Self-Aware Intelligent Model (SAIMOD) – A fault-tolerant UAV-based communication system for Disaster Recovery

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Abstract

When disasters such as landslides, floods, earthquakes, forest fires or avalanches occur, preserving human lives is the most critical issue that needs to be solved. As such, Search and Rescue (SAR) operations must begin quickly and efficiently. A key aspect of SAR missions is creating or re-establishing the destroyed or damaged communication links/infrastructure in the disaster recovery area. There is usually a demand for communication links between the entities involved, such as people to be rescued and rescue team members. One possible solution that has gained traction over the years is *ad hoc* networks. These networks allow the concerned entities, namely people to be rescued, rescue team members, etc., to form decentralised communication links quickly by using common devices like PDAs and mobile phones. As the backbone communication infrastructure might be missing or damaged within the affected area, an external means of providing a temporary communication infrastructure must be considered.

This Research proposes a Self-Aware Intelligent Model (SAIMOD) as a framework designed to be an integrated emergency communication system that relies on Mobile Ad Hoc Networks (MANETs) formed by Unmanned Aerial Vehicles (UAVs) deployed in an example scenario within disaster recovery. The UAVs would form auxiliary MANETs, connecting the rescue teams and the people to be rescued (survivors). Each deployed UAV acts as a 'router/relay' to restore bi-directional connectivity between the ground nodes made up of the rescue team and the people to be rescued. It could also be used to gather and send crucial information. The MANETs formed would allow data transmission in an energy-efficient and timely manner. Intelligent networking amongst the deployed UAVs will ensure adequate coverage of the disaster area and fault-tolerant UAV formation control in real-time.

SAIMOD demonstrates self-awareness in its network resilience, allowing it to quickly adapt to unexpected changes in the UAV-based Mobile Ad hoc Network (MANET), such as a UAV failure. In the context of this framework, resilience refers to the system's ability to maintain functionality and adapt to unexpected changes or failures within the UAV-based MANET. It utilises reinforcement learning based on a path-planning algorithm to optimise coverage and connectivity among the UAVs and ground nodes. SAIMOD is designed to adapt to real-time network changes, like a UAV failure. By employing reinforcement learning, the UAVs within SAIMOD can apply knowledge gained from one task to another. This approach ensures seamless connectivity and networking among the UAVs while preventing duplicated efforts to cover the network.

A suitable routing protocol is used in combination with a designated mobility model. Four mobility models (Random Waypoint mobility model, Reference Point Group Mobility Model (RPGMM), Manhattan and Gauss Markov mobility models) were integrated with five different routing protocols (AODV, DSR, DSDV, TORA and OLSR) in similar UAV-deployed MANETs to select the best-fit routing protocol and best-fit mobility model for use in SAIMOD via simulation. The networks formed were evaluated for a range of given metrics, and the Reference Point Group Mobility Model and the OLSR protocol were selected based on desired network performance metrics such as real-time connectivity, Throughput, MOS (Mean Opinion Score) value, etc. OLSR was further optimised for energy conservation in a two-layer modification process. This modified OLSR, MODOLSR, a novel protocol, is used with the RGPMM in

SAIMOD.

This study also presents a mathematical model for using the proposed framework as an assessment model for resource management. It compares the proposed framework, the Self-Aware Intelligent Model (SAIMOD), with similar existing systems.

Keywords: UAV-based MANETs, Disaster Recovery Framework, Disaster Management, Routing, Fault-Tolerant Control, Energy conservation

Dedication

To Him who sits forever enthroned, the glory and the lifter of my head, the lover of my soul.

To my parents, John Egbon (Emperor J.E) Ojei and Mrs Rose Ekawele Ojei, till we meet to part no more.

To my husband, Moses (my D) and my amazing children, Zahra, Daniel, Melody and David, without you, there would be no me.

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List of Symbols

∩ Intersection of sets
∪ union of both sets
∑ Some of
θ Directional angle
α tuning parameter

> Greater than

≥ Greater than or equal to

k Constant

> Less than

≤ Less than or equal to

V Velocity

s_n New speed

μsecs Milliseconds

Π Pi

d_n New direction

α Tuning parameter in the range [0, 1]

$\bar{s}$ Mean speed

$\bar{d}$ Mean direction

$s_{x_{n-1}}$ = random variable from Gaussian distribution in the range (0, 1)

$d_{x_{n-1}}$ = random variable from Gaussian distribution in the range (0, 2π)

T time

List of Abbreviations

ABR Associativity-Based Routing
ADR Angle Deviation Ratio
AODV Ad-Hoc On-Demand Distance Vector
AOLSR Airborne-OLSR
APTEEN Adaptive Periodic Threshold Sensitive Energy Efficient Sensor Network
CDMA Code Division Multiple Access
C-DTSAP Cluster-Dynamic TDMA Slot Assignment Protocol
CSMA Carrier Sense Multiple Access
3D Three-Dimensional
DAGs Directed Acyclic Graphs
DBS Drone Base Station
DCFM-OLSR Denial Contradictions with Fictitious Node Mechanism OLSR
DFOLSR Denial-of-service free OLSR
DMT Disaster Management Team
DQN-OLSR Deep Q-Network Optimised Link State Routing
DSDV Destination Sequenced Distance Vector
DS-OLSR Disaster Scenario Optimised Link State Routing
DS-OLSRMP Disaster Scenario Optimised Link State Routing and Message Prioritisation
DSR Dynamic Source Routing
E-EOLSR Energy-Efficient OLSR routing protocol
EEM-OLSR Energy Efficient Mechanism OLSR
EIGRP Enhanced Interior Gateway Routing Protocol
ETX Expected Transmission Count
ET-OLSR Energy-based Threshold Optimised Link State Routing
EWS Early Warning Systems
FANET Flying Ad-hoc Network
FC-USAP Fast Convergence USAP
FDMA Frequency Division Multiple Access
FTMC Fault-Tolerant Maximum Coverage
GRP Geographic Routing Protocol
HBDA Human Behaviour for Disaster Areas
HL-TDMA Hybrid Link Time Division Multiple Access
IoT Internet of things

IS-IS Intermediate System to Intermediate System

ITU-T International Telecommunication Union Telecommunication Standardization Sector

JAC Jaccard Similarity Index

LD-OLSR Link-Duration OLSR

LTA-OLSR Link-Quality and Traffic-Load Aware OLSR

LTE Long-Term Evolution

MA-DDPG Multi-Agent Deep Deterministic Policy Gradient algorithm

MANET Mobile Ad-hoc Network

MA Mobile Agent

MAC Medium Access Control

MDP Markov Decision Process

MLOLSR Mobility and Load-Aware OLSR

MOLSR Mobile Agent OLSR

MOS Mean Opinion Score

MODOLSR Modified Optimised Link State Routing Protocol

MPR Multipoint Relay

NRL Network Routing Load

OLSR Optimised Link State Routing Protocol

OLSRv1 Optimised Link State Routing Protocol version 1

OLSRv2 Optimised Link State Routing Protocol version 2

OSPF Open Shortest Path First

PDA Personal Digital Assistant

PDF Packet Delivery Fraction

PDR Packet Delivery Ratio

P-OLSR Predictive-OLSR

PID Proportional Integral Derivative

PSO Particle Swarm Optimisation

P2P Peer-to-Peer

QoS Quality of Service

RoF Radio over Fiber

RPGMM Reference Point Group mobility model

RWP Random Waypoint

SAIMOD Self-Aware Intelligent Model

SAR Search and Rescue

SDR Speed Deviation Ratio

SHARP Sharp Hybrid Adaptive Routing Protocol

SLAW Self-Similar Least-Action Walk

SMLR_OLSR Smooth Mobility and Link Reliability based OLSR

TC Topology Control

TCP Transmission Control Protocol

TDMA Time Division Multiple Access

TORA Temporally Ordered Routing Algorithm

UAV Unmanned Aerial Vehicles

UAV-BSs UAV-Base Stations

UDP User Datagram Protocol

VANET Vehicular Ad-hoc Network

VoIP Voice over Internet Protocol

WiFi Wireless Fidelity

WiMAX Worldwide Interoperability for Microwave Access

WIND Wi-Fi Network on Drone

WLAN Wireless Local Area Network

ZHLS Zone-based Hierarchical Link State

ZRP Zone Routing Protocol

Chapter 1

Introduction

1.1 Introduction

Wireless networks comprising *ad hoc* networks have evolved into advanced architectures with the development of hardware and software technologies. An *ad hoc* network is a decentralised wireless network which forms spontaneously. It is a self-organising, self-healing and distributed network which usually uses wireless transmission (Singh, Singh, and Sharma, 2017; Sharma et al., 2016; Simaya, Shrivastava and Keer, 2014). Examples of Ad hoc networks are Mobile Ad hoc Networks (MANETS) (Rishiwal, Agarwal and Yadav, 2016), Flying Ad Hoc Networks (FANETS) (Oubbati et al., 2017; Hua et al., 2022) and Vehicular Ad hoc Networks (VANETS) (Kumar, Mishra and Chand, 2013).

Mobile Ad Hoc Networks (MANETs) are not dependent on existing infrastructure. Instead, the nodes form an *ad hoc* network and communicate through wireless communications. Each node can forward data packets from other nodes in the ad-hoc network (Erim and Wright, 2017; Jelassi and Rubino, 2013). An advantage of MANETs, due to the mobility of their nodes, is that they can either operate by themselves or may be connected to a more extensive network or the Internet. MANETs can be used as relays to form networks needed on the fly when established infrastructures are not readily available. This is the case, for example, in a disaster recovery situation when stringent user specifications like the need for wireless connectivity are required to provide a framework that allows functions such as streaming voice or sending video and data between devices (Kaur, 2016; Ismail, Zulkifli and Samsudin, 2016).

Mobile Ad Hoc Networks (MANETs) encompass all the components for a suitable architecture using heterogeneous networks. Research on real-life applications for such heterogeneous MANETs has been rapidly growing in recent years with advancements in technology ranging from aerial robotics to big data analytics, 5G networks, innovative technology, and the Internet of Things (IoT). They have paved the way for several real-life applications, such as infrastructure inspection and maintenance (Máthé and Buşoniu, 2015), Search and Rescue operations (Wheeb et al., 2023; Tomic et al., 2012) and agriculture (Honkavaara et al., 2013). Table 1.1 illustrates some real-life applications and examples.

Table 1.1: MANET Network Applications and Examples

Applications	Examples
Home networks	◙ Home wireless networks ◙Security lights ◙ Heating ◙ Alarm systems ◙ Doors
Military networks	◙ Tactical Operations ◙ Surveillance and Reconnaissance ◙ Training
Training networks	◙ School network settings ◙ Virtual classrooms ◙ lectures ◙ Study rooms
Business networks	◙ Airports ◙ E-commerce ◙ mobile office ◙ Traffic control ◙ Cyber cafes ◙ Shops ◙ Conferences, ◙ Retreat centres ◙ Office wireless networking
Emergency services	◙ Search and rescue operations ◙ Accident and Emergency ◙ Disaster recovery ◙ Policing
Agricultural networks	◙ Farm gates ◙ Security ◙ Production chains

Search and Rescue (SAR) operations must begin quickly and efficiently. A key aspect of SAR missions is to create or re-establish damaged communication links in the disaster recovery area. Usually, Search and Rescue operations are mainly carried out using boats, helicopters, and other vehicles, but this may be challenging in hard-to-reach places. An alternative to these conventional modes, which has gained traction over the years, is using *ad hoc* networks to form decentralised communication links using handheld devices like mobile phones (Höchst et al., 2020). UAVs are currently being used for their quick and efficient coverage of search areas, especially in rugged terrains, enabling coverage that allows rescue teams to respond faster. In addition, they are more affordable than conventional rescue modes and can overcome network partitioning problems in a dynamically changing environment.

1.2 Impact of the Research

1.2.1 Search and Rescue Missions

The use of MANET-based networks such as Unmanned Aerial Vehicles (UAVs) and FANETs (Flying ad-hoc Networks), to re-establish communication links by providing wireless coverage to ground user devices is a promising technology for disaster recovery. These networks can easily and quickly be deployed for efficient coverage, achieving desired metrics such as maximising Throughput, Packet Delivery Fraction (PDF), and Delay. They can also overcome network partitioning problems in a dynamically changing environment.

The impact of UAVs in SAR missions has been profound since the 2010 Haiti earthquake when they were first successfully deployed in a major Search and Rescue (SAR) effort. In the aftermath of that earthquake, UAVs provided critical aerial imagery that aided in disaster response and recovery, ultimately saving lives. UAVs are fast becoming one of the vital resources used as part of SAR efforts in various countries. This successful history of using UAVs in Search and Rescue (SAR) missions has shown their reliability and effectiveness as a vital resource in disaster recovery efforts in various countries (Vincent-Lambert, Pretorius, and Van Tonder, 2023; Van Tilburg, 2017). For example, the UK Maritime and Coastguard Agency uses UAVs to search for missing people along coastlines and in remote areas. In 2020, UAVs were used in a high-profile search for a missing hiker in the Scottish Highlands; they covered large areas of rugged terrain and provided live video feeds and thermal imaging that greatly enhanced the search operation.

In 2018, one of the best-known and most accomplished mountaineers in the world, Rick Allen, was presumed dead after falling from an ice cliff of the 12th-tallest mountain in the world, Pakistan's Broad Peak, when he had attempted a solo climb to its peak. After a cook at the mountain's base camp spotted his rucksack, a UAV (specifically, a DJI Mavic Pro drone, known for its long flight time, high-quality camera, and obstacle avoidance features) was used to locate him and guide the SAR team to his location. He was successfully rescued (McRae et al., 2019).

1.2.2 Disaster Management

Natural and man-made disasters can have adverse effects on the environment; they can cause damage to infrastructure such as buildings, base stations, and road networks, badly affect the economy, and cause varying degrees of injuries and even death (Vassiliades et al., 2023; Saif et al., 2021). Access to time-sensitive information, like the number of people found under an avalanche or drone failure, can help the decision-making process. A good example is that with Search and Rescue (SAR) workers being typically organised into teams, identifying areas of greatest need can help effectively distribute resources promptly, rather than working with estimates. UAV-assisted networks/MANETs can help gather this information in real-time or be used as a relay for restoring network links, which can be sent and received from rescue team members in the disaster recovery zone.

An advantage of deploying the framework proposed in this Research is that it can be applied as an assessment tool in resource management by evaluating the network in areas such as bandwidth usage, connectivity, and remaining energy. This evaluation can answer questions such as how long the batteries of the mobile devices held by the rescue team leaders will last before they require replacement and/or when to replace the UAVs in the network. This can be a means of increasing the robustness of the Disaster Management plan or system.

1.2.3 Routing in Ad-hoc Wireless Networks

The need for an efficient routing protocol, especially in disaster recovery Search and Rescue (SAR) missions where time is ticking away, cannot be over-emphasised. This calls for improvements in critical areas of the network, such as optimising energy conservation by reducing energy consumption, enhancing network performance by maximising Throughput and Packet Delivery Fraction (PDF), and reducing Delay. A significant challenge in MANETs has been the demand placed on the network by their dynamically changing topology, especially limited energy and available bandwidth. Energy consumption is one of the most critical problems, and numerous routing protocols, both traditional and Variations of them, have been developed for wireless *ad hoc* networks. The aim of these has been to efficiently optimise the energy available in the nodes and network lifetime, etc. (Venkatesh and Chakravarthi, 2022; Singh and Prakash, 2020; Wzorek et al., 2018; Vemuri, and Mirkar 2021).

1.3 Research challenges and motivation for the Thesis

One main area of concern in Search and Rescue (SAR) missions is creating or re-establishing damaged communication links in the disaster recovery zone. Various studies have been carried out on using *ad hoc* networks to form decentralised communication links using handheld devices to meet this need. UAV-based *ad hoc* networks have gained traction over the years. The greater the number of UAVs deployed in hard-to-reach search areas, the faster those areas can be covered because each additional UAV adds more coverage, and UAVs move faster than humans in broken terrain (Gonçalves and Damas, 2022; Mohsan et al., 2022).

UAV-based MANETs can be used as relays for restoring network links by which information can be sent and received in the disaster recovery zone (ur Rahman et al., 2018; Adam et al., 2014). However, one challenge faced when using MANETs is that they are constrained by bandwidth, as wired networks usually have higher bandwidths than their wireless counterparts. In addition, there is a limitation to the available energy in devices that make up a MANET, which is an operational constraint (Pariselvam et al., 2021). Therefore, the choice of routing protocols and the mobility models used in the MANETs are usually affected by considering these constraints. Consequently, selecting routing protocols and mobility models plays a significant role in the overall network performance.

In the current use of UAV deployment for restoring communication links in disaster recovery, choosing a suitable mobility model and a suitable routing protocol has been a trade-off of optimising either the routing protocol or the mobility model. This Research proposes that the combination of the two works in tandem. A challenge this Research addresses is establishing communication links by UAVs in a disaster recovery scenario to create a scalable *ad hoc* network that can handle the complexity of data packets, increase network density, and allow bi-directional data transfer.

Additional challenges in the use of these UAV-based MANETs have been how to create, in real-time, a reliable, fault-tolerant formation algorithm to introduce networking amongst the UAVs and to overcome issues such as UAV failure in the network and avoid over coverage (duplication of efforts). Although several attempts and studies have been carried out to improve unmanned systems' formation control and coordination, there are still significant challenges. Existing solutions do not fully address this demand, as they are generally based on heavy infrastructure or over-processing (Shrit et al., 2017). This study addresses these challenges by introducing intelligent networking amongst UAVs.

Furthermore, due to their dynamic topology, UAV-based MANETs face limited resource problems. This study also proposes an assessment model for resource management, such as when to replace batteries, by applying the information gathered from the network performance.

(This Thesis reports on the Research carried out based on the proposed further study of my master’s degree project with further adaptations. Some initial assumptions, network setup and initial results are the same as in my unpublished master's dissertation at Liverpool John Moores University, 2015 and IEEE Conference paper, 2017).

1.4 Aim and Objectives

The aim of this Research is to design and evaluate a self-aware and intelligent framework (SAIMOD) for mobile wireless networks using energy-efficient protocols and mobility models in disaster recovery scenarios.

The Objectives are to:

I. Review protocols and mobility models for wireless networks in disaster recovery scenarios.

II. Design and evaluate suitable mobility models and cross-layer protocols for energy-efficient mobile wireless networks for disaster recovery applications.

III. Design and evaluate self-aware path planning and communication links between the super-node layer (UAV) and the mobile ground nodes.

IV. Integrate the self-aware layer with the mobile wireless network layer within the Self-Aware Intelligent Model (SAIMOD) framework for disaster recovery applications.

V. Evaluate the SAIMOD framework using benchmark parameters for energy efficiency and connectivity.

1.5 Description of Objectives

1.5.1 Review protocols and mobility models for wireless networks in Disaster Recovery

Mobility models are pre-defined movement patterns of mobile users. They determine how the mobile nodes will move in terms of their velocity, location, and even change in acceleration over time. The mobility models of the nodes in a wireless network affect the network's overall performance because the choice of mobility model plays a vital role in protocol performance, mainly dependent on the deployed environment and their mobility pattern. Several types of mobility models exist in wireless networks. Most researchers usually favour the Random

Waypoint (RWP) mobility model as a mobility model of choice (Althunibat et al., 2019). However, it has the disadvantage of not accurately considering the real-life demography of locations where buildings, for instance, might pose an obstruction.

This Research critically evaluates a set of MANET routing protocols for an example scenario within disaster recovery. The evaluation process involved testing the Random Waypoint (RWP) mobility model and other mobility models (Reference Point Group mobility model (RPGMM), Manhattan and Gauss Markov mobility models) using five different routing protocols (Ad-hoc On Demand Vector (AODV), Dynamic Source Routing (DSR), Destination Sequenced Distance Vector (DSDV), Optimised Link State Routing (OLSR) and Temporally Ordered Routing Algorithm (TORA)) in similarly deployed networks. Each of the tested routing protocols was carefully selected as a representation from each of the different types of routing protocols (two reactive protocols, two proactive protocols and one hybrid protocol) using example mobility models from each of the four classifications of mobility models (Random models, Models with temporal dependency, Models with spatial differentiation and Models with geographic restrictions).

The specific criteria used to select the different mobility models and routing protocols in this Research included their characteristics and suitability for the disaster recovery scenario being tested. This involved considering how each mobility model and routing protocol performs under relevant network parameters such as Throughput, Network Routing Load (NRL), and Delay. Additionally, the protocols were chosen to represent a balance from the different types (reactive, proactive, and hybrid protocols), ensuring a comprehensive evaluation across the four classifications of mobility models (Random models, Models with temporal dependency, Models with spatial differentiation and Models with geographic restrictions). The ease of implementation of these models and protocols was also a key factor in the selection process. Other researchers have also generally used this selection from the different classes of mobility models and routing protocols based on their characteristics and ease of implementation. The evaluation of the network to select a suitable mobility model by considering relevant network parameters, such as Throughput, Network Routing Load (NRL) and Delay, is carried out.

The mobility models selected for testing were evaluated to enable accurate analysis of the impact of the choice of mobility model(s) on a MANET network's overall performance, particularly in disaster recovery scenarios. The Reference Point Group mobility model was chosen for its significant impact on the MANET network's overall performance. It had better Throughput performance and an acceptable level of Delay, making it suitable for disaster recovery scenarios where efficient and reliable communication is crucial.

Routing protocols employed in wireless networks are deemed vital because they play a significant role in network performance by significantly contributing to the energy consumption of the nodes and thus affecting the overall network lifetime (Thiagarajan, 2020). The network lifetime of MANETs is affected by the type of applications being run on the networks and the network architecture. The choice of routing protocols for networks is based on the ability of the selected protocol to establish a correct and efficient route from the source node to the destination node within the boundaries of the active route timeout interval. Route discovery and maintenance for selected protocols should have low overhead and bandwidth consumption.

Further experimentation is conducted to test the suitability of individual routing protocols, AODV, DSR, DSDV, OLSR and TORA when combined with the identified / selected mobility model, Reference Point Group Mobility Model, for use with SAIMOD in terms of network Throughput and Delay. The results for the applications (Email, Peer-to-Peer (P2P) file sharing, File Transfer Protocol (FTP) and Voice over Internet Protocol (VoIP)) run in the network, such as HTTP Throughput, Jitter, Mean Opinion Score (MOS), etc., are also analysed. The simulation results gathered from the network provided valuable insights into the network's performance under different application scenarios, which is crucial for understanding the practical implications of the Research.

The scalability of the MANET network with varying nodal densities is also tested. Based on its overall performance, the OLSR routing protocol is selected as the most suitable routing protocol for use with the Reference Point Group mobility model in SAIMOD. This protocol was then modified to enhance energy conservation, which could have significant implications for wireless networking and disaster recovery.

1.5.2 Design and evaluate suitable mobility models and cross-layer protocols

The second objective of this Research is to design and evaluate suitable mobility models and cross-layer protocols for energy-efficient mobile wireless networks for disaster recovery applications. It is envisioned that the selected protocols will show an explicit agreement between the UAVs and the ground nodes regarding communication and data transfer. The sources of energy wastage in the routing layer can be attributed to the packet size of the data, collision overhearing, collision, packet size of the data, energy expended on idle listening, protocol overheads, emitting and fluctuations in traffic, etc. (Khriji et al., 2018; Chowdhury and Hossain, 2020). A viable solution is for the selected protocol, OLSR, to be further optimised for energy efficiency and connectivity to achieve this. This will be done by modifying its MAC components using a multiple-access technique.

The interaction and overall performance of the MAC/routing protocols in an ad-hoc network can be modelled by dividing the various parts of the protocol into components. Based on the OLSR protocol (the protocol selected for use in SAIMOD), there are three main components, namely the Neighbour Discovery Component (NDC), Selector of Information for Dissemination Component (STIDC) and Route Selection Component (RSC) (Liu et al., 2023; Paraskevas and Baras, 2015).

(a) Neighbour Discovery Component (NDC): This component gathers local neighbourhood information, such as the location of the next-hop neighbour.

(b) Selector of Information for Dissemination Component (STIDC): This component floods a concise version of the local neighbourhood information.

(c) Route Selection Component (RSC): The routing protocol uses this component to select the most suitable routes based on available information.

These components can be optimised to improve the routing protocol's performance.

Energy conservation techniques that use the Topology Control Approach (TCA) (Feng et al., 2024; Coutinho et al., 2018; Boukerche and Coutinho, 2018; Coutinho and Boukerche, 2019), a modified protocol with an efficient path maintenance scheme that reduces the network's energy consumption using a quick and low-overhead path discovery scheme, could be incorporated into the design. There is existing Research on the Multipoint Relay (MPR) node selection process in OLSR, as well as Research on Time Division Multiple Access (TDMA) techniques for data exchange between the cluster head and the cluster nodes in clustering routing protocols like LEACH (Liu et al., 2019; Tazibt et al., 2017). By manipulating the TDMA technique, the energy efficiency of clustering protocols' MAC layer activities can be controlled and improved (Rozas and Araujo, 2019; Sony, Sangeetha and Suriyakala, 2015).

This study explores using the same multiple access technique (TDMA) and modifying the MPR node selection process to optimise the energy efficiency of the selected routing protocol. A two-layer modification is carried out on the routing protocol, OLSR, to create a novel protocol, MODOLSR (Modified OLSR). These modifications were carried out on the MPR node selection process at the network layer based on the residual energy in the nodes.

Meanwhile, TDMA schedules time slots for data transmission at the Medium Access Control (MAC) layer. A schedule-based communication, contention-free approach to support cluster mobility will be employed. This modified OLSR, named MODOLSR (Modified OLSR), removed the need for the protocol to keep rescheduling because of frequent movements of nodes in the MANET and for collision avoidance, thereby ensuring the protocol's efficiency.

1.5.3 Design and evaluate self-aware path planning and communication links

This Research proposes the Self-Aware Intelligent Model (SAIMOD), a novel disaster recovery framework. SAIMOD is designed to be an integrated emergency communication system that would restore broken communication links or form new ones by creating UAV-based Mobile Ad Hoc Networks (MANETs). These (MANETs) are formed by Unmanned Aerial Vehicles (UAVs) deployed in the disaster recovery area and the ground nodes (made up of the disaster recovery team/ personnel and the people to be rescued). It is intended that the UAVs would be super-node layer UAVs that act as relays/routers that allow bi-directional communication and connectivity. (The super-node layer UAVs refer to all the UAVs in the network that act as central nodes, coordinating communication and data transfer among other nodes).

The UAVs deployed would create a wireless mobile network with devices such as mobile phones carried by the ground nodes to facilitate network connectivity and transmission of data. SAIMOD would also allow multi-hop connectivity in the network and facilitate transmissions and data retransmission between ground nodes and the UAVs. Each group of ground nodes has a group leader equipped with a device with a unique identifier number that they follow. The group leaders play a crucial role in the network, coordinating the group's actions and ensuring effective communication with the UAVs. This unique identifier number is captured and stored in the UAV's memory cache when the group leader exchanges information with a UAV (which also has a unique identifier number encoded in the data sent to the covered ground nodes). The UAVs would also be able to communicate with each other in range and transfer information such as the unique identifier numbers of groups covered and their unique identifier numbers. Each UAV is designed to be connected to at least one other UAV in the SAIMOD network when more than one UAV is deployed to form the SAIMOD framework, highlighting the system's adaptability and robustness.

UAV Path planning in disaster recovery areas is usually made by considering the route that best avoids static and dynamic obstacles in the zone (such as debris in the disaster zone or other UAVs) while offering desired performance metrics such as energy conservation and less Delay (Liu, H., 2023). This will enhance the UAVs' performance in restoring broken communication links or creating new ones in the MANET network formed promptly.

SAIMOD is not just a disaster recovery framework but an energy-efficient one. It integrates a positioning algorithm for the super-node layer UAVs with a suitable mobility model for the ground nodes. An appropriate mobility model and a suitable routing protocol are used in SAIMOD. The ground nodes, operating within the MANET network, move using the Reference Point Group Mobility Model, while the modified selected protocol, MODOLSR, manages the routing. The energy efficiency of the framework ensures sustainability and resilience of the SAIMOD network and makes it a cost-effective solution for disaster recovery.

SAIMOD is designed to be a reliable solution for disaster recovery. This disaster recovery framework has a fault-tolerant control system integrated into the path planning algorithm that enhances the positioning of the UAVs in the disaster zone. This system ensures the intelligent autonomous networking of the UAVs in the framework, ensuring that SAIMOD remains operational despite unexpected challenges such as changes in the MANET network topology or UAV failure.

1.5.4 Integrate the self-aware layer with the mobile wireless network layer

Integrating the self-aware layer with the mobile wireless network layer within the proposed framework enhances the network's resilience and efficiency. SAIMOD is designed to be self-aware in terms of network resilience. It can adapt to unexpected changes in the topology of the MANET, such as UAV failure, highlighting its robustness and reliability. The remaining UAV(s) would adapt since the information of already covered areas and the UAV that covered them has been gathered earlier and stored in the UAV's memory cache when it was in the range of the failed UAV or from another UAV that has gathered that information previously from the failed UAV(s). Each UAV is always connected to at least one other UAV in the network at the formation of the MANET network.

This adaptability leads to a more efficient and resilient network capable of addressing issues often like overlapping coverage of the disaster area and duplication of efforts and continued Quality of Service even with unexpected changes in the network topology like drone failure, which are often encountered in networks with multiple UAVs. Such networks like those formed by UAVs that use the lawnmower movement pattern (where the UAV must move back and forth over the disaster area to ensure complete coverage) or grid-based networks that form a blanket over the disaster zone (Lee et al., 2020) typically struggle to adapt these issues. This adaptable approach helps conserve limited resources, such as energy, while saving time.

This algorithm would address three key issues:

- Creating an efficient UAV distributive model
- Incorporating some form of intelligence in the UAV path planning
- Proposing an assessment model for resource management in the MANET network within

the disaster recovery area

1.5.5 Evaluate the SAIMOD Framework

A critical design specification of wireless networks is effectively utilising the limited energy resources available and seeking the best route for sending data (Ketshabetswe et al., 2019). In MANETs, the design of energy-efficient routing protocols is essential because an energy-efficient routing protocol would make the system more efficient in areas such as improving the network lifetime and maximising bandwidth usage. The larger the MANET network, the greater the bandwidth requirement to maintain accurate routing information, memory, and processing power. This invariably introduces traffic overhead into the network as the nodes communicate routing information. Hence, more battery power is used**.**

A novel protocol, MODOLSR, based on a two-layer modification of the traditional OLSR protocol, is developed to enhance or optimise energy efficiency and lend itself to scalability. This protocol (MODOLSR) is combined with the chosen mobility model, the Reference Point Group mobility model, a crucial component in the SAIMOD network. The SAIMOD deployed network is tested for desired performance metrics such as Throughput, Network Routing Load and Delay. It is also tested for resilience and scalability using varying nodal densities, ensuring it can perform optimally under different conditions.

Summary:

The SAIMOD (Self-Aware Intelligent Model), a framework for disaster recovery scenarios, is proposed to address the various issues faced by setting up the ad hoc network. SAIMOD combines a modified Optimised Link State Routing protocol, MODOLSR, that manages routing and the deployed network's selected mobility model (Reference Point Group mobility model), which handles the movement trajectory of the ground nodes. The combined optimised protocol and mobility model chosen are designed to be highly adaptive to topology change within the network and show network resilience in terms of routing load, network density and mobility of nodes. The MANET is deployed and evaluated for various preferred network metrics, such as packet delivery fraction (PDF), network Throughput, End-to-End Delay, energy efficiency, and Network Routing Load (NRL).

The SAIMOD framework is intended to incorporate a suitable algorithm for managing the movement of UAVs within the network. This algorithm is based on the degree of similarity or dissimilarity in the geographical position of UAVs relative to other UAVs in the MANET network. The goal is to achieve seamless networking among the UAVs to ensure, for instance, that the UAVs avoid covering the same area (duplication of effort) and adapt to changes in the network conditions, e.g., UAV failure. It is also intended that an assessment model, which applies information such as energy consumption gathered from the network in which the framework is deployed, can be used in resource management.

1.6 Contributions of the Research to the State-of-the-art

This study explores the design of an innovative integrated emergency communication system. This system relies on the formation of MANETs (Mobile Ad Hoc Networks) by UAVs (Unmanned Aerial Vehicles) deployed in a disaster recovery scenario. The key highlight of this Research is the introduction of a novel disaster recovery framework, SAIMOD (Self-Aware intelligence model). This framework is designed to tackle the challenges of establishing a fault-tolerant and efficient communications backbone in a disaster recovery scenario.

The following summary provides a short overview of this work's four key contributions that address the challenges introduced in the previous sections.

I. The proposed framework, SAIMOD, will be a framework which employs a combination of a novel protocol, the Modified Optimised Link State Routing protocol (MODOLSR) for routing and the best-fit mobility model, the Reference Point Group Mobility model (RGPMM) by which the ground nodes will move in groups. This study uses a clustering-based approach for the movement pattern of the ground nodes, and the selected mobility model, RPGMM, is implemented to ensure better connectivity in the network. This is achieved by the ground nodes always being within range of the group leader node as they mimic the leader's movement pattern.

Previous Research has primarily focused on one-layer modification of the routing protocol. Modifications of OLSR in MANETs have focused either on improving the Multipoint Relay selection process or modifying the MAC transferability properties of the protocol by using one of the multiple access methods (CSMA, FDMA or TDMA). However, in this study, a novel protocol, MODOLSR, is developed by carrying out a two-layer modification of the routing protocol, OLSR, to enhance the routing process of the protocol. One modification occurs at the network layer (optimising the MPR node selection process), while the other is at the Medium Access Control layer (optimising the MAC using the Time Division Multiple Access technique). The MODOLSR protocol is shown to have improved the network's performance based on desired performance metrics, with an emphasis on energy efficiency.

II. Intelligent networking amongst UAVs

SAIMOD uses a reinforcement learning method that ensures adequate coverage of the disaster area by the UAV-based MANETs formed. The UAVs use real-time fault-tolerant formation control to avoid issues such as physical drone collision. These auxiliary MANETs are formed by self-aware UAVs equipped with GPS that use a suitable algorithm to determine movement patterns amongst themselves based on the degree of similarity or dissimilarity in their geographical position. This aims to ensure seamless networking so UAVs can efficiently avoid covering the same area.

III. The SAIMOD framework is also designed to enhance the deployment of UAVs by adapting to dynamic changes, such as UAV failure, in real-time. This adaptability is achieved by applying knowledge learned from one task to another. The UAVs are equipped to communicate with each other when in range and transfer information, such as unique identifier numbers of the covered groups. Each group of ground nodes has a group leader with a unique identifier number that they follow. This unique identifier number is captured when the group leader exchanges information with a UAV, ensuring seamless communication and adaptability in the system.

IV. Energy conservation and cost

Collating the advantages of the two-layer modification of the routing protocol, the suggested best-fit mobility model, and the intelligent networking amongst the UAVs paints a picture of a fault-tolerant, intelligent UAV deployment framework that can be cost-effective in ways not previously explored within a small-scale disaster recovery scenario. For instance, because it is adaptive to change, the system might not require a replacement UAV in the case of a UAV failure in the network, as it can make decisions based on information gathered. The resilient framework can adapt to the shortage, pending the availability of replacement UAVs. Being able to deduce this change and quickly proffer a solution can significantly reduce delay in the network deployment that stems from activities such as UAV replacement, delay in locating a gap in the network and the inability of UAVs to decide on how to remain resilient when an unexpected event occurs.

1.7 Thesis Structure

This Thesis comprises six Chapters:

Chapter 1

This Chapter provides an overview of the Thesis. It highlights the need for a quick and resilient establishment of communication links in the advent of a small-scale disaster to facilitate Search and Rescue operations. It further describes the challenge of creating a fault-tolerant controller for the UAV positioning and problems associated with ad hoc networks, such as limited energy and bandwidth constraints. In addition, an innovative solution is presented, specifically, a disaster recovery UAV deployment framework, SAIMOD (Self-Aware Intelligent Model), which will be deployed in the disaster recovery area. This Research's aim, objectives, challenges, and contributions are stated. Finally, the Chapter concludes with an outline of the Thesis structure. The rest of the Thesis is organised as follows:

Chapter 2

This Chapter introduces some underlying concepts that are used throughout this Thesis. It discusses existing literature on the classifications of routing protocols and mobility models, including those relevant to this Research and the use of UAV deployment to restore communication links in disaster recovery. The proposed framework, SAIMOD, is also briefly introduced.

Chapter 3

The choice of routing protocols and mobility models can affect the overall network performance. Selecting a suitable routing protocol and an appropriate mobility model is the first step in developing the proposed Self-Aware Intelligent Model (SAIMOD) framework. This Chapter introduces the simulation software used, the network set-up and parameters, the performance metrics such as Packet Delivery Fraction (PDF), Throughput, average End-to-End Delay and Network Routing Load (NRL) selected, and why. The applications run (data type sent) in the network, and the simulation results are presented and analysed. Four mobility models - the Random Waypoint mobility model, the Gauss Markov mobility model, the Reference Point Group mobility model and the Manhattan mobility model - are tested, and the best-performing mobility model is selected. This selected mobility model is then used to test five routing protocols, namely, the Dynamic Source Routing (DSR) protocol, the Ad-Hoc On-Demand Distance Vector (AODV) routing protocol, the Optimised Link State routing (OLSR) protocol, the Geographic Routing Protocol (GRP), and Temporally Ordered Routing Algorithm (TORA). The best-performing routing protocol amongst them was selected. These selections (best-performing mobility model and routing protocol) were based on desired performance metrics.

Chapter 4

This Chapter presents the proposed framework, SAIMOD and its underlying principles and assumptions. Here, intelligent networking of the UAVs is discussed in detail, including using unique identifier numbers for the ground node group leaders and the UAVs and the Jaccard sequence algorithm by which the UAVs are positioned. The network's scalability and resilience are tested with increasing nodal densities. A mathematical model for assessing the network to determine resource management is also addressed. The SAIMOD framework is also compared to some disaster recovery frameworks.

Chapter 5

This Chapter presents a two-layer modification of the OLSR routing protocol. Here, OLSR is modified by optimising the Multipoint Relay (MPR) node selection process in the network layer and modifying the multiple access transferability of the routing process in the data link layer using TDMA. This modified time-aware OLSR (MODOLR) is evaluated for energy efficiency and compared to other modified OLSR protocols.

Chapter 6

This Chapter concludes the Research in this Thesis by summarising its contributions and proposing considerations for future study.

Chapter 2

Routing Protocols, Mobility Models and UAVs in Disaster Recovery

2.1 Introduction

This Chapter briefly introduces the proposed communication framework of this Research, SAIMOD, introduces some underlying concepts used throughout this Thesis and explores existing literature on the classifications of routing protocols and mobility models in MANETs. It also highlights some existing network protocols relevant to this Research. In addition, Unmanned Aerial Vehicles (UAVs) in disaster management are also discussed, emphasising intelligent management of communication coverage for the ground nodes using them (UAVs). In addition, a literature survey is presented on the state-of-the-art UAV deployment to restore communication links in disaster recovery.

2.2 Brief Introduction to the proposed framework SAIMOD

This Research proposes the Self-Aware Intelligent Model (SAIMOD) as a framework designed to be an integrated emergency communication system that restores broken communication links or creates new ones in an example scenario within disaster recovery. This framework relies on the Mobile Ad Hoc Networks (MANETs) formed by Unmanned Aerial Vehicles (UAVs) deployed in the disaster recovery area and the ground nodes (people to be rescued and the disaster recovery personnel(s)). The UAVs act as relays/routers that facilitate bi-directional connectivity and communication in an energy-efficient manner by using a selected mobility model in conjunction with an optimised routing protocol.

SAIMOD will allow data collection and transmission and support intelligent networking amongst the deployed UAVs in the network to ensure real-time fault-tolerant UAV formation control. This will ensure that the disaster recovery area has adequate coverage, the UAVs avoid overlapping coverage of the disaster area, and the UAVs are adaptable to changes in the UAV network topology, such as UAV malfunction or failure. SAIMOD is also designed as an assessment model for resource allocation and management.

2.3 Overview of Routing protocols and Mobility models

2.3.1 Routing Protocols

Routing protocols use several metrics to determine the best path for routing data packets from source to destination. These metrics are standard measurements, such as the number of hops, which the routing algorithm uses to determine the optimal path for the data packet from source to destination. Path determination is when routing algorithms initialise and maintain routing paths containing the packet's route information (Joy and Dudhe, 2021).

Route information differs among routing algorithms; therefore, developing an efficient and reliable routing protocol is challenging because of changing network conditions, such as limited bandwidth, available power, node density and other network conditions. A primary challenge faced in routing data in MANETs is their dynamic network topology due to the mobility of the nodes that form them (Sharma et al., 2016; Umar, Alrajeh and Mehmood, 2016).

Researchers have proposed various routing protocols for MANETs based on the scenario's application requirements, such as maximising Throughput and reducing overhead (Mohsin, 2022; Abushiba and Johnson, 2015). Depending on how infrastructures are created and maintained during data routing, routing protocols in ad hoc networks can be separated into two basic categories: proactive and reactive. There is, however, a third category of routing protocols proposed by researchers: the hybrid routing protocol that combines features from both proactive and reactive protocols (Kumar, Katiyar and Kumar, 2016; Kaur, Singh and Sharma, 2016; Hmalik et al., 2014). Network protocols will be reviewed, including those relevant to this study. Table 2.1 shows the classification of some ad-hoc routing protocols, their routing type, features, advantages, and disadvantages.

Table 2.1: Classification of Routing Protocols

	Type	Features	Advantages	Disadvantages
DSDV	Proactive	Solves the routing loop problem by adding sequence numbers to new routes. Flat Uni-cast protocol.	A better choice for low-speed networks. Requires less bandwidth in comparison to other proactive protocols.	Time consuming. Fluctuations. Increased size of routing table.
GRP	Proactive	Used to find the geographical location of nodes in the network	Does not require a routing table. Low control overheads.	Congestion. High overhead.
OLSR	Proactive	Flat Uni-cast protocol. Disseminates topology information using an adaptation of the link-state algorithm/ scheme.	Loop free. Suitable for large networks with many nodes. Uses Multipoint Relays (MPRs) to reduce routing overhead.	High bandwidth usage. High energy usage.
DSR	Reactive	Flat Uni-cast protocol. Designed mainly for large MANETs. Source routing. Reliable in networks with high mobility rates.	Loop Free. Multiple routes. No periodic hello message and fast recovery.	Large networks overhead. Scalability issues. Large Delay.
AODV	Reactive	On-demand routing protocol. Flat Uni-cast. It uses sequence numbers for each route.	Loop free. Avoids the problem of counting to infinity. Does not require additional organisational methods to handle the routing process (It uses sequence numbers for	High control overhead. The connection setup Delay is lower. Poor scalability.
ABR	Reactive	Association stability metric.	Gives same importance to all routing nodes. Good link quality. Loop free.	Complexity in processing, Scalability issues. High overhead.
ZRP	Hybrid	Hierarchical Uni-cast protocol. Uses border casting.	Reduces the cost of topological updates Decreases the control overhead. Reduces latency.	Can cause large overhead in large networks. Requires high memory.
TORA	Hybrid	Flat Multicast/ Uni-cast protocol. Suitable for large MANETs.	Loop free. Supports multicasting. Adapts quickly to topology change. Good in high-	High Delay to form new routes. The algorithm is dependent on external time source. Overhead is high.

2.3.1.1 Proactive Protocols

Proactive protocols, or table-driven protocols, are crucial in maintaining consistent and up-to-date fresh links to other nodes within the network. These protocols strive to keep all nodes informed by periodically disseminating topology updates throughout the network. This proactive approach ensures a reliable and efficient network, as it maintains probable unfailing route information across the network by propagating updated changes in the topological structure of the network. The periodic updates of their routing table enable the immediate selection of a forward node, thereby minimising initial delays in the data transfer.

However, the excessive generation of control traffic incurs communication overhead, causing additional consumption of scarce resources across nodes, which can be very costly, particularly in an environment of highly mobile nodes at the peak (Kashap et al., 2013). There are several examples of proactive routing protocols: Destination Sequenced Distance Vector routing (DSDV), Geographic Routing Protocol (GRP), Optimised Link State routing (OLSR), Open Shortest Path First (OSPF), etc. (Al-Dhief et al., 2018; Kumar et al., 2013; Purohit and Keswani, 2017; Shruthi, 2017). A selection of proactive routing protocols relevant to this Research is discussed below.

A. Optimised Link State routing (OLSR)

The Optimised Link State routing (OLSR) protocol is a table-driven, proactive protocol that maintains information in various constantly updated tables. While flooding the link-state data is shared in table-driven protocols, OLSR stands out using the Multipoint Relaying technique. This routing protocol, known for its flexibility, disseminates topology information by adapting the link-state algorithm/scheme. The message flooding aspect of the protocol to get link-state information is optimised by reserving the available bandwidth in the network using Multipoint Relay (MPR) nodes (Lansky et al., 2023; PANDIAN, 2024).

This innovative approach conserves valuable bandwidth within the network by designating specific nodes as MPR nodes. Instead of using all nodes to transmit data, OLSR designates specific nodes as Multipoint Relay nodes. This MPR node is responsible for relaying messages and significantly streamlining communication. This allows the protocol to effectively and economically flood its control messages by communicating only a selected subset of links with neighbouring nodes rather than sending information about all available links.

In OLSR, a decentralised MPR selection method enables nodes to cover all their two-hop neighbours with the fewest MPR nodes. Each node selects its MPR from its one-hop neighbours and communicates its decision to the other nodes. To identify MPRs, each node determines its one-hop and two-hop neighbours by exchanging Hello messages that include its node ID and a list of neighbour IDs along with their link statuses. These Hello messages are only processed by neighbouring nodes and are not further retransmitted. Next, each node selects an MPR set from its one-hop symmetric neighbours, those with bi-directional links. The chosen MPRs must collectively cover all strictly symmetric two-hop nodes within range. The MPR group then creates and retransmits Topology Control (TC) messages containing network connectivity information. Using this process, OLSR effectively reduces message overhead as redundant messages between neighbours are eliminated. Additionally, the MPR mechanism decreases the flow of messages by allowing only the designated MPRs to retransmit link-state information. (Hong et al., 2021; Soualfi, Agoujil, and Qarai, 2019).

Advantages of the Optimised Link State Routing Protocol

1. **Efficient Bandwidth Usage**

   Bandwidth usage is optimised by reducing relay messages because of the usage of MPR nodes for data transmission.

2. **Rapid Convergence**

   OLSR can quickly respond to network changes, such as node mobility, allowing for timely route updates and improved network performance.

3. **Decentralised Control**

   The protocol's resilience is enhanced as OLSR does not rely on a central controller. This reduces single network failure points.

4. **Scalability**

   OLSR is a suitable protocol for use in networks with increasing modal densities as it can handle varying-sized networks. This makes it ideal for small to medium-sized ad hoc networks and dense networks.

5. **Support for Different Link Characteristics**

   OLSR can work with symmetric and asymmetric links, providing flexibility depending on the network environment.

Disadvantages of the Optimised Link State Routing Protocol

1. **Overhead Due to Control Messages**

   While OLSR reduces message overhead, it still requires the periodic exchange of control messages (e.g., Hello and TC messages), which may lead to increased overhead in very dynamic networks.

2. **Limited MPR Selection**

   The network topology affects the effectiveness of the MPR selection process. If the selections are inefficient, there could be inadequate coverage of two-hop neighbours.

3. **Complexity in MPR Selection**

   Computational complexity sometimes results from the MPR node selection process used by OLSR in more extensive networks because nodes need to evaluate their neighbours and maintain updated lists.

4. **Assumption of Node Cooperation**

   OLSR assumes that all nodes cooperate and participate in relaying messages, which may not be the case in opportunistic networks where nodes can behave selfishly.

5. **Sensitivity to Node Density**

   The MPR technique may lead to excessive control message transmission in extremely high-density networks, negating some of its intended benefits.

B. Geographic Routing Protocol (GRP)

The Geographic Routing Protocol (GRP) employs geographic-based routing techniques, leveraging position data from systems like GPS to overcome the challenges typically associated with topology-based routing methods (Taha and Alhassan, 2018). One key advantage of GPR is that it does not require traditional routing tables as it is a position-aware protocol; it keeps track of the geographical position of all the nodes. This enables the protocol to operate and is well-suited for dynamic networks with rapidly changing topologies, such as Mobile Ad Hoc Networks (MANETs). GRP uses a straightforward methodology to identify optimal routes for data transmission. It sends data directly from source to destination, and this streamlined process eliminates the need to update routes continuously.

However, GRP has high overhead due to the bandwidth requirement needed to maintain a distributed location database of all nodes in the network (Arshad et al., 2019). This complexity can lead to increased resource consumption and potential delays in route establishment, particularly in more extensive networks where nodes are constantly moving. GRP utilises the geographical coordinates of the intended destination node and keeps track of the information concerning the nodes one hop away from it. GRP incorporates two primary strategies used in proactive routing protocols to facilitate efficient data forwarding: Greedy Forwarding and Face-2-Face Routing. Greedy Forwarding sends packets to the neighbour closest to the destination. At the same time, Face-2-Face Routing enables the protocol to navigate around obstacles in the network by exploiting the planar nature of the graph formed by the node locations. A significant advantage of GRP is its remarkable adaptability to changes in network topology. GRP's mechanisms allow it to find alternative optimal routes if the initial routes become unavailable or compromised. This ensures a continuous flow of data because the protocol can respond quickly to topological changes despite disruptions in the mobile networks (Verma and Sharma, 2016).

Advantages of the Geographic Routing Protocol (GRP)

1. Simplicity in Route Finding

GRP sends data directly from the source node to the destination once its location is known, simplifying the routing process.

2. Position Awareness

GRP does not use traditional routing tables but uses data from the geographic location of nodes in the network.

3. Adaptability to Dynamic Topologies

GRP suits dynamic networks like Mobile Ad Hoc Networks (MANETs), where nodes frequently change positions. GRP adapts to dynamic network topologies by recomputing and establishing alternative routes when the original routes become unavailable.

4. Efficient Data Forwarding Strategies

GRP efficiency is enhanced in data transmission by using methods like Face-to-Face Routing and Greedy Forwarding. which minimises network obstacles.

Disadvantages of the Geographic Routing Protocol (GRP)

1. Complexity and Overhead

GRP tracks the geographical information of every node in the network, which increases resource consumption and causes unavoidable delays.

2. Dependence on Geographic Information.

GRP's reliance on accurate geographical data can be a limitation in scenarios where such data is challenging to obtain or when node mobility causes rapid changes.

3. Scalability Issues

GRP has scalability issues in denser networks because maintaining a distributed location database can become complex, leading to communication delays.

4. Vulnerability to Location Errors

Positional data errors from GPS inaccuracies or other sources can result in routing failures or suboptimal paths, impacting the overall network performance.

2.3.1.2 Reactive Protocols

In this type of routing protocol, also known as an on-demand routing protocol, a dialogue that involves a query-reply routine is enacted only when there is a requirement for a path from any source to destination. For instance, should a node want to communicate with another, and there is no known route, the reactive routing protocol will look for the best route by trying to establish a possible route. Once a change beyond a predetermined threshold value is reached, the nodes react immediately. Reactive protocols are on-demand routing protocols because routes are found and established only when a source node sends data packets to a destination node (Sampoornam et al., 2020). A selection of reactive routing protocols relevant to this Research is discussed below.

A. Ad-Hoc On-Demand Distance Vector routing protocol (AODV)

AODV is a reactive routing protocol that searches for routes when needed, unlike the proactive protocols that maintain routing tables. AODV uses three control messages, namely: RREQ (Route Request), RREP (Route Reply message) and RERR (Route Error message). Assuming node-A wants to send data across to a destination node, Node-D, and there is no available route to send the traffic, it will initiate an RREQ message and broadcast it to all the nodes in the network. A node with an available route will unicast an RREP message back to Node-A. Nodes in active routes monitor the next hops, and when there is a link breakage, a RERR message is sent out to notify other nodes of the link breakage (Kashap et al., 2013; Sodagudi and Kurra, 2014). The counting to infinity problem from the classical distance vector algorithm in which nodes continuously update in a loop is avoided in AODV since it uses sequence numbers for each route (Ismail, Zulkifli and Samsudin, 2016; Alam and De, 2016; Abdullah, Ozen and Bayramoglu, 2019).

Advantages and Disadvantages of AODV

1. AODV reduces overhead by using on-demand routing and only establishing routes when needed.

2. It is suitable for use in dynamic networks.

3. AODV uses sequence numbers to prevent routing loops.

4. AODV uses unicast and broadcast methods for route discovery, increasing communication efficiency.

5. There is low latency for data transmission as route discovery is fast.

Disadvantages of the protocol

1. Route discovery delays could occur when a source node needs new routes.

2. The frequency of control messages increases in high-mobility networks, which increases the routing overhead.

3. AODV struggles to predict the next hop in dynamic networks since it does not maintain complete routing tables.

4. The protocol could have security vulnerabilities as it relies on control messages. This leaves it susceptible to security attacks such as sinkholes and spoofing.

5. AODV is suitable for unicast routing and less reliable for multicast communications.

B. Dynamic Source Routing (DSR)

DSR is an on-demand routing protocol. It uses two main mechanisms to transmit data packets from source to destination: route discovery and route maintenance. In its route discovery mechanism, a source node (also called the initiating node) transmits data packets to a destination by first adding a source route in the header of the data group before transmission (Almazok and Bilgehan, 2020). The data packet is sent via the identified route in the initiating node's local routing memory. If no available route is found, the initiating node will dynamically initialise routing discovery to find a route to the target node (Zhang et al., 2018).

In DSR's Route maintenance mechanism, each intermediate node (nodes that transmit data from the initiator node to the target node) that sends a data packet must verify that the data packet can pass through it to the next hop node. Each node keeps and maintains an update of routes (route maintenance) in its route cache until the information of a newly discovered route expires. When the route expires, the node seeking a new route will broadcast a Route Request packet (RREQ) and will get back a Route Reply packet (RREP) from other nodes (Chatterjee and Das, 2015).

Advantages of Dynamic Source Routing

1. **On-Demand Routing**

   DSR establishes routes only when needed, reducing the overhead required to maintain routes in dynamic networks.

2. **Source Routing**

   Path optimisation has increased flexibility as route information is contained within the packet header due to source routing.

3. **Adaptability**

   DSR adapts to changes in the network by discovering new routes quickly.

Disadvantages of Dynamic Source Routing

1. **Overhead needed for Route Discovery**

   Delay values are high in denser networks or networks with a high frequency of route requests due to route discovery.

2. **Scalability Issues**

   Denser networks could reduce performance due to congestion, as the protocol would require larger packets to hold the necessary amount of route information.

3. **Packet Size Limitation**

Larger packet sizes could cause fragmentation or loss, as the DSR protocol includes the entire route in the packet header, which could exceed the Maximum Transmission Unit (MTU).

2.3.1.3 Hybrid Routing Protocols

These protocols combine attributes from both proactive and reactive routing protocols in their algorithm. Several hybrid routing protocols exist today, such as Temporally Ordered Routing Algorithm (TORA), Zone Routing Protocol (ZRP), Enhanced Interior Gateway Routing Protocol (EIGRP), Adaptive Periodic Threshold Sensitive Energy Efficient Sensor Network (APTEEN), Sharp Hybrid Adaptive Routing Protocol (SHARP) Zone-based Hierarchical Link State (ZHLS), etc.

Temporally Ordered Routing Algorithm (TORA)

The Temporally Ordered Routing Algorithm (TORA) is a hybrid routing protocol that adapts well to changes in network topology, such as node failures, new node additions, or link quality variations. One key advantage of TORA is its scalability, making it suitable for highly dynamic networks. This adaptability also supports multicasting (Kaur and Mittal, 2014). Due to their dynamic nature, TORA is particularly effective for Mobile Ad hoc Networks

(MANETs). The protocol identifies multiple routing options from the source to the destination, which can be a disadvantage. When a single source and destination pair have several possible routes, some may not be the shortest.

TORA primarily relies on externally synchronised clocks to maintain the consistency of routing information across the network. If the synchronised clocks fail, the protocol may experience prolonged delays as it seeks to establish new routes (Dhiman, 2017). The Synchronised clocks help nodes coordinate their actions, such as when to regenerate routes or initiate route discovery processes, minimising delays and improving overall network performance. TORA mitigates the risk of routing loops through a sequence of timestamps and call events. While the use of synchronised clocks in TORA introduces complexity into the network, there is a trade-off as they invariably enhance the reliability and efficiency of the protocol when managing dynamic networks. (Sharma and Kumar, 2016; Ismail, Zulkifli, and Samsudin, 2016).

Advantages of the Temporally Ordered Routing Algorithm

1. **Scalability**

   TORA easily adapts to increases in network size and is designed to handle denser networks effectively.

2. **Flexible Reconfiguration**

   TORA promptly reconfigures its routing structure to adapt to unexpected changes in network topology, such as a failed node, without recalculating all routes. This leads to faster convergence and minimal disruption.

3. **Resource Efficiency**

   TORA is bandwidth-efficient because it does not require extensive updates.

4. **Dynamic Nature**

   TORA is particularly well-suited for mobile ad hoc networks (MANETs), where nodes frequently move, which can enhance the reliability of data transmission across the network.

Disadvantages of TORA

1. **Complexity**

   TORA requires time synchronisation among all nodes, which introduces network setup and maintenance complexity.

2. **Overhead with Large Changes**

   TORA may experience significant overhead adjusting the routing tables and may not perform optimally when multiple link changes occur.

3. **Latency**

   Since TORA relies on a reaction-based mechanism for updating routes, there may be latency in identifying and establishing new routes, especially in rapidly changing networks.

4. **Synchronised Clocks Requirement**

   TORA functions with synchronised clocks and can limit where TORA can be deployed.

5. **Potential for Partitioning**

   Network partitioning is an issue in TORA when there are rapid network changes or high mobility. This could hinder communication until new routes are established to stabilise the network.

2.3.2 Mobility Models

Mobility models are designed to describe the movement pattern of mobile users and how their location, velocity and acceleration change over time. In MANETs, all nodes are mobile and can be connected dynamically arbitrarily. The mobility of nodes causes frequent topology changes and may break existing paths (Chitra and Ranganayaki, 2020). Thus, when evaluating MANET protocols, choosing the proper underlying mobility model is necessary. The mobility characteristics of mobile nodes represent their movement pattern and how they change over time (Zarifneshat and Khadivi, 2013). Mobility patterns play a significant role in the performance of routing protocols, and as such, selected mobility models should reasonably resemble the movement pattern of targeted real-life applications (Wahanani et al., 2016). Simulation results, observations, interpretations, and conclusions could be misleading if this is not considered.

A range of mobility models have been designed to mimic real-life scenarios and are used to evaluate the network performance of wireless networks via simulation. These models are classified into two categories: synthetic and trace models. Synthetic models try to mimic real-life mobility patterns, while trace mobility patterns are the mobility patterns that are observed involving a large group of participants in real-life systems (Aschenbruck, Munjal, and Camp, 2011; Batabyal and Bhaumik, 2015).

Synthetic models are preferred for simulating mobility models since some real-life patterns seen in trace mobility models cannot be accurately modelled in new *ad hoc* networks, as the mobility patterns have not yet been created. The choice of mobility model deployed in a MANET network depicts the pattern of movement of the nodes contained in the network and how their velocity and acceleration vary over time (Aung et al., 2015). The random waypoint (RWP) mobility model has generally been the accepted choice of mobility models that most researchers use, since modelling this mobility model in a simulation environment is more straightforward. While the RWP mobility model may be more straightforward to carry out in a simulation environment, other mobility models could prove to have a better trade-off in terms of scalability, energy efficiency or other desirable network parameters (Medjo Me Biomo et al., 2020; Younes and Albalawi, 2020).

Geographic restrictions faced by the RWP mobility model can be overcome by incorporating a pre-defined map, which will be used to model real-life areas. Recently, position-aware routing protocols, due to their simplicity, position awareness, and scalability, have become the most used routing protocols deployed with MANETs (Almomani et al., 2015). However, in recent years, various position-aware routing protocols have been developed. However, the efficiency of such protocols can be affected by the underlying mobility model used. This implies that an inappropriate selection of mobility models may have devastating consequences for the performance of MANETs. Figure 2.1 shows categories of mobility models in MANETs and some examples.

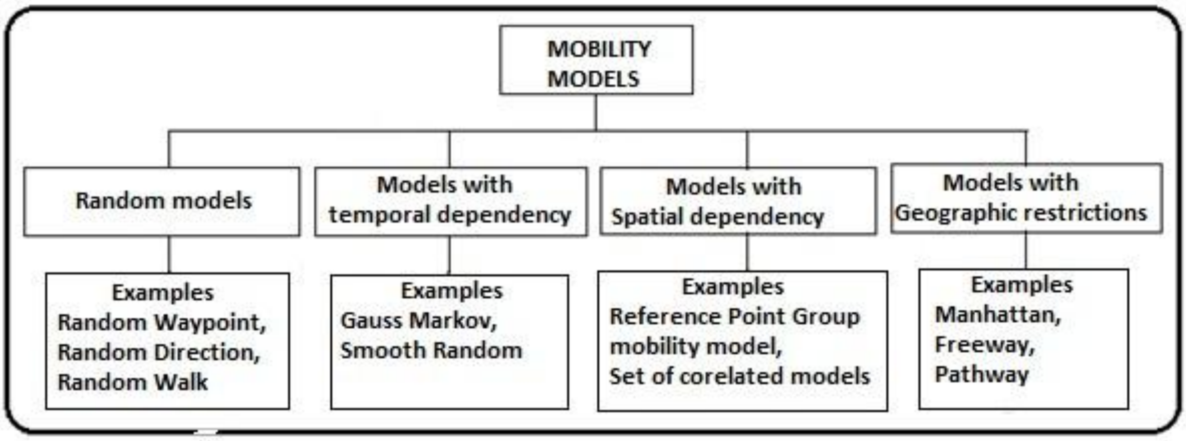

Figure 2.1: Categories of Mobility Models in MANETs, with some Examples

A selection of mobility models relevant to this Research is discussed below.

2.3.2.1 Random Mobility Models

Random Waypoint (RWP) Mobility Model

In this mobility model, the node remains in a specific location for a time interval, moving to a randomly selected location within the network coverage area at a chosen speed (Liu, Liu, and Yue, 2018). This mobility model (RWP) and its variants are very effective because they can mimic the movements of mobile nodes in real-life scenarios.

The major drawback in using the Random Waypoint mobility model, though, is its inability to model some real-life scenarios effectively due to its geographic constraints, temporal dependency, and spatial dependency. Geographic restrictions faced by RWP can be overcome by incorporating a pre-defined map to model real-life areas (Zhong et al., 2020). The widely accepted and reliable Random Waypoint Model is generally the mobility model of choice due to its implementation and analytical simplicity (Gupta, Sadawarti and Verma, 2013).

Advantages of the Random Waypoint Mobility Model

1. Researchers usually choose the RWP mobility model because it is easy to simulate.

2. This RWP mobility model is suitable for diverse research and application contexts as it mimics

realistic movement patterns. Network parameters such as the size (area) and the node speed can be easily adjusted.

3. Random Waypoint mobility models can be used to study the impact of specific mobility patterns on network performance because they allow the model's parameters to be adjusted.

4. The Random Waypoint mobility model is the standard framework for benchmarking and comparing results across various studies when evaluating routing protocols' performance.

5. The mobility model is suitable for small and dense network scenarios.

Disadvantages of the Random Waypoint Mobility Model

1. The RWP model assumes that the movement patterns of nodes in the network are random without considering real-world constraints such as obstacles in the network or human behaviour.

2. Pausing at random waypoints could result in inaccuracies, as these points may not reflect actual human or device behaviour.

3. The model often assumes that all nodes are moving at a uniform speed, but speed variations based on factors such as human behaviour could give skewed results.

4. Performance outcomes depend heavily on node density, and scenarios with very high or low densities may not accurately represent network behaviour.

5. The relevance of the simulation in practical applications could be limited as Nodes in the model make decisions based solely on random waypoints without considering their environment or network conditions.

2.3.2.2 Models with Temporal Dependency

Models with temporal dependency consider the time-based aspects of movement patterns in various scenarios, such as traffic modelling, pedestrian movement, or wireless network simulations. These models recognise that the future state of a moving entity (like a vehicle or a person) is often influenced by its past behaviour and the temporal context. They incorporate temporal dependencies such as historical data, events and environmental factors, which may influence how entities move over time in creating more realistic mobility simulations. This helps improve predictions of movement patterns and analyses in urban planning, transportation logistics, and network performance (Medjo Me Biomo et al., 2015).

Gauss-Markov Mobility (GMM) Mobility Model

The Gauss-Markov Mobility model can adapt to changing levels of randomness, like turning progressively, decelerating, or accelerating, or changes in the network area of coverage, motivated by the need for a model closer to reality (Liu et al., 2024; Naser and Wheeb, 2022). It uses a more predictable approach to determining the best route/ movement pattern for nodes in the network. The Gauss-Markov mobility model is a good example of a mobility model with temporal dependency. Its dependency on past direction and speed is controlled, and the current movement of a node (direction and speed) is related to its previous movement through Gaussian equations, using average speed and direction, as well as Gaussian random noise. Each node's initial speed and direction are calculated at a given time, t; the node will then move at the stipulated speed for a given time, T (constant). The process is repeated until the movement pattern is concluded (Medjo Me Biomo et al., 2015; Kumar et al., 2023).

Advantages of the Gauss-Markov Mobility Model

1. Theoretical Foundation

The estimators of the Gauss-Markov model are efficient, unbiased, and reliable under certain conditions because this model is well-grounded in established statistical theory.

2. Statistical Efficiency

It offers optimal estimation properties to minimise the mean squared error when the assumptions are met, particularly when considering linear relationships.

3. Applicability

This versatile model suits various domains, such as communication networks, environmental systems, and economics.

4. Simplicity

The Gauss-Markov mobility model is user-friendly as it is relatively easy to implement and understand.

Disadvantages of the Gauss-Markov Mobility Model

1. Assumptions

The model is based on several assumptions, such as linearity and the independence of errors, and these assumptions must be met to maintain its integrity.

2. Non-stationarity

When statistical properties change over time, such as in non-stationary data, the Gauss-Markov model struggles with implementation, which could affect its effectiveness in real-world applications where mobility patterns can change.

3. Limited to Linear Relationships

While the model performs well for linear relationships, it may not adequately capture complex, non-linear mobility patterns.

4. Inaccurate predictions

The performance of the Gauss-Markov mobility model is affected by outliers in data, causing inaccurate predictions because the results are skewed.

5. Lack of Spatial Considerations

The model may not fully account for spatial dependencies and interactions among mobile entities in a real environment, leading to oversimplified mobility predictions.

2.3.2.3 Models with Geographical Restrictions

Manhattan Mobility Model (MM)

The Manhattan mobility model simulates how mobile nodes move through real-life street intersections. The nodes can move straight, turn left, or turn right, and the probabilities for changing direction are as follows: there is a 50% chance of continuing straight, a 25% chance of turning left, and a 25% chance of turning right. This mobility model exhibits high temporal and spatial dependencies (Wahanani et al., 2015).

Advantages of the Manhattan Mobility Model

1. It is straightforward to implement in simulations requiring modelling of how people navigate intersections and streets in urban settings.

2. The model is helpful in urban planning and traffic management applications because it is a valuable tool that simulates correlated movement patterns. It has high Spatial and temporal correlation.

3. Predicting the location of nodes over time is essential in network design; this model's structured nature makes it easy to do so.

4. It is a widely used, well-documented mobility model in Research. Since research results are available, it can help compare simulation results within the field.

Disadvantages of the Manhattan Mobility Model

1. It does not account for complex human behaviour, such as navigating around obstacles or stopping to interact with others on the streets. Still, it assumes a simplified movement pattern of turning left, right, or continuing straight.

2. Congestion affects the types of mobile nodes in the network, which can prevent the varying speeds used from being accurately captured.

3. Since the movement pattern in the Manhattan mobility model is predictive, this could be a disadvantage in networks such as MANETs because of the networks' dynamic topologies.

4. The model may not fully capture the interactions between moving nodes, leading to inaccuracies in scenarios where nodes influence each other's movements.

Figure 2.2 is a diagram showing the Manhattan mobility model.

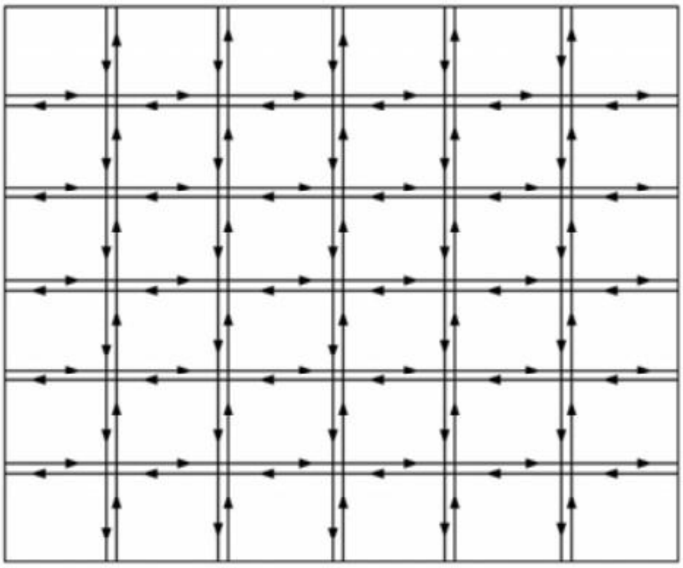

Figure 2.2: Manhattan Mobility Model

2.3.2.4 Models with Spatial Dependency

Models with Spatial Dependency Models with spatial dependency in mobility refer to frameworks that account for the influence of geographic location and the relationships between different entities in a given space. Individuals' or objects' movement patterns or behaviour are influenced by their surrounding environment and proximity to other moving entities. These models integrate spatial interactions and geographic data using statistical methods to analyse and predict mobility patterns based on spatial relationships and behaviour (Dianti et al., 2022).

Reference Point Group mobility model (RPGMM)

In the Reference Point Group Mobility Model (RPGMM), the nodes are organised into groups, and each group must have an assigned leader whose movement pattern they follow, allowing for some deviation. The structure of the RPGMM dictates that the nodes’ movements must adhere to a pre-defined pattern (specifically the movement of the group leader) (Gu et al., 2022). As a result, nodes in a Mobile Ad Hoc Network (MANET) can coordinate their movements for various mobility applications. Potential areas for deployment include military communications on the battlefield, platoon movements, emergency services, and disaster recovery scenarios (Dianti et al., 2022; Dorge and Meshram, 2018).

Below is a breakdown of how the Reference Point Group Mobility Model (RPGMM) operates.

Structured group

All the nodes in RPGMM are divided into groups, and each group has a leader whose movement defines its overall trajectory.

1. **Follower Behaviour**

   The movement of the nodes in RPGMM is closely coordinated, although they follow the group leader by mimicking its movement pattern.

2. **Pre-defined Movement Pattern**

   The predictability of group behaviour in terms of mimicking the group leader's movement trajectory is a systematic approach that enhances the mobility model's performance, as it is predictive.

3. **Random Motion**

   Although they follow the group leader, the remaining nodes still have random motion, which allows them some autonomy in their movement trajectory.

4. **Mobility Applications**

   RPGMM is particularly useful in scenarios requiring a structured approach, such as disaster recovery and military communications, where teams need unit cohesion and coordinated movement patterns.

Advantages of the Reference Point Group Mobility Model (RPGMM)

1. **Structured Coordination**

   The coordinated movement of nodes in RPGMM enhances the network's efficiency by reducing disconnections in MANETS.

2. **Enhanced Safety**

   Coordinated movement can maintain unit integrity and reduce risks associated with isolated movements in military operations or disaster recovery scenarios.

3. **Realistic Mobility Patterns**

   Simulations produce realistic mobility patterns, which are beneficial for modelling and analysis. Other nodes in an RPGMM-based network mimic the leader's movement while allowing some deviation in trajectory.

4. **Predictability**

   RGPMM is suitable for use in applications like emergency services, disaster recovery, and military operations. These applications benefit from the follower nodes' predictable behaviour of aligning with the group leader's pre-defined movement patterns.

5. **Scalability**

   RPGMM is scalable for denser networks as it efficiently manages multiple groups. This makes it a good fit for such networks when implemented, like in disaster recovery, where many teams might be needed and required to operate simultaneously.

Disadvantages of the Reference Point Group Mobility Model (RPGMM)

1. **Dependence on the Leader**

   The entire group's reliance on the group leader's movement pattern creates vulnerabilities in the network if the leader makes poor navigation decisions or becomes immobile.

2. **Limited Flexibility**

   While randomness is incorporated in RPGMM, the overall movement may still lack the flexibility that individual node mobility might require in unpredictable topologies.

3. **Complexity in Leadership Dynamics**

   In dynamic environments with fluid roles, the need to designate group leaders and manage leadership changes can become complicated.

4. **Possible Congestion**

   Coordinating multiple groups can lead to navigational issues and network congestion, especially in high-density areas, which can disrupt communication.

5. **Overhead**

   Processing the leader's communication among nodes for monitoring and adapting to the leader's movements might increase overhead.

2.4 Related work

2.4.1 Introduction

In February 2023, a magnitude 7.8 earthquake hit central Turkey and northwest Syria. This was followed by a second 7.7 quake barely nine hours later, while rescue efforts in both countries were still making attempts to search for survivors. Entire sections of major cities, including buildings, roads, and communication infrastructure, were wiped out. With the advent of the second quake, the number of people that were buried under the debris increased, thousands more were injured, the death toll rose steadily, and people were generally in a state of panic. The second quake undermined the rescue attempt from the first quake as the initial post-disaster analysis changed due to the aftershock. Not all disasters are on such a massive scale. However, the need to deploy an efficient and effective disaster management plan is crucial, irrespective of the disaster area size, as lives could be at stake. Some disasters could occur in hard-to-reach places, such as mountainous regions or remote areas without internet connectivity.

Many challenges are faced in small-scale disasters, especially in hard-to-reach areas and areas without communication infrastructure. These challenges stem from the need to alert and coordinate rescue teams and deploy them effectively and promptly. In the case of an avalanche, for example, knowing the precise location of the coordinated rescue effort teams is very important as it supports the decision-making of the rescue mission coordinator, who is usually in the control room/mission coordination headquarters. United Nations Disaster Assessment and Coordination (UNDAC) teams, for example, aim to deploy anywhere in the world on the occurrence or early warning of an emergency at short notice, usually between twelve and forty-eight hours (United Nations Office for the Coordination of Humanitarian Affairs (OCHA)). The most critical period is the first seventy-two hours (usually known as the Golden Relief time) after the disaster (Reina et al., 2014). The probability of finding survivors after that time is very low. Similarly, in the case of smaller-scale disasters, such as avalanches, deploying rescue operations quickly could be a determining factor in the mission's success, as it might make a real difference between the survival or death of the trapped people. Waiting for a more organised Search and Rescue mission involving professionals not likely to be situated in the disaster zone will typically require a lengthy intervention time. Some of these rescue operations are time-sensitive, such that the best bet for a quick and effective rescue operation might be the use of companion rescue or people already on the ground. This could be a more viable solution with a more resilient and robust communication link network that is adaptive to network topological changes.

2.4.2 UAVs in Disaster Management

The deployment of UAVs in Disaster Management is becoming popular because of their recent affordability and increased flexibility of use. They can be used as a remote disaster sensing system, monitoring, providing infrastructure, and collecting disaster assessment information. UAVs can also be used to remotely acquire aerial disaster images for appropriate mapping after a disaster without risk to human life. Similarly, victims stuck in dangerous and hard-to-reach areas could be reached without the need for human rescuers (Asad et al., 2023; Mohsan et al., 2023; Hildmann and Kovacs, 2019; Boukerche and Coutinho, 2018).

Erdelj and Natalizio (2016) proposed a three-stage operational lifecycle for UAV participation in natural disaster management. The first stage is the pre-disaster preparedness stage, which includes surveying related events that precede the natural disaster, setting up Early Warning Systems (EWS), etc. The next stage was logistics planning based on damage studies and assessment from collated data, while the last stage of disaster management was disaster response and recovery. This includes Search and Rescue (SAR) missions.

After the golden relief time, the probability of finding survivors is extremely low, so coordinating first responders and/or people to be rescued plays a vital role in maximising the first 72 hours. Communication systems like base stations would be destroyed or malfunctioning. In this study, the focus is on Search and Rescue (SAR) missions, particularly disaster recovery in terms of forming the communications backbone using UAVs to provide situational awareness (area mapping and restoration of communication links) during the disaster in real-time by sending feedback to the base station (Control Centre). Nowadays, people mostly communicate with each other by mobile phones and smartphones, making calls or sending text messages through the Internet and social networks via applications such as WhatsApp, Facebook, Twitter, and others. However, cellular-based communications may not be possible after a disaster occurs (Deepak et al., 2019). These devices and the UAV will form MANETs. The Mobile Ad hoc Networks formed by the UAVs will spontaneously establish standalone bi-directional communication systems.

Simulations have been carried out to mimic the movement patterns of the UAVs, the ground nodes such as the rescue teams/ ground crew, the victims in disaster recovery, or both. Evaluation results infer that most Research into new mobility models is based on modelling generic human movement patterns. In addition, selecting routes from source to destination for data packets is equally essential. Research into routing protocols has emphasised finding the shortest possible routes.

A mobility model called Human Behaviour for Disaster Areas (HBDA) was proposed by Conceição and Curado (2014). This new mobility model was designed to imitate the movement of actual nodes in the search missions. It was based on a force vector. They considered the change in topology, coverage area, node density, node degree, and Throughput. The authors concluded that HBDA mobility was a better representation of the real-life movement of nodes in a disaster scenario than random-based mobility models such as the Random Waypoint mobility model. Their Research, however, did not consider the scalability of the network.

Panda et al. (2019) considered deploying a UAV-assisted emergency Wi-Fi chain network, Wi-Fi Network on Drone (WiND), to support rescue operations in a disaster recovery area. Their proposed model focused on collecting surveillance data, maintaining effective communication links, and synchronising the UAVs in the network. They designed a portal, which they called a captive portal, for the available Wi-Fi network coverage area, which would be used to alert survivors and direct them to rescue stations. They used UDP (User Datagram Protocol) and TCP (Transmission Control Protocol) in two WiND-deployed networks and compared their simulation results. Their results showed that the UDP-based network performed better and had higher Throughput values over smaller distances (area of coverage) when compared to the TCP-based network. They also compared the performance of their Wi-Fi AP to a traditional ad-hoc mode of operation using different frequency bands, and their results showed that theirs was better. However, their model Wi-Fi Network on Drone (WiND) did not consider changing the position of the UAVs in the event of a change in the deployment environment.

Research by Fotouhi, Ding, and Hassan (2017) proposed the deployment of free-moving Drone Base Stations (DBSs), which will use a more innovative user association technique to cruise the network. Their framework also requires global knowledge of the network and attempts to overcome the dual issues of UAV collision and user association conversant with free-moving base stations. The authors experimented and compared the performance of their proposed scheme in which the flying base stations moved freely while ignoring cell boundaries with a network in which the Drone Base Stations were fixed (restricted to flying within their cell boundary). Their simulation results showed that their proposed framework performed better. However, it was a trade-off between having a higher Throughput using an intelligent and complex user association scheme, which required global knowledge of the network or a lower Throughput value when a simpler network algorithm was used, which was less complicated and required less computation.

The study by Hayajneh et al. (2018) focused on developing an analytical framework to statistically evaluate the coverage probability and energy efficiency performance metrics for cluster-based drone-enabled recovery networks. They found that factors such as the disaster recovery area radius, drone altitudes and drone densities can affect a ground user's energy efficiency and the network's coverage probability. Their solution was a suggestion to optimise these factors. However, in their analytical framework, they assumed that there would be independent thinning of base stations to simplify their analysis. They did acknowledge, however, that in practicality, it may be non-realistic for urban areas of the city and that the thinning of base stations in an actual, real-life, post-disaster scenario would likely depend on their geographical location.

Duruyck et al. (2016) proposed using UAVs to send numerous femtocell base stations to pre-defined locations to act as unmanned aerial base stations. These femtocells would provide a temporary network in emergencies such as disaster recovery scenarios. Their results looked promising, but they would need to deploy many drones to get their desired results. Realistically, increasing the number of drones to this level might be counterproductive as it would not be cost-effective or energy-saving.

Furthermore, Lee et al. (2020) proposed a framework, DroneDR, for positioning UAVs using reinforcement learning. Their main objective was maximising the number of active connections while considering the importance of the type of ground nodes. Their proposed framework uses information about the position of the user node in the network and their connectivity requirements to determine where to position the UAVs in the UAV grid network. In their work, the UAVs must always be connected, and the search for the location of nodes in the network must be carried out in discrete timesteps. They tested their network using a small-scale and a large-scale disaster area, focusing on the maximum connection in the network, and compared their results to a greedy Steiner heuristic algorithm and the Random Waypoint mobility model. DroneDR performed better regarding the maximum number of connected nodes in the network.

A clustering-based approach was proposed by Saif et al. (2021) in which the UAVs are concerned with connection to the cluster head of the ground node as a check to show connectivity in the network. Their study was focused on finding the optimum altitude for the UAVs. Also, their concern was connectivity with the cluster head; it was the cluster head's job to ensure the other nodes were connected. However, the Research work presented here differs from theirs as they did not attempt to introduce adaptive intelligence networking for UAVs. In SAIMOD, nodes within the range of the UAV can connect to them, and there is bi-directional data transfer between the ground nodes and the UAVs.

Some other researchers have suggested using different parameters to determine optimum UAV positioning. The Research by Chenxiao and Huang (2022) explored achieving energy efficiency by optimising the UAVs' flight radius and transmission power in their test scenario as the criteria for determining UAV positioning in the network. Their Research studied the energy efficiency gap between ground users and flying base stations. They proposed optimising the energy efficiency of the network by adjusting the UAVs' flight radius and transmission power. They tested their proposed solution by carrying out simulations, and their results showed that the convergence speed of their algorithm was fast and could find the optimal flight radius and transmission power for use by the UAVs within a few iterations. However, they were not concerned with creating a bi-directional information exchange between the UAVs, ground nodes, or control rooms. In addition, avoidance of physical drone collision was not considered.

Faraci et al. (2023) considered a green alternative to solve the limited energy issues in the network by using wind-powered charging stations for the UAVs. They proposed an algorithm to determine the scheduled use of the charging stations. Their framework depends on the wind-powered generator generating enough energy to charge the stations. Their solution to limited energy sources in the network is to have charging stations deployed as close to the UAV network as possible. This UAV network will be a FANET, which will use reinforcement learning to manage resource allocation, such as how many UAVs will take off, based on the power-generating ability of the wind turbine. However, as this framework depends on the availability of wind, its application is limited in disaster scenario areas where this cannot be effectively harnessed. Also, where the terrain is unfavourable for moving the wind-powered generator, this limits the use of this framework.

Using UAVs as a bridge in restoring communication links in disaster recovery scenarios is a fast-growing solution that is rapidly gaining traction due to its recent affordability and ease of deployment. Many researchers have proposed various approaches to maximising the effectiveness of these *ad hoc* networks, either on a large scale or in small-scale disaster scenarios. Proposals have included mesh networks and the use of machine learning methods such as reinforcement learning (Purushotham, Priya, and Kiran, 2022; Tsai et al., 2019; Sharma, Kumar and Rana, 2015; Zuluaga et al., 2018; Zhang et al., 2022), deep learning (Seid et al.; 2023; Tang et al., 2023; Abbas et al., 2023; Bălaşa, Bîlu, and Iordache, 2022; Moon et al., 2021; Niroui et al., 2019), convolutional neural network (Barik et al., 2022), mathematical and analytical algorithms (Faraci et al., 2023; Fu et al., 2023; Jia, Chen and Jian, 2022; Kashino, Nejat and Benhabib, 2019), theoretical frameworks (Papaioannou et al., 2021; Boukerche and Coutinho, 2018; Ruan et al; 2018), and many more approaches.

Previous works have proposed positioning the UAVs to establish communication links and optimise connectivity in the *ad hoc* networks created. This Research differs from previous works. It designs and develops a framework, the Self-Aware Intelligent Model (SAIMOD), that stipulates the optimum routing protocol and model to use with an intelligent, self-aware UAV network. In addition to restoring connectivity, this network will transfer bi-directional data with the ground nodes and the base station if required. The UAVs will not only restore connectivity, as has been the goal of several previous studies, but also act as a support system for Search and Rescue teams / Disaster Management Teams (DTMs). They can also be used to receive and transmit time-sensitive data that can make a difference in the decision-making process of the SAR mission, such as the severity of wounded persons. In addition, the results collated from the framework's performance could form part of an assessment model for resource management.

Consequently, the key contributions in this work are the incorporation of intelligence networking amongst the UAVs to avoid overlapping coverage, SAIMOD's ability to adapt to changes in the UAV network topology, such as UAV malfunction or failure, with energy conservation as a plus, and the use of the framework's results as part of an assessment model for resource management.

Chapter 3

Selection of Mobility Model and Routing Protocol

3.1 Introduction

As discussed in the previous Chapter, selecting routing protocols and mobility models plays a vital role in overall network performance. They can affect network performance metrics such as average Throughput, End-to-End Delay, Network Routing Load, energy consumption, and Packet Delivery Fraction.

In this Chapter, a suitable mobility model and an appropriate routing protocol are selected based on the evaluation of the network performance metrics for the proposed framework (SAIMOD). The network setup using Riverbed Modeller 18.0 (OPNET) is explained in detail, together with the initial assumptions made on the network scenarios and boundary conditions.

3.2 Simulation software

The first step of this Research is testing suitable mobility models and routing protocols using simulation. The Riverbed Modeller 18.0 (OPNET), a Discrete Event Simulator (DES), is used in this selection to find a suitable routing protocol and mobility model that meets the desired metrics. What makes the OPNET software suitable for building simulations is its ability to model and manage simple to complex hierarchical network models with network topologies (both static and dynamic) of varying complexity.

Network models with varying communication links, such as wireless networks, multi-point and point-to-point, can be created with unlimited sub-network nesting as the user desires. OPNET has robust traffic and generation parameters that allow for the simulation of applications such as email, voice, video, and FTP. Another advantage of using Riverbed Modeller 18.0 is that it allows the geographic modelling of nodal movement (mobility models) by controlling movement using pre-defined trajectories or allowing nodes to change their positions dynamically. Background graphics, such as maps, can also be added to enhance the geographic representations of network models.

Using the Riverbed 18.0 platform, mobility models and routing protocols can be simulated in network models, allowing analysis of the performance metrics of various networks, like MANETS, WLANs, Wi-Fi, WiMAX, LTE and ZigBee. Its model library has many routing protocols, such as OLSR, AODV, TORA and DSR. Riverbed 18.0 also allows the incorporation of physical layer characteristics into network models during setup, and already-built networks can later be edited. The user can also collect statistics on performance metrics, such as the Throughput characteristics of links, routing packets generated, environmental effects, link availability, and Delay when communication links are modelled. OPNET's comprehensive display tools enhance and simplify the interpretation of simulation results. All simulation results are from 10 discrete event simulation (DES) runs, which are averaged for each point.

3.3 Performance Metrics

In MANETs, there is usually a communication path between two nodes in the network. This implies that path loss and Delay values depend heavily on parameters such as node distribution, node density, link breakage, etc. (Al-Essa and Al-Suhail, 2022; Sharma and Kumar, 2020). The results generated by the simulation model must be compared to well-defined performance metrics, which ensure that its performance reflects how it would behave in a real-life test-bed scenario. The parameters chosen for this piece of Research work are:

I. Throughout

This represents the average number of bits successfully received in bits per second. It is given by the average number of packets that are successfully received at the receiver per second (Atefi et al., 2016)

OPNET calculates Throughput with the formula below:

$$\text{Throughput} = \text{Packet Average}/\text{Sim\_Time} \qquad (3.1)$$

Where 'Packet Average' represents the total number of packets that were accepted and

'Sim_Time' represents each simulation's cumulative simulation time (current).

II. Average End-to-End Delay (seconds)

This is the average time taken for all the data packets from the source to reach their destination. It is also the End-to-End Delay of all successfully received data packets from the WLAN MAC forwarded to a higher layer. It includes retransmission Delays at the MAC, buffering Delay, transfer and propagation times, medium access Delay (source), queuing and delay due to time taken for the reception of all the fragments individually, as well as Delay caused during route discovery latency, queuing at the interface queue, etc.

III. Packet Delivery Fraction (PDF)

This is the ratio of the number of packets successfully delivered at the destination node to the number of packets sent by the source node. PDF is usually inversely proportional to mobility. That is, it decreases as mobility increases.

IV. Network Routing Load (NRL)

This represents the ratio of control/routing packets a source node generates to the number of packets successfully delivered to the destination node.

V. Retransmission Attempts

This is the total number of Retransmission attempts in a network until a packet is either successfully transmitted or discarded (Abdullah, Ozen and Bayramoglu, 2019).

VI. Jitter

Jitter is the Variation of the End-to-End Delay across the network. As the Delay varies, bits arrive early or late at the destination. If they arrive too quickly, bits might overflow a buffer. If they arrive too late, silence results. Gaps in the conversation occur either way. The G.114 recommendation for good voice quality by the ITU-T (International Telecommunication Union Telecommunication Standardization Sector) stipulates that no more than 150 μs of End-to-End Delay should occur for one-way voice transmission. The ITU-T recommendation notes also acknowledge that conversations sometimes occur outside this acceptable voice quality range. This implies that voice quality could be whatever the end users will accept (Patel et al., 2019; Goralski, 2017; Razavi, 2021). However, for Quality of Service, this Research would use 150 µ secs or less for Jitter values as a benchmark for voice quality.

VII. Mean Opinion Score (MOS)

This is a numerical indication of the perceived quality of the media received after transmission. It is usually given a value that ranges between 1 and 5, with 1 being the worst performance and 5 the best (Lepcha et al., 2023; Arnez and De Souza, 2023). This is summarised in Table 3.1.

Table 3.1: Voice MOS (Mean Opinion Score) grading system (Lepcha et al., 2023; Arnez and De Souza, 2023)

Grade	Meaning
1	It is graded as being impossible to communicate.
2	MOS is graded as nearly impossible to communicate.
3	The voice quality is annoying.
4	This value of MOS is rated as fair/ acceptable. This is the acceptable MOS values for cellular communication (mobile phones).
5	This is the best MOS quality. Rated as perfect. It can be likened to having a very good quality radio reception or face-to-face conversation

3.4 Network Setup and Parameters:

This Research makes some assumptions for simulating the small-scale disaster recovery scenario.

I. Communication infrastructure, such as base stations in a fixed-sized disaster area, has been destroyed or damaged due to a natural or man-made disaster.

II. The disaster area will contain a pre-defined number of ground nodes (a combination of rescue teams and people to be rescued).

III. Unmanned aerial vehicles (UAVs) will be deployed to re-establish destroyed or damaged communication links in the disaster recovery area.

IV. The Unmanned Aerial Vehicles (UAVs) move and maintain a pre-defined altitude above the ground at a constant speed with a pre-defined pulse time.

V. Each UAV will create a MANET to set up bidirectional wireless communication links between it and the ground nodes.

VI. The simulation assumes that people (ground nodes) positioned randomly have some portable device, such as mobile phones.

VII. The trajectory/mobility pattern of the ground nodes will be set to one of the four mobility models being tested: the Gauss Markov mobility model, the Random Waypoint mobility model, the Manhattan mobility model, and the Reference Point Group mobility model.

VIII. The UAVs will be distributed to ensure complete coverage of the ground nodes in the disaster recovery area.

IX. Each UAV will be connected to other UAVs in the network and to the ground nodes. If a ground node cannot connect to a UAV, it can exchange data via a node connected to any of the UAVs. The UAVs will act as relays.

X. No ground node is isolated from exchanging packets.

XI. Debris is randomly scattered in the network.

XII. The nodes in the simulated network will support four applications: Voice over Internet Protocol (VoIP), email, peer-to-peer file sharing and FTP.

XIII. Each UAV will be able to connect to at least one ground node, which must be the group leader node (one of the rescue team members).

3.4.1 Justification for Applications Selected

Selecting these applications is a strategic decision to enhance overall efficiency and effectiveness within the SAIMOD framework. Below is a description of the selected applications.

1. File Transfer Protocol (FTP)

File Transfer Protocol (FTP) is a user-friendly tool designed for fast and efficient data transfer. Its benefits are particularly evident during emergencies, as it allows for quickly distributing crucial data and images. It operates over a client-server architecture where the client initiates the connection to the server to upload or download files. FTP is a reliable resource for disaster recovery, ensuring timely access to information, minimising downtime, and facilitating the recovery process (Liu, Liu, and Wu, 2023).

2. VoIP (voice over Internet Protocol)

VoIP is a versatile tool that allows users to transmit voice and multimedia content. It also enables call recording, custom caller ID, and voicemail to email. In disaster recovery, this versatility could be helpful in the ground nodes (rescue team and people to be rescued) to send voice mail or communicate with one another in their group should they become disconnected from the group leader or if the group size grows more extensive due to unexpected changes in network topology.

VoIP can also route calls through existing telephone networks if available. Ideally, each group should have an approximate number of ground nodes in line with the disaster management plan; however, unplanned changes could arise in a disaster scenario that could mean the number of ground nodes is more than expected.) The specific features of VoIP that are most beneficial for disaster recovery scenarios include call recording, custom caller ID, voicemail to email, and the ability to function over various networks, including existing telephone lines. These features enhance communication flexibility and ensure critical messages can still be transmitted even in challenging conditions.

VoIP systems can be integrated with existing emergency communication infrastructure by establishing compatibility protocols and using gateways to connect VoIP networks with traditional telephone systems. This integration allows for seamless communication among all parties involved, ensuring that everyone can stay connected regardless of their platform (Jelassi and Rubino, 2013; Jelassi et al., 2012; Mewara and Manghnani, 2015).

3. Peer-to-Peer (P2P)

Peer-to-peer (P2P) is a decentralised system that eliminates the need for intermediaries when transmitting data. This allows information to be easily shared directly among the ground nodes in a network or unmanned aerial vehicles (UAVs). The P2P model creates a robust network by enabling devices to connect directly for data transfer or file sharing without relying on a central server. This makes it especially suitable for mobile ad hoc networks (MANETs).

This model is effectively used in decentralised applications, blockchain networks, and file-sharing platforms, improving efficiency and scalability while significantly reducing dependence on centralised control. In a P2P system, the seamless sharing of resources such as files occurs efficiently, as each user, known as a "peer" or ground node, holds equal status within the network. Peer-to-peer (P2P) is a decentralised system that eliminates the need for intermediaries when transmitting data. This allows information to be easily shared directly among the ground nodes in a network or unmanned aerial vehicles (UAVs). The P2P model creates a robust network by enabling devices to connect directly for data transfer or file sharing without relying on a central server. This makes it especially suitable for mobile ad hoc networks (MANETs).

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4. Email

Emails continue to be a commonly used communication tool that spans various demographics. Almost everyone has an email account, making it more universally accessible than social media platforms or messaging apps. This reliability in communication is one of its significant advantages. Email allows for quick exchanges and enables users to send bulk messages simultaneously. Additionally, it offers flexibility by allowing the transmission of diverse types of data, including images, videos, and text. For example, pictures of meeting locations or essential messages about those locations can be emailed to the groups involved in a disaster recovery plan (Chien and Khethavath, 2023).

These selected applications (FTP, VoIP, P2P and Email) have the following advantages:

1. **Functionality and Features**

   Each application offers robust functionality that aligns with the Research Aim and Objectives. Its critical features enhance productivity and make it a good fit for SAR operations.

2. **Integration Capability**

   A key consideration for SAIMOD is its ease of deployment and use. The selected applications can be seamlessly integrated with existing systems.

3. **Scalability**

   The applications can accommodate increasing user demands and additional features without compromising their performance in the network.

3.4.2 Justification for Mobility Models and Routing Protocols chosen for evaluation

The criteria for selecting the mobility models and routing protocols evaluated in this study were aligned with the Research objectives. The primary goals included identifying a suitable mobility model and an appropriate routing protocol for use in the SAIMOD framework. With these goals in mind, the following criteria were considered:

1. **Scenario Requirements**

Different mobility models may be better suited for specific applications. This Research evaluated the SAIMOD for disaster recovery scenarios, so mobility models suited for such scenarios were selected for testing.

2. **Network Topology**

The network's static or dynamic structure influences the choice of mobility models and protocols. For example, some protocols perform better in specific topologies than others.

3. **Mobility Patterns**

The movement trajectory/pattern of nodes within the network can affect the network's performance.

4. **Compatibility**

The selected protocols must be compatible with the underlying technology and standards being used in the Research. For example, group members are supposed to follow the group leader to enhance communication and ease the SAR operation.

5. **Performance Metrics**

Different protocols and mobility models optimise for different metrics. A key consideration was how each mobility model and protocol performed under relevant network parameters such as Throughput, Network Routing Load (NRL), and Delay.

6. Previous Work

Another factor considered was existing literature and previously successful models and protocols used in related works.

These protocols and mobility models provide a robust routing and mobility patterns framework in mobile ad hoc networks. Still, their effectiveness can vary based on network conditions and topologies. A range of protocols encompassing reactive, proactive, and hybrid routing protocols were strategically chosen to ensure a thorough assessment. This approach allowed for the comprehensive evaluation of their effectiveness across the four distinct mobility model classifications (Random models, Models with temporal dependency, Models with spatial differentiation, and Models with geographic restrictions), which were also chosen for the same reason (to represent a balance of choice across classification). These protocols and mobility models provide a robust routing and mobility patterns framework in mobile ad hoc networks. Still, their effectiveness can vary based on network conditions and topologies.

Additionally, the simplicity and ease of implementation of these models and protocols played a crucial role in guiding the selection process, as the main aim for this aspect of the Research (selecting a suitable routing protocol and an appropriate mobility model) was to develop practical solutions that could be efficiently deployed in real-world scenarios. Different routing protocols and mobility models have various characteristics, advantages, and disadvantages that depend on network size, topology, scalability, security, performance requirements, etc. This complexity makes them less suitable for the fast-paced and dynamic nature of Search and Rescue (SAR) missions (Affandi, Mahiddin and Mohamad, 2024). It is worth noting also that various researchers involved in disaster recovery simulations have similarly opted for this method of selection, prioritising mobility models and routing protocols that demonstrate a high degree of compatibility with Search and Rescue (SAR) operations (Mahiddin, Affandi and Mohamad, 2021; Hasan et al., 2021; Safaei et al., 2021).

Furthermore, some protocols, such as the Open Shortest Path First (OSPF) link-state routing protocol and the Associativity-Based Routing (ABR), require a network topology to calculate routes and efficiently maintain a reliable routing table. Others, such as the Interior Gateway Routing Protocol (IGRP), can operate in dynamic environments but often involve substantial overhead in data exchange (Alhihi, 2017). Protocols like these can face challenges in highly dynamic or unstable network environments, leading to inefficiencies and increased communication overhead. They rely on stable network topology, which can be challenging to establish and maintain during disaster recovery operations, and they usually require significant communication overheads.

Additionally, some mobility models, such as the Community-based Mobility Model (CMM), impose substantial routing overhead, which can introduce delays and inefficiencies, making them unsuitable for scenarios where rapid response is critical (Ryu et al., 2019; Vastardis and Yang, 2014). Some mobility models, like the Self-Similar Least-Action Walk (SLAW), operate under the assumption that there are no obstacles in the path of human movement. According to this model, once a person decides on a destination, they can move directly to the next waypoint without any disturbances or interference, as the path is free of obstacles. Consequently, the person's speed and direction remain unchanged (Solmaz and Turgut, 2019; Luca et al., 2021). However, debris often makes this assumption inaccurate in a disaster recovery scenario, as obstacles can significantly affect movement in the disaster area.

In this Research, for example, the Associativity-based routing (ABR) protocol that requires extensive initialisation or maintenance processes was deemed impractical for timely response in emergency scenarios. It was excluded due to the complexity of its implementation. In contrast, the protocols and mobility models selected for testing in this Research are easier to deploy and manage. As such, they were prioritised, ensuring rescue teams could effectively utilise them in the field without getting bogged down by complicated processes. Some other protocols and mobility models, such as the Routing Information Protocol (RIP) and the SLAW, are not scalable in denser networks (Medhi and Ramasamy, 2017; Verma and Bhardwaj, 2016). This led to the selection of mobility models and routing protocols for testing focused on those that offered a more streamlined and effective solution. This approach maximises operational efficiency and enhances the overall effectiveness of SAR efforts.

In summary, the specific criteria for selecting the various mobility models and routing protocols in this Research were established by focusing on their characteristics and how well they align with the demands of disaster recovery scenarios. An essential aspect of the evaluation process was to analyse the performance of each mobility model and routing protocol based on key network parameters, which include Throughput (the rate of successful data transmission), Network Routing Load (NRL, measuring the overhead and traffic generated by routing processes), and Delay (the time taken for data packets to travel from the source to the destination). These mobility models and routing protocols were evaluated to enable accurate analysis of the impact of the choice of mobility model(s) and routing protocol(s) on a MANET network's overall performance, particularly in disaster recovery. The Reference Point Group mobility model and the Optimised Link State Routing Protocol (OLSR) were the most suitable choices for use in SAIMOD. Their significant impact on the MANET network's overall performance, showing better Throughput performance and an acceptable level of Delay as detailed in this Chapter, underscores their suitability for disaster recovery scenarios where efficient and reliable communication is crucial.

3.4.3 Selection of Group Leaders

The MANETs, formed in the disaster area by the UAVs and the ground nodes (comprising the SAR teams and people to be rescued), to support emergency information exchange are greatly facilitated by devices such as Wi-Fi-enabled notebooks, mobile phones, and more. This approach supports push-to-talk, mobile social networking, email, Voice over Internet Protocol, instant messaging, and more, ensuring effective and reliable communication. The information can be transmitted between UAVs and ground nodes (typically, each group of ground nodes would have a leader they follow).

The group leaders in each disaster recovery scenario are not randomly selected. Instead, they are chosen based on a pre-selection process. This deliberate and strategic approach is integral to the overall disaster management plan. The designated group leader would typically be a member of the rescue team making efforts on the ground, such as directing/leading people to the safe zones.

To enhance communication and coordination, these leaders are equipped with mobile devices coded with unique identifier numbers, essential for record-keeping and recognising other personnel relevant to the SAR operation. The unique identifier numbers assigned to each device are established during a thorough network setup phase. This process ensures that every device has a distinct identifier and can be seamlessly integrated into the more extensive disaster management system. This is necessary to effectively deploy the UAVs (Unmanned Aerial Vehicles) that form part of the SAIMOD network, as using these identifiers helps facilitate accurate tracking and communication; this invariable enhances the efficiency and effectiveness of the response efforts.

The following were included in the initial network using the object creation pallet in Riverbed Modeller 18.0:

- One Application Configuration node
- One Profile Configuration node.
- Thirty users (WLAN Workstations).
- Three UAVs having onboard processors, this is represented by three mobile workstations

(MANET workstations; each will be given a unique identifier number).

Application configuration node:

The FTP application was set up in the application configuration node, as shown in Figure 3.1.

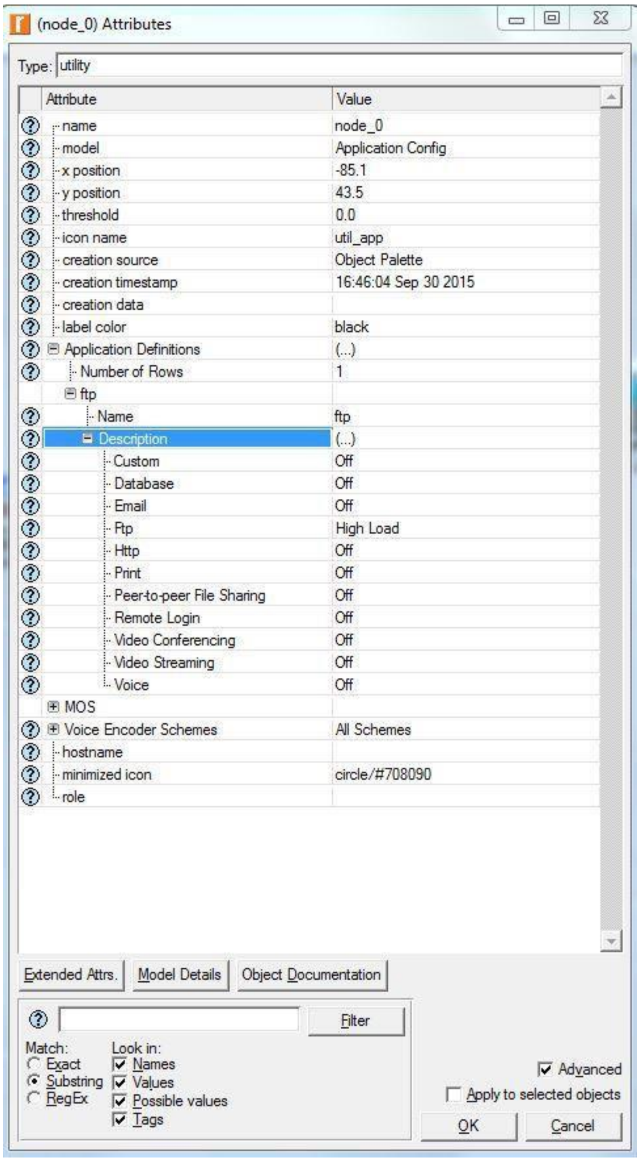


Figure 3.1: Application Configuration Node set-up menu

The Application Information specifies an Exponential function's mean value (in seconds) describing the Inter-repetition time for that application within the profile. This controls how this application runs during the simulation.

Profile configuration node:

The profile configuration creates a profile called PROFILE_1. Figure 3.2 illustrates the profile configuration set-up menu.

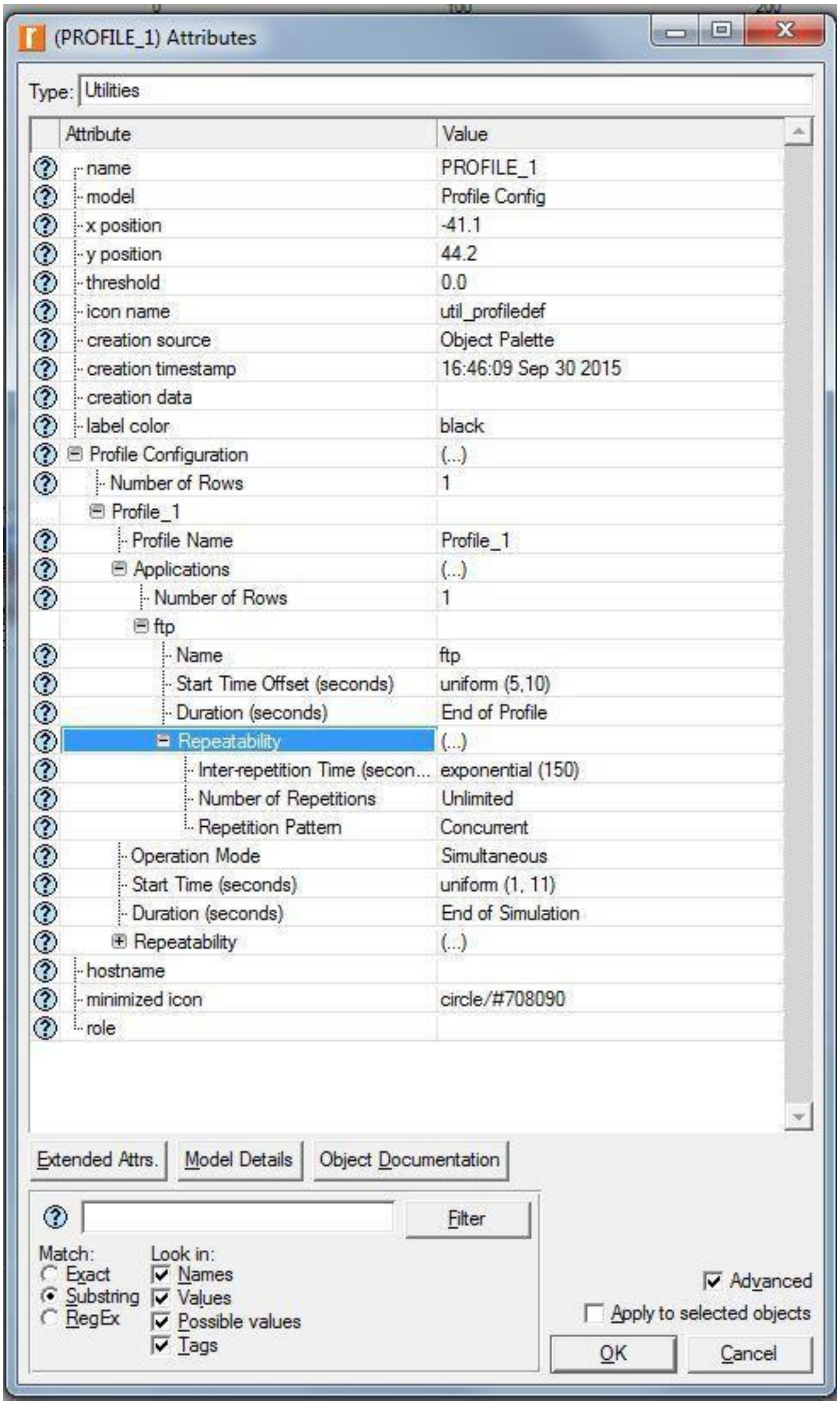


Figure 3.2: Profile Configuration Node set-up menu

The profile contains the specified application, FTP, which is configured as follows: Start of Time offset => “Uniform (5, 10)”

Duration (seconds) => “End of Profile” Repeatability was also set as follows:

Inter-repetition time (seconds) => “exponential 150” Number of repetitions => “Unlimited”

Repetition Pattern => “Concurrent”

For the profile as a whole:

Operation Mode => “Simultaneous” Start Time (Seconds) =>uniform (11) Duration (seconds) => “End of Simulation”

Table 3.2 shows two sets of information:

- The application information that specifies the mean value of an exponential function describing the inter-repetition time for that application within the profile. This controls how each application is set to run during the simulation.
- The mobility models incorporated in the nodes in each network scenario.

Table 3.2: Mobility model and Application information

Mobility model and application information for each scenario					
		Application Information			
Scenario	**Mobility model**	**VoIP**	**email**	**FTP**	**P2P file sharing**
1	Random waypoint	165	142	172	150
2	Reference Point Group	165	142	172	150
3	Gauss Markov	165	142	172	150
4	Manhattan	165	142	172	150

WLAN workstation: Figure 3.3 and Figure 3.4 show the WLAN architecture and the set-up menu of one of the ground nodes, USER3. The same type of WLAN workstation is used throughout the simulation.

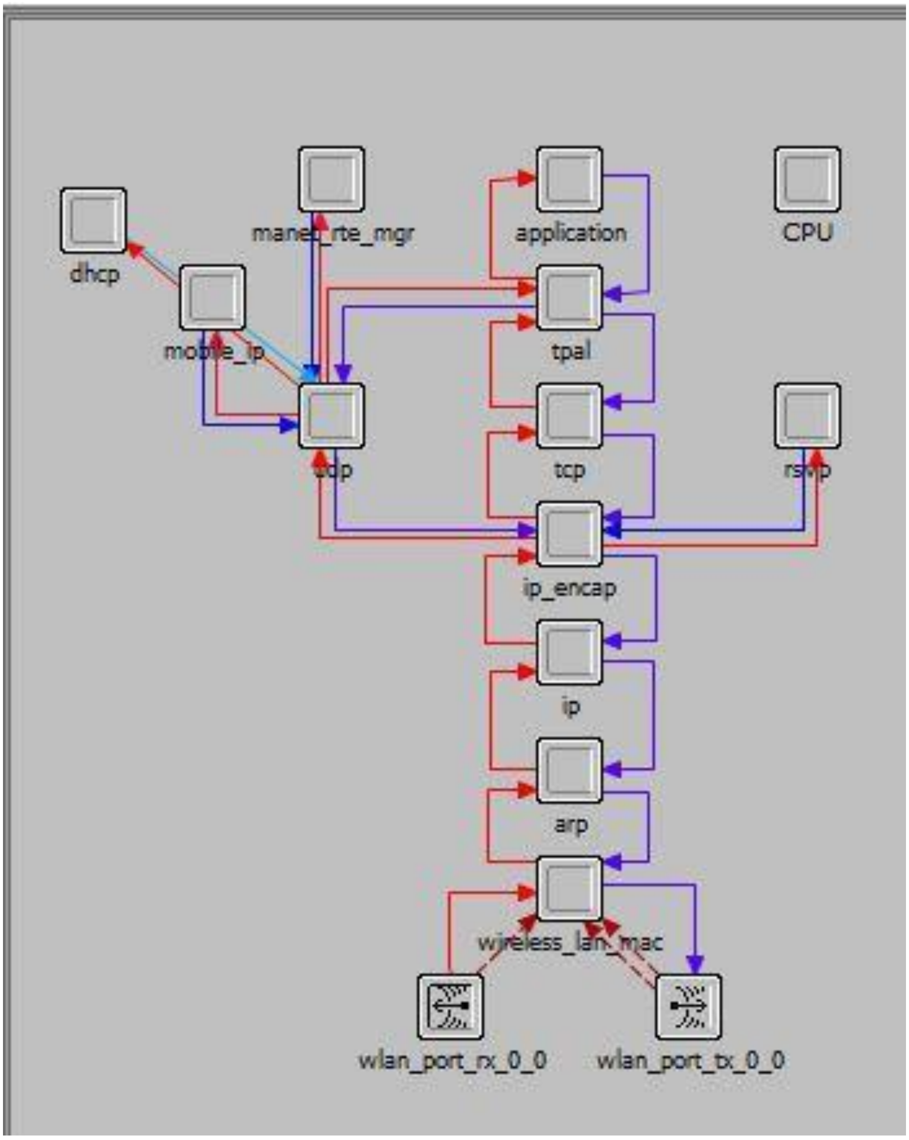


Figure 3.3: WLAN Architecture

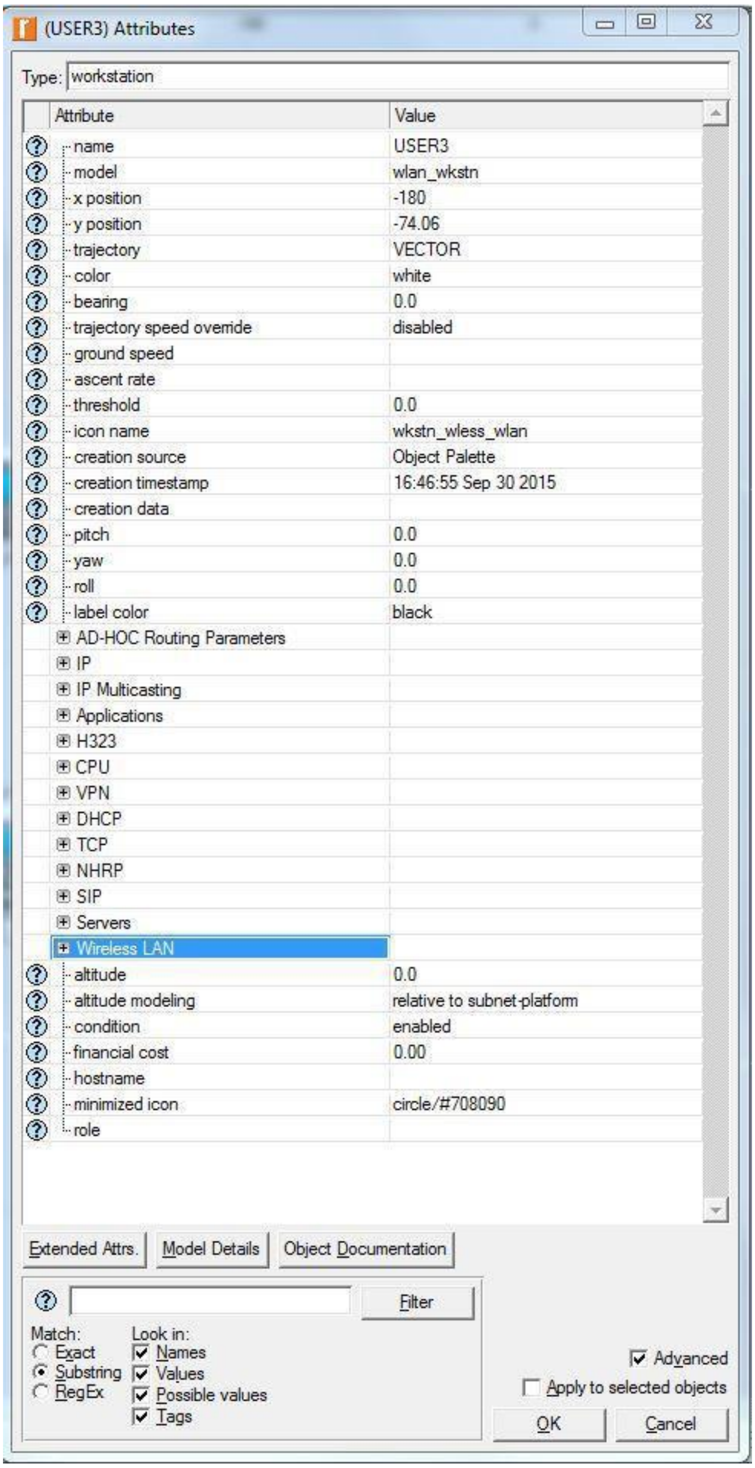


Figure 3.4: WLAN Setup menu for USER 3

Mobile workstation: The MANET used to represent the onboard processor on the UAVs is shown in Figure 3.5.

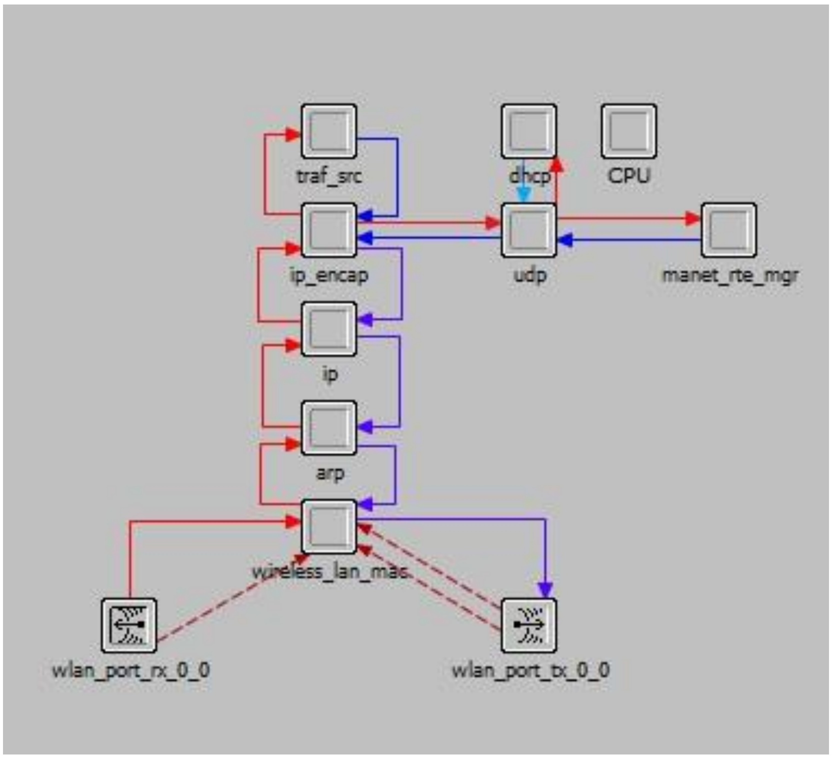


Figure 3.5: Manet Workstation Architecture

The three MANETS workstations are assigned unique identifier numbers (mobile_node_0, mobile_node_1, and mobile_node_2). Table 3.3 shows some general parameters used for the MANET workstation.

Table 3.3: General parameters used for the MANET Workstation

Description			
Name	mobile_node_0	mobile_node_1	mobile_node_2
Packets supported	IPV6	IPV6	IPV6
Initial Altitude	20Meters	20meters	20meters
Data Rate	24mbs	24mbs	24mbs
Buffer Size (Bits)	256,000	256,000	256,000
Transmission power o f Ground nodes	0.005 W	0.005 W	0.005 W

3.4.4 Unique Identifier Numbers

The MANET network was formed by deploying UAVs to act as relays and restore connectivity between ground nodes in the disaster recovery area. There should be bi-directional communication amongst the nodes in the networks. This includes UAV-UAV communication, UAV-Ground node communication links and Ground node- Ground node communication. A device (such as a phone, PDA, etc.) pre-coded with a unique identifier number for ease of identification is carried by each group leader assigned to a group of ground nodes that follow that group leader (as described in the network setup parameters). The unique identifier numbers were assigned to each device during the network setup phase to ensure each device had a distinct identifier. This unique identifier number is captured when the group leader sends or receives data from a UAV, and this identifier number is also transferred during data exchange when the UAVs communicate with each other in the range. This makes the network aware at any given point after the data exchange, which group leaders have been covered by recognising their unique identifier numbers.

In this experiment, the UAVs are numbered mobile_node_0 (UAV1), mobile_node_1 (UAV2), and mobile_node_2 (UAV3). This implies that if UAV1 communicates with USER3, it collects the unique identifier number in its data stream. When it communicates with either UAV2 or UAV 3, it sends that number along with its unique number to it. Other information that would be passed along is the IP addresses of the originator nodes.

3.4.5 Node Statistics

Every UAV's location-based IP address is known. It is included in transmitted messages, as seen in Table 3.4 and Table 3.5, which show the node statics and IP location and the following hop address of one of the nodes in the network. This implies that the positioning of the UAVs will be known.

Table 3.4: Node Statistics

Preview

	Module Name	[Total]	aodv	gna	ip_dgram_v4	tcp_seg_v2	wlan_control	wlan_mac	[Unformatted]	[SAR Segments]
1	application	890		183						707
2	application config	0								
3	arp	0								
4	CPU	0								
5	dhcp	0								
6	ip	18,777	7,686		10,865					226
7	ip_encap	10,563			10,563					
8	manet_rte_mgr	0								
9	mobile_ip	0								
10	profile config	0								
11	rsvp	0								
12	tcp	5,846				3,863				1,983
13	tpal	863							863	
14	traf_src	6,700							6,700	
15	udp	0								
16	wireless_lan_mac	63,101					13,951	24,575		24,575
17	wlan_port_rx_0_0	0								
18	wlan_port_tx_0_0	0								
19	[Total]	106,740	7,686	183	21,428	3,863	13,951	24,575	7,563	27,491

Table 3.5: IP forward mobile_node_0

	Destination	Source Protocol	Route Preference	Metric	Next Hop Address	Next Hop Node	Outgoing Interface	Outgoing LSP	Insertion Time (secs)
1	192.0.0.4/32	AODV	1	1	192.0.0.4	Office Network.mobile_node_1	IF0	N/A	103.002
2	192.0.0.6/32	AODV	1	1	192.0.0.6	Office Network.mobile_node_2	IF0	N/A	103.003
3									
4	Gateway of last resort is	not set							
5									

The first set of simulations aimed to identify a suitable mobility model for the network that would support the selected applications.

3.5 Implementation of Mobility Models

The Random Waypoint mobility model nodes move independently, travelling with randomly selected velocities to a randomly chosen destination. This mobility model quickly became the benchmark mobility model, frequently used in MANET simulations due to its wide availability and simplicity (Pramanik et al., 2015). However, MANETs are being deployed in different applications where complex mobility patterns exist, and recent research focuses on using alternative mobility models to account for different mobility characteristics. In the Research presented here, four different mobility models, namely, the Random waypoint mobility model, Gauss Markov mobility model, Reference Point Group mobility model (RPGMM) and the Manhattan mobility model, were tested in evaluating the network's performance.

This aimed to ascertain the best mobility model for use with the SAIMOD framework by analysing desired network performance metrics, Throughput, and End-to-End Delay. Throughput and End-to-End Delay were considered because, in the example scenario (disaster recovery) being tested, getting data sent successfully and promptly was essential. The information needed, such as changes in the disaster area map, updates, directions, number of people to be rescued, number of wounded or the severity of the wound that could be used in making decisions such as resource allocation, would need to have the successful packets delivered to match the data packets sent. The time taken for all the data packets sent from the source to reach their destination (End-to-End Delay) would also determine the suitability of the mobility model and routing protocol. The Throughput being considered is the average number of packets sent within a specified period. The routing protocol implemented in the networks was AODV. This was the default routing protocol in the network simulation tool.

The parameters used in setting up the trajectories of the individual nodes in both the Random Waypoint mobility model and the Manhattan mobility model scenarios are based on the individual behaviour pattern of each mobility model. In contrast, those used in implementing the Gauss Markov and Reference Point Group mobility models are based on their model equations.

- The initial speed and direction of all the ground nodes are assumed to be zero.
- The mean speed of the ground node is set to average human speed, which is 1.0 m/s on the OPNET platform.
- The maximum speed of the ground node is 1.5m/s for human walking speed on the OPNET platform.
- The mean direction angle of the ground node is 90^0.
- The maximum direction angle of the ground node is 180^0.

Table 3.6 shows some of the general network parameters.

Table 3.6: General Network parameters

Other setup parameters selected	Configuration used
Supported IP packets	IPV6
Data Rate used	24 Mbps
Buffer Size (bits)	256000

Disaster area	500m x 500m
No. of UAVs	3
No. of ground nodes	30
Transmission power of ground nodes	0.005 W
Transmission power of UAVs	0.100W

I. Random Waypoint Mobility Model

In implementing the Random Waypoint mobility model, each node in the network chooses its destination location stochastically. It will then move with a steady velocity [0, V(max)] towards that randomly selected destination. V(max) represents the highest movement velocity permitted in the network, while zero (0) is the lowest. The system also allows for pause time T (secs), which occurs periodically to enable the nodes to mimic how people behave/move in real life. Another random destination is again selected after T (secs), and it randomly selects another next hop. The process is repeated at each hop until the node reaches its destination.

This Research incorporates random speed and pause time (T) between each movement. Each ground node has five movement sequences and a pre-defined speed of 1.0 m/s (the average human speed on the OPNET platform). Figure 3.6 shows the Random waypoint mobility model's movement pattern (white lines) on the OPNET platform.

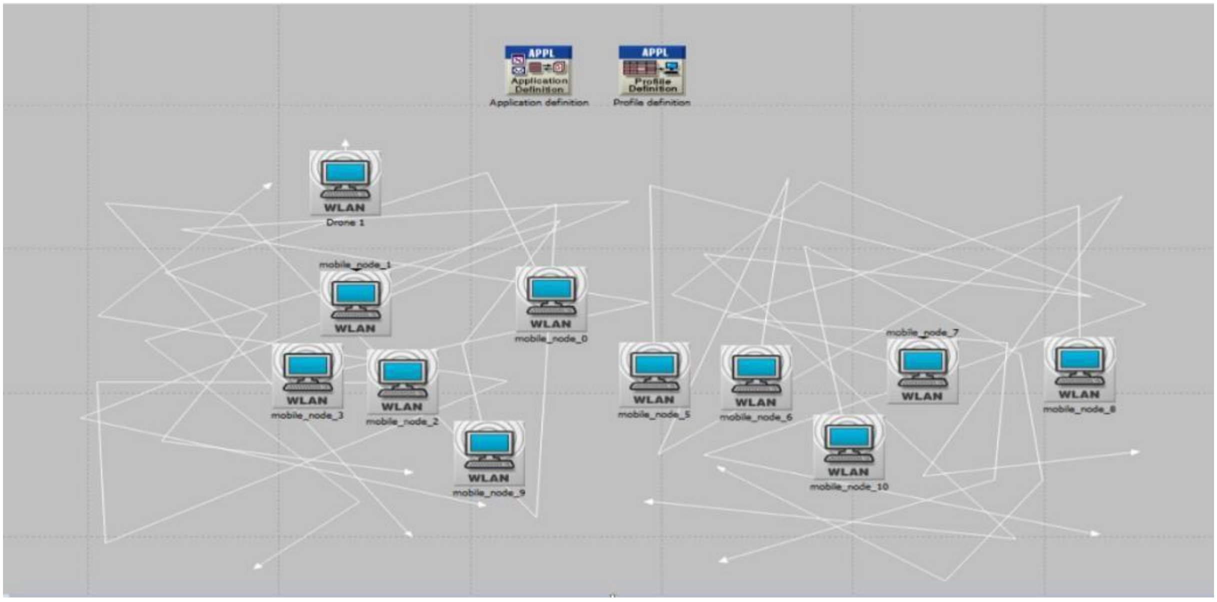


Figure3.6: Random Waypoint Mobility Model

II. Gauss Markov Mobility Model

In implementing the Gauss Markov mobility model, each node starts with initial values for speed and their direction is set to zero. This eliminates the sudden sharp turns in the Random Waypoint mobility model while retaining a certain degree of randomness. A new speed (n_s) and direction (d_n) are chosen, as shown in Figure 3.7, at fixed intervals in time. In the Gauss-Markov model, temporal dependency plays a key role in determining mobility behaviour. Each mobile node begins moving with an initial speed and direction and an average speed and direction. After the node gets to its first point in its movement sequence, at a set time interval, the model updates the speed and direction of the mobile node, depending on its previous speed and direction, to get a new speed and direction. This process is repeated when the node moves to the next hop until it reaches its destination. This model has only one tuning parameter, alpha α, which decides the amount of memory and variability in the movement of the node (He et al., 2017; Chenghao, 2015; Hajisami et al., 2014).

The speed and direction of the node are calculated as follows:

$$s_n = \alpha s_{n-1} + (1-\alpha)\bar{s} + \sqrt{(1-\alpha^2)}s_{x_{n-1}} \quad (3.1)$$

$$d_n = \alpha d_{n-1} + (1-\alpha)\bar{d} + \sqrt{(1-\alpha^2)}d_{x_{n-1}} \quad (3.2)$$

Where;

s_n = new speed

d_n = new direction

α = tuning parameter in the range [0, 1]

s = mean speed

d = mean direction

$s_{x_{n-1}}$ = random variable from Gaussian distribution in the range (0, 1)

$d_{x_{n-1}}$ = random variable from Gaussian distribution in the range (0, 2π)

Here, α determines the degree of randomness, which represents the variability in the movement pattern of the node.

To obtain the maximum speed and direction, α should be zero.

$$s_n = s + s_{x_{n-1}} \tag{3.3}$$

$$d_n = d + d_{x_{n-1}} \tag{3.4}$$

At the point where α is zero, the current speed and direction will not depend on its previous speed.

Also, when α is one, the speed and direction are at its minimum value given by:

$$s_n = s_{n-1} \tag{3.5}$$

$$d_n = d_{n-1} \tag{3.6}$$

In this instance, the movement of mobile nodes is linear.

At every movement interval, the position of each node is calculated using the following equation:

$$x_n = x_{n-1} + s_{n-1} cos d_{n-1}$$

$$y_n = y_{n-1} + s_{n-1} sin d_{n-1}$$

Where;

x_n= x coordinate of destination position.

y_n = y coordinate of destination position.

x_{n-1} = x coordinate of the current position.

y_{n-1} = y coordinate of the current position.

In this study, the scenario in which the Gauss Markov mobility model was implemented was designed to have five movement sequences, where the direction, speed and distance covered by the ground nodes are calculated and implemented using the above equations. Figure 3.7 shows the Gauss Markov mobility model's movement pattern (white lines) on the OPNET platform.

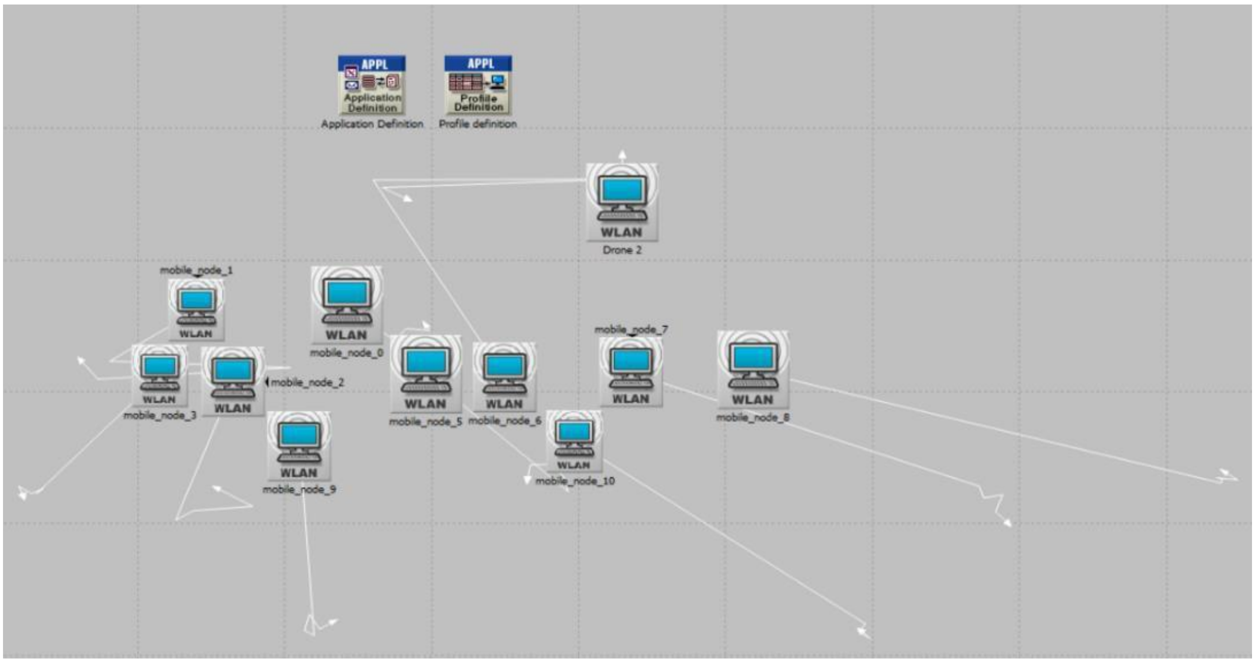


Figure 3.7: Gauss Markov Mobility Model

III. Reference Point Group Mobility Model

In the Reference Point Group mobility model, the movement pattern of every node is determined by that of the Group Leader (logical centre or cluster head), as each node follows the Group Leader, who acts as their reference point. The nodes are usually randomly distributed in a group that forms a cluster around a reference point (group leader). Each node has a speed and direction derived by randomly deviating from the speed and direction of the group leader by some degree. In the scenario depicting the Reference Point Group mobility model, the nodes were set up as below:

- Five movement sequences are enacted for each ground node.
- Groups of 10 are created among the ground nodes.
- The group leader is chosen based on the ground node (rescue team member) having the best connectivity to the UAV. Each group leader is expected to continuously maintain connectivity to one of the UAVs to exchange data packets.

- Each group has one leader, followed by nine group members.
- Each ground leader has a unique identifier number.
- The leader's direction and velocity are chosen randomly, and the equations below are used to calculate the velocity and direction of the group members, who must follow the leader.

The movement pattern followed by the nodes in each cluster and their group leader is represented by the following equation:

$$V_{member}\ (t)\ =\ V_{leader}(t) +\ random\ .SDR.Max\_speed \tag{3.10}$$

$$\theta_{member}\ (t)\ =\ \theta_{leader}(t)\ +\ random\ .ADR.Max_{angle} \tag{3.11}$$

Where;

V_{member} = Velocity of each member of a group.

θ_{member} = Direction angle of each member of a group.

V_{leader} = Velocity of the group leader.

θ_{leader} = Direction angle of the group leader.

random = Function returning a value in the interval [-1,1]

SDR = Speed Deviation Ratio, where $0 \leq SDR \leq 1$

ADR = Angle Deviation Ratio, where $0 \leq ADR \leq 1$

Max_speed = the maximum speed of the node.

Max_angle = the maximum angle turned by the node

Here, SDR and ADR are used to deviate the magnitude and direction of the group members from that of the group leader (Divya and Srinivasan, 2021).

Figure 3.8 shows the movement sequence of the Reference Point Group mobility model (white lines) as deployed in the network.

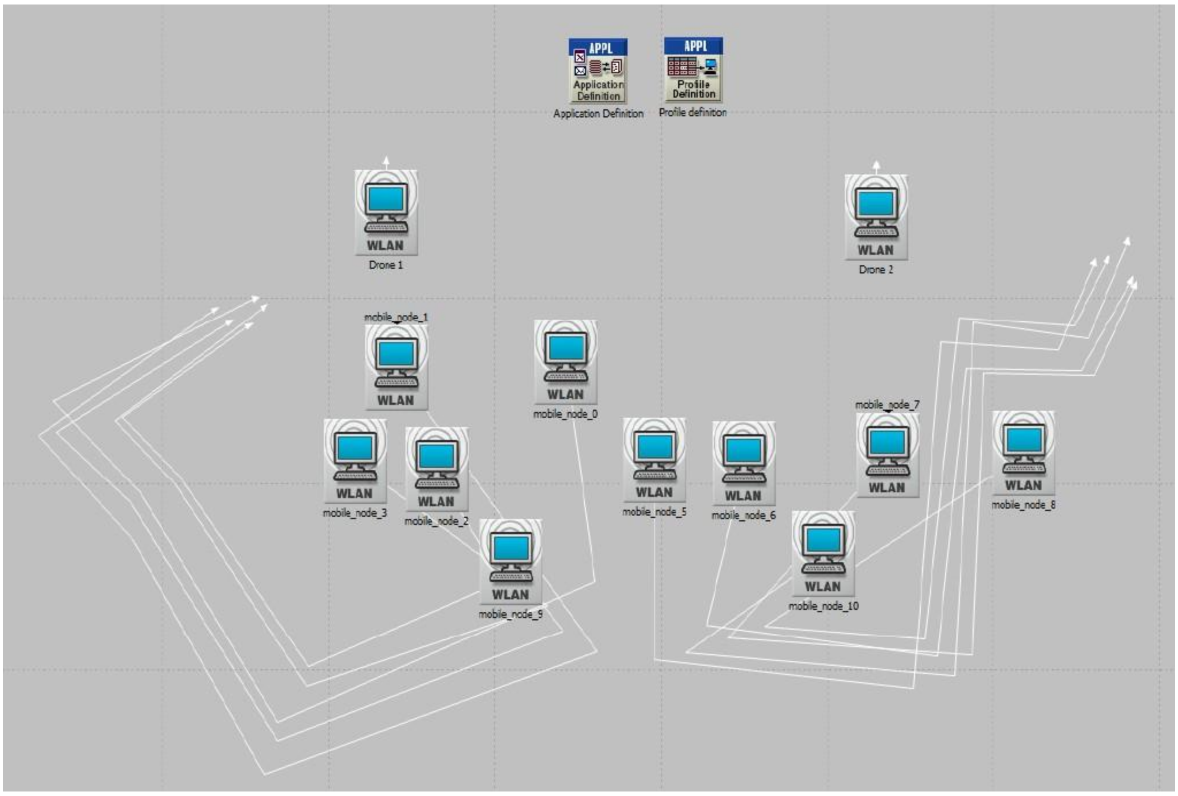


Figure 3.8: Reference Point Group Mobility Model

IV Manhattan Mobility Model

The Manhattan mobility model is set to imitate the movement of vehicles in a metropolitan area. It uses a grid road topology, assuming that the disaster area still has numerous vertical and even roads. Figure 3.9 shows the Manhattan mobility model's movement pattern (white lines) on the OPNET platform.

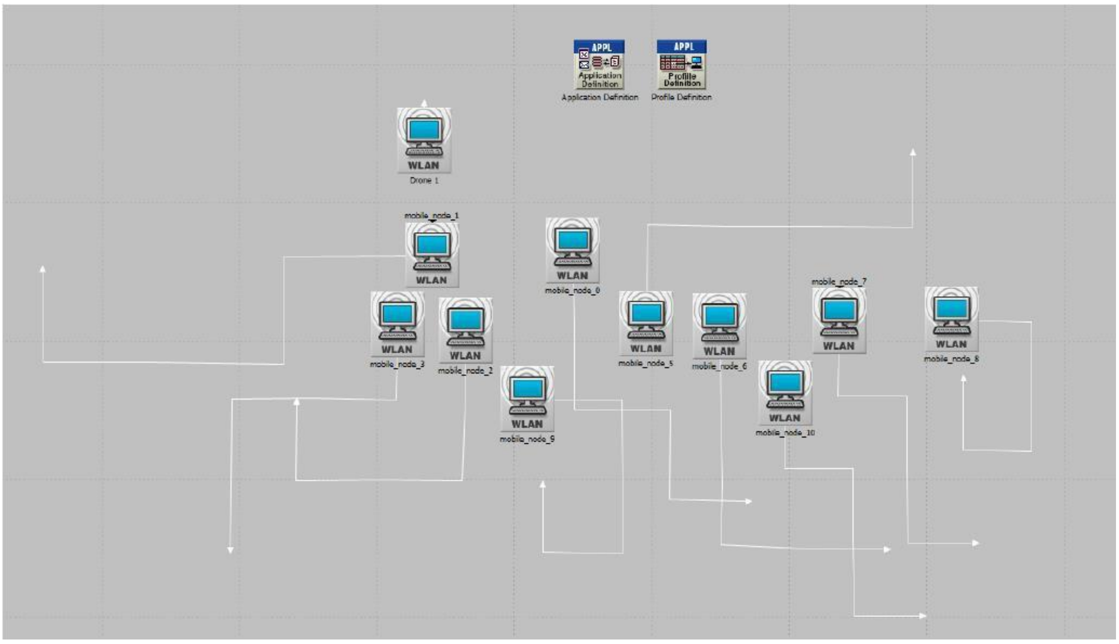


Figure 3.9: Manhattan Mobility Model

3.6. Mobility Models' Simulation Results and Analysis

3.6.1 Evaluation of Throughput in the AODV-based Network

Figure 3.10 illustrates the wireless LAN Throughput in bits/sec in an hour-long simulation. The Manhattan mobility model (red line) achieved the highest Throughput (1,890,000 bits/sec), but the simulation was prematurely terminated after 15 minutes due to excessive dropped packets. This high Throughput and significant packet loss indicates a trade-off between data transmission speed and reliability. The Random Waypoint mobility model (green line) also demonstrated a high Throughput, peaking at approximately 1,375,000 bits/sec. However, like the Manhattan model, the simulation was halted due to many dropped packets from the 50-minute mark of the simulation period. The Throughput of this model gradually decreased as the simulation time increased after 15 minutes, with a baseline of approximately 905,00 bits/ secs.

In contrast to these two mobility models (Random Waypoint (green line) and Manhattan (red line)), Figure 3.10 shows that the Throughput of the Reference Point Group (blue line) and Gauss Markov (orange line) mobility models increased as the simulation progressed with that of the RPGMM being approximately 800,000 bits/ secs and that of the Gauss-Markov model (orange line), approximately 750,000 bits/secs. The Reference Point Group mobility model (RPGMM) (blue line) performed better among the two mobility models (RPGMM (blue line) and the Gauss-Markov mobility model (orange line) that completed the simulation for the stipulated simulation time (60 minutes).

RPGMM (blue line) had the highest Throughput. This could be because the movement pattern in the Reference Point Group mobility model (blue line) dictates that all the ground nodes follow their logical centre or group leader, which is always connected to the UAV throughout the simulation time. The group leader acts as a cluster head. The group members are uniformly distributed in the neighbourhood of their cluster head, and the overall movement of every member in each cluster group is organised, with slight Variation in speed and angular direction from that of the group leader /cluster head. Each group member moves in a pre-defined manner, taking its lead from the movement of the cluster head, ensuring minimal dropped packets across the network. This results in the ground nodes being in phase with one another and their group leader, who always maintains connectivity to the UAV.

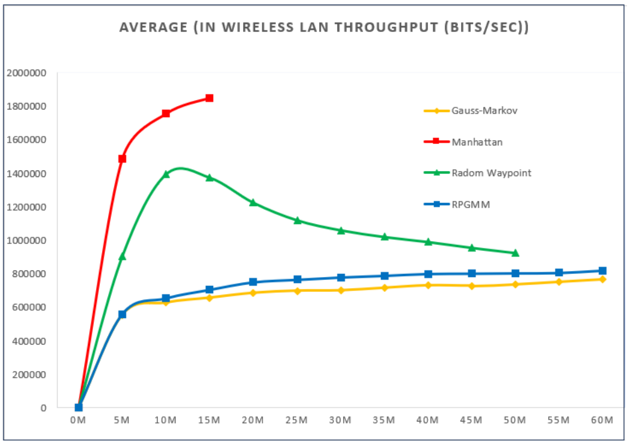


Figure 3.10: Average WLAN Throughput using AODV

3.6.2 Evaluation of Network Routing Load in the AODV-based Network

Figure 3.11 highlights a significant difference in the average Network Routing Load among the four mobility models. The Manhattan mobility model (red line) and the Random Waypoint (RWP) mobility model (green line) had the highest Network Routing Loads (approximately 775,000 bits/sec and 665,000 bits/sec, respectively). In contrast, the Reference Point Group mobility model (blue line) and the Gauss Markov mobility model (orange line) exhibited the lowest Network Routing Loads.

Notably, the RPGMM (blue line) and the Gauss Markov mobility model (orange line) models demonstrated a striking reduction of 30% in network routing load compared to the two models with the highest Network Routing Load, RWP (green line) and the Manhattan mobility model (red line). RPGMM (blue line) (490,000 bits/sec) and Gauss Markov (orange line) (490,000 bits/sec) were particularly noteworthy, with approximately a striking 36% less network routing load when compared to the highest two (RWP (green line) and Manhattan mobility model (Red line). The higher Network Routing Load in the Manhattan and Random Waypoint mobility models could be attributed to several specific factors. One key factor is the movement pattern in the Manhattan model, which tends to create more predictable paths that can lead to congestion at certain points. In contrast, the Random Waypoint model involves nodes moving to random destinations with pauses, which can result in traffic bursts as nodes frequently change direction and location.

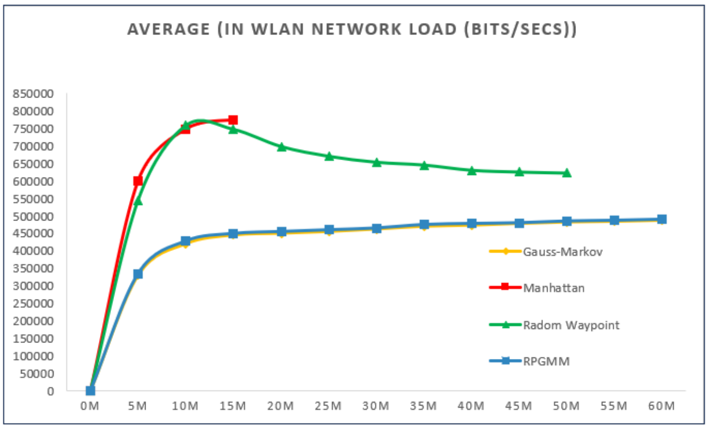


Figure 3.11: Average Network Routing Load (NRL) using AODV

3.6.3 Evaluation of Delay in the AODV-based Network

The simulation results of the network Delay in Figure 3.12 show that the RPGMM (blue line) and Gauss Markov mobility model (orange line) had the least Delay. RPGMM (blue line) had Delay values between 0.00006 secs and 0.0003, while the Gauss Markov mobility model (orange line) had Delay values ranging between 0.0006 secs and 0.0005 secs. The Random Waypoint (RWP) mobility model (green line) had the highest Delay with values ranging between 0.025 and 0.090 seconds, and is followed by the Manhattan mobility model (red line) with Delay values ranging between 0.4 seconds and 0.0545 secs. The lower Delay observed in the RPGMM and Gauss Markov mobility models compared to others can be attributed to several factors. First, the mobility models (RPGMM and Gauss Markov) allow for more predictable movement patterns of the nodes, reducing the complexity of routing decisions and improving data transmission efficiency. Second, mobile nodes have better spatial and temporal coherence due to their nature. This creates more opportunities for successful handoffs and lower packet loss in the network. In addition, the delays associated with establishing and maintaining network connections are reduced due to the structure of the RPGMM and the Gauss Markov models, which optimise connectivity and communication intervals between nodes.

Figure 3.12 suggests that the mobility models that perform best based on the Delay statistics are the RPGMM and the Gauss-Markov mobility models, and they would be best suited for use in SAIMOD. However, the RPGMM had a higher Throughput value than the Gauss-Markov mobility model, as shown in Figure 3.11. The Manhattan mobility model (red line) and the RWP mobility models had no Throughput beyond 15 minutes (for the Manhattan mobility model) and 50 minutes (for the RWP mobility model) of simulation time, as seen in Figure 3.10 and had no Delay as there were no packets delivered beyond those points.

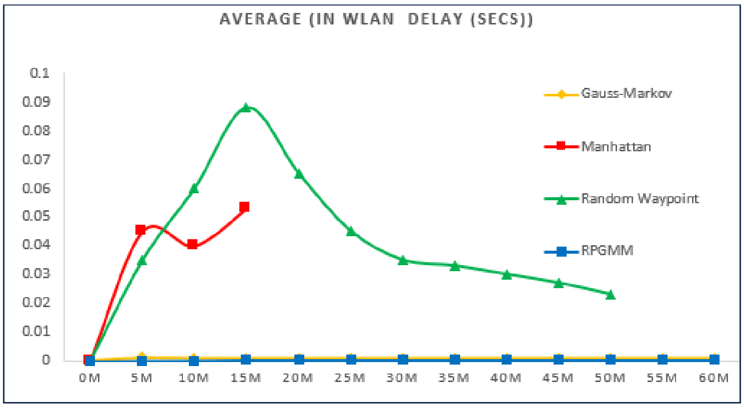


Figure 3.12: Average Delay using AODV

Summary

Based on the simulation results' analysis and comparison, specifically Throughput, NRL, and Delay, it was determined that the Reference Point Group mobility model performed the best within the specified network conditions. Table 3.7 presents the performance ranking of the mobility models based on evaluating the simulation results. The RWP and Manhattan mobility models were classified as second and third, mainly because the simulations had massive packets dropped and stopped before the end of the simulation run time. They also had higher Delay values and NRL.

Table 3.7: Performance Rank of Mobility Models

MOBILITY MODEL	Throughput	Network Routing Load	Delay	Overall Ranking
Reference Point Group mobility model	800,00bits/sec	500,000bits/sec	Max: 0.0006 secs	1st ranked
Gauss-Markov mobility model	780,00bits/sec	500,000bits/sec	Max: 0.0006	2nd ranked
Random Waypoint mobility model	905,000 bits/s (No results beyond 50 mins simulation time)	760,000 (No results beyond 50 mins simulation time)	Max: 0.09 secs (No results beyond 50 mins simulation time)	3rd ranked
Manhattan mobility model	1,375,000 bits/sec (No results beyond 15 minutes simulation time)	780,000 (No results beyond 15 minutes simulation time)	Max: 0.055 secs (No results beyond 15 minutes simulation time)	4th ranked

3.7 Implementation of Other Routing Protocols

The ranking of mobility models presented in Table 3.7 was determined by comparing the results for Throughput, network reachability (NRL), and Delay in simulated networks using AODV. This reactive routing protocol is the default protocol in OPNET. Similar network scenarios with the same parameters and boundaries were used to maintain consistency and fairness in selecting the most suitable mobility model for SAIMOD. The simulations last an hour each, with results from 10 discrete event simulation (DES) points averaged for every point.

Other routing protocols were implemented using the same selection of mobility models as those used with AODV. A combination of reactive, proactive, and hybrid routing protocols was chosen based on their relevance to the tested scenarios. This comprehensive approach enabled an assessment of the networks' overall performance to determine whether the results from AODV would significantly change the ranking of the mobility models, as summarised in Table 3.7.

The additional routing protocols implemented in this analysis were:

- Dynamic Source Routing (DSR) - a reactive routing protocol
- Optimised Link State Routing (OLSR) - a proactive routing protocol
- Geographic Routing Protocol (GRP) - a proactive routing protocol
- Temporally Ordered Routing Algorithm (TORA) - a hybrid protocol

The results are analysed below.

3.7.1 Evaluation of Throughput

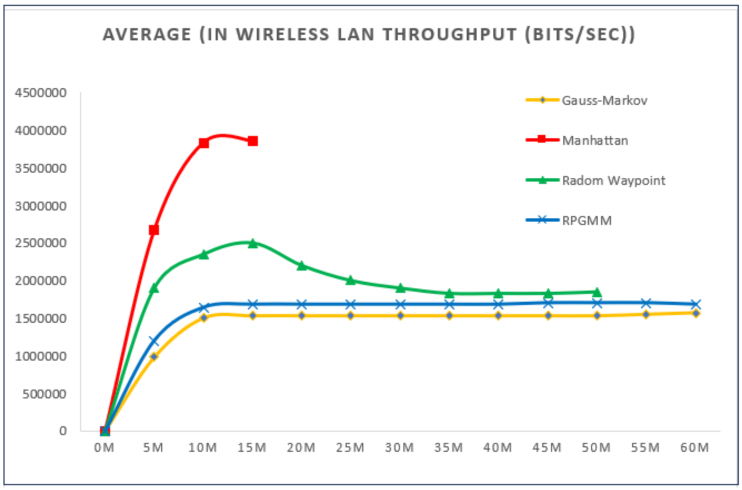


Figure 3.13: Average WLAN Throughput using DSR

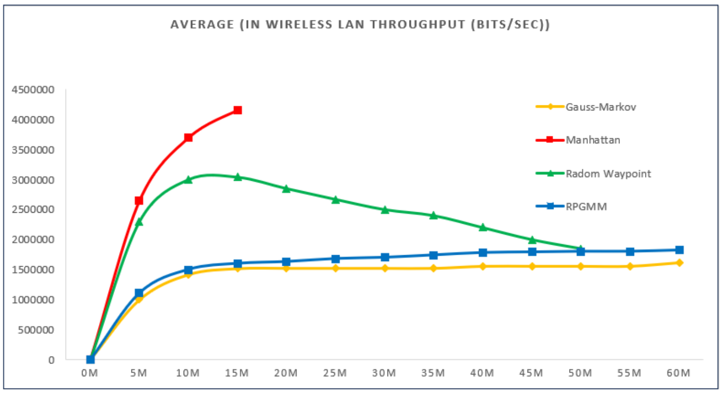


Figure 3.14: Average WLAN Throughput using OLSR

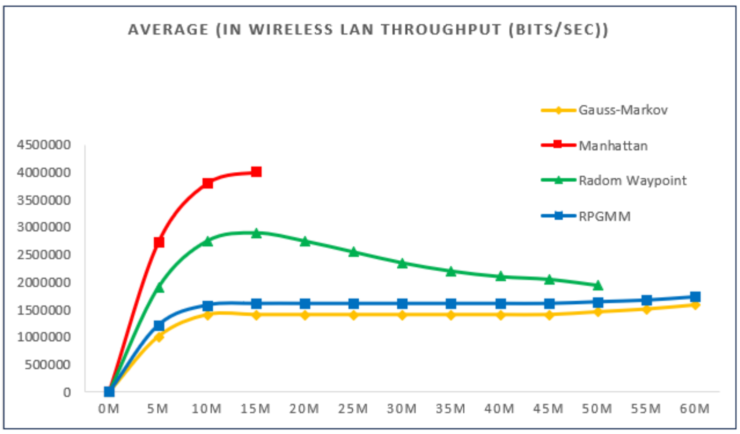


Figure 3.15: Average WLAN Throughput using GRP

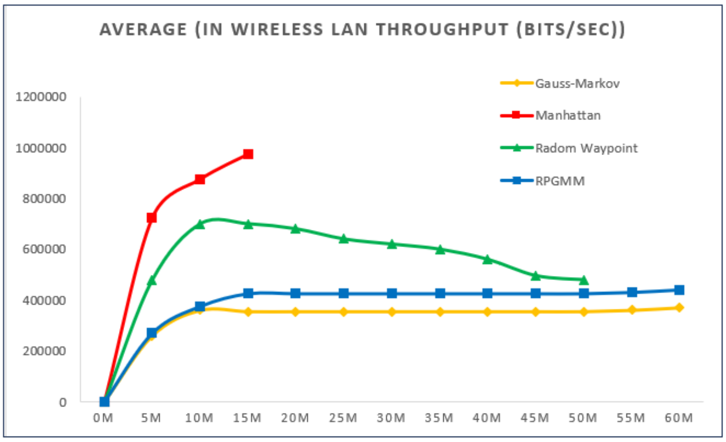


Figure 3.16: Average WLAN Throughput using TORA

Figures 3.13 to 3.16 illustrate the network Throughput for four routing protocols: DSR (Figure 3.13), OLSR (Figure 3.14), GRP (Figure 3.15), and TORA (Figure 3.16). Compared to the AODV network (Figure 3.10), the behaviour of the mobility models shows similarities, though there are differences in their respective values. The performance of the mobility models, ranked by their Throughput values, aligns consistently with their classification in Table 3.7. Notably, the RPGMM ranks first, followed closely by the Gauss-Markov model.

The Random Waypoint (RWP) model initially demonstrated the highest Throughput in all the networks, but the simulation results show a decline in performance over time, mainly due to packet loss. This decline can be attributed to the RWP mobility model's random movement patterns. In contrast, the Manhattan model requires a structured, unobstructed pathway to achieve optimal performance. The simulation also ended at the 50-minute mark due to dropped packets.

When comparing the Throughput values of different mobility models across four networks (DSR (Figure 3.13), OLSR (Figure 3.14), GRP (Figure 3.15), and TORA (Figure 3.16)) to those of the AODV network, it is observed that the DSR network shows an approximate increase of 205% in Throughput for all protocols. The GRP network exhibits an approximate increase of 214%, while OLSR demonstrates an increase of about 221%. In contrast, the TORA network experiences a 50% reduction in Throughput compared to AODV.

The behaviour of the routing protocols supports these observations. Although DSR is a reactive protocol like AODV, it offers better Throughput performance. As proactive protocols, both OLSR and DSR have pre-established routes, making them well-suited for mobile ad hoc networks (MANETs), which likely contributes to their superior Throughput compared to AODV. However, TORA sometimes encounters loop issues due to synchronised clocks, which may explain the fluctuations in Throughput experienced by the different mobility models. Despite these variations, the performance ranking of the various mobility models remains consistent, as previously discussed.

3.7.2 Evaluation of Network Routing Load

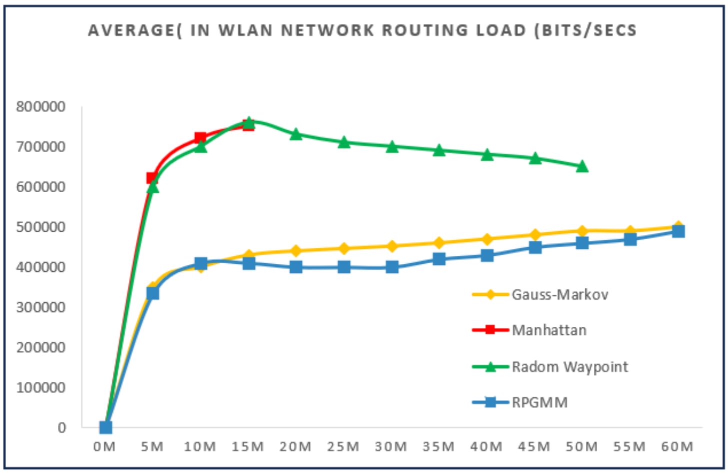


Figure 3.17: Average Network Routing Load (NRL) using DSR

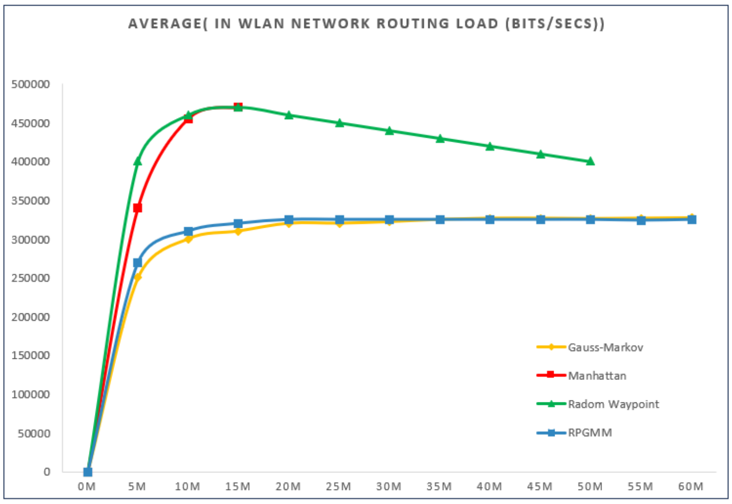


Figure 3.18: Average Network Routing Load (NRL) using OLSR

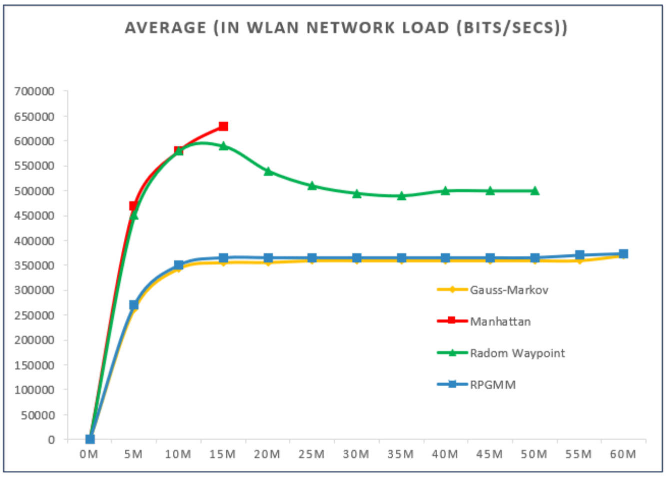


Figure 3.19: Average Network Routing Load (NRL) using GRP

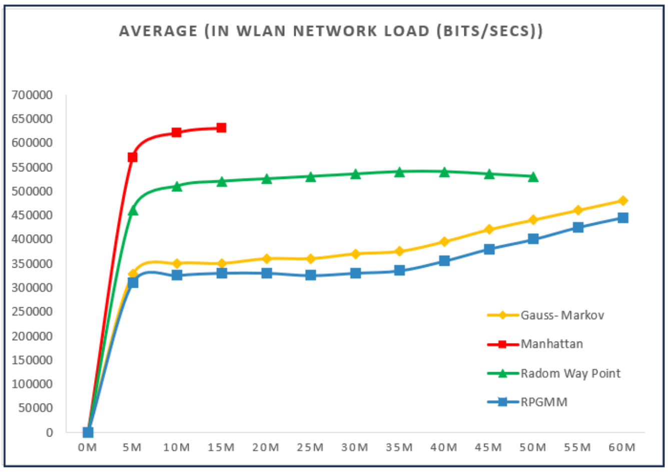


Figure 3.20: Average Network Routing Load (NRL) using TORA

Similar to the results for Throughput, the results for NRL (Figure 3.17- Figure 3.20) also show that the mobility models in the tested networks behaved like those in the AODV network, with the RPGMM having the best results among the two mobility models (RPPGMM and Gauss-Markov) that completed the simulations. From the results for the RPGMM (blue line; Figure 3.17- Figure 3.20) performance, it is observed that the network in which the two proactive protocols, OLSR and GRP, were implemented had the least NRL values; this could be attributed to their already established routing tables. However, the OLSR network performed better, with a value of approximately 325,000 bits/sec compared to the GRP's network of approximately 373,000 bits/sec.

TORA had the third-lowest value for NRL, but it does increase gradually over time. This could be due to the use of synchronised clocks. TORA has increased overhead when multiple link changes occur, and the protocol tries to adjust routing tables to accommodate these changes. Although TORA has less Delay, as seen in Figure 3.24, finding optimal routes in dynamic topologies causes a significant increase in overhead. This means that it may not perform optimally when multiple link changes occur. This is supported by the Throughput values for RGPMM (blue line), approximately 490,000 bits/sec seen in the TORA network (Figure 3.16). DSR had the second-highest NRL (480,000) for the RGPMM (blue line) after AODV, as seen in Figure 3.17.

3.7.3 Evaluation of Delay

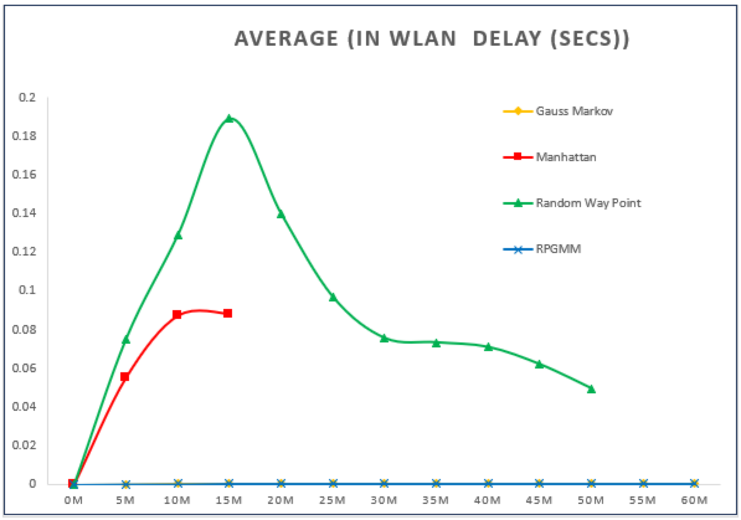


Figure 3.21: Average Delay using DSR

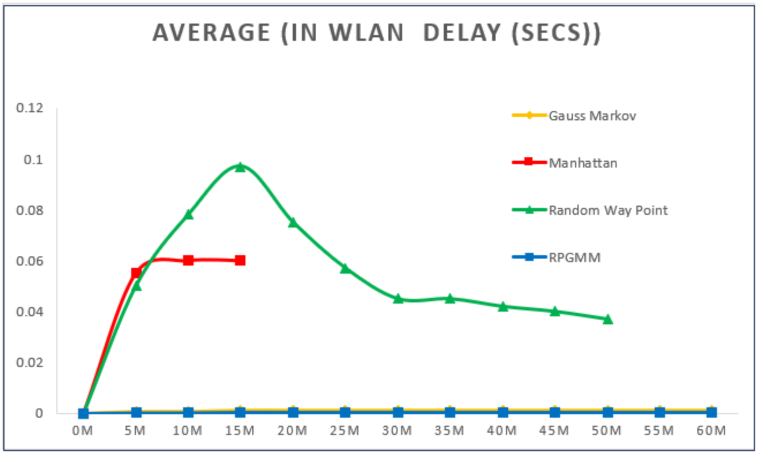


Figure 3.22: Average Delay using OLSR

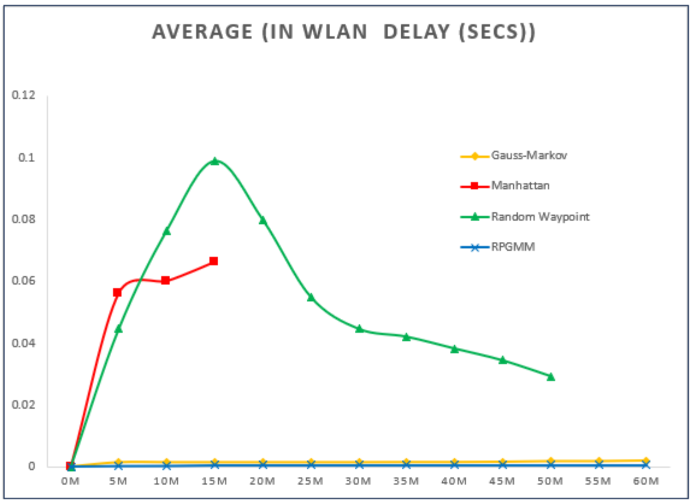


Figure 3.23: Average Delay using GRP

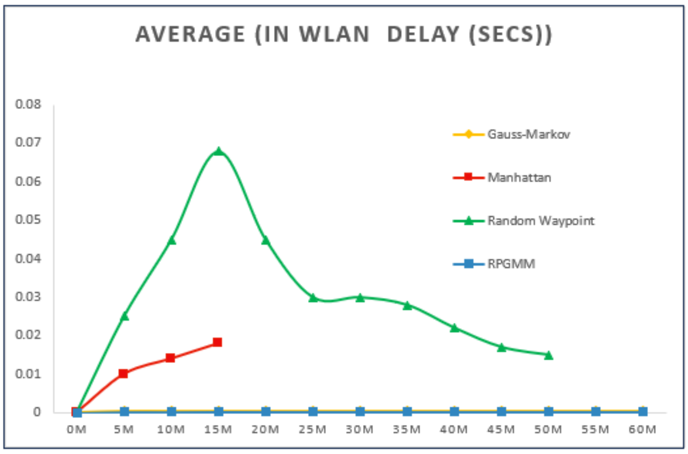


Figure 3.24: Average Delay using TORA

Figures 3.21 to 3.24 illustrate the Delay results for four networks: DSR, OLSR, GRP, and TORA. Similar to the AODV-based network, the mobility models in these networks exhibited comparable behaviour. While the individual Delay values varied, the overall ranking of the mobility models remained consistent. The RPGMM model (represented in blue) and the Gauss-Markov model (yellow line) completed the simulation, with RPGMM achieving the best performance. In contrast, the Manhattan mobility model (indicated in red) and the RWP model experienced simulation interruptions at the 15-minute and 50-minute marks due to significant packet loss.

The analysis of the results for RPGMM (blue line) across all networks shows that the TORA network (Figure 3.24) had the lowest Delay (approximately 0.00008 seconds). This reduced Delay can be attributed to TORA's synchronised clocks, eliminating the need for routing tables. Maintaining updated routing tables can introduce delays in proactive protocols, especially in denser or high-frequency networks. Both proactive protocols exhibited higher Delay values, with GRP-based networks (Figure 3.23) showing approximately 0.00010 seconds and OLSR-based networks (Figure 3.22) demonstrating approximately 0.00012 seconds. GRP's Delay is primarily due to a distributed location database requirement that can cause communication delays, particularly in denser networks. OLSR, meanwhile, must maintain an updated Multipoint Relay (MPR) node table. It was observed that the DSR-based network (Figure 3.21) experienced the highest Delay (approximately 0.00022 seconds). A noted disadvantage of DSR, as discussed in Subsection 2.3.1.2, is the high Delay values attributed to route discovery in environments with a high frequency of route requests or denser networks.

3.7.4 Selecting a suitable mobility model (summary)

The comparative analysis of various routing protocols showed several similarities in the performance of the different mobility models (Gauss-Markov, Manhattan, Random Waypoint and the Reference Point Group mobility models) across key metrics such as Throughput, Network routing load, and Delay. Each mobility model exhibited consistent behaviour, indicating stable performance characteristics regardless of the routing protocol implemented. However, the mobility models in some of the networks outperformed the results obtained from simulations using the AODV protocol in some cases, achieving higher Throughput, lower Network Routing Load (NRL), and reduced Delay. Based on these findings, the Reference Group Mobility Model (RGPMM) was the most suitable mobility model for SAIMOD.

The effectiveness of this mobility model is primarily due to its cluster-based movement pattern, in which all ground nodes follow a designated group leader. Each member's movement is organised and slightly varies in speed and direction compared to the cluster heads. Members adhere strictly to a pre-defined movement strategy, which helps them stay connected and in sync with the cluster head. This coordinated movement significantly reduces packet loss across the network while ensuring that the ground nodes maintain connectivity with one another and their group leader, who is connected to the UAV.

3.8 Analysis of the Reference Group Mobility Model Network

This section further tests the performance of the five routing protocols (DSR, AODV, OLSR, GRP, and TORA) when combined with the strategically chosen RGPMM in simulating different Mobile Ad Hoc Networks (MANETs) under the same boundary conditions, such as network area size, number of nodes, and chosen applications. The mobility model selected was further evaluated using the five routing protocols to assess performance metrics, including Throughput, Delay, and the individual performance of various applications running within the network (such as peer-to-peer file sharing Throughput, voice packet Delay Variation, Mean Opinion Score, and the analysis of HTTP traffic sent versus traffic received). The network's scalability and resilience were also tested with increasing nodal densities, underscoring the significance of the RGPMM in this Research.

The analysis involved setting up five scenarios tailored to a specific routing protocol. These scenarios were designed with identical network parameters, including network area size, number of nodes, and applications to be run. The five selected protocols were implemented in these scenarios to identify the most promising protocol based on the chosen performance metrics. Each scenario ran for an hour, and the results were methodically collated and analysed.

3.8.1 Routing Protocols' Simulation Results and Analysis

3.8.1.1 Evaluation of Throughput

In Figure 3.25, OLSR (depicted by the blue line) exhibited the highest WLAN Throughput, reaching approximately 687,500 bits per second. This was closely followed by GRP (represented by the grey line), which achieved around 675,000 bits per second, and DSR (illustrated by the red line), with a Throughput of about 650,000 bits per second. AODV, shown by the purple line, recorded Throughput values of approximately 350,000 bits per second, less than 54% of the Throughput of OLSR, GRP, and DSR. TORA, indicated by the orange line, had the lowest Throughput, peaking at 180,000 bits per second. These results align with the Throughput values observed for RGPMM in Figures 3.13 to 3.16, showing minimal variation across the data.

OLSR uses a proactive approach, using MPR nodes, which minimises overhead and reduces the number of retransmissions required for broadcasting routing information. In addition, it keeps an updated MPR table and maintains routes even when there is no data traffic. This proactive approach led to faster data delivery and reduced latency, contributing to OLSR's achieving the highest WLAN Throughput compared to the other protocols. From the analysis of the Throughput results, the top three best-performing routing protocols will be considered for use in the proposed model (SAIMOD).

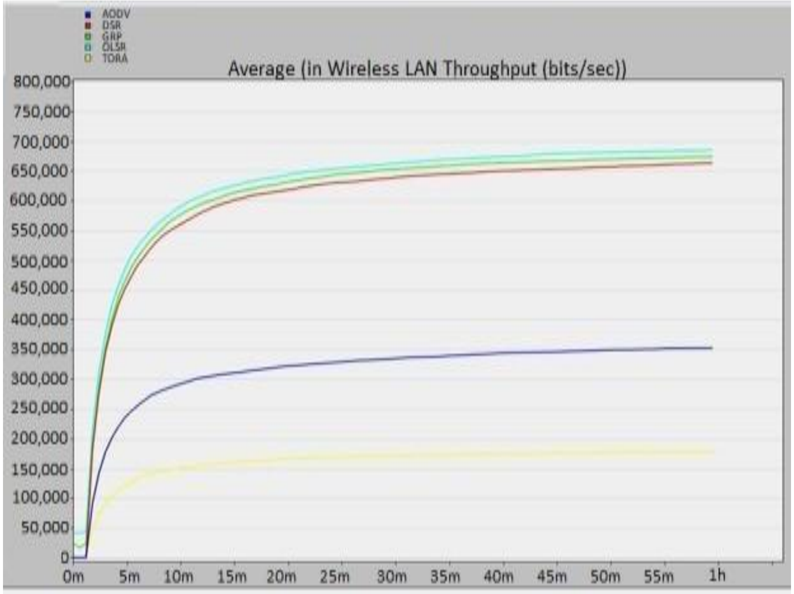


Figure 3.25: Average WLAN Throughput for the Routing Protocols

3.8.1.2 Evaluation of Delay

TORA (yellow line) had the least Delay, as shown in Figure 3.26. However, its Throughput value of approximately 180,000 bits per second (refer to Figure 3.25) was the lowest among the protocols, accounting for about 25% of the three highest performing routing protocols: OLSR (cyan line) with about 687,500 bits per second, GRP (green line) with approximately 675,000 bits per second, and DSR (red line) at approximately 650,000 bits per second. TORA's Throughput was also about 50% that of AODV (purple line), which had a Throughput of 350,000 bits per second.

Among the three routing protocols (OLSR, GRP, and DSR) considered based on their Throughput values, GRP (green line) exhibited the lowest Delay values over time (OLSR (cyan line) had a Delay value of approximately 0.00014, GRP (green line) approximately 0.00010 seconds, and DSR (red line), approximately 0.00022 seconds.) However, at the beginning of the simulation, GRP recorded the highest Delay value of 0.00048 seconds.

The initial spike at the beginning of a simulation can occur for several reasons. One common cause is the protocol's initial route discovery phase, which typically generates a surge of routing updates as it gathers information about the network topology. Over time, this value gradually decreased and aligned with OLSR (represented by the cyan line), which had an average Delay of 0.0014 seconds around the 13-minute mark of the simulation. Notably, GRP's Delay at its peak was approximately 242% of OLSR's maximum Delay. This spike could lead to communication issues in a real-life scenario, mainly since the framework is designed for time-sensitive disaster recovery. Therefore, an ideal protocol for SAIMOD would minimise delays and is not susceptible to spikes. In contrast, DSR (red line) consistently showed the highest Delay value of 0.00022 seconds from the 7th minute of the simulation, when all the routing protocols established a baseline until the end.

These results also align with those obtained in Figures 3.21-3.24, with slight variations in Delay values.

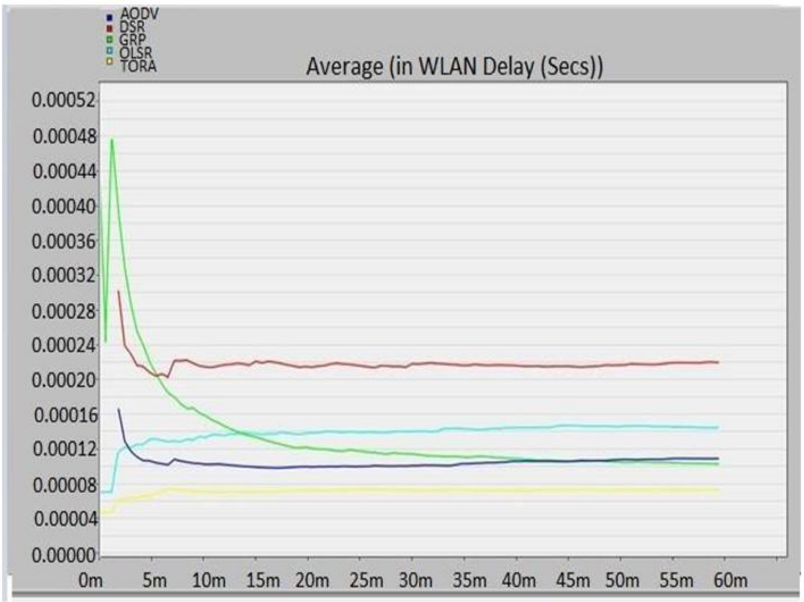


Figure 3.26: Average WLAN Delay for the Routing Protocols

3.8.2 Testing Individual Applications

For this aspect of the Research, the simulation time is set to 20 minutes, and the number of nodes is kept at 100. The idea behind this is to check the suitability and scalability of the routing protocol, assuming each group comprises a mix of rescue team members, such as firefighters, police officers, medical personnel, emergency response team and volunteers and the people to be rescued. In addition, it is desirable to have a scalable network that can handle an increasing number of nodes in a disaster recovery scenario. Search and Rescue missions aim to rescue as many people as possible in the quickest and safest way possible.

3.8.2.1 Peer- To -Peer file sharing

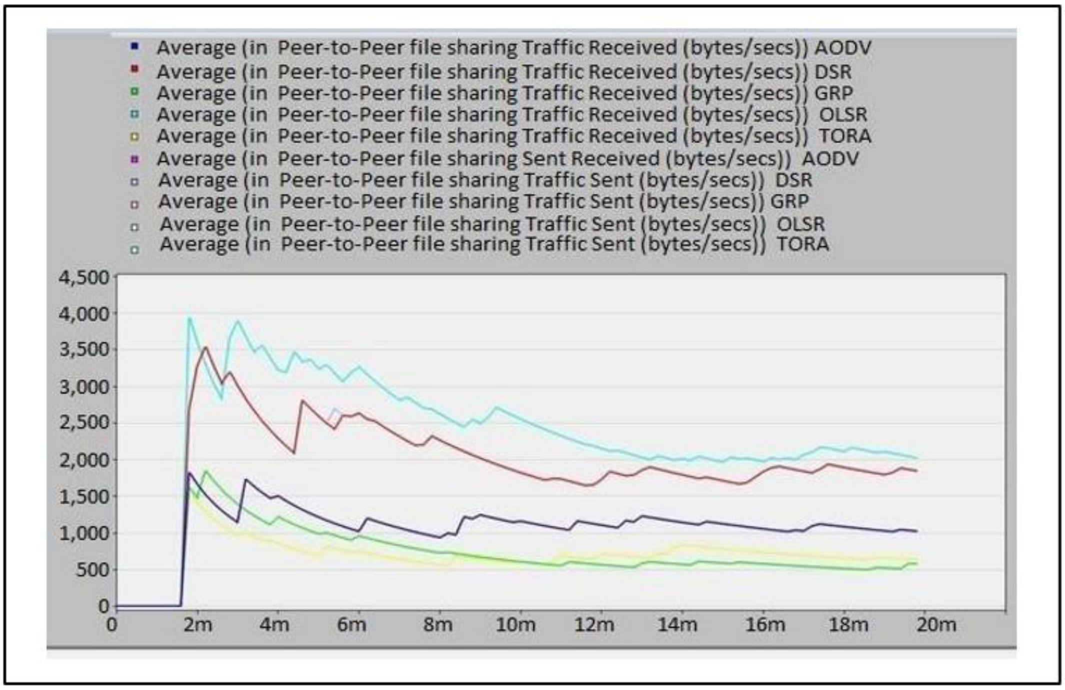


Figure 3.27: Average Peer-to-Peer Throughput (bytes/secs)

Figure 3.27 presents the average Throughput of Peer-to-Peer applications in the network. The Throughput values, ranging from 1,600 bytes/sec to 4,000 bytes/sec, highlight the superior performance of OLSR (cyan line) compared to the other four routing protocols evaluated: DSR (red line), GRP (green line), AODV (purple line), and TORA (yellow line). OLSR (cyan line) had Throughput values between 2,000 bytes/sec and 4,000 bytes/sec. This performance results from its optimised proactive routing protocol nature, continuously establishing and maintaining routes from source to destination nodes, minimising delay and significantly enhancing reliability.

3.8.2.2 Evaluation of Voice Packet Delay Variation (Jitter)

The TORA protocol exhibited the lowest Jitter (Voice Packet Delay Variation), as illustrated in Figure 3.28. It had average Jitter values of 0.00002 µsecs, with its highest recorded value at the beginning of transmission being 0.00012 µsecs. This suggests that TORA would be an ideal protocol for use in the network if Jitter values were the sole consideration. As a hybrid protocol, TORA employs synchronised clocks and Directed Acyclic Graphs (DAGs) to maintain loop-free routes, enhancing the reliability of data transmission across the network and resulting in favourable Jitter values.

The GRP protocol's jitter results, shown in Figure 3.29, ranged from 0 to 0.2 µsecs, with most packets delivered exhibiting Jitter values below 0.1 µsecs. This makes it the second-lowest Voice Packet Delay Variation among the five tested protocols. For the AODV protocol, depicted in Figure 3.30, the Jitter values ranged between 0 and approximately 0.06 µsecs, making it the third-best performing protocol based solely on Jitter results. In Figure 3.31, DSR's Voice Packet Delay Variation values ranged from 0 to 0.18 µsecs, marking it as having the second-highest Jitter value in the network. OLSR recorded the highest Jitter values (Figure 3.32). However, its average Jitter remained below 0.1 µsecs until around the 82% mark of the transmission. At that point, the Voice Packet Delay Variation spiked to 0.050 µsecs before dropping to below 0.1 µsecs.

Voice Packet Delay Variation (Jitter) and Delay (latency) are crucial factors researchers assess when categorising voice quality, as voice transmission is susceptible to variations in these network parameters. This sensitivity arises because data is typically processed only after receiving the complete stream. Therefore, while the order of packet arrival is irrelevant as long as all packets representing the entire file are eventually delivered, some packets may arrive faster than others (this variation is termed Jitter). Table 3.8 presents the maximum Voice Packet Delay Variation for the tested protocols. The observed Jitter range is acceptable, as indicated by the Quality of Service for the voice messages received. This is further supported by the Mean Opinion Score (MOS) results shown in Figure 3.22, which are compared using the MOS value standards in Table 3.1. Additionally, the acceptable value for Voice Packet Delay Variation is 150 µsecs, and the highest Jitter recorded among the tested protocols was 0.6 µsecs, which is lower than the threshold for acceptable Quality of Service (QoS) for voice communication.

Figures 3.28 - 3.32 show the Voice Packet Delay Variation (Jitter) results in milliseconds (µsecs) for the individual protocols run in the network.

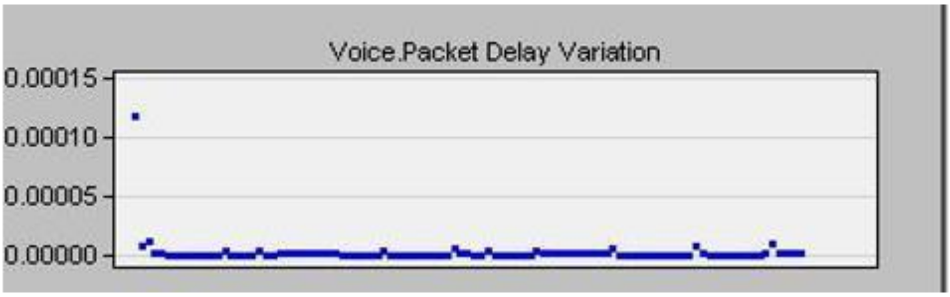


Figure 3.28: TORA Voice Packet Delay Variation (Jitter)

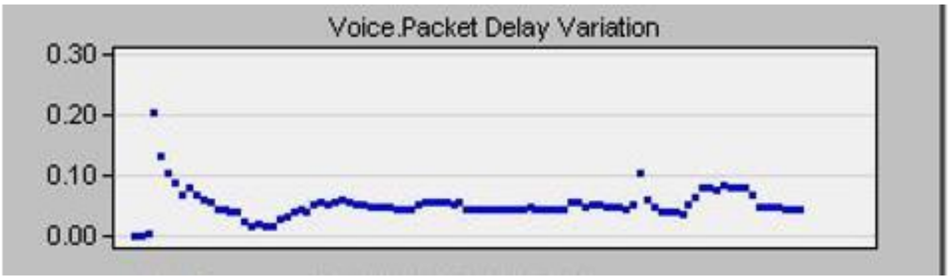


Figure 3.29: GRP Voice Packet Delay Variation (Jitter)

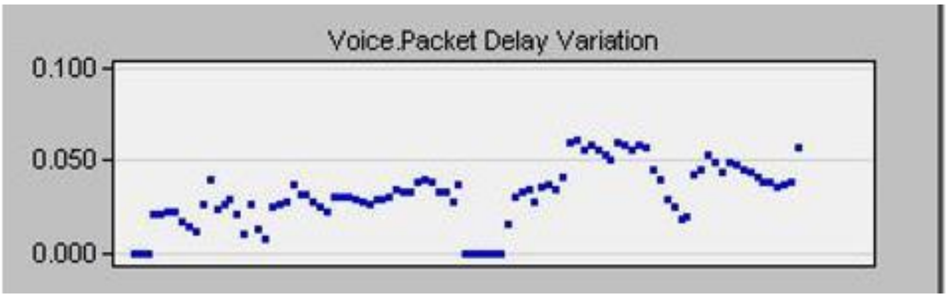


Figure 3.30: AODV Voice Packet Delay Variation (Jitter)

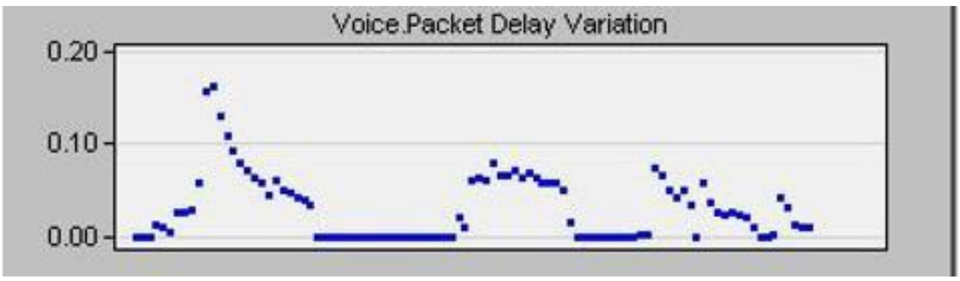


Figure 3.31: DSR Voice Packet Delay Variation (Jitter)

Figure 3.32: OLSR Voice Packet Delay Variation (Jitter)

Table 3.8 is a summary of the Maximum Vice Packet Delay Variation (Jitter)

Table 3.8: Maximum Noise Packet Delay Variation (μs)

Routing Protocol	Maximum Noise Packet Delay Variation (μs)
TORA	0.00012
GRP	0.2
AODV	0.7
DSR	0.17
OLSR	0.6

3.8.2.3 Evaluation of MOS (Mean Opinion Score Value)

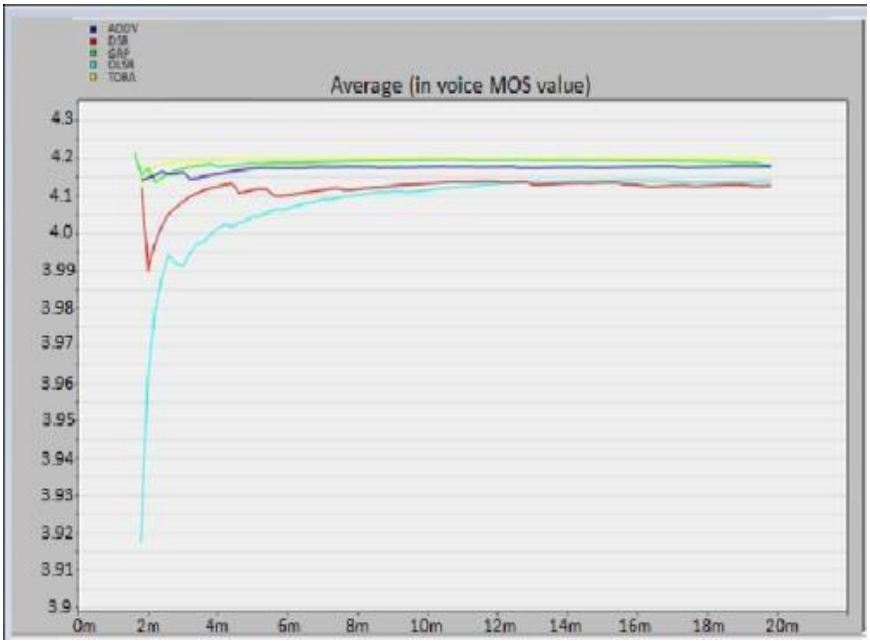


Figure 3.33: MOS (Average voice Mean Opinion Score)

The Acceptable Quality of Service (QoS) for VoIP requires Mean Opinion Score (MOS) values between 4 and 5, as outlined in Table 3.1. The simulation results in Figure 3.33 indicate that all the tested protocols achieved MOS values exceeding 3.99, ranging between 3.99 and 4.21.

In addition, the Voice Packet Delay Variation results, shown in Figures 3.28 to 3.32, reveal that TORA (Figure 3.28) exhibited the lowest jitter, with values ranging from 0 to 0.0002 microseconds. This finding is further corroborated by the average MOS values for each protocol in Figure 3.33.

There is a strong correlation between each protocol's MOS values and their recorded Voice Packet Delay Variation values. This suggests that any routing protocol could be used in the tested scenario for voice applications.

3.8.2.4 Evaluation of HTTP (Traffic sent vs traffic received)

The simulation results for HTTP packets sent versus packets received (see Figure 3.34) indicate that the OLSR routing protocol (represented by the cyan line) had the second-highest performance, trailing only behind the DSR protocol (shown in red), which maintained a rate of 200 to 230 bytes per second. This advantage for DSR may be attributed to its ability to establish new routes quickly.

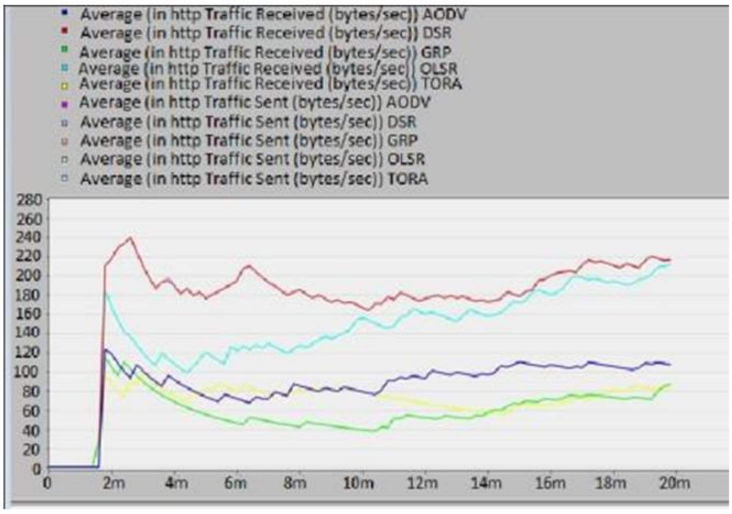


Figure 3.34: HTTP traffic sent vs traffic received

3.9 Testing the scalability of the network using one UAV

SAIMOD is designed as an integrated emergency communication system that relies on Mobile Ad Hoc Networks (MANETs) formed by Unmanned Aerial Vehicles (UAVs) to restore or create communication links quickly. The initial simulations were conducted using 3 UAVs. Following the suitability check for the routing protocol, the network was rerun in five different scenarios using a single UAV.

The system was then tested with a single UAV for two main reasons. First, it was tested to assess its scalability in handling networks with increasing nodal densities. Second, SAIMOD is built to operate as a standalone, single-UAV-based system. It can function effectively with just one UAV and remains resilient to network changes, such as UAV failure. The UAVs used have a coverage of 500 X 500m, the approximate size of five football fields.

- The network size is maintained (500m X 500m).
- Applications run are the same.
- Only one UAV is placed in the network.
- The number of ground nodes is increased – 10 nodes, 30 nodes, 50 nodes, 80 nodes, and 100 nodes.

3.9.1 Evaluation of Packet Delivery Fraction (PDF)

From the simulation results collated in Figure 3.35, OLSR (blue line) has the best Packet Delivery Fraction. It performed better among all the three classes of routing protocols in high-density networks. In addition, OLSR (blue line) showed the best network resilience compared to the other protocols, as it had fewer fluctuations with increasing nodal density.

AODV (orange colour) and DSR (grey line) initially had good values that were on par with the other protocols. Still, as the nodal densities increased, their Packet Delivery Fractions began to drop. This could be because of the need for route discovery. On the other hand, TORA (yellow line) performed average compared to the other routing protocols. Its value ranged from 85% to 87%. OLSR (dark blue colour), an improved table-driven protocol, only requires MPR (Multipoint Relay) nodes to send messages from source to destination. It consistently maintains high PDF values above 99%, irrespective of the increase in the number of nodes. The values of PDF in the OLSR (dark blue colour) network showed that the percentage of successful packets delivered generally increased as the node density increased. This makes the protocol suitable for high-density networks. The results for PDF imply that the network is scalable and can handle increased traffic.

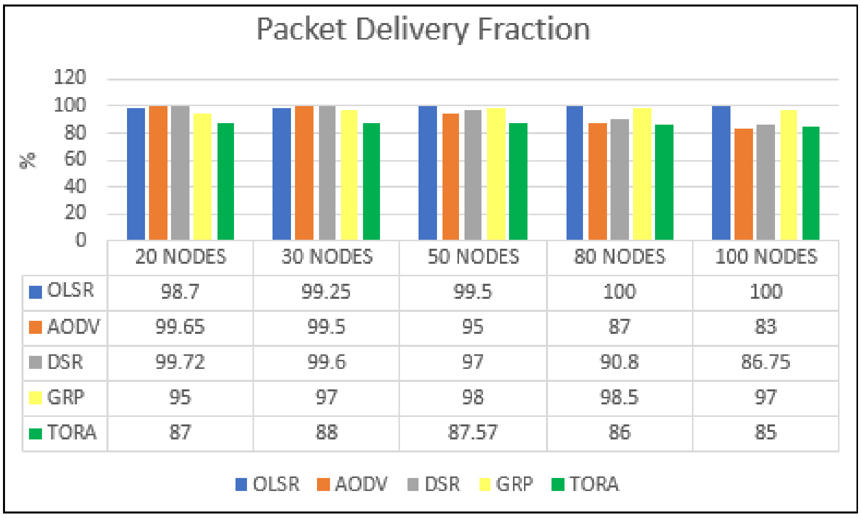


Figure 3.35: PDF in percentage for Nodal densities up to 100

It was also observed that the PDFs (Packet Delivery Fractions) of OLSR (blue line) and AODV (orange colour) were close to each other, but as the number of nodes increased, there was a drop in that of AODV (orange colour) as compared to OLSR's (dark blue colour). AODV had 83% at 100 nodes. Compared to these two protocols (OLSR (dark blue colour) and AODV (orange colour)), DSR (grey colour) maintained good delivery performance when there were 10 mobile nodes (99.72%) and maintained this percentage till about 30 nodes (99.6%). However, the performance degraded as the nodal density increased from 30 nodes (99.6%) to 50 nodes (97%) and continued with a steep decline to 100 nodes (86.75%). The initial performance achieved by DSR could be attributed to data link acknowledgements in DSR architecture, which enables mobile nodes within the network to quickly learn about any lost links as soon as they occur and act accordingly. Furthermore, the nodes in DSR have an overhearing property' that allows intermediate nodes in the network to learn about available routes to destinations and, in turn, cache these routes for future use.

3.10 Further Scalability Testing

The network scalability was initially conducted under one UAV to ensure that shortfalls in the network coverage were not augmented by other UAVs covering the network as the overall network PDF was collated, and it was also to check the resilience of one UAV covering the disaster recovery area. SAIMOD, a model designed for adaptability, is intended to work as a standalone model with one UAV or a group of UAVs, depending on availability and suitability. It also demonstrates SAIMOD's resilience in the case of change in topology, such as UAV failure, as One UAV can handle the Network requirement for the disaster area covered.

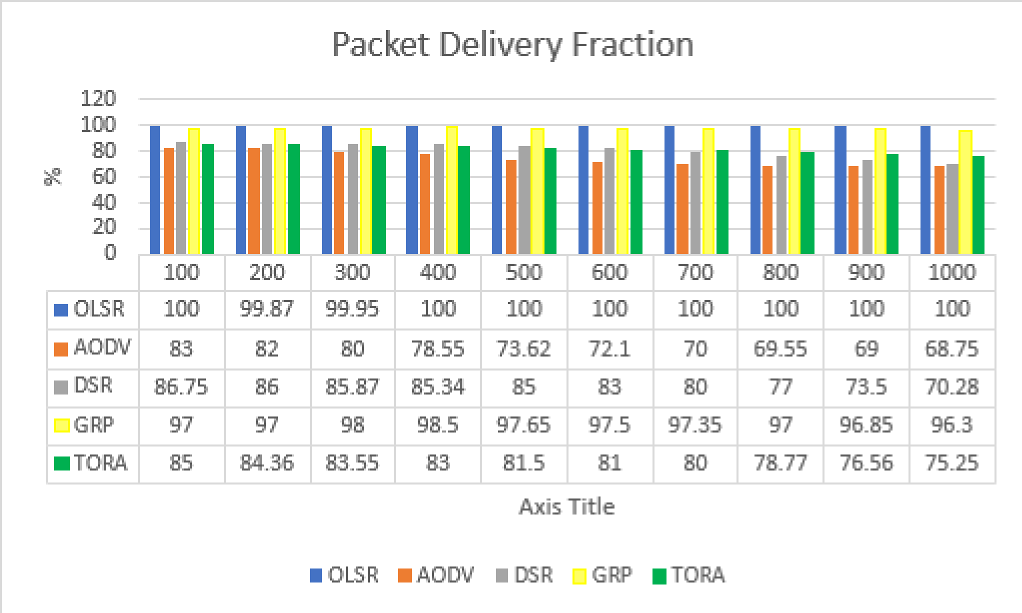
Another experiment is carried out to test the network's scalability further. The network parameters are maintained, and two types of networks are simulated: the first with 1 UAV and the second with 3 UAVs. The nodal densities, representing the number of nodes in each area, are increased incrementally to 1000. This increase in nodal densities is a key factor in assessing the scalability of the network. Further in-depth testing under more UAVs is conducted to assess the impact of more UAVs on the scalability in a more expansive (extensive) network with increasing nodal densities. This could be more rescue team members, a secondary team sent in, in line with the disaster management plan, auxiliary rescue groups formed, or even more people to be rescued as SAIMOD was designed to care for a 500m X 500m disaster area. This coverage area is approximately the size of five football fields.

Both networks are compared. (The initial scalability test using PDF (Figure 3.35) was done under one UAV with nodal densities up to 100; testing both networks with nodal densities up to 1000 would give a balanced view of the network performance).

The network size is maintained (500m X 500m).

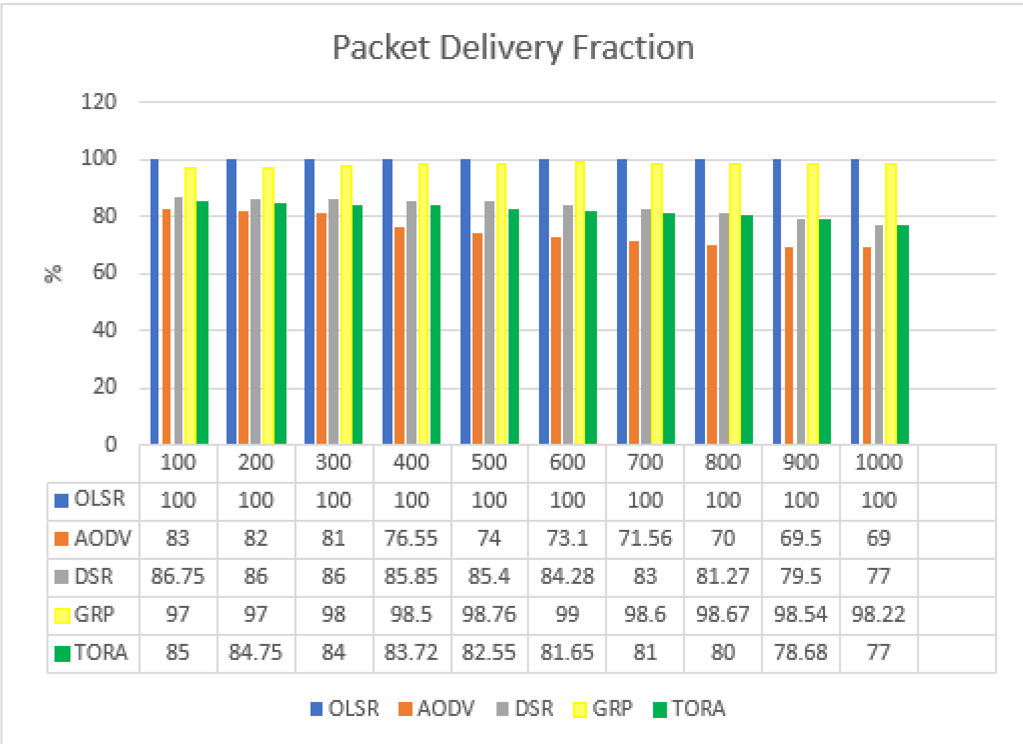
- Applications set up are the same.
- The number of ground nodes is increased incrementally from 100 to 1000.

3.10.1 Evaluation of PDF for Nodal Density up to 1,000



	100	200	300	400	500	600	700	800	900	1000
OLSR	100	99.87	99.95	100	100	100	100	100	100	100
AODV	83	82	80	78.55	73.62	72.1	70	69.55	69	68.75
DSR	86.75	86	85.87	85.34	85	83	80	77	73.5	70.28
GRP	97	97	98	98.5	97.65	97.5	97.35	97	96.85	96.3
TORA	85	84.36	83.55	83	81.5	81	80	78.77	76.56	75.25

Figure 3.36: PDF in Percentage for Nodal densities up to 1000 using 1 UAV



	100	200	300	400	500	600	700	800	900	1000
OLSR	100	100	100	100	100	100	100	100	100	100
AODV	83	82	81	76.55	74	73.1	71.56	70	69.5	69
DSR	86.75	86	86	85.85	85.4	84.28	83	81.27	79.5	77
GRP	97	97	98	98.5	98.76	99	98.6	98.67	98.54	98.22
TORA	85	84.75	84	83.72	82.55	81.65	81	80	78.68	77

Figure 3.37: PDF in Percentage for nodal densities up to 1000 using 3 UAVs

The PDF results, as seen in Figure 3.36 and Figure 3.33 for the network with a single UAV and that with 3UVAs, show that the network is scalable, more so in the one in which the OLSR protocol was implemented. OLSR maintained a PDF of 100%, a performance ranking consistent with that of Figure 3.35. This consistency proves the OLSR protocol's reliability and the suitability of the selected mobility model, RPGMM, in maintaining network scalability. Although PDF is a significant metric used to evaluate the quality of service in packet forwarding, a more comprehensive test for scalability would also involve evaluating the Throughput and Delay results. Throughput is a key performance metric that measures the rate of successful message delivery over a communication channel in each scenario. In contrast, the Delay metric gives an understanding of how long it would take for the network to transmit data successfully. These metrics (PDF, Throughput, and Delay) provide a comprehensive view of the network's performance, ensuring a thorough and reliable analysis. They are crucial in evaluating dense networks, as they are relevant indicators that point to the network's efficiency in handling data packets, thereby validating the Research findings.

An additional test for scalability using network Throughput and Delay with increasing nodal densities up to 1000 was carried out. This comprehensive test, which involved the network with the selected routing protocol, OLSR, and the chosen mobility model, RGPM, was designed to thoroughly understand the network's performance under varying conditions.

3.10.2 Evaluation of Throughput for Nodal Density up to 1,000

Figure 3.38 shows the results for the Throughput percentages of the two networks. The network where the 3 UAVs were deployed demonstrated consistency, achieving a 100% Throughput value across all scenarios with increasing densities of up to 1,000 nodes. Although the single UAV deployed network initially mirrored this success, maintaining an uninterrupted Throughput of 100% up to the 500-node mark, as the network expanded beyond this threshold, the Throughput had a slight decline, dipping to approximately 99.95% at 900 nodes where this slight reduction in performance stabilised till the network reached 1,000 nodes.

The decrease in Throughput values (approximately 0.05%) is minimal and does not significantly affect the network's performance. Instead, it validates the scalability of the SAIMOD system in handling the challenges faced in managing communication links in denser networks. However, the minimal decline of about 0.5% suggests that the mobility of the nodes could have played a role in this slight variation.

These positive outcomes can be attributed to the synergistic efforts of the RPGMM model, which adeptly promotes seamless connectivity among nodes as they navigate within a cluster-like formation. Furthermore, the OLSR protocol significantly enhances the performance of dense networks by swiftly adapting to changes in MANET, such as increasing nodal densities. This results in a lower incidence of packet drops, which is particularly advantageous when dealing with link failure, as OLSR can quickly assign new links to maintain connectivity.

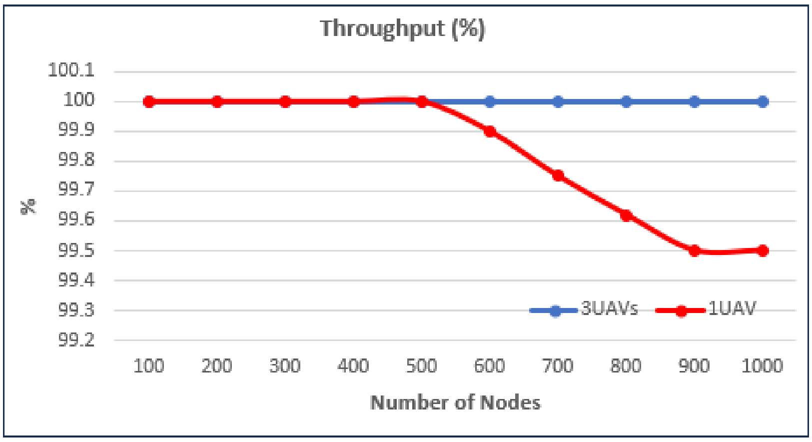


Figure 3.38: Throughput for Nodal densities up to 1000

3.10.3 Evaluation of Delay for Nodal Density up to 1,000

As shown in Figure 3.39, the 3-UAV network exhibited the same Delay value of 0.00018 seconds when the nodal density was 100. However, this Delay value increased to 0.00018 seconds for the 3-UAV network and 0.00025 seconds for the single UAV network at a density of 200 nodes. These Delay values were maintained up to 500 nodes, where they began to decline to approximately 0.00022 seconds and 0.00015 seconds for the 1-UAV and 3-UAV networks, respectively, at 600 nodes. These values were maintained up to 1000 nodes.

This data strongly suggests that the SAIMOD framework is robust and can effectively handle increasing nodal densities. As shown in the simulation results, the Delay values for both networks are within acceptable limits, indicating that the network is scalable as nodal densities increase. This success can be attributed to the combined use of the RPGMM model and the OLSR protocol, which are crucial in enhancing connectivity and optimising performance in dense networks.

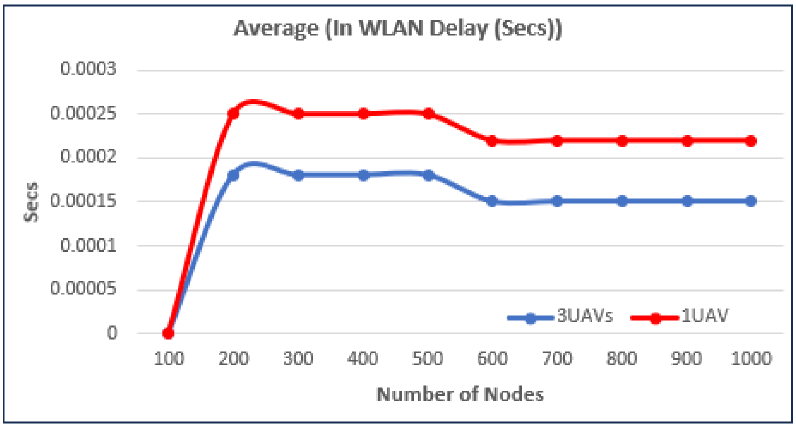


Figure 3.39: Delay for Nodal densities up to 1000

Based on the simulation results for PDF, Throughput and Delay, both networks functioned effectively, validating the network's scalability. However, the network with three UAVs demonstrated better performance than the single UAV**,** further boosting confidence in the framework's capabilities.

3.11 SAIMOD's usage beyond a 500m X 500m disaster zone

The innovative SAIMOD system has been meticulously designed to maintain the expected Quality of Service (QoS) within a focused area of 500 by 500 meters. This area is approximately the size of five standard football fields, marking a significant advancement in disaster response technology. It is important to note that this size is not arbitrary but a carefully calculated area, ensuring efficient and comprehensive coverage in various disaster scenarios. SAIMOD is intended to be the first response system deployed before any other major rescue forces are summoned. In events like landslides, floods, or when a child goes missing in areas with poor network coverage, access to personnel and resources can be severely restricted.

One possible future direction to optimise SAIMOD's usage is testing its suitability beyond 500 X 500 meters. Theoretically, for a system beyond 500m X 500m, the rescue team could cover larger areas by dividing the area to be covered. The disaster zone could be split into small grids of 500m X 500 m at the start, and the SAIMOD framework (made up of the UAVS and rescue teams) will scour one grid and then move on to the next grid area. They could complete one area before moving to the next. One of SAIMOD's key advantages is its ability to avoid over-coverage of the disaster zone. Over-coverage is when multiple UAVs cover the same area, wasting resources and time. Unlike grid-based mesh UAV disaster recovery systems, which require UAVs to be in a fixed position for the MANETs formed to be effective, SAIMOD's flexibility allows the rescue team to cover an area efficiently. SAIMOD provides blanket coverage, as the UAVs are mobile and not restricted to a zone, enabling them to move to the next area without unnecessary duplication of efforts.

Using SAIMOD to divide the zone into grids that are covered sequentially or consecutively by the teams ensures that the rescue teams can effectively cover the areas while avoiding duplication of efforts and over-coverage. This approach allows the rescue teams, typically organised into groups according to the disaster management plan, to operate efficiently without being spread too thin or wasting resources on overlapping coverage.

SAIMOD's potential as an assessment model for resource allocation and distribution is a promising aspect of its capabilities. An assessment model is a tool that helps determine the optimal allocation of resources based on the characteristics of the disaster area. SAIMOD could be used as an assessment model to determine how much ground personnel and resources (such as the number of UAVs) are needed to effectively cover the zones, as resources are limited, and coverage areas likely overlap at the boundaries of the grids.

The proposed methods hold immense potential for reducing damage and minimising loss of life and property. (However, it is essential to note that these theoretical suggestions require testing to validate their effectiveness, which is beyond the scope of this Thesis).

3.12 Chapter Summary

This Chapter details the experimentation in selecting a suitable routing protocol and mobility model for use in the proposed Self-Aware Intelligent Model (SAIMOD) framework. The selection of mobility models and routing protocols used in any network could significantly impact the overall network performance. The initial step in crafting the proposed framework, the Self-Aware Intelligent Model (SAIMOD), is selecting an appropriate mobility model and routing protocol.

Four diverse mobility models, each representing a different class, were selected and tested using AODV (the simulation software's default routing protocol). The mobility models tested and their classifications are listed below.

1. Random Waypoint mobility model (Random model),

2. Gauss Markov mobility model (Mobility model with temporal dependency)

3. Reference Point Group mobility model (Mobility model with spatial dependency)

4. Manhattan mobility model (Model with geographic restrictions)

The goal was to comprehensively test a mix of different mobility models, one from each class, to determine which model would best suit SAIMOD based on a range of performance metrics. The performance metrics tested included Packet Delivery Fraction (PDF), Throughput, average End-to-End Delay, and network routing load (NRL). The Reference Point Group mobility model (RPGMM) emerged with promising results and was chosen.

These were then individually combined with each routing protocol also made up of a selection from the different classifications of routing protocols: proactive, reactive and hybrid routing protocols to analyse the overall performance of the networks under the same network parameters such as network area size, number of nodes and choice of applications run in the network and to determine if the results from AODV would significantly change the selection of RPGMM as the best-fit mobility model for use with SAIMOD.

The five routing protocols tested were:

1. Ad-Hoc On-Demand Distance Vector routing protocol (AODV) (Reactive routing protocol)
2. Dynamic Source Routing (DSR) (Reactive routing protocol)
3. Optimised Link State routing (OLSR) (Proactive routing protocol)
4. Geographic Routing Protocol (GRP) (Proactive routing protocol)
5. Temporally Ordered Routing Algorithm (TORA) (Hybrid protocol)

The selected mobility model, RPGMM, was then further tested using the five routing protocols, as it is intended to find the most suitable routing protocol that would perform at the desired performance threshold stipulated for the scenario in which SAIMOD is designed to be used. The network parameters are kept the same, and in addition to testing the Throughput and Delay of the network, the performance of the individual applications run in the network is also tested. Peer-to-peer file sharing Throughput, Voice Packet Delay Variation (Jitter), Mean Opinion Score, and HTTP traffic sent vs traffic received were analysed.

The network's scalability and resilience were also tested with increasing nodal densities. Finally, a discussion on the novelty of SAIMOD beyond a network size area of 500m X 500m is also presented.

Chapter 4

Proposed Framework- SAIMOD (Self-Aware Intelligent Model)

4.1 Introduction

This Chapter provides a literature review of various existing frameworks for deploying UAVs (Unmanned Aerial Vehicles) in disaster recovery. It introduces a novel framework called SAIMOD (Self-Aware Intelligent Model), detailing the algorithm enabling an intelligent network of deployed UAVs. This algorithm ensures fault-tolerant and resilient positioning control within SAIMOD. Additionally, the Chapter demonstrates how the SAIMOD framework can be utilised to gather statistical data to serve as an assessment model in disaster management, along with a mathematical model for its implementation. Furthermore, the Chapter compares SAIMOD with four existing reinforcement learning UAV deployment frameworks.

4.2 Literature review on existing UAV deployment framework for disaster recovery

The use of Unmanned Aerial Vehicles (UAVs) in various application scenarios is gradually becoming widely adopted in areas such as military surveillance and disaster recovery due to its recent affordability and ease of deployment. In critical scenarios, such as in a disaster recovery situation, where communication links and infrastructure might be inadequate, the use of UAVs could be a cost-effective way to resolve communication issues (Wang et al., 2022). Researchers have proposed various frameworks, and a cross-section is given below of some frameworks proposed for use in disaster recovery.

A statistical framework aimed at managing the interference problem faced with device-to-device intercommunication in deployed UAV-assisted emergency communication networks was proposed by Zhang and Cheng (2019). Their algorithm centred around improving the network's Quality of Service (QoS) and managing diverse levels of Delay. They optimised the network's capacity while considering its peak rate and power constraints. Their simulation results showed that their proposed algorithm could manage varying levels of Delay while maintaining the expected Quality of Service compared to similar schemes. Their Research was focused on improving interference management by maintaining an acceptable threshold for QoS.

Trotta et al. (2020) proposed a framework that relies on a swarm mobility algorithm for positioning UAVs in an aerial mesh deployment topology called ELAPSE (aErial LocAl Positioning System for Emergency) for QoS management. Their framework was intended to facilitate communication links between ground nodes (rescue teams and people to be rescued) in hazardous disaster recovery conditions while pinpointing their location. Their simulation results on small and dense networks showed an improvement in positioning support, maximum coverage area and Quality of Service compared with some other models. Their focus was restoring connectivity between ground nodes but not bi-directional communication between the UAVs and the ground nodes.

An exploratory framework for studying the challenges faced in Search and Rescue operations using the Internet of Things (IoT) was proposed by Kao et al. (2019). They reviewed key machine-learning concepts for path planning and object detection in disaster areas. They evaluated the practicality of their proposed framework via simulation using a proof-of-concept prototype. Their results showed that their framework could improve the existing IoT architectures for disaster recovery. They focused on using UAVs to obtain and monitor victims' location and status in the disaster recovery area and sending the data received to the rescue team. They posited that it could also be used to send relief items such as medicine to the victims. However, it was not designed to restore communication links in the disaster recovery area.

Kargbo et al. (2018) proposed an electrical grid restorative architectural framework based on the International Electrotechnical Commission (IEC) 61850 standard using a Location Set Covering Problem (LSCP) for improved restoration practices in UAV post-disaster recovery scenarios. They aimed to reduce the distance travelled by emergency crews working in the disaster area, using the supervisory control and data acquisition (SCADA) algorithm in disaster management. They deployed UAVs in convergence with Regional Mutual Assistance Groups (RMAGs) using a Multi-Agent System (MAS) scheme and a System of Systems (SOS) outlook in designing the network that will be a decentralised control and monitoring framework. Their SoS model supports using a decentralised tactic to handle electric grids in the network. They focused on restoring the electrical grid network to aid Search and Rescue.

A real-time imaging framework for long-distance multistrip UAV flights to enhance UAV image mosaic creation was proposed by Zhang et al. (2020). Their algorithm constructs images using information captured by a single camera and does not require additional information, such as the Global Positioning System (GPS). It does this by carrying out three key functions: tracking current frames, automatic initialisation, and generating images in real-time. Their proposed framework demonstrated better algorithm speed when compared with five contemporary image-stitching schemes. In addition, their experimentation showed that the framework could adapt to changes in features and illumination in the network. Their Research focused on optimising aerial mapping for search and rescue operations where time is constrained and other activities such as monitoring traffic, agricultural patrols, and conducting post-earthquake surveys promptly while offering high stitching accuracy.

Nguyen et al. (2021) proposed a communication optimisation framework for resource allocation, such as the number of UAVs to be deployed as flying base stations in restoring network connectivity in disaster recovery scenarios as part of spectrum-sharing cognitive radio networks (CRNs). In addition, they suggested the use of a deep neural network (DNN) model to minimise execution time. Their objective was to optimise the overall network Throughput based on strict stipulated thresholds for interference imposed on the primary users. Their results showed that the networks had reduced execution time in optimising Throughput issues due to their algorithm's structure simplifying computational processes.

Wang et al. (2022) proposed a framework within a UAV swarm environment focused on the dynamic routing issue faced in deploying such networks. This framework implements a centralised multi-agent reinforcement learning algorithm which optimises the network quality in terms of Throughput, packet delivery ratio (PDR) and survival time. Their experiment, through wide-ranging simulations, aimed to validate the algorithm's efficiency. Their proposed algorithm, designed to be a gradient-based UAV routing scheme that updates each node, proved to be more effective when compared with other contemporary algorithms.

Sha and Wang (2022) proposed a framework designed to enhance UAV navigation in environments with complex resource limitations. Their proposed framework combined the Proximal Policy Optimisation (PPO) and the Proportional Integral Derivative (PID) algorithms for enhancing navigational planning and controlling the UAV's altitude, respectively. Their objective was to use technical details to optimise these navigational tasks based on deep learning schemes using state representation, well-built reward function and domain-specific information. Using a single quadcopter UAV, they carried out general tests to validate the efficiency of their proposed framework. Their focus was on path and navigation planning for the UAVs, and their simulation showed promising results in UAV performance in selected environments with limited resources.

A three-dimensional (3D) modelling framework for UAV swarm networks using Visual Structure from Motion (VisualSfM) was proposed by Lundberg, Sevil and Das (2018). This framework was designed for operational planning, such as military deployments, Search and Rescue operations and disaster recovery scenarios. They aimed to use onboard sensors to provide timely information by interpreting the data from the sensors into 3D contexts for surveillance and reconnaissance as and when needed. They tested their framework using diverse UAV simulations with varying capacities and selective 3D mapping on specific marked-out areas and not the entire global map in their simulations. This significantly reduced the human agents' mental load and the network's computational costs. The focus of their research was on optimising the aerial mapping process.

Bălaşa, Bîlu, and Iordache (2022) proposed a navigational framework to enhance UAV navigation in scenarios with complex trajectories. They used Proximal Policy Optimisation (PPO) and an irregularly shaped trajectory for the UAV to prove that their framework is adaptable in multiple scenarios (not only in straight-line trajectories or classical manoeuvres). They conducted general tests to validate the efficiency of their proposed framework using varying network conditions. Their simulation results showed that the UAV in the network was adaptable in complex trajectories as the Quality of Service was not reduced.

Wang and Peng (2022) studied the cooperative working mode of multiple UAVs (Unmanned Aerial Vehicles). They proposed a framework for enhancing accuracy in spectrum sensing for large cooperative multi-UAV cognitive networks. They used a cooperative spectrum sensing algorithm based on detection probability performance at low signal-to-noise ratio (SNR) values. In their simulations, using received signal energy matrix data and convolutional neural network for spectrum sensing, they considered the shortage of spectrum resources and compared their algorithms using a Rayleigh fading channel to the K-out-of-N algorithm and support vector machine to test their proposed framework. Their simulation results showed better performance in detection probability at low Signal-to-Noise Ratio (SNR) compared to other available schemes. They focused on enhancing the performance of large, cooperative multi-UAV cognitive networks.

4.3 Self-Aware Intelligent Model (SAIMOD)

When a disaster like an avalanche occurs, especially in hard-to-reach places, Unmanned Aerial Vehicles (UAVs) can be used as a support system by acting as a mobile wireless communication system that will aid rescue operations conducted in the disaster recovery area. Communication may be hindered for several reasons, such as broken communication links due to destroyed base stations, no pre-existing communication network (probably due to being in a dead zone), or the affected individual might even be incapacitated.

As discussed in Chapter 2, in disaster recovery scenarios that take place in remote locations or are time-sensitive due to the urgent nature of the disaster, the fastest and most effective rescue operations may involve using companion rescue teams (people already on the ground) alongside a resilient and adaptive communication network. In these situations, having an emergency network infrastructure that can be readily deployed is essential to support the Disaster Management Team (DMT) in their planning and decision-making processes. This approach can significantly help mitigate damage and loss of life and property.

This Research proposes the Self-Aware Intelligent Model (SAIMOD), a novel distributed disaster recovery framework for UAV deployment. The UAVs will establish a dynamic wireless mobile network that connects devices operated by ground crews. This ensures seamless and dependable communication, even in challenging environments. SAIMOD supports multi-hop connectivity in the network. This means that information can be relayed through multiple devices, ensuring critical data reaches the decision-makers swiftly and accurately.

SAIMOD demonstrates self-awareness in its approach to network resilience, empowering it to swiftly adapt to unexpected disruptions within the UAV-based Mobile Ad Hoc Network

(MANET), such as a UAV failure or malfunction. "Resilience" refers to the framework's inherent capability to maintain operational functionality while effectively navigating unforeseen changes or failures within the MANET.

SAIMOD employs a blend of reinforcement learning techniques and a path-planning algorithm, which work in tandem to enhance both coverage and connectivity between the UAVs and the ground nodes (see Subsections 4.31-4.34). SAIMOD's design emphasises a proactive response to real-time network fluctuations, ensuring it can adequately adjust and recalibrate its operations if a UAV fails or encounters other challenges. This flexibility improves the network's reliability and efficiency, facilitating smooth communication and coordination despite unforeseen challenges.

SAIMOD is developed by addressing the following challenges:

I. Selection of a suitable mobility model for use with SAIMOD

The selection of a mobility model for a Mobile Ad Hoc Network (MANET) determines how mobile nodes move and how their acceleration, velocity, and location fluctuate over time. This Research, which included comparative experiments with three other mobility models, has identified the Reference Point Group Mobility Model (RPGMM) as the most suitable model for the proposed framework.

II. Selecting a suitable routing protocol for use with SAIMOD

The selection of routing protocols used in MANETs is challenging due to the unpredictability of their topology. This dynamic nature of their topology causes varying network conditions, such as available energy in the network, node densities, and limited bandwidth. However, the OLSR protocol, as suggested by the simulation results in Chapter 3, is not only the best-fit routing protocol for the network but also highly adaptable to handle such dynamic network conditions. Further optimisation for the energy efficiency of this protocol is detailed in Chapter 5.

III. Intelligent networking amongst the UAVs in SAIMOD

The issues faced in developing automatic flight control systems for deploying Unmanned Aerial Vehicles have been resolved in recent years. However, one main concern is creating a fault-tolerant control system that would allow for the intelligent autonomous networking of UAVs in the deployed network. This fault-tolerant formation control must be reliable and resilient in real time. It is intended that SAIMOD would have intelligent networking amongst the UAVs to address this concern by using a suitable algorithm.

An autonomous, fault-tolerant control system has a lot of advantages and practicality in battlefield environments, Search and Rescue operations, etc. Although several attempts and studies have been conducted to improve unmanned systems' formation control and coordination, significant challenges remain. In the current literature, existing solutions do not meet this demand, as the majority are based on heavy infrastructure, human agents, over-processing or are not carried out in real-time (Shrit et al., 2017). This study addresses this by incorporating intelligent networking amongst the UAVs, using a suitable algorithm to efficiently control individual UAV areas of coverage within the disaster recovery zone, and using unique identifier numbers by key nodes in the network. This would ensure that the network is resilient and adaptable to changes such as drone failure. This would also enable the UAVs to avoid duplication of efforts efficiently.

The proposed framework is an energy-efficient model that synergises a positioning algorithm for the UAVs and a suitable mobility model for the ground nodes. In SAIMOD, the modified routing protocol OLSR (MODOLSR) should be used with the mobility model Reference Point Group Mobility Model by the ground nodes in the MANETs formed. These MANETs will be formed using self-aware UAVs that are equipped with GPS. An appropriate algorithm by which the UAVs will move amongst themselves would be incorporated into the model, and this would be based on the degree of similarity/dissimilarity in their geographical positioning. The goal of incorporating this algorithm would be to ensure seamless networking among the UAVs in such a way as to make the network more efficient, as the UAVs, for instance, can exchange relevant information and avoid covering the same area, which would conserve resources such as time and reduce cost. Three issues tackled here are:

- Creating an efficient UAV distributive model.
- Incorporating Intelligence in UAV path planning.
- Proposing an assessment model.

4.3.1 Creating an efficient UAV distributive model

The MANET (Mobile Ad-hoc Network) will be established by deploying UAVs (Unmanned Aerial Vehicles) as relays. These UAVs are crucial in restoring connectivity between ground nodes in the disaster recovery area. This bi-directional communication will be a key feature of the network, enabling seamless communication between UAVs and ground nodes.

Each group of ground nodes will have a designated group leader equipped with a device that has a unique identifier number. This unique identifier system is a robust security measure that ensures organisation within the network. Similarly, the UAVs will possess unique identifier numbers, allowing them to communicate with one another and the group leaders when they are within range, further enhancing the security and reliability of the system.

The UAVs will be equipped to transfer information, such as their unique identifier numbers and those of the ground node groups they cover. These identifiers will be captured during interactions between group leaders and UAVs, ensuring efficient communication throughout the network.

5.3.2 Incorporating Intelligence

Junior and Yen (2019) classified the path planning models currently being used into three major types: Deep neural network-based algorithms, Particle swarm algorithms, and Ant colony algorithms, as described below.

a. Deep neural network-based algorithm: This involves using an advanced deep neural network to avoid obstacles by UAVs when deployed in unknown environments effectively. Path planning for obstacle avoidance is achieved by maintaining key information obtained in long observation sequences.

b. Ant colony algorithm: When searching for food, ants tend to efficiently find the shortest path from their nests to the food source. A UAV path planning modelled after this algorithm can be easily optimised and have positive information feedback.

c. Particle swarm algorithm: Individual group UAVs are differentiated using information sharing in the particle swarm algorithm. This enables the algorithm to differentiate these individuals and deduce suitable path solutions in the space domain. It perceives them from chaos to order and from single to concrete. However, in complex environments, particle swarm algorithms usually act on a local optimum, but this can be overcome by adjusting determining parameters, such as factors affecting acceleration and inertia weights, to ascertain global optimal path planning solutions (Guo et al., 2023; Saoji and Rao, 2021).

SAIMOD is designed to be user-friendly, allowing any path-planning algorithm. This study specifically focused on optimising the selected path planning of the UAV to cover the disaster area efficiently. The system ensures that efforts are not duplicated, regardless of the path-planning algorithm chosen by the user.

The UAVs in SAIMOD will utilise a reinforcement learning method to ensure that the UAVs adequately and efficiently cover the disaster area. Reinforcement learning (RL) is the aspect of machine learning that depicts the decision-making process of intelligent agents in dynamically changing environments. Each UAV will be equipped with GPS that will use an algorithm to determine movement patterns among the UAVs based on the degree of similarity or dissimilarity in their position geographically. This will ensure seamless networking so the UAVs can efficiently avoid covering the same area and have a collision-free path (a path that avoids dynamic and static threats) for the UAVs in the network.

Moreover, SAIMOD is designed to enhance the current deployment of UAVs. It is designed to be self-aware, and this model can intelligently adapt to changes, such as UAV failure in their dynamic environment in real-time, by applying knowledge learned from one task to another. For instance, the UAVs could communicate with each other when in range and transfer information such as unique identifier numbers of groups covered, showcasing the robust adaptability of SAIMOD.

As shown in the simulation conducted in Chapter 3, each group of ground nodes is led by a group leader equipped with a unique identifier device. This identifier number is captured when the group leader exchanges information with a UAV. The UAV and the group leader each receive their numbers from the data stream sent, which is encoded in the information. For example, when mobile_node_0 (UAV1) receives a message from USER3, it adopts the unique identifier number of USER3 by extracting it from the received data stream and transmits both its unique identifier number and that of USER3 when it communicates with mobile_node_1(UAV2). The unique identifier numbers identify the group leader and the UAV that covered the group, enhancing the network’s resilience and adaptability.

The unique identifier numbers contribute to the network's adaptability by identifying the group leader and the UAV covering the group. Should a UAV fail in the network when it has already passed on the information of the group covered, that group will not be duplicated (covered again) as the information is already stored in another UAV’s memory cache. This adaptability, facilitated by the unique identifier numbers, enhances the network’s resilience and flexibility.

If a UAV fails while it has already transmitted information about its coverage area, that group will not be redundantly covered again. When a UAV transmits information about its coverage area, it efficiently stores that data in the memory cache of another UAV, ensuring robust data storage and preventing redundant coverage. This efficient data storage is a testament to the strength of the interconnected SAIMOD network, where every UAV is linked to at least one other, ensuring seamless operations and enhancing the overall effectiveness and resilience of the network when multiple UAVs are deployed as part of the SAIMOD framework.

4.3.3 Comparison of SAIMOD to the State-of-the-art

The section compares SAIMOD to state-of-the-art to highlight the novelty of the Research and its potential impact on disaster recovery. It involves evaluating its performance, features, and effectiveness against existing Research on UAV-based mobile ad hoc networks (MANETs) for disaster recovery. This comparison highlights SAIMOD’s novel contributions, potential to address the specific challenges of disaster recovery and advantages over traditional approaches. Key aspects of this comparison include:

I. Optimised Routing protocol and mobility model

SAIMOD uniquely combines a novel routing protocol called Modified Optimised Link State Routing protocol (MODOLSR) and a best-fit mobility model known as Reference Point Group Mobility Model (RPGMM). This mobility model uses a clustered approach to determine ground node movement patterns, while the routing protocol enhances Throughput and makes the network more energy efficient. Many existing models focus on either routing or mobility but not their integration, often neglecting the interplay between them. Integrating the routing protocol with the mobility model significantly improves the network’s efficiency, providing a practical and beneficial solution. Combining a designated mobility model with the novel protocol in SAIMOD significantly enhances network Throughput and mobile node management.

II. Self-awareness, Resilience and Scalability

SAIMOD demonstrates self-awareness in its network resilience, quickly adapting to unexpected changes in the network topology (such as UAV failure) and maintaining its functionality. SAIMOD employs reinforcement learning based on its path-planning algorithm to optimise disaster zone coverage. SAIMOD utilises algorithms to process data in real time, ensuring that UAVs can make informed decisions based on current situational awareness. They apply knowledge gained from one task to another, ensuring seamless communication and adaptability of the framework while preventing duplicated efforts to cover the network. Each UAV operates autonomously by employing a decentralised control system while communicating and coordinating with other UAVs, enhancing the framework’s overall operational efficiency and adaptability. The distributive model is designed to scale effectively. This innovative approach allows the addition of more nodes to the network without significantly complicating the control and communication mechanisms. Even as the network grows, the consistent performance demonstrates that SAIMOD can effectively adapt to changing conditions and maintain reliable connectivity.

III. Intelligent networking amongst the UAVs deployed

SAIMOD uses an autonomous, fault-tolerant control system for UAV path planning, coordination and formation control. Previous studies have aimed at improving or creating fault-tolerant UAV formation control and coordination systems, but there remains a gap as substantial challenges remain. The framework’s self-aware UAVs can make real-time adjustments based on their GPS data and proximity, often lacking state-of-the-art solutions that depend on heavy infrastructure and may require human intervention for operational changes. SAIMOD Integrates with a ground control system for better mission planning, and real-time adjustments are made based on changing circumstances in the network, ensuring that UAVs operate synergistically with other assets. The self-aware UAVs in SAIMOD are equipped with GPS and use a suitable algorithm integrated into their path-planning process based on the degree of similarity or dissimilarity in the geographical position of the UAVs. This ensures seamless networking and prevents network over-coverage or under-coverage.

IV. Efficiency and Simplicity

SAIMOD is designed for rapid deployment and ease of use, contrasting with many current state-of-the-art solutions that tend to be complex and require significant technical knowledge. This simplicity can be beneficial in time-sensitive disaster scenarios. More complicated does not necessarily mean better regarding time-sensitive disaster recovery, especially in hard-to-reach places. Most Research efforts have focused on developing intricate systems or frameworks that require technical skill to operate effectively. The strength of SAIMOD lies in its straightforwardness and effectiveness. SAIMOD requires little or no technical expertise as it is easy to deploy and can be customised to meet users' needs.

SAIMOD is intended to serve as an initial response solution before regularly organised first responders such as firefighters, paramedics, and volunteers can arrive on the scene. Typically, the response to a disaster is conducted by trained professionals who address issues like rescuing trapped individuals and searching for missing people. However, getting these professionals on-site is not always possible within the time limit demanded by time-sensitive disasters, especially in remote areas. SAIMOD aims to be quickly deployed in such situations, particularly in hard-to-reach locations.

V. Resource Management

Most existing systems primarily deal with establishing communication links. However, SAIMOD not only restores communication but also assesses and allocates resources in real-time, a feature that instils confidence in its effectiveness for disaster management scenarios. These existing systems are designed to restore communication links but are not suited for assessing resource allocation needs in the network. They typically either have the Disaster Management Team access the network as part of a pre-disaster plan or have another system or framework for assessing the resource needs of the network. SAIMOD can be used as a pre-disaster resource allocation and assessment model on the fly while providing connectivity/ restoring or creating communication links in the MANET formed.

IV. Energy conservation and cost

SAIMOD is a fault-tolerant, intelligent UAV deployment framework that can be cost-effective in ways not previously explored within a small-scale disaster recovery scenario. Its resilience, as previously explained, can mean the network adaptability can manage limited resources more than other frameworks as it adapts to the shortage by recalibrating network coverage needs when there is a shortage in a resource (pending the availability of a replacement), thereby reducing cost.

As the saying goes, time is money; by being able to deduce this change and quickly proffer a solution can significantly reduce delay in the network deployment that stems from activities such as UAV replacement, delay in locating a gap in the network and the inability of UAVs to decide on how to remain resilient when an unexpected event occurs. In addition, SAIMOD can be used as a stand-alone unit with a single UAV or would need a minimum of two UAVs. In the state of the art, similar frameworks are multi-UAV based. They are also mostly grid-based and cannot adapt to changes such as UAV failure as they would require a replacement UAV to cover the network gap created by the UAV failure.

4.3.4 Proposed Algorithm based on Similarity Measure

The similarity measure, as used in the machine learning perspective or for data mining, measures the degree of similarity between objects using a specified similarity index. In this context, the degree of similarity between two objects being compared is approximated to reflect the degree to which the two objects compared are similar to each other. SAIMOD, in its framework, has UAVs equipped with GPS capabilities, and Euclidean distance would be a good fit for determining similarity measures.

Euclidean distance

The Euclidean distance can be used to calculate similarity and dissimilarity measurements and map the UAVs in the network (Zhuang and Cao, 2023; Srikaewsiew et al., 2022; Shongwe, Swart, and Ferreira, 2018). The Euclidean distance between two geographic positions of two UAVs: $a = (x_1, y_1)$ and $b = (x_2, y_2)$ is calculated by using their positioning on the cartesian coordinates and Pythagoras theorem as:

$$\text{Euclidean distance } (a, b) = \sqrt{\sum i = 1k(a_i + b_i)^2} \qquad (4.1)$$

However, to use the Euclidean distance in determining similarity coefficients, the geographic positions of the nodes in the network would have to be known using a GPS. This might not always be achievable due to the application scenario being considered. Reina et al. (2014) demonstrated using the Jaccard distance as a reliable estimator of the Euclidean distance between two nodes without GPS and validated the correlation in their Research.

Jaccard Similarity Index

While the design of SAIMOD will work well if the UAVs are equipped with GPS, SAIMOD offers flexibility in using different algorithms, such as the Jaccard Similarity index, to avoid duplication of effort based on calculating the degree of similarity/dissimilarity. This means that, in cases where there is no onboard GPS facility on the UAVs, such as in an emergency rescue operation (unexpected landslide or an avalanche) which could require a time-sensitive rescue operation and the teams must manage the available resources, SAIMOD could still be deployed, and another similarity measure could be used.

In addition, it is well known that GPS can be highly inaccurate in providing location and time data in certain areas, such as underwater, due to the damping of the orbiting satellites by water bodies and in arctic regions where GPS faces limitations due to ionospheric activities and the satellites' orbital inclination (de Jong et al., 2014). Also, in areas with electrical grid substations, the GPS readings could be inaccurate when deployed UAVs fly close to or under complex metal structures with an electromagnetic field (Suh et al., 2023).

While many infrastructures in the disaster zone may have been severely impacted or destroyed, there is still a possibility that some structures will remain intact. These existing buildings could present unexpected hazards during operations. Additionally, inaccurate GPS readings can cause navigation errors and cause the UAVs to stray from their intended flight paths or even miss their target locations entirely. Unreliable GPS signals can undermine flight stability, and GPS reliability can affect stable flight, increasing the likelihood of crashes, especially near complex metal structures that can further distort signal integrity. These can jeopardise critical mission objectives, especially when precision is paramount, like coordinating disaster recovery efforts or SAR operations.

When a disaster occurs in such areas, having a fallback intelligent networking system that incorporates a suitable algorithm such as the Jaccard Similarity Index could solve an issue with unreliable GPS. The Jaccard Similarity Index measures the similarity between two sets of data based on the intersection of the sets (Ertl, 2022; Verma, Agarwal, and Khan, 2017; Sulaiman and Mohamad, 2012).

The Jaccard Similarity Index would measure the degree of similarity between two UAVs in proximity within the SAIMOD deployed network. The aim would be to avoid over-coverage of the same ground nodes when the UAVs move in clusters or are in similar zones of the disaster area. This algorithm will depend on the intersection area between any two UAVs under consideration in the network. The UAV data that would be considered would be the coverage area of each UAV, which would be directly proportional to their radio transmission ranges and inversely proportional to their distance from the ground leader node.
The Jaccard similarity index is calculated as:

$$JAC(A,B) = \left(\frac{|A \cap B|}{|A \cup B|}\right) \tag{4.2}$$

Where;
JAC= Jaccard Similarity Index
A= coverage area of UAV1
B= coverage area of UAV2
A∩B= Intersection of both sets
A∪B= union of both set

The Jaccard similarity index has values ranging from 0 to 1; the closer the value is to 1, the greater the degree of similarity of the compared data sets.

4..4 Simulation incorporating Jaccard similarity index for UAV movement pattern

This section discusses the simulation incorporating the Jaccard similarity index for UAV movement patterns. The Research methodology, initial assumptions, and implications for UAV network coverage will also be addressed. For this aspect of the Research, the initial assumption for the network remains the same, with the network having three ground nodes as pivotal group leaders and the UAVs still having the same unique identifier numbers (see Section 3.4.3). The idea behind this is to check the cut-off area for similarity/ dissimilarity by testing for connectivity in the network. Simulations are run to find the cut-off point without communication between

USER1 (ground node) and UAVs. This will help address the issue of network over-coverage and under-coverage. This cut-off point will be given the threshold value of 0 for the Jaccard similarity index. This will be the cut-off threshold at which the UAVs would move together. If the value of the Jaccard similarity index is between 0 and 1, the UAVs will move apart.

Figure 4.1 is a Flow Chart for the proposed decision-making process.

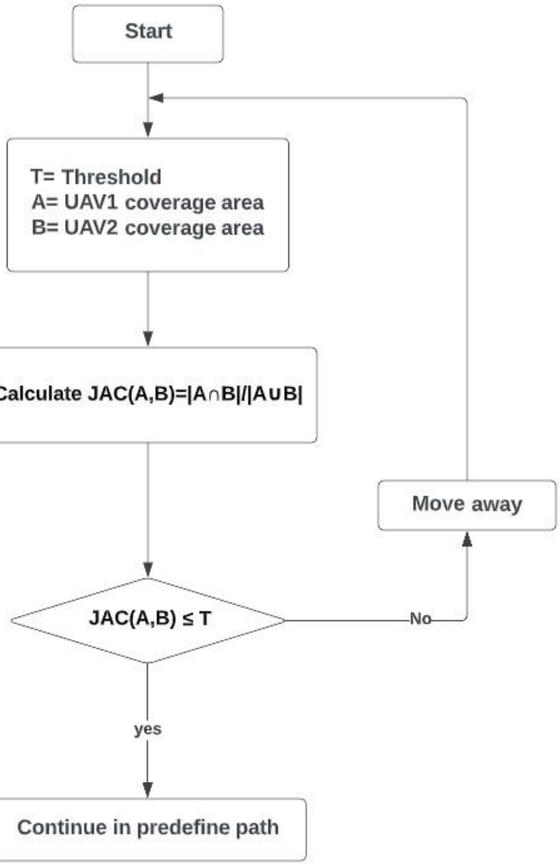


Figure 4.1: Flow Chart for the proposed decision-making process

4.5 Network Analysis

The Quality of Service (QoS) of a network ensures its performance meets pre-defined standards required by the user. Defining the acceptable QoS for any network or system ensures the performance of critical applications within the constraints of limited network bandwidth or capacity. This can be achieved by managing data traffic to reduce network Jitter, latency, and packet loss. QoS ensures that transmitted data within the network does not become disorganised and prevents clogging, a common issue that could degrade overall network performance. QoS is the use of mechanisms or technologies that operate on a network to control traffic, overheads, transmission of data, etc. Regarding disaster recovery, having good QoS in terms of Throughput and network connectivity is crucial for the effectiveness of the SAIMOD Network.

In ensuring communication in the network, the first step will be to check the successful transmission of data between UAVs and the ground node and then check that this is also true between UAVs. The results from the network taken at different positions of the UAVs are presented below.

4.5.1 FTP traffic from the Group Leader (USER1) received by the UAVs

This simulation analysed the FTP traffic from the Group Leader (USER1) to the UAVs. The results for FTP traffic received, illustrated in Figure 4.2, show that UAV 1 (TUJ-Scenario 10 DES-1 (blue line)) had an approximate reception rate of 0 bytes/sec. This trend is also depicted in Figure 4.3, which shows the traffic sent and received between USER 1 and UAV 1.

UAV 2 (TUJ-Scenario 11 DES-1 (red line)) stood out with its exceptional reception. Its initial value for FTP traffic received was approximately 0.05 bytes/sec, which was maintained until around the 6-minute mark. Although the value of FTP traffic fluctuated between the 18- and 22-minute marks, it consistently recorded intermittent FTP traffic until the end of the simulation, surpassing the other two UAVs.

UAV 3 (TUJ-Scenario 14 DES-1 (green line) performed roughly 50% of UAV 2's performance. Its reception rates fluctuated between 0 and 0.05 bytes/sec from the 18-minute mark to the end of the simulation. The MANETs and the WLAN in the simulated networks exhibit similar characteristics, indicating that the network coverage in this configuration was insufficient (under coverage). The notable differences in the performance levels between the UAVs in the network are likely due to the UAVs' positioning within the Mobile Ad-hoc Network (MANET) in relation to the ground leader node (USER 1). Under-coverage in networks could lead to packet loss and increased latency, negatively affecting the performance of the UAVs.

Figure 4.2: FTP traffic received by UAV1(blue), UAV2(red), and UAV3 (green)

4.5.2 Results of FTP traffic sent by USER1 vs FTP traffic received by UAV1

The results for FTP traffic received by the UAVs presented in Figure 4.3 indicate that UAV1 (blue) received a negligible number of packets from USER1(Group Leader) when compared to the FTP traffic transmitted from USER1 (Group Leader). This minimal reception suggests a significant issue with data transmission, likely due to the considerable distance between UAV1 and USER1. This distance can negatively impact signal strength, resulting in a weak connection and poor reception of FTP traffic originating from USER1, the primary ground node. The efficiency of transferring files between these two locations is significantly hindered, leading to considerable delays and potential data loss during the process.

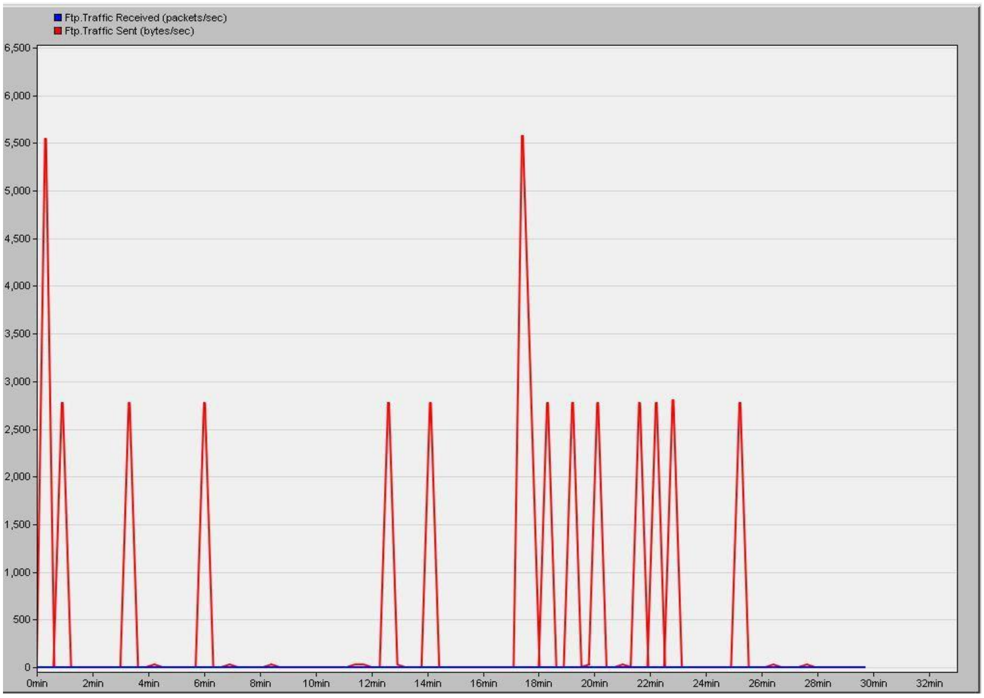


Figure 4.3: FTP traffic sent by User 1 vs FTP traffic received by UAV 1

4.5.3 Results of the overlay of the FTP traffic sent by USER1 received by the UAVs

This analysis examines the performance of various UAVs' reception of FTP traffic from USER1. The distinct positioning of the UAVs resulted in different outcomes, as shown in Figure 4.4. In this scenario, the results indicate that UAV 2-TUJ-Scenario 11 DES-1(red) achieved the best FTP performance, with transfer rates varying from approximately 2,800 to 8,485 bytes per second. It maintained consistent FTP reception throughout the observation period (0-30 minutes). Figure 4.5 illustrates the results for FTP traffic sent from USER1 to UAV 2 (red) and the traffic received by UAV 2 (red) from USER1.

In contrast, UAV 3-TUJ-Scenario 14 DES-1 (green) recorded similar FTP traffic rates ranging between 2,800 bytes/sec and approximately 8,485 bytes/sec. However, it exhibited fewer peaks within this range than UAV 2 (red). Additionally, UAV 3 (green) experienced a drop in FTP traffic, receiving approximately 0 bytes/sec around the 18.45-minute mark. UAV 1-TUJ-Scenario 10 DES-1 (blue) performed the poorest among the three UAVs. It recorded an FTP traffic rate close to 0 bytes/sec, with a brief peak of approximately 50 bytes/sec noted at the 18-minute mark. Overall, UAV2’s (red) positioning provides an acceptable Quality of Service (QoS) for FTP traffic transmission within the network.

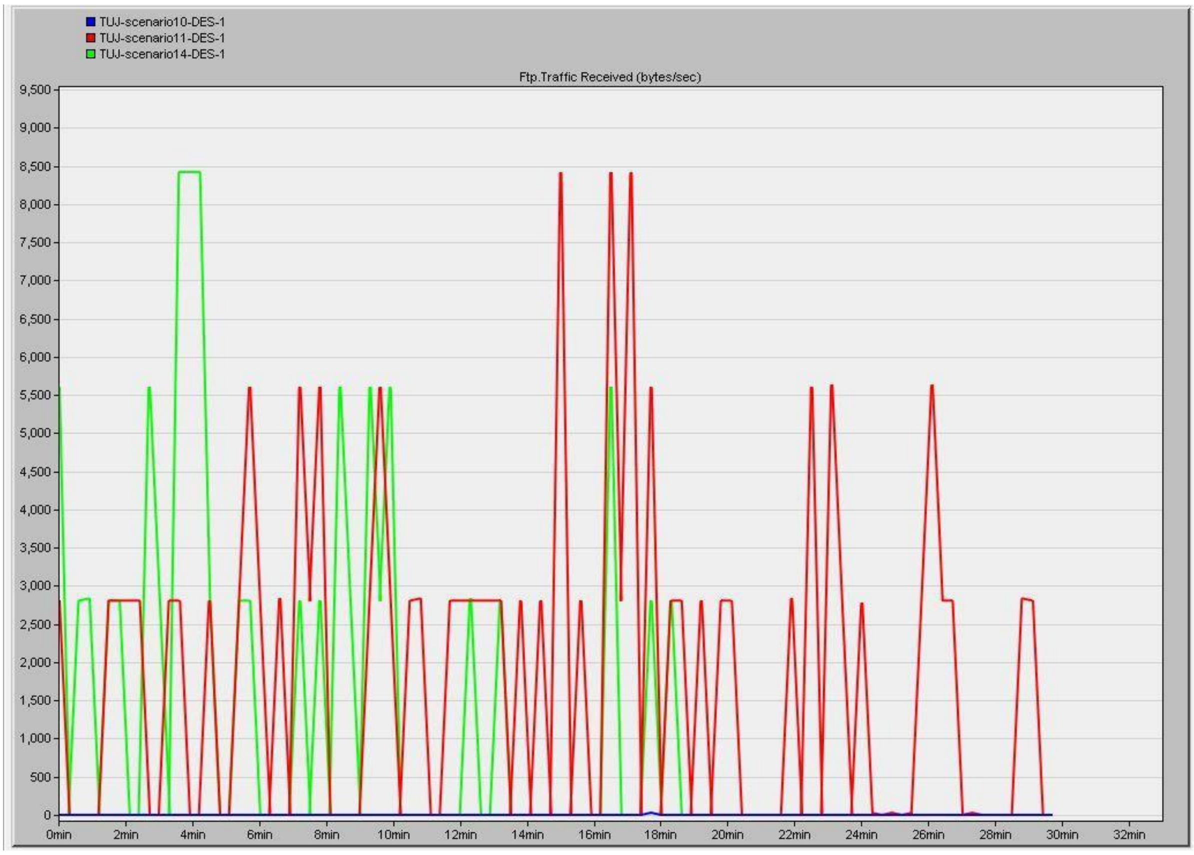


Figure 4.4: FTP traffic received from Group Leader (USER1) by UAV1(blue), UAV2 (red) and UAV3 (green)

4.5.4 FTP traffic sent by USER1 vs FTP traffic received by UAV2

The results shown in Figure 4.5 illustrate the FTP traffic sent by USER1 (red line) compared to the FTP traffic received by UAV2 (blue line). The data indicates that UAV2 has an impressive performance rating, successfully handling approximately 95% of the traffic sent and received. This performance was consistent throughout the simulation period from the start to the 30-minute mark. Based on these findings, UAV2 is the most effective option among the three UAVs for covering the area associated with USER1. Therefore, positioning UAV2 relative to USER1 provided better/acceptable positioning for UAV2 relative to USER1 for the ground nodes.

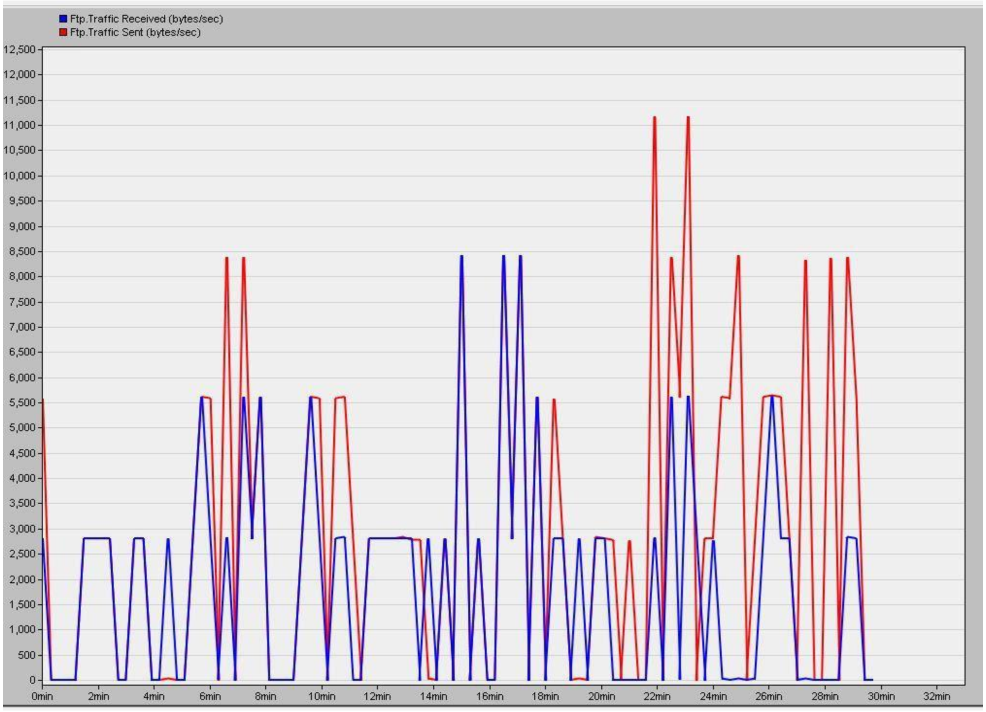


Figure 4.5: FTP traffic sent by USER1 vs FTP traffic received by UAV2

4.5.5 WLAN Throughput taken at under coverage position

Figure 4.6 illustrates the WLAN Throughput for USER 1, revealing some notable challenges that all three UAVs faced. A significant observation is that periods of inactivity or severe connectivity issues were interspersed with sporadic spikes of improved performance. This was indicated by around 50% of the Throughput results, which were concentrated around a mere 0 bytes/sec. UAV2 (red line) was the top performer, with a recorded Throughput of approximately 48,000 bits/sec. It, however, had noticeable dips in its overall performance during specific time intervals, mainly between 3 to 15 minutes and 20 to 30 minutes. These findings provide crucial insights into the UAVs' operational efficiency, underscoring this analysis's value. The positioning of the UAV affects the connectivity, which in turn influences the Throughput, as shown in Figure 4.10.

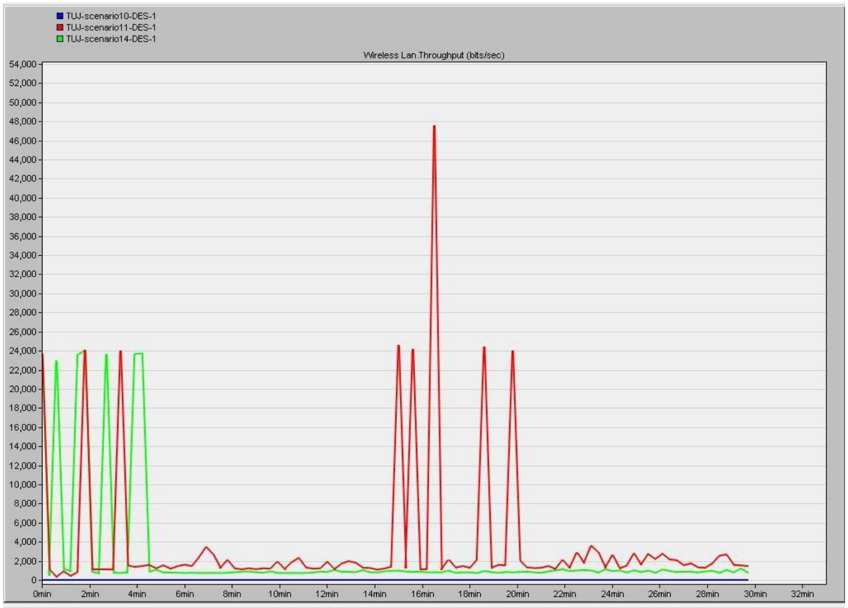


Figure 4.6: WLAN of Throughput (USER 1) during under coverage by UAV1 (blue), UAV2 (red) and UAV3 - (green)

4.5.6 WLAN Throughput taken at acceptable QoS coverage position

The WLAN Throughput for the network at the specific location depicted in Figure 4.4 indicates the following: USER1 exhibited better Throughput performance when communicating with UAV2 (TUJ-Scenario 11 DES-1, shown by the red line), achieving a peak of approximately 69,500 bits per second. In contrast, USER 1's WLAN Throughput, when interacting with USER 3 (TUJ-Scenario 14 DES-1, indicated by the green line), displayed significant fluctuations, with an average peak of around 25,000 bits per second. This accounted for approximately 58% of the overall WLAN Throughput values related to this UAV (UAV3 (green line)), about 0.05 bits per second. This value is notably observed from the 17-minute mark to the end of the simulation. USER1's WLAN Throughput in relation to UAV1 (TUJ-Scenario 10 DES-1 (blue line)) at this location did not show any improvement, further reinforcing the conclusion that UAV1 (blue line) was effectively out of range. The Throughput values fluctuated between approximately 0 and 0.05 bits per second. This suggests that both UAV1 (blue line) and UAV3 (green line) are inadequate for providing coverage for the group led by USER1.

Furthermore, the results illustrated in Figure 4.7, when compared to the WLAN Throughput data in Figure 4.6, indicate that the positioning of the UAV significantly impacted the WLAN Throughput outcomes for the network.

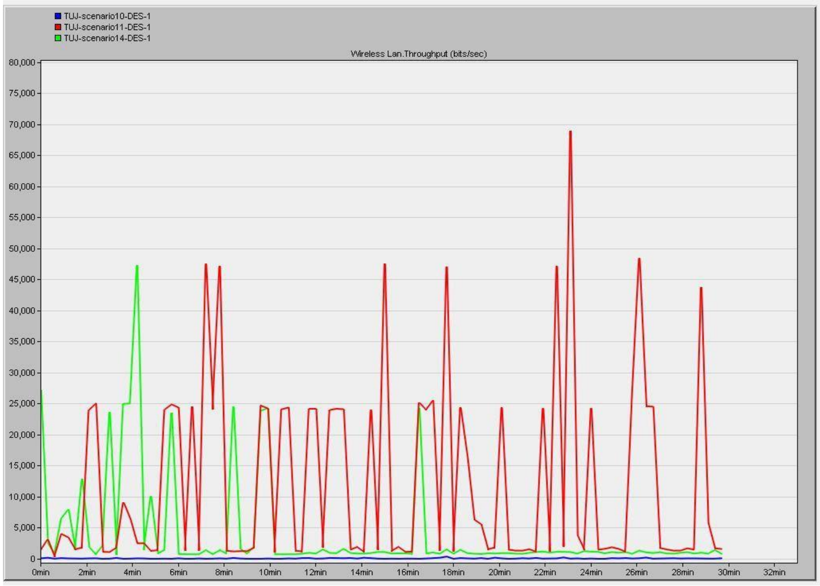


Figure 4.7: WLAN Throughput (USER1) during best coverage by UAV1 (blue), UAV2 (red) and UAV3 (green)

4.5.7 Evaluation of Retransmission Attempts

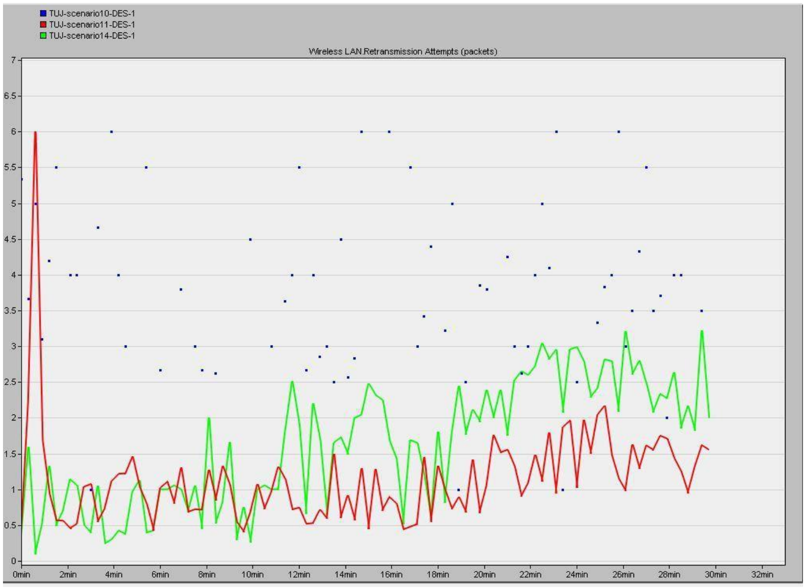


Figure 4.8: Retransmission attempts

Figure 4.8 shows the result of the Retransmission Attempts in packets. UAV 2 (TUJ-Scenario 11 DES-1, red line) recorded the lowest average Retransmission Attempts, with approximately 1.5 packets. However, it initially experienced a spike of 6 packets. This spike may be attributed to UAV 2's initial positioning, which was far from USER 1, as indicated by the initial FTP traffic received (see Figure 4.2, red line). UAV 3 (TUJ-Scenario 14 DES-1, green line) had the second-lowest retransmission attempts, averaging about 2.5 packets. Notably, the number of Retransmission Attempts for UAV 3 (green line) increased as the simulation progressed. This trend could be due to UAV 3 (green line) moving further away from the ground node leader, USER 1, potentially resulting in dropped packets. UAV 1 (TUJ-Scenario 10 DES-1, blue line) exhibited the least favourable performance, recording the highest Retransmission Attempts. Its value fluctuated between 2.5 packets (the average for UAV 2) and 6 packets (the highest recorded for all UAVs). Overall, these results suggest that the positioning of the UAVs in relation to USER 1 (the ground node leader) significantly influenced the necessity for each UAV to resend packets, which may have been lost or damaged due to link failure.

4.5.8 Results of MANET traffic received by the three UAVs

Figure 4.9 shows the results of the traffic received by the Group Leader (USER1) from three distinct UAVs: UAV 1 (blue line), UAV 2 (red line), and UAV 3 (green line). The traffic value for UAV 1 (blue line) is zero. This could imply that UAV 1 is positioned too far from USER1 to establish a reliable communication link, leading to the absence of traffic data.

In contrast, UAV 2 (green line) and UAV 3 (green line) show notable levels of traffic received by USER1. UAV 2 (red line) receives approximately 2,050 bits/sec, suggesting a strong connection to USER1. In comparison, UAV 3 (red line) receives around 1,000 bits/sec. This illustrates that UAV 2 (red line) is experiencing roughly 50% more traffic than UAV 3 (green line), indicating a more effective communication link with the Group Leader.

The differences in traffic levels can likely be attributed to the positioning of the ground nodes in relation to USER1. The closer proximity of UAV 2 (red line) to USER1 enhances its connectivity, facilitating a higher data transfer rate than UAV 3 (green line). Furthermore, the FTP data (Figures 4.1-4.5) corroborates these observations, confirming that UAV 2 (red line) has superior connectivity. This conclusion is supported by the analysis of the UAVs' positional changes relative to the Group Leader node (USER1), as illustrated in Figure 4.9, emphasising the impact of spatial dynamics on the communication efficiency of the three UAVs and USER1 in the network.

Figure 4.9: MANET traffic received from Group Leader (USER1) by UAV1(blue line), UAV 2 (red line) and UAV 3(green line)

4.5.9 Evaluation of the MANET traffic sent vs traffic received between two UAVs

A fundamental assumption for the SAIMOD network architecture is that at least two UAVs must always be interconnected to ensure reliable communication. This interconnectivity is necessary as it allows for seamless data packet exchanges, essential for the disaster recovery scenario for which the framework was developed. The results in Figure 4.10 for MANET traffic sent vs. received for UAV 2 (red line) and UAV 3 (blue line) support this. The data shows the traffic sent and received for UAV2 (red line) and UAV3 (blue line). In Figure 4.10, the traffic sent was approximately 4,100 bits per second, closely matching the received traffic. A slight dip in traffic was observed around the 27-minute mark. At that point, the traffic sent decreased to approximately 4,000 bits/sec. Despite this brief reduction, the data packets in the network continued to be transmitted successfully, indicating resilient link performance.

A network's ability to maintain data packet transmission irrespective of slight fluctuations in traffic rates demonstrates effective data handling within that network. The continuous exchange of information between UAV 2 (red line) and UAV 3 (blue line) not only reinforces the stability of the SAIMOD network but also emphasises its potential for operational effectiveness in real-world scenarios.

The location of the UAVs directly impacts their performance due to several factors, including line-of-sight, signal strength, and interference from obstacles. When UAVs are positioned closer to the users they serve, like USER1's interaction with UAV2, the signal strength is generally higher, leading to higher Throughput. Conversely, UAVs that are out of range, like UAV1, exhibit poor performance due to weak signals and increased latency, resulting in significantly lower Throughput. It's important to note that environmental factors such as physical barriers, terrain, and other wireless signals can also significantly affect performance, adding a layer of complexity to the task. Therefore, optimal positioning of UAVs is crucial for maximising WLAN Throughput and ensuring effective communication in various scenarios.

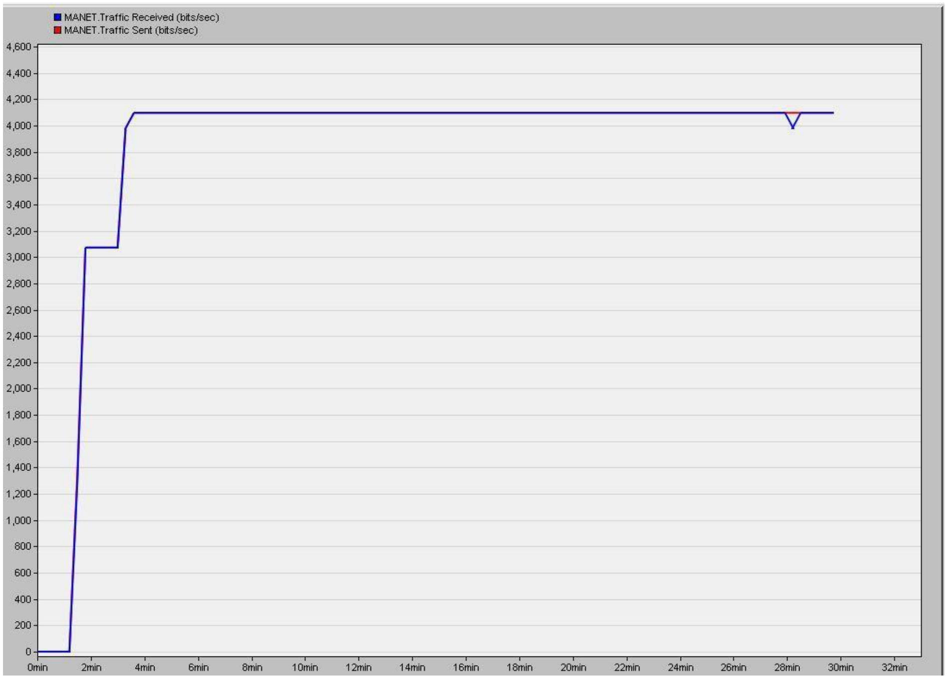


Figure 4.10: MANET traffic sent vs traffic received between UAV2(red line) and UAV 3 (blue line)

4.5.10 Evaluation of Delay

Figure 4.11 presents the detailed Delay graph for the MANET nodes (UAV onboard processors), showing values ranging from 0.001 seconds to approximately 0.003 seconds. Figure 4.12 provides a statistical analysis of this Delay. Analysing both figures, it is observed that mobile_node_0 (blue line) experienced a Delay of 0.0010999 seconds with a standard deviation of 0.00021. Mobile_node_2 (red line) had a Delay of 0.0014427 seconds with a standard deviation of 0.00033, while mobile_node_1 (green line) recorded a Delay of 0.0013104 seconds with a standard deviation of 0.00018. Overall, the system maintained an acceptable Delay rate.

(It shows values ranging from 0.001 seconds to approximately 0.003 seconds, suggesting the network experiences relatively low latency in its communication).

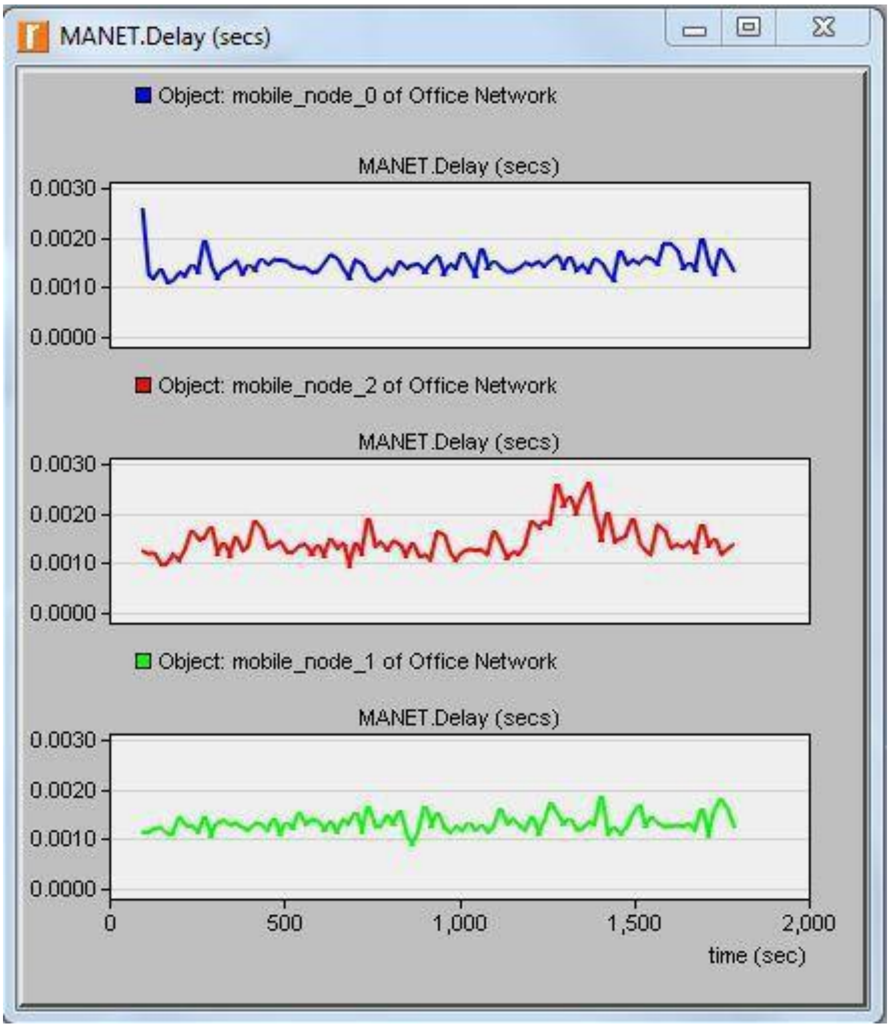


Figure 4.11: MANET Delay

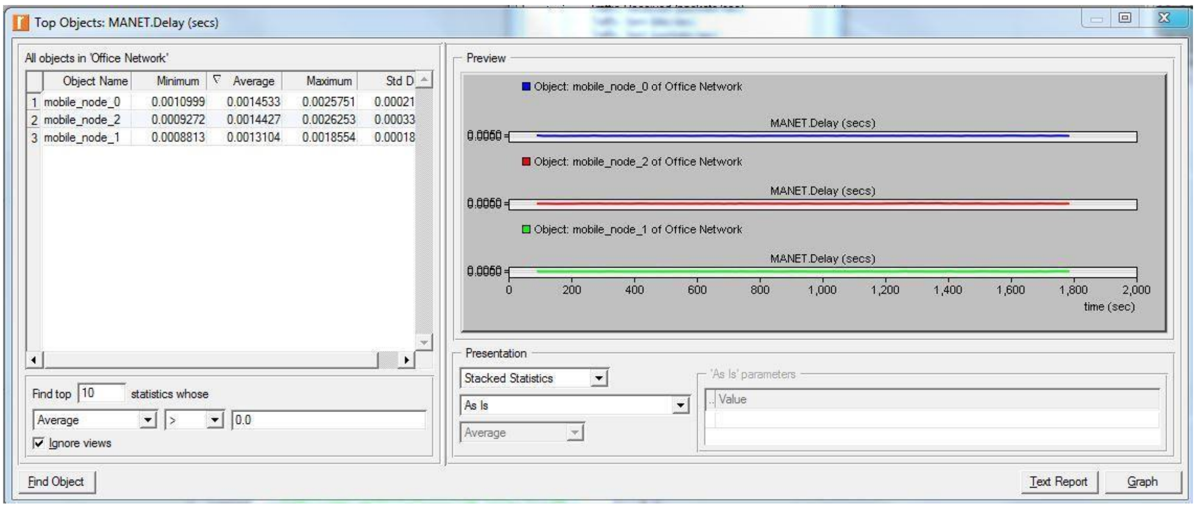


Figure 4.12: Statistical Analysis of the Delay for the MANET Nodes

4.6 Assessment Model

Unmanned Aerial Vehicles (UAVs) can be deployed for disaster management and planning. Following a disaster, it is crucial for the disaster management team to mitigate damage: having time-sensitive information can make the disaster recovery procedures more effective. It can also help prioritise resource allocation and reduce costs. UAVs fitted with cameras and onboard sensors can be used in the initial damage assessment in the disaster area. For example, nano-UAVs have been integrated with robotic capabilities, which are programmed to detect structural damage, take pictures, etc. Furthermore, UAVs can also help restore broken network communication links, such as flying base stations, mesh networks, or relays. They can also be used as a delivery system to send supplies to emergency crew members and victims.

Unmanned Aerial Vehicles (UAVs) have gained notable Research interest; numerous Research proposals and findings have been published, and patents have been registered. In addition, the demands placed on designing such deployed UAV networks by the individual unique application scenario requirements, such as broader coverage area range, increased flexibility and autonomy and greater precision in positioning, have brought about the design and development of novel systems to tackle these issues (Alam et al., 2022). Such systems include those designed with energy conservation, reduced power consumption, and precision landing.

Significant areas of Research have been on ways to make UAV networks scalable, resilient, more autonomous, capable of real-time decisions and adaptable to dynamic changes in the network, such as UAV failure. Research has proposed various solutions, including novel routing protocols, mobility models, reinforcement learning techniques, machine learning algorithms and deployment frameworks, all in a bid to tackle these challenges (Lin et al., 2023; Alam et al., 2022). In the current literature, several challenges are identified in deploying UAVs based on their limitations and the unique application scenarios in which they are being deployed. These challenges include slower speed, limited processing capability, data security, transmission range, and available power. Numerous Research studies have been aimed at solving these issues and developing more scalable, resilient, and efficient UAV-based networks.

A notable area of concern is the power limitation of UAVs in relation to energy consumption and limited battery life. UAVs are usually battery-powered, and the more demand is placed on the energy capacity, such as wireless communication, hovering and data processing, the faster the batteries will run down. This implies that UAVs will need charging stations as an alternate energy source or to be replaced. In Search and Rescue operations, for example, this is a drawback, as essential time could be lost from the need to recharge power sources for UAVs deployed in such scenarios. A possible solution is using UAVs in coordinated swarm formation to overcome the energy limitations of using a single drone (Kang, Joung and Kang, 2020; Luan et al., 2020).

This Research takes a more versatile approach. SAIMOD (Self-Aware Intelligent Model) has a diversity of applications. It is a standalone UAV deployment framework to restore communication links. However, it could also be used to form a grid network and play a role in a multi-UAV collaborative scheme. In addition, SAIMOD is also suitable as an assessment model for disaster management based on user specifications. One advantage of SAIMOD is that it allows the user to program the UAVs deployed in the SAIMOD framework to collect data and statistics from the ground nodes and amongst themselves. These statistics, such as remaining battery power and remaining UAVs in the network, can be used in assessment and proffering solutions to solve capacity planning issues by the user in resource management. Examples of these issues faced with setting up and maintaining the network are determining when to replace mobile phones or the UAVs in the network.

The ability of resource management software to handle uncertainty with minimal human intervention is a challenge faced in developing such software (Adenowo et al., 2019; Affonso and Nakagawa, 2015). SAIMOD, when used in gathering network statistics such as bandwidth and energy usage, connectivity, etc., will enable the user to assess the network resource needs and make decisions about resource optimisation and replenishment. This is done by analysing the collected statistics using suitable analytical methods. One key thing in SAIMOD is the capacity for the bi-directional data transmission by the UAVs in the network. This means that the statistics required for evaluation can be collected by SAIMOD and sent to the control room. This information can be used by the network manager or Disaster Management team in decision-making. A proposed mathematical model for use with SAIMOD in assessing the remaining resources in the network is presented here. The mathematical model presented in this Research is developed based on the following assumptions:

I. The user determines the resource to be replaced based on an analysis of the collated data.

II. The selected resource, R, will be assumed to be a resource depleted by demand or based on other determining factors, xn, that affect its availability. For instance, the user could decide to replace a UAV (resource) when the remaining battery power is at a percentage chosen by the user (determining factor), recall a UAV (resource) when the level of disaster coverage reaches a certain percentage (determining factor) or when a certain number of victims have been rescued (determining factor). It could also be based on more than one factor, such as the battery being at 5% and the distance to the closest UAV in the network.

III. The resource to be replaced at the time, *t,* is a function of determining factor(s), which is user-specific. This determining resource is subject to demand or the level of use in the network over time.

$$R_n = f(x_n(t)) \tag{4.3}$$

Where;

R= resource
$x_n(t)$ = Determining factor whose usage is a function of demand at a specific time stamp, t.
$n{:}\, 0 < n$

Based on the principle of the equilibrium price and the demand curve in economics, there will be an equilibrium point on the demand graph, at which the optimum value of the available resource usage is equal to the required resource that meets the network demand. At that point, the demand for the resource (R) is equal to the supply and does not need replacement or additional resources. In other words, it shows the optimum value of a resource that would efficiently cover the network. In addition, from the demand graph, the user can also ascertain the resource level in the network at chosen time intervals and make decisions such as recalling a UAV when an area of the network is already covered. That UAV can be redeployed for use elsewhere.

Figure 4.13 is an example graph showing the equilibrium point (P) for the resource (R) at which the resource will be optimally utilised. The graph also allows users to make informed resource allocation and optimisation decisions.

Figure 4.13: Demand graph showing equilibrium point (P) for Resource, R

The linear demand graph is plotted by using the demand equation for the network, as shown below:

$$Q(t) = x_n(t) - y(t) \tag{4.4}$$

Where;

$x(t)$ = value of determining factor(s) affecting the allocation/replacement of resource, R

$y(t)$= the slope of the demand curve

$n: 0 < n$

t = time stamp; $t: 0 \leq t \leq n$

$Q_{(t)}$ = quantity of resource, R required at time stamp, t

From equation 3, $R_n = f(x_n(t))$

$$\Rightarrow Q_{(t)} = R_n \tag{4.5}$$

Also;

$$\sum x(t) = \{x_n(t)\} \tag{4.6}$$

Where;

x = value of determining factor(s) affecting the allocation/replacement of Resource, R at time stamp, t.

$$n: 0 < n$$
$$t: 0 \leq t \leq n$$

At the equilibrium point, P, the equilibrium quantity for the required resource, will be equal to the available/ supplied quantity of the resource at which the system has an optimal number of required resources.

This implies that at the equilibrium point, P,

the total number of resources required = the total number of available resources in the network. This is express as:

At equilibrium point, P,

$$\boldsymbol{R_a} = \boldsymbol{R_e} \tag{4.7}$$

Where;

$\boldsymbol{R_e}$= Required resource at equilibrium point

$\boldsymbol{R_a}$ = Available resource in the network

Substituting $\mathbf{R}_{(e)}$ into equation (4.5), Q_t at equilibrium point = $\boldsymbol{R_e}$ This implies

When

$\boldsymbol{R_a}$= $\boldsymbol{R_e}$)------------- The network is at equilibrium point

$\boldsymbol{R_a} \neq \boldsymbol{R_e}$, The value of $\mathbf{R}$ will be either:

0 < $\boldsymbol{R_a}$> $\boldsymbol{R_e}$-------- Over coverage

0 < $\boldsymbol{R_a}$) < $\boldsymbol{R_e}$ -------- Under coverage

Assessing the network's needs for resource allocation/replenishment, determining the optimum time the determining factor would need to be replaced, and determining the required quantity would save time, optimise resource usage, and reduce operational costs. Figure 4.14 is a flowchart of the proposed mathematical model for resource allocation.

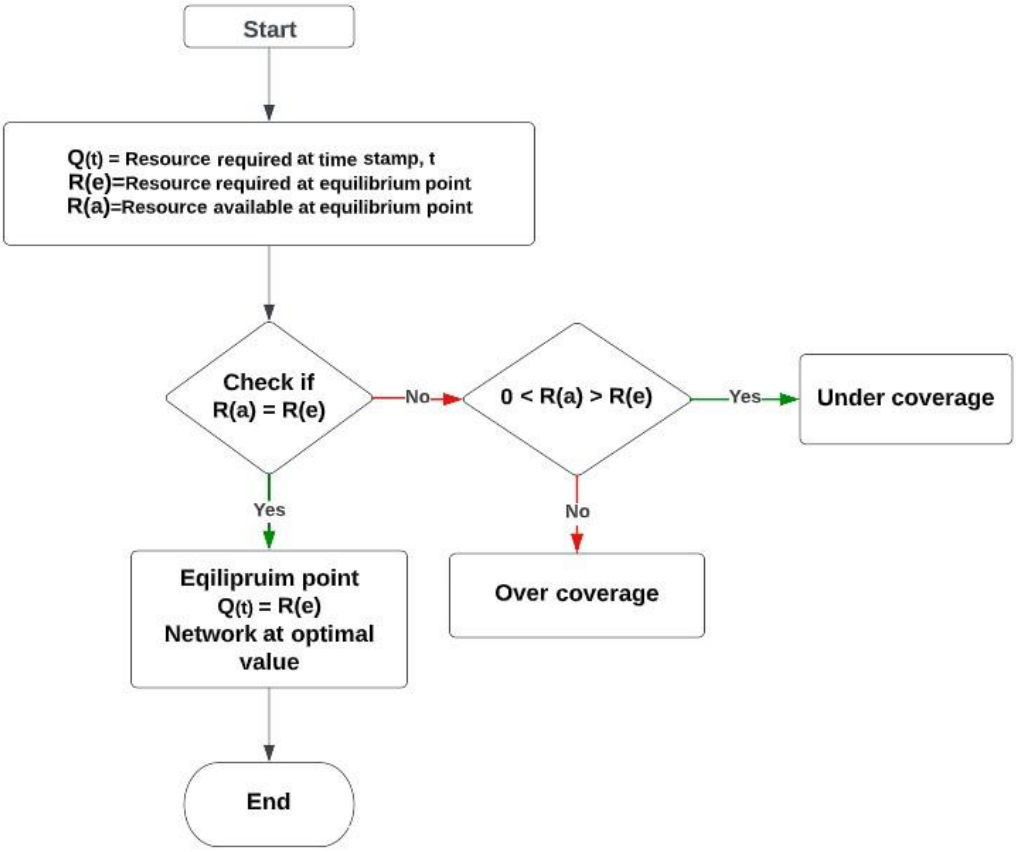


Figure 4.14: Flow Chart of the Mathematical Model

The validity of the proposed mathematical model is tested using MATLAB. Initial values for resources required (in this case, UAVs) to cover the network are assumed, and a random number of available UAVs is used.

4.6.1 Graphical representation of the mathematical model

The red line in Figure 4.16 indicates the zone at which the network's optimum number of resources is deployed. At the green line, the number of available resources equals the equilibrium number of UAVs; R(a) = R(e). The zone labelled 0 < R(a) < R(e) represents the under-coverage area, in which the number of available resources is less than the required/ equilibrium number of resources. This indicates that more resources would need to be sent into the network.

The zone, $0 < R_a > R_e$ depicts the over-coverage zone where the available resources exceed the required or equilibrium resources. The resource manager can decide to withdraw the resource overage or deploy that resource overage, in this example, UAV(s), to another network area or zone not yet covered or under-covered. This is also applicable in situations such as UAV failure, in which the disaster management team can ascertain if the remaining UAVs can handle the demands of the resulting network. The red line represents the equilibrium point.

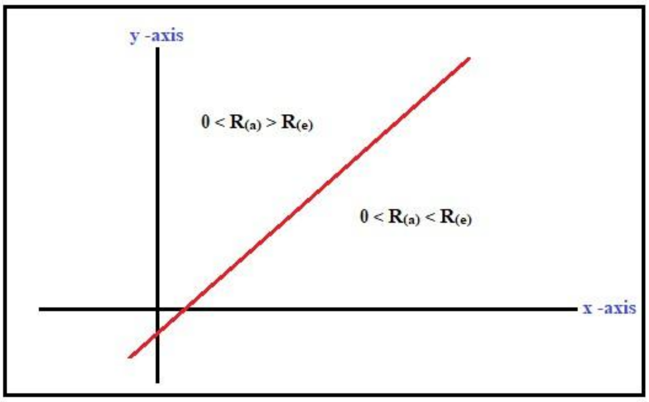


Figure 4.15: Mathematical Model Graph showing under coverage, over coverage and equilibrium line

4.7 Comparison of SAIMOD with four Other Disaster Recovery Frameworks

This section compares SAIMOD with four other UAV-based integrated emergency communication systems for disaster recovery with similar functionalities. Table 4.1, found at the end of this section, summarises the comparison.

Lee et al. (2020) proposed DroneDR, a reinforcement learning framework, for positioning UAVs in the disaster recovery area. Their Research focused on maximising the number of active connections in the UAV grid network, and they made specific nodes more important than others. The UAVs' positioning in the network was based on the information collected about the user nodes' position and connectivity requirements. They stipulated that the UAVs must always be connected to maintain the grid network and that the search for the location of user nodes should be conducted in discrete timesteps, specific, individual time intervals. They used this information to find the best transmission range for the UAVs in the network. In addition, they evaluated their network via simulation using a small-scale and a large-scale disaster area, focusing on maximum connections in the network and comparing their results to a greedy Steiner heuristic algorithm and the Random Waypoint mobility model. DroneDR performed better regarding the maximum number of connected nodes in the network. However, a notable limitation of their work was the assumption of unlimited energy availability for the UAVs, which posed challenges in real-world applications, particularly in dynamic environments where issues such as drone failures may disrupt network functionality.

Another framework being compared to SAIMOD is that proposed by Hayajneh et al. (2018), called Drone-based small cellular networks (DSCNs), which will be deployed in disaster recovery to replace destroyed base stations, using a clustering algorithm. This framework was designed to be a statistical framework. This method uses statistics to estimate the parameters that influence the optimal deployment of the recovery network, such as the radius of the recovery area, transmission power, altitude of the drones, and number of drones. Their simulation results showed that the network could be more energy-efficient and more likely to cover the zone. They took advantage of the assumption that ground users would usually cluster around hotspots in a post-disaster scenario.

They acknowledged, however, that each DSCN would require a multitude of drones to manage the gap in network area coverage and solve the problem of backhauling and capacity. They had also assumed that the thinning of base stations was done independently. They acknowledged that in some scenarios, such as earthquakes, this may be based on the actual geographical location of the base stations. They also acknowledged that the location of the intended users and the number of required clusters in the network would need to be estimated. This would create a distribution estimation problem, as it would be difficult to accurately choose the number of required drones or hotspot clusters for optimisation. They suggested a future study in which real-time k-mean clustering could be a solution to overcome this.

Qi et al. (2023) proposed a three-phase post-disaster recovery strategy for distribution networks, utilising multi-cooperative UAV base stations (UAV-BSs) that operate on the Multi-Agent Deep Deterministic Policy Gradient (MA-DDPG) algorithm. They called it the UAVBSs using MA-DDPG. This approach aims to restore and reconfigure power loads to cover the disaster areas effectively. The primary goal of their work was to restore and reconfigure the network to effectively cover the disaster zone and restore power loads based on their analyses. They used the Markov Decision Process (MDP) reinforcement learning optimisation to analyse the network.

In phase one, they converted the communication recovery process of the UAV Base Stations into a Markov decision process (MDP). Next, they configured a model to manage the UAV distributive network. In the third phase, they used reinforcement learning (MA-RL) to manage issues arising from multi-UAV base stations. The strategy was verified using the IEEE 33-bus system, a widely accepted benchmark for power system studies. However, the UAVs assumed unlimited energy, and their Research did not consider energy conservation. The authors intend to focus future Research on coordinating the recovery process using various flexible resources.

Khan, Gupta and Gupta (2022) proposed a grid-based cooperative Fault-Tolerant Maximum Coverage (FTMC) multi-UAV framework as an emergency communication system in disaster management. They used flood disasters as a case study in which communication disruptions are likely to occur. They sought to solve the communication disruptions for the rescue team or Disaster Management Team (DMT), which cannot communicate with each other or the people to be rescued. Their framework was designed to restore communication links by the multi-agent UAVs covering the disaster zone in a grid pattern. While their system worked, they had not accounted for changes in the topology, such as UAV failure, in their design. They assumed that all UAVs were functional. They proposed creating a fault-tolerant UAV control system that is computationally more stable and faster as a possible further study. They aimed to incorporate the UAVs as fog and edge nodes.

SAIMOD distinguishes itself from other frameworks through its practicality. It is a highly simplified, user-friendly assessment model that can function as a standalone UAV disaster recovery framework with just one UAV. This practicality is a significant advantage, particularly in small-scale, time-sensitive disaster recovery scenarios in hard-to-reach locations.

SAIMOD restores connectivity, calculates the optimal positioning for UAVs, and is designed to operate effectively in constantly changing environments. It optimises energy efficiency and serves as a resource optimisation and control model. SAIMOD's adaptability provides users with flexibility in their deployment options. The UAVs in the framework can operate either as standalone units or as part of a cooperative UAV mobile grid network. Additionally, SAIMOD is well-suited for accessing challenging areas where traditional grid-based UAV networks are impractical.

Table 4.1 summarises the comparison between SAIMOD and the four other frameworks (Drone DR, DCSN, FTMC Multi-UAVs and UAV-Bs with MA-DDPG) described in this session.

Table 4.1: Comparison of SAIMOD with four other disaster recovery frameworks

S/N	Parameters	SAIMOD	DroneDR	DCSN	FTMC Multi-UAVs	UAV-BSs with MA-DDPG
1	Can it be used as an assessment model for resource control?	Yes	Yes	Yes	Yes	Yes
2	Energy conservation	Yes	No, assumed unlimited energy	No	No	No
3	Required number of UAVs	At least two or can be used as a standalone with only one drone.	Many (to form the grid)	Many (to handle gaps in network coverage)	Many (to form the grid)	Many (to form the grid)
4	Network size	500m X 500m	Very small (5m X 5m) or large with an increasing number of drones	large with an increasing number of drones	large with an increasing number of drones	large with an increasing number of drones
5	Formation	Standalone, dual connectivity or grid pattern	Grid pattern	Grid pattern	Grid pattern	Grid pattern
6	Suitable for use in hard-to-reach areas	Yes	No	No	No	No
7	Reinforced learning	Yes	Yes	Yes	Yes	Yes
8	Complexity	No. easy to use and deploy	Yes	Yes	Yes	Yes
9	Key consideration	Throughput, Delay, connectivity and energy conservation	Number of active connections and fairness	Connectivity	Connectivity	Connectivity
10.	Designated mobility model	RPGM	RPGM	Not a consideration.	Not a consideration.	Not a consideration.
11.	Designated routing protocol	OLSR	Not considered	Not considered	Not considered	Not considered
12.	Overcoming drone failure in the network	Yes	No	No	No	No
13.	Cost-effective	Yes	No	No	No	No
14	Is it required to have the geographical location of the nodes before use?	Not necessarily (can be acquired from the UAVs/ ground nodes).	Needs to be known for the network to be effective	Needs to be known for the network to be effective	Needs to be known for the network to be effective.	Needs to be known for the network to be effective
15	Can adapt to changes in the network, such as UAV failure?	Yes, requires at least one UAV to function, as the UAVs are mobile	No, requires numerous UAVs to form a blanket grid network	No, requires numerous UAVs to form a blanket grid network	No, requires numerous UAVs to form a blanket grid network	No, requires numerous UAVs to form a blanket grid network

4.8 Chapter Summary

This Chapter presents a literature review of some existing UAV deployment frameworks used in disaster recovery. The proposed framework SAIMOD (Self-Aware Intelligent Model), with its innovative principles and assumptions, is also discussed in detail. This includes the intelligent networking of the deployed UAVs in SAIMOD designed for use in covering the disaster recovery area to ensure fault-tolerant resilient positioning control in SAIMOD, the use of unique identifier numbers for the ground node, group leaders and the UAVs, together with the incorporation of the Jaccard sequence algorithm in the UAVs' positioning system.

In this Chapter, how SAIMOD would be applied in gathering statistics for use as an assessment model in the disaster management plan, together with a suitable mathematical model for its implementation as a resource management tool, was also discussed and analysed. The SAIMOD framework was then compared to existing reinforcement learning frameworks for UAV deployment.

Chapter 5

Modification of the Routing Protocol

5.1 Introduction

This Chapter begins with a description of the proposed novel protocol, MODOLSR (Modified Optimised Link State Routing protocol, a review of related literature on OLSR's MPR node selection process is presented, and the modification of the MPR node selection process based on the available energy in the nodes, using an adapted MATLAB code is shown. The modified protocol, MODOLSR, in which the MPR node selection process is optimised based on the available energy in the nodes, while TDMA is used to schedule time slots for data transmission, is then evaluated for energy efficiency. In addition, a review of previous Research on the Medium Access Control (MAC) layer is presented, and MODOLSR is compared to a cross-section of other modified OLSR protocols.

5.2 The Modified Optimised Link State Routing (MODOLSR) Protocol

In recent years, researchers have paid significant attention to the problem of selecting suitable routing protocols for Mobile *ad hoc* networks (MANETs) and modifying them to meet specific network requirements. Most research on routing protocols in MANETs focused on network resilience and scalability while maximising Throughput and Packet delivery, reducing Delay, and optimising network connectivity. This Research aims to improve the energy efficiency and network performance of the selected Optimised Link State Routing (OLSR) protocol.

OLSR, a proactive, table-driven routing protocol, is flat. Unlike conventional table-driven protocols that perform network-wide flooding of route information, it uses an optimised version of the link-state algorithm. Individual nodes maintain their network information routes, and the protocol does not need central administrative control in handling the routing process. Consequently, this minimises the control overhead needed in its routing process, using fewer control messages. Furthermore, OLSR is well suited for dense *ad hoc* networks as it provides optimum paths while periodically maintaining them (Maret et al., 2021; Lakrami, Elkamoun and El Kamili, 2016; Soni and Shah, 2015). It achieves this using the Multipoint Relay (MPR) node selection process, which reduces the traffic overhead of data transfer paths from source to destination in the *ad hoc* network (Zhang, Cui and Zhang, 2019).

In OLSR's MPR node selection process, the network is divided into groups with pre-defined roles, among which is the MPR node group. All groups in the network cooperate to conform with the optimisation process in OLSR. This involves selecting the optimal MPR node-set, which will contain all the nodes with the minimum required number of symmetric "one-hop" neighbours to reach all symmetrical strict "two-hop" neighbours with bi-directional links. This is achieved by link-sensing using "Hello" messages. Also, MPR nodes minimise routing overheads by being the only nodes in the network that can retransmit "Hello" messages, leading to a significant reduction in control and retransmitted messages, as well as redundancy in the flooding process (Barki, Guennoun, and Addaim, 2020; Nabou, Laanaoui, and Ouzzif, 2018).

The broadcasting of control messages by network-wide flooding, standard with other table-driven protocols, is limited in OLSR since control messages are only retransmitted by nodes selected as MPRs. In addition, this reduces redundancy in the network by eliminating unnecessary broadcasting of similar information messages. Each node maintains a list of all the MPR nodes in the network, and there are no retransmissions of link-sensing messages, thereby reducing the overall control traffic overhead. However, there are some issues with OLSR, such as the greedy algorithm used by OLSR in determining MPR nodes, which increases energy consumption and redundant packets across each node as it does not have an algorithm to resolve the ties (Vinayagam, 2017; Zougagh et al., 2014). Furthermore, MPR nodes are randomly chosen when the choice is between nodes having the same degree, willingness, and reachability. Since the selection of MPR nodes can affect network properties such as routing overhead and the efficiency of the routing protocol, the need arises to optimise the MPR node selection process to overcome these issues.

This Research proposes a two-layer modification of the selected protocol, Optimised Link State Routing (OLSR). The first layer modification involves optimising the Multipoint Relay (MPR) selection algorithm at the network layer based on the available energy in the nodes. The second layer involves scheduling time slots for data transmission at the Medium Access Control (MAC) layer using the Time Division Multiple Access (TDMA) technique. This two-layer modification aims to improve the network's lifetime by conserving energy and optimising Throughput.

5.3 Related Literature on the OLSR protocol and MPR nodes

Mobile *ad hoc* networks (MANETs) allow communication between mobile nodes without any centralised controller. However, due to their dynamic topology, they are fraught with issues such as recurrent link breakage, bandwidth constraints, packet loss, limited energy source, and route discovery. It is, therefore, essential to have a suitable routing protocol for efficient data transmission while optimising the allocation of limited resources (Sun, Li, and Zhang, 2021; Sharma and Ali, 2019).

Research into the MPR node selection process has been carried out, and new techniques are being developed that consider some desired metrics, such as optimisation of bandwidth usage, signal strength, Quality of Service (QoS), and available energy (Barki, Guennoun, and Addaim, 2020; Li and Wu, 2018).

Belkhira et al. (2020) proposed an MPR node selection technique based on energy conservation. The method aims to increase network lifetime by improving the network's load-balancing capacity and Quality of Service (QoS). They incorporated an algorithm to calculate the weighting ratio between the energy available in the node and the reachability value. Simulation results showed that their methodology, compared with the traditional OLSR protocol, considerably enhanced the MANET lifetime by reducing the number of dead nodes in the network.

Oyakhire and Gyoda (2020) proposed a new algorithm to reduce control traffic by considering the node density and residual energy in the nodes. This algorithm aimed to increase the Packet Delivery Fraction (PDF) of the network and only considered a grid-format network with stationary nodes. In their simulation, the residual energy of the MPR nodes in the network improved, and they had better PDF. However, they could not demonstrate how the MPR nodes' residual energy depleted with time.

Kaur and Aulakh (2014) proposed a modified OLSR, Energy-based Threshold Optimised Link State Routing (ET-OLSR) protocol. This protocol uses their algorithm to ensure the maximum lifetime of the nodes. Their algorithm ensured that only nodes with a pre-defined threshold energy value could engage in path discovery. While considering energy conservation, their protocol had better PDR and was more energy efficient than traditional OLSR but had less Throughput.

El-Hajj et al. (2015) proposed modifying the OLSR routing protocol by making every node in the network create its own Mobile Agent (MA) to replace MPR nodes in OLSR. These MAs will transverse the network to get network-wide topology information from every node. They called their novel protocol MOLSR (Mobile Agent OLSR). Unlike the traditional OLSR, whose MPR nodes use a multicast broadcasting methodology, their MA nodes will not use flooding but a unicast scheme for obtaining and maintaining topology information. Their simulation results showed increased Throughput and a significant reduction in utilisation time compared to the traditional OLSR. However, the protocol had more delays and increased traffic size.

Ouacha et al. (2013) proposed an algorithm to improve the lifetime of MPR nodes by reducing node mobility. Their algorithm, RTTQ (Remaining Time-To-Quit), was meant to predict the remaining lifetime of available links between nodes and their neighbours using a radio scoop and the distance between them. MRR nodes were then selected based on the nodes having an RTTQ greater than the stipulated threshold. Their simulation results showed an increase in the MPR nodes' lifetime, Average Throughput, and Packet Delivered Ratio (PDR) compared to the basic OLSR.

The researchers, Nilsson and Sterner (2015), proposed using additional MPR nodes and the physical layer information to increase the robustness of the routing protocol. They simulated to ascertain how terrain characteristics affect the protocol's performance. Their Research was focused on improving network connectivity while also considering the effects of node mobility. They simulated mobile networks in varying terrains using different models. Their results showed that the terrain type can significantly influence the performance of the MPR nodes and, consequently, the networks.

Zheng et al. (2014) proposed the Mobility and Load-aware OLSR (MLOLSR) routing protocol, which uses statistical information of the nodes' distance to determine communication link stability. It gives each node a value for stability degree called SDN (Stability Degree of Node). This protocol is better suited for smaller networks, as more extensive networks would require continuous topology information updates. This would considerably increase the routing overhead and invariably mean more energy consumption as the network size increases.

Predictive-OLSR (P-OLSR), a modified OLSR, was designed by Rosati et al. (2015) to enhance traditional OLSR's performance by combining the position information and relative speed of the nodes in selecting the best route based on the Dijkstra algorithm and the ETX (Expected Transmission Count) technique. The ETX value is calculated using a formula that incorporates the position and speed of two nearby nodes relative to each other. They did not consider the residual energy of nodes, which is a valuable parameter for determining estimated link quality, and their protocol might also not be suitable for a highly dynamic UAV network.

Denial Contradictions with Fictitious Node Mechanism OLSR (DCFM-OLSR) protocol, a modified version of the traditional OLSR, was proposed by Rani and Reddy (2017) to counteract attacks on the traditional OLSR protocol's performance by using the same strategy employed by possible attacks to avoid them. They proposed using the DCFM (Denial Contradictions with Fictitious Node Mechanism) method. Their simulation results support the use of DCFM-OLSR protocol to address the issue of possible attacks on OLSR's performance, as many attacks were avoided. Their Research was, however, not based on energy conservation.

Mostafaei and Pashazadeh (2016) suggested optimising the OLSR protocol to increase network lifetime by reducing number of control packets used and the packet loss ratio in the network. Their method was to prevent mobile nodes from being chosen as MPR nodes, and their work assumed that some nodes were stationary while others were mobile. Their simulation results showed that their proposed method reduces the packet loss ratio of the MANET by 15% and that of the mobile nodes by 10%, reducing the control overhead and improving the network lifetime.

Malik, Mahajan, and Rizvi (2014) proposed a Denial-of-Service-Free OLSR (DFOLSR), an algorithm in which the MPR selection method is modified by detecting malicious nodes in the network. This modified protocol was meant to handle the energy conservation issues faced in the MPR node selection process in OLSR and give it more security.

Liu et al. (2015) applied their research to develop an algorithm to improve the QoS in voice and video applications by modifying the MPR selection technique in MANETs. They simulated a network with voice applications and video streaming, and their results showed improved throughput, reduced end-to-end delay, and better Quality of Service compared with traditional OLSR.

A key criterion in choosing a suitable routing protocol for deployment in MANETs is its ability to create reliable routing links. Li and Wu (2017) proposed a Smooth Mobility and Link Reliability based OLSR protocol named (SMLR_OLSR) for MANETs. They did so by designing a mobility model based on the Markov mobility model. Their results showed that SMLR_OLSR gave a more practical routing evaluation, increased average MPR lifetime and reduced control overhead.

Prajapati, Patel and Patel (2015) considered the importance of energy source utilisation using Optimised Link State Routing (OLSR). In the OLSR protocol, more energy is expended by MPR nodes than other nodes, which causes the MPR nodes to deplete their energy faster than other nodes. Their paper theorised an energy-efficient routing method that will improve network lifetime.

5.4 Modification of the MPR node selection process

This section focuses on modifying the OLSR protocol at the network layer. The network layer in MANET architecture contains the routing protocol responsible for transmitting data packets from source to destination. In this study, the available energy in the nodes was considered when modifying the MPR node selection process.

The OLSR (Optimised Link State Routing) protocol employs Multipoint Relay (MPR). In this approach, each node dynamically selects a set of neighbour nodes to act as its “Multipoint Relays” (MPR) nodes. These chosen nodes carry out tasks such as forwarding control traffic messages and announcing their availability to the network for transmitting data. This dynamic selection process enhances the protocol’s efficiency because only the MPR nodes can periodically disseminate link state information throughout the network. Also, MPR selections are not static;

they are reevaluated over time to update the network when changes occur to the network topology, such as when link quality fluctuates, or nodes leave the network.

The MPR nodes in this Research are selected based on their ability to efficiently forward messages while reducing the overall network traffic and considering the available energy in the nodes. By using the MPR selection technique, which prioritises energy efficiency, the modified protocol ensures that the selected MPRs effectively relay control messages while optimising bandwidth in the network in a sustainable and energy-efficient manner.

Figure 5.1 is a Flowchart depicting the MPR node selection process. The selection process involves the following steps:

I. **Neighbour Discovery**

Each node identifies its neighbouring nodes by periodically sending out "Hello messages," which are essentially short packets containing information about the sender. These messages help the node retain an accurate view of its immediate network topology. When it exchanges "Hello messages," it classifies them based on the quality and reliability of the links.

II. **Link Quality and Reachability**

The quality and reliability of links to their neighbours are classified. The best node is identified as a possible node to act as an MPR node called X. This classification is based on metrics such as link stability, which measures the consistency of the link's performance, or signal strength, which indicates the power of the signal transmitted over the link. All other nodes are classified, and the 1-hop and 2-hop neighbours to the selected node are classed into two sets: NI and N2. N1 contains X's 1-hop neighbours, while N2 contains X's 2-hop neighbours.

4. **MPR Selection Criterion**

(Each node selects its MPR nodes from its neighbours based on how many two-hop neighbours they can reach. The goal is to ensure that chosen MPRs can cover all the node's one-hop and two-hop neighbours).

5. **Coverage**

The selection process aims to select the smallest number of MPRs that can still reach all a node's neighbours. This is to minimise redundancy in message forwarding. If there are two nodes with the same link quality and reachability, the one with the highest amount of available energy is designated X. The workflow is completed, and the nodes selected as X are outputted into a new set, S. S is a set containing all MPR nodes for the initiating node, A. When A wants to send a message, it uses an MPR node from set S and does not need to flood the network with “Hello messages” to find routes.

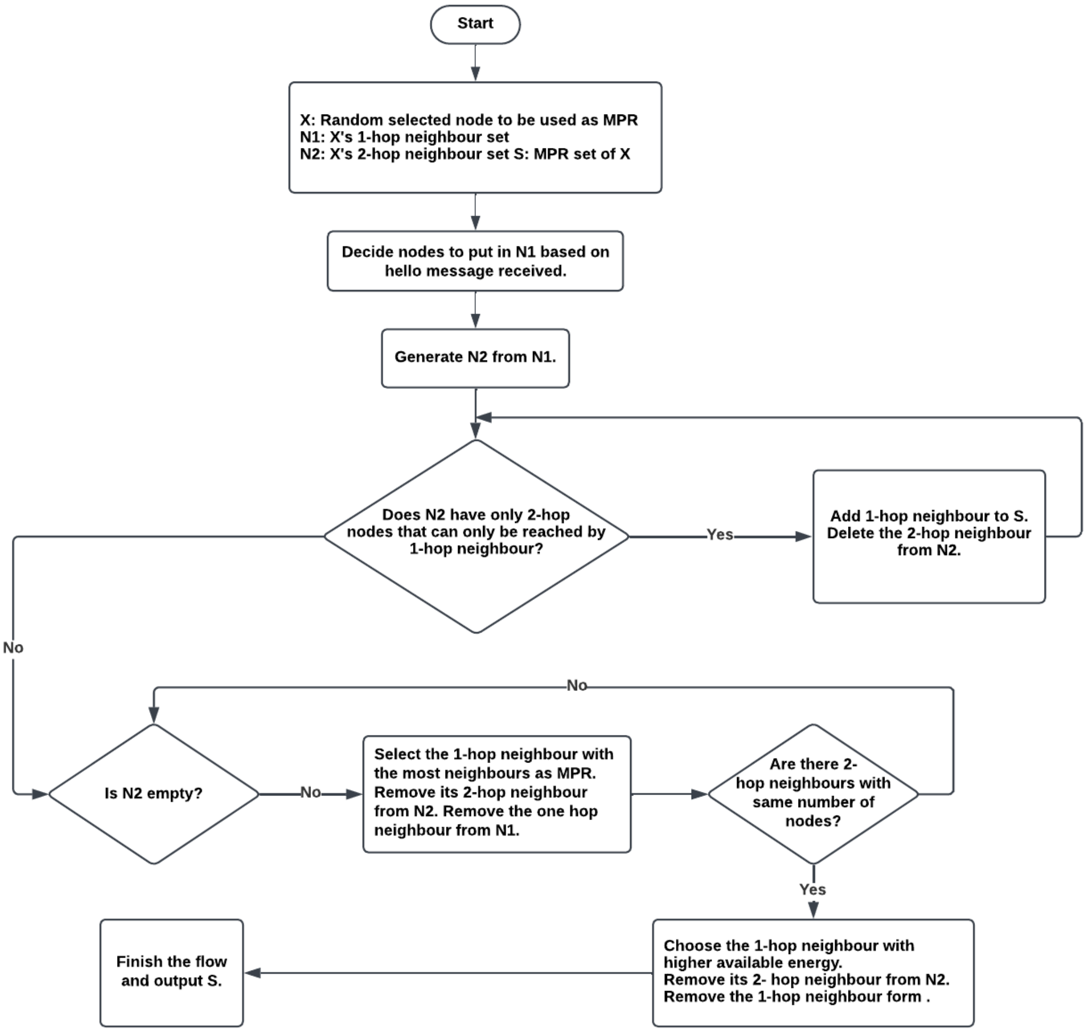


Figure 5.1: Flowchart of MPR Node selection process based on available energy

5.4.1 Simulation Results and Analysis

The algorithm used to modify the nodal densities is adapted MATLAB code by MS (2023).
The simulation is run with different node densities ranging from 10 to 100, which are increased incrementally in tens. The results are shown below.

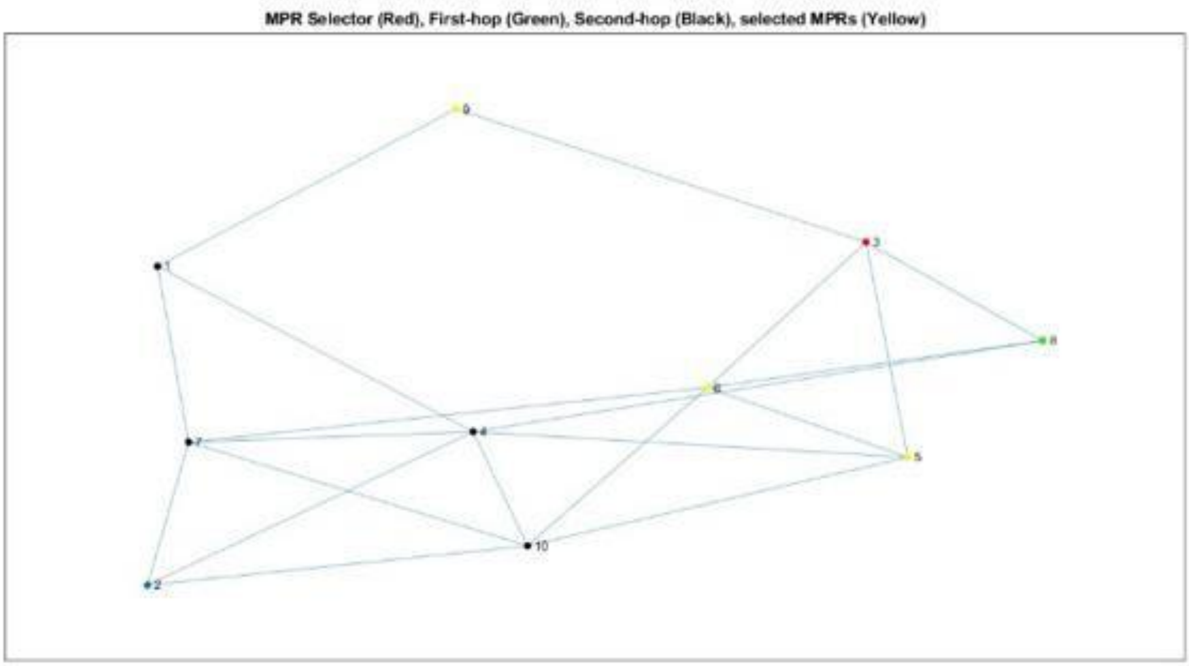


Figure 5.2: MPR Node selection for a network with 10 nodes

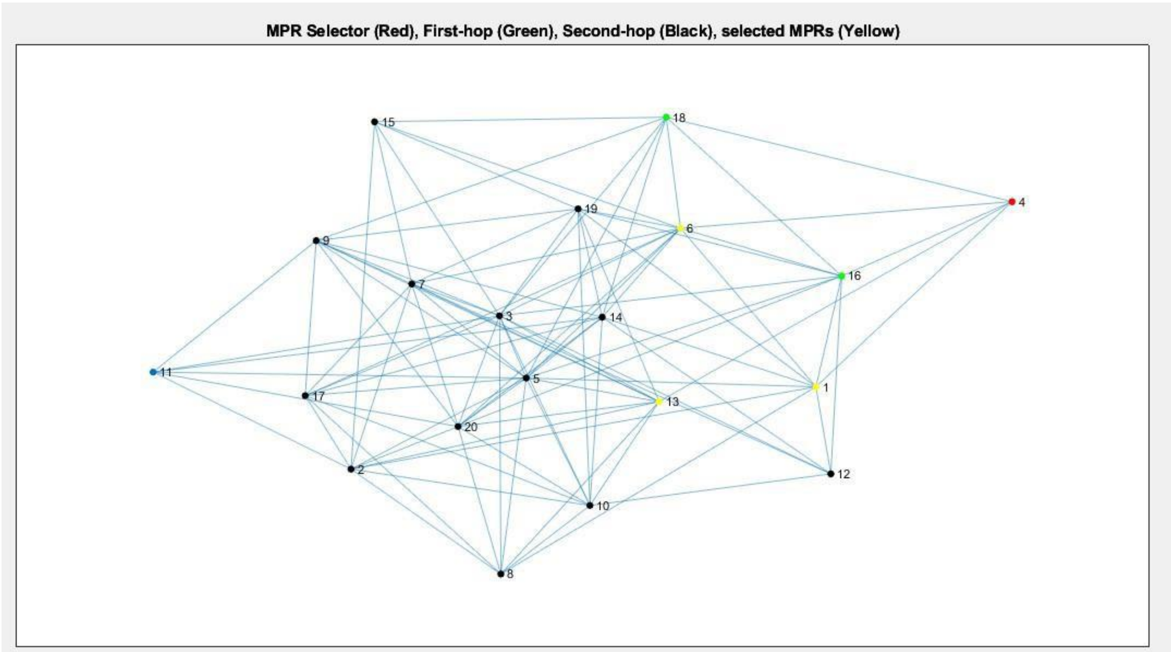


Figure 5.3: MPR Node selection for a network with 20 nodes

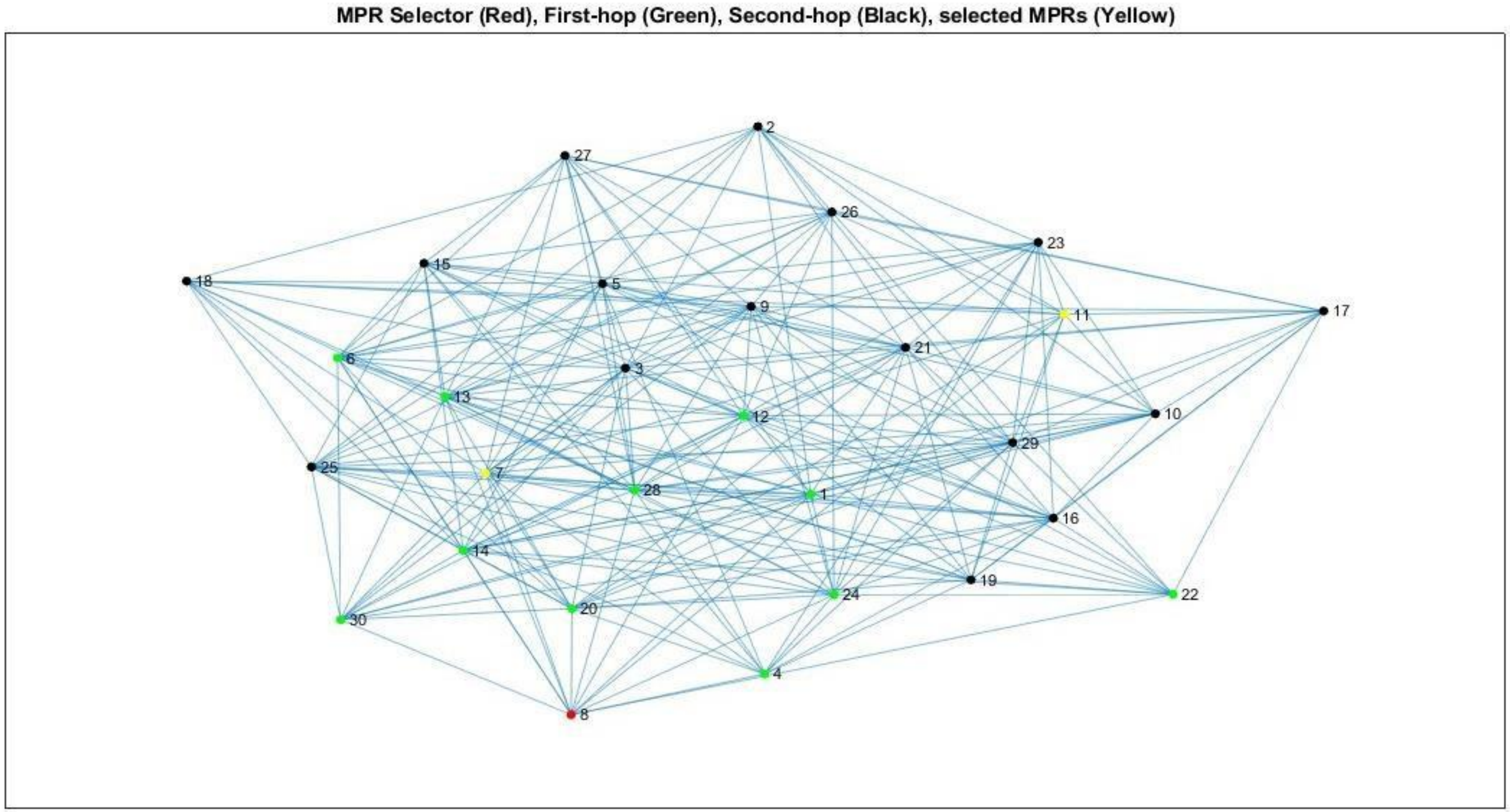


Figure 5.4: MPR Node selection for a network with 30 nodes

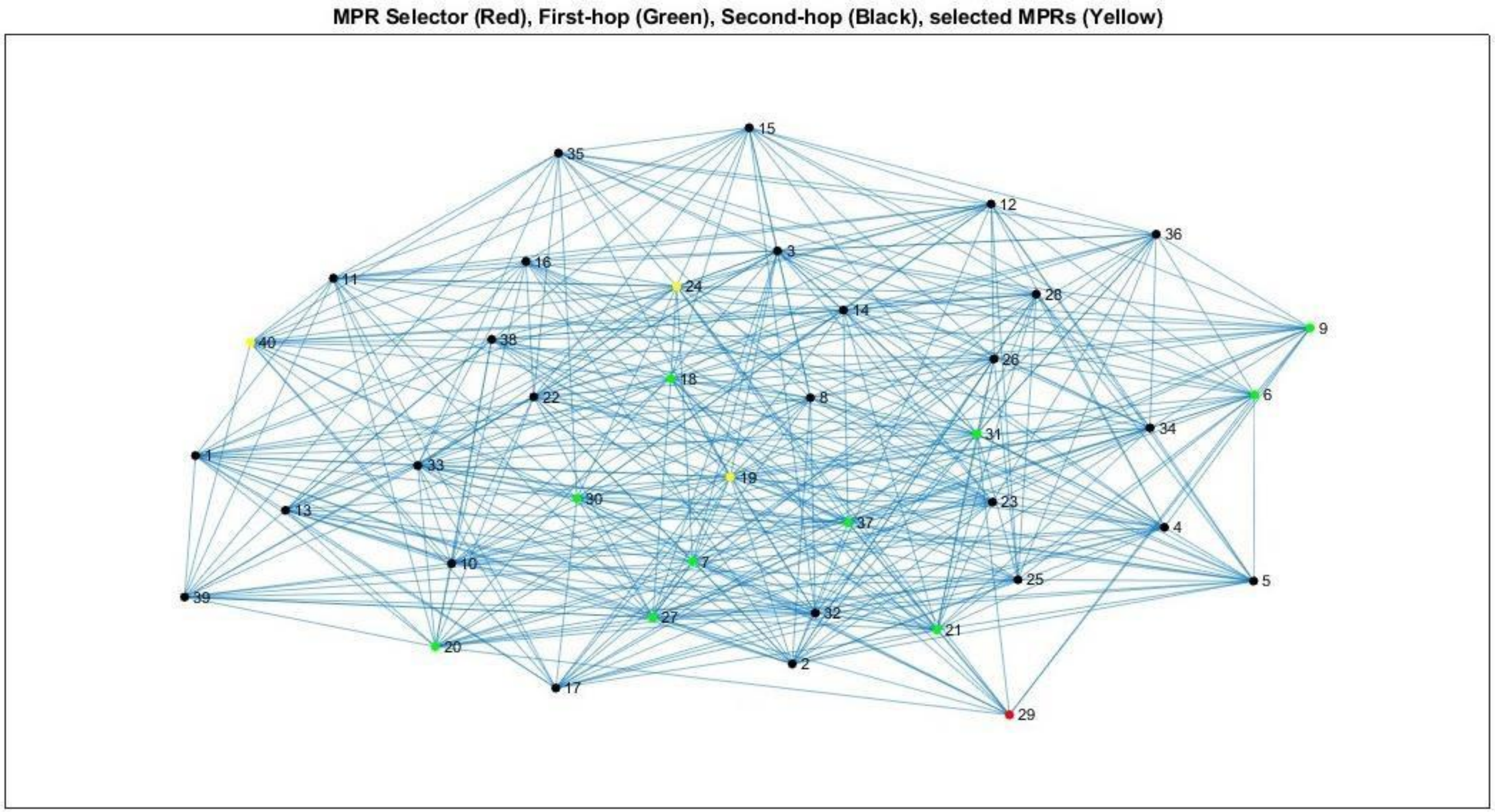


Figure 5.5: MPR Node selection for a network with 40 nodes

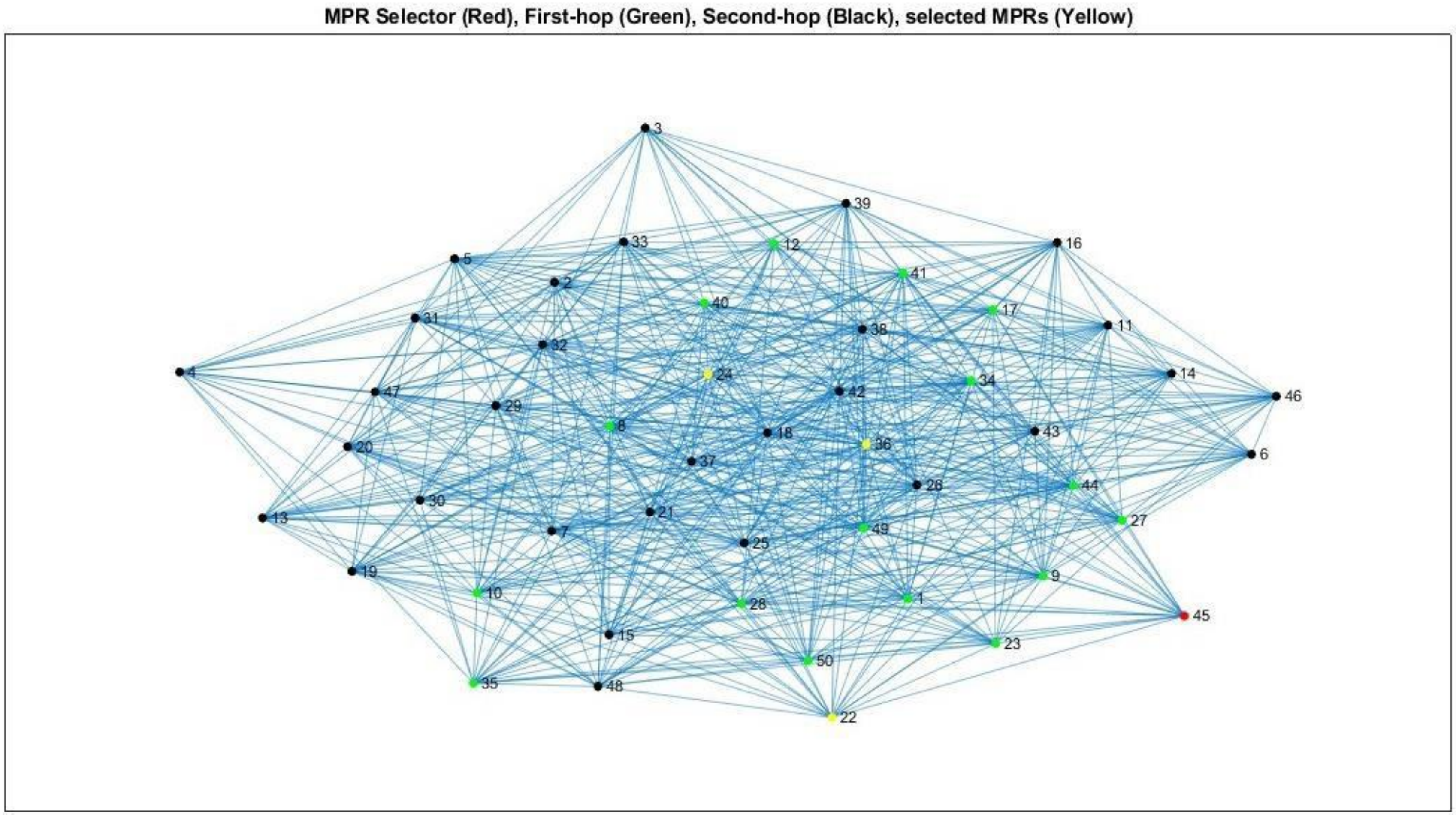


Figure 5.6: MPR Node selection for a network with 50 nodes

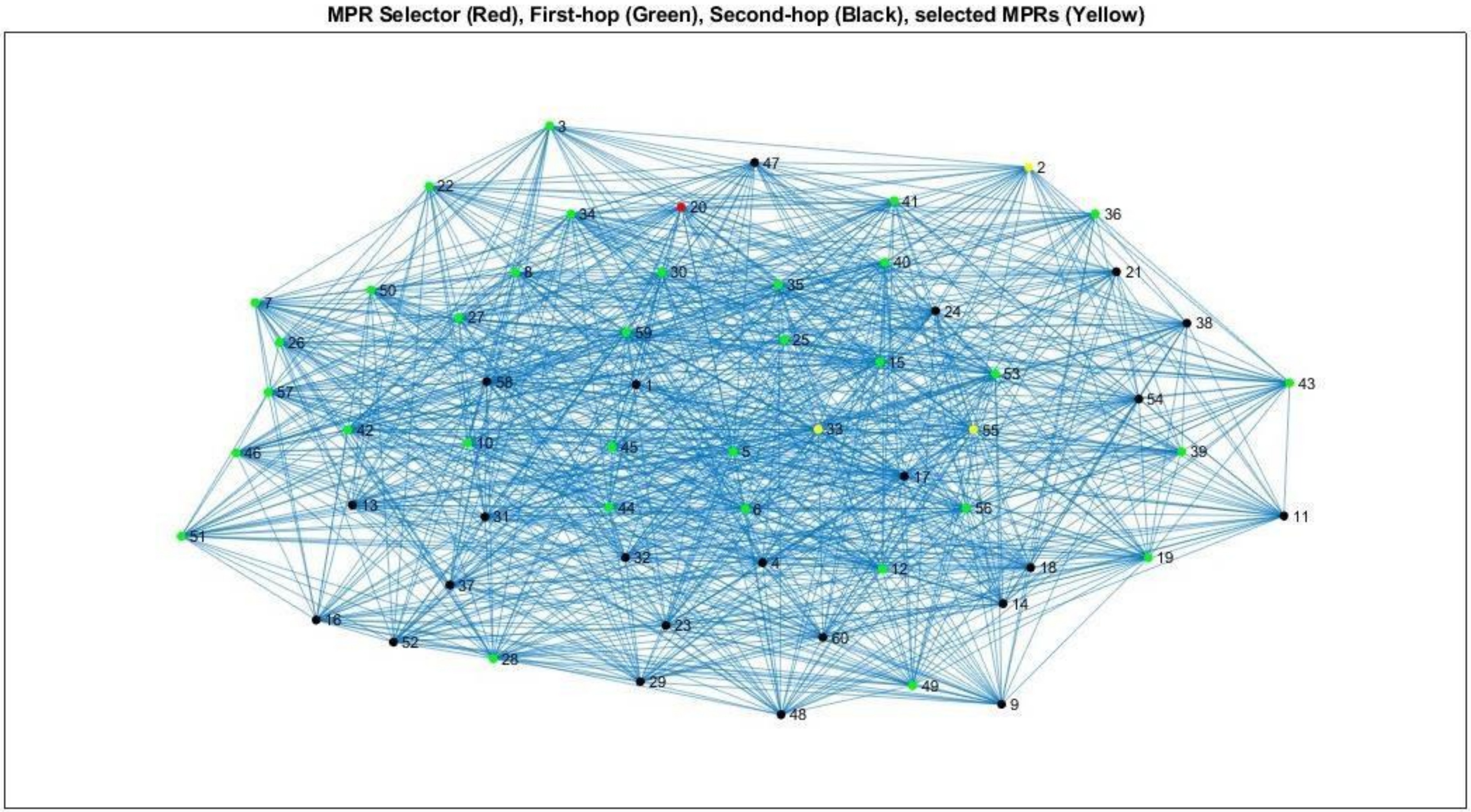


Figure 5.7: MPR Node selection for a network with 60 nodes

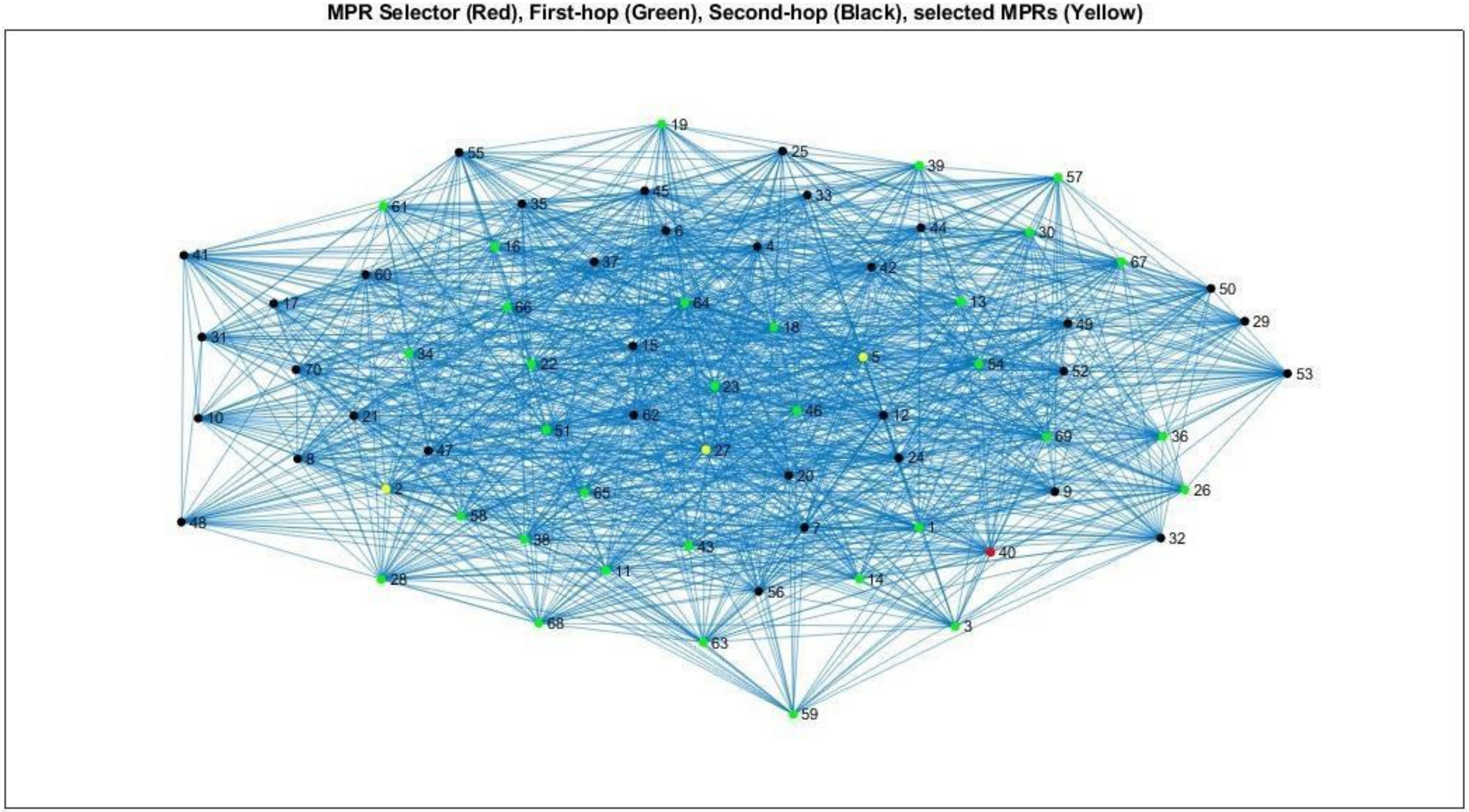


Figure 5.8: MPR Node selection for a network with 70 nodes

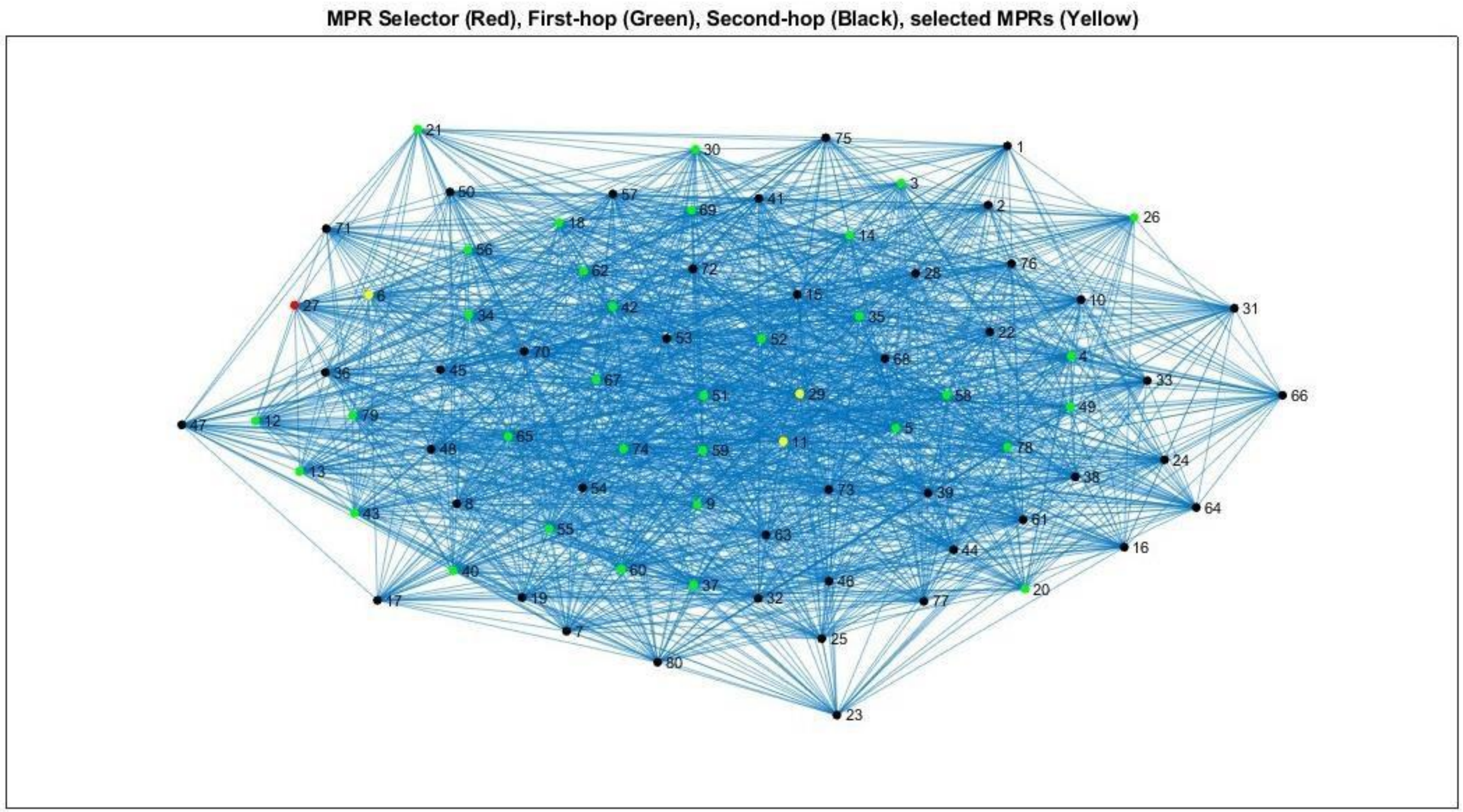


Figure 5.9: MPR Node selection for a network with 80 nodes

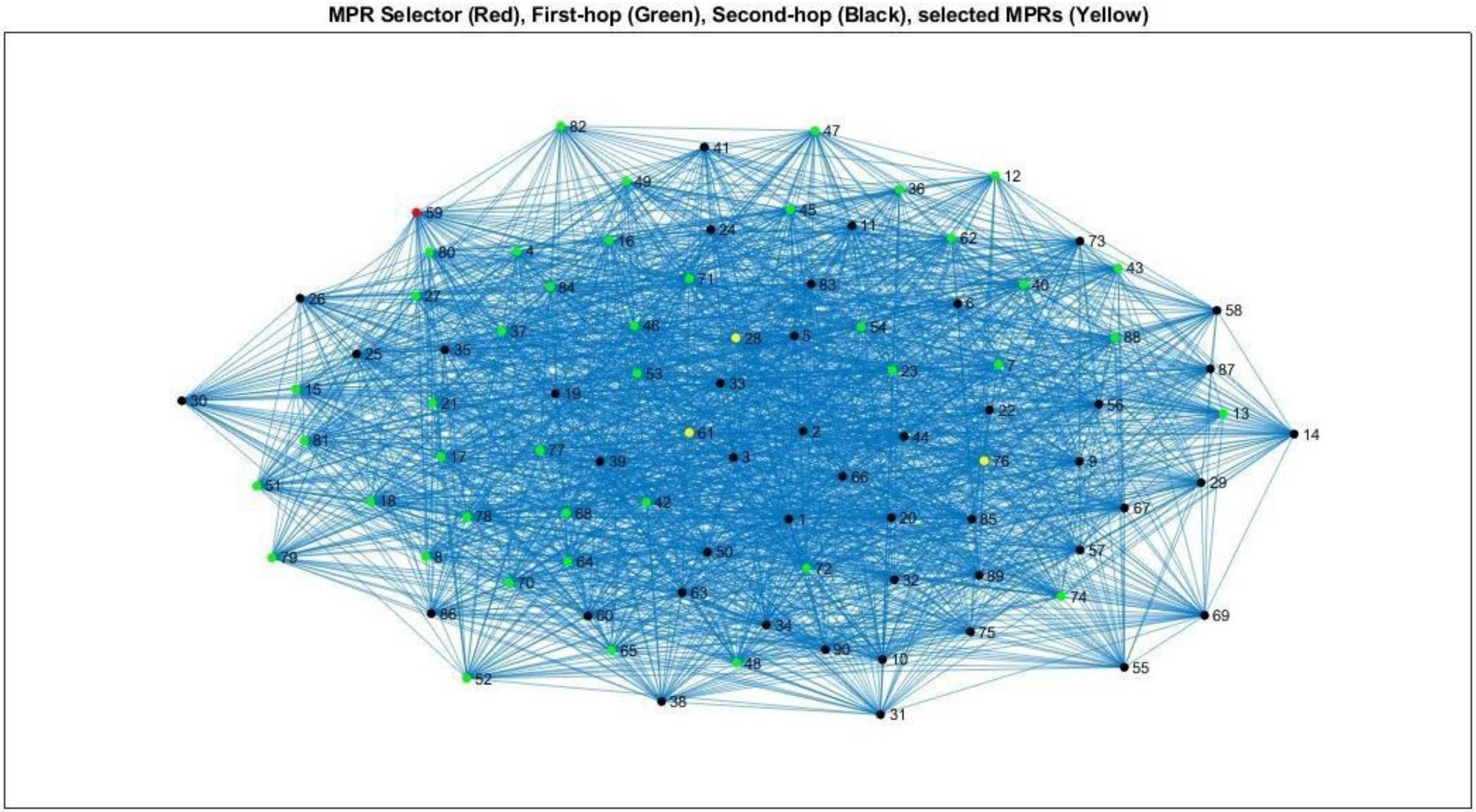


Figure 5.10: MPR Node selection for a network with 90 nodes

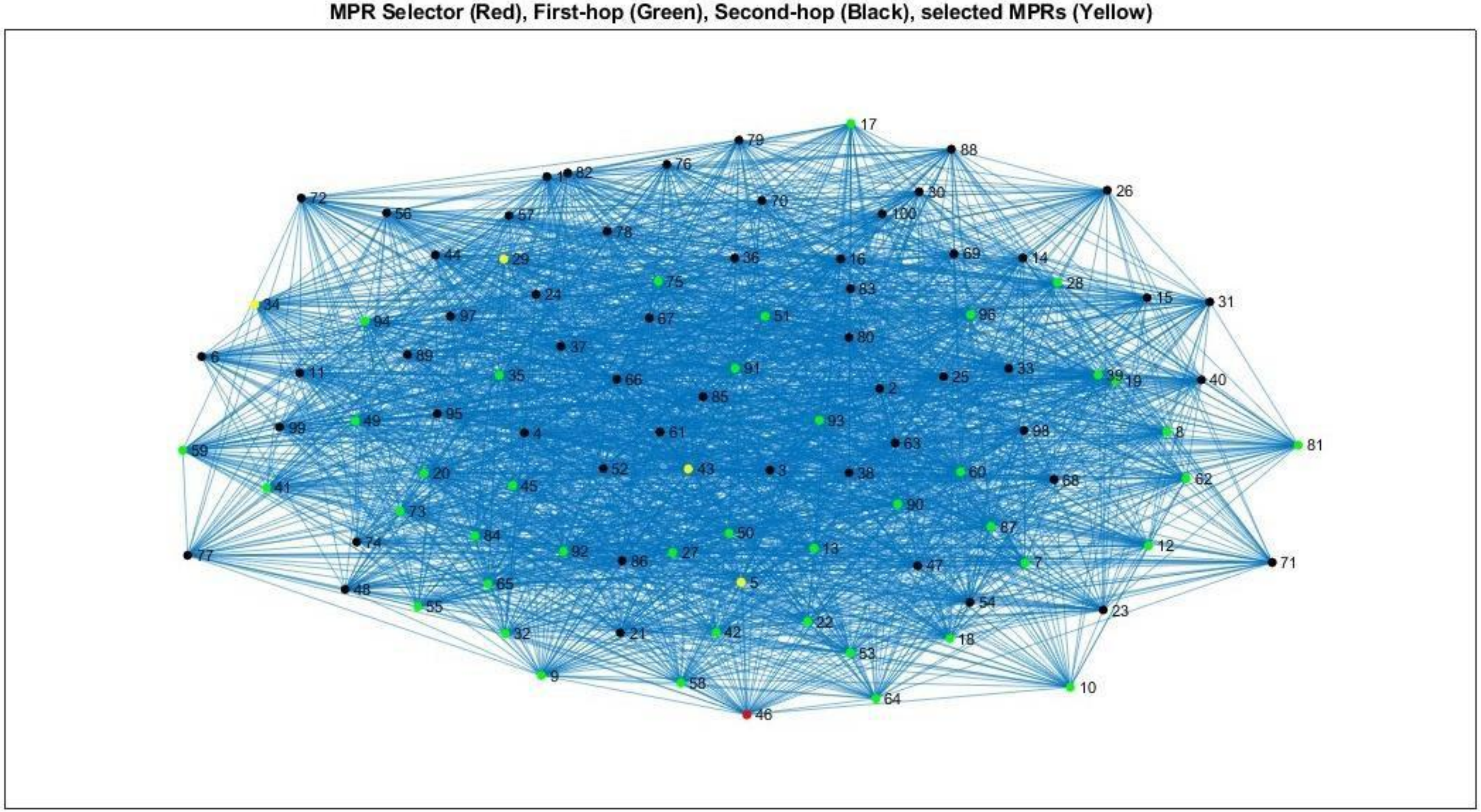


Figure 5.11 MPR Node selection for a network with 100 nodes

5.42 MPR Node selection (summary)

Modifying the MPR node selection process by involving the value of the available energy in the nodes in the decision-making process of the MPR selection contributes to developing a cross-layer protocol for use in SAIMOD (from Objective 2). Unlike typical MPR selection methods focusing solely on maximising signal strength, reducing overhead, or minimising latency, these results emphasised a more nuanced approach. This approach considers not only the various network conditions and traffic patterns but also the network lifetime by choosing the nodes with higher energy values to be MPRs, potentially leading to improved efficiency and reliability in communication by enhancing the decision-making process for Multipoint Relay (MPR) selection. Ultimately, this aligns better with the overall objectives of optimising network performance and improving user experience.

By integrating these findings, this Research implements a more adaptive and responsive energy conservation strategy that differs significantly from traditional MPR methodologies. The selection of MPRs is influenced not only by the availability of next-hop neighbours but also by the energy levels of the nodes. Modification at the network layer enhances energy conservation. Traditional Optimised Link State Routing (OLSR) primarily identifies next-hop neighbours. This often results in high overhead traffic due to the increased control messages necessary for network-wide broadcasts. Such an approach can create significant control traffic, leading to inefficiencies.

While previous Research has predominantly concentrated on single-layer modifications that focus on metrics such as reducing overhead or residual energy, this advances the protocol through a two-layer modification approach. This novel two-layer modification of the traditional OLSR significantly enhances the system's sustainability and energy efficiency. While the modification process on the network layer optimises Throughput and energy conservation, modifying the protocol at the MAC layer in which the MAC components of the protocols are modified using TDMA would improve channel quality. This results in lower channel occupation during packet transmission and reduced overall control packet overhead. Additionally, utilising TDMA for scheduling data transmission addresses issues with increased node density in the network, such as increased Delay, as TDMA allows for collision-free transmission.

5.5 Related Literature on the Medium Access Control (MAC) layer

The choice of routing protocols used in *ad hoc* networks plays a significant role in overall network performance as they are used to establish paths/links to the destination node from the source node. These protocols, nestled in the protocol stack of *ad hoc* networks, encompass the network layer routing protocols and the Media Access Control (MAC) layer protocols. The MAC protocols manage how multiple devices access a shared media network. It ensures no collision of transmitted data packets from different stations across the same channel in the network. The MAC layer's primary function is to manage the nodes in the network in terms of resource allocation, such as bandwidth, scheduling of network access, and utilisation of available energy, underscoring their significance in the network landscape (Unk et al., 2016; Reddy and Meenakshi, 2016; Azad, Kabir and Hossain, 2013).

Protocol overhead, overhearing, and collisions are three potential sources of energy waste in ad hoc networks, and they can significantly impact the network's energy efficiency.

- Protocol Overhead: The routing protocol could have increased overhead when sensing available routes from source to destination due to additional energy consumption from control traffic, link-sensing, and route allocation.
- Overhearing occurs when a node picks up data packets not intended for it due to flooding.
- Collision of data packets: Data packets may need to be re-transmitted as they may be dropped due to collision with other data packets during transmission, resulting in increased latency and costs.

Most MAC layer protocols are either schedule-based or contention-free.

Contention-based protocols

These Contention-based protocols use multiple access techniques that allow users to share the same communication channel. However, this comes with the risk of collisions, which occur when multiple users attempt to access the channel simultaneously. In this setup, each node in the network can access the channel, and nodes transmit data on a first-come, first-served basis. The node that successfully accesses the channel is allowed to transmit its data. These protocols typically include mechanisms for initiating new transmissions, determining channel availability, and managing retransmissions when the channel is occupied. Contention-based protocols are generally employed in sparse networks, where they can optimise bandwidth utilisation. These protocols include Carrier Sense Multiple Access (CSMA) and ALOHA (Baek and Lim, 2019; Tsokalo et al., 2017).

A. Carrier Sense Multiple Access (CSMA)

The CSMA routing protocol employs a Collision Avoidance (CA) or Collision Detection (CD) mechanism. In Carrier Sense Multiple Access with Collision Detection (CSMA/CD), when a data frame is sent from the source to a channel, it waits for an acknowledgement to confirm whether the channel is clear. The channel is considered clear if it only receives the acknowledgement and the data frame has been transmitted successfully. If it detects two signals, this indicates that the frame has collided in the shared channel. The CSMA/CD technique senses the channel before the data frames are broadcast. A station checks the channel to determine if it is idle, then sends a frame to confirm that the transmission was successful. The station can send another frame if the transmission succeeds and the channel is still evident. However, if a collision is detected, the station sends a stop signal to terminate the data transmission and will repeat the process after waiting for a random time interval.

B. ALOHA

ALOHA is primarily used for wireless Local Area Networks (LAN) but can transmit data in a shared medium. There are two types of ALOHA schemes: Pure ALOHA and Slotted ALOHA. In Pure ALOHA, any station can transmit data across the network whenever a data frame becomes available. This scheme does not require carrier sensing and provides acknowledgements for the frames, meaning it does not need collision detection. In contrast, Slotted ALOHA organises time into uniform slots. In this technique, a central clock synchronises the stations, and transmissions can only begin at the boundaries of these time slots (Wong et al., 2018).

Advantages of Contention-based MAC Protocols

1. Simplicity

Contention-based protocols can achieve high Throughput and efficient channel usage in scenarios with low contention (few users).

2. Flexibility

They can adapt quickly to changes in network conditions, making them suitable for highly dynamic environments.

3. High Throughput in Light Traffic

In scenarios with low contention (few users), these protocols can achieve high Throughput and efficient channel usage.

Disadvantages of Contention-based MAC Protocols

1. Collisions

The risk of collisions increases as traffic grows, leading to retransmissions and increased latency, which can degrade performance.

2. Unpredictable Performance

Since access to the channel is based on competition, the performance can be unpredictable, especially in congested networks.

3. Inefficient in High Traffic:

These protocols may struggle to maintain efficiency under high load conditions, leading to significant energy waste from collisions and retries.

Schedule based protocols

These are also known as contention-free protocols based on a scheduling technique. The nodes are synchronised and do not need to compete for channel access transmission. Frames are divided into slots. They can avoid issues during data transmission, such as overhearing and collisions, by using pre-allocated periods for transmission in the channels. The main challenge is allocating the available channel resources among the nodes so that information is independently and simultaneously transmitted within the same bandwidth. Each station can simultaneously transmit data frames on the shared channel using the entire frequency. The bandwidth is not divided;

instead, the individual data frames are separated by each station, which has a unique sequence that it uses to transmit data over the shared channel. This could be likened to a scenario where multiple users continuously speak in a room. Examples are Code Division Multiple Access (CDMA), Frequency Division Multiple Access (FDMA), and Time Division Multiple Access (TDMA).

A. Code Division Multiple Access (CDMA)

This channel access protocol enables multiple users (stations) to transmit information independently and simultaneously within the same bandwidth. Each station can send data frames over the shared channel using the entire frequency without dividing the bandwidth. Instead, the data frames from each station are uniquely sequenced to prevent overlapping during transmission. This scenario can be likened to a situation where several people in a room are continuously speaking simultaneously (Swalem, Halim, and El Hennawy, 2023; Mizuyoshi and Han, 2023).

B. Frequency Division Multiple Access (FDMA)

This multiple-access technique divides the available bandwidth into equal frequency bands, allowing multiple users to transmit data over subchannels. Each user is dynamically assigned a specific frequency band, which helps prevent interference, or crosstalk, among transmissions. A central controller plays a crucial role in FDMA by managing this allocation during call setup, ensuring that frequency bands are reserved based on the specific needs of users. This enables simultaneous transmissions without interference. While FDMA is well-suited for connection-oriented networks, one limitation is its inefficiency in optimising available by optimising power.

C. Time Division Multiple Access (TDMA)

TDMA is a method of data transmission that divides the same frequency bandwidth into time slots, allocating these slots to various stations for transmitting data frames. This organisation prevents collisions and enhances efficient use of the available bandwidth. In this system, each node in the network sequentially sends data, which eliminates interference that could occur from simultaneous transmissions. Each node can transmit only during its designated time slot, ensuring that each node's transmission is unique and helps reduce battery consumption since data transmission is based on demand (Latif et al., 2022; Murkya, Singh, and Bhatia, 2019).

Advantages of Schedule-based MAC Protocols

1. **Reduced Collisions**

Since access to the channel is predetermined, the likelihood of collisions is minimised, leading to more efficient data transmission.

2. **Guaranteed Bandwidth**

These protocols can provide guaranteed bandwidth and predictable performance, making them suitable for time-sensitive applications.

3. **Energy Efficiency**

These protocols can optimise energy consumption by scheduling transmissions and reducing the wastage of idle listening and collisions.

Disadvantages of Schedule-based MAC Protocols

1. Complexity

Implementing scheduling mechanisms can complicate the protocol design, requiring more sophisticated algorithms and coordination.

2. Reduced Flexibility

These protocols may not perform well in dynamic or highly variable network conditions, as changes to the scheduling may be needed to adapt to new traffic patterns.

3. Overhead

The need for synchronisation and coordination between nodes can introduce additional overhead, offsetting the benefits in low-voltage scenarios.

In summary, the choice between schedule-based and contention-based MAC protocols will often depend on a given network's specific requirements, including its traffic patterns, energy constraints, and need for predictable performance.

5.6 Optimising the selected protocol at the MAC layer using TDMA

Schedule-based channel Schedule-based channel access schemes, especially TDMA-based protocols, have an advantage over contention-based channel access techniques. This is because Schedule-based MAC protocols can avoid collisions, overhearing and idle listening problems by avoiding collisions when the number of contending nodes in the network increases. This is done by providing collision-free transmissions (Shayo, Mafole and Mwambela, 2020; Wagen, Adalid and Maret, 2020; Pawar, Kulkarni, and Mantri, 2018).

Scheduling in TDMA-based protocols can be either dynamic or static. In static scheduling, a user can only transmit during the time slots allocated to it, irrespective of whether the time slots allocated to the other users are idle. The dynamic scheduling method is applied to improve the Throughput in such situations. Several researchers have proposed TDMA-based MAC layer scheduling because of its advantages.

Sami, Noordin and Khabazian (2016) proposed a TDMA-based, cooperative Medium Access Control (MAC) protocol called Cooperative Cognitive TDMA (CC-TDMA) for cognitive networks. This protocol aimed to improve the quality of service (QoS) for all types of users in the network. Compared to standard TDMA, their simulation results improved performance metrics such as Throughput and Packet Delivery Ratio (PDR).

Various studies have been aimed at resolving the issue of resource allocation and access collision using TDMA. In the study by Zhang and Zhu (2020), they proposed using EVC- TDMA, an optimised TDMA-based MAC layer protocol, to improve network Throughput in vehicular *ad hoc* networks (VANETs). VANETs are generally used to solve issues related to safety in vehicular environments, such as developing delay-tolerant communication infrastructure, improved Throughput, and low latency. The use of TDMA-based scheduling techniques in such networks has been effective. The enhanced protocol was intended to choose Multipoint Relay nodes based on their buffer lengths and speeds. The simulation showed that the EVC-TDMA deployed network had the best output when the vehicular speeds were stable.

Similarly, El Joubari, Othman and Vèque (2021) proposed a traffic-aware MAC layer routing protocol, TA- TDMA, designed for use in VANETs. The proposed protocol was designed to solve safety issues faced in VANETs, such as the secure transmission of critical data. Their Research investigated the need for traffic prediction to optimise resource allocation in VANETs and proposed using the algorithm to allocate resources within the network. They used Markov mobility models to compare their simulation results with traditional VeMAC to check its validity. The channel utilisation rate and collision results showed that the TA-TDMA efficiency performed better than VeMAC.

Some other Research has explored the vulnerability of the medium access control layer and routing schemes of MANETs to attacks. It is, therefore, important to design efficient medium access control protocols for network security. Mohammadani et al. (2020), in their study into improving network security, carried out simulated MANET networks under blackhole attacks and applied TDMA and CSMA schemes for channel optimisation at the MAC layer. Simulation results indicated that the CDMA-based network did not show scalability in high-density networks as it experienced high delays, while the TDMA-based protocols performed better with fewer delays in similar network densities.

Suman, Mangal and Sharma (2013) proposed using TDMA-based MAC layer protocols to improve the performance of tactical MANETs that are intended to be scalable in handling voice calls with minimum Jitter and Delay. Their study evaluated the challenges in designing MAC frames for such networks and considered the impact of network Throughput and size on their performance. In addition, they developed an analytical framework for determining the Throughput for different medium access control frames.

Valkanis, Nicopolitidis and Papadimitriou (2020) proposed a TDMA-based protocol called Hybrid Link Time Division Multiple Access (HL-TDMA) to tackle issues such as the inability to overcome long propagation delays and poor utilisation of PHY data rate in the Radio over Fiber (RoF) networks in the contention-based MAC protocols of IEEE 802.11. They experimented with simulation in which Wireless LANs (Local Area Networks) were deployed to evaluate the performance of their proposed protocol. Simulation results showed that the HL- TDMA Throughput performance was improved in a RoF WLAN compared to other RoF MAC protocols, including the IEEE 802.11 MAC protocol.

The offline design for protocol stack performance does not meet modern applications' requirements. To overcome this challenge, Yaman, van der Lee, and Iacca (2023) proposed designing a 3-state (TDMA) Medium Access Control (MAC) protocol using an environment-driven Distributed Hill Climbing (DHC) algorithm. They considered energy consumption in enhancing network performance with increasing node densities. Their proposed algorithm showed robustness and scalability despite dynamic network topology in simulated results.

Asgharian and Amirshahi (2015) proposed a TDMA-based MAC protocol called AD-TDMA that is resilient to changes in the network topology of MANETs, such as node failure. Their objective was to demonstrate adaptability in updating the topology information of nodes when there is node failure and the corresponding modification of the scheduling step. Their simulation results showed that AD-TDMA performance showed reduced energy consumption and overall Delay.

Zhao et al. (2019) proposed C-DTSAP, a cluster-based TDMA MAC protocol, for dense MANETs. Their protocol divides the network into clusters where nodes can move and use the proper network structure to manage the whole network. Within these clusters, all nodes can allocate time slots as needed. Their simulation results showed that C- DTSAP, compared with Fast Convergence USAP (FC-USAP), reduced End-to-End Delay and improved traffic received and time slot reuse ratios in a large-scale MANET.

Xu, Song and Zhang (2022) proposed an algorithm for time-slot allocation based on TDMA scheduling in the medium access control layer of MANETs that is resilient in meeting traffic demands in dynamic network topologies. Their proposed algorithm optimised Throughput and ensured the network's fairness. Simulation results showed that their proposed scheme could meet the traffic demands in dynamic networks by ensuring fairness in the network and that the packets sent were received (Throughput).

5.7 Evaluating MODOLSR for energy efficiency and connectivity

A cross-layer optimisation of the modified OLSR (MODOLSR) using TDMA was performed with adapted MATLAB codes (Code work 2023; Voitenko 2023; Joshi 2023).

5.7.1 Simulation Results and Analysis:

5.7.1.1 Evaluation of Packet Delivery Fraction (PDF) vs Number of Nodes

The results for Packet Delivery Fraction, presented in Figure 5.12, highlight the performance of both protocols: MODOLSR (represented by the blue line) and OLSR (represented by the orange line). As nodal densities increased, both protocols consistently achieved impressive Packet Delivery Fraction values, ranging from 98.3% to 100%. This indicates that only a few packets were dropped throughout the network, as the number of packets sent was nearly equal to the number of packets received.

A higher Packet Delivery Fraction (PDF) value, usually expressed as a percentage, signifies better network performance. This means a more significant portion of the packets sent is successfully delivered. Maintaining a high PDF is essential for ensuring the reliability and efficiency of data transmission within the network.

The PDF increased as the number of nodes grew. Proactive protocols can quickly adapt to dynamic network topologies and are well-suited for dense networks. These findings further support the implementation of OLSR and, by extension, MODOLOSR within the proposed framework, SAIMOD.

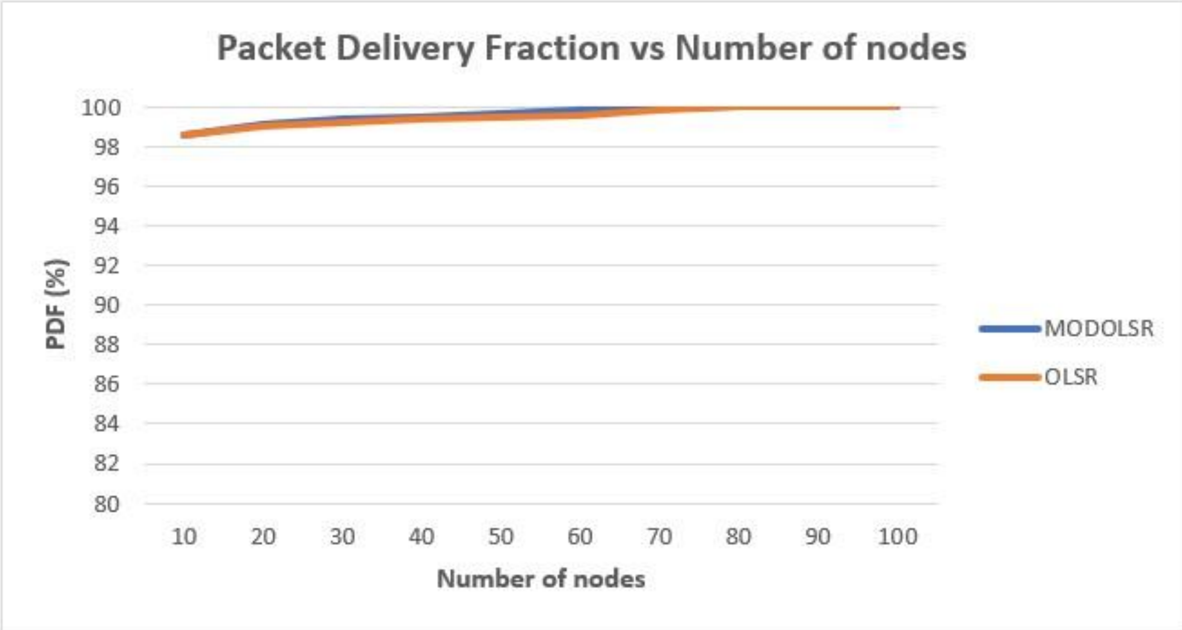


Figure 5.12: Packet Delivery Fraction

5.7.1.2 Evaluation of Energy Consumption

Figure 5.13 shows the energy consumption for the two protocols, MODOLSR and OLSR. The results indicate that MODOLSR consistently demonstrates higher energy efficiency across various network nodes.

When the nodal density was set at 10 nodes, the energy consumption recorded for MODOLSR was approximately 400 Joules. In contrast, the OLSR protocol consumed around 500 Joules, indicating a significant difference. This difference represents a 20% reduction in energy consumption when using MODOLSR, emphasising its efficiency advantages.

As the network expands and the number of nodes increases, both protocols experience a gradual rise in energy consumption. However, MODOLSR experiences a more controlled increase, demonstrating its effectiveness in conserving energy.

This study optimised the OLSR routing protocol by integrating cross-layer activities at both the network and MAC (Medium Access Control) layers, as described in earlier sections. The results indicated that the modified OLSR (MODOLSR, represented by the blue line) achieved approximately 42.42% lower energy consumption than the traditional OLSR (orange line) when the number of nodes reached 100. Moreover, as the number of nodes increased, the modified protocol exhibited improved energy conservation.

This enhanced energy efficiency can be attributed to the cross-layer optimisation at the Network layer to modify the Multipoint Relay (MPR) node selection process based on the available energy in the nodes and at the MAC layer, where modifications were made to the MAC components of the protocol using TDMA (Time Division Multiple Access) to improve the channel quality by reducing channel occupancy during packet transmission and decreasing the overall control packet overhead.

Additionally, TDMA for scheduling data transmission effectively manages the increased delays that often occur with higher node densities in the network, as TDMA enables collision-free transmission.

OLSR is generally an effective protocol for conserving energy over time because it uses Multipoint Relay (MPR) nodes. These nodes help eliminate the need to flood the network during route discovery, reducing routing overhead. The design of OLSR aims to minimise energy consumption through this MPR mechanism. However, it is important to note that the energy required for selecting MPR nodes increases as the number of nodes in the network grows, which could undermine the protocol's energy-saving benefits.

In contrast, MODOLSR has shown a significant capacity for energy conservation, showcasing it as a more sustainable protocol as the network size increases. These results can be attributed to the optimisation of the traditional OLSR protocol. This optimised approach to the MPR node selection process and integration of the Time Division Multiple Access (TDMA) techniques to manage the channel significantly enhanced its energy conservation feature. This method improves the network's overall energy efficiency and demonstrates the advantages of using MODOLSR in more extensive networks where energy conservation is crucial.

In this study, the OLSR routing protocol was optimised by making its optimisation a cross-layer activity. The results indicated that the MODOLSR (blue line) achieved approximately 42.42% lower energy consumption than the traditional OLSR when the number of nodes reached 100.

Furthermore, as the number of nodes increased, the modified protocol demonstrated better energy conservation. This improved energy conservation can be attributed to cross-layer optimisation, particularly in the Multipoint Relay (MPR) node selection process, which was based on the available energy of the nodes. The TDMA-modified MAC components enhanced channel quality, reducing channel occupancy during packet transmission and decreasing overall control packet overhead. Moreover, by using TDMA for scheduling data transmission, the increased delays that typically occur with higher node densities in the network were effectively managed, as TDMA provides collision-free transmission.

Generally, OLSR is a suitable protocol that uses less energy in the long run because of its MPR nodes that remove the need to flood the network in the route discovery process, as explained in earlier sections, and reduce routing overhead. Despite its effectiveness compared to MODOLSR, OLSR has its advantages; it is designed to be an efficient protocol that minimises energy use over the long term through its MPR nodes. However, it is critical to recognise that the energy required for the MPR node selection process escalates with the growing number of nodes in the network, potentially undermining its energy-saving advantages.

On the other hand, MODOLSR has demonstrated a significant capacity for energy conservation, particularly as nodal densities increase. This improvement can be attributed to its optimised approach to MPR node selection, which integrates Time Division Multiple Access (TDMA) techniques. This method enhances the network’s overall energy efficiency and highlights the advantages of employing MODOLSR in more extensive networks where energy conservation is crucial.

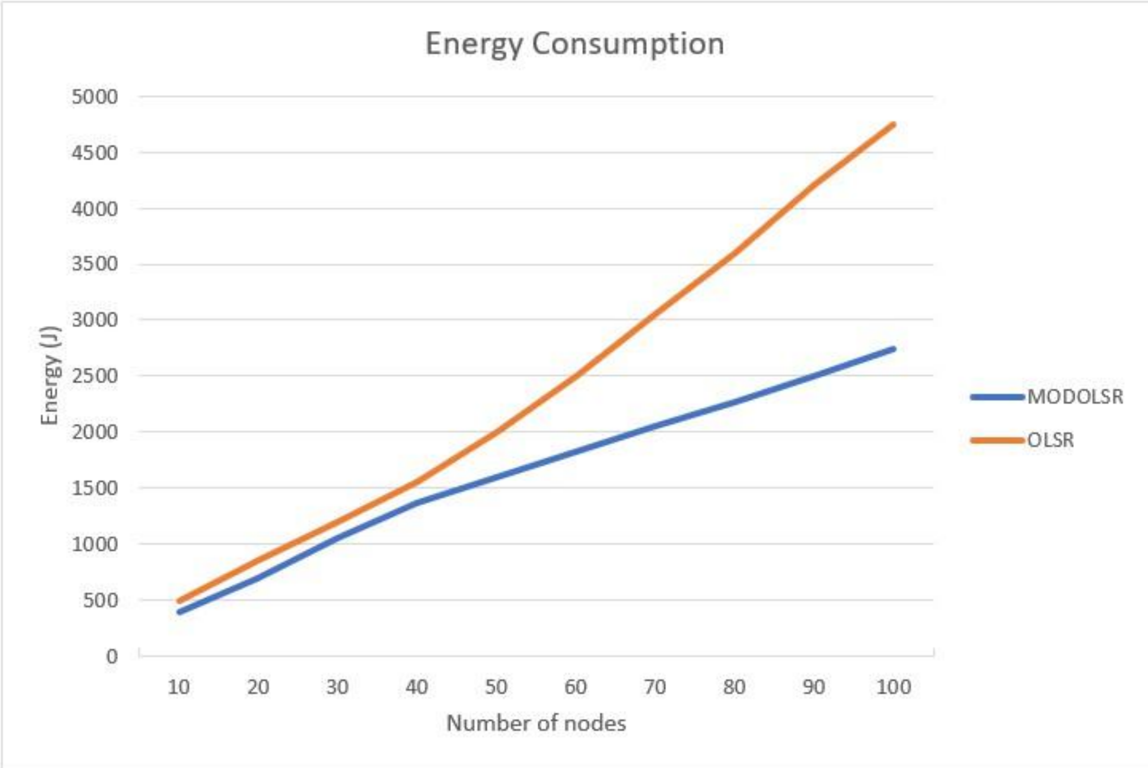


Figure 5.13: Energy consumption of the two routing protocols: OLSR and MODOLSR

5.8 Comparison of MODOLSR with a cross-section of other modified OLSR protocols

Kumar and Verma (2022) proposed the Airborne-OLSR (AOLSR), a modified OLSR that was aimed at reducing the routing overhead associated with link breakage between two communicating aircraft due to topology updates in Airborne Ad-hoc Networks (AANETs) because of the fast movements of the aircraft. In their proposed protocol, the Multipoint Relay (MPR) selection process is modified by selecting the MPR nodes on the right or left side of the source node based on the node's location to which data will be sent. This optimises the protocol as the routing overhead in the network is reduced, increasing bandwidth availability and decreasing the possibility of link breakage. They compared their proposed protocol with the traditional OLSR protocol for UDP and TCP environments having varying node speeds in the 3-D Gauss Markov Mobility model using network simulator-3(NS-3). The simulation results showed that their airborne-OLSR (AOLSR)protocol performed better than OLSR in terms of Throughput, Delay, PDR, and routing overhead.

Aliyu et al. (2023) proposed a modified Disaster Scenario Optimised Link State Routing (DS-OLSR) protocol. They combined the DS-OLSR Protocol and Message Prioritisation (DS-

OLSRMP), which modifies the MPR node selection mechanism and classes the nodes into four priority groups, namely Critical, High, Medium, and Low priorities, by using a prioritisation technique based on residual battery energy. They compared the DS-OLSRMP with the DS-OLSR, OLSRv1 and OLSRv2.a Network Simulator, version 3.29, in sparse and dense network scenarios. The DS-OLSRMP protocol performed better than OLSRv1, OLSRv2 and DS-OLSR in terms of energy conservation and packet delivery.

The Energy Efficient Mechanism OLSR (EEM-OLSR) was designed by Laqtib et al. (2021) to choose the shortest path when selecting routes to conserve energy. They achieved this by modifying the routing table's structure to allow the inclusion of more path information. Their protocol performed better than the traditional OLSR and reduced energy consumption. However, it seemed better suited for denser networks as significant improvement (approximately 40% more) could be seen as the number of nodes increased.

Pu (2018) designed the Link-quality and Traffic-Load-Aware OLSR (LTA-OLSR) protocol to improve network performance by using signal strength, in which statistical information on received signal intensity is used to define link quality. Its performance showed promising results, but it would need to update the topology table frequently as the protocol does not access the geographical location of the nodes. It would also be challenging to implement in large UAV networks as more UAVs would invariably bring about more statistical complexity in determining the optimum path by the UAVs.

Purnama, Setijadi, and Purnomo (2018) modified OLSR using the min-max algorithm in the MPR selection process. Their results showed improved network performance regarding energy efficiency, Topology Control (TC), and Packet Delivery Ratio (PDR). However, Throughput and Delay values only improved with increasing nodal densities. The protocol was approximately 22% more energy efficient than traditional OLSR.

Huang et al. (2020) proposed Link-Duration OLSR (LD-OLSR). This optimised protocol sets up the best route paths using node information, such as their 3-D position from their GPS address. It determines possible link duration, and optimal routing paths reflect this. They did not consider the nodal energy, which plays a vital role in link quality estimation of Flying *ad hoc* networks

(FANET).

Dong and Zhang (2021) proposed a set theorem-based method for MPR node selection. They combined cycles and set operations to eliminate redundant nodes. Their simulation results improved the data transmission rate compared to standard OLSR.

Kadadha et al. (2022) carried out another work that proposed optimising the MPR node selection process based on Quality of Service (QoS). They proposed a cluster-based QoS-OLSR protocol where the nodes' reachability and transmission counts were estimated in their QoS algorithm. Their simulation results were compared to the BATMAN routing and performed better in terms of selected metrics such as Packet Delivery Fraction (PDF).

Ibrahim, Shanmugaraja and Raj (2022) developed an energy-efficient OLSR routing protocol (E-EOLSR) to improve network performance based on network lifetime and Quality of Service (QoS). They modified two critical variables that can affect optimal route selection: the interval for sending Topology Control (TC) information and the willingness of each node to be an MPR. They simulated their protocol using OPNET under varying network conditions. E-OLSR showed improved energy conservation while maintaining Quality of Service in terms of Throughput, reduced delay, etc.

Zeng et al. (2023) proposed the Deep Q-Network Optimised Link State Routing (DQN-OLSR) protocol based on the Deep Q-Network algorithm. Their modified protocol uses the DQN algorithm to modify the sending intervals between Hello messages by stipulating how the protocol's topology control messages are sent. They tested their protocol via simulation using UANETs, and their results showed less packet loss and higher Throughput than traditional OLSR.

A modification of the traditional OLSR was carried out by Addanki and Kumar (2023) to enhance Quality of Service (QoS). Their hybrid protocol combined the Genetic Algorithm (GA) and the Particle Swarm Optimisation (PSO) technique to improve traditional OLSR. Their simulation results showed an improved quality of service and energy consumption when compared to traditional OLSR. However, their modified protocol had better results as the network density increased beyond 100 nodes.

Table 5.1 compares MODOLSR with a cross-section of modified OLSR protocols, which have been compared to the traditional OLSR.

Table 5.1: Comparison of MODOLSR with a cross-section of modified OLSR protocols

Protocol	Energy efficiency	Advantages	Limitations
Airborne-OLSR (AOLSR)	No	Uses the position of the nodes for optimal link, reduces overhead and increases bandwidth availability	Not suitable for networks with high-density
DS-OLSRMP	Yes	Prioritises nodes based on residual battery energy	Not suitable for networks with high-density
EEM-OLSR	Yes	Improved network performance by modifying the routing table	More suitable for denser networks
LTA-OLSR	No	Uses signal strength to grade link quality	Not suitable for networks with high mobility due to complex computational issues face as mobility increases
OLSR+ Minmax algorithm	Yes	Improved performance such as Throughput and reduced Delay	More suitable for denser networks
LD-OLSR	No	Uses 3-D position of the nodes to select optimal link pathway	Energy efficiency was not considered
Set theorem based OLSR	No	Eliminates redundant nodes which results in improved data transmission	Energy efficiency was not considered
QoS OLSR	Yes	Improved performance such as Throughput and reduced Delay	Better suited for dense networks
E-EOLSR	Yes	Use willingness to become an MPR and varying of TC information interval to determine link quality	Not suitable for networks with high mobility
DNQ-OLSR	No	Uses speed and position of the nodes to grade link quality	Not suitable for networks with high mobility
OLSR+GA+PSO	Yes	Improved QoS and energy conservation	More suitable for denser networks
MODOLSR	Yes	Modification of MPR node selection criteria based on energy and the use of TDMA for scheduling	Was not tested for very dense networks (Although this is because it is designed for use with SAIMOD where key connections are between ground leader nodes and UAVs. It is also expected that SAIMOD is best suited for small-scale disaster areas).

5.9 Chapter Summary

This Chapter provided a literature review on the OLSR (Optimised Link State Routing) protocol, specifically focusing on its MPR (Multipoint Relay) node selection process and the modifications made to the Medium Access Control (MAC) layer. The Chapter also introduced a proposed modified routing protocol called MODOLSR.

In Chapter 3, based on specific performance metrics, traditional OLSR was identified as the most suitable routing protocol for the proposed disaster recovery framework, SAIMOD. The Chapter discussed and implemented a two-layer modification of the traditional OLSR routing protocol to create a novel protocol. MODOLSR. First, the protocol was modified at the network layer by optimising the MPR node selection process based on the available energy within the nodes. Additionally, the routing process in the data link layer was modified by implementing TDMA (Time Division Multiple Access) techniques. These modifications enhanced the network's lifetime through improved energy conservation and efficiency. Furthermore, the performance of MODOLSR was compared with that of a range of other modified OLSR protocols and traditional OLSR to evaluate its effectiveness.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This Chapter concludes the Research conducted and presented in this Thesis. It will present a Research summary and an overview of the proposed disaster recovery framework, highlighting its outstanding features and drawbacks. The Chapter concludes with proposals for further Research.

6.2 Summary of Research Work

In line with the common thread running through previous Chapters, in the aftermath of a disaster, Unmanned Aerial Vehicles (UAVs) can play an essential role by supporting disaster recovery teams and even disaster management teams. This could be in areas such as providing a mobile communication system supporting rescue operations on the ground by restoring or creating communication links, sending and receiving communications from ground nodes to the control room, or collecting networking statistics. With technological advancement, recent affordability and ease of deployment, the use of UAVs in disaster recovery scenarios is becoming an alternative to traditional methods for tackling dynamic communications link solutions, and their flexibility facilitates their deployment in hard-to-reach areas with time constraints.

Below are the main conclusions drawn from the Research work, cross-referenced against the stated Objectives.

I. Review protocols and mobility models for wireless networks in disaster recovery scenarios.

The mobility models used in the simulations are pre-defined movement patterns of mobile users in the network based on their location, velocity, and acceleration, which change with time. Four mobility models were tested, namely, the Random Waypoint (RWP) Mobility model, Reference Point Group Mobility Model (RPGMM), Manhattan mobility model and Gauss Markov mobility models, and their impact on the network was evaluated from collated results for network performance metrics such as Throughput, Network Routing Load (NRL) and Delay. The Reference Point Group mobility model (RGPMM) was chosen based on its performance in the simulated network. Simulation results showed it had the highest Throughput amongst the networks whose simulations were completed, likely because all ground nodes are in phase. They all follow the group leader node based on an algorithm that allows little or no Variation in speed and angular direction.

2. Design and evaluate suitable mobility models and cross-layer protocols

The choice of routing protocols in *ad hoc* networks is usually based on the selected protocol's ability to successfully establish an efficient route for data transmission from the source node to the destination node. In this study, a set of MANET routing protocols (AODV, DSR, GRP and OLSR) have been critically evaluated via simulation within a disaster recovery scenario using the Reference Point Group Mobility Model (chosen in Objective One) to test their scalability. Various applications were tested: email, VoIP, HTTP, and peer-to-peer file sharing. The OLSR routing protocol was selected based on desired performance metrics such as MoS (Mean Opinion Score) values, Jitter, Throughput, and Delay. Its simulation results showed its adaptability to changing nodal densities (scalability) and efficiency in delivering data packets.

A two-layer modification of the selected protocol, OLSR, was conducted to create a novel protocol, MODOLSR. These modifications were done at the network layer, where the MPR node selection process was based on available energy and its MAC components at the data link layer using TDMA. OLSR, a link-state routing protocol, relies on the periodic flooding of Topology Control (TC) information by designated nodes (MPR nodes), which invariably reduces the amount of TC information or flooding undertaken. On the other hand, the Medium Access Control (MAC) layer determines how multiple devices access a shared media network. It is primarily responsible for efficiently transmitting data packets across the same channel from source to destination while avoiding collisions. It acts as a resource manager for the nodes in the network by allocating network resources such as available energy and bandwidth and scheduling network access. This two-layer modification further optimised the protocol's performance.

One major area of concern in wireless networks is effectively utilising the limited energy resources available for sending data. The availability of an energy-efficient routing protocol would make the network more efficient by maximising bandwidth usage and improving its network lifetime. The OLSR protocol selected based on desired performance metrics was modified and evaluated for energy efficiency and connectivity.

3. Design and evaluate self-aware path planning and communication links

SAIMOD integrates a positioning algorithm for the super-node layer UAVs and an appropriate mobility model for the ground nodes. This allows it to effectively address the diverse needs of disaster recovery operations. UAV path planning in disaster recovery areas typically involves identifying routes that avoid obstacles in the network while achieving desired performance metrics. These metrics include energy conservation (for example, minimising battery usage) and reduced Delay (such as shortening the time required to establish a communication link). This Research achieved this objective.

4. Integrate the self-aware layer with the mobile wireless network layer within SAIMOD

Integrating the self-aware layer with the mobile wireless network layer within the SAIMOD framework allowed for real-time monitoring and self-optimisation, which enhanced the network's resilience and operational efficiency. The framework can also adapt to dynamic changes in the network topology—this ability to adjust in real time underlines the SAIMOD network's robustness, resilience, and operational efficiency.

5. Evaluate the SAIMOD Framework

The SAIMOD network was evaluated for several selected metrics, as shown in Chapters 3-5. These metrics were selected based on their importance for the disaster recovery scenario. The metrics were Throughput, Delay, Network Routing Load (NRL), Packet delivery, and energy conservation. The network scalability was also evaluated with nodal densities up to 1000. The results were positive and promising, showing that SAIMOD contributes significantly to the state-of-the-art, especially as a support system for use in small-scale, time-sensitive disasters in hard-to-reach places.

The Self-Aware Intelligent Model (SAIMOD) framework proposed uses the best-fit routing protocol, OLSR, for routing. At the same time, the ground nodes would move using the Reference Point group Mobility Model (RPGMM) to ensure optimum connectivity in the energy-efficient, UAV-based network. The beauty of the proposed framework, SAIMOD, lies in its inherent simplicity. SAIMOD reduces the need for complex system designs as it can be easily deployed. This would be of immense value in situations where trained emergency response teams with state-of-the-art equipment are not readily available. In other words, SAIMOD does not require specialised training to use. This means that anyone can use it. SAIMOD can also be used as a standalone UAV communication system, acting as relays in which one or more UAVs are deployed in its network or as part of a multi-UAV collaborative scheme. An essential advantage of this design approach is its adaptability of use, as it does not require global knowledge of the total disaster area's network topology but can work concurrently with individual ground node clusters and support ongoing rescue operations. This means that SAIMOD can quickly adapt to suit varying network topology needs.

Another advantage of the SAIMOD framework is that it can be used as part of an assessment model in resource management by gathering relevant statistics/data needed for evaluating the network, such as bandwidth usage, connectivity, and remaining energy. This data can then be used to answer questions such as how long the batteries of the UAVs would last before they need replacement or if their batteries need charging. Based on the evaluation results of the graphical representation, the mathematical assessment model successfully manages the deployment of resources in the network. Clear-cut areas showed under-coverage, over-coverage, and optimum coverage zones. This would facilitate management decisions regarding resource utilisation and management.

Access to time-sensitive information, like the number of people needing immediate medical attention, changes in disaster area demography, or the number of people buried under an avalanche, can help the decision-making process. This would impact deciding areas needing effective and accurate resource allocation instead of working based on near estimates. Making timely decisions and reducing costs would invariably enhance the robustness of the Disaster Management plan or system, especially in resource allocation and replenishment.

6.3 Future work

It is important to note that SAIMOD is primarily designed for hard-to-reach places or as an initial emergency response communication system in areas where access to emergency response systems, complex machinery, etc., is not readily available, and the rescue operation is time-sensitive. This Research aimed to design and evaluate a self-aware and intelligent framework (SAIMOD) for mobile wireless networks using energy-efficient protocols and mobility models in disaster recovery scenarios. This was done by optimising Throughput and connectivity in a delay-tolerant network, with energy efficiency as an added benefit in an example disaster recovery scenario.

The proposed framework (SAIMOD) has shown positive results when tested, but some issues still need to be addressed. Reproducing the disasters is a significant challenge in validating decision-making software applications designed for use as a communication support system in disaster recovery scenarios. Usually, natural disasters are complex to scale down, unpredictable, and irreproducible. As such, conducting an extensive assessment of reproduced natural disasters could be nearly impossible. A more viable solution is to use simulation in testing these software solutions (Rosas et al., 2016). Arguably, testing via simulation and not a real-life test bed has many advantages; it could also be a limitation, as factors such as wind speed could affect its suitability in a real-life scenario, as this could be unpredictable in a natural disaster. In addition, although SAIMOD is intended to be resilient, it could be worth varying network conditions and parameters to find a threshold for change. A straightforward solution to this would be testing with varying network conditions using real-life test beds and comparing them with simulation results to further validate the network's resilience.

Another limitation is the scalability of the network. The network was checked with varying nodal densities from 10 nodes to 1,000 nodes. A possibility for further investigation concerning the scalability of the network could be its practicality in increasing the nodal density beyond 1,000 or increasing the size of the disaster area while keeping the nodal density constant. This would mean testing for optimum conditions, like transmission ranges, while considering limited resources. Ultimately, this might be a trade-off among factors in the network. As such, a possible future study is to find the optimum number of nodes it can cover. However, this might give contradictory results, as different UAVs have different capabilities. For instance, one UAV in the network could cover 100 nodes, but a different UAV under the same network conditions could cover more. The scalability of the network can become an area of concern when the number of users or the size of the disaster area increases, and there are no alternative means to handle this, especially when the rescue operation is time-constrained. This increases the processing time for data transfer, which would consequently impact available resources, such as the battery power of the UAVs, since battery usage is directly proportional to the amount of processing being carried out, either in transmitting messages or in gathering data. SAIMOD, therefore, might need to be integrated with other algorithms to monitor the user's connectivity and location in real time. A possible solution could be to increase the number of people in a cluster rather than increase the number of group leaders. However, its practicality would need to be investigated. Adopting sectioning the increased area into 500m by 500m and SAIMOD scours grid by grid could be another solution, as described in SECTION 3.11; further testing to ascertain the capacity and scalability of the network could be conducted.

Another possible area for future work is exploring the use of LiDAR scans to update the disaster area map. UAVs use LiDAR scans to create a map of the disaster recovery area by using distance sensing. These self-aware UAVs can update the map of the disaster area in real time as they are fitted with GPS and sensors that take LiDAR readings. This could be used to update the disaster area map and send it to the control room. This would be an advantage as there might be changes in the disaster area after the initial disaster map has been taken in the pre-disaster recovery stage. The use of Google Maps updates could also be explored.

Finally, each aspect of the Research was tested piece-meal rather than as one complete network. If this study were to be started afresh, one possible exploration would be to take a different approach and carry out the Research as an entire network, incorporating all aspects to test resilience and scalability. In this vein, using the SAIMOD framework as part of a collaboration of multi-UAV schemes for managing communication link services during disaster recovery and other possible UAV-assisted solutions could also be explored in a simulation environment or a real-life test bed.

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