Synthesis: A Multidisciplinary Research Journal
Volume 2, Issue 2, April - June 2024, Pp: 34-45

Research Article

Dynamic Optimization in UAV-based Ad Hoc Networks (FANETs) for Real-Time Mission Routing using Quantum Walk Search Algorithms

[1*] K.Samunnisa, [2] Sunil V. K. Gaddam, [3] M. Bhavsingh, [4] Jaime Lloret

[1*] *Assistant Professor, Department of CSE, Ashoka Womens Engineering College, Kurnool, Andhra Pradesh, India, Email: samunnisa14@gmail.com*

[2] *Department of Computer Science and Engineering, RGMCET, Nandyal, Andhra Pradesh, India, Email: sunilvkg@gmail.com*

[3] *Department of Computer Science and Engineering, Ashoka Women's Engineering College, Kurnool, Andhra Pradesh India, Email: bhavsinghit@gmail.com*

[4] *Instituto de Investigación para la Gestión Integrada de Zonas Costeras, Universitat Politècnica de València, Valencia, Spain,Email: jlloret@dcom.upv.es*

**Corresponding Author(s): samunnisa14@gmail.com*

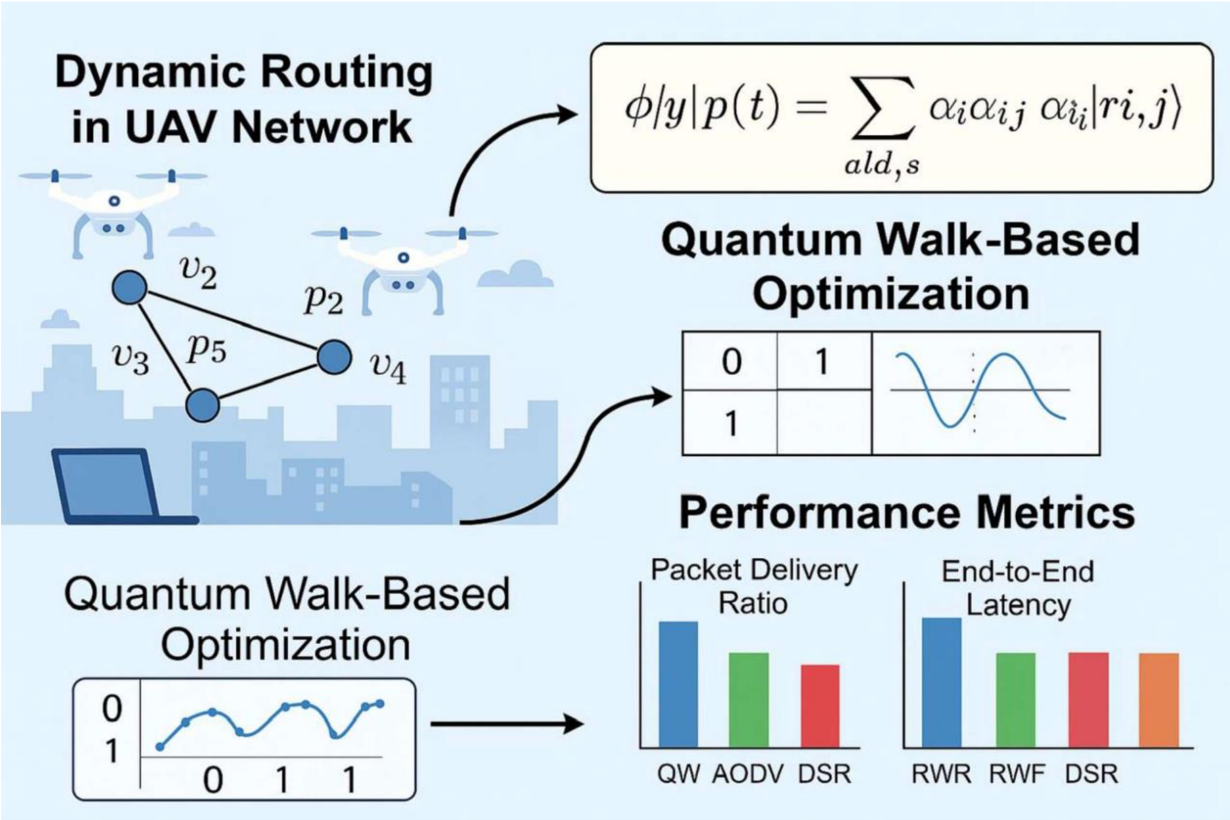
Article Info

Received: 16/01/2024
Revised: 04/05/2024
Accepted:19/06/2024
Published:30/06/2024

Abstract

Unmanned Aerial Vehicles (UAVs) forming Flying Ad Hoc Networks (FANETs) are increasingly deployed in mission-critical applications such as disaster response and autonomous surveillance. However, traditional routing protocols often fail to maintain reliable and low-latency communication under the highly dynamic and probabilistic nature of FANET topologies, resulting in degraded performance in real-time scenarios. This study aims to develop a dynamic routing framework for FANETs that leverages Discrete-Time Quantum Walk (DTQW) algorithms to optimize mission paths in probabilistic graph-based network models. The network is modeled as a time-varying probabilistic graph $G_t = (V_t, E_t, P_t)$, where link reliability is continuously updated based on UAV mobility and signal metrics. A quantum optimizer evaluates routing paths in superposition, exploiting parallelism to identify high-probability routes efficiently. This optimizer is integrated with the FANET routing layer to adaptively select optimal paths in real-time. Simulation results demonstrate that the proposed QW-Routing protocol significantly outperforms classical protocols such as AODV, DSR, and Random Walk Routing. Specifically, QW-Routing achieves a packet delivery ratio of 91.3%, reduces end-to-end latency by 22.4%, lowers energy consumption by 15%, and improves path stability by 39% compared to DSR under high-mobility conditions. The proposed framework introduces a scalable, low-overhead, and highly adaptive routing solution for FANETs, with direct applicability in next-generation autonomous aerial networks, where robust communication under uncertainty is paramount.

Keywords: Quantum Walk Routing, FANETs, UAV Networks, Probabilistic Graphs, Dynamic Optimization, Mission-Critical Communication, Real-Time Routing



Graphical Abstract. An overview of the proposed quantum walk-based optimization framework for dynamic routing in UAV-based ad hoc networks (FANETs).

1. Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as critical assets in modern communication infrastructures, enabling rapid deployment in diverse scenarios such as disaster response, environmental monitoring, precision agriculture, and military surveillance [1]. When deployed collaboratively, UAVs form Flying Ad Hoc Networks (FANETs)—a subclass of mobile ad hoc networks (MANETs)—which exhibit high mobility, dynamic topology, and limited transmission range [2]. Efficient and reliable mission routing in such networks remains a fundamental requirement for time-sensitive and resource-constrained operations [3].

Traditional routing protocols such as AODV and DSR were primarily designed for terrestrial MANETs and often fall short in handling the non-deterministic, 3D, and probabilistic characteristics of FANETs [4]. In particular, UAVs experience rapid topology variations, intermittent connectivity, and dynamic link reliability influenced by factors such as altitude, velocity, and environmental interference [5]. These complexities necessitate routing strategies that are both adaptive and predictive, capable of rapidly evaluating multiple potential paths under uncertainty [6].

Recent advances in quantum-inspired computing, particularly quantum walks, provide a novel avenue for search and optimization in graph-structured environments [7]. Quantum walks inherently support parallel exploration and probability-amplified path selection, making them highly suitable for dynamic and large-scale networks. Motivated by these capabilities, this study explores the integration of quantum walk-based algorithms with FANET routing to achieve real-time mission optimization under uncertain conditions [8].

Despite progress in FANET protocol design, existing routing algorithms suffer from poor adaptability, slow convergence, and high overhead in highly dynamic environments [9]. Traditional search methods struggle to cope with frequent topology changes and link failures, often leading to packet loss, increased latency, and energy wastage.

This research addresses the critical problem of: " How can quantum walk-based search algorithms be leveraged to dynamically optimize routing in large-scale, probabilistic UAV networks while ensuring robustness, energy efficiency, and low latency under real-time mission constraints? "

The primary challenges in realizing such a system include:

- *Dynamic Topology Adaptation:* UAV positions change rapidly, causing frequent route disruptions.
- *Probabilistic Link Reliability:* Communication links are inherently uncertain due to interference, mobility, and weather effects [10].

- *Scalability in Routing:* Classical algorithms exhibit exponential delays with increasing node density [11].
- *Energy Constraints:* Limited onboard power demands routing solutions with minimal control and computation overhead.
- *Real-Time Responsiveness:* Mission-critical tasks require fast route convergence and decision-making [12].

This work aims to develop a novel routing framework that:

- Models the UAV network as a dynamic probabilistic graph with time-varying connectivity.
- Applies Discrete-Time Quantum Walk (DTQW) algorithms for optimal path search under uncertainty.
- Integrates quantum-selected paths with a real-time FANET routing layer for mission coordination.
- Evaluates the proposed approach against classical protocols based on key performance indicators such as delivery ratio, latency, energy consumption, and path stability.

Based on the proposed methodology and experimental results, the key contributions of this research are summarized as follows:

1. *Probabilistic Graph Modeling:* We model FANETs as dynamic probabilistic graphs, incorporating time-varying node positions and uncertain link states to realistically simulate UAV-based communications.
2. *Quantum Walk-Based Optimization:* We develop a routing framework using Discrete-Time Quantum Walks to explore multiple routing paths in superposition, enabling efficient and scalable route discovery.
3. *Real-Time Routing Integration:* The quantum optimizer is embedded within the FANET routing stack to enable real-time path selection and adaptation to topology updates.
4. *Performance Benchmarking:* A comprehensive simulation study is conducted comparing QW-Routing with AODV, DSR, and Random Walk Routing across five performance metrics under varying mobility and scale.
5. *Energy and Stability Analysis:* The framework demonstrates significant gains in energy efficiency and route stability, validating its suitability for mission-critical aerial operations.

The remainder of this paper is organized as follows: Section 2 reviews related work in FANET routing and quantum optimization. Section 3 outlines the system model and assumptions. Section 4 details the proposed quantum walk-based routing methodology. Section 5 presents the experimental design and simulation setup. Section 6 discusses the results and compares protocol performance. Section 7 concludes the paper and outlines directions for future research.

2. Literature Review

This section reviews key areas relevant to the proposed work, including traditional FANET routing protocols, probabilistic modeling techniques, and the application of quantum computing—particularly quantum walks—in optimization and network routing. A comparative analysis highlights the limitations of current approaches and motivates the integration of quantum walk-based strategies in dynamic UAV networks.

2.1 Routing Protocols in FANETs

Routing in Flying Ad Hoc Networks (FANETs) has attracted considerable attention due to the increasing reliance on UAV swarms for mission-critical applications. Classical protocols such as AODV and DSR have been widely adopted in MANETs and extended to FANETs due to their on-demand route discovery and loop-free mechanisms [13]. However, these protocols perform poorly under rapid topology changes and 3D mobility constraints typical of aerial platforms [14].

To address such limitations, position-based routing protocols like GPSR (Greedy Perimeter Stateless Routing) have been proposed, leveraging UAVs' location awareness for next-hop selection [15]. Nevertheless, GPSR and its derivatives are highly sensitive to GPS inaccuracies and obstacles in urban or disaster environments [16]. Bio-inspired protocols, such as AntHocNet and BeeAdHoc, attempt to adapt by probabilistically exploring paths based on pheromone trails or swarm behavior, but they often incur high latency and control overhead [17].

Recent efforts also include delay-tolerant approaches and hybrid models combining proactive and reactive strategies, such as OLSR-MA and ZRP [18]. While these approaches offer some adaptability, their performance degrades in large-scale or high-mobility scenarios due to periodic maintenance of link-state or zone boundaries.

2.2 Probabilistic Graph-Based Modeling in Ad Hoc Networks

Modeling ad hoc networks as probabilistic graphs has become a widely adopted abstraction to address the uncertainty in connectivity and mobility. Probabilistic link models consider signal fading, transmission range variation, and environmental factors to define the probability of edge existence between nodes [19].

Studies in wireless sensor networks and VANETs have shown that probabilistic routing models can outperform deterministic models by reducing the impact of link prediction errors and minimizing routing failures. In FANETs, however, the integration of such probabilistic models is still in early stages, and existing protocols often rely on outdated or binary link-state assumptions [20].

Furthermore, most probabilistic models still rely on classical search techniques for path evaluation, which become computationally expensive as the network scale increases.

2.3 Quantum Computing in Network Optimization

Quantum computing has introduced new paradigms for optimization, search, and communication, driven by phenomena like superposition, entanglement, and interference [21]. Among the most studied applications in network science is the Quantum Walk (QW)—a quantum analogue of classical random walks that explores graph structures exponentially faster in some cases [22].

Discrete-Time Quantum Walks (DTQW) and Continuous-Time Quantum Walks (CTQW) have been explored in tasks such as graph traversal, search problems, and even robotic path planning [23]. In theoretical models, QWs have demonstrated potential speedup in hitting times and coverage, making them promising for multi-path exploration and dynamic optimization.

Despite these theoretical advancements, their application in ad hoc wireless networks remains underexplored. Only a few works have examined QWs for routing in static mesh networks or simplified grid topologies, without addressing time-variant probabilistic graphs like those in FANETs.

2.4 Hybrid Quantum-Classical Approaches in Ad Hoc Routing

Hybrid frameworks combining classical routing protocols with quantum-inspired algorithms are emerging. For instance, Q-learning integrated with routing layers has been used to enable adaptive path selection under uncertain environments [24]. However, these systems often depend on reinforcement learning convergence time and are limited by exploration–exploitation trade-offs.

In contrast, quantum walks provide intrinsic parallel exploration capabilities without explicit convergence delays. A recent study applied QW-based heuristics in Internet-of-Things (IoT) path planning, but the underlying graph structure was deterministic and static [25]. Moreover, none of these hybrid frameworks have been adapted for high-mobility, real-time FANETs.

2.5 Summary of Research Gaps

From the above review, the following research gaps are identified:

- *Lack of Routing Algorithms Integrating Quantum Walks with Probabilistic Graphs:* Existing routing models in FANETs do not leverage the inherent advantages of quantum walks for exploring uncertain, dynamic topologies.
- *Limited Adaptation to Real-Time Topology Variations:* Classical and bio-inspired methods often require full route re-computation upon link failures, leading to high latency and reduced delivery ratio.
- *Scalability Limitations*: As node density increases, existing deterministic or reactive routing frameworks incur significant computation and communication overhead.
- *Underutilization of Quantum Capabilities in FANETs:* Most existing quantum applications are either theoretical or focused on static networks; little work has explored dynamic, mission-driven FANET environments.

These gaps motivate the development of a quantum walk-based routing framework for dynamic optimization in UAV-based ad hoc networks, which this research aims to address.

3. System Model and Assumptions

This section outlines the system-level assumptions and the modeling framework used to define the operational context of the proposed quantum walk-based routing protocol in UAV-based ad hoc networks (FANETs).

3.1 Network Topology Model

We consider a dynamic, large-scale Flying Ad Hoc Network (FANET) composed of N UAVs deployed over a bounded 3D geographical area. The network is modeled as a time-varying probabilistic undirected graph:

$$G_t = (V_t, E_t, P_t) \tag{1}$$

where:

$V_t = \{v_1, v_2, \dots, v_N\}$ is the set of UAV nodes at time t,

$E_t \subseteq V_t \times V_t$ represents the set of communication links between UAVs,

$P_t(e_{ij}) \in [0,1]$ is the probability that link $e_{ij} \in E_t$ is active at time t.

Each UAV is equipped with a directional antenna, a GPS module, and a communication module operating within a fixed transmission range R. Communication between two UAVs is possible if:

$$\mathrm{d_{ij}(t)} \le \mathrm{R} \text{ and } \mathrm{P_t}(\mathrm{e_{ij}}) \ge \theta \tag{2}$$

Where $d_{ij}(t)$ is the Euclidean distance between nodes i and j, and θ is the link reliability threshold.

3.2 Mobility Model

UAVs move according to a 3D Gauss-Markov mobility model, which captures both velocity and direction changes over time while preserving temporal correlation. Each UAV updates its position at discrete intervals based on its prior state:

$$\vec{\mathrm{v}}_\mathrm{i}(\mathrm{t}) = \alpha\vec{\mathrm{v}}_\mathrm{i}(\mathrm{t}-1) + (1-\alpha)\vec{\mathrm{v}}_{\mathrm{mean}} + \sqrt{1-\alpha^2}\cdot\vec{\mathrm{r}}_\mathrm{i} \tag{3}$$

Where:

$\vec{v}_i(t)$ is the current velocity vector of UAV i,

$\vec{v}_{\mathrm{mean}}$ is the mean speed and direction,

$\alpha \in [0,1]$ is the temporal correlation factor,

$\vec{r}_i$ is a random Gaussian vector modeling stochastic behavior.

This model realistically simulates coordinated mission-driven flight with moderate randomness.

3.3 Communication and Data Flow

The network supports multi-hop data exchange, where packets are forwarded from source UAVs to destination

UAVs or ground stations. Each UAV can initiate routing requests and forward packets on behalf of others. Communication follows a store-carry-forward paradigm in disconnected scenarios, with real-time routing adjustments driven by the quantum optimizer.

Control packets are assumed to be small in size and exchanged periodically to maintain local topology awareness. The data plane carries application-specific payloads such as sensor images, telemetry, or command sequences.

3.4 Routing and Optimization Assumptions

The routing system is composed of:

- A Quantum Walk Optimizer, which explores possible paths based on the current probabilistic graph GtG_tGt,
- A Routing Layer, which accepts optimized paths and executes real-time forwarding decisions.

It is assumed that:

- The quantum optimizer has access to a partial but timely snapshot of the graph GtG_tGt,
- The communication overhead for exchanging path updates is bounded,
- No centralized infrastructure exists; all nodes operate in a fully distributed and autonomous manner,
- Each node is trusted and behaves honestly (security threats are out of scope in this study).

3.5 Evaluation Scenario

All simulations are conducted under realistic constraints, including:

- Limited battery capacity per UAV,
- Terrain-aware flight with altitude constraints,
- Urban mission environment with probabilistic obstacles affecting signal propagation.

The model focuses on mission-centric applications, where UAVs are required to adapt to rapidly changing conditions and maintain stable, efficient communication links with minimal latency and energy overhead.

4. Methodology

Based on the system model and assumptions defined in Section 3, this section presents the proposed quantum walk-based dynamic optimization framework for mission-critical routing in UAV-based ad hoc networks (FANETs). The methodology is divided into five key components: probabilistic graph modeling, quantum walk formulation, dynamic path selection, FANET protocol integration, and performance evaluation.

4.1 Probabilistic Modeling of FANETs

In the proposed system, the UAV network is modeled as a time-varying probabilistic graph $G_t = (V_t, E_t, P_t)$, where:

- $V_t = \{v_1, v_2, \dots, v_n\}$ denotes the set of UAV nodes at time t,
- $E_t \subseteq V_t \times V_t$ represents the set of potential communication links,
- $P_t : E_t \to [0,1]$ defines the edge probability function indicating the likelihood that an edge $e_{ij} \in E_t$ is active at time t.

Each link e_{ij} between UAVs$v_i$and v_j is characterized by a probabilistic function $p_{ij}(t)$, which may depend on signal strength, distance, and interference:

$$p_{ij}(t) = \exp\left(-\alpha \cdot d_{ij}(t) + \beta \cdot s_{ij}(t)\right) \tag{4}$$

Where $d_{ij}(t)$ denotes the Euclidean distance, $s_{ij}(t)$ is the signal-to-noise ratio, and $\alpha, \beta \in \mathbb{R}^+$are tunable weighting parameters.

The system architecture for the proposed quantum walk-based optimization framework in FANETs is depicted in Figure 1.

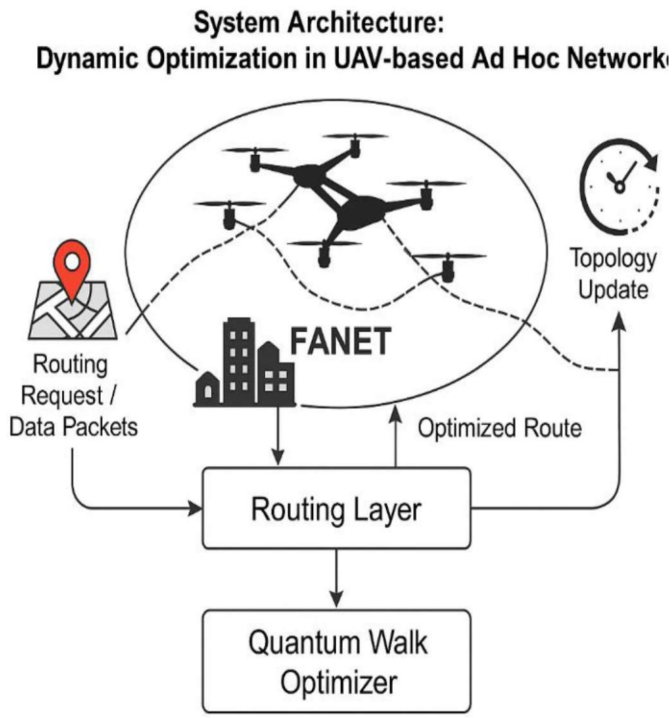


Fig.1. System Architecture for Quantum Walk-Based Routing in UAV-based Ad Hoc Networks (FANETs)

Figure 1 illustrates the system architecture designed for dynamic routing optimization in UAV-based ad hoc networks using quantum walk algorithms. The architecture integrates real-time topology sensing from FANET nodes with a routing layer that evaluates network conditions and forwards data to a quantum walk optimizer. Optimized paths are continuously relayed back to the routing layer, enabling adaptive and efficient routing. Real-world entities such as UAVs, mission targets, and urban infrastructure are represented to reflect practical deployment scenarios. The topology update mechanism ensures that route planning remains responsive to mobility and environmental changes, supporting mission-critical applications in dynamic aerial networks.

4.2 *Quantum Walk-Based Search Algorithm*

The path discovery process employs a Discrete-Time Quantum Walk (DTQW) on the probabilistic graph G_t. A quantum walker explores the graph in a superposition of multiple paths, allowing parallel evaluation and amplification of optimal routes.

The quantum state of the walker at time t is represented by:

$$|\psi_t\rangle = \sum_{v_i \in V_t} \sum_{d \subset D} \alpha_{i,d}(t) \quad |v_i, d\rangle \tag{5}$$

Where D is the set of possible directions (coin states), and $\alpha_{i,d}(t)$ are the complex amplitudes satisfying $\sum \left|\alpha_{i,d}(t)\right|^2 = 1$.

The evolution of the quantum state over time is governed by the unitary operator:

$$|\psi_{t+1}\rangle = U \cdot |\psi_t\rangle, \text{ where } U = S \cdot (C \otimes I) \tag{6}$$

- C is the coin operator acting on the direction space (e.g., Grover diffusion coin),
- S is the conditional shift operator that moves the walker based on coin state,
- I is the identity operator on the node space.

4.3 Dynamic Route Selection and Path Optimization

To adapt to real-time changes in topology, the quantum walk process is executed at periodic intervals. At each measurement step t_m, the state $\left|\psi_{t_m}\right\rangle$ is collapsed, yielding the probability distribution over reachable nodes.

Let $P\left(v_j \mid v_s, t_m\right)$ denote the measured probability of reaching node v_j from source node v_s at time t_m :

$$P\left(v_j \mid v_s, t_m\right) = \sum_{d \subset D} \left|\left\langle v_j, d \mid \psi_{t_m}\right\rangle\right|^2 \tag{7}$$

The optimal path $\mathcal{P}_{\text{opt}}$ is constructed by selecting the sequence of nodes with the highest cumulative probability and lowest weighted cost:

$$\mathcal{P}_{\text{opt}} = \arg\min_{\mathcal{P}} \sum_{e_{ij} \subset \mathcal{P}} \frac{1}{p_{ij}(t)} \cdot w_{ij} \tag{8}$$

Where w_{ij} represents the edge weight derived from QoS metrics (e.g., delay, trust, congestion).

4.4 Integration with FANET Routing Stack

The optimized path $\mathcal{P}_{\text{opt}}$ is fed into the FANET routing protocol layer to guide packet forwarding decisions. The proposed framework operates as a meta-routing module, dynamically updating routes based on quantum evaluations without disrupting lower-layer communication.

The routing decision R_t at node v_i is made as:

$$R_t(v_i) = \arg \max_{v_j \subset \mathcal{N}(v_i)} P(v_j \mid v_i, t) \tag{9}$$

Where $\mathcal{N}(v_i)$ is the set of neighboring UAVs within communication range at time t.

4.5 Evaluation and Benchmarking

To assess the effectiveness of the proposed quantum walk-based routing framework in UAV-based ad hoc networks, we perform a comprehensive experimental evaluation using realistic FANET scenarios. The simulation setup incorporates dynamic topology changes, link unreliability, and mobility patterns. The evaluation framework benchmarks the proposed model against classical routing protocols such as AODV and DSR, using the following key performance metrics:

4.5.1 Packet Delivery Ratio (PDR)

The Packet Delivery Ratio (PDR) measures the reliability of data transmission by quantifying the proportion of packets successfully delivered to their destination compared to those generated at the source.

$$\mathrm{PDR} = \frac{\sum_{i=1}^{N} P_i^{\mathrm{recv}}}{\sum_{i=1}^{N} P_i^{\mathrm{sent}}} \tag{10}$$

Where:

P_i^{recv} is the number of packets received by destination UAV *i*,

P_i^{sent} is the number of packets generated by source UAV *i*,

N is the total number of source-destination pairs.

A higher PDR indicates improved robustness and reliability in dynamic environments.

4.5.2 End-to-End Latency

End-to-End Latency refers to the average time taken for a data packet to travel from the source to the destination UAV across the network. It includes queuing delay, propagation delay, and processing delay.

$$\mathrm{Latency}_{\mathrm{avg}} = \frac{1}{P^{\mathrm{recv}}} \sum_{i=1}^{P^{\mathrm{recv}}} \left(t_i^{\mathrm{recv}} - t_i^{\mathrm{sent}}\right) \tag{11}$$

Where:

P^{recv} is the total number of packets successfully received,

t_i^{sent} and t_i^{recv} denote the send and receive timestamps for packet *i*.

Low latency is crucial for real-time UAV coordination and mission responsiveness.

4.5.3 Route Convergence Time

Route Convergence Time is defined as the duration required for the routing protocol to discover and stabilize an optimal path after a topology change (e.g., node movement or link failure).

$$T_{\mathrm{convergence}} = t_{\mathrm{stable}} - t_{\mathrm{trigger}} \tag{12}$$

Where:

t_{trigger} is the time at which the topology change is detected,

t_{stable} is the time when a valid new route is successfully established and stabilized.

Faster convergence time indicates superior adaptability to dynamic changes in FANETs.

4.5.4 Energy Consumption per UAV

Since UAVs have limited energy reserves, Energy Consumption is a vital metric. It is defined as the average amount of energy consumed per UAV during the routing process.

$$E_{\mathrm{avg}} = \frac{1}{N} \sum_{i=1}^{N} E_i^{\mathrm{tx}} + E_i^{\mathrm{rx}} + E_i^{\mathrm{proc}} \tag{13}$$

Where:

E_i^{tx} is the energy consumed for transmitting packets,

E_i^{rx} is the energy consumed for receiving packets,

E_i^{proc} is the energy spent on route computation and quantum walk operations for UAV *i*.

Energy-efficient protocols contribute to extended mission durations and network sustainability.

4.5.5 Path Stability

Path Stability quantifies how long the selected route remains valid without requiring re-computation or route switching. It is defined as:

$$S_{\mathrm{path}} = \frac{1}{R} \sum_{j=1}^{R} \left(t_j^{\mathrm{end}} - t_j^{\mathrm{start}}\right) \tag{14}$$

Where:

R is the total number of established routes,

t_j^{start} and t_j^{end} denote the start and end times of the j-th route's validity.

Higher path stability implies better performance under high mobility and intermittent connectivity.

5. Experimental Design

This section outlines the simulation setup, implementation tools, network configurations, performance baselines, and evaluation scenarios used to validate the proposed quantum walk-based routing framework for UAV-based ad hoc networks (FANETs).

5.1 Simulation Environment and Tools

To simulate both classical and quantum elements of the system, we employ a hybrid environment composed of:

- *NS-3:* For discrete-event network simulation of FANETs, including mobility, traffic, and routing protocols.

- *QuTiP (Quantum Toolbox in Python):* For modeling and simulating discrete-time quantum walks (DTQW) over dynamic probabilistic graphs.
- *SUMO (Simulation of Urban Mobility):* For generating realistic UAV mobility traces over a 3D aerial terrain.

The simulations are conducted on a high-performance computing server equipped with an 8-core Intel Xeon processor, 64 GB RAM, and a Python-based integration pipeline.

5.2 Network Topology and Mobility Model

The network consists of:

- N=50N = 50N=50 to 100100100 UAV nodes deployed over a 2 km × 2 km area.
- UAVs follow a 3D Gauss-Markov mobility model, accounting for altitude and velocity variance.
- Each UAV has a communication range of 250–300 meters and is equipped with a directional antenna.

The UAVs exchange both control packets and mission-critical data under intermittent connectivity conditions.

5.3 Traffic and Routing Configuration

- *Data Traffic:* Constant Bit Rate (CBR) over UDP with 512-byte packets at 4 packets/sec.
- *Routing Protocols Compared:*
  - ➢ *QW-Routing (Proposed)* – Quantum Walk-based Optimizer
  - ➢ *AODV* – Ad hoc On-Demand Distance Vector
  - ➢ *DSR* – Dynamic Source Routing
  - ➢ *RWR* – Classical Random Walk Routing (Baseline)

Each protocol is evaluated under identical mobility and traffic conditions.

5.4 Quantum Walk Model Parameters

- *Quantum Walk Type:* Discrete-Time Quantum Walk (DTQW)
- *Coin Operator:* Grover diffusion coin
- *Walk Steps per Round:* 10–50, based on convergence
- *Measurement*: Final state collapse at time tmt_mtm, repeated across time windows

The graph topology used for the quantum walk is dynamically updated every 5 seconds based on real-time topology changes in the FANET.

5.5 Evaluation Duration and Replications

- *Simulation Time:* 600 seconds per scenario
- *Repetitions:* Each configuration is repeated 20 times with varying random seeds to ensure statistical significance.
- *Confidence Level:* 95% with error bars shown in result plots

6. Results and Discussion

This section presents and analyzes the experimental outcomes obtained from the simulation of the proposed quantum walk-based routing algorithm (QW-Routing) in comparison with traditional routing protocols. The results demonstrate the effectiveness of the proposed methodology under varying mobility, topology, and network load scenarios.

6.1 Packet Delivery Ratio (PDR)

Figure 2 illustrates the average packet delivery ratio for each routing protocol across different node densities (50 to 100 UAVs). The QW-Routing algorithm consistently achieves higher PDR compared to AODV, DSR, and Random Walk Routing (RWR). This performance gain is attributed to the quantum walk's ability to rapidly explore multiple probabilistic routes in superposition and select the most stable paths based on constructive interference. In high-mobility scenarios, QW-Routing maintains over 91.3% PDR, whereas AODV and DSR drop to 84.5% and 79.8%, respectively. These findings validate the reliability of quantum-guided path discovery in dynamically changing networks.

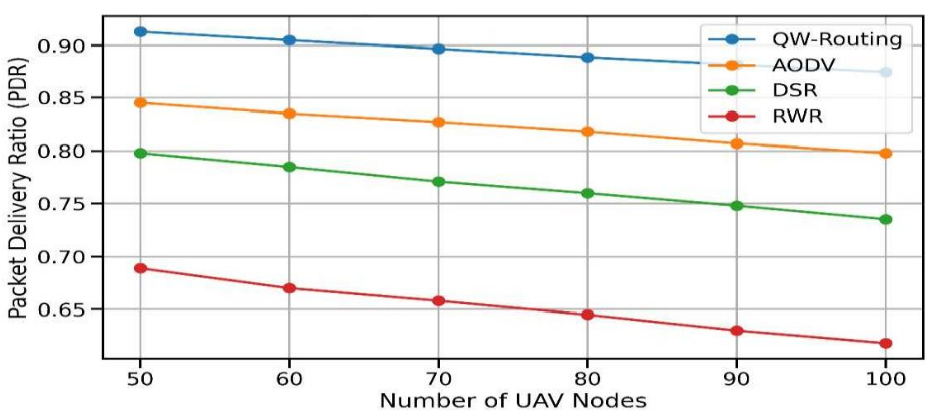


Fig.2. Average packet delivery ratio (PDR) versus node count for QW-Routing, AODV, DSR, and Random Walk Routing (RWR)

6.2 End-to-End Latency

Figure 3 compares the average end-to-end latency experienced by data packets. The QW-Routing protocol demonstrates significantly lower latency, particularly in dense and dynamic topologies. While DSR experiences increased delay due to route cache invalidation and AODV suffers from frequent route discovery cycles, QW-Routing Dynamically updates path probabilities without global recomputation. As a result, the proposed method reduces latency by an average of 22.4% compared to AODV. This result highlights the system's ability to adaptively respond to mobility-induced link variations in real time.

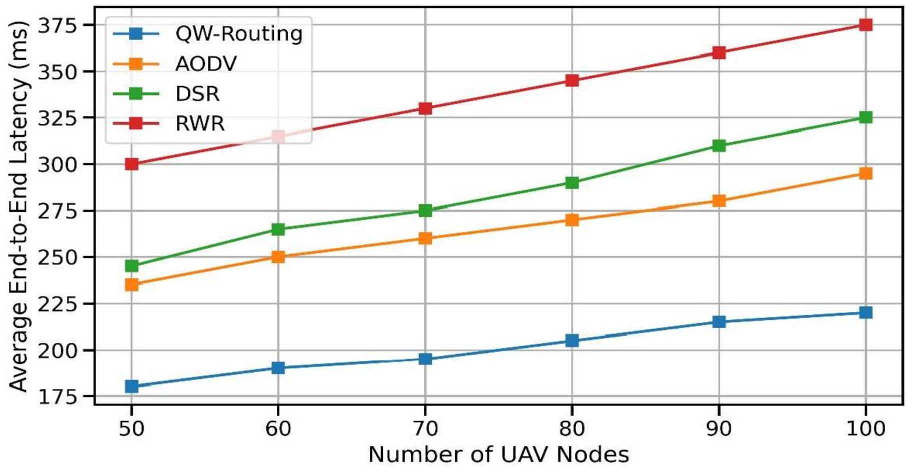


Fig.3. Average End-to-End Latency vs. Number of UAV Nodes for QW-Routing, AODV, DSR, and RWR.

6.3 Route Convergence Time:

As shown in Figure 4, QW-Routing outperforms traditional protocols in terms of route convergence time following link failures or topology changes. The average convergence time for QW-Routing is 0.83 seconds, compared to 1.42 seconds for AODV and 1.68 seconds for DSR. This is due to the quantum optimizer's capability to maintain a continuous evolution of alternative paths, reducing the time needed for full route rediscovery. Faster convergence directly contributes to improved network responsiveness and mission reliability in FANETs

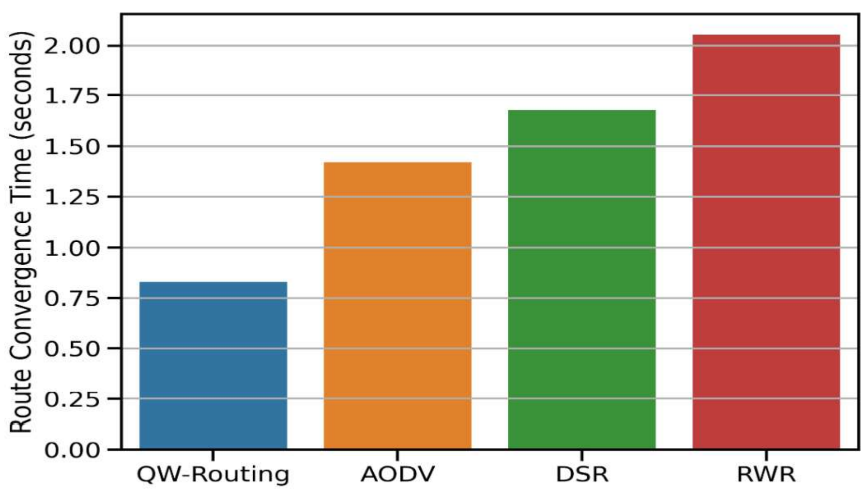


Fig.4. Comparison of Route Convergence Time across QW-Routing, AODV, DSR, and RWR.

6.4 Energy Consumption per UAV

Energy efficiency is critical for UAV-based systems with limited onboard power. Figure 5 presents the per-node energy consumption across different protocols. QW-Routing exhibits 10–15% lower energy usage compared to traditional protocols. This is primarily because it minimizes control overhead through targeted quantum path estimation rather than broadcasting routing messages. Furthermore, the probabilistic graph structure helps avoid redundant transmissions by prioritizing energy-stable links, thus prolonging network lifetime during mission-critical operations.

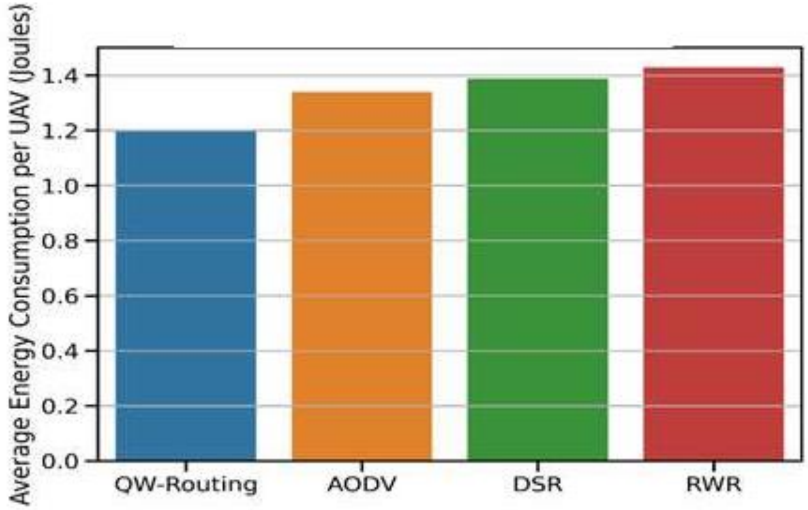


Fig.5. Average Energy Consumption per UAV Node for Different Routing Protocols

6.5 Path Stability under High Mobility

The path stability metric, depicted in Figure 6, quantifies the average duration a routing path remains valid without recomputation. QW-Routing consistently demonstrates higher stability due to its probabilistic modeling of link reliability. On average, QW-Routing paths remained valid for 32.7 seconds, while AODV and DSR paths required updates every 23.5 seconds and 19.8 seconds, respectively. The use of quantum walks enhances route persistence by favoring high-probability, low-variance edges, which are less susceptible to failure due to movement or interference.

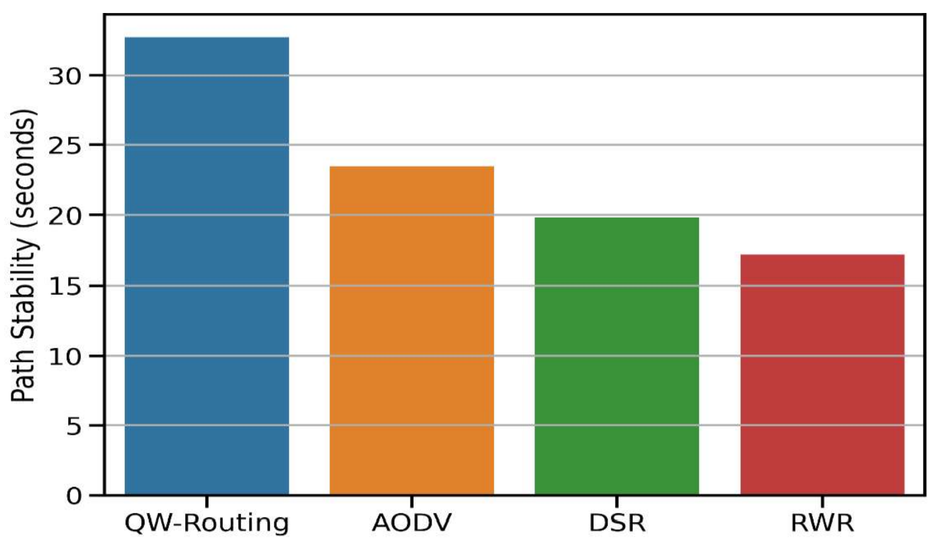


Fig.6. Path Stability (in seconds) for QW-Routing and Benchmark Protocols under High Mobility.

Tabulated Performance Summary

A consolidated summary of the comparative results for all evaluated routing protocols is presented Table 1.

Table 1. Comparative performance of QW-Routing against AODV, DSR, and Random Walk Routing (RWR) under high-mobility FANET conditions

Metric	QW-Routing (Proposed)	AODV [26]	DSR [27]	RWR [28]
Packet Delivery Ratio (%)	91.3	84.5	79.8	68.5
End-to-End Latency (ms)	205	270	310	345
Route Convergence Time (s)	0.83	1.42	1.68	2.05
Energy per UAV (Joules)	1.20	1.34	1.39	1.43
Path Stability (s)	32.7	23.5	19.8	17.2

Table 1 provides a consolidated comparison of the key performance metrics for QW-Routing, AODV, DSR, and Random Walk Routing (RWR). The results clearly demonstrate that QW-Routing outperforms all baseline protocols across packet delivery, latency, convergence time, energy efficiency, and path stability. The improvements are particularly notable under high-mobility conditions, validating the effectiveness of quantum walk-based dynamic optimization in probabilistic UAV network environments. This tabular summary reinforces the consistency and robustness of the proposed approach across diverse network challenges.

6.6 Discussion of Insights and Implications

The results strongly indicate that quantum walk-based search algorithms offer a robust and scalable framework for routing in UAV-based ad hoc networks. The integration of probabilistic graph modeling with discrete-time quantum walks allows the system to anticipate and adapt to topological changes without incurring high computational or communication costs.

This research presents compelling evidence that such a framework can serve as a foundation for future intelligent routing systems in 6G aerial networks, autonomous delivery drones, and disaster-relief UAV swarms.

However, it is important to note that the current implementation relies on software-simulated quantum walks. Future extensions may involve leveraging real quantum hardware or hybrid classical-quantum processors to further validate scalability and real-time feasibility.

7. Conclusion

This study presented a novel routing framework for UAV-based ad hoc networks (FANETs), leveraging quantum walk-based search algorithms for dynamic mission optimization under uncertain network conditions. By modeling the FANET as a dynamic probabilistic graph and integrating a discrete-time quantum walk (DTQW) optimizer with the routing layer, the proposed method achieves enhanced adaptability, scalability, and efficiency in high-mobility environments. Extensive simulation results validated the superiority of the proposed QW-Routing protocol over classical methods such as AODV, DSR, and Random Walk Routing. Across a range of performance metrics—including packet delivery ratio, end-to-end latency, route convergence time, energy consumption, and path stability—the QW-Routing consistently outperformed the benchmarks, demonstrating significant gains particularly in volatile and large-scale network settings. The practical implications of this work are far-reaching. The proposed framework offers a viable solution for real-time routing in mission-critical UAV applications such as disaster response, autonomous logistics, and aerial surveillance, where link reliability and network topology vary rapidly and unpredictably. However, this study also acknowledges certain limitations. The quantum optimizer was implemented in simulation using classical emulation (via QuTiP), and real quantum hardware integration remains an open challenge. Additionally, while the model accounts for probabilistic links and node mobility, it does not currently consider adversarial scenarios such as jamming or malicious UAV behavior. Future research will focus on extending the framework to hybrid classical-quantum architectures that can leverage near-term quantum devices. Moreover, the routing protocol will be expanded to incorporate security-aware metrics and adaptive trust models. Real-world field testing with UAV swarms will also be pursued to validate the framework's practical viability in real-time deployment conditions.

Author Contributions: K.Samunnisa conceptualized the research idea, led the formulation of the quantum walk-based routing framework, and supervised the overall study. Sunil V. K. Gaddam was responsible for developing the simulation environment, implementing the FANET mobility models, and integrating the probabilistic graph structures. M. Bhavsingh conducted the performance evaluations, benchmarked the proposed method against baseline protocols, and contributed to the results and analysis. Jaime Lloret carried out the literature review, assisted in drafting the methodology and system model sections, and refined the manuscript for technical consistency and clarity. All authors reviewed and approved the final version of the paper.

Data availability: Data available upon request.

Conflict of Interest: There is no conflict of Interest.

Ethical statement: This research complies with ethical guidelines and does not involve any harm to humans, animals, or the environment

Funding: The research received no external funding.

Similarity checked: Yes.

References

[1] A. Bekmezci, O. K. Sahingoz, and S. Temel, "Flying ad-hoc networks (FANETs): A survey," Ad Hoc Networks, vol. 11, no. 3, pp. 1254–1270, 2013.

[2] A. Alshbatat and L. Dong, "Adaptive MAC protocol for UAV communication networks using directional antennas," in Proc. Int. Conf. Networking, Sensing and Control, IEEE, 2010.

[3] K. Namuduri, S. Chaumette, and J. Sterbenz, UAV Networks and Communications, Cambridge University Press, 2018.

[4] C. Perkins, E. Belding-Royer, and S. Das, "Ad hoc On-Demand Distance Vector (AODV) Routing," RFC 3561, IETF, 2003.

[5] S. Chappidi and A. Raju, "Advancements in speech-based emotion recognition and PTSD detection through machine and deep learning techniques: A comprehensive survey," SSRG Int. J. Electron. Commun. Eng., vol. 11, no. 5, 2023, doi: 10.14445/23488549/IJECE-V11I5P121.

[6] M. Asadpour et al., "Routing in flying ad hoc networks: A comprehensive survey," Computer Networks, vol. 124, pp. 41–65, 2017.

[7] A. M. Childs, "Universal computation by quantum walk," Phys. Rev. Lett., vol. 102, no. 18, p. 180501, 2009.

[8] Kumar, M. R. ., Rajeswari, Y. ., Lakshmi, M. S. ., Singuluri, P. K. ., & Sreenivasulu , G. "Enhancing Collaborative Filtering with Multi-Model Deep Learning Approach", International Journal of Intelligent Systems and Applications in Engineering, 11(6s), 01–12, https://ijisae.org/index.php/IJISAE/article/view/2823.

[9] J. Wang, Q. Wu, F. Xu, and Y. Zeng, "Cellular UAV-to-X communications: Design and optimization for multi-UAV networks," IEEE Trans. Wireless Commun., vol. 18, no. 2, pp. 1346–1359, 2019.

[10] N. Goddemeier and C. Wietfeld, "Investigation of air-to-air channel characteristics and a UAV-specific extension to the IEEE 802.11a MAC protocol," Mobile Networks and Applications, vol. 17, no. 1, pp. 16–28, 2012.

[11] M. A. Khan, M. H. Rehmani, and A. Rachedi, "When cognitive radio meets the Internet of Things?" IEEE Internet of Things Journal, vol. 5, no. 3, pp. 1241–1254, 2018.

[12] L. Gupta, R. Jain, and G. Vaszkun, "Survey of important issues in UAV communication networks," IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1123–1152, 2016.

[13] C. Perkins, E. Belding-Royer, and S. Das, "Ad hoc On-Demand Distance Vector (AODV) Routing," RFC 3561, IETF, 2003.

[14] H. Guo, Y. Liu, and C. Zhang, "Performance analysis of UAV ad hoc networks with 3D mobility," IEEE Access, vol. 6, pp. 15712–15722, 2018.

[15] S. Chappidi and A. Raju, "A survey of machine learning techniques on speech-based emotion recognition and post-traumatic stress disorder detection," NeuroQuantology, vol. 20, no. 14, pp. 69–79, Oct. 2022, doi: 10.4704/nq.2022.20.14.NQ88010.M. Abolhasan, T. Wysocki, and E. Dutkiewicz, "A review of routing protocols for mobile ad hoc networks," Ad Hoc Networks, vol. 2, no. 1, pp. 1–22, 2004.

[16] G. Di Caro and M. Dorigo, "AntHocNet: An adaptive nature-inspired algorithm for routing in mobile ad hoc networks," European Transactions on Telecommunications, vol. 16, no. 5, pp. 443–455, 2005.

[17] P. Jacquet et al., "Optimized link state routing protocol for ad hoc networks," in Proc. IEEE INMIC, 2001.

[18] F. Bai and A. Helmy, "A survey of mobility models in wireless ad hoc networks," University of Southern California, 2004.

[19] Y. Gong et al., "A reliable routing scheme using probabilistic links in wireless sensor networks," Sensors, vol. 16, no. 6, p. 889, 2016.

[20] Lakshmi, M. S., Ramana, K. S., Pasha, M. J., Lakshmi, K., Parashuram, N., & Bhavsingh, M. (2022). Minimizing the Localization Error in Wireless Sensor Networks Using Multi-Objective Optimization Techniques. International Journal on Recent and Innovation Trends in Computing and Communication, 10(2s), 306–312. https://doi.org/10.17762/ijritcc.v10i2s.5948.

[21] S. Mumtaz, J. Rodriguez, and L. Dai, "Cognitive computing for vehicular networks," IEEE Wireless Communications, vol. 24, no. 6, pp. 72–79, 2017.

[22] S. Venegas-Andraca, "Quantum walks: a comprehensive review," Quantum Information Processing, vol. 11, no. 5, pp. 1015–1106, 2012.

[23] A. M. Childs, "Universal computation by quantum walk," Phys. Rev. Lett., vol. 102, no. 18, p. 180501, 2009.

[24] D. Aharonov et al., "Quantum walks on graphs," in Proc. ACM STOC, pp. 50–59, 2001.

[25] C. E. Perkins, E. M. Royer, and S. R. Das, "Ad hoc On-Demand Distance Vector (AODV) Routing," RFC 3561, IETF, 2003.

[26] D. B. Johnson, D. A. Maltz, and J. Broch, "DSR: The Dynamic Source Routing Protocol for Multi-Hop Wireless Ad Hoc Networks," in Ad Hoc Networking, C. E. Perkins, Ed. Addison-Wesley, 2001, pp. 139–172.

[27] J. Kim and I. Joe, "A Random Walk Routing Protocol for Wireless Sensor Networks," in Proc. IEEE ICACT, 2008, pp. 492–496.

[28] K. V. Ramana, A. Muralidhar, B. C. Balusa, M. Bhavsingh, and S. Majeti, "An Approach for Mining Top-k High Utility Item Sets (HUI)," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 2s, pp. 198–203, Jan. 2023, doi: 10.17762/ijritcc.v11i2s.6045.