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Optimizing Network Reliability and Fault Detection in WSN-Assisted Autonomous Vehicle Systems Using QHHO-GNN Model

Eldho K J
Department of Computer Science, Mary Matha Govt Aided Arts & Science College, Mananthavady, Kerala, India.
eldhorvs@gmail.com

Nithyanandh S
Department of MCA, School of Computational Sciences, PSG College of Arts & Science, Coimbatore, Tamil Nadu, India.
✉ nknithu@gmail.com

Kowsalya R
Department of Computer Science (PG), PSGR Krishnammal College for Women, Coimbatore, Tamil Nadu, India.
rkowsalya31psg@gmail.com

Donu Jose V
Department of Computer Science, St. Mary's College, Sulthan Bathery, Kerala, India.
donujosev@gmail.com

Received: 21 May 2025 / Revised: 20 July 2025 / Accepted: 28 July 2025 / Published: 30 August 2025

Abstract – Wireless Sensor Networks (WSNs) enable real-time environmental monitoring and unified, seamless communication within Autonomous Vehicle Systems (AVS). However, these WSN-assisted AVS often face reliability issues due to frequent sensor node failures, dynamic topology changes, and delayed fault detection, compromising vehicular safety and decision-making accuracy. To address these critical challenges, this research focuses on a novel hybrid framework called QHHO-GNN, which combines Quantum Enhanced Harris Hawks Optimization and Graph Neural Networks for efficient network optimization and intelligent automatic fault detection. Using exploration methods inspired by quantum mechanics, the QHHO optimizes the network characteristics, including energy consumption, routing paths, and connection stability, ensuring reliable communication even in highly mobile AV environments. Simultaneously, the GNN model effectively captures complex spatial and relational dependencies within WSN topologies, enabling accurate and real-time fault detection with minimal false alarms. Extensive network simulation is done using NS-3, and PyTorch is used for GNN fault detection with the data exchange of CSV/JSON files. The simulation results demonstrate that the proposed QHHO-GNN framework outperforms existing AVS routing and energy-efficient methods in terms of Packet Delivery Ratio, End-to-End Delay, Network Life Time, Energy Efficiency, Fault Detection Accuracy, and False Alarm Rate. With its adaptive optimization and AI-enabled predictive capabilities, this model presents a transformative solution for enhancing the resilience and operational safety of WSN-assisted AVS.

Index Terms – Wireless Sensor Networks, Autonomous Vehicle Systems, Automatic Fault Detection, Graph Neural Networks, Network Reliability Optimization, Bio-Inspired Model.

1. INTRODUCTION

The rapid technological advancement of Autonomous Vehicle Systems (AVS) has developed with transformation in promotion of safety, efficiency, and real-time decision making by utilizing intelligent transportation via Wireless Sensor Networks (WSNs) [1], which is central to this innovation, facilitating the seamless communication between vehicles and their environments. However, these WSN-based AVS have grown dynamically, ensuring reliable network communication and prompt fault detection, which has become a critical challenge. The hybrid multimodal renewable energy harvesting model [2] helps power wireless monitoring systems such as humidity sensors, accelerometers, and light sensors in remote areas by integrating the solar photovoltaic setup to harvest solar and wind energy simultaneously. The average power output of 12.31W is achieved under optimal conditions, which is highly suitable for railway monitoring and is guaranteed by techno-economic optimization software.

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The operational efficiency of Autonomous Ground Vehicles (AGVs) is improved and to optimize path planning, a hybrid control strategy is employed along with A* algorithm, Dynamic Window Approach (DWA) and Adaptive Neuro Fuzzy Inference System (ANFIS) [3] which reduces computational overhead and pathfinding speed to make real-time sensor adjustments based on its feedback. Multi (Unnamed Aerial Vehicles) UAV-WSNs and applications of ML algorithms [4] improve network coverage, efficiency, and autonomous decision-making with improvised ML classifications.

As there is a rising demand for UAVs in areas like security, environment monitoring, and crisis management, integrating WSNs with ML models helps systems work more autonomously and self-adaptively. EH-WSNs [5] are used to explore battery-free systems using capacitors and super capacitors to overcome the limitations of battery life. Sufficient power is produced by piezo electric systems, especially for low energy consumption devices like thermal resonators and hydro-voltaic systems, which are the emerging and promising future solutions of battery-free WSN deployments. Intelligent water-drop bio-inspired algorithm (IWD-ARP) [6] is used to detect dynamic failures in WSNs and to achieve optimal routing from the source to the destination to deliver packets without any delay. The network lifetime is boosted by the sensor nodes, which consume less energy during the installation of IWD-ARP. LCC-S-Booster wireless charging system [7] in autonomous UW vehicles is implemented by a dynamic power adaptation strategy using a nonlinear Riemann algorithm. This model enhanced the global search and solution speed of UW vehicles. An inverse learning initialization strategy and nonlinear rime adsorption factor are the main reasons for the high effectiveness and accuracy of the UW wireless charging system. The threats and faults are detected in mini electric autonomous WSN-based vehicles using AI-based Random Forest Algorithm [8] (AI-RFA).

The network faults, traffic threats, and DDoS & MiTM attacks are detected to enhance electric vehicles' cybersecurity resilience and uninterrupted performance. Bio-Inspired RBC [9] is used as a key algorithm to detect dynamic link failure in WSNs, which helps to boost energy by adaptive routing and a lower node failure rate. As some nodes are deployed in a complex environment, they require multi-support, such as self-awareness and self-decision-making, to act according to the requests from the source node. As some WSNs witness coverage holes leading to network failure and redundancy, the swarm intelligence [10] helps to detect the same to speed up healing and avoid redundancy to boost the scalability, flexibility, and restoration of the WSNs in a dynamic environment. An adaptive sleep scheduling [11] and secured data transmission are required for IoT-based WSNs to address the failure tolerance and reliability issues. An improvised bio-inspired flower pollination method helps optimize the network and transfer the data from the source to the destination robustly. Traditional fault management systems fail to meet AVS's stringent latency and reliability demands, leading to system degradation and poor performance.

To address these challenges, this research mainly concentrates on the hybrid framework by combining QHHO and GNN for adaptive network optimization, fault detection to manage energy and communication resources, which helps to bridge the gap between network optimization and proactive fault management to pave the way for resilient and fault-tolerant AVS.

1.1. Problem Statement

The primary focus of this work is the integration of WSNs into AVS in environment sensing, real-time decision making, and vehicle-to-everything (V2X) communications. However, the dynamic and unpredictable nature of WSN-based vehicular environments poses significant challenges in maintaining the network reliability and detecting faults promptly. Increased rate of delayed fault responses and communication failure due to frequent topology changes, high mobility, variable signal quality, and limited energy sources of sensor nodes. Existing fault detection and network reliability optimization models are inadequate in handling the complexity and scale of highly dynamic networks due to computational overhead, slow convergence, and poor adaptability to changing network conditions, leading to system performance degradation. Moreover, the traditional systems highly depend on threshold-based techniques, which are incapable of identifying complex and hidden patterns within large-scale sensor networks. These limitations result in high FAR and network failures. Therefore, a robust and intelligent framework that can dynamically optimize network operations and ensure timely fault detection is needed to build a resilient, fault-tolerant, and efficient autonomous vehicle communication infrastructure.

1.2. Motivation

The increasing dependency on WSN-based autonomous vehicles for transportation demands highly reliable and resilient communication networks to guarantee safety and operational efficiency. As WSNs form a backbone of inter-vehicle communication and environment perception, even minor faults or data transmission delays can lead to catastrophic outcomes, which include collision risks and navigation failures. Conventional WSN optimization methods fail to adapt to the real-time demands of rapidly changing vehicular environments. Similarly, existing fault detection methods lack the power to discriminate between transient anomalies and critical faults accurately, resulting in frequent false alarms or detections. This research is motivated to overcome the limitations of network optimization and fault

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detection through an intelligent and adaptive approach. By utilizing the strength of QHHO for network management and the powerful learning capabilities of GNN for fault detection, this study aims to enhance the fault detection accuracy, minimize communication failures, and ensure continuous data flow in AVS to contribute to the development of safer and innovative WSN-based transportation solutions.

1.3. Objective

This research aims to design a novel, hybrid deep learning framework to enhance the network reliability and fault detection in WSN-assisted AVS. The proposed framework employs the Quantum-Enhanced Harris Hawks Optimization (QHHO) model to optimize network reliability, dynamically manage the routing paths, balance energy depletion, and sustain stable communication under dynamic vehicular environments. Through the implementation of Graph Neural Networks, the proposed model enables intelligent fault detection, which can identify and classify complex fault patterns in real-time AVS with minimal false rates. This framework enhances the energy and network lifetime without compromising the fault detection and optimization performance. The simulations and real-world applications validate that the model aspires to significantly improve the resilience, reliability, and safety of WSN-based autonomous vehicle ecosystems.

1.4. Research Contribution

The primary contribution of this research is the design and implementation of a novel hybrid model by integrating QHHO for robust network optimization and GNN for fault detection with high accuracy. The proposed framework simultaneously addresses the challenges of existing models in terms of energy-aware routing, real-time fault classification, and low-latency communication within WSN-assisted autonomous vehicle systems. The QHHO enhances network longevity and packet delivery by optimizing network routing and resource distribution, whereas GNN enables precise fault detection by capturing spatial and temporal relationships in node behavior. The model is simulated and validated under increasing node levels and network stress. This integrated approach sets a strong base for developing scalable, reliable, fault-detection communication frameworks in autonomous transportation systems.

1.5. Organization of the paper

This paper is systematically organized to provide a comprehensive research framework. Section 1 describes the background of WSN-assisted AVS, highlights the prevailing challenges in network reliability, routing issues, energy of sensor nodes, and fault detection. It further elaborates with research motivation, problem statement, and defined objectives. Section 2 presents the state-of-the-art network optimization techniques and fault detection methods to identify the limitations and research gaps. Section 3 focused on methodology by incorporating QHHO and GNN models for intelligent fault detection. Section 4 discusses the simulation results comparing the performance of the proposed model against baseline protocols using key performance metrics such as Packet Delivery Ratio, End-to-End Delay, Network Life Time, Energy Efficiency, Fault Detection Accuracy, and False Alarm Rate. Finally, Section 5 concludes the paper by summarizing the research findings and limitations, and highlighting future research directions.

2. LITERATURE REVIEW

"WSN-based Machine Learning Centric Resource Management" [12] discussed node deployment in heterogeneous and distributed networks integrated with sensors, receivers, and software. The study shows WSNs struggle to manage resources due to limited sensor power, computational capacity, memory, range, and bandwidth. The model focuses on resource identification, scheduling, allocation, utilization, and monitoring; it lacks adaptability and fails to optimize resources dynamically. Utilization of machine learning offers dynamic and intelligent resource management for autonomous WSN-based systems with minor limitations of optimized resource utilization under varying operational conditions.

"WSN-based Wave Powered Autonomous Underwater Vehicle (WPAUV)" [13] optimizes energy efficiency by utilizing wave energy to recharge sensor batteries, which extends battery lifetime. The extended range of battery power under different wave frequencies and amplitudes has improved drastically, and the protocol is self-adaptive and dynamically adjusts the topology changes, enhancing reliability and data integrity.

"Bio-Inspired Protocols" [14] detects dynamic node link failure in WSNs and optimizes the routing paths to deliver the packets robustly. These protocols work on population-based techniques like bees, viruses, etc. The central focus of bio-inspired protocols is optimizing network reliability and routing paths for self-adaptive and autonomous decision making. "Trusted Autonomous Vehicle Routing Protocol (TAVRP)" [15] supports 6G networks in terms of energy efficiency and routing process by annealing optimization method between IoT-based vehicles. Also, TAVRP provides security in the data transmission process with high coverage and robust service. The latency is drastically minimized even in an unpredictable environment and changing states of IoT sensors.

"Multi-Objective Particle Swarm Optimization" [16] protocol provides intelligent routing and optimizes energy in 6G based network communications. Security attacks are addressed in the model by integrating epileptic curve cryptography and key rotation technique during WPA2/PSK authentication. The model was tested using NSL dataset with high traffic and different environmental conditions. The model is used in many IoT security-based networks to detect faults using centralized and decentralized methods to coordinate with WSNs to balance the network load and optimization specifically to AVS.

"LM-Based Intelligent Transportation Systems" [17] enhanced the unique capabilities like WSN traffic optimization, human-like reasoning, environmental understanding, and safety enhancement. The practical adaptation of LM-based models in AVS ensures potential target task achievement, reduction of structural & weight dependencies, overcoming computational demands, high latency, and throughput demands.

"Hybrid Random Walk Assisted Zone-Based (HRWZ)" [18] protocol helps to detect the clone nodes in WSNs to enhance the security of data transmission and the lifetime of the network. The grid sensor network is deployed in multiple zones, and each node is assigned a unique ID by the trusted authority. The zone leader will share the key to transferring the data from the source to the destination, which helps make the data transfer more secure. Using the node-revoke method, the clone nodes are detected in all zones, both in the global and local searches.

"6G-Edge based multi UAV protocol" [19] employs decentralized ML models to facilitate the training to transmit the data in a distributed 6G environment. Distributed Edge-Based Collaborative Knowledge Sharing (DECKS) architecture used federated learning in UAV networks allows the model to be trained locally and globally in the search space to reduce energy consumption, latency, and computational overhead. "DT-Based Connected Autonomous Vehicles" [20] adapts digital twin architecture with CORTEX and CARLA to ensure high performance and scalability in AVS. The probabilistic models predict the road hazards in the distributed environment, demonstrating practical applicability and self-decision making in anticipating scenarios.

"Energy-Aware Hardware and Link Fault Diagnosis (EAHLFD)" [21] enhances quality of service in WSNs by detecting the hardware faults and link faults simultaneously to optimize the recovery link to produce a seamless connection between the sensor nodes in an IoT-based distributed environment. As the key limitations of sensor nodes are battery life and deployment, it isn't easy to recharge or exchange instantly in any environment. This EAHLFD model detects the link faults and sends feedback to the base station for action taken consistently without interrupting data delivery and network failure, making the model self-adaptive in a dynamic environment.

"DBN-Based WSN" [22] helps to detect faults like SPF, IF, and TF in large-scale WSNs. The complete fault status is reported to the base station for instant recovery, which boosts the model's adaptability to fault detection and robust routing process for efficient data delivery in a dynamic environment. Though the search space is expanded in large-scale WSNs, the DBN-based model works in multiple channels to detect faults with continuous data transfer.

"An integrated MCDM Framework" [23] enhances the operational efficiency of CAVs by employing Fuzzy LMAW and Fuzzy WASPAS techniques to make the model self-powered IoT sensors act dynamically in vehicular environments. The model ensures reliability and efficient resource allocation in the changing WSN-based environments. "Energy-Efficient Unequal Multi-Level Clustering (EEUMC)" [24] selects clusters based on energy and proximity metrics to extend the lifetime when using in underwater WSNs. The model adapts to underwater communication constraints like depth, pressure, and link reliability, providing energy-aware communication frameworks.

"Ai-Based UAV Assisted WSNs" [25] focused on energy optimization and efficient data collection by integrating clustering and UAV mobility using the greedy-inter cluster communication algorithm to form an energy-conscious route map to deliver the data from the source to the destination. The system dynamically balances the load and minimizes the energy waste during the UAV's travel, which makes the model scalable and intelligent in the distributed environment. "Deep Learning-Based CNN" [26] model enhances the object detection mechanism in a real-time environment where the system is trained to detect malicious signals for robust data transmission and fault detection to improve the communication technologies for the conference-grade environment.

"RVSRP Fault Tolerant Routing Protocol" [27] detects dynamic link failure in WSNs to maintain reliable communication paths by adapting the rerouting strategy. The model helps AVS to detect link failures in a real-time environment to maintain uninterrupted data transmission in volatile conditions. The model enhances network reliability in changing environments, making it suitable for WSN-based AVS applications.

"Data Transmission GAN-Based Protocol" [28] detects malicious nodes and patterns in communication to ensure data integrity and minimize the packet loss. The model achieves dual goals, such as attack protection and resource utilization, by incorporating AI in the routing and security layers. This helps the model mode to be intelligent, resilient, and secure in data communication between sensor nodes. Table (1) shows the diverse range of prevailing fault tolerance and network reliability models includes wave energy harvesting with self-adaptive topology control, population-based optimization using bees, ants, and virus swarm, and LM-based reasoning

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for traffic control. It also covers HRWZ-based node identification, federated learning with DECKS, EAHLFD for fault diagnosis, RVSRP for dynamic link rerouting, and GAN-based secure routing in WSN environments.

Table 1 Comparative Analysis of Specific State-of-Art on Network Reliability and Fault Tolerance

Name of the Model	Methods Adapted	Merits	Demerits	Limitations of Network Reliability & Fault Tolerance
WSN-based Wave Powered AUV [13]	Wave Energy Harvesting and Self-Adaptive Dynamic Topology Control	Extends battery life, improves data integrity under dynamic ocean conditions	Limited to environments with wave energy availability	Restricted to specific environments, lacks adaptability in network lifespan in calm seas
Bio-Inspired Protocols [14]	Population-Based Optimization (Bees, Ant and Virus Swarm)	Enhances routing reliability, self-adaptive decision making	Need of High computational resources for LoRA networks	Fails under extremely dynamic environments with unpredictable link failures
WSN Traffic Optimization [17]	LM-Based Human-Like Reasoning and Traffic Control	Improves safety, reduces latency, optimizes WSN traffic flow	High computational demand for real-time reasoning	Limited scalability in highly dense vehicular networks
Clone Node Detection [18]	Hybrid Random Walk with Zone-Based Node Identification (HRWZ)	Enhances security by detecting clone nodes, improves data transmission	Depends on trusted authority for ID management	Ineffective against insider attacks without additional verification
Decentralized Multi UAV Protocol [19]	Federated Learning with DECKS Architecture	Reduces energy consumption, supports decentralized learning	Complex implementation and communication overhead	Struggles with high mobility scenarios and fast topology changes leads to poor network reliability
Hardware & Fault Link Diagnosis [20]	Energy-Aware Hardware and Link Fault Diagnosis (EAHLFD)	Detects hardware and link faults in real-time, ensures continuous delivery	Limited to fault diagnosis, not full recovery solutions	Cannot fully prevent data loss during multiple simultaneous faults
Fault Tolerant Routing Protocol [27]	RVSRP with Dynamic Link Failure Detection and Rerouting	Maintains reliable communication paths during dynamic link failures	May introduce latency during rerouting process	Latency increases with frequent path failures in unstable WSN environments
GAN Based Secured Protocol [28]	Generative Adversarial Networks (GAN) for Secure Routing	Detects malicious patterns, ensures data integrity and security	High computational overhead during GAN training	Training complexity affects real-time applicability in critical systems

2.1. Research Gap

Optimizing network reliability and fault detection in WSN-based AVS remains an unsolved challenge. Existing optimization solutions like HRWS and EAHLFD often fail to adapt to vehicular networks' highly dynamic and resource-constrained nature, leading to network failure and inefficient routing. Conventional fault detection methods depend on static thresholds that lack the potential to analyze complex and linear relationships among the sensor nodes. These limitations result in high FAR and poor performance of AVS, which directly impacts the safety and decision-making accuracy.

Also, there is limited research integrating bio-inspired optimization with a deep learning-based framework to detect faults in WSN-based AVS environments and for holistic network management. This proposed research addresses the

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critical need for an intelligent and adaptive solution that simultaneously optimizes network performance and real-time fault detection in AVS.

3. QUANTUM-ENHANCED HARRIS HAWKS OPTIMIZATION (QHHO) WITH GRAPH NEURAL NETRORKS (GNN)

The first phase of this proposed work is employing the QHHO algorithm initialized by hawk populations using Quantum State Vectors (QSV), providing a diverse search space using route optimization. The energy-efficient optimal routes are discovered through Quantum Tunneling Effect (QTE) and Levy Flight Exploitation (LFE) to ensure minimized energy consumption and latency. The dynamic fitness function of this algorithm is optimized for PDR, EC, and Latency. At the end of optimization, nodes with low residual energy are completely excluded from routing decisions to achieve network lifetime and improved energy efficiency. The model is tested using synthetic and WSN datasets for performance analysis and compared with existing methods. The following is the 10-step process of QHHO, which shows the detailed WSN-assisted AVS optimization work model.

3.1. Node and Network Initialization

The QHHO process begins with the initialization of the WSN-assisted AVS environment. The nodes represent both static infrastructure (roadside units) and mobile sensor nodes (on vehicles). The main objective is to create a dynamic and resource-constrained environment that represents WSN challenges in AVS scenarios. The dynamic initialization ensures that the optimization process operates on realistic data, influencing convergence speed and solution accuracy. Here, each sensor node is assigned with multiple parameters like energy level E_i, location x_i, y_i with a transmission range R_t , and buffer capacity which is expressed in equation (1).

$$E_i = E_{initial} \ \forall_i \in N \tag{1}$$

where, $E_{initial}$ is initial energy of sensor node and N is the total number of sensor nodes deployed in the environment. The search space for optimization is defined by node position and the energy levels, which set the base for optimal route discovery and allocation of resources.

3.2. Population Initialization Using QSV

Instead of random initialization of candidate solutions, QHHO represents each hawk's position using Quantum State Vector (QSV), enhancing exploration is derived using equation (2).

$$|\,\psi\rangle = \alpha\,|0\rangle, with\ |\alpha|^2 + \ |\beta|^2 = \ 1 \tag{2}$$

where the quantum state representation allows each solution (hawk) to exist multiple states, increasing chances of finding the global optimum in complex WSN environment search space. The α and β represent the probability amplitudes, allowing each hawk to exist in superposition states, exploring the multiple routing paths rather than committing to a single early solution that enhances the dynamic, high-dimensional solution spaces of typical WSN environments. This quantum behavior strategy ensures that the solution space is covered extensively in early-stage iterations, increasing the robustness and optimization process.

3.3. Evaluation of Fitness Function

The quality of each solution is evaluated in a quantitative manner which drives the fitness function optimization process. The fitness function is formulated to optimize the key parameters such as PDR, EC and EED. Equation (3) shows the fitness function of key parameters.

$$Fitness = w_1.PDR - w_2.EC - w_3.EED \tag{3}$$

The weights $w_1, w_2, and\ w_3$ are carefully tuned to prioritize the key performance objectives. Minimizing energy and maximizing delivery rates are prioritized over energy consumption to ensure safety-critical AV systems. This multi-objective function ensures that selected routing paths are reliable and energy-efficient with low latency. For each iteration, a fitness evaluation is done, which dynamically influences the movement and behavior of hawks to find a better solution. The feedback loop between the optimization process and the fitness quality solution is recorded to handle the dynamic nature of WSN-based SV environments.

3.4. Exploration Using QTE

The exploration phase is crucial in the early optimization stage to search for a vast solution space to avoid local minima. QHHO uses Quantum Tunneling Effect (QTE) to simulate the hawk's ability to jump across local optima (barriers), which is mathematically expressed in equation (4).

$$X_i^{t+1} = X_i^t + Q.\sin(\theta).e^{-r} \tag{4}$$

where, Q represents quantum potential, θ is a random angle of stochastic behavior and r is the target solution (prey) distance. This allows hawks to explore the unexplored region in the search space to increase the probability of finding the optimal routes. This QTE helps to discover the alternate low-energy communication paths and balanced node load distribution and outperforms existing methods.

3.5. Prey-Energy based Adaptive Switching

In this step, the QHHO algorithm evaluates whether to continue exploring or start exploiting the known best solutions based on 'prey-energy', which the WSN context refers to availability of resources and network stress. The prey-energy is modeled as expressed in equation (5).

$$E_{prey} = 2\left(1 - \frac{t}{T_{max}}\right) \tag{5}$$

where, t is current iteration and T_{max} is the maximum number of iterations. If $E_{prey} > 1$, it implies that the sensor node has sufficient energy for exploration. Else, the model switches to the exploitation phase to refine the existing solutions. This adaptive behavior of prey-energy in QHHO ensures that the time spent is more on exploration in early stages, focusing on effective resource optimization, where the available energy and link stability are measured.

This dynamic switching prevents premature convergence and ensures a perfect balance between finding new candidate solutions and enhancing the existing ones.

3.6. Exploitation Phase with Quantum Levy Flight

To fine-tune the candidate solutions, the QHHO algorithm utilized the Quantum Levy Flight mechanism, which is

enhanced by quantum properties once the algorithm transitions into the exploitation stage. This QLF effectively covers both the local and global search space in the WSN, which is mathematically expressed in the equation (6 & 7).

$$X_i^{t+1} = X_{best} + Levy\ (\lambda).Q \tag{6}$$

$$Levy\ (\lambda) = 0.01\ .\frac{rand\ .\sigma}{|u|\ ^{1/\lambda}} \tag{7}$$

which denotes the long-distance movements while refining solutions in nearby regions. This QLF mechanism $Levy\ (\lambda)$ in WSN-AVS mode efficiently discovers communication paths balances the energy consumption with high reliability under various topology changes.

The Levy Flight allows the model to explore less visited areas in the search space, prevents data transfer stagnation which improves PDR, latency and route discovery.

3.7. Position and Energy Updates of Hawks (Nodes)

Based on the selected optimal paths, the positions of hawks (nodes) are updated after determining the movement strategy. In addition, the residual energy of each node is recalculated considering data transmission and reception costs which is expressed in equation (8 & 9).

$$E_i^{t+1} = E_i^t - E_{tx}(d) - E_{rx} \tag{8}$$

$$E_{tx}(d) = E_{elec}.k + E_{amp}.k\ .d^2 \tag{9}$$

where, k is the data packet size, d is the distance between communicating hawks (nodes) and E_{elec},E_{amp} are energy parameters related to electronic circuit and amplifier power consumption respectively.

These calculations ensure that nodes with less energy are excluded from routing decisions promotes balanced energy consumption and network lifetime to maintain energy efficient communication in a resource constrained WSN based AVS.

3.8. Quantum Observation and State Collapse

Once the candidate solutions (hawks) are explored and exploited, the quantum observation process collapses their superposition states into definitive solutions. This step is measured by quantum principle which is shown in equation (10).

$$P = |\alpha|^2 or\ |\beta|^2 \tag{10}$$

where, P is probability which is selected as the final path corresponding to the solution with higher probability amplitude. This approach is called controlled randomness to handle the dynamic changes inherent in vehicular communication networks. By collapsing the state based on probabilistic observation, the model ensures that stable and finite communication paths are selected, improving the PDR's effective rate with minimized latency.

3.9. Model Convergence Check

In this step, the QHHO algorithm checks the convergence by comparing the fitness value change between consecutive iterations. The below equation (11) shows the fitness check convergence between iterations.

$$\Delta Fitness = \frac{|Fitness_{current} - Fitness_{previous}|}{Fitness_{previous}} \tag{11}$$

If, $\Delta Fitness$ is below the threshold level €, the optimization process considered as complete. Else, the model proceeds for next iteration. This convergence check ensures that the model terminates effectively once it reached optimum level which helps to avoid the computational overhead.

3.10. Final Attainment and Optimal Route Selection

In the final stage, the QHHO selects and outputs the finest routes and network configurations discovered throughout the optimization process using various quantum mechanisms. The selected finite routes ensure maximum packet delivery ratio, low latency, and balanced energy utilization across all deployed sensor nodes.

The sensor node behavior is monitored completely during the data transmission process and topology changes in order to record the communication links in the search space which is used for feature initialization for robust fault detection. Also, the network operates under optimal conditions for real-time AVS, which addresses the system's safety and reliability requirements.

The identified paths demonstrate improved resilience to dynamic topology changes and node link failures, which is highly required to maintain uninterrupted service in high mobile and unpredictable environments. The Quantum Harris Hawks Optimization model step-by-step process is shown in algorithm 1.

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Input: Network Topology, Node Parameters, Max Iterations

Output: Optimized Routes and Resource Allocation

Pseudocode Steps:

1. Initialize Network Nodes N and Parameters P
2. $N = 1000$ and Simulation Area 1000m x 1000m
3. Initialize hawks (solutions/nodes) using QSV
4. Evaluate fitness of each solutions/nodes
5. While ($t < Max\ Iterations$) do
    a. Calculate prey energy E_{prey}
    b. If $E_{prey} > 1$, perform exploration using QTE
    c. Else, perform exploitation using QLF
    d. Update positions and energy levels
    e. Perform Quantum Observation and State Collapse
    f. Evaluate new fitness and update best solutions
6. End While
7. Output optimized network routes and energy allocations

Algorithm 1 QHHO Optimization for Network Reliability

3.11. Graph Construction and Feature Initialization

The next phase of this research work is employment of Graph Neural Networks (GNN) for fault detection in WSN-based AVS. To begin this, the first stage is Graph Construction and Feature Initialization where the WSN is fully modeled as graph $G = (V, E)$, where $v \in$ V represents the sensor node and each node $e \in$ E denotes the communication link between the nodes in the space. The feature vectors X_v are initialized for each node contains the key attributes like residual energy, packet loss rate, signal strength and fault status history of the particular network.

The adjacent matrix captures the connectivity between the nodes. This structured graph allows GNN effectively captures the spatial relationships and communication dependencies which is essential for fault pattern recognition across WSNs. Equation (12) shows the graph construction with attributes.

$$X_v = [E_v, PDR_v, PLR_v, Latency_v, ErrorRate_v] \qquad (12)$$

where, energy vector, packet delivery, error rate and latency are the attributes are initialized in a graph model with each node.

3.12. Graph Convolution and Neighborhood Aggregation

By aggregating the information from each neighbor node, GNN performs the feature propagation to achieve the core objective. The model uses Graph Convolutional Network (GCN) operation, the new representation for each node is calculated, which is shown in equation (13).

$$H^{l+1} = \sigma(\widehat{D}^{-\frac{1}{2}}\widehat{A}\widehat{D}^{-\frac{1}{2}} H^l W^l) \qquad (13)$$

where, $\widehat{D}$ is the degree matrix, $H^l W^l$ are the feature matrix at layer and learnable weight matrix. $\hat{A}$ represents self-connections in WSN. The non-linear activation function σ introduces the learning capacity which allows the network to learn the complex patterns and spatial dependencies for fault detection in the distributed changing environment.

3.13. Temporal Feature Learning using LSTM

As the sensor faults shows the temporal patterns, LSTM is used to capture those patterns where the output convolution is passed through LSTM layer which process the time-series data associated with each node which is shown in equation (14). This can be expressed as,

$$h_t = LSTM\ (X_t, h_{t-1}) \qquad (14)$$

where, the model learns the temporal dependencies like energy drain and increase in packet loss which are the strong indicators of potential faults. In dynamic vehicular environments combining the spatial and temporal learning ensures more accuracy in early stage fault detection in WSNs.

3.14. Fault Probability Estimation and Calculation

In order to estimate the fault probability, each node's final representation is passed through a fully connected to Softmax classifier to detect the real-time faults in WSN-assisted vehicular environments. The representation is expressed in equation (15).

$$P_{fault} = Softmax\ (W_f . h + b_f) \qquad (15)$$

where, W_f and b_f are classifier weights and bias, h is the learned node representation. The max function provides the final class probabilities for 'N or 'F' states. (N = Normal and F=Faulty). This strategy allows the model to identify the real-time faults in VAS with minimal false alarm rates.

3.15. GNN Model Training and Optimization

The GNN model is trained using a cross-entropy loss function to minimize the classification error rates, as the model uses probability outputs for fault detection. CE provides large gradients when the predictions are far from true labels, enabling faster learning and accelerating convergence, which is essential for autonomous vehicular systems. The true label and predicted probability class is expressed in the equation (16).

$$L = -\sum_i y_i \log\ (y^{\mathrm{i}}) \qquad (16)$$

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where, y_i is the true label (1 for correct and 0 for others) and (y^{i}) is the predicted probability for class i. Also, the cross-entropy handles the class imbalance effectively to ignore the false negative rates.

3.16. Fault Isolation and Real-Time Decision Making

Once the faults are detected by the system, the affected nodes are completely isolated from routing paths and triggers the QHHO module for re-construction and re-optimization of routes. The fault nodes are flagged for replacement or maintenance. The status of the nodes will be updated every time and expressed in equation (17).

$$Node\ Status = \begin{cases} Faulty\ (isolate), if\ P_{fault} \geq \theta_{\mathrm{f}} \\ Normal\ (Active), if\ P_{fault} < \theta_{\mathrm{f}} \end{cases} \quad (17)$$

where, P_{fault} is predicted fault probability for a node and θ_{f} is fault detection threshold, Example (0.7), which ensures only high probability faulty nodes are isolated to minimize unnecessary re-routing. As QHHO dynamically triggers and reconfigures the new routing, the route selection function is formulated which is shown mathematical equation (18).

$$R_{optimal} = \arg{}^{max}_{R_i} \left(\frac{\overset{(Route\ Selection)}{PDR\ (R_i)}}{EC\ (R_i) + \lambda\ .\ \text{Latency}\ (\mathrm{R_i})} \right) \quad (18)$$

where, R_i is candidate routing path of PDR, Latency and Energy Consumption. The weight factor λ controls the trade-off between the energy and latency. The step-by-step process of GNN is shown in algorithm 2.

Input: Network Graph $G\ (V, E)$, Node Features X_v and Labels y

Output: Fault Status of Nodes

Pseudocode Steps:

1. $N = 1000$ and Simulation Area 1000m x 1000m
2. Construct adjacency matrix A and initialize feature matrix X_v
3. Apply Graph convolutional H^{l+1} to learn spatial features
4. Feed output to LSTM h_t for temporal pattern recognition
5. Calculate fault probabilities using P_{fault} softmax classifier
6. Compute CE loss function L and update model weights
7. Classify nodes and update $Node\,Status$ based on probability
8. Isolate faulty nodes $R_{optimal}$ and notify QHHO for re-route optimization
9. Output final fault detection and node status

Algorithm 2 GNN-Based Fault Detection

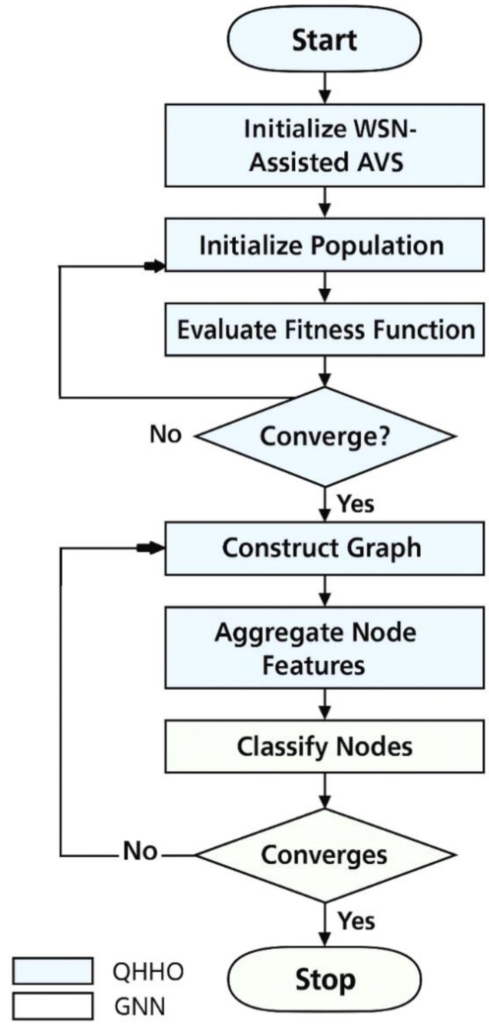

Figure 1 Flowchart of QHNN-GNN Model

3.17. Real-Time Implementation Steps

- Step 1: Data Preprocessing (Synthetic Dataset) and Graph Construction
- Step 2: Apply QHHO for Network Optimization
- Step 3: Fault Detection using GNN
- Step 4: Calculate Performance Metrics
- Step 5: Comparison with Existing Models

The flowchart of QHHO-GNN model is portrayed in Fig. (1). It begins with initiating the simulation environment setup for WSN-assisted AV systems, followed by the QHHO phase, where sensor nodes and vehicles are deployed in the simulation area. The initial parameters include node energy, transmission range, and mobility patterns. Then, the population (hawks) will be initialized using QHHO, and each

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candidate solution will represent the routing and resource allocation configuration. Evaluate the fitness function for each candidate based on KPM, and if convergence criteria aren't met, the algorithm loops back for further optimization. Once the process ends, create a graph model using GNN with node features. Aggregate the node features and classify them to predict the faulty nodes and those flagged for isolation. If the fault detection results are stabilized and no significant new faults are found, the process terminates; otherwise, the system loops back for further monitoring and analysis. In the final stage, the optimal routes and identified for network reliability and faulty nodes are detected for stable and reliable communication, enhancing AVS's safety.

4. RESULTS AND DISCUSSIONS

This section showcased the simulation results of the proposed protocol QHHO-GNN against the existing protocols HRWZ and EAHLFD, followed by a detailed discussion on how the proposed approach works to achieve the study's objective. Each metric is given with a performance metrics table and a comparative analysis graph for better visualization to the readers.

4.1. Performance Evaluation Metrics (PEM) and Simulation Settings

The efficiency of QHHO-GNN protocol is assessed using five key performance metrics such as Packet Delivery Ratio (PDR), Energy Efficiency (EE), Network Lifetime, Fault Detection Accuracy (FDA) and False Alarm Rate (FAR). These metrics are used for comparative analysis from existing and proposed work. The PEM are mathematically expressed in equation (19-23).

$$EE = \frac{(Initial\ Energy - Remaining\ Energy\ )}{(Time\ (Duration))} \tag{19}$$

$$Network\ Lifetime = \frac{Total\ Energy}{Energy\ Depletion\ Rate} \tag{20}$$

$$PDR = \frac{Total\ Packets\ Received}{Total\ Packets\ Sent}\ x\ 100 \tag{21}$$

$$FDA = \frac{TP+TN}{TP+TN+FP+FN} \tag{22}$$

$$FAR = \frac{FP}{FP+TN}\ x\ 100 \tag{23}$$

The simulation settings to evaluate the proposed QHHO-GNN framework using NS-3 and PyTorch is given in Table 2.

Table 2 Simulation Settings

Parameters	Values
Simulation Area	1000m x 1000m
Number of Sensor Nodes	1000
Initial Node Energy	2 Joules
Communication Range	100 meters
Size of the Packet	512 Bytes
Data Transmission Rate	250 Kbps
Mobility Model	Random Way Point
Simulation Time	1000 Seconds
Transmission Energy E_{tx}	50 nj/bit
Reception Energy E_{rx}	50 nj/bit
Amplifier Energy E_{amp}	100 pj/bit/m^2
Threshold Energy E_{th}	0.5 Joules
Fault Detection Threshold	0.7
QHHO Max Iterations	100
GNN Layers	2 GCN + LSTM + Softmax
Activation Function	ReLU
Optimizer	Adam
Loss Function	Cross Entropy
Batch Size	32 or 64
Learning Rate	0.001
Weight Decay	1e-5
Epochs	100-300
LSTM Hidden Units	64
GCM Hidden Units	64 r 128

4.2. Packet Delivery Ratio (PDR)

The proposed QHHO-GNN model consistently outperforms the existing HRWZ and EAHLFD models across all node densities. The proposed model maintains a high PDR of 92.6% even as the network size increases, while the other models drop in delivery ratio which is shown in Table 3 & Figure 2. This superior performance is due to efficient route optimization and intelligent fault node detection, which makes the model highly suitable for large-scale vehicular WSN-assisted environments.

Table 3 Node Counts vs PDR

Node Counts	HRWZ	EAHLFD	QHHO-GNN
100	74.8	79	96.4

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200	74.04444	78.75555556	95.7
300	73.28889	78.51111111	95
400	72.53333	78.26666667	94.3
500	71.77778	78.02222222	93.6
600	71.02222	77.77777778	93
700	70.26667	77.53333333	92.8
800	69.51111	77.28888889	92.7
900	68.75556	77.04444444	92.65
1000	68	76.8	92.6

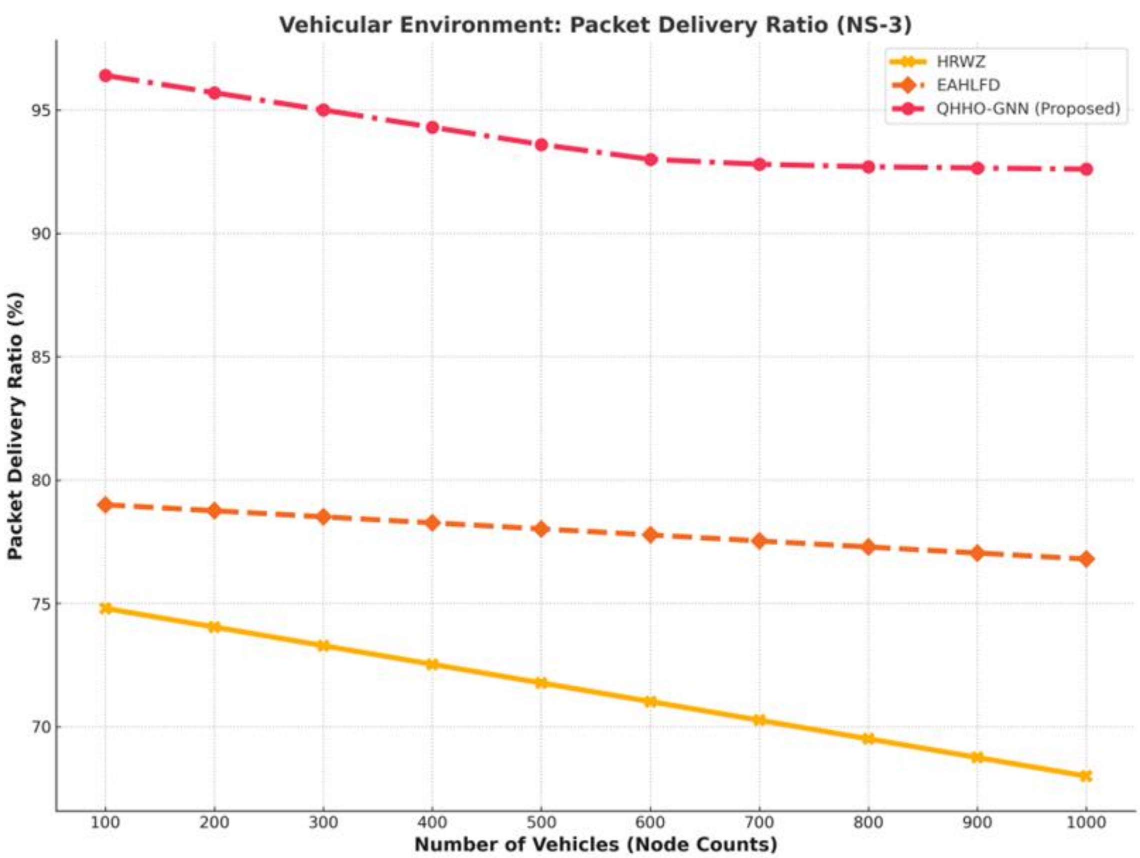

Figure 2 Node Counts vs PDR

4.3. Network Lifetime

The network lifetime comparative analysis clearly illustrates the superior performance of the proposed QHHO-GNN framework in an extended network compared to existing models. QHHO-GNN, attributed to its intelligent energy-aware routing and balanced node distribution, makes the 97.5% network lifetime significantly higher is portrayed in Table 4 & Figure 3.

Additionally, isolating faulty and energy-drained nodes prevents unnecessary energy consumption, ensuring prolonged network operation and making QHHO-GNN highly effective for energy-constrained WSN-assisted AVS.

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Table 4 Node Counts vs Network Life Time

Node Counts	HRWZ	EAHLFD	QHHO-GNN
100	72.5	76.8	97.5
200	72	74.9	96.8
300	71.5	73	96
400	71	71.1	95.3
500	70.5	69.2	94.5
600	70	67.3	93.7
700	69.5	66	93
800	69	65.3	92.7
900	68.5	64.8	92.4
1000	68	64.5	92.2

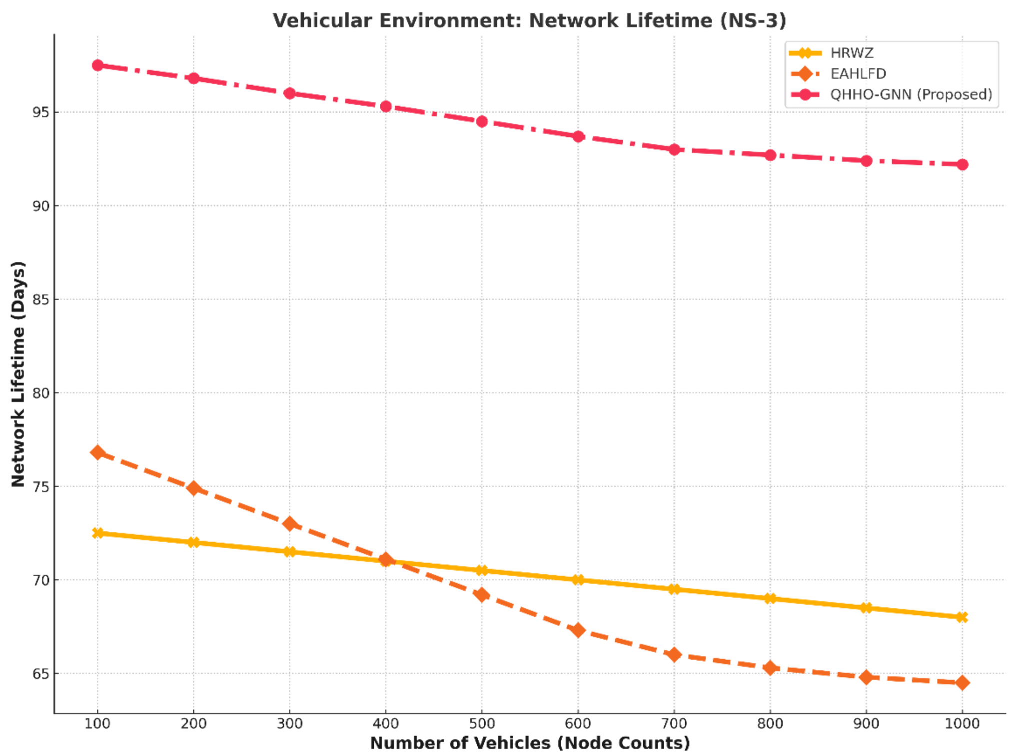

Figure 3 Node Counts vs Network Lifetime

4.4. Energy Efficiency (EE)

The comparative analysis of energy efficiency highlights the effectiveness of the proposed QHHO-GNN in managing the energy of sensor nodes across varying node densities. A remarkable 96.8% efficiency (Low Energy Consumption) results from optimizing routing strategies, which minimizes unnecessary energy transmissions and balances energy usage among the nodes. The results are showcased in Table 5 & Figure 4. The significant conservation of network resources ensures the prolonged and efficient operation of WSN assisted WVS and large-scale autonomous vehicle systems.

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Table 5 Node Counts vs Energy Efficiency

Node Counts	HRWZ	EAHLFD	QHHO-GNN
100	69.3	77.4	96.8
200	69.15556	77.33333	96.4
300	69.01111	77.26667	96
400	68.86667	77.2	95.5
500	68.72222	77.13333	95.1
600	68.57778	77.06667	94.6
700	68.43333	77	94.2
800	68.28889	76.93333	94
900	68.14444	76.86667	93.8
1000	68	76.8	93.7

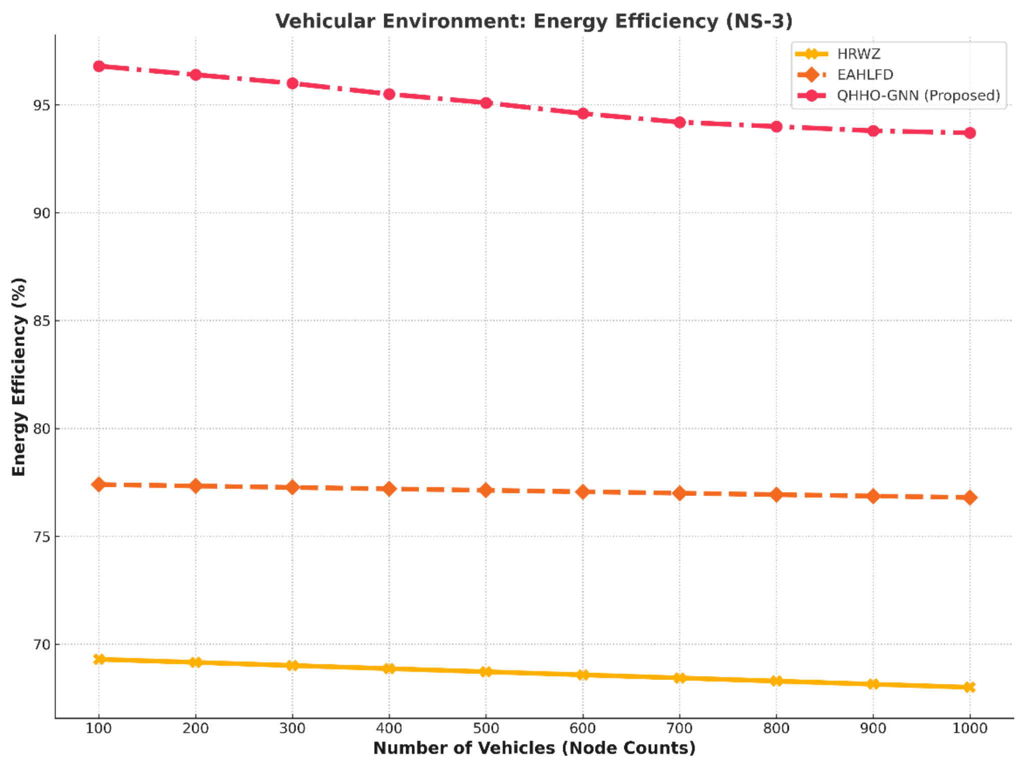

Figure 4 Node Counts vs Energy Efficiency

4.5. Fault Detection Accuracy (FDA)

The FDA analysis demonstrated the efficiency of the proposed QHHO-GNN model in consistently delivering precise fault node identification even in dense network environments, as shown in Table 6 & Figure 5. As the existing nodes face significant drops in fault identification, QHHO-GNN maintains a high accuracy of 96.2% in fault

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detection and isolation through advanced feature aggregation and temporal pattern recognition, which enables accurate differentiation between transient errors and actual faults. This timely fault detection enhances network stability and communication reliability in high dynamic AV environments.

Table 6 Node Counts vs FDA

Node Counts	HRWZ	EAHLFD	QHHO-GNN
100	71.2	78.5	96.2
200	70.84444	78.31111	95.6
300	70.48889	78.12222	95
400	70.13333	77.93333	94.5
500	69.77778	77.74444	94
600	69.42222	77.55556	93.5
700	69.06667	77.36667	93
800	68.71111	77.17778	92.7
900	68.35556	76.98889	92.5
1000	68	76.8	92.4

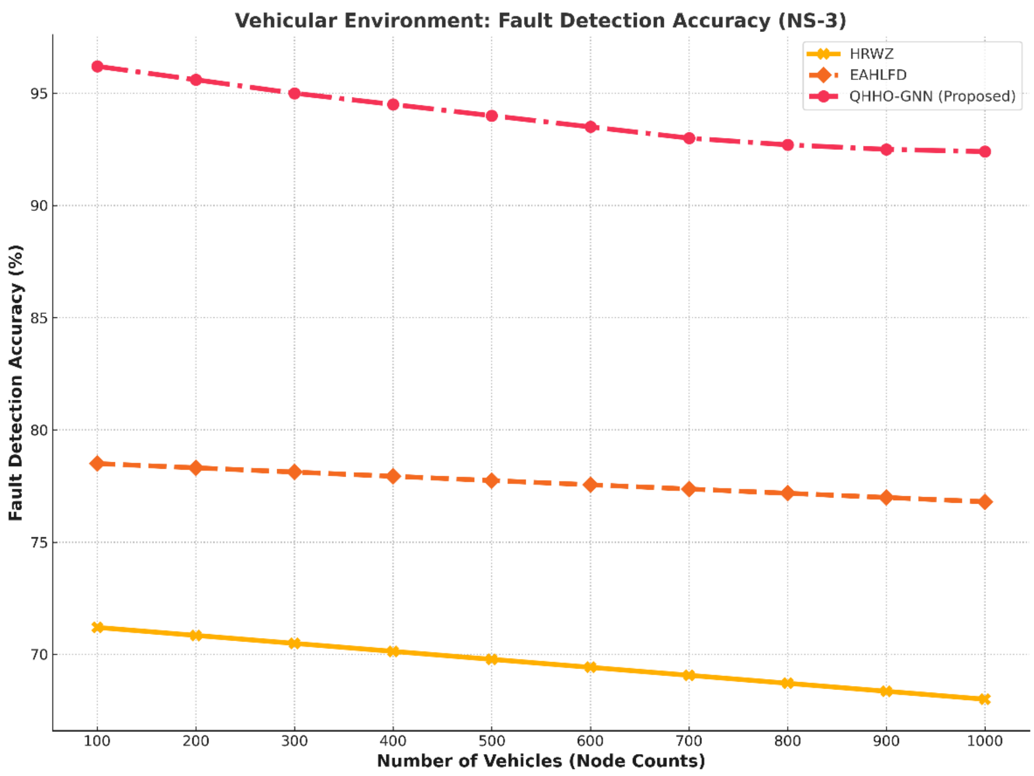

Figure 5 Node Counts vs FDA

4.6. False Alarm Rates (FAR)

The FAR analysis reflects the robustness of the QHHO-GNN model in minimizing the incorrect fault detections. As the network size increases, the existing models exhibit a sharp rise of 14% and 8.8% false fault detections, leading to an unnecessary re-routing process. The QHHO-GNN effectively controls the false alarm rates to 3.2% and 4.8% through its advanced feature learning method that dynamically discriminates between genuine and temporary anomalies, ensuring stable network paths, as portrayed in Table 7 & Figure 6. As a result, the interventions are minimized, preserving network efficiency and stability.

Table 7 Node Counts vs FAR

Node Counts	HRWZ	EAHLFD	QHHO-GNN
100	10.4	6.5	3.2
200	10.8	6.7	3.5
300	11.2	6.9	3.8
400	11.6	7.1	4.1
500	12	7.3	4.3
600	12.4	7.6	4.5
700	12.8	7.9	4.6
800	13.2	8.2	4.7
900	13.6	8.5	4.75
1000	14	8.8	4.8

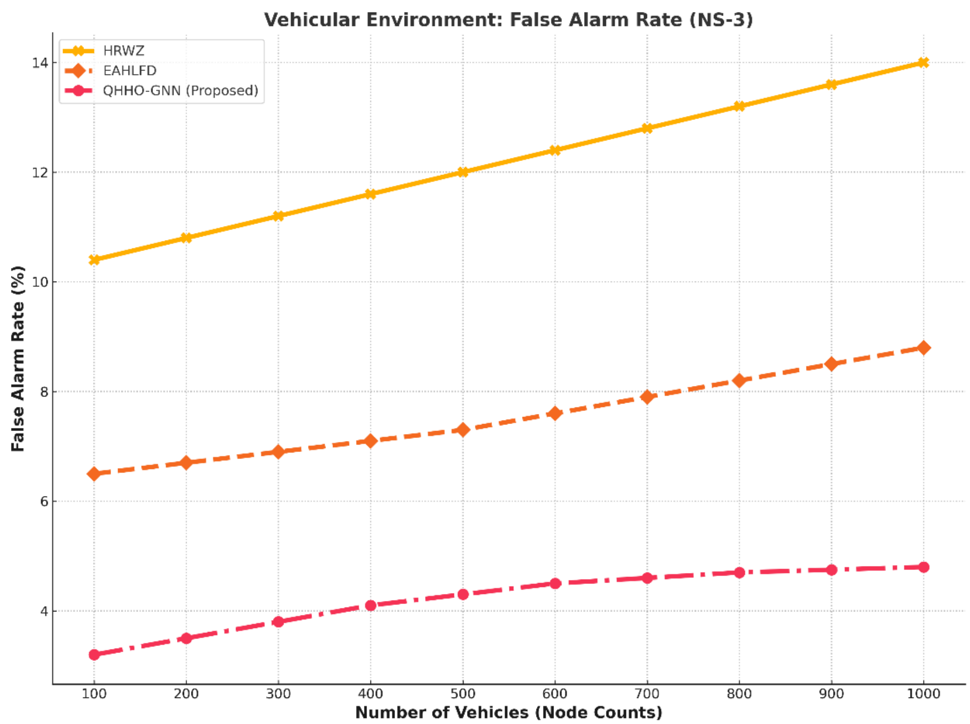

Figure 6 Node Counts vs FAR

5. CONCLUSION

This proposed hybrid deep learning framework, QHHO-GNN, enhances the network reliability in WSNs and achieves accurate fault detection in WSN-assisted Autonomous Vehicle Systems (AVS). By addressing the critical challenges of the existing models, the new model sets a benchmark in playing the dual role of dynamic network optimization and real-time fault detection using Quantum-Enhanced Harris Hawks Optimization and Graph Neural Networks. The energy-efficient routing and adaptive resource allocation of QHHO significantly improve the network stability under high mobile and resource-constrained environments. Simultaneously, GNN detects complex fault patterns accurately to minimize FAR and ensures timely decision-making in autonomous systems. This novel approach strengthens the resilience of autonomous vehicular communication but also shows the path for future intelligent and self-healing networks. The QHHO-GNN model outperforms all metrics (20% - 38% increase) than the existing models and contributes towards safer, reliable, and energy-efficient transportation systems that can adapt to a rapidly changing environment. issues like re-routing, security, data transmission also focused in this framework at the back end to achieve the objectives. Despite its effectiveness, the model incurs limitations, such as substantial processing resources for GNN training, which could limit its deployment in highly resource-constrained WSN environments.

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Authors

Dr. Eldho K J, working as an Assistant Professor and Research Guide in PG & Research Department of Computer Science at Mary Matha Govt Aided College, Mannathavady, affiliated with Kannur University, Kerala. He obtained his Ph.D degree from Bharathiar University in the year 2017. With a strong research background, he has published 5 books and 12 academic papers in Scopus and Web of Science indexed journals and hold three patents. Currently, he serves as a Research Supervisor at Kannur University, guiding four scholars in diverse fields such as NLP, Machine Learning, Data Mining, and Networking. Additionally, he is an active Board of Studies (BoS) member for various universities and autonomous colleges in Kerala and Tamil Nadu. He is also an active reviewer in various journals.

Dr. Nithyanandh S, working as an Assistant Professor in Department of Computer Applications (MCA) at PSG College of Arts and Science, Coimbatore. He is a distinguished academician with over 15 years of teaching and 9 years of research experience. He is specialized with Advanced Networking, AI, and Machine Learning. He obtained Ph.D. in Computer Science & Applications from Bharathiar University in the year 2020. He has published 12 research articles, 12 book chapters, authored 4 books, and holds 3 design patents and 1 utility patent publication. His passion for innovation and continuous learning ensures he remains at the forefront of technological advancements in AI, deep learning, and image processing. He is also a doctoral committee member in Bharathiar University, an active BoS and Academic Council member for various autonomous colleges in and around tamilnadu. He is an active review member for various peer-reviewed, scopus and WoS journals. He is also an active reviewer in IEEE and Springer conference series. nHe severs an an innovation ambassador expert in various colleges under institution's innovation council.

Dr. Kowsalya R is currently working as an Assistant Professor and Head of the PG Department of Computer Science at PSGR Krishnammal College for Women. She obtained her Ph.D. degree from Bharathiar University in 2022. With a strong research background, she has published 5 books and 7 academic papers in Scopus and Web of Science-indexed journals and holds three patents. Currently, she is recognized as a Research Supervisor at Bharathiar University. Her areas of interest include Advanced Networking, Machine Learning, and Deep Learning. Additionally, she actively serves as a Board of Studies (BoS) member for various universities and autonomous colleges across Tamil Nadu.

Dr. Donu Jose V holds a Ph.D. in Computer Science from Bharathiar University. Currently, she serves as an Assistant Professor at St. Mary's College, Sulthan Bathery, where she imparts her expertise and passion for the field to aspiring computer science students. Her research interests lies specifically in data mining and advanced simulations with multi predictions. Her academic pursuits contribute to the advancement of knowledge in computer science. Furthermore, she has actively participated in the global academic community by attending and presenting research papers at numerous international conferences. Her scholarly work is also reflected in her publications in prominent journals, including those indexed in Web of Science (WOS) and Scopus.

How to cite this article:

Eldho K J, Nithyanandh S, Kowsalya R, Donu Jose V, "Optimizing Network Reliability and Fault Detection in WSN-Assisted Autonomous Vehicle Systems Using QHHO-GNN Model", International Journal of Computer Networks and Applications (IJCNA), 12(4), PP: 614-630, 2025, DOI: 10.22247/ijcna/2025/37.