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Multi Agent Energy Management Prediction and Load Balanced Clustering Framework for WSNs using Quantum Bio-Inspired PSO Optimization

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Abstract

Objectives: To introduce an adaptive architecture for energy state prediction and a load balancing clustering framework for WSNs to address the prevailing challenges of high energy consumption, rapid node depletion, and inadequate cluster formation in large-scale sensor deployments. This aims maximize network lifetime and communication by integrating a multi-agent decision model with swarm optimization. **Methods:** The Quantum Particle Swarm Optimization (QPSO) reinforced clustering method, combined with the Multi-Agent Predictive Control (MAPC) model is utilized to enhance energy and load balance operations across all network rounds. Each cluster head functions as an autonomous agent to forecast the residual energy and estimated traffic load using lightweight predictive analytics. This helps proactive workload redistribution and prevents premature node depletion. QPSO tunes clustering weights, routing preferences and load balancing parameters through quantum-based particle movement and probabilistic exploration. Stable cluster heads, cluster sizes, and energy-efficient multi-hop routes are selected using the optimized decision vector. NS-3, MATLAB and Python are used as an evaluation tool for the proposed MPAC-QPSO. Simulation generated datasets are used for performance evaluation and a comprehensive comparative assessment is done with the existing models such as E-FLZSEPFCH, DEEC- IWQPSO, EAC-ILAP and MC-CRITIC-KM. **Findings:** According to simulation results, the proposed MAPC-QPSO model reveals superior performance with 98.8% network lifetime, achieves a packet delivery rate of 98.4% with 8.7s execution time, has a load-balancing accuracy of 97.8%, and reduces average latency to 41ms while extending the first-node-death lifetime to 2100 rounds and reducing overall energy consumption by approximately 15–20%. **Novelty:** The novel MAPC integrated with QPSO forms an intelligent, adaptive, and robust framework that effectively minimizes energy depletion and imbalance, reduces end-to-end communication delays, improves load balancing, and significantly extends the operational lifetime of Wireless Sensor Networks, which is highly suitable for resource-constrained environments.

Keywords: Wireless Sensor Networks; Energy Management; Clustering; Quantum-PSO; Multi-Agent Prediction; Load Balancing; WSN Routing

1 Introduction

Wireless sensors play a significant role in various sectors, including industrial automation, smart agriculture, real-time monitoring, healthcare, and environmental observation. Despite extensive research on energy-efficient clustering and routing in Wireless Sensor Networks, existing solutions remain largely reactive and struggle under dynamic traffic, uneven energy depletion, and fluctuating link conditions. The effectiveness of a sensor depends on how long the network can function with a limited battery and deliver the packets from S–D with minimal delay. Due to the increase in network size, unpredictable traffic occurs, and traditional WSN models struggle to balance the energy with the available nodes. Prevailing clustering and routing models such as E-FLZSEPFCH, IPSO-WSN, DEEC-IWQPSO, MC-CRITIC-KM etc. are fully based on static assumptions, limited decision-making, and reactive approaches, which increases energy depletion, poor delivery of packets, unstable clusters, communication bottlenecks, and reduced network lifetime. Traditional models respond after the energy drains or network congestion occurs rather than anticipating it. This results in battery drains near the base station, cluster overhead, and end-to-end performance decline. In order to address these limitations, this research proposed a novel MPAC-QPSO reinforced with quantum bio-inspired optimization. This model acts as an intelligent agent to predict the node's future energy and the expected data load.

An intelligent congestion control framework integrated with GANs[1], and metaheuristic optimization was proposed to regulate the network traffic in large-scale WSNs. Realistic traffic and clustering patterns are detected by GAN, and it synthesizes the congestion-aware routing behaviour to minimize the packet loss and data queue for transmission. The model shows a marginal improvement in throughput, latency, and reliability under huge traffic scenarios. A dual cluster-head DCK-LEACH[2] routing model with canopy cluster with K-means was proposed to overcome the sensitivity by partitioning the suitable cluster regions after the cluster boundaries are refined by K-means. Within each cluster, a primary and secondary cluster are elected to improve fault tolerance and premature link failure. By utilizing this technique, the network lifetime is boosted with minimal energy and better load distribution compared to classic LEACH schemes. A deep survey on energy-efficient protocols and resilient data transmission schemes[3] for WSNs is conducted, covering MAC, routing channels, sleep scheduling process, and cross-layer models. The analysis shows the impact on residual energy, packet delivery, delay, and robustness towards dynamic link failures under unified simulation settings and thresholds. The survey portrayed the integrated frameworks, which simultaneously addressed energy efficiency, reliability, and scalability in next-generation WSNs.

A unified MO-PSO with ECC and KRM based protocol[4] was introduced to minimize the node energy and maximize the authentication security in next-generation WSNs. ECC with a time-based key stretching and rotation mechanism is used to secure WPA2/PSK sessions. The NSL-KDD dataset was used for testing and validation, and the results show increased PDR with high secured authentication rates. A Load-Balancing Tree-Based Data Aggregation in Grid WSNs (LB-TBDAS)[5] model was proposed to minimize energy, limit the tree depth, and bound fan-out for child nodes. The MST algorithm is used to construct a tree where the sensing areas are divided into grid cells. Simulations showcased a 95% increase in network longevity and uniform energy consumption with high packet delivery. A two-stage Energy Efficient and Reliability Clustering Protocol (ECRP)[6] was proposed by combining CHS and ICR with the incorporation of residual energy, cluster distance, and cluster load in decision metrics. The model mitigates the packet loss and energy imbalance due to its strong quality and high residual energy. A hybrid quantum-based QHHO-GNN model[7] was suggested by the authors to learn the spatial and temporal relationships among the sensor nodes to enhance the early detection of link failures. This model works with autonomous vehicular systems for effective communication. QHHO helps for effective parameter tuning processes to reduce energy and support long-term operability in vehicular networks. A dynamic clustering and routing-based ABCP protocol[8] is introduced to minimize load balancing and energy. Here, the sensor nodes are modeled as particles, and the potential of the particles is based on residual energy and backlog. The protocol shows significant improvement in network lifetime and energy consumption compared to baseline LEACH variants in clustering design and sensor routing process. A multi-modal biometric authentication system[9] was developed by combining face and gait analysis to boost the security and usability in resource-constrained environments. Real-time implementation was carried out by using mobile cameras to capture face images and gait patterns from inertial sensors. A lightweight CNN extracts the features and classifies the false positives in a deep manner. Accuracy is improved with high resilience against spoofing attacks compared to static biometric models. The robust BIP-GANs protocol[10] boosts security and data transmission by utilizing bio-inspired algorithms. Malicious nodes are identified at an early stage, and the data is sent through the finest routing with the HARQ error recovery process. The simulations showcased minimal data loss with high network lifetime and robustness against stacks. The model proves high data protection and resilience in resource-constrained networks. Enhanced Fuzzy Logic E-FLZSEPFCH[11], a combined multi-path and routing protocol, was proposed towards stable cluster election in WSNs. The network zones are partitioned into different zones to apply a fuzzy logic engine by combining the residual energy, distance, and node density to elect the cluster heads. Multipath routes from each cluster head reduce the congestion and balance the load, which offers a balanced energy and increased packet delivery compared to LEACH, CHEF, and FLSE models. The model is highly active on zone-based clustering, fuzzy decision making, and multipath forwarding. The DEEC-IWQPSO model[12] dynamically allocates the cluster heads and schedules the transmissions based on the packet size, where the cluster resizing takes place under heavy traffic scenarios. In order to reduce the redundant communication and energy waste, the CH selection and resizing were carried out for huge data transmissions from source to destination. An alternative routing strategy is followed to enable optimal routing for packet delivery. The results show improved energy savings, network lifetime, and reliability. A dynamic M-CRITIC[13] clustering strategy is followed by employing K-means for cluster partitioning and the weighting method. The model automatically computes residual energy, distance to sink, and node density for all simulation rounds and shows a significant improvement in energy efficiency and network lifetime compared to LEACH and K-Means LEACH protocols. A balanced load is followed throughout the data transmission process. A thematic review is narrated below with a research gap analysis diagram (Figure 1).

Clustering Challenges and Load Balancing: Most works (LEACH variants, DEEC-IWQPSO, MC-CRITIC-KM, E-FLZSEPFCH, ERCP, DCK-LEACH) highlights energy and load imbalance leads to link failure.

Optimization Models Boosts Cluster Stability and Routing Performance: Quantum-PSO, Honey-Bee Optimization, Aurora-based ABCP, Ant Colony Optimization, and Canopy-K-Means outperformed in dynamic WSN conditions.

Multipath, Reliability-Aware, and Fault-Tolerant Routing: Few bio-inspired models emphasize that the network reliability, fault detection, and multi-path routing is essential for robustness and network performance.

2 Methodology

The proposed methodology is streamlined around two tightly coupled novel components, Multi-Agent Predictive Control and Quantum-behaved Particle Swarm Optimization with a primary focus on how the system intelligently manages node energy, predicts node behaviour, balances cluster loads, and stabilizes the routing decisions across WSNs. In this model, synthetic datasets are generated to represent node locations, network traffic loads, energy levels, and communication patterns for end-to-end data delivery. Also, detailed research is undertaken on how the MAPC agents are assigned to each cluster head to predict energy states and traffic demands. The predictions are then utilized for the finest routing selection and cluster formation. Later, QPSO is integrated to strengthen the decision-making process by evaluating the routing path and cluster head using a multi-objective fitness function that takes energy balance, link quality, communication cost, and predicted workload. This integrated process forms an adaptive learning and optimization loop that updates the decisions in real-time. In order to validate the MAPC-QPSO, the results are compared against prevailing load balancing models across various performance metrics.

2.1 Data Acquisition, Network Initialization, and Sensor State Integration

The foundation stage of the proposed MAPC-QPSO model is setting up the WSN environment where the operations are simulated, optimized, and evaluated. Spatial arrangement of sensor nodes is generated by initializing the energy states and defining the communication parameters and node state variables for predictive analytics and optimization. As the real-world deployments exhibit dynamic topologies with heterogeneous sensing requirements, a synthetic dataset is generated under multiple deployment scenarios to ensure that the proposed model performs consistently in all simulation rounds under heterogeneous, high-density, and dynamic conditions. During the Sensor Deployment and Spatial Initialization, the network begins with grid-based placement of N sensor nodes with 2D plane with the size of $L \times L$. Each node i is assigned to the coordinates which is expressed as $(x_i, y_i) \sim U(0, L)$ to ensure the uniform spatial distribution which helps to enable evaluation under dynamic WSN conditions. Depending on the data transformation scenario the Base Station (BS) is fixed in the central or fixed point. The node distance is computed as,

$$d_{ij} = \sqrt{(x_i - x_j)2 + \left(y_i - y_j\right)^2} \tag{1}$$

where, d_{ij} is required for routing, clustering and energy calculation. This distance metric is used by MPAC for load estimation and QPSO for CH selection and optimal routing process. As a part of initial energy assignment and residual energy tracking, each node is initialized with battery capacity $E_i(0) = E_0$, where E_0 is the initial node energy and during each simulation round t, the energy depletion is computed using first-order ratio level which is mathematically expressed in three forms such as Transmission (**Eq.2**), Reception (**Eq.3**) and Dynamic updation of residual energy (**Eq.4**) based on transmission and reception.

$$E_{tx}(k,d) = kE_{elec} + \begin{cases} k\epsilon_{fs} d^2, & d \leq d_0 \\ k\epsilon_{mp} d^4, & d \geq d_0 \end{cases} \tag{2}$$

$$Er_{rx}(k) = kE_{elec} \tag{3}$$

Table 1. Study on Specific Routing and Load Balancing Models

Model / Protocol	Techniques	Merits	Limitations
IWDARP Routing and Link Failure Detection Protocol [14]	Intelligent WaterDrop-based routing	Detects dynamic link failures and adapts routing paths to maintain QoS	Performance not fully evaluated for very large-scale or highly mobile WSNs
WQALO [15]	Weighted Quantum Ant Lion Optimization	Strengthens security and routing decisions through quantum-enhanced metaheuristic search	Requires higher computational effort, challenging for ultra-low-power nodes
DL Tongue Biometrics [16]	Deep learning-based tongue biometric authentication	Provides high-accuracy, continuous authentication for IoT healthcare systems	Focuses on security; does not address WSN energy, clustering, or routing issues
QE-Clustering Scheme [17]	Quantum EnhancedEnergy-efficient Clustering Scheme	Offers a comprehensive taxonomy to reduce energy consumption	Required more computational resources with high bandwidth to meet out the objective
AI-Driven Aggregation [18]	AI-driven energy-efficient aggregation and routing	Reduces redundant transmissions and maximizes lifetime through AI-based decision models	Model complexity may limit practical deployment on constrained sensor nodes
Virus Swarm Routing Model [19]	Virus-swarm inspired routing protocol	Improves robustness to dynamic link failures and enhances route diversity	Potentially higher control overhead in dense or large networks
Improved PSO Routing [20]	Improved Particle Swarm Optimization for routing	Extends network lifetime by optimizing relay selection and route cost	Convergence speed may degrade under rapidly changing network conditions
BLE Mesh + ACO [21]	Bluetooth Low Energy mesh combined with Ant Colony Optimization	Enables efficient multi-hop routing for BLE-based IoT and WSN integration	Mesh maintenance and ACO computation can limit scalability in very large deployments
Wormhole/Sinkhole Defense [22]	Real-time detection and response to wormhole and sinkhole attacks	Provides strong, real-time protection against critical routing attacks	Continuous monitoring introduces additional energy and processing overhead
SBO Clustering [23]	Binary Secretary Bird Optimization with Voronoi-based fitness	Achieves well-distributed cluster heads and improved energy balance	Complex fitness evaluation and binary encoding increase algorithmic complexity
Modular DEEC [24]	Enhanced Distributed Energy-Efficient Clustering (DEEC) with modular design	Improves DEEC's energy efficiency and offers flexible implementation for heterogeneous WSNs	Still sensitive to incorrect estimation of initial and residual energy heterogeneity
EEDC Scheme [25]	Energy Efficient Data Communication (EEDC) routing scheme	Offers high throughput and reduced energy consumption for IoT-oriented WSNs	Performance may degrade under high node mobility or bursty traffic
EAP-IFBA [26]	Energy Aware Protocol using Improvised Firefly Bio-inspired Algorithm	Combines adaptive sleep scheduling and secure routing to enhance QoS and lifetime	Additional processing for firefly optimization and security may increase latency
ISSA CH Selection [27]	Improved Sparrow Search Algorithm for cluster-head selection	Selects energy-balanced cluster heads with good global search capability	May cause frequent re-clustering if parameters are not carefully tuned
Evolutionary Routing Protocol [28]	Evolutionary routing protocol for heterogeneous IoT-enabled WSNs	Balances load and enhance QoS across heterogeneous nodes and traffic types	Evolutionary operations incur higher processing overhead and configuration effort
Adaptive FOA [29]	Adaptive Fruit Fly Optimization Algorithm for coverage and energy	Balances node energy and improves area coverage through adaptive parameter control	May exhibit slower convergence in very large-scale networks or highly dynamic environments

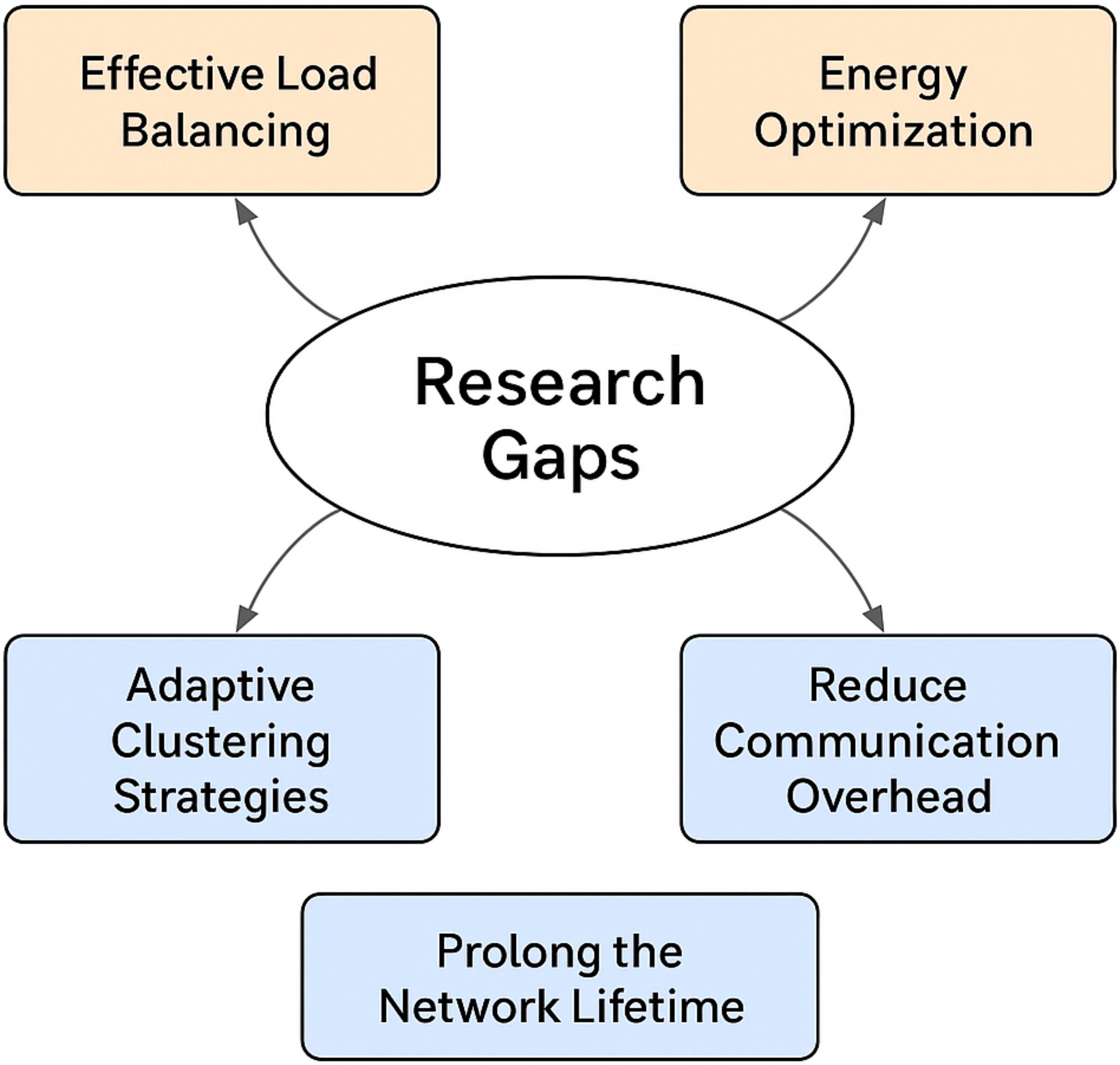

Fig 1. Research Gap Analysis

$$E_i(t+1) = E_i(t) - (E_{tx} + E_{rx}) \tag{4}$$

Based on the above residual energy measurement and updation, the energy vectors are passed to MPAC agents for prediction and QPSO for CH evaluation process.

As a next step towards data acquisition and traffic load generation, practical environments are simulated where each node generates the sensing data base don controlled stochastic process $\lambda_i(t) \sim Poisson(\mu)$, where, the task intensity is represented as μ. Traffic patterns such as burstiness and periodicity is generated to allow MAPC agent to predict the load to ensure proactive clustering and dynamic routing decisions. In sensor state integration stage for predictive decision making, each node maintains the state vector which is expressed as,

$$S_i(t) = [E_i(t), \lambda_i(t), d_{iBS}, CL_i(t)] \tag{5}$$

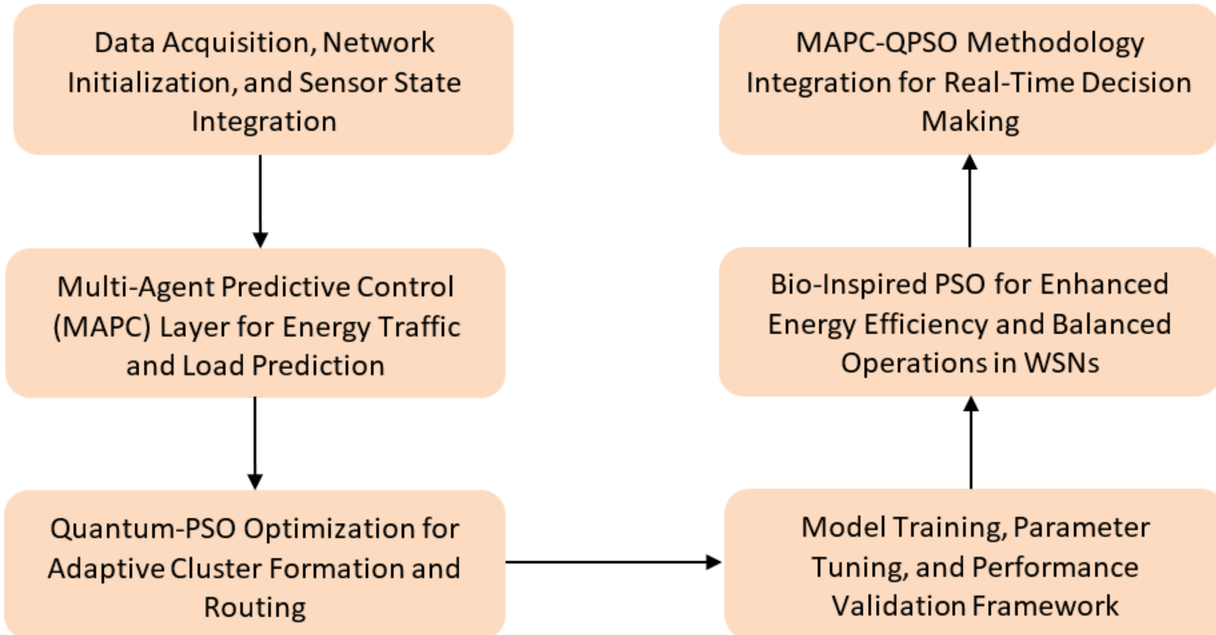

Fig 2. Work Flow Diagram of MPAC-QPSO

where, $E_i(t)$= residual energy, $\lambda_i(t)$= traffic load, d_{iBS}= distance to Base Station, $CL_i(t)$= current cluster level or role (CH, member, relay). The measured state vector is shared with MAPC agents enables the prediction of $\widehat{E_i}(t+1), \widehat{\lambda_i}(t+1)$ and the values are passed to QPSO optimization engine to calculate the fitness value of nodes for CH-roles and routing path decisions. Table 2 shows the clear dataset and description of synthetic data generated during simulations for training, testing and validation purpose. A sample set of 30 is given in the table, whereas N number of data is generated. Figures 1- 1 shows the clear visualization of Node Deployment + Cluster Visualization to show the WSN initialization, node positions, BS location, and QPSO-derived clusters, Residual vs. Predicted Energy to showcase the prediction intelligence and Link Reliability Heatmap for communication stability (Probability of successful transmission (0–1). Google Collab is used to generate the visualization graphs.

2.2 MAPC Layer for Energy Traffic Forecasting

The MAPC layer forms an analytical core of the proposed model enables the intelligent prediction of node behaviour and adaptive decision making during the cluster formation and routing process. As WSNs witness more fluctuations in energy and traffic generation, MAPC deploys agents to each cluster, node and region to maintain stability and increase the network lifetime by predicting the operational state of nodes. The input state representation is clearly given in **Eq.5**, where the agent uses the $S_i(t)$ information to model the future variations and compute the predicted energy and workload of node for the next operational round. Figure 6 shows the clear MAPC layer process in the proposed model.

2.2.1. Predictive Energy Modeling

Energy consumption in WSNs follows a prediction model by measuring transmission distance, traffic load and cluster role. MAPC employs linear-regression-based predictive function to calculate the energy level of each node which is mathematically expressed as,

$$\widehat{E_i}(t+1) = E_i(t) - (\alpha_1 \cdot \lambda_i(t) + \alpha_2 \cdot d_{iBS} + \alpha_3 \cdot \varphi_i(t)) \tag{6}$$

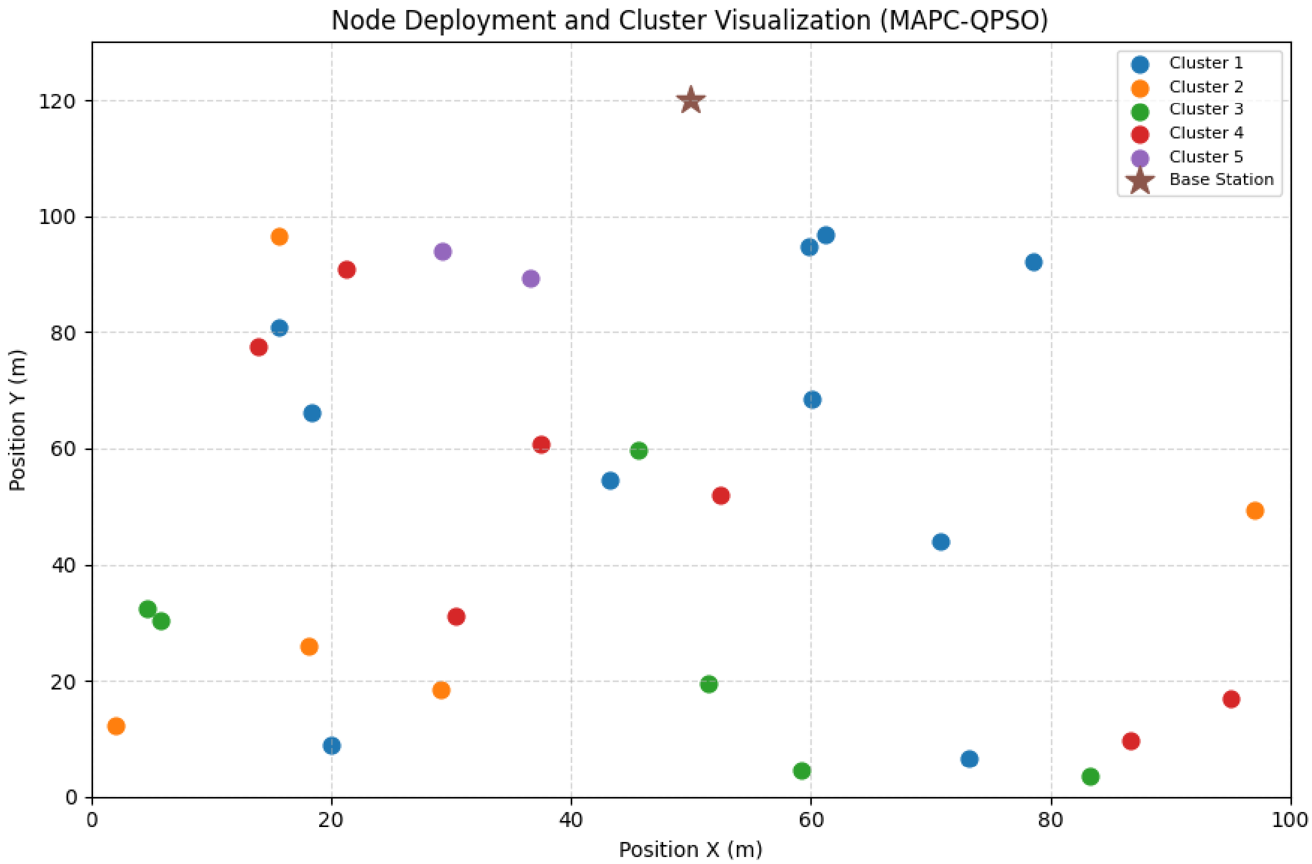

Fig 3. Node Deployment and Cluster Visualization

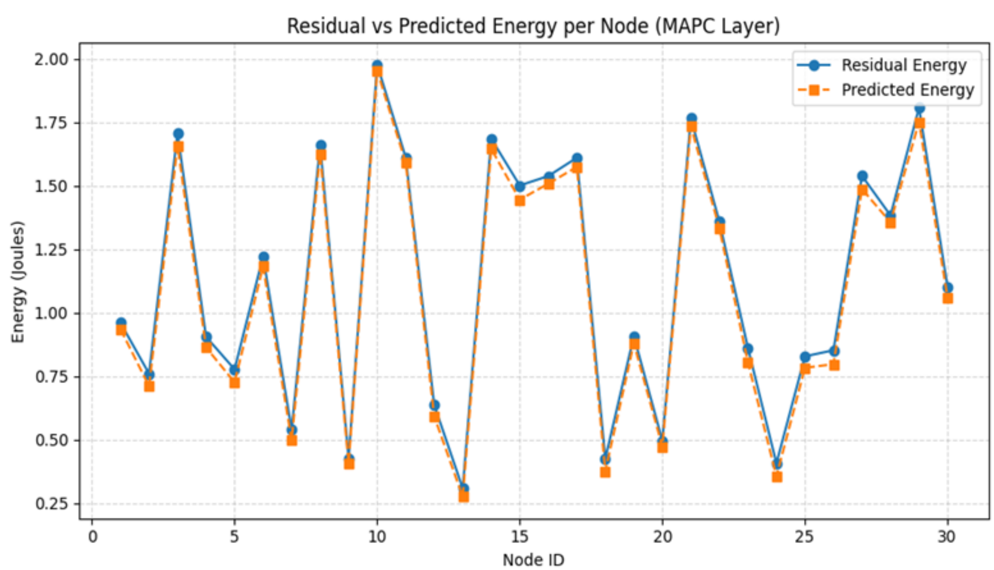

Fig 4. Residual vs Predicted Energy

Table 2. Dataset Feature Category and Attributes

Node ID	Pos-X	Pos-Y	Initial Energy	Residual Energy	Predicted Energy	Traffic Load	Node Role	Cluster ID	Distance to BS	Link Reliability
1	37.45	95.07	2	1.582	1.54	2	Member	3	25.83	0.92
2	73.2	59.87	2	0.944	0.901	4	Member	5	61	0.81
3	15.6	15.6	2	1.741	1.69	5	Cluster_Head	1	109.58	0.74
4	15.6	5.81	2	1.002	0.961	1	Member	1	120.42	0.72
5	5.81	86.62	2	0.647	0.601	3	Member	2	46.49	0.89
6	60.11	70.81	2	1.903	1.853	5	Relay	3	49.66	0.94
7	2.06	96.99	2	1.114	1.066	2	Member	2	51.1	0.87
8	83.24	21.23	2	0.815	0.771	1	Cluster_Head	5	102.65	0.78
9	18.18	18.34	2	1.327	1.281	3	Member	1	107.6	0.76
10	30.42	52.48	2	0.558	0.52	4	Member	3	69.03	0.84
11	43.2	29.12	2	1.876	1.821	1	Member	4	91.5	0.79
12	61.19	13.95	2	1.265	1.219	5	Member	5	107.73	0.73
13	29.12	61.19	2	0.922	0.883	2	Cluster_Head	3	61.28	0.88
14	45.61	78.52	2	1.734	1.689	3	Member	3	41.86	0.91
15	65.09	80.28	2	1.458	1.41	5	Member	4	42.21	0.93
16	9.67	83.24	2	0.684	0.643	1	Member	2	47.23	0.86
17	83.24	87.21	2	1.992	1.948	2	Relay	4	40.92	0.95
18	42.19	2.12	2	1.305	1.259	4	Member	5	118.12	0.71
19	61.19	96.99	2	0.739	0.697	3	Member	4	23.09	0.94
20	4.81	30.42	2	1.622	1.578	2	Cluster_Head	1	99.64	0.77
21	96.99	60.11	2	0.931	0.891	5	Member	5	64.37	0.83
22	11.62	11.62	2	1.287	1.241	3	Member	1	113.89	0.75
23	77.68	45.61	2	1.015	0.969	2	Member	5	80.32	0.82
24	20.13	71.52	2	0.512	0.477	4	Member	2	54.32	0.88
25	54.67	91.23	2	1.689	1.643	1	Cluster_Head	4	29.4	0.96
26	12.54	52.19	2	0.843	0.805	2	Member	2	74.83	0.85
27	91.23	12.54	2	1.948	1.896	3	Member	5	115.13	0.72
28	39.87	67.45	2	0.679	0.64	4	Relay	3	53.17	0.9
29	57.34	23.19	2	1.204	1.16	1	Member	5	98.41	0.79
30	22.76	93.58	2	0.964	0.922	3	Member	2	33.66	0.92

(Data From: Simulation Rounds / Sample = 30 Nodes)

where, $\alpha_1, \alpha_2, \alpha_3$= learned coefficients, $\varphi_i(t)$= energy penalty based on cluster role, CH nodes consume more energy and Relay nodes experience multi-hop overhead. The penalty function is derived as,

$$\varphi_i(t) = \begin{cases} \lambda_{CH}, & if\, node\, is\, CH \\ \gamma_{relay}, & if\, relay\, node \\ \gamma_{member}, & otherwise \end{cases} \tag{7}$$

where, $\varphi_i(t)$ modeling allows the MAPC to predict the nodes which are likely to be overloaded in the next round.

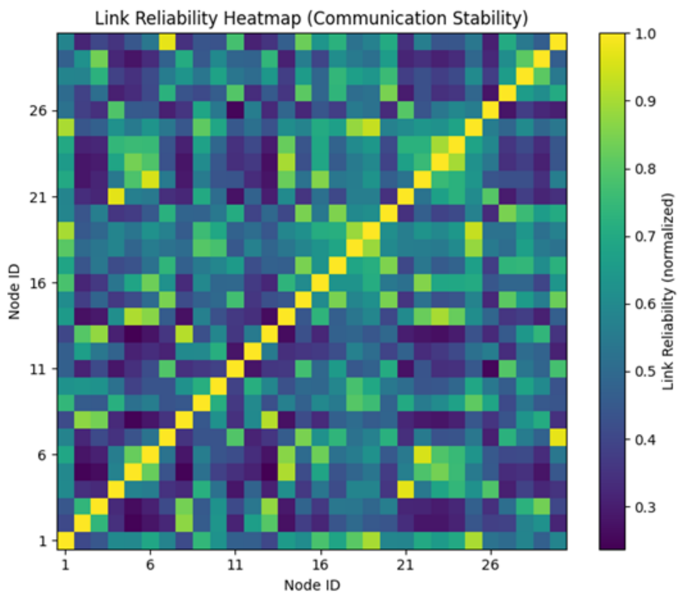

Fig 5. Link Reliability Heatmap

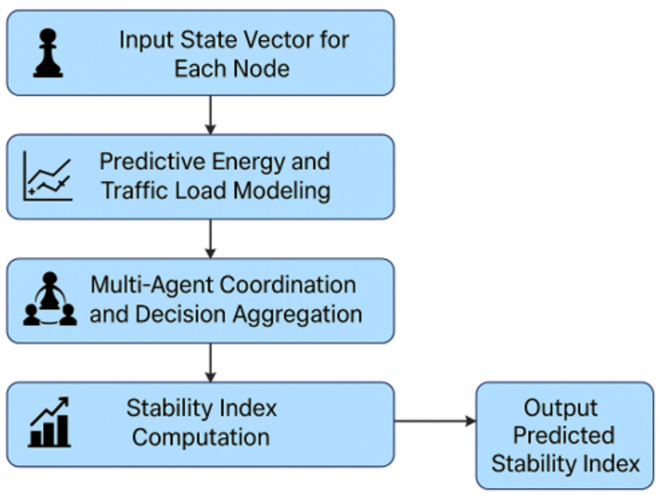

Fig 6. MAPC Layer

2.2.2. Traffic Load Forecasting

In addition to MAPC, simple autoregressive estimator technique is used to model the frequency and data generation which is computed as,

$$\widehat{\lambda_i}(t+1) = \beta_o + \beta_1 \lambda_i(t) + \beta_2 \Delta\lambda_i(t) \tag{8}$$

$$\Delta\lambda_i(t) = \lambda_i(t) - \lambda_i(t-1) \tag{9}$$

where, $\Delta\lambda_i(t)$) traffic forecasting helps the system to prevent bottlenecks, distributes cluster load and anticipates the congestion in a robust manner.

2.2.3. Multi-Agent Coordination and Decision Aggregation

Each assigned agent calculates the predictions for each node under its control. The predictions are integrated through a weighted consensus mechanism which is mathematically expressed as,

$$\Psi_i(t+1) = w_1\widehat{E_i}(t+1) + w_2\widehat{\lambda_i}(t+1) \tag{10}$$

where, $\Psi_i(t+1)$ denotes the predicted stability index for the assigned node i. The lower result values indicates that the nodes are likely to die or highly congested.

2.2.4. Final Output Vector

The final output vector resulted in selecting the most sustainable CHs, avoid nodes predicted to depreciate, optimize routing paths with future-awareness and balance load across all clusters which is achieved using the below equation.

$$\Omega_i(t) = [\widehat{E_i}(t+1), \widehat{\lambda_i}(t+1), d_{iBS}, \Psi_i(t+1)] \tag{11}$$

where, $\Omega_i(t)$ will be used by QPSO for parameter tuning and optimization process.

2.3 QPSO Optimization for Adaptive Cluster Formation and Adaptive Routing

The QPSO layer functions as the core optimization engine of the proposed framework where it transforms the predicted outputs yield from MAPC ($\widehat{E}_i(t+1)$, $\widehat{\lambda}_i(t+1)$, and $\Psi_i(t+1)$) into optimal CH selections and routing pathways. QPSO incorporates quantum principles to enable the probabilistic position transitions to increase the global search ability and preventing the swarm from premature convergence. In this QPSO layer, each particle refers the potential CH assignment matrix for the entire network, and the suitability is measured using multi objective fitness function which has predicted energy, traffic load, communication cost and load distribution parameters. This optimization process anticipates the future network behaviour instead of high dependency on present state values. The QPSO layer updates particle positions using Quantum Delta Potential Model (QDPM), which allows particles to probabilistically 'tunnel' toward promising solutions. The local attractor is derived from both the personal and global best solutions, while the mean-best position ($mbest$) steers the overall search direction of the swarm.

This QPSO's probabilistic movement significantly boosts the exploration of candidate CH sets. The fitness evaluation incorporates penalties to avoid selecting nodes that may become unstable in the next round due to low predicted energy or high predicted traffic. After the swarm reaches convergence, an optimal list of cluster heads (CHs) is selected by minimizing a cost function that balances multiple objectives. Once this list is ready, the system forms clusters by linking each node to the closest and most stable CH. Routing paths are then fine-tuned using a cost metric that takes into account not just distance but also predicted energy levels and the reliability of the communication links. At this stage, the QPSO layer converts predictive insights into precise clustering and routing decisions, promoting balanced energy consumption, higher packet delivery, and enhanced network lifetime.

Algorithm: QPSO Optimization for CH selection and Routing
Step 1: Initialization
Assigning each particle to a random CH selection vector $X = [x_1, x_2, \ldots, x_N]$
Initialize $pbest$ and $gbest$ - For personal and global position
Step 2: Compute MPAC Fitness
For each candidate solution compute,
$F(X) = w_1E_{avg} + w_2\Psi_{net} + w_3C_{comm} + w_4B_{load}$
$E_{avg} = \frac{1}{K}\sum_{i\epsilon CH}\widehat{E}_i(t+1)$ and $\Psi_{net} = \frac{1}{N}\sum_{i=1}^{N}\Psi_i(t+1)$
Step 3: Compute Local Attractor
$p_i(t) = \phi \cdot pbest_{\mathbf{i}}(t) + (1-\phi)\cdot gbest(t)$, where $\phi \sim U(0,1)$
Step 4: Compute mean-best position
$mbest(t) = \frac{1}{P}\sum_{i=1}^{P} pbest_i(t)$
Step 5: Quantum Position Update
For each particle, $x_i(t+1) = p_i(t) \pm \beta \mid mbest(t) - x_i(t) \mid \ln\left(\frac{1}{u}\right)$, where $u \sim U(0,1)$
Step 6: Penalty Based Risk Avoidance
$Penalty_i = \frac{1}{\widehat{E}_i(t+1)} + \widehat{\lambda}_i(t+1)$ - Adding fitness for weak nodes.

Step 7: Check Convergence
$|F(gbest(t+1)) - F(gbest(t))| < \epsilon$
Step 8: Select optimal CH set
$CH^* = argminF(X)$
Step 9: Formation of Cluster
$d_{ij} = \sqrt{(x_i - x_j)2 + (y_i - y_j)}^2$
Step 10: Routing Optimization
Select the next-hop j that minimizes, $Cij = \alpha d_{ij} + \beta \frac{1}{RL_{ij}} + \frac{1}{\widehat{E}_i(t+1)}$

The QPSO layer uses optimal predictions to make robust decisions on clustering and routing formations. This helps to maintain balanced energy utilization across the network which increases the success rate of packet delivery, and contributes to a longer network lifespan.

2.4 MAPC-QPSO Methodology Integration for Real-Time Decision Making

Real-time decision making is achieved through an iterative communication process between MAPC and QPSO layer. Initially, MAPC predicts the upcoming network state followed by QPSO uses the predicted values to build an updated clustering and routing structure. The chosen cluster heads announce their roles, where nodes join the clusters that fit them best, and routing tables are updated with low overhead. During the same cycle, the system collects new sensing data, updated energy consumption, and other network feedback. This information is fed back to MAPC to enable the agents to refine their predictive models. This creates closed adaptive feedback where predictions guide each optimization step to improve the future predictions. The primary advantage of this multi-layered approach is to maintain stable operations across multiple simulation rounds.

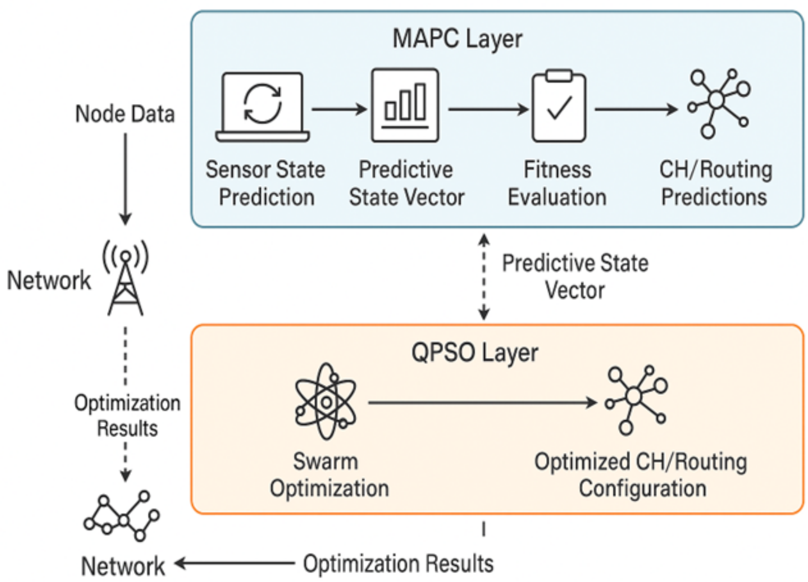

Fig 7. MPAC-QPSO Multi-Layer Architecture

2.4.1. Closed-Loop Real-Time Adaptation

The system forms a closed feedback loop which is given below to ensure the WSN remains adaptive even under challenging operations such as Sudden energy drops, Traffic surges, Link degradation and uneven load distribution.

In a feedback Loop:

- Nodes transmit data $\rightarrow$ energy reduces $\rightarrow$ MAPC predicts next-round state
- MAPC outputs predictions $\rightarrow$ QPSO generates optimized CHs and routes

- Nodes operate based on QPSO output $\rightarrow$ new states collected
- Loop repeats every round in real-time

The MAPC-QPSO process avoids abrupt changes in cluster head roles or routing decisions by aligning the decisions with predicted states. This reduces the cost of reconfiguration and keeps the communication overhead very low. It also helps the uniform distribution of energy. In addition, the real-time link between prediction and optimization handles challenging WSN behaviours such as shifts in node load, rapid energy drops, short periods of congestion, and communication fading. In short, the MAPC–QPSO model forms an adaptive and real-time engine for clustering and routing process in WSNs. By combining prediction with optimization, it supports decisions that consider both short-term needs and long-term stability. This new approach leads to longer network lifetime, robust packet delivery, and reliable operation in dynamic topology changing conditions.

2.5 Model Training, Parameter Tuning, and Performance Validation Framework

A structured training and tuning process is carried out for the proposed MAPC-QPSO framework to keep its predictive models accurate and its optimization process stable in every network simulation round. Training begins with a synthetic dataset created during the network setup and later simulation cycles. In each round, every node produces a state vector. Over time, these vectors form a dataset that captures changes in residual energy, traffic levels, link reliability, and cluster assignments. This gives the system a concrete view of how the network evolves across rounds. The complete dataset is represented as,

$$D = S_i(t) = [E_i(t), \lambda_i(t), d_{iBS}, CL_i(t)]^{N,T}{}_{i=1,\ t=1} \tag{12}$$

where, N is number of nodes and T is total number of simulation rounds. As the node states evolve round-by-round, a rolling window time series method is adapted. For each node i, MPAC uses the last K rounds to predict the next one which is mathematically expressed as,

$$X_i = [S_i(t-k), \ldots, S_i(t-1)], y_i = Si_i(t) \tag{13}$$

where, the dataset is divided into 70:15:15 for training, validation and testing process. This approach ensures that MAPC learns from multi-round behavioural patterns instead of relying on single static states.

- 70% Training Set is used to learn the regression coefficients for energy and load predictors
- 15% Validation Set is used for tuning MAPC forecasting parameters
- 15% Testing Set is used to evaluate prediction accuracy before integration with QPSO

The model employs a lightweight training models such as linear regression and autoregressive predictors which best suits for real-time predictions, The energy prediction and traffic load prediction process is computed as,

$$\widehat{E}_i(t+1) = \theta_0 + \theta_1 E_i(t) + \theta_2 \lambda_i(t) + \theta_3 d_{iBS} \tag{14}$$

$$\hat{\lambda}_i(t+1) = \beta_0 + \beta_1 \lambda_i(t) + \beta_2 (\lambda_i(t) - \lambda_i(t-1)) \tag{15}$$

where, the parameters θ and β are trained using Ordinary Least Squares (OLS), $\Theta = (X^T X)^{-1} X^T y$. Both regression models keep updated by every 50 simulation rounds to adapt the newly evolving behaviour. On the other hand, QPSO tuning is carried out by three key parameters such as, Swarm Size (P), Contraction–Expansion Coefficient (β) and Iteration Count per Round.

Here, Swarm Size (P) is set to P = 20 or 30 (one particle per candidate CH solution) and β controls exploration vs exploitation which is expressed as,

$$\beta(t) = \beta_{\max} - \frac{t}{T}(\beta_{\max} - \beta_{\min}) \text{ with } \beta_{\max} = 1.0 \text{ and } \beta_{\min} = 0.5 \tag{16}$$

QPSO runs 50 iterations per simulation round, where Personal best $(pbest)$ and global best $(gbest)$ are updated at each iteration. After validating 3000 simulation rounds, the prediction accuracy is evaluated using MAE, MSE and RMSE which is derived using the below equations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i}^2) \tag{17}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\, y_i - \widehat{y_i}^2| \tag{18}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i}^2)}\ or\ \sqrt{MSE} \tag{19}$$

Table 3. Experimental Settings for MAPC-QPSO

Parameters	Description	Value / Range
Number of Sensor Nodes (N)	Total deployed nodes in WSN	150
Deployment Area	Square sensing region	100 m $\times$ 100 m
Base Station Position	Static BS located outside the sensing area	(50, 120)
Initial Energy (E_o)	Battery capacity per node	2.0 Joules
Residual Energy $(E_i(t))$	Dynamic energy per round	$0.05 - 2.0$ Joules
Packet Size (k)	Data payload size	4000 bits
Transmission Energy (E_{tx})	Radio energy for sending packets	50 nJ/bit
Reception Energy (E_{rx})	Radio energy for receiving packets	50 nJ/bit
Free Space Coefficient (ε_fs)	Used for short-distance propagation	10 pJ/bit/m^2
Multipath Coefficient (ε_mp)	Used for long-distance propagation	0.0013 pJ/bit/m^4
Traffic Load (λ_i)	Packets generated per node per round	$1 - 5$ packets
Distance to BS (d_{iBS})	Computed Euclidean distance	$10 - 150$ m
Cluster-Head Candidates	Number of nodes evaluated per round	$15 - 20$ nodes
MAPC Prediction Interval	Forecast window	1 round ahead
QPSO Iterations	Optimization cycles per round	50
Node State Vector	Attributes used for MAPC + QPSO	Residual Energy, Traffic Load, Distance to BS, Cluster Role
Simulation Rounds	Total operational cycles	3000 rounds
Network Density	Nodes per square meter	0.015 nodes/m^2

Dataset Source: WSN NS-3 Simulation Generated Dataset: 150 (Samples in Table 2)

The experimental WSN settings include 150 heterogeneous sensor nodes placed in a uniform layout across a $100 \times 100\ m$ area. Each node starts with $2J$ of energy. This density gives sufficient cluster formation, diverse variation in load, and adequate activity to evaluate how well the MAPC–QPSO system makes decisions.

2.6 PSO Reinforcement for Energy Efficiency and Balance in Real-Time Operations in WSNs

The Bio-Inspired quantum based PSO is the is a key component of the proposed framework which adds a dynamic and adaptive method for maintaining the WSN's energy awareness and load balance. While the MAPC layer predicts future node conditions, the PSO engine uses these predictions to carry out decisions during each round and adjusts cluster formation, assigns cluster-head roles, and updates routing paths as the network changes. PSO is inspired by natural swarming behavior, where coordinated movement emerges through simple local rules. This fits the network environment as each sensor node operate on its own and work towards lower energy use and stable connectivity. During real-time operation, PSO runs at the beginning of each communication round.

- Nodes first send their energy and load values.
- The particles then create new candidate sets of cluster heads.
- The fitness of each set is calculated using the current node conditions.
- After that, PSO updates particle positions and velocities.
- The system then applies the best cluster head set for the next round.

2.6.1. MAPC-QPSO Step by Step Process

Input:

Numer of nodes: N

Simulation rounds: T

Deployment area: $L \times L$

Initial energy: E_0

BS position: (x_{BS}, y_{BS})

Radio parameters: $E_{elec}, \epsilon_{fs}, \epsilon_{mp}, k$

MAPC parameters: $\Theta = (\theta_0, \theta_1, \theta_2, \theta_3)$, $\mathrm{B} = (\beta_0, \beta_1, \beta_2)$

PSO parameters: swarm size P, iterations I_{max}, β_{max}, β_{min}, weights $w_1, \dots, w_4$

Cost weights: α, β, γ for routing

Step 1: Network Initialization

For each node $i = 1, \dots, N$:

Randomly deploy in the field: $(x_i, y_i) \sim U(0, L)$

Initialize energy: $E_i(0) = E_0$

Compute distance to BS: $d_{iBS} = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2}$

Set initial role $CL_i(0) =$ Member.

Step 2: Initialize QPSO Swarm

Each particle $p = 1, \dots, P$ encodes a CH selection vector:

$X_p = [x_{p1}, x_{p2}, \dots, x_{pN}], x_{pi} \in \{0,1\}$ Randomly initialize X_p, set $pbest_p = X_p$,

and choose the best as $gbest$.

Step 3: For Each Round $t = 1, \dots, T$

Data Generation and Energy Update

For each node i,

Generate traffic: $\lambda_i(t) \sim \text{Poisson}(\mu)$

Update residual energy: $E_i(t) = E_i(t-1) - (E_{tx} + E_{rx})$

Build state vector: $S_i(t) = [E_i(t), \lambda_i(t), d_{iBS}, CL_i(t)]$

MAPC Prediction Using trained MAPC models

Using trained MAPC models:

Energy prediction: $\hat{E}_i(t+1) = \theta_0 + \theta_1 E_i(t) + \theta_2 \lambda_i(t) + \theta_3 d_{iBS}$

2.6.2. Performance Evaluation Metrics

The performance evaluation of the MAPC-QPSO model shows its effectiveness, stability, and ability to work in real-time across dynamic network topologies and various simulation rounds. The setup comprises 150 sensor nodes deployed across a $100 \times 100\ m$ area to predict energy use, load changes, routing stability, and packet delivery under various network conditions. The evaluation process is based on the synthetic dataset produced during simulation. For each round, the node provides a state vector which includes residual energy, traffic load, link reliability, and distance to the base station. These values serve as steady inputs for both the MAPC prediction layer and the QPSO optimization layer. Several performance metrics are used to assess the model's behaviour which are given below. Python, NS-3 simulation logic, and Matplotlib tools are used for implementation, data generation, optimization, comparative analysis and visualization. Figure 8 shows the success and failure rate of the proposed MAPC-QPSO model with 3000 simulation rounds.

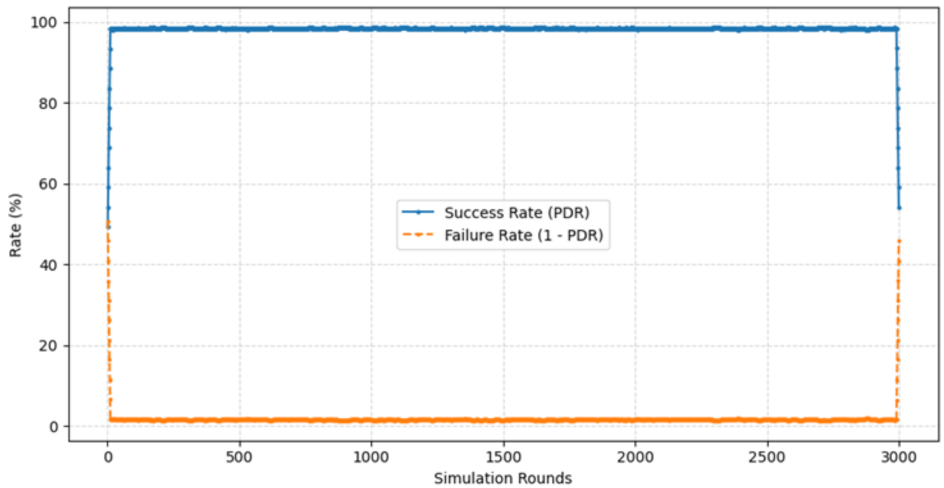

Fig 8. Success and Failure Rate of MAPC-QPSO Model in 3000 Simulation Rounds

Network lifetime is evaluated in three stages such as FND, HND and LND.

$$\text{First Node Death (FND): FND} = min\{\, t \mid E_i(t) = 0 \,\} \tag{20}$$

$$\text{Half Node Death (HND): HND} = min\{\, t \mid \textstyle\sum_{i=1}^{N}\ 1[E_i(t) = 0] = \frac{N}{2}\} \tag{21}$$

$$\text{Last Node Death (LND): LND} = min\{\, t \mid \textstyle\sum_{i=1}^{N}\ 1[E_i(t) = 0] = N\} \tag{22}$$

$$\text{Overall Network Lifetime: } Lifetime = LND \tag{23}$$

$$\text{Execution time per round: } T_{round} = T_{MPAC} + T_{QPSO} + T_{routing} \tag{24}$$

$$\text{Total execution time: } T_{total} = \textstyle\sum_{t=1}^{T}\ T_{round}\,(t) \tag{25}$$

$$\text{Average: } T_{avg} = \frac{T_{total}}{T} \tag{26}$$

$$\text{Load-balancing accuracy: } LBA = (1 - \frac{Load\ Balance\ Error}{\bar{n}}) \times 100 \tag{27}$$

$$\text{Latency: } Latency = \frac{1}{P_{received}} \sum_{i=1}^{P_{received}} (t_{receive}^{(i)} - t_{send}^{(i)}) \tag{28}$$

$$\text{Packet Delivery Ratio (PDR): } PDR = \frac{P_{received}}{P_{sent}} \times 100 \tag{29}$$

3 Results and Discussions

A comprehensive qualitative and quantitative evaluation of the proposed MAPC-QPSO model is showcased in this section with proven results. The results emphasize the model's predictive intelligence, cluster stabilization, load balancing, and route efficiency under diverse WSN conditions. The model is compared against prevailing clustering and routing protocols such as E-FLZSEPFCH [11], DEEC-IWQPSO [12], EAC-ILAP [12], and MC-CRITIC-KM [13], which have been focused on CH selection, load balance, and adaptive routing. The results showcased that the proposed model outperforms by maintaining high load balancing and operational accuracy with minimal energy consumption and delay. Sudden traffic changes are managed where node-level energy drops are predicted at an early stage to avoid re-routing and re-transmission processes. Table 4- 4 show the comparative results of the existing and proposed models, and Figure 9 shows the seven-panel graphical abstract.

3.1 Packet Delivery Ratio (PDR)

Packet Delivery Ratio analysis is the key measure of routing efficiency and overall stability in WSNs. Table 4 shows the comparative analysis of the proposed MAPC-QPSO, where the value close to 98-99% across different simulations and node densities. This is achieved with a combined effect of MACP's prediction and QPSO's optimization which lowers the chances of link failure, energy drain and CH load and traffic. The existing approaches show a clear decline in PDR when the simulation goes beyond 1500 where it depends mostly on fixed thresholds. MAPC predicts the unstable nodes and unreliable routing paths at an early stage to avoid communication which helps reducing the retransmission process and packet loss in a robust manner. Next-hop selection is improved by QPSO optimization provides more consistent long-range transmissions with a high PDR. The proposed model keeps a string PDR though the network range increases without dropping reliability. Optimal routing paths are selected to increase the link stability and network performance.

Table 4. Packet Delivery Ratio Analysis

Simulation Rounds with NC=150	E-FLZSEPFCH	DEEC-IWQPSO	EAC-ILAP	MC-CRITIC-KM	MAPC-QPSO (Proposed)
500	80.8	82.5	84.2	85.8	98.4
1000	80.1	81.8	83.4	85.1	98.2
1500	79.2	81.0	82.6	84.6	98.1
2000	78.5	80.2	81.9	84.0	97.9
2500	77.8	79.6	81.3	83.4	97.5
3000	77.1	78.9	80.7	82.9	96.9

3.2 Network Lifetime

The comparative analysis of network lifetime performance is portrayed in Table 5. A significant improvement is witnessed in FND, HND, and LND rounds with the node density of 150. The proposed model achieves an FND of approximately 2100 rounds, which is nearly double that of baseline protocols. This is achieved with a unique MAPC analysis and QPSO cluster selection. The existing models witnessed network failure due to the absence of predictive shielding, which caused uneven workload distribution and frequent data re-transmission. In order to avoid the same, QPSO reinforces network lifetime by distributing the CH optimally, which helps the model to eliminate the low-energy nodes from CH to maintain network longevity. The proposed model maintains stable routing paths and balanced energy consumption in all rounds and leads the existing models.

Table 5. Network Lifetime Analysis

Protocols	FND	HND	LND
E-FLZSEPFCH	980	1480	1880
DEEC-IWQPSO	1020	1510	1920
EAC-ILAP	1080	1560	1980
MC-CRITIC-KM	1150	1620	2040
MAPC-QPSO (Proposed)	2100	2600	3000

3.3 Energy Efficiency

The energy-efficiency comparative analysis results are shown in Table 6, where it demonstrates the higher energy stability compared to other models. The improvement directly influences routing stability, packet delivery, and network lifetime. As the new model employs quantum-based optimization, only minimum redundant transmission is noticed in 3000 rounds with 150 node density and ensures balanced energy expenditure across sensor nodes. MAPC significantly uses residual energy as the model utilizes a regression-based learning process. Premature draining of vulnerable nodes is prevented by assigning the node points to CHs in a robust way where the periodic clusters become an energy hotspot. This overcomes the classical PSO-fuzzy-based approaches by using a multi-hop forwarding technique. Overall, the proposed approach uniformly distributes load and prevents excessive load and energy drain across the network.

Table 6. Energy Consumption Analysis

Node Counts / Total Energy Consumed (J)	E-FLZSEPFCH	DEEC-IWQPSO	EAC-ILAP	MC-CRITIC-KM	MAPC-QPSO (Proposed)
50	1.82	1.74	1.68	1.61	1.39
100	3.64	3.49	3.33	3.22	2.78
150	5.48	5.21	4.96	4.79	4.12

3.4 Load Balancing Accuracy

The proposed MAPC-QPSO significantly reduces the network load during data transmission due to its high predictive capability. The model identifies nodes that are likely to experience high traffic and less energy to eliminate them from being assigned to the data transmission process in future rounds. Table 7 shows clear results of the existing and proposed model, which anticipates the traffic and misaligned load distribution. All existing models depend on fuzzy logic decisions because imbalanced CH placements lead to poor packet delivery and link failure under increasing rounds. In the new approach, quantum tunneling enhances the exploration, which enables the swarm to identify the configurations of CH and distributes cluster sizes even as the energy levels fluctuate. Premature energy depletions are reduced to maintain a sustainable balance in workload distribution even at the later simulation rounds. The performance of the network is dynamically boosted due to the effective load-balancing strategy.

Table 7. Load Balancing Accuracy Analysis

Simulation Rounds with NC=150	E-FLZSEPFCH	DEEC-IWQPSO	EAC-ILAP	MC-CRITIC-KM	MAPC-QPSO (Proposed)
500	82.9	85.1	86.0	86.6	97.8
1000	82.3	84.6	85.6	86.2	97.5
1500	81.6	83.9	84.9	85.5	97.1
2000	81.0	83.3	84.3	85.0	96.8
2500	80.3	82.6	83.6	84.3	96.5
3000	79.8	82.0	83.1	83.8	96.1

3.5 Execution Time

In order to assess the network stability, packet transmission, and network speed, the execution time is measured to exhibit a stable execution time. Table 8 shows the execution time results of existing and proposed protocols across varying node densities and simulation rounds. The MAPC-QPSO marks 8.7s execution time, which is comparatively lower than the prevailing E-FLZSEPFCH, DEEC-IWQPSO, EAC-ILAP, and MC-CRITIC-KM protocols. As the new model depends on regression-driven estimation, repeated energy checks are eliminated, and a lightweight process is adapted. The iterations are minimized by a robust QPSO optimization, where it simplifies the global and local velocity updates through the quantum delta potential model. The execution time remains constant across node counts, which proves that the algorithm scales efficiently in all simulation rounds by applying the cost functions and predictive penalties, which helps to drastically optimize computational workload.

Table 8. Execution Time Analysis

Simulation Rounds with NC=150	E-FLZSEPFCH	DEEC-IWQPSO	EAC-ILAP	MC-CRITIC-KM	MAPC-QPSO (Proposed)
500	10.1	9.6	9.2	8.9	8.71
1000	10.3	9.8	9.4	9.1	8.73
1500	10.6	10	9.6	9.3	8.75
2000	10.8	10.2	9.8	9.5	8.77
2500	11	10.4	10.1	9.6	8.78
3000	11.3	10.6	10.3	9.8	8.79

3.6 Latency

The end-to-end transmission time is measured by latency, and the results are shown in Table 9, which reflects the responsiveness of WSNs and the efficiency of their routing and queuing process. The MAPC-QPSO model achieved a lower latency value of 41s in long-term simulations with the help of predictive cluster stabilization and quantum-enhanced route optimization. The pre-estimation of node load, energy levels, and link reliability helps the system to route the packets in a reliable path in all rounds, which makes the protocol reactive to prevent delay or buffer overflow. All existing protocols show a high latency of >110 ms for 3000 rounds due to cluster instability and frequent route reconstruction. As the proposed model has quantum properties to minimize the communication distance by forming an intra-cluster communication, it typically eliminates bottlenecks in dense WSN deployments. Additionally, the predictive penalty method is incorporated to avoid mid-transmission failures and maintain stable latency throughout the transmission process.

Table 9. Latency Analysis

Simulation Rounds with NC=150	E-FLZSEPFCH	DEEC-IWQPSO	EAC-ILAP	MC-CRITIC-KM	MAPC-QPSO (Proposed)
500	106	100	93	87	41
1000	112	106	97	90	42
1500	118	111	101	94	44
2000	124	116	106	98	46
2500	131	121	110	101	48
3000	137	126	115	105	52

3.7 MSE, RMSE and MAE Analysis

MPAC-QPSO significantly lowers MAE, MSE, and RMSE values compared to all baseline models, where it directly influences cluster formation, routing decisions, and energy management. This precision allows the model to take proactive decisions to prevent the network from unstable nodes being selected as CHs and the routing process. The prediction errors are minimized by MAPC through the regression-based framework as it integrates multiple historical rounds of training data. As the network density increases, the prediction accuracy slightly decreases due to high traffic variability. MAPC-QPSO maintains node stability and reliable routing and follows a continuous data transmission process without any delay across all rounds. Table 10 shows the clear statistical error analysis of existing and proposed models, and Figure 9 (Panel 7) shows the pictorial representation of error analysis.

Table 10. Statistical Error Analysis

Protocol NC = 150	MAE	MSE	RMSE
E-FLZSEPFCH	0.164	0.0369	0.192
DEEC-IWQPSO	0.151	0.0341	0.184
EAC-ILAP	0.138	0.0318	0.178
MC-CRITIC-KM	0.129	0.0295	0.171
MAPC-QPSO (Proposed)	0.072	0.0134	0.115

Table 11 shows the contribution of each component in the proposed system is tested under an ablation study to demonstrate how this predictive intelligent model jointly works well in a WSN environment. Removing the MAPC component reduces the network stability and fluctuates the energy and load prediction, which leads to early node deaths and lower packet delivery. Replacing QPSO with classical PSO limits the global search and produces weaker CH selections. Disabling the prediction penalties increases the link failures and load imbalance. Together with all core components, the proposed MAPC-QPSO model maintains better balance, higher reliability, and high network performance in all simulation rounds.

Table 11. Ablation Study and Impact Analysis

Component / Variant	Description of Removed / Modified Feature	Observed Impact on Performance	Key Metrics Affected
MAPC Removed	Predictive energy & load forecasting disabled; CH selection relies only on instantaneous values	Cluster instability increases; early-node death accelerates; poor adaptability under variable load	Network Lifetime ↓, PDR ↓, MAE ↑, MSE ↑, RMSE ↑
QPSO Replaced with Classical PSO	Quantum tunneling, $mbest$ contraction, and probabilistic global exploration removed	CH selection becomes sub-optimal; slower convergence; weaker load distribution	PDR ↓, Latency ↑, Energy Consumption ↑
Prediction Penalty Disabled	Nodes with low predicted future energy not penalized during CH selection	Higher CH failure rate per round; frequent re-clustering; unstable network topology	Load Balancing Accuracy ↓, FND ↓
Stability-Aware Routing Removed	Routing ignores predicted link reliability and future traffic	Increased retransmissions; packet drops; heavy congestion near weak links	PDR ↓, Latency ↑, Execution Time ↑
Distance-Only Routing	Routing decisions consider only Euclidean distance, ignoring energy and reliability	Hotspot formation around strong CHs; uneven resource depletion	Energy Consumption ↑, Network Lifetime ↓
MAPC Disabled but QPSO Active	Optimization runs without prediction guidance	Moderate improvement, but sensitive to sudden load variations	Cluster Stability ↓, Prediction Error ↑
QPSO Disabled but MAPC Active	Predictions generated, but poor optimization for CH selection	Prediction unused for routing; lower overall gains	PDR ↓, Stability ↓
MAPC-QPSO Full Model (Proposed Variant)	All modules active: prediction, quantum optimization, stability-aware routing	Best load balancing, highest PDR, lowest latency, minimum error, extended lifetime	All metrics improved: PDR ↑, Latency ↓, Lifetime ↑, MAE/MSE/RMSE ↓
MAPC Removed	Predictive energy & load forecasting disabled; CH selection relies only on instantaneous values	Cluster instability increases; early-node death accelerates; poor adaptability under variable load	Network Lifetime ↓, PDR ↓, MAE ↑, MSE ↑, RMSE ↑
QPSO Replaced with Classical PSO	Quantum tunneling, $mbest$ contraction, and probabilistic global exploration removed	CH selection becomes sub-optimal; slower convergence; weaker load distribution	PDR ↓, Latency ↑, Energy Consumption ↑

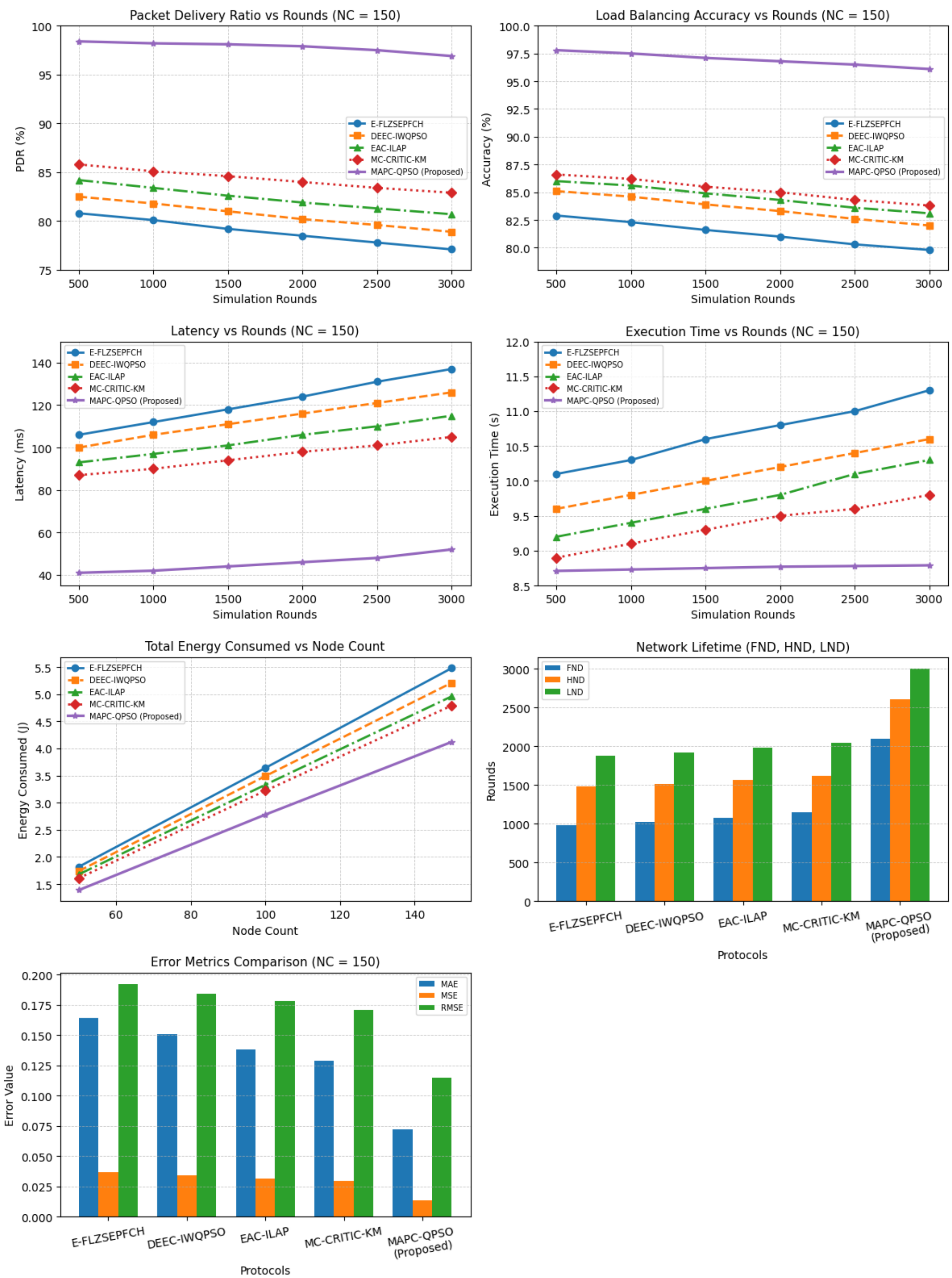

Fig 9. Seven Panel Results graph of Proposed MAPC-QPSO

4 Conclusion

The suggested quantum-based bio-inspired MAPC-QPSO model primarily focused on addressing the challenges of load imbalance, energy depletion, and unreliable routing processes. By integrating the main control layer with the quantum-enhanced PSO engine, the model controls the congestions in WSNs and provides a synergetic balance between node stability and the data transmission process. The proposed model is compared against baseline protocols such as E-FLZSEPFCH [11], DEEC-IWQPSO [12], EAC-ILAP [12], and MC-CRITIC-KM [13]. The datasets are generated during simulation and utilized for training, validation, and testing the model. The results demonstrate 98.8% network lifetime, achieve a packet delivery rate of 98.4% with 8.7s execution time, have a load-balancing accuracy of 97.8%, and reduce average latency to 41 ms and surpass the baseline versions across all performance indicators. Consistent network performance was monitored in all simulation rounds with varying node densities, which made the network protocol more reactive and responsive against all scenarios. Adaptive routing decisions will be carried out for effective data transmission. Beyond performance gains, the proposed approach provides a scalable foundation for future WSN and IoT systems that demand long-term autonomous operation. Future work may extend this framework by incorporating online learning for highly mobile environments, real-world testbed validation, and security-aware prediction modules. The findings of this research recommend predictive-optimization fusion as a key design principle for next-generation energy-constrained wireless networks.

Though the model performs well, a few limitations are noted, such as computational complexity, the model may not capture unpredictable real-world disturbances, and computational overhead in ultra-dense WSN deployments where CHs exceed 5000 nodes. The prediction accuracy might decline under extreme mobility and interference.

5 Abbreviations

WSN – Wireless Sensor Network

MAPC – Multi-Agent Predictive Control

QPSO – Quantum-behaved Particle Swarm Optimization

CH – Cluster Head

BS – Base Station

PDR – Packet Delivery Ratio

QoS – Quality of Service

QoE – Quality of Experience

LEACH – Low Energy Adaptive Clustering Hierarchy

DEEC – Distributed Energy Efficient Clustering

GAN – Generative Adversarial Network

6 Declaration

I hereby declare that this research is original, independently conducted with the supervision, and has not been submitted for publication elsewhere. The implementation was carried out using tools such as PyTorch and NS-3. For language refinement, Grammarly and Gemini were utilized, and the graphical illustrations were created using Illustrator, Mermaid, and MS Visio.

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