficient.

DMRWP evaluates short-term variations in routing delay by comparing a recent observation window against a historical reference window. To accomplish this, the scheme computes a window-averaged delay for both the current and previous intervals as

$$\bar{d}_{\text{cur}}(t) = \frac{1}{W}\sum_{n=t-W+1}^{t} d[n], \qquad \bar{d}_{\text{prev}}(t) = \frac{1}{W}\sum_{n=t-2W+1}^{t-W} d[n], \tag{5.6}$$

where:

- $d[n]$ denotes the one-way routing delay sample at discrete time index n.
- W represents the number of samples within a DMRWP observation window, computed as
$$W = \frac{T_{\text{DMRWP}}}{\Delta t}, \tag{5.7}$$
- T_{DMRWP} denotes the window duration.
- Δt denotes the sampling interval.

This windowed averaging mechanism mitigates transient fluctuations and provides a smoother estimate of routing performance [?]. By contrasting $\bar{d}_{\text{cur}}(t)$ and $\bar{d}_{\text{prev}}(t)$, DMRWP is able to identify whether network delay is improving, degrading, or remaining stable. Such trend information is subsequently incorporated into the routing decision process, enabling the scheme to react adaptively to evolving congestion and mobility conditions.

The delay stability coefficient is defined as [?]:
$$C_S(t) = \frac{\bar{d}_{\text{cur}}(t) - \bar{d}_{\text{prev}}(t)}{\bar{d}_{\text{cur}}(t)}. \tag{5.8}$$

This coefficient captures relative delay variations:

- $C_S(t) \approx 0$ indicates a steady regime,
- $C_S(t) > 0$ indicates worsening delay,
- $C_S(t) < 0$ indicates improvement or transient recovery.

DMRWP triggers adaptation when
$$C_S(t) > C_{S,\text{threshold}}. \tag{5.9}$$
where $C_{S,\text{threshold}}$ is the minimum admissible score determined by the clustering policy.

Metric Normalization.

Because raw metrics exhibit heterogeneous units and scales, normalization is essential to avoid scale-induced bias [?, ?]. Distance values may span hundreds of meters, velocities tens of meters per second, reliability scores lie in $[0, 1]$, and energy is already normalized. Thus, DMRWP applies metric-wise scaling:

Distance Normalization

To ensure that the spatial contribution to the weighting mechanism remains scale-invariant with respect to cluster geometry, the instantaneous distance $D(t)$ is normalized by the cluster communication radius r_c [?]. The normalized distance metric is defined as:
$$D_{\text{norm}}(t) = \frac{D(t)}{r_c + \varepsilon}, \tag{5.10}$$
where:

- r_c denotes the nominal intra-cluster communication radius.
- ε is a small positive constant introduced to avoid numerical division issues in degenerate cases (i.e., $r_c \approx 0$).

Velocity Normalization

To prevent excessively large velocity magnitudes from dominating the multi-metric weighting process, the instantaneous UAV velocity $V(t)$ is normalized with respect to the maximum velocity observed within the current cluster. The normalized velocity metric is defined as

$$V_{\text{norm}}(t) = \frac{V(t)}{\max(V(t)) + \varepsilon}, \tag{5.11}$$

Reward Normalization

To ensure that the contribution of reward-based metrics remains comparable with other normalized clustering factors, the instantaneous reward value $R(t)$ is scaled with respect to the maximum reward observed within the current decision context. The normalized reward is defined as:

$$R_{\text{norm}}(t) = \frac{R(t)}{\max(R(t)) + \varepsilon}, \tag{5.12}$$

Energy Normalization

Since the energy metric $E(t)$ is already defined as a dimensionless quantity within the range $[0, 1]$, no additional scaling is required. The normalized energy value is therefore given by

$$E_{\text{norm}}(t) = E(t). \tag{5.13}$$

Normalization ensures:

- no metric dominates due to scale,
- adaptation reflects true performance trends,
- favored-metric selection is consistent across conditions.

Metric Variation and Selection.
The metric variation vector is defined as:

$$\mathbf{m}(t) = \Big[\mu_D(t)-\mu_D(t-\Delta t),\ \mu_R(t)-\mu_R(t-\Delta t),\ \mu_V(t)-\mu_V(t-\Delta t),\ \mu_E(t)-\mu_E(t-\Delta t)\Big]. \tag{5.14}$$

A normalized sensitivity score is computed:

$$C_{S_i}(t) = \frac{m_i(t) - m_i(t^-)}{|m_i(t^-)| + \varepsilon}, \qquad i \in \{D, R, V, E\}. \tag{5.15}$$

The favored metric is selected via [?, ?, ?]:

$$i(t) = \arg\max_i C_{S_i}(t). \tag{5.16}$$

Selective-Freeze Weight Update Mechanism.
The Selective-Freeze Weight Update mechanism dynamically adjusts the importance assigned to each routing metric while preserving system stability [?, ?, ?, ?]. Let the weight vector at time t be defined as

$$\mathbf{w}(t) = \Big[w_D(t),\ w_R(t),\ w_V(t),\ w_E(t)\Big],$$

subject to the normalization constraint $\sum_i w_i(t) = 1$, ensuring that the relative contribution of each metric remains bounded.

Metric Reliability Criteria.

To ensure stable weight adaptation and prevent routing decisions from being influenced by inaccurate information, each routing metric is subjected to a set of reliability checks before being considered valid. These checks evaluate the freshness, feasibility, temporal stability, neighbor consistency, and energy availability of the reported measurements [?, ?, ?, ?, ?].

Freshness. Metrics must reflect the current network state and therefore should not be outdated. A metric is considered fresh if the time elapsed since its last update satisfies [?, ?] :

$$t_{\text{current}} - t_{\text{last-update}} < T_{\max}, \tag{5.17}$$

where:

- t_{current} denotes the current system time,
- $t_{\text{last-update}}$ represents the timestamp of the most recent metric update,
- $T_{\max}$ is the maximum allowable age beyond which the metric is considered outdated.

Outdated measurements may no longer represent the true topology due to rapid UAV mobility, leading to unreliable clustering decisions. Enforcing freshness prevents routing based on stale neighbor information [?, ?].

Physical Feasibility. Reported values must lie within physically realizable bounds. Any measurement violating system constraints is rejected. A metric is considered physically feasible if it satisfies:

$$m_i \in [m_{\min}, m_{\max}], \tag{5.18}$$

where:

m_i observed metric value,

$m_{\min}$ minimum permissible bound,

$m_{\max}$ maximum permissible bound.

The bounds are determined by platform capabilities and communication constraints. For instance, negative residual energy is physically impossible, velocities must not exceed UAV operational limits, and distances should remain within the communication range [?]. Enforcing this constraint prevents the protocol from reacting to sensor faults, corrupted packets, or anomalous measurements, thereby improving clustering stability.

Temporal Stability. Reliable metrics should not exhibit abrupt fluctuations between consecutive observations. A metric is considered temporally stable if the variation between successive observations satisfies:

$$|m_i(t) - m_i(t-1)| < \delta, \tag{5.19}$$

where δ denotes a predefined tolerance threshold [?].

Significant deviations may indicate measurement noise, packet delays, GPS inaccuracies, or transient link disruptions [?]. Enforcing this constraint reduces oscillatory cluster formation and enhances routing stability.

Neighbor Consistency. Since FANETs operate in a distributed manner, each UAV can cross-validate its measurements against those reported by neighboring nodes [?]. A metric is considered consistent if it satisfies:

$$|m_i - \bar{m}_{\mathrm{nbr}}| < \lambda, \tag{5.20}$$

where:

- m_i is the observed metric value,
- $\bar{m}_{\mathrm{nbr}}$ is the neighborhood average,
- λ is the consistency threshold.

Significant deviations may indicate faulty sensing or compromised nodes [?, ?]. Enforcing neighbor consensus enhances robustness and supports cooperative decision-making.

Energy Availability. Residual energy plays a critical role in leadership selection. Nodes approaching energy depletion are unlikely to sustain cluster coordination duties [?]. Accordingly, a metric associated with UAV k is considered unreliable for leadership decisions when:

$$E_k < E_{\min}, \tag{5.21}$$

where:

- E_k is the residual energy of UAV k,
- $E_{\min}$ is the minimum energy threshold required for CH eligibility.

This constraint prevents the election of CHs that are at risk of imminent failure, thereby improving network longevity and reducing the likelihood of route disruption.

Only metrics satisfying the above criteria are included in the valid set $\mathcal{V}(t)$. Restricting weight adaptation to this set ensures that the clustering process is guided by trustworthy information, thereby enhancing stability, robustness, and overall routing performance in highly dynamic UAV environments [?].

Metrics that do not satisfy the validity criteria are temporarily frozen, such that

$$w_i(t^+) = w_i(t), \tag{5.22}$$

where:

- $w_i(t)$ is the weight of metric i at time t,
- $w_i(t^+)$ is the updated weight after the adaptation step.

This selective freezing prevents unreliable measurements from influencing weight redistribution while preserving the normalization of the weight vector. Once the metric regains validity, it is reinstated into the update set without requiring reinitialization. This strategy avoids permanent metric elimination, maintains multi-criteria decision capability, and enhances clustering stability under transient sensing errors and rapid topology changes [?, ?, ?].

At any update instant, only metrics deemed valid—i.e., those providing reliable and meaningful information—are allowed to participate in the adaptation process. For each valid metric $j \in \mathcal{V}(t)$, the removable slack is defined as

$$s_j(t) = w_j(t) - c_1, \tag{5.23}$$

where:

- $s_j(t)$ is the removable slack of metric j,
- $w_j(t)$ is the weight of metric j at time t,
- c_1 is the minimum stability threshold.

The slack quantifies how much of a metric's weight can be safely redistributed without violating the lower stability bound, thereby preventing abrupt weight depletion and avoiding destabilization of the clustering process.

To ensure conservative adaptation, the maximum feasible increment is defined as

$$\Delta^+(t) = \min\left(\frac{c_2}{10}, \sum_{j\in\mathcal{V}(t)} s_j(t),\right), \tag{5.24}$$

where:

- $\Delta^+(t)$ is the allowable weight increment,
- c_2 is a design constant controlling the adaptation rate,
- $\mathcal{V}(t)$ denotes the set of valid metrics.

Bounding the increment guarantees gradual weight evolution and mitigates oscillatory behavior that could arise from rapid metric fluctuations in highly dynamic UAV environments.

Favored metrics—typically reflecting improved reliability, energy availability, or mobility stability—receive an additive increase:

$$w_i(t^+) = w_i(t) + \Delta^+(t), \tag{5.25}$$

where t^+ denotes the post-update time instant.

Conversely, non-favored metrics relinquish weight in proportion to their available slack:

$$\Delta_j^-(t) = \Delta^+(t)\frac{s_j(t)}{\sum_{k\in\mathcal{V}(t)} s_k(t) + \varepsilon}, \tag{5.26}$$

where:

- $\Delta_j^-(t)$ is the weight reduction assigned to metric j,
- ε is a small positive constant introduced to prevent division by zero.

This proportional redistribution ensures fairness while preventing any single metric from dominating the adaptation process.

To further enhance robustness, a hard lower bound is enforced:

$$w_i(t^+) \leftarrow \max\Big(w_i(t^+),\, w_{\min}\Big), \tag{5.27}$$

where $w_{\min}$ is the minimum allowable metric weight. This constraint guarantees that every metric retains a baseline influence in the cluster index computation, preventing permanent metric exclusion and preserving multi-criteria decision capability.

Weight adaptation occurs only at discrete instants defined as

$$\mathcal{T}_{\text{upd}} = \{t \in \mathcal{T}_{\text{DMRWP}} \mid \text{update occurred}\}, \tag{5.28}$$

where $\mathcal{T}_{\text{DMRWP}}$ denotes the operational timeline of the protocol [?, ?].

This event-driven strategy separates routing operations from parameter tuning, reduces control overhead, and ensures that updates are triggered only when meaningful network changes are detected [?].

Overall, the Selective-Freeze mechanism balances adaptability and stability. By redistributing weights selectively while enforcing bounded updates and minimum thresholds, the protocol remains responsive to evolving network conditions without compromising clustering consistency—an essential property in S-UAVs environments characterized by rapid topology changes, node failures, and energy constraints [?].

Step-Consistency Constraint. Weight modifications satisfy:

$$c_2 = 3c_1. \tag{5.29}$$

ensuring normalization:

$$(w_D + w_R + w_V + w_E) + c_2 - 3c_1 = 1. \tag{5.30}$$

Upper and lower bounds enforce physical validity and prevent unstable oscillations. If either bound is violated, step sizes are reduced or updates frozen [?].

DMRWP employs a freeze mechanism when updates are marginal, unstable, or yield negligible benefit.

Figure ?? illustrates the operational workflow of DMRWP, beginning with uniform weight initialization followed by cluster formation and routing based on MRWP. At discrete decision instants, the protocol evaluates delay trends and triggers weight adaptation when performance degradation is detected. Favored metrics are selected based on sensitivity, validated through reliability checks, and updated using a Selective-Freeze mechanism that preserves stability while enabling adaptive routing. If no adaptation is required, the network continues normal operation, ensuring efficient and resilient clustering in dynamic UAV environments.

5.3 Simulation and Analysis

A discrete-time MATLAB simulation of an S-UAV network operating in a constrained 3D environment was used to evaluate DMRWP. A swarm of 100 UAVs was initially deployed uniformly at random within a 1000 m × 1000 m × 200 m region. The simulation was executed for 300 s with a time step of $\Delta t = 1$ s. Bounded stochastic updates to the UAVs' positions and velocities were applied at each time step to emulate mobility while ensuring containment within the deployment volume. To capture time-varying yet piecewise-stationary link and resource conditions, the pairwise distance matrix, relative velocity matrix, reward matrix, and node energy vector were updated every 20 s. Clustering was performed at each time step.

Two configurations were compared: (i) a constant-weight baseline using static weights $w_D = w_R = w_V = w_E = 0.25$; and (ii) the proposed DMRWP-based dynamic

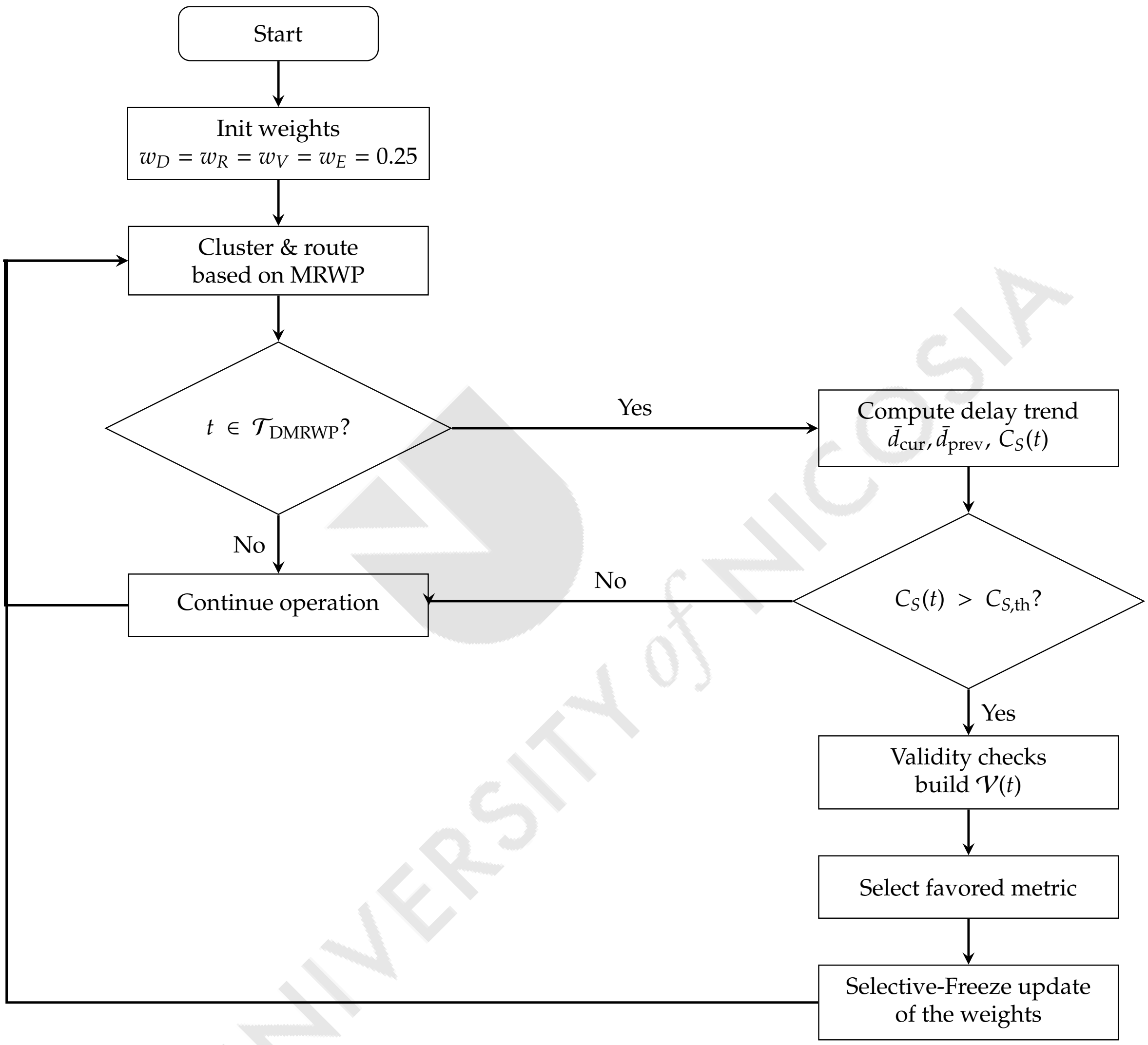

Figure 5.1: Flowchart of the Dynamic Multi-Redundant Weighted Cluster Routing Protocol (DMRWP).

scheme initialized with the same uniform weights but subsequently updated at discrete decision instants based on performance feedback. At each DMRWP decision time, the mean end-to-end delay over two successive windows was used to compute a delay stability coefficient C_S. A weight update was triggered whenever C_S exceeded a predefined threshold, reallocating weight toward the most degraded normalized metric distance, reward, velocity, or energy using a bounded update mechanism with a minimal weight floor to ensure stability.

Figure **??** presents the evolution of end-to-end delay for both schemes. The constant-weight system maintains an almost invariant delay trajectory with only minor fluctuations due to stochastic network effects, indicating stable but non-adaptive behavior. In contrast, the DMRWP-based system shows a piecewise trajectory segmented by discrete update events which are marked with dashed vertical lines. After several updates, the dynamic-weight configuration exhibits consistently lower-delay regimes, demonstrating the controller's ability to re-prioritize parameters as network conditions evolve. Brief delay spikes appear prior to some updates, reflecting transient mismatches between the active weights and the current network state; however, these are rapidly corrected following adaptation. Between updates, delay remains stable, showing that DMRWP avoids oscillatory behavior and unnecessary reconfiguration. Overall, the dynamic scheme achieves a lower long-term average delay than the constant-weight baseline while preserving temporal stability.

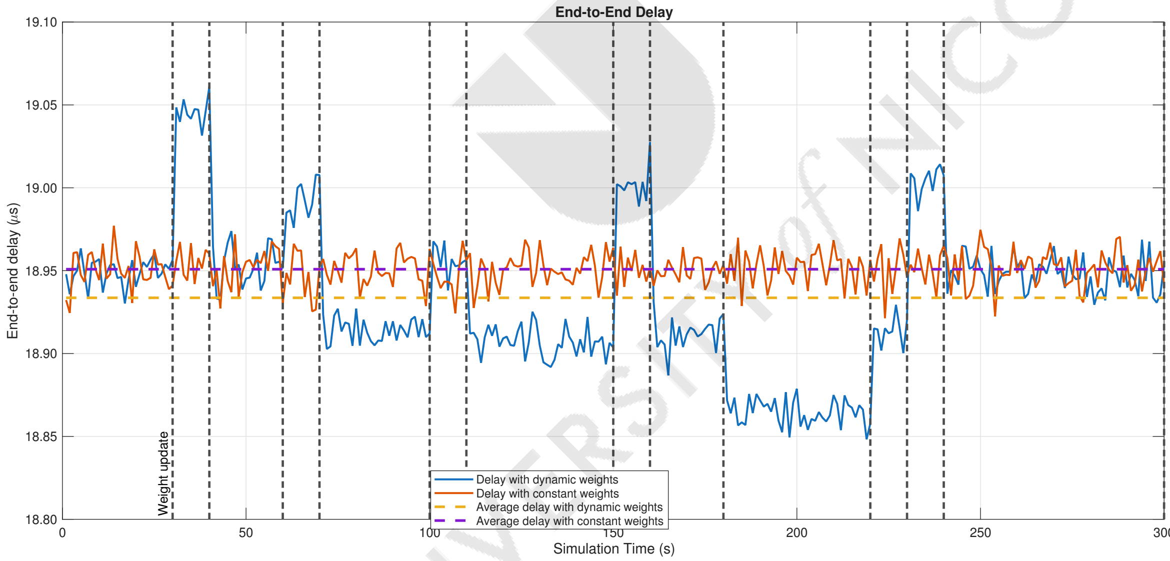

Figure 5.2: End-to-end delay comparison between DMRWP and MRWP.

PDR results are shown in Figure **??**. The constant-weight configuration maintains a nearly flat PDR profile with no substantial improvement over time. The DMRWP-based system, in contrast, exhibits discrete PDR regimes aligned with the same update events. After several weight reallocations, the dynamic scheme achieves noticeably higher PDR values—including intervals approaching near-ideal delivery—outperforming the constant baseline. Temporary PDR degradation appears prior to some updates, analogous to the delay behavior, but is quickly compensated once DMRWP reassigns weights. PDR remains stable between updates, indicating that the adaptive mechanism does not introduce harmful oscillations. On average, the dynamic weighting scheme achieves a higher PDR than the static configuration, demonstrating that sparse, metric-aware adaptation can enhance delivery reliability despite short-term variability.

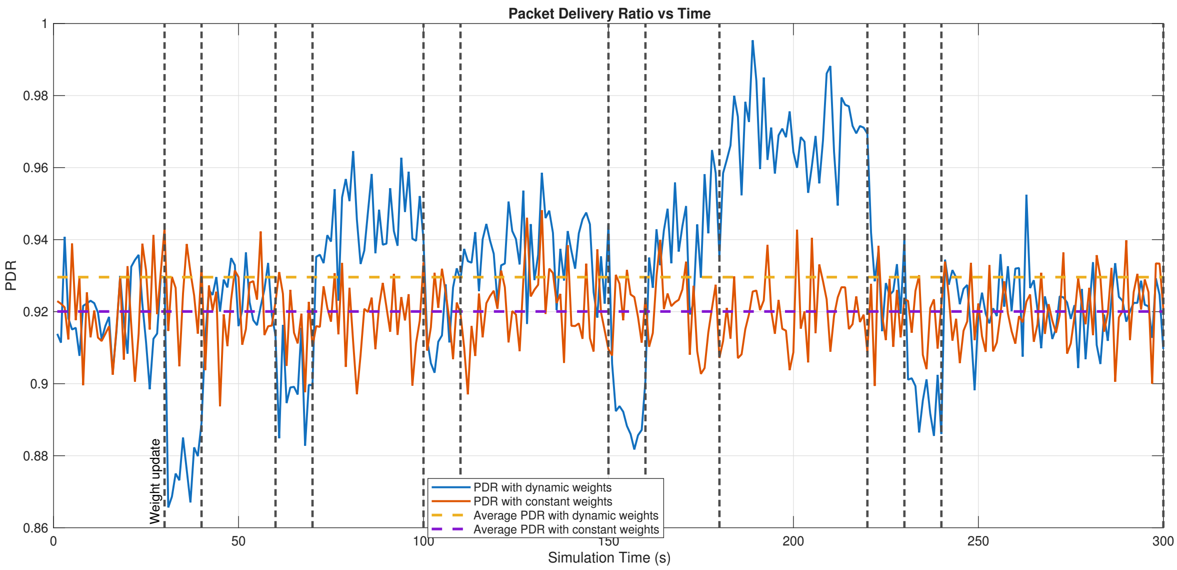

Figure 5.3: Impact of DMRWP weight adaptation on packet delivery ratio over time.

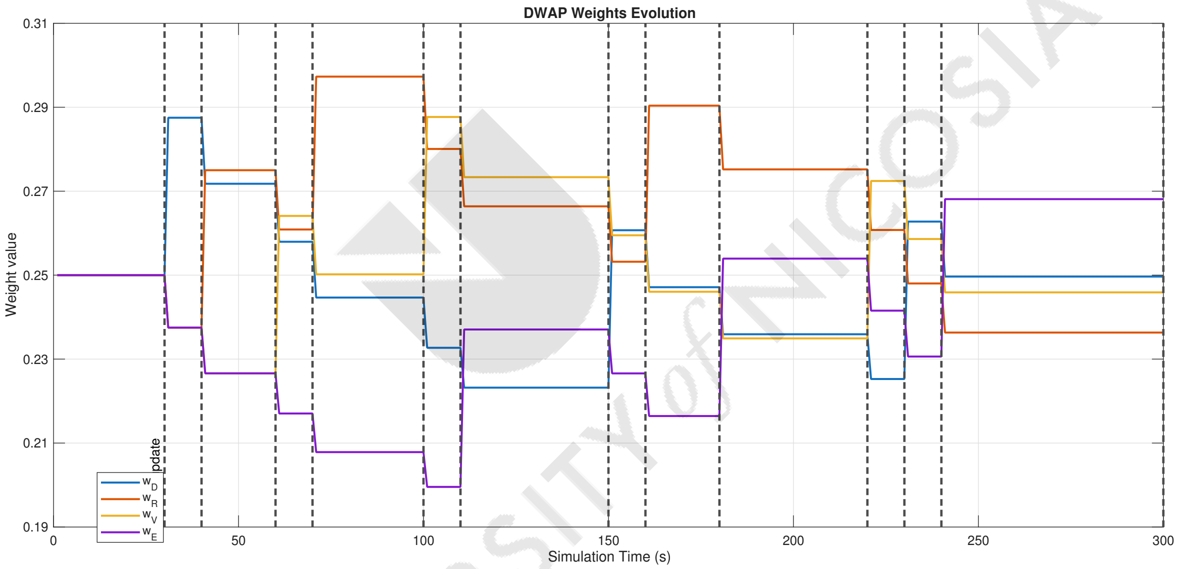

Figure 5.4: Temporal evolution of DMRWP weights under adaptive control.

Figure **??** illustrates the temporal evolution of the DMRWP weight vector. Because the adaptation procedure is event-driven, the weights remain constant between update instants, forming a staircase-like profile characteristic of stable discrete-control systems. At each update, the weight of the most degraded metric increases while the remaining weights decrease proportionally, bounded by a predefined lower limit. Several dominance intervals are observable: early updates primarily emphasize reward and distance reflecting topology and link reliability effects, whereas later updates prioritize velocity and energy reflecting increased mobility dynamics and cumulative CH depletion. Importantly, all weights remain within a narrow interval (approximately 0.19–0.31), preventing extreme prioritization and ensuring balanced clustering decisions. The strong alignment between update events and subsequent improvements in delay and PDR demonstrates that DMRWP successfully translates performance feedback into meaningful reconfiguration of routing priorities. From a control-theoretic viewpoint, DMRWP behaves as a discrete-time feedback controller acting on the weight vector.

A quantitative comparison of key performance metrics is summarized in Table **??**. The dynamic scheme achieves a marginally lower mean end-to-end delay and a higher mean PDR compared to the constant-weight baseline, at the cost of slightly increased variance—an expected outcome for adaptive control systems that periodically explore alternative operating regimes. Viewed holistically, the results confirm that DMRWP provides improved performance while preserving stability and avoiding the excessive reactivity characteristic of continuous or overly aggressive adaptation.

Table 5.1: Performance comparison between DMRWP and MRWP.

Metric	**DMRWP**	**MRWP**
Mean end-to-end delay (μs)	18.93	18.95
Std. deviation of delay (μs)	0.05	0.01
Median delay (μs)	18.92	18.95
Mean PDR	0.94	0.92
Std. deviation of PDR	0.02	0.01

The empirical distribution of end-to-end delay for the dynamic (DMRWP-based) and constant-weight configurations is compared in the histogram of Figure **??**. The constant-weight case exhibits a narrow, unimodal distribution centered near 18.95 μs, indicating highly consistent but inflexible performance with limited ability to adapt to network fluctuations. In contrast, the dynamic-weight configuration produces a broader, multi-modal distribution, reflecting the system's adaptive operation across several distinct performance regimes induced by periodic weight adjustments. Notably, the dynamic setup achieves a substantial concentration of samples at lower-delay values (below 18.90 μs) that the constant-weight scheme never attains. These lower-delay modes correspond to periods in which DMRWP correctly identifies delay as the dominant degradation factor and temporarily increases its associated weight, yielding latency-optimized clustering and routing configurations. Although occasional higher-delay outliers appear in the dynamic case, forming a small right tail, these samples represent short-lived reactions to disruptive events or transients immediately preceding adaptation. Overall, the histogram illustrates a trade-off between reduced minimum delay and increased variance: whereas the constant scheme remains locked at a single equilibrium point, the dynamic scheme actively explores improved operating regions. This behavior is characteristic of a feedback-controlled adaptive system that prioritizes performance potential and responsiveness over static uniformity—an advantageous property in highly dynamic UAV networks.

The temporal evolution of the Delay Stability Coefficient (CS) at DMRWP decision instants is shown in Figure **??**. The CS metric is the primary feedback signal used to trigger adaptation, capturing the normalized change in average delay between two successive assessment windows. Positive CS values indicate delay degradation, while negative values indicate improvement. The observed CS values remain bounded within a narrow interval on the order of 10^{-3}, confirming that the system operates in a stable regime without uncontrolled drift. Distinct positive spikes occur around $t \approx 40$ s, $t \approx 160$ s, and $t \approx 240$ s, each corresponding to periods of performance deterioration that prompt DMRWP to reallocate weights. Conversely, negative excursions typically follow these events, reflecting successful corrective action and improved delay performance. The alternating sign transitions demonstrate closed-loop behavior in which each update compensates for prior degrada-

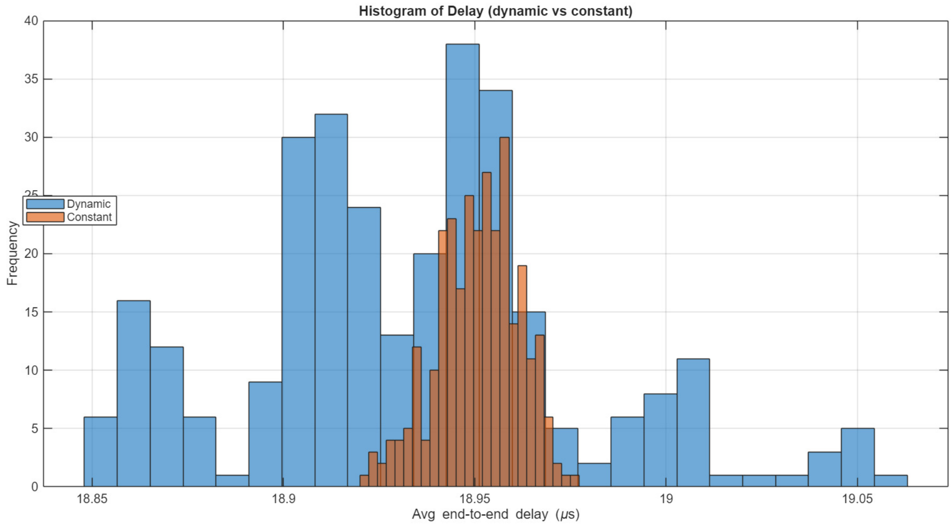

Figure 5.5: Distribution of end-to-end delay under dynamic and constant weighting.

tion. Crucially, the absence of sustained positive CS levels indicates that long-term performance erosion is prevented by the adaptation mechanism. From a control perspective, CS acts as an error signal in a discrete-time feedback controller, while the bounded update rule functions as a proportional correction term. The small CS magnitude and rapid sign reversals validate the robustness and non-oscillatory nature of the proposed dynamic weighting method.

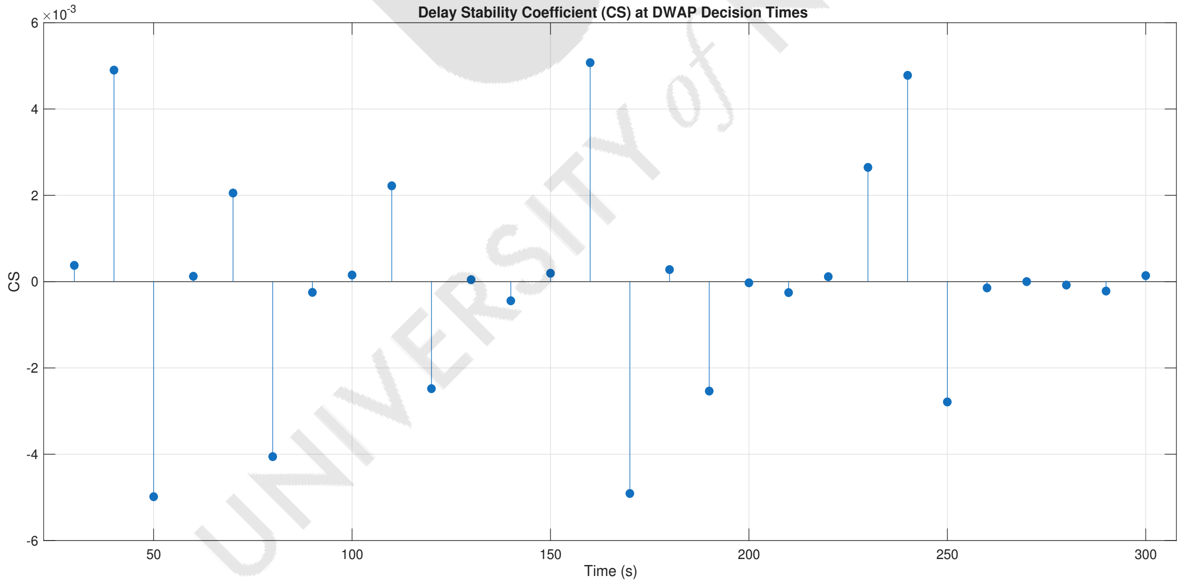

Figure 5.6: Temporal behavior of the Delay Stability Coefficient (CS) during DMRWP updates.

Figure **??** presents the DMRWP-selected favored metric at each update instant, identifying which parameter—distance, reward, velocity, or energy—was deemed most responsible for performance degradation. Each stem corresponds to a triggered update event and encodes the dominant degradation channel. The results show that DMRWP does not prioritize a single metric, but instead shifts attention according to evolving network conditions. During early clustering stages, distance and reward-related selections are more frequent, indicating that spatial topology and link quality dominate delay fluctuations when the network structure is still forming. As the mission progresses, velocity and energy metrics become more prevalent, capturing the increasing influence of mobility patterns and cumulative CH energy consumption. The delayed emergence of energy selections is consistent with progressive resource depletion effects, validating DMRWP's sensitivity to long-term sustainability rather than short-term opportunistic gains. In feedback-control terms, the metric index represents the predominant error source in a multi-input control loop; DMRWP adjusts the weight vector to counteract the largest normalized performance gradient at each update. This adaptive prioritization prevents over-optimization of any single parameter and balances stability, mobility, reliability, and energy efficiency over time—an essential property for dynamic S-UAV network operation.

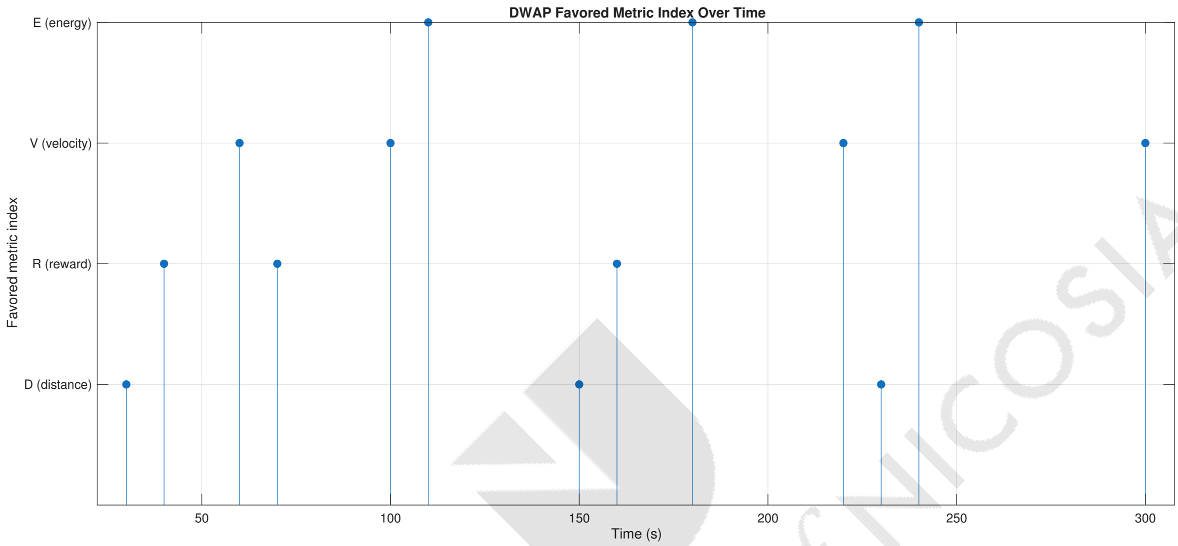

Figure 5.7: DMRWP-selected performance metric over time.

5.4 Conclusion

This chapter addressed the third major limitation identified in the previous protocols: the dependency on manually configured, fixed clustering weights that cannot adapt to rapidly changing S-UAV operating conditions. Although the multi-redundant weighted clustering scheme introduced in Chapter 4 significantly improved energy balance, robustness, and fault tolerance, its performance remained constrained by static weights. These static weights occasionally led to suboptimal CH selection during highly dynamic mission phases.

To overcome this limitation, DMRWP was proposed. DMRWP is a distributed and lightweight mechanism that continuously adjusts the importance of distance, reward index, velocity, and residual energy during CH selection. Rather than relying on fixed presets, the protocol monitors key performance indicators—including average end-to-end delay, PDR, energy imbalance, and re-clustering frequency—and modifies the weight vector accordingly. Bounded updates, normalization, and safety constraints ensure that the adaptation process remains stable, non-oscillatory, and with minimal control overhead.

Simulation results demonstrated that, under diverse network densities, mobility regimes, and mission conditions, dynamic weighting improves both routing performance and clustering stability. Specifically, DMRWP reduces unnecessary re-clustering during topological disturbances, balances residual energy across UAVs during prolonged operations, and lowers latency during high-mobility periods. Furthermore, because DMRWP operates within the same multi-redundant architectural framework established in Chapter 4, it preserves resilience against CH failures and continues to function under adverse conditions.

Despite these benefits, dynamic weighting introduces new trade-offs. The protocol increases the complexity of monitoring and adaptation and requires careful tuning of thresholds and learning rates to prevent excessive sensitivity. Additionally, DMRWP currently assumes homogeneous UAV agents and does not account for heterogeneous roles, risk profiles, or mission priorities associated with other autonomous platforms that may coexist in disaster-response scenarios.

These limitations motivate further refinement. Chapter 6 therefore extends the clustering concept to multi-agent environments, integrating UAVs and vehicles into a unified cooperative system capable of maintaining low latency, high connectivity, and operational continuity even under severe mission disruption.

Chapter 6

Multi-Agent Dynamic Multi-Redundant Weighted Cluster Routing Protocol (MADMRWP)

Introduction

In the preceding chapters of this thesis, it was shown that S-UAV networks can substantially strengthen the resilience of crisis communication systems. Specifically, adaptive clustering techniques, energy-aware CH selection, and dynamic weight adjustment mechanisms were introduced to reduce single points of failure, improve load balance, extend operational lifetime, and minimize latency. UAV platforms offer a number of advantages in crisis environments that make them attractive candidates for such roles, including rapid deployment, aerial mobility, and wide-area sensing coverage. However, a UAV-only solution also exhibits important limitations that constrain performance under certain mission conditions. UAVs remain highly sensitive to environmental factors such as wind, rain, and turbulence, and are subject to aerodynamic instability and energy depletion. These constraints impose mission time limits, reduce link reliability, and create scenarios where prolonged reliance on UAVs alone introduces a new form of single-domain vulnerability.

In real-world disaster response operations, communication tasks are rarely executed by UAVs in isolation. Instead, UAVs commonly coexist alongside ground vehicles, mobile robots, or sensor-equipped rescue units that contribute complementary capabilities. For example, ground vehicles with communication modules can operate as mobile gateways or local aggregators and provide extended processing and energy resources that UAVs lack. Conversely, UAVs can reach damaged areas that are inaccessible to terrestrial assets due to debris, flooding, or structural collapse. Importantly, these heterogeneous agents exhibit different mobility behaviors, link characteristics, risk profiles, and failure modes. Their operational characteristics are also shaped by the nature of the crisis. Floods or earthquakes may immobilize ground vehicles while UAVs remain fully operational; severe storms may ground UAV fleets while vehicles maintain connectivity. Failure correlations within a single agent type therefore represent a non-trivial threat to system survivability. A network that relies exclusively on UAVs may suffer cascading failures that reduce packet delivery performance, increase latency, and diminish situational awareness when information flow is most critical [?].

These observations motivate a shift toward heterogeneous, multi-agent communication architectures. Rather than assigning identical roles to all network elements, a multi-agent system distributes tasks based on the strengths, limitations, and operational contexts of the participating entities. From this perspective, clustering becomes not only a method of organizing communication but also a mechanism for coordinating heterogeneous roles during crisis operations. Extending the adaptive clustering paradigm to a multi-agent setting makes it possible to assign leadership and relay functions to the most suitable agents at any moment—whether aerial or terrestrial—based on energy availability, mobility, environmental exposure, and network performance demands [**?**].

In this chapter, a Multi-Agent Adaptive Clustering framework, MADMRWP, is introduced as an evolution of the redundancy-aware clustering strategy developed, DMRWP, in earlier chapters. The proposed framework unifies UAVs and ground vehicles within a single adaptive clustering architecture that explicitly accounts for agent heterogeneity and correlated risks. Unlike traditional homogeneous clustering schemes, which implicitly assume that all nodes share similar operational constraints, the proposed approach incorporates agent-aware weighting and dynamic role allocation. This allows the system to not only adapt to network dynamics but also to proactively avoid over-reliance on fragile or depleted agents. The framework further supports the concept of multi-agent redundant CH selection, where primary and backup CHs originate from different agent types when possible. This form of cross-domain redundancy significantly mitigates the impact of correlated failures and preserves end-to-end data flow even under extreme environmental degradation [**?**].

By broadening the decision space of DMRWP to include multi-agent operational context, the proposed framework leverages complementary capabilities and balances risk across domains. The results presented in this chapter show that heterogeneity-aware, adaptive clustering can achieve lower latency, higher packet delivery, and stronger resilience than UAV-only architectures. More importantly, it advances beyond theoretical scenarios toward a practical communication paradigm suitable for real-world disaster response and critical infrastructure protection.

Ultimately, this chapter addresses the final research challenge that has guided the development of this thesis: how to achieve dependable, low-latency, and fault-tolerant communication in complex crisis environments involving diverse agents operating under harsh and uncertain conditions. In moving toward a multi-agent perspective, the thesis aligns itself with emerging trends in autonomous crisis response, where resilience is achieved not through perfection of a single platform but through cooperation across multiple, differently capable entities.

Figure **??** illustrates the proposed MADMRWP framework, where UAVs and ground vehicles collaboratively form a hierarchical clustered communication network for disaster-response scenarios. UAVs operate as aerial CMs and CHs, providing wide-area sensing and rapid connectivity, while ground vehicles act as mobile nodes that extend coverage and support data relaying in areas with limited aerial access [**?**]. Within each cluster, blue communication links represent intra-cluster coordination between CMs and their respective CH, enabling efficient data aggregation from affected zones such as wildfire regions and collapsed infrastructure. The CH establishes a long-range communication link with the BS, ensuring that critical information is transmitted to command centers in near real time. The integration of ground agents enhances network resilience by providing alternative routing paths and reducing the risk of connectivity loss caused by UAV mobility or energy depletion. Overall, the architecture demonstrates how multi-agent cooperation, combined with multi-redundant clustering, improves network robustness, coverage continuity,

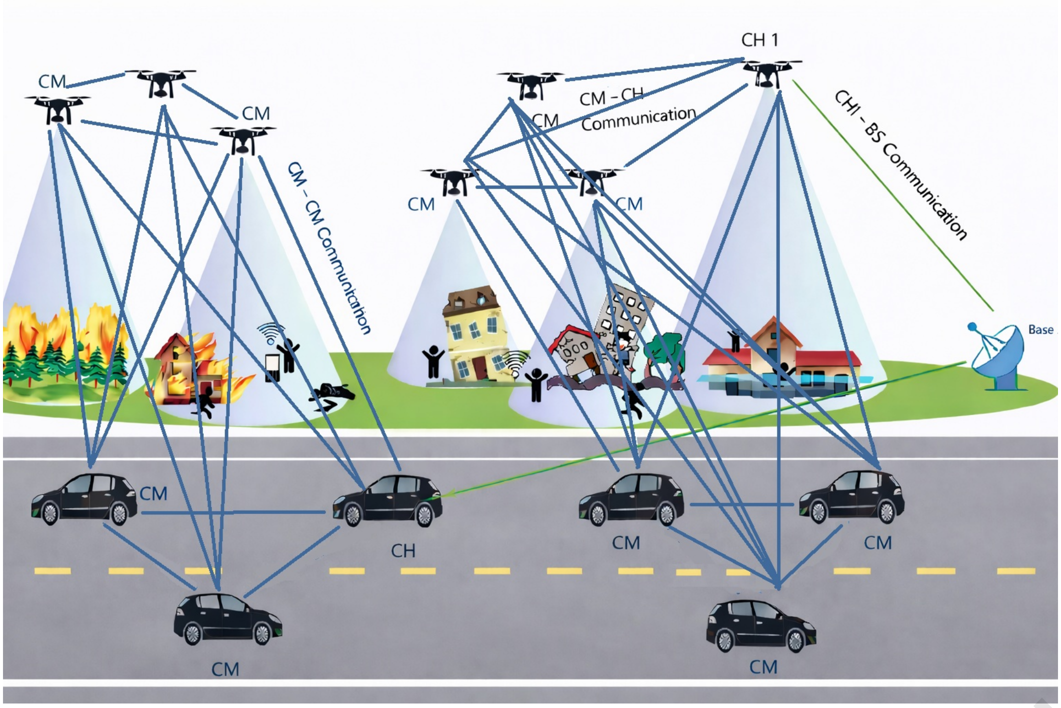

Figure 6.1: Multi-Agent Dybamic Multi-Redundant Weighted Cluster Routing Protocol (MADMRWP) Scheme.

and situational awareness in highly dynamic emergency environments.

To structure the remainder of this chapter, the key components of the proposed framework are organized as follows:

- Section 6.1 reviews the literature on heterogeneous clustering, redundancy mechanisms, and multi-agent cooperation, identifying limitations in existing UAV-, VANET-, and IoT-based approaches.
- Section 6.2 introduces the proposed Multi-Agent Dynamic Multi-Redundant Weighted Cluster Routing Protocol (MADMRWP), detailing the agent-aware clustering indices, redundancy model, and routing architecture.
- Section 6.3 evaluates the protocol through discrete-time simulations, comparing heterogeneous node performance under normal operation, under CH non-functional conditions, and against the baseline DMRWP scheme.
- Section 6.4 concludes the chapter and summarizes key observations, highlighting improvements in delay performance, survivability, and multi-agent resilience while outlining future research directions.

6.1 Literature Gap and Research Opportunity

Although the three research domains outlined above—UAV/FANET clustering, vehicular/VANET clustering, and UAV-assisted WSN/IoT data collection—offer valuable insights into scalable topology control and mobility-aware communication, a closer examination of the literature reveals several persistent gaps that limit their applicability to crisis-oriented, multi-agent infrastructures.

First, most clustering techniques are developed under the assumption of homogeneous networks. UAV-only FANETs assume shared mobility constraints and failure modes; VANET clustering presumes road-constrained mobility and energy abundance; and WSN/IoT systems typically assume static or semi-static sensor nodes [?]. These homogeneity assumptions overlook the operational diversity present in real emergency-response environments, where aerial and terrestrial agents co-exist and encounter different hazards, sensing capabilities, mobility envelopes, and endurance constraints. Without explicitly modeling this heterogeneity, clustering decisions may over-optimize for one agent class at the expense of systemic resilience.

Second, even in studies that incorporate redundancy at the CH level, redundancy is typically intra-cluster. Dual-CH or backup-CH strategies provide robustness against individual node failures but remain vulnerable to correlated failures within the same class of agents. For example, UAV-only redundant clustering remains fragile during high-wind events; likewise, vehicle-only redundancy cannot sustain communication during road blockages or terrain isolation. Effective resilience in critical infrastructure protection requires redundancy spanning multiple agent types rather than confined within them.

Third, although recent work increasingly adopts adaptive or context-aware weighting to improve cluster stability, these adaptive frameworks are computationally demanding, centralized, or optimized for single-agent contexts. Reinforcement learning, fuzzy logic, or heuristic adjustment methods show promise in dynamic settings, but they rarely consider the interaction of distinct mobility patterns and failure domains, nor do they incorporate risk asymmetry across heterogeneous platforms [?]. Furthermore, existing adaptive schemes often optimize a narrow QoS objective such as delay rather than balancing delay, energy, PDR, and survivability under crisis constraints [?].

Fourth, research on UAV-assisted WSN/IoT systems recognizes multi-agent collaboration but treats UAVs primarily as external collectors or relay assets, not as peer agents participating in a unified, hierarchical clustering architecture [?,?]. Consequently, role allocation remains lopsided, and CH selection is not shared across heterogeneous agents [?].

Finally, the literature diminishes attention to failure correlation and cascading breakdowns induced by environmental hazards or mission disruptions [?]. Disaster scenarios are dominated by clustered risk—storms disrupting airspace, floods immobilizing ground vehicles, fires disabling infrastructure—which challenges the simplistic failure independence assumptions implicit in most clustering designs [?].

In summary, the literature demonstrates:

- strong foundations for clustering in homogeneous agent classes,
- scattered evidence of redundancy for robustness,
- emerging interest in adaptive weighting for dynamic conditions,
- isolated examples of multi-agent cooperation primarily for sensing/data collection,

but lacks an integrated architecture that combines:

1. heterogeneous multi-agent clustering,
2. correlated-failure-aware redundancy,
3. adaptive, performance-driven weight adjustment, and

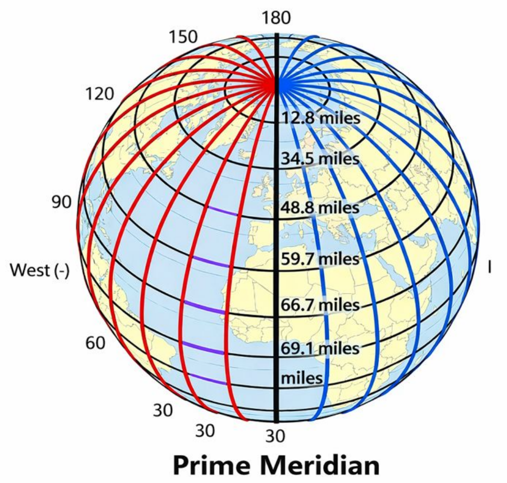

Figure 6.2: Geographic coordinates relative to the Prime Meridian showing longitude lines.

4. disaster-oriented communication reliability and survivability.

This gap motivates the multi-agent adaptive clustering approach proposed in this chapter. By extending the dynamic and redundant clustering concepts developed in Chapters 4 and 5, the framework presented here introduces heterogeneity-aware role assignment and multi-agent redundancy to enhance communication resilience in crisis environments where single-domain architectures are insufficient [**?**].

6.2 Proposed Protocol

In the proposed hybrid UAV-vehicular routing model, two different cluster index functions are defined to differentiate between ground vehicles and aerial UAV nodes. This distinction is motivated by the fundamental operational differences between the two platforms. Ground vehicles are typically less energy-constrained owing to the availability of large propulsion energy reserves, whereas UAVs are highly energy-constrained and rely on stable air-to-air communication links for sustained network participation and data forwarding [**?**].

Within the proposed multi-agent crisis network, positional information for both UAVs and ground vehicles is represented using geographic coordinates—specifically latitude and longitude, as illustrated in Figures **??** and **??**—rather than a synthetic Cartesian coordinate framework. This modeling choice aligns with real-world deployments, where node locations are typically acquired through global navigation satellite systems (GNSS) such as GPS and where mobility occurs over extensive terrestrial regions. Accordingly, inter-node distance and topological proximity are computed using the Haversine formula, which provides a geodesic distance over the Earth's surface by accounting for its curvature. Unlike planar Euclidean approximations, this approach preserves geographic fidelity and yields more accurate spatial measurements for large-scale outdoor environments. Such realism is particularly important in disaster-response scenarios, where precise distance estimation directly influences clustering stability, routing decisions, and overall network reliability [**?**].

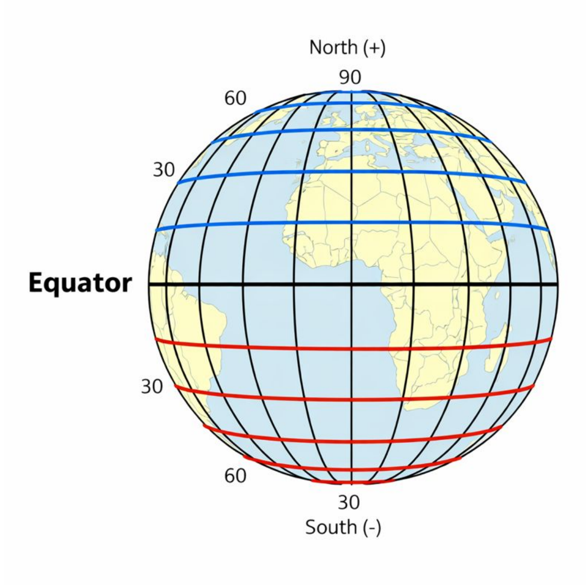

Figure 6.3: Geographic coordinates relative to the Equator showing latitude lines.

Unlike Euclidean (x, y, z) distances, which implicitly assume a flat local coordinate system and are therefore more appropriate for small-scale indoor experiments or simulation-oriented scenarios, the Haversine distance preserves geographic realism by accounting for the Earth's curvature [?]. This property makes it particularly suitable for large-scale outdoor UAV deployments, where accurate spatial representation is essential for reliable distance estimation and network coordination. It remains compatible with GPS-based mobility, road-constrained vehicular motion, and heterogeneous node deployment across wide-area operational environments. This geodesic formulation more accurately captures communication adjacency and cluster-formation constraints in crisis-area deployments, where UAVs serve as aerial relay nodes above terrain and infrastructure, and vehicles remain anchored to the Earth's surface [?]. By grounding clustering and routing decisions in geospatially meaningful distances, the resulting proximity index becomes more consistent with real-world mobility patterns, line-of-sight constraints, and mission-oriented coverage requirements.

The distance–topological proximity index between UAV k and UAV l is computed using the Haversine formula as [?]

$$d_{(k,l)} = 2R \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_k)\cos(\phi_l)\sin^2\left(\frac{\Delta\chi}{2}\right)} \right), \tag{6.1}$$

where:

- $d_{(k,l)}$ denotes the geodesic distance between UAV k and UAV l (in kilometers),
- R denotes the Earth's radius (typically $R \approx 6371$ km),
- ϕ_k, ϕ_l denote the latitudes of UAV k and UAV l expressed in radians,
- χ_k, χ_l denote the longitudes of UAV k and UAV l expressed in radians,
- $\Delta\phi = \phi_k - \phi_l$ denotes the difference in latitude,
- $\Delta\chi = \chi_k - \chi_l$ denotes the difference in longitude.

Vehicle Cluster Index

For a vehicle node, the cluster index is expressed as a weighted sum of distance, relative velocity, and trust as shown in DMRWP. The vehicle's dynamic cluster index is then defined as

$$C_{(k,l)}(t) = -\, w_D(t)\, D_{(k,l)}(t) + \, w_R(t)\, R_{(k,l)}(t) - \, w_V(t)\, V_{(k,l)}(t), \tag{6.2}$$

This formulation prioritizes mobility and trust, while energy plays no role, consistent with the observation that gasoline vehicles are not energy-constrained. Gasoline vehicles are commonly modeled as non–energy constrained nodes because their propulsion energy is orders of magnitude larger than the energy required for wireless communication and onboard processing. Unlike UAVs, vehicular nodes neither employ duty cycling nor energy-aware routing, and their networking functions do not shorten their operational lifetime.

In the case where the vehicle is electric, the remaining energy $E(k)$ at discrete simulation step k is expressed as [**?**]

$$E(k) = \text{BatteryCapacity} \times \text{SOC}(k), \tag{6.3}$$

where:

- BatteryCapacity denotes the nominal usable energy storage of the vehicle's traction battery,
- $\text{SOC}(k) \in [0, 1]$ denotes the dimensionless state of charge, representing the fraction of usable capacity remaining in the battery and directly reflecting the operational lifetime of the electric vehicle with respect to onboard electronics and communication tasks.

In a discrete-time simulation framework, $\text{SOC}(k)$ evolves based on the incremental energy expenditure of the vehicle node. Let $\Delta E(k)$ denote the net energy consumed during the interval $[k, k + 1]$; then the SOC update equation becomes

$$\text{SOC}(k + 1) = \text{SOC}(k) - \frac{\Delta E(k)}{\text{BatteryCapacity}}, \tag{6.4}$$

with a saturation condition

$$\text{SOC}(k + 1) = \max\{0, \text{SOC}(k + 1)\}, \tag{6.5}$$

ensuring that the SOC remains physically meaningful.

In the implemented model, energy of gasoline vehicle consumption is exclusively attributed to communication-related activities such as packet transmission, reception, and the coordination overhead associated with CH responsibilities [**?**]. The energy variation for vehicle k is therefore modeled as

$$\Delta E(k) = E_{\text{comm}}(k) = E_{\text{tx}}(k) + E_{\text{rx}}(k) + E_{\text{oh}}(k). \tag{6.6}$$

where:

$E_{\text{tx}}(k)$ energy required for data transmission,

$E_{\text{rx}}(k)$ energy consumed during packet reception,

$E_{\text{oh}}(k)$ overhead energy associated with processing, control signaling, and CH coordination.

The individual communication energy components are computed using a first-order radio energy model commonly adopted in wireless network studies.

Transmission Energy The transmission energy required to send a packet of L bits over a distance d is given by [?]

$$E_{\mathrm{tx}}(k) = LE_{\mathrm{elec}} + L\epsilon_{\mathrm{amp}}d^{n}, \tag{6.7}$$

where:

- E_{elec} is the electronic circuitry energy per bit,
- ϵ_{amp} is the transmit amplifier coefficient,
- d is the transmission distance,
- n is the path-loss exponent (typically 2 for free space and 4 for multipath environments).

Reception Energy The energy consumed during packet reception depends solely on the radio electronics and is expressed as

$$E_{\mathrm{rx}}(k) = LE_{\mathrm{elec}}, \tag{6.8}$$

where L is the packet size in bits [?].

CH Overhead Energy CH operation introduces additional processing and coordination costs. The overhead energy is modeled as

$$E_{\mathrm{oh}}(k) = LE_{\mathrm{proc}} + N_{\mathrm{cm}}LE_{\mathrm{agg}}, \tag{6.9}$$

where:

- E_{proc} denotes the processing energy per bit,
- E_{agg} represents the data aggregation energy per bit,
- N_{cm} is the number of cluster members served by the CH.

However, in more comprehensive EV energy models, propulsion-related consumption $E_{\mathrm{drive}}(k)$ may also be incorporated, yielding

$$\Delta E(k) = E_{\mathrm{comm}}(k) + E_{\mathrm{drive}}(k), \tag{6.10}$$

allowing the SOC to reflect realistic vehicle discharge dynamics under mobility [?].

The SOC representation offers two key advantages for networking-oriented simulations: (i) it decouples the physical battery capacity from the communication protocol design, enabling comparative analysis across heterogeneous EV platforms, and (ii) it provides a normalized metric suitable for CH selection, resource allocation, and energy-aware routing policies [?]. As SOC(k) decreases, the available energy budget for communication diminishes, potentially limiting participation in energy-intensive roles such as CH operation. Consequently, SOC captures the interplay between energy availability and network functionality, which is central to evaluating the sustainability of UAV-assisted vehicular networks [?].

Therefore, for electric vehicles, the cluster index calculation reconsiders the role of energy such that it is computed as

$$C_{(k,l)}(t) = -\,w_D(t)\,D_{(k,l)}(t) + \,w_R(t)\,R_{(k,l)}(t) - \,w_V(t)\,V_{(k,l)}(t) + \,w_E(t)\,E_k(t), \tag{6.11}$$

where $w_E(t)$ denotes the weighting coefficient associated with the residual energy metric.

UAV Cluster Index

In crisis scenarios, the Global Positioning System (GPS) cannot be assumed to be continuously available. Therefore, the enhanced scheme estimates the pairwise distance using the Received Signal Strength Indicator (RSSI). RSSI converts signal attenuation into a distance estimate according to the logarithmic path-loss model [**?**].

$$\mathrm{RSSI}\Big(D(k,l)\Big) = \mathrm{RSSI}\Big(D_0(k,l)\Big) - 10p\ \log_{10}\left(\frac{D(k,l)}{D_0(k,l)}\right) + x_\phi, \tag{6.12}$$

where:

- $\mathrm{RSSI}(D(k,l))$ is the received signal strength at UAV k when separated from UAV l by distance $D(k,l)$,
- $D_0(k,l)$ is a reference distance,
- $\mathrm{RSSI}(D_0(k,l))$ denotes the received signal strength at that reference distance,
- p is the path-loss exponent,
- x_ϕ is a Gaussian random variable with mean 0 and standard deviation ϕ.

By rearranging (**??**), an estimate of the physical distance between UAV k and UAV l can be obtained as

$$D(k,l) = 10^{\frac{\mathrm{RSSI}(D_0(k,l)) - \mathrm{RSSI}(D(k,l)) + x_\phi}{10p}}. \tag{6.13}$$

Relative velocity between two UAVs does not depend solely on the magnitude of their motion but also on the direction in which each UAV is traveling. In particular, two UAVs moving at high speed may still maintain a stable link if their trajectories are similar, and they travel in the same direction, whereas even moderate velocity differences can cause rapid link breakage if the UAVs move apart [**?**].

To capture this directional effect, the relative velocity metric is extended into an angular velocity component that accounts for both speed and trajectory alignment [**?**]. This observation motivates the definition of an angular velocity metric that augments the scalar velocity term by incorporating directional information:

$$v_a(k,l) = v_s(k,l)\,\mathrm{Dir}, \tag{6.14}$$

where Dir is a scalar direction indicator given by

$$\mathrm{Dir} = \begin{cases} +1, & \text{UAVs moving in the same direction,} \\ -1, & \text{UAVs moving in opposite directions.} \end{cases} \tag{6.15}$$

The scalar relative velocity magnitude is defined as

$$\begin{aligned} V_{s(k,l)} &= \sqrt{v_{x(k,l)}^2 + v_{y(k,l)}^2 + v_{z(k,l)}^2} \\ &= \sqrt{\begin{aligned} &\Big(v_k\cos(\alpha_k) - v_l\cos(\alpha_l)\Big)^2 \\ &\quad + \Big(v_k\sin(\alpha_k) - v_l\sin(\alpha_l)\Big)^2 \\ &\quad + \Big(v_k\sin(\theta_k) - v_l\sin(\theta_l)\Big)^2 \end{aligned}} \end{aligned} \tag{6.16}$$

where:

- v_k and v_l denote the magnitudes of the velocities of UAV k and UAV l,
- α_k and α_l denote horizontal angular components,
- θ_k and θ_l denote vertical angular components along the corresponding axes.

To determine directional agreement, UAV trajectories are compared across successive time instants along the x-axis [**?**]. Specifically,
Same Direction:

$$\begin{cases}(x_k(t) - x_k(t-1)) > 0 \;\wedge\; (x_l(t) - x_l(t-1)) > 0, \\ (x_k(t) - x_k(t-1)) < 0 \;\wedge\; (x_l(t) - x_l(t-1)) < 0,\end{cases}$$

Opposite Direction:

$$\begin{cases}(x_k(t) - x_k(t-1)) > 0 \;\wedge\; (x_l(t) - x_l(t-1)) < 0, \\ (x_k(t) - x_k(t-1)) < 0 \;\wedge\; (x_l(t-1)) > 0.\end{cases}$$

In the proposed routing model, UAV-UAV link stability is explicitly accounted for due to the high mobility, rapid trajectory changes, and three-dimensional motion of UAV platforms, all of which may significantly shorten link lifetime [**?**]. To quantify this behavior, a link-stability metric $S_{(k,l)}$ is computed between UAV nodes k and l. The metric captures both the spatial separation and the relative motion between the UAVs.

The inter-UAV distance $d_{(k,l)}$ and the relative velocity magnitude $|\Delta v_{(k,l)}|$ are normalized with respect to their maximum admissible values as

$$\tilde{d}_{(k,l)} = \frac{d_{(k,l)}}{d_{\max}}, \qquad \tilde{v}_{(k,l)} = \frac{|\Delta v_{(k,l)}|}{v_{\max}}, \tag{6.17}$$

- $\tilde{d}_{(k,l)}$ denotes the normalized distance between UAV k and UAV l,
- $\tilde{v}_{(k,l)}$ denotes the normalized relative velocity between UAV k and UAV l,
- $d_{\max}$ denotes the maximum communication radius,
- $v_{\max}$ denotes the maximum expected relative speed within the UAV swarm.

The link-stability metric is defined as

$$S_{(k,l)} = \left(1 - \tilde{d}_{(k,l)}\right)\left(1 - \tilde{v}_{(k,l)}\right), \tag{6.18}$$

which yields values within the interval $S_{(k,l)} \in [0, 1]$. Under this formulation, $S_{(k,l)} \to 1$ when UAVs are spatially close and exhibit small relative velocity, indicating a highly stable link, whereas $S_{(k,l)} \to 0$ indicates that the link is highly unstable and likely to break due to displacement or rapid motion [**?**, **?**].

The resulting stability value is incorporated as a factor within the UAV routing cluster index calculation.

For vehicles, link stability is implicitly captured through normalized distance and relative velocity. Due to the ground mobility constraints of vehicles, these two metrics already provide a reliable estimate of link lifetime. In contrast, UAVs exhibit high-mobility 3D trajectories, making explicit link stability modeling necessary to avoid frequent aerial link breaks [**?**, **?**, **?**].

The dynamic UAV cluster index is then defined as

$$C_{(k,l)}(t) = w_R(t)\,R_{(k,l)}(t) + w_S(t)\,S_{(k,l)}(t) + w_E(t)\,E_k(t), \tag{6.19}$$

6.3 Simulation and Analysis

The simulation is conducted as a discrete-time MATLAB experiment running for $T = 1000$ time steps with a sampling interval of $\Delta t = 1$ ms within a two-dimensional area of 1500×1500 Km^2. The network consists of 50 ground vehicles operating at a fixed altitude of $z = 0$, and 50 UAVs uniformly distributed within a z-range of $[10, 15]$ Km. A fixed BS is located at the center of the simulation area, with position $\mathbf{p}_{\text{BS}} = (500, 500, 0)$.

The main communication parameters and link assumptions used in our simulation are summarized in Table **??**.

Table 6.1: Communication parameters and link assumptions

R_{veh}	180 m (vehicle–vehicle)
R_{uav}	350 m (UAV–UAV)
pktSize	4000 bits
pktRate	1 packet/ms
$p_{\text{LoS}_{\text{vehicle–vehicle links}}}$	0.35
$p_{\text{LoS}_{\text{UAV–UAV links}}}$	0.9

At each discrete time instant, node mobility evolves according to a kinematic update rule,

$$\mathbf{p}_i(t+1) = \mathbf{p}_i(t) + \mathbf{v}_i(t)\,\Delta t, \tag{6.20}$$

where:

- $\mathbf{p}_i(t)$ denotes the position of node i at time t,
- $\mathbf{v}_i(t)$ denotes the instantaneous velocity vector of node i at time t, capturing both speed and motion direction,
- Δt denotes the discrete simulation step size,
- t indexes simulation time in discrete steps.

This Euler-style integration updates two-dimensional vehicle trajectories in the horizontal plane while enforcing reflective boundaries to prevent nodes from exiting the operational region. UAV altitude dynamics are modeled independently through a bounded stochastic process,

$$z_i(t+1) = \text{clip}(z_i(t) + 0.2\,\mathcal{N}(0,1),\ 80,\ 140)\,, \tag{6.21}$$

where:

- $z_i(t)$ denotes the altitude of UAV i at time t,
- $\mathcal{N}(0,1)$ is a zero-mean, unit-variance Gaussian random variable modeling small perturbations in vertical motion,
- $0.2\,\mathcal{N}(0,1)$ introduces a mild stochastic fluctuation to emulate environmental effects and hover corrections,
- $\text{clip}(\cdot, 80, 140)$ is a saturation operator constraining altitude to the interval $[80, 140]$,

- the interval [80, 140] defines the admissible flight corridor for UAV vertical motion.

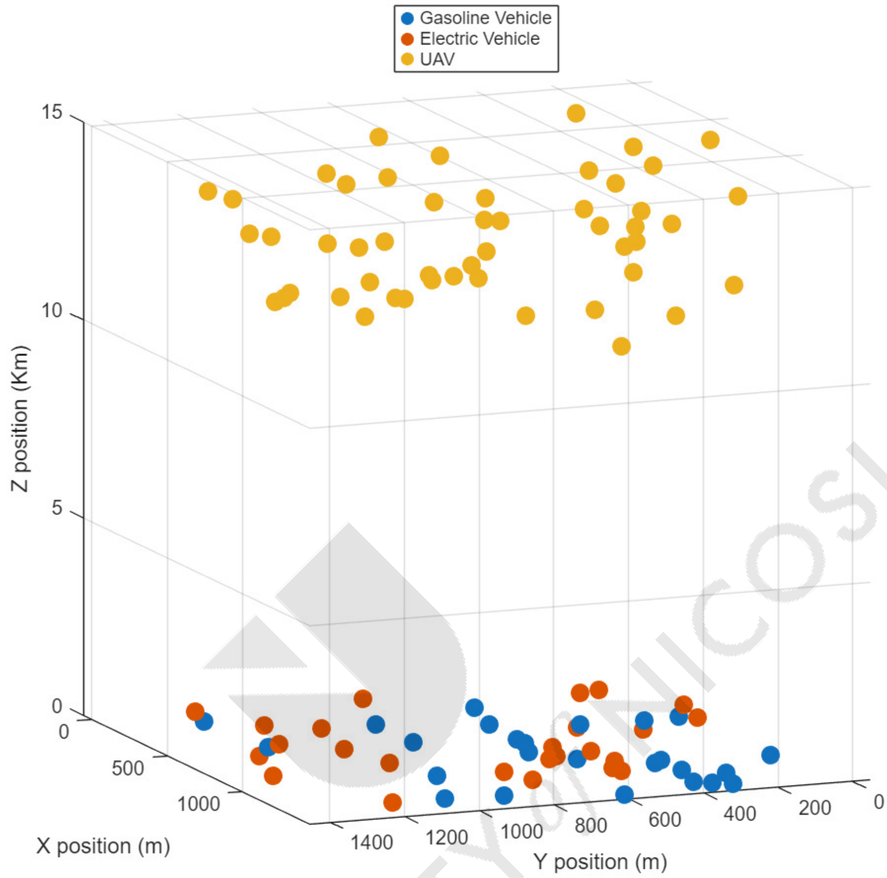

Figure 6.4: UAV and vehicle spatial distribution.

The three-dimensional spatial distribution of ground vehicles and UAVs in the operational environment under consideration is shown in Figure **??**. While UAV nodes occupy elevations between roughly 10 and 15 Km, establishing an aerial communication layer above the cars, gasoline and electric vehicles are positioned at ground level ($z = 0$), reflecting their terrestrial mobility limits. In order to improve connectivity and coverage, this vertical separation creates a heterogeneous network topology. Additionally, there is no discernible clustering bias or limited functioning region, and the figure depicts a rather uniform deployment in the horizontal X–Y plane for all node types. While the ground vehicles continue to be dispersed throughout the sensing layer, the spatial structure emphasizes the benefit of UAVs in delivering line-of-sight communication. This spatial heterogeneity allows for cooperative data forwarding and situational awareness in emergency response settings when airborne and terrestrial agents act concurrently.

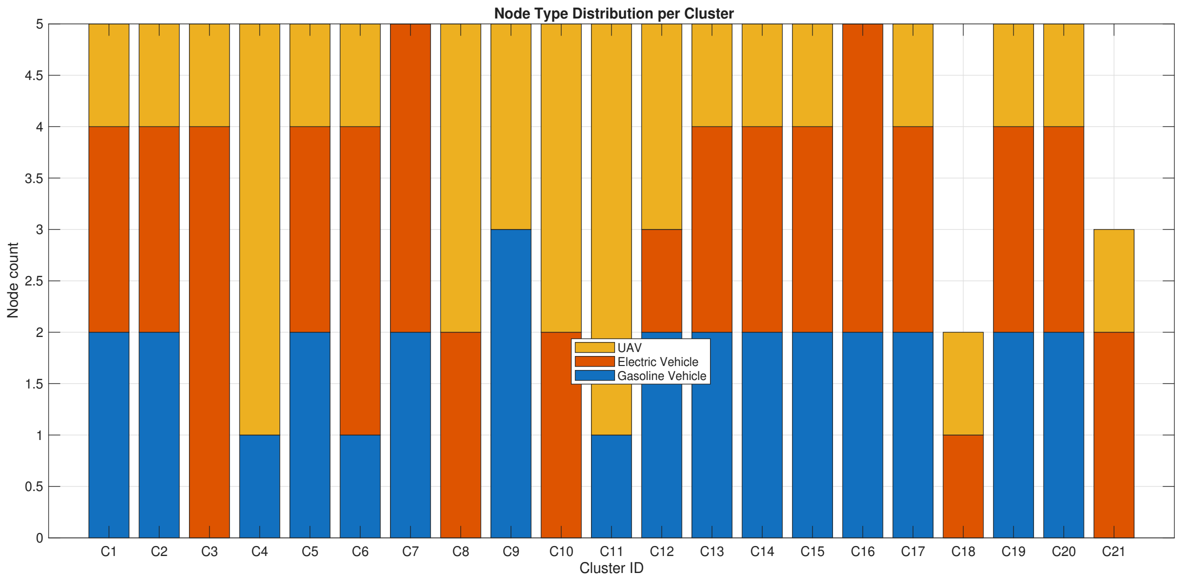

Figure 6.5: Cluster composition with respect to node types.

Figure **??** illustrates the composition of each cluster with respect to node type by showing the distribution of gasoline vehicles, electric vehicles, and UAVs within the formed clusters. The stacked bar representation highlights the heterogeneity of the network and confirms that individual clusters generally contain a mix of aerial and ground nodes. The figure also shows variability in the balance of node types across clusters, with some clusters exhibiting a more dominant UAV composition and others containing a relatively even distribution of the three node categories. This heterogeneity reinforces the practicality of the clustering mechanism for emergency communication scenarios where diverse agents cooperate to enhance network resilience and coverage.

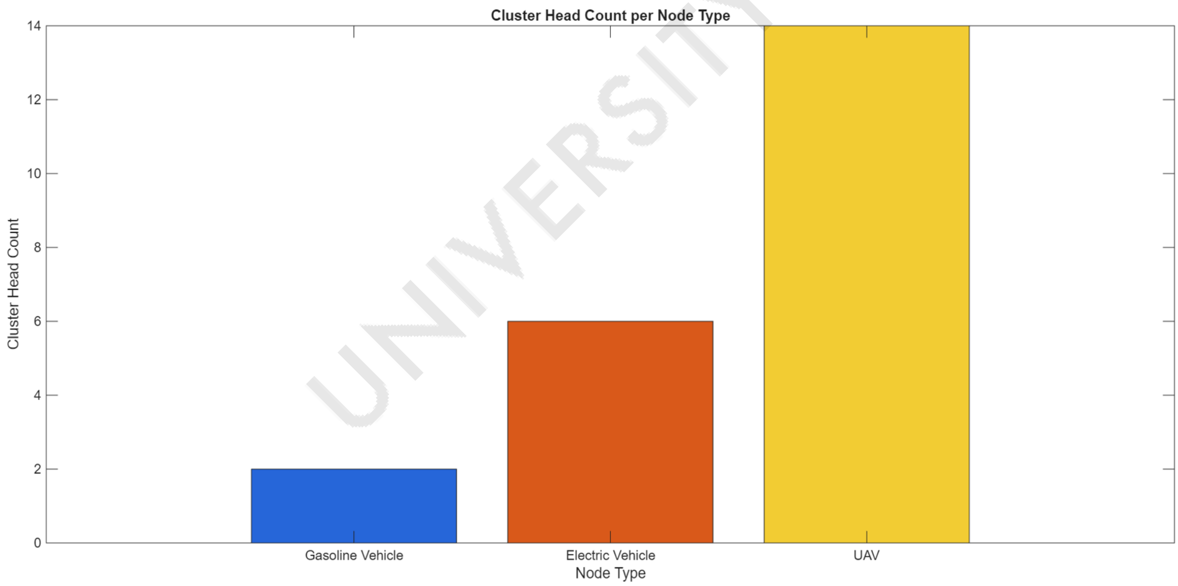

Figure 6.6: CH count across heterogeneous node types.

The CH selection patterns among the three heterogeneous node types used in the suggested hybrid UAV–vehicular network are shown in Figure **??**. According to the data, UAVs have the best chance of being chosen to lead clusters, followed by electric vehicles (EVs) and gasoline-powered vehicles. This behavior results from

UAV platforms' greater mobility and spatial coverage advantages, which increase their usefulness as aerial relays by enabling stronger multi-hop communication and a higher neighborhood degree. Due to their energy-conscious operation and larger available communication budget, EVs have an intermediate CH participation rate. In contrast, gasoline-powered vehicles have the lowest contribution because road topology limits their movement, resulting in less adjacency and fewer opportunities for optimal CH positioning. Overall, the outcome demonstrates that UAVs naturally become dominant coordinating nodes in clustered networking environments and that varied mobility and energy characteristics have a major impact on cluster formation and routing hierarchy.

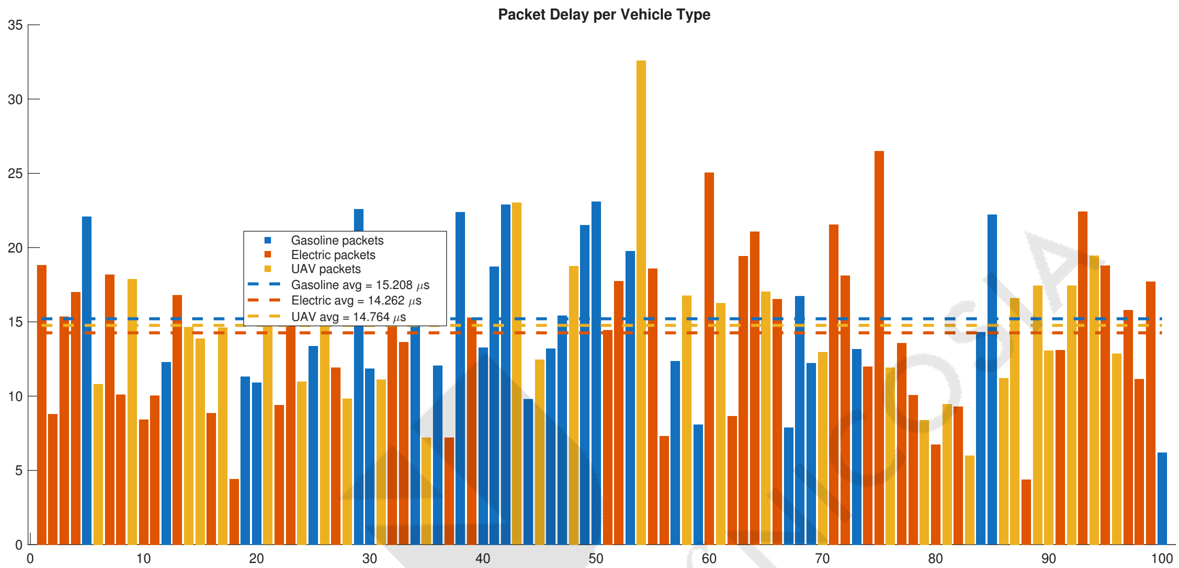

Figure 6.7: End-to-end delay using MADMRWP.

Figure **??** compares the forwarding performance of heterogeneous node types using packet-level delay measurements. The instantaneous delay values exhibit substantial variability across the 100 transmitted packets, reflecting the intrinsic temporal unpredictability of packet forwarding arising from interference, mobility patterns, and dynamic conditions. Despite this variability, the three vehicle types display comparable average delays: gasoline vehicles yield the mean delay (approximately 15.21 μs), electric vehicles the lowest (approximately 14.26 μs), and UAVs a slightly higher mean delay (approximately 14.76 μs).

Although these differences are modest (on the order of $\sim$1 μs), the ordering aligns with expected behavioral characteristics: electric vehicles follow smoother mobility trajectories, UAVs benefit from unobstructed line-of-sight communication yet experience additional fluctuations due to three-dimensional mobility, whereas gasoline vehicles exhibit more bursty ground mobility, resulting in slightly greater delay variability. The primary implication is that delay performance in this heterogeneous setting is governed predominantly by networking factors—such as link quality, routing, and clustering—rather than propulsion type or vehicle platform.

This conclusion is reinforced by the fact that packet-level variance exceeds the inter-type mean differences. The clustering of delay samples around their respective average lines, without systematic divergence or temporal drift, indicates that the routing protocol maintains stable forwarding behavior throughout the simulation horizon. Moreover, none of the vehicle types produce persistent hotspots or identifiable outlier patterns, suggesting that the hybrid design supports cross-type interoperability without imposing additional forwarding burdens on any specific category. From an architectural perspective, these results confirm that the network can accommodate heterogeneous mobility profiles while maintaining delay fairness among node types—a critical requirement for cooperative vehicular systems and UAV-assisted communication frameworks.

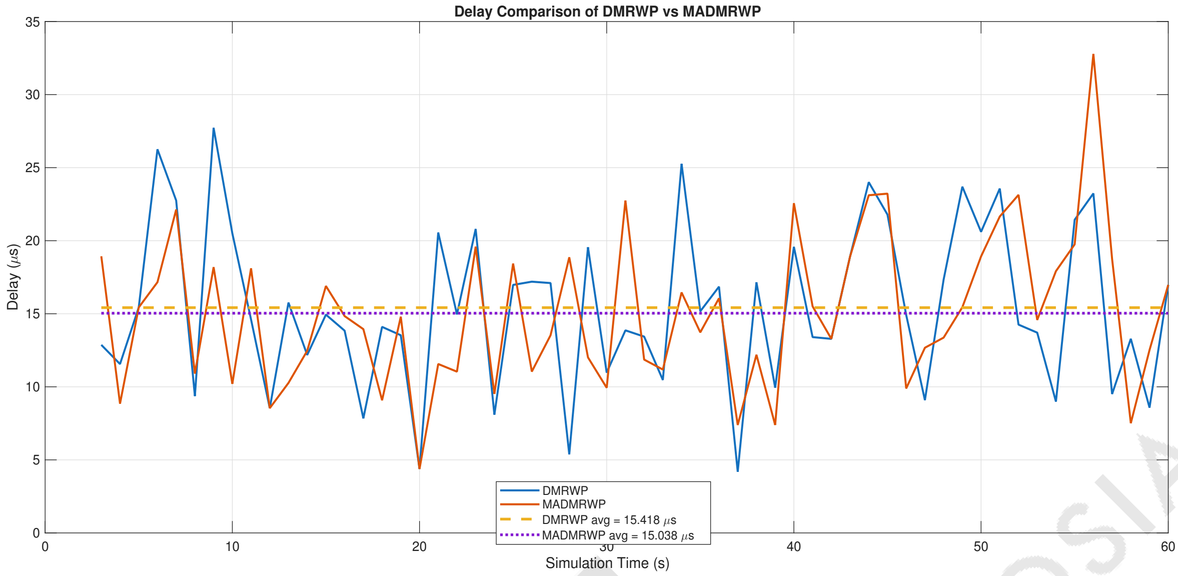

Figure 6.8: Comparison of delay performance between MADMRWP and DMRWP.

Figure **??** illustrates the comparison plot between MADMRWP and DMRWP based on end-to-end delay over the simulation horizon. Both protocols exhibit considerable temporal fluctuation due to the dynamic characteristics of the heterogeneous network environment, where mobility, interference, and cluster reconfiguration continuously influence forwarding performance. Despite these fluctuations, MADMRWP achieves a slightly lower mean delay (approximately 15.04 μs) compared to DMRWP (approximately 15.42 μs), while their instantaneous profiles largely overlap. This marginal improvement indicates that MADMRWP more effectively stabilizes the weight adaptation process, mitigating oscillatory effects in routing decisions and cluster formation.

Although the difference in average delay is modest, it implies that MADMRWP can provide incremental performance gains without introducing additional computational complexity or inducing instability. Furthermore, the instantaneous delay traces show that MADMRWP produces fewer high-amplitude peaks, suggesting smoother cluster maintenance and more consistent link behavior. In contrast, DMRWP occasionally generates pronounced spikes, indicative of transient route instabilities or aggressive cluster adjustments. These events suggest that DMRWP's weight update mechanism may overreact to short-term performance variations or converge more slowly. Overall, the comparison reveals that MADMRWP retains the benefits of DMRWP's adaptive behavior while reducing transient disruptions, leading to improved delay consistency and slightly better average performance across the simulation period.

Figure **??** compares the baseline MADMRWP performance without failures with the temporal evolution of end-to-end latency in MADMRWP under CH nonfunctional situations. The findings demonstrate that when CH failures mount up over time, MADMRWP shows a graceful performance deterioration. At first, both arrangements' delay curves are nearly identical, suggesting that early failures have little effect. The delay under the problematic configuration starts to deviate from the baseline as the simulation goes on and more CHs stop working; the difference becomes increasingly noticeable after about 25 seconds. The variance curve, which rises continuously over the course of the simulation, captures this tendency and shows that the impact of failures is cumulative rather than temporary. Importantly, the system stays limited and avoids instability or collapse even when latency grows as the number of nonfunctional CHs increases. This shows that MADMRWP continues to offer acceptable delay performance even under fault pressure, maintaining operational resilience and adapting to the increasing loss of CH capability. These findings demonstrate that MADMRWP is a viable option for fault-tolerant and resource-constrained clustering applications since it can maintain network performance without catastrophic degradation and is resilient to partial CH failures.

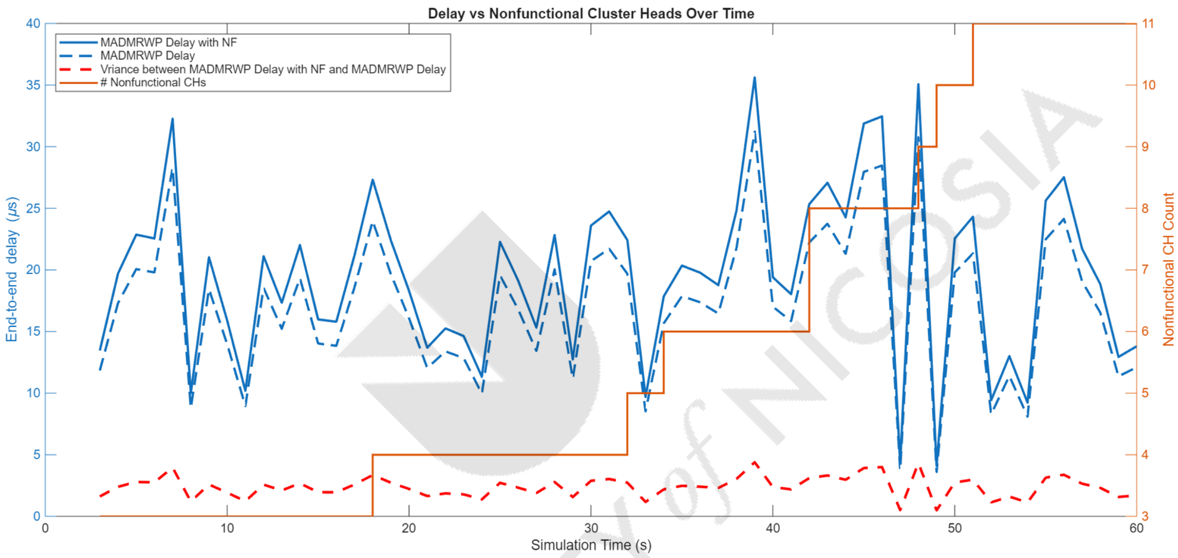

Figure 6.9: Evolution of end-to-end delay in MADMRWP with and without nonfunctional CHs including delay difference and cumulative number of CH failures.

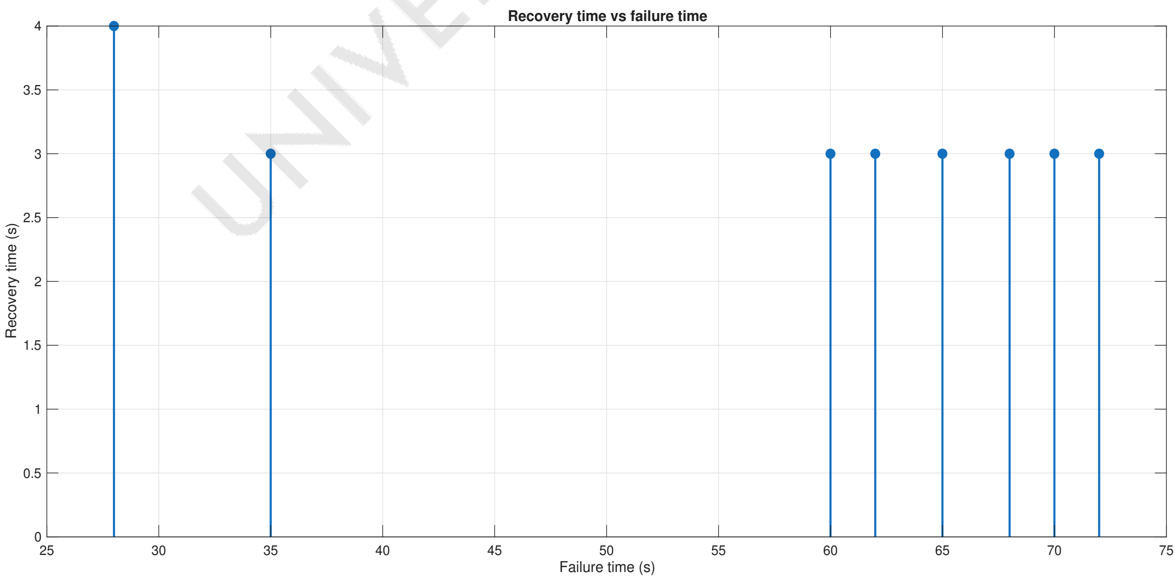

Figure 6.10: Recovery time versus failure time.

In Figure **??**, the x-axis shows the failure time, while the y-axis represents the recovery time (s) for that event. Two main clusters of failures can be observed: an early cluster around 28–35 s and a later cluster around 60–72 s. This behavior reflects periods of increased energy depletion where nodes cross the failure threshold more frequently. Despite variations in the failure time, the recovery duration remains bounded between approximately 3–4 s, indicating a stable and predictable recovery mechanism. Early failures exhibit slightly higher recovery time in one instance (around 4 s), while later failures consistently recover within about 3 s, demonstrating robustness of the recovery process under prolonged operation. Overall, the figure confirms that the proposed recovery strategy maintains low and nearly constant recovery latency, even as failures occur at different stages of the network lifetime.

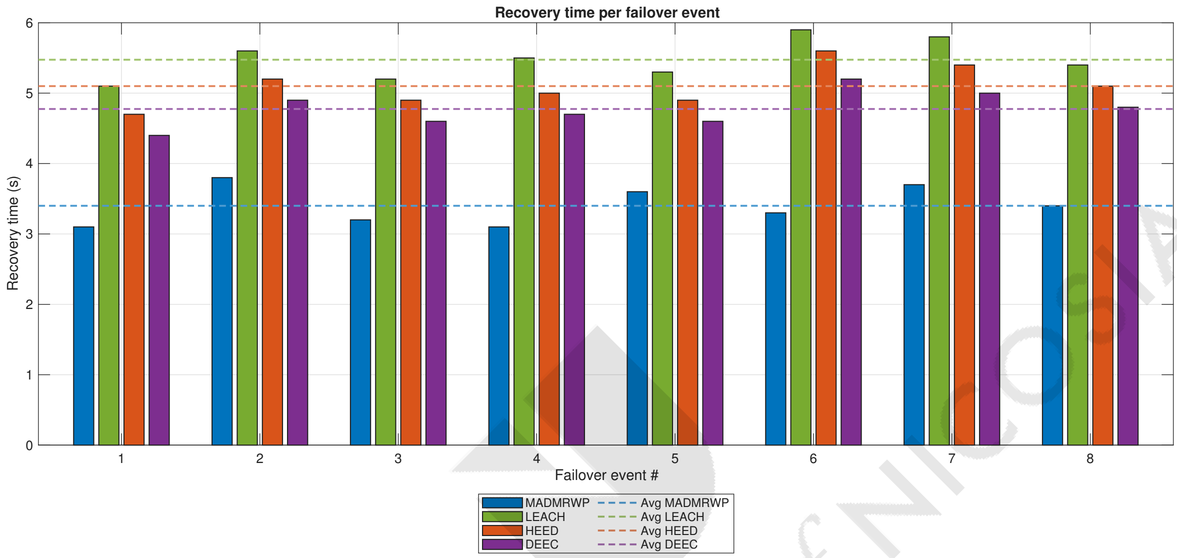

Figure 6.11: Recovery time per failover event for different clustering protocols.

In Figure **??**, the x-axis represents the failover event index, while the y-axis shows the recovery time required to restore network operation after a failure. For every failover event, MADMRWP consistently achieves the lowest recovery time, typically around 3–3.8 s, demonstrating faster fault handling and re-clustering compared to the benchmark protocols. Among the reference schemes, LEACH exhibits the highest recovery time (approximately 5.1–5.9 s), due to its randomized CH reselection and lack of energy-awareness during recovery. HEED improves upon LEACH by incorporating residual energy and communication cost, resulting in moderately lower recovery times. DEEC further reduces recovery delay by exploiting node energy heterogeneity, but still remains slower than MADMRWP. The dashed average lines clearly highlight this trend: MADMRWP has the lowest average recovery time, followed by DEEC, HEED, and LEACH. Overall, the figure demonstrates that MADMRWP clustering mechanism enables faster and more stable recovery across repeated failover events, enhancing network resilience and reducing service disruption.

Figure **??** consists of four subplots that collectively highlight the effectiveness of the proposed MADMRWP protocol against well-known clustering schemes.

Average Delay (top-left): MADMRWP achieves the lowest average delay, indicating faster data delivery. LEACH shows the highest delay due to random CH selection, while HEED and DEEC reduce delay slightly through energy-aware mechanisms but still lag behind the proposed approach.

Forwarding Efficiency (top-right): MADMRWP attains the highest forwarding efficiency, demonstrating more effective packet forwarding with reduced retransmissions. LEACH exhibits the lowest efficiency, whereas HEED and DEEC provide moderate improvements.

Packet Delivery Ratio (PDR) (bottom-left): MADMRWP achieves the highest PDR, reflecting improved reliability and robustness in data transmission. The energy-aware designs of HEED and DEEC outperform LEACH but do not match the delivery performance of the proposed method.

Throughput (bottom-right): MADMRWP delivers the highest throughput, confirming its ability to sustain higher data rates under network load. LEACH records the lowest throughput, while HEED and DEEC show intermediate performance.

Overall, this figure demonstrates that MADMRWP consistently outperforms LEACH, HEED, and DEEC across all evaluated metrics, achieving lower delay and higher efficiency, reliability, and throughput. This validates the effectiveness of the proposed clustering and routing strategy in enhancing network performance.

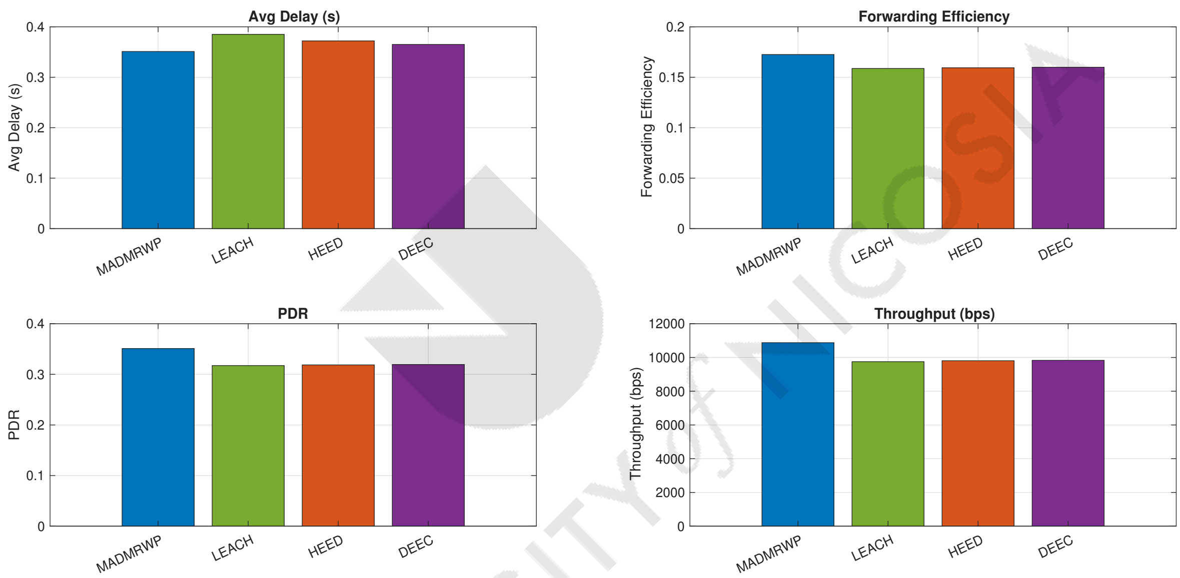

Figure 6.12: Performance comparison of clustering protocols in terms of delay, forwarding efficiency, PDR, and throughput.

Figure **??** presents four energy-related performance metrics that collectively evaluate the efficiency and sustainability of the compared clustering protocols.

Energy Consumed (top-left): MADMRWP consumes the least energy, demonstrating efficient clustering and reduced redundant transmissions. LEACH exhibits the highest energy consumption due to frequent re-clustering and random CH selection, while HEED and DEEC achieve moderate energy savings through energy-aware mechanisms.

Residual Energy (top-right): The proposed MADMRWP protocol maintains the highest residual energy at the end of the simulation, indicating balanced energy utilization across nodes. LEACH records the lowest residual energy, whereas HEED and DEEC improve energy retention but remain less effective than the proposed approach.

Control Overhead (bottom-left): MADMRWP introduces the lowest control overhead, reflecting fewer control packet exchanges during clustering and route maintenance. LEACH incurs the highest overhead, while HEED and DEEC reduce overhead by structured and energy-aware CH selection.

Network Lifetime (bottom-right): MADMRWP achieves the longest network lifetime, confirming its ability to prolong network operation. HEED and DEEC extend the lifetime compared to LEACH by improving energy distribution, but neither matches the longevity provided by MADMRWP.

Overall, the figure demonstrates that MADMRWP consistently outperforms conventional clustering protocols in energy efficiency and network longevity, making it well suited for energy-constrained UAV and wireless sensor network applications.

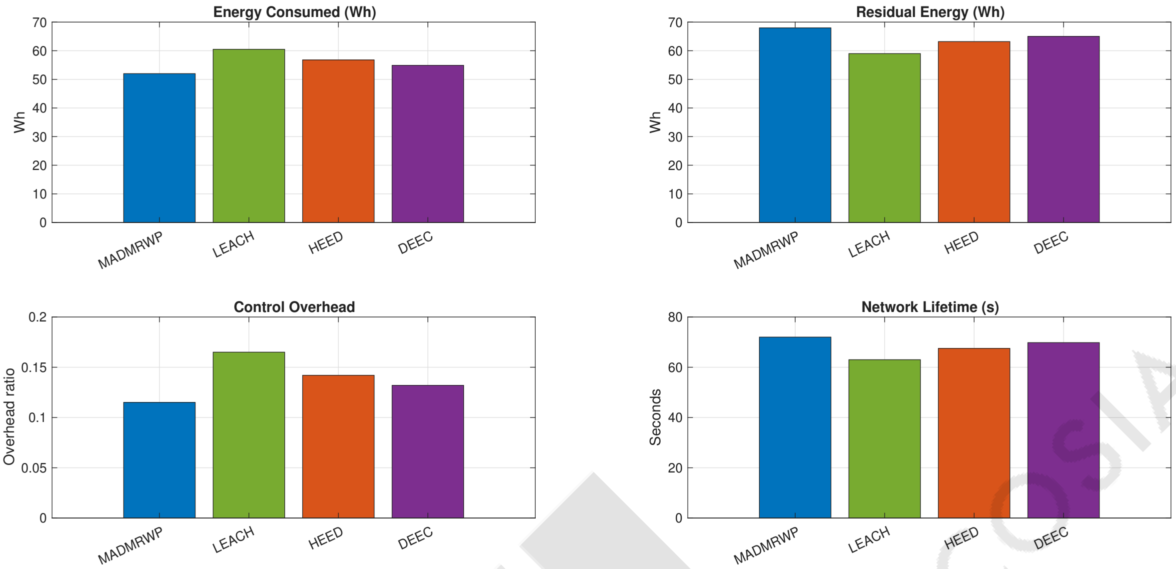

Figure 6.13: Energy efficiency and lifetime performance comparison of clustering protocols.

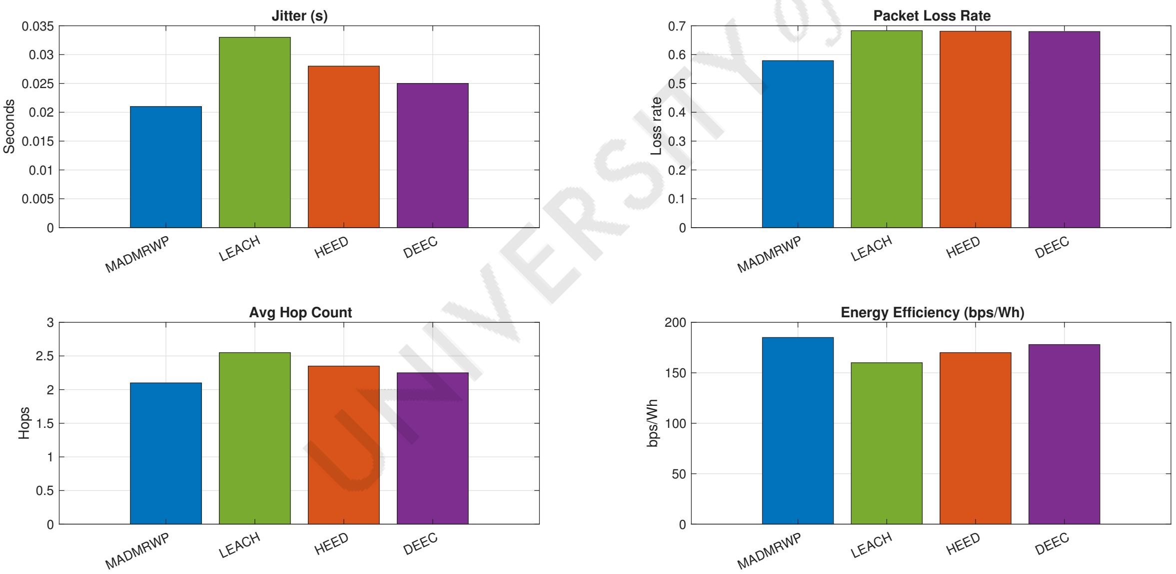

Figure 6.14: Reliability and efficiency performance comparison of clustering protocols.

Figure **??** evaluates additional reliability and efficiency oriented metrics that highlight the quality of service and routing effectiveness of the compared protocols.

Jitter (top-left): MADMRWP achieves the lowest jitter, indicating more stable and consistent packet delivery with minimal delay variation. LEACH exhibits the highest jitter due to frequent topology changes and re-clustering, while HEED and

DEEC reduce jitter by improving cluster stability but remain less effective than the proposed approach.

Packet Loss Rate (top-right): MADMRWP records the lowest packet loss rate, reflecting improved reliability and robust routing decisions. LEACH suffers from the highest packet loss because of inefficient CH selection and unstable communication links. HEED and DEEC mitigate packet losses through energy-aware clustering, yet they do not achieve the reliability level of MADMRWP.

Average Hop Count (bottom-left): MADMRWP maintains the smallest average hop count, demonstrating more efficient routing paths and reduced forwarding overhead. LEACH results in the largest hop count due to suboptimal routing structures, while HEED and DEEC offer moderate improvements by forming more balanced clusters.

Energy Efficiency (bottom-right): The proposed MADMRWP protocol achieves the highest energy efficiency (bps/Wh), confirming its ability to deliver more data per unit of energy consumed. LEACH shows the lowest energy efficiency, whereas HEED and DEEC improve efficiency through better energy utilization but still lag behind the proposed scheme.

Overall, this figure demonstrates that MADMRWP consistently provides superior reliability, routing efficiency, and energy efficiency, reinforcing its suitability for energy-constrained and performance-critical UAV and wireless sensor network environments.

6.4 Conclusion

In this chapter, a multi-agent adaptive clustering framework, MADMRWP, was presented to enhance communication resilience in emergency environments. Extending the UAV-centric approach developed earlier, the proposed system enables cooperation among UAVs, gasoline vehicles, and electric vehicles. By incorporating agent type, residual energy, mobility, and link stability into the clustering process, the method mitigates correlated failures within a single agent class and overcomes limitations of UAV-only solutions, establishing a flexible communication backbone suitable for degraded infrastructure.

The design relies on type-specific cluster indices. For vehicles, distance, velocity, and reward determine cluster roles, with SOC added for electric vehicles to distinguish energy-constrained from energy-abundant platforms. UAVs employ a cluster index combining trust, residual energy, and a dedicated link-stability metric derived from relative velocity and spatial separation to reduce transient aerial links. To maintain compatibility with realistic deployments, geographic coordinates and the Haversine formula are used for distance computation, while topology dynamics are handled through node-arrival, departure, and redundant CH substitution mechanisms using lightweight control messages.

Simulations show that the architecture naturally forms mixed-type clusters, enhancing connectivity diversity and forwarding redundancy. Delay performance remains similar across gasoline vehicles, electric vehicles, and UAVs, indicating protocol-level fairness and platform independence. Compared to DMRWP, the modified MADMRWP variant exhibits smoother behavior and slightly lower average delay.

Overall, heterogeneity-aware adaptive clustering improves robustness, delay performance, and survivability in multi-agent crisis networks. By integrating vehicles and UAVs into a unified clustering framework, applying context-aware indices, and enabling dynamic weight adjustment, the proposed method advances beyond homogeneous and UAV-only schemes toward fault-tolerant, scalable communication infrastructures for disaster response.

From a practical perspective, the proposed MADMRWP scheme provides a deployable communication framework for real-world crisis management environments where infrastructure damage and agent non-functionality are highly probable. The integration of multi-agent cooperation between UAVs and ground vehicles enhances operational resilience and ensures sustained data transmission to the BS, even under simultaneous agent failures. This capability is particularly relevant for emergency response agencies, civil protection authorities, and smart city operators who rely on timely and reliable situational awareness during disasters such as floods, earthquakes, or large-scale fires. By enabling adaptive clustering, redundant leadership, and dynamic weight adjustment, the proposed scheme can support rapid network reconfiguration in the field, thereby reducing communication downtime and improving coordination efficiency. Consequently, the MADMRWP framework offers a technically feasible foundation for policy-driven deployment of UAV-assisted resilient communication infrastructures in mission-critical scenarios.

Future work includes richer energy models for UAV and EV propulsion, learning-based weight adaptation for improved trade-offs under nonstationary conditions, incorporation of additional agent types such as ground robots or IoT sensors, and validation through hardware-in-the-loop or field trials to support real-world deployment.

Chapter 7

Conclusion, Contributions and Future Research Directions

This dissertation investigated the design and evaluation of resilient and adaptive clustering mechanisms for S–UAV networks operating under crisis conditions. As S-UAV systems are increasingly deployed for mission-critical tasks such as disaster response, emergency communication support, and infrastructure assessment, ensuring reliable, efficient, and timely data transmission is paramount. Existing cluster routing approaches have improved scalability and communication efficiency; however, they typically assume static environmental conditions and do not adequately address the consequences of CH non-functionality. In real-world UAV environments, no UAV is exempt from potential failure due to battery depletion, hardware malfunction, communication disruption, collisions, or harsh environmental factors. Therefore, tolerating CH failure is essential to prevent network fragmentation, data loss, and mission interruption. This dissertation addressed this gap by proposing clustering schemes that tolerate CH failure, adapt to dynamic environments, and leverage multi-agent cooperation to sustain network connectivity and mission progress.

The research was structured around four main thrusts. First, the dissertation identified and analyzed the vulnerability associated with CH non-functionality in S–UAV crisis scenarios. This analysis demonstrated that the failure of a CH can precipitate cluster collapse, high packet loss, and severe degradation of end-to-end communication performance. Second, a redundant weighted clustering scheme was developed to enable seamless CH substitution and improve the robustness of cluster-based routing. Third, a dynamic weight adjustment protocol was introduced to adapt CH selection to real-time network states. Finally, a multi-agent extension incorporating UAVs and vehicles was designed to enhance system reliability during crisis operations. The resulting architecture provides a fault-tolerant, context-aware, and collaborative networking solution for S–UAV deployments.

Beyond its technical contributions, this research offers important strategic implications for the deployment of UAV-assisted communication systems in crisis scenarios. The proposed resilient and adaptive clustering frameworks provide a systematic approach for ensuring communication continuity in environments where infrastructure damage and agent non-functionality are expected rather than exceptional. From a strategic perspective, the ability to tolerate CH failure and dynamically adapt routing decisions supports the development of robust national and regional emergency communication architectures that can operate independently of centralized infrastructure.

For policymakers and regulatory authorities, the findings of this thesis highlight the importance of incorporating redundancy, adaptability, and multi-agent cooperation as core design principles in future emergency response and smart infrastructure policies. The proposed schemes can inform guidelines for the operational deployment of swarm UAV networks in disaster management, including requirements for fault tolerance, interoperability between aerial and ground agents, and resilience under extreme conditions. Moreover, the results underscore the value of UAV-assisted networking as a complementary layer to terrestrial communication systems, particularly in scenarios where conventional infrastructure is partially or fully compromised.

Summary of Findings and Observations

Simulation results revealed that the proposed clustering mechanisms significantly improve network resilience and operational reliability compared to traditional CH-based schemes. Four key observations emerged from the evaluation:

- **Optimized weight-calculation parameters:** Mobility patterns, residual energy, reward index, and connection stability were all incorporated into the weighting model. Parameter tuning through normalization and adaptive scaling enhanced the accuracy of CH elections by reducing bias toward any individual metric. This optimization improved overall cluster stability and energy efficiency while mitigating premature CH depletion.

- **Fault-tolerance through redundancy:** Redundant CHs enabled the network to sustain communication despite primary CH failure. Comparative analysis demonstrated reductions in packet loss and improvements in packet delivery ratio under conditions of high mobility and failure-triggered reconfiguration, validating the benefits of redundancy for maintaining service continuity.

- **Adaptation through dynamic weighting:** The dynamic weight adjustment protocol exhibited superior responsiveness to variations in mobility, link stability, and energy availability compared to static selection schemes. This adaptability reduced reclustering time and routing overhead while extending cluster lifetime and enhancing operational throughput.

- **Multi-agent enhancement:** The integration of multiple agent types promoted architectural flexibility, alleviating single-agent dependency and providing alternative communication paths. This resulted in reduced end-to-end delay, increased connectivity stability, and improved data transmissison performance in crisis environments.

These findings collectively underscore that resilience, adaptability, and cooperation are indispensable characteristics for crisis-oriented communication systems.

Thesis Hypothesis and Validation

The central hypothesis of this dissertation posited that:

Integrating redundancy, dynamic weight adjustment, and multi-agent collaboration into cluster-based routing can significantly enhance the resilience, adaptability, and communication efficiency of S–UAV networks in crisis scenarios.

This hypothesis was validated through simulation-based experimentation and systems-level analysis. In particular, the empirical results demonstrated the following improvements relative to baseline schemes from the literature:

- improvements in packet delivery ratio and reductions in packet loss during CH failure events;
- reductions in end-to-end delay and reclustering overhead during mobility-induced topology changes;
- improved link stability and network connectivity duration under high-demand crisis conditions;
- reduced reliance on single-agent pathways, enhancing mission continuity during partial network failures.

These results support the hypothesis and show that the proposed mechanisms achieve both theoretical and engineering objectives for resilience and mission-critical performance.

Engineering Relevance and System Implications

Beyond theoretical contributions, the proposed approach holds significant engineering implications for S–UAV systems deployed in real emergency environments. The redundancy mechanisms introduced in this dissertation reduce the risk of catastrophic communication failure by enabling graceful degradation during CH malfunction. Dynamic weighting provides a systems-level adaptation mechanism that aligns communication decisions with evolving mobility and resource conditions. This reflects principles of autonomic computing and distributed control. Finally, multi-agent integration reflects emerging cyber-physical architectures in which heterogeneous assets collaborate to enhance resilience and operational capability.

Such capabilities are essential for crisis scenarios characterized by uncertainty and volatility.

Major Contributions of the Dissertation

The core contributions of this dissertation are summarized in the contribution box below for clarity and consistency with doctoral assessment standards:

Dissertation Contributions

1. Comprehensive survey and classification of clustering schemes in S-UAV networks for crisis environments, revealing the impact of CH non-functionality.
2. Development of a novel weighted clustering scheme to enhance cluster stability under dynamic network conditions.
3. Design of a single-redundant cluster head (RCH) mechanism to improve fault tolerance and maintain connectivity during primary CH failure events.
4. Introduction of a multi-redundant CH framework to further increase network resilience and prolong cluster stability in highly dynamic scenarios.
5. Integration of multi-agent collaboration into cluster routing to improve communication resilience and mitigate single-agent dependency.
6. Simulation-based demonstration that the proposed schemes outperform baseline cluster routing mechanisms in terms of resilience, reliability, and operational continuity.

Limitations and Scope for Improvement

While successful in achieving its objectives, this dissertation acknowledges several limitations:

- Real-world evaluation was limited to simulation environments; hardware-in-the-loop and field trials were not conducted.
- Security and adversarial behavior were not modeled, despite their relevance in contested or hostile communication environments.
- Mission semantics and task allocation were not explicitly integrated into network decisions, even though they influence crisis-oriented operations.

Addressing these limitations will further strengthen the deployment feasibility and operational maturity of the proposed solutions.

Future Research Directions

Several promising research directions emerge from this dissertation:

- **Experimental validation:** Hardware and field-testing under realistic mobility, interference, and environmental conditions.
- **Machine learning for CH selection:** Reinforcement learning and adaptive policies for proactive clustering and routing.
- **Cross-layer co-optimization:** Integrating routing decisions with mission planning and autonomous task allocation.
- **Cognitive situational networks:** Enhancing distributed situational awareness through semantic data exchange and cooperative sensing.

Future Vision

Looking toward future crisis-management architectures, S–UAV networks are expected to evolve into integrated, cognitive, and cooperative cyber-physical systems. In such environments, clusters of UAVs, vehicles, and infrastructure nodes will operate as mission-oriented agents capable of dynamic role delegation, self-healing, and autonomous coordination. Communication networks will no longer function as passive conduits for data, but rather as active participants in decision-making and mission execution. This dissertation contributes foundational mechanisms toward this future by demonstrating that resilience, adaptability, and cooperation are essential properties for crisis-oriented S-UAV communication systems.

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