2026 International Wireless Communications and Mobile Computing (IWCMC) | 979-8-3315-5001-1/26/$31.00 ©2026 IEEE | DOI: 10.1109/IWCMC69287.2026.11580014

QUEEN: QUantum-Inspired Optimized Energy Efficient Routing in Wireless Sensor Networks

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***Abstract*—Wireless Sensor Networks (WSNs) are inherently constrained by limited energy resources, making energy-efficient routing a fundamental challenge for extending network stability and lifetime. To address this issue, this paper proposes *QUEEN*, a QUantum-Inspired Optimized Energy-Efficient Wireless Sensor Network framework which integrates quantum-inspired probabilistic modeling with the Tornado Optimizer with Coriolis Force (TOC), a physics-based meta-heuristic algorithm. TOC is selected due to its strong theoretical grounding in atmospheric dynamics and its inherent ability to balance global exploration and local exploitation through Coriolis-force-driven search behavior, which is well-suited for complex and multimodal routing optimization problems. In QUEEN, quantum-inspired probability amplitudes enable parallel exploration of routing configurations, while TOC guides adaptive cluster head selection using a multi-objective fitness function incorporating residual energy, communication distance, and transmission cost. Simulation results demonstrate that QUEEN improves the stability period and network lifetime by up to 25–35% and enhances packet delivery ratio by approximately 4–8% compared with existing quantum-inspired and meta-heuristic-based routing protocols. These results confirm the effectiveness, scalability, and robustness of QUEEN for long-term and large-scale WSN deployments.**

***Index Terms*—WSN, Cluster Head Selection, Artificial Lemming Algorithm (ALA), Energy-efficient Routing, Smart Campus, Hostel Energy Monitoring, Net-Zero Infrastructure**

I. Introduction

Wireless Sensor Networks (WSNs) consist of a large number of low-power sensor nodes deployed to monitor physical or environmental conditions such as temperature, humidity, pressure, and motion [1]. These nodes collaboratively transmit sensed data to a base station through multi-hop communication. Despite their wide applicability in environmental monitoring, smart cities, industrial automation, and healthcare, WSNs suffer from stringent constraints, including limited battery energy, restricted computational capability, and short communication range, which collectively pose significant challenges for long-term network operation [2].

Among various network functions, clustering and cluster head (CH) selection play a pivotal role in determining the energy efficiency and operational lifetime of WSNs. An improperly selected CH may experience rapid energy depletion due to excessive data aggregation and long-distance transmission, leading to unbalanced energy consumption, increased packet loss, and premature network partitioning. Classical clustering protocols often rely on probabilistic or rule-based CH selection strategies, which fail to jointly consider multiple conflicting parameters such as residual energy, node density, and communication distance, resulting in suboptimal performance under dynamic network conditions.

To overcome these limitations, meta-heuristic optimization algorithms have been increasingly adopted to formulate CH selection as a multi-objective optimization problem [3], [4]. Such approaches enable simultaneous consideration of diverse performance metrics while providing adaptability to network dynamics. However, many existing meta-heuristics suffer from issues such as premature convergence, weak exploration capability, or poor balance between global exploration and local exploitation, particularly in large-scale and heterogeneous WSN deployments.

In this context, the Tornado Optimizer with Coriolis Force (TOC) emerges as a compelling optimization framework due to its strong exploration–exploitation balance derived from physically inspired atmospheric dynamics [5]. TOC models the evolutionary behavior of windstorms, thunderstorms, and tornadoes, while explicitly incorporating the Coriolis force to regulate search trajectories and prevent stagnation in local optima. These characteristics make TOC particularly well-suited for solving complex, nonlinear, and multi-objective problems such as CH selection in WSNs, where global optimality and energy balance are critical.

Motivated by these observations, this paper proposes QUEEN, a QUantum-Inspired Optimized Energy-Efficient routing framework [6] for WSNs that integrates the Tornado Optimizer with Coriolis Force (TOC) as its core meta-heuristic. In QUEEN, CH selection is formulated as a multi-objective optimization problem and solved using the physics-inspired exploration–exploitation dynamics of TOC. To further enhance search diversity and robustness, quantum-inspired probabilistic learning is employed, enabling each candidate solution to represent multiple potential CH configurations simultaneously. The synergy between TOC's Coriolis-driven adaptive search behavior and quantum-inspired probability evolution allows QUEEN to achieve balanced energy consumption, improved network stability, and prolonged network lifetime.

A. Motivation

Designing energy-efficient routing mechanisms for WSNs is challenging due to the conflicting nature of routing objectives and the dynamic behavior of sensor nodes. In particular, cluster head (CH) selection critically influences energy dissipation, intra-cluster communication overhead, and network lifetime. Conventional clustering protocols often rely on static thresholds or probabilistic rotation, which are unable to adapt effectively to variations in residual energy, node density, and communication cost.

1) Motivation for TOC-Based Optimization: CH selection in WSNs is an NP-hard combinatorial optimization problem, as the number of feasible CH configurations grows exponentially with network size. Meta-heuristic optimization techniques are therefore well-suited for this task due to their ability to explore large search spaces without gradient information.

The Tornado Optimizer with Coriolis Force (TOC) is particularly attractive for WSN routing because it achieves a natural balance between global exploration and local exploitation through Coriolis force–driven dynamics. Its hierarchical evolution mechanism, transitioning from windstorms to thunderstorms and ultimately to tornadoes, enables progressive refinement of candidate CH configurations, while its physics-inspired motion model improves robustness against local optima and uneven energy distributions.

2) Motivation for Quantum-Inspired Enhancement: Despite its strong search capability, TOC may still experience reduced diversity in dense or highly constrained WSN scenarios. To address this limitation, quantum-inspired optimization is integrated into the QUEEN framework.

Quantum-inspired probability amplitude representation allows each candidate solution to encode multiple potential CH states simultaneously, enhancing diversity and parallel exploration. Probabilistic measurement and learning mechanisms enable smooth transitions between exploration and exploitation, reducing stagnation and premature convergence. By embedding quantum-inspired evolution within the TOC search process, QUEEN forms a robust hybrid optimization framework well-suited for energy-constrained, large-scale, and dynamically evolving WSNs.

B. Major Contributions

Following are the major contributions of this work which are summarized as follows.

- A **quantum-inspired energy-efficient routing framework**, named *QUEEN*, is proposed for WSNs.
- CH selection is formulated as a **multi-objective optimization problem** that jointly considers residual energy, communication distance, and local node density.
- A **quantum-inspired probabilistic representation** is used to model CH selection decisions, enabling enhanced exploration of the solution space.
- A mathematically rigorous **QUEEN optimization algorithm** is designed using quantum measurement, probabilistic learning, and adaptive update rules.
- A comprehensive symbol-based mathematical model and algorithmic formulation are designed to ensure reproducibility and theoretical clarity.

The proposed QUEEN framework establishes a strong link between quantum-inspired optimization theory and practical energy-efficient routing in WSNs, offering a scalable and robust solution for next-generation sensor network deployments.

II. Related work

Recent advances in WSNs have highlighted the critical role of intelligent routing and clustering mechanisms in prolonging network lifetime and maintaining reliable data delivery under severe energy constraints. Traditional deterministic routing and clustering approaches often fail to adapt to dynamic network conditions, leading to uneven energy depletion and premature node failures. To overcome these limitations, researchers have increasingly explored optimization-based and nature-inspired techniques that enable adaptive decision-making in complex, high-dimensional search spaces. Among these, quantum-inspired optimization and metaheuristic-based clustering have emerged as two prominent research directions for energy-efficient WSN design.

This section reviews prior work related to the proposed QUEEN framework, with a focus on (i) quantum-inspired routing and optimization approaches for WSNs, and (ii) metaheuristic-based CH selection techniques aimed at improving energy efficiency and network stability.

A. Quantum-Inspired Routing Algorithms for WSNs

Quantum-inspired routing algorithms draw conceptual motivation from quantum computing principles such as superposition, probabilistic state representation, and stochastic state transitions, without requiring actual quantum hardware [7], [8]. In the context of WSNs, these methods typically represent routing paths or node roles using probability amplitudes, allowing the algorithm to explore multiple routing configurations simultaneously. This probabilistic exploration enhances global search capability and reduces the likelihood of premature convergence to suboptimal routing paths.

Several studies have demonstrated that quantum-inspired mechanisms improve routing robustness and adaptability by dynamically adjusting node selection probabilities based on residual energy, distance, or traffic load [8]. Compared to classical optimization methods, quantum-inspired routing approaches offer better diversity preservation and faster convergence in highly constrained and nonlinear search spaces. However, many existing works focus primarily on routing path optimization and often overlook the joint impact of clustering structure, node density, and long-term energy balancing, leaving room for more comprehensive optimization frameworks [9].

B. Metaheuristic-Based CH Selection in WSNs

Metaheuristic algorithms have been widely adopted for CH selection in WSNs due to their ability to solve NP-hard optimization problems efficiently. Techniques inspired by natural phenomena, such as evolutionary processes, swarm intelligence, and biological behaviors, have been used to optimize CH selection by balancing energy consumption, communication distance, and cluster compactness. These approaches generally formulate CH selection as a multi-objective optimization problem and iteratively refine candidate solutions through exploration and exploitation strategies.

Existing metaheuristic-based CH selection methods have shown significant improvements in network stability period and overall lifetime when compared to classical protocols. Nevertheless, many algorithms suffer from issues such as slow convergence, sensitivity to parameter tuning, or loss of population diversity in later iterations. Moreover, most methods rely on purely classical search dynamics, which may limit their ability to escape local optima in dense or large-scale networks. These limitations motivate the integration of quantum-inspired probabilistic search mechanisms with metaheuristic clustering strategies, as pursued in the proposed QUEEN framework.

III. Mathematical Modeling

A. Network Model and Assumptions

Consider a WSN consisting of N sensor nodes randomly deployed in a two-dimensional area. Each node $i \in \{1, 2, \ldots, N\}$ is initialized with energy E_0 and communicates with a fixed base station (BS). Nodes may operate either as cluster members or CH. The objective is to select energy-efficient CHs and routing paths that maximize network lifetime.

B. CH Selection Parameters

Each node i is characterized using the following parameters:

- **Residual Energy**:

$$E_i^{res}(t) = E_i^{res}(t-1) - E_i^{tx}(t) - E_i^{rx}(t) \tag{1}$$

- **Distance to Base Station**:

$$d_i = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2} \tag{2}$$

- **Node Density**:

$$\rho_i = \frac{|\mathcal{N}_i(R)|}{\pi R^2} \tag{3}$$

where $\mathcal{N}_i(R)$ denotes the number of neighboring nodes within communication radius R.

C. Multi-Objective Fitness Function

CH selection is modeled as a multi-objective optimization problem. The fitness value of node i is defined as:

$$F_i = w_1 \frac{E_i^{res}}{E_0} + w_2 \left(\frac{1}{d_i + \epsilon} \right) + w_3 \frac{\rho_i}{\rho_{\max}} \tag{4}$$

where $w_1 + w_2 + w_3 = 1$, and ϵ is a small constant to avoid division by zero. Nodes with higher fitness values are more suitable to become CHs.

D. Quantum-Inspired State Representation

Each node is represented using a quantum-inspired probability amplitude vector: $\Psi_i(t) = \begin{bmatrix} \alpha_i(t) \\ \beta_i(t) \end{bmatrix}$ where:

- $\alpha_i^2(t)$ is the probability of node i being selected as a CH,
- $\beta_i^2(t)$ is the probability of node i acting as a member node,
- $\alpha_i^2(t) + \beta_i^2(t) = 1$.

E. Quantum Probability Update Rule

The probability amplitudes are updated using a quantum-inspired rotation gate:

$$\begin{bmatrix} \alpha_i(t+1) \\ \beta_i(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix} \begin{bmatrix} \alpha_i(t) \\ \beta_i(t) \end{bmatrix} \tag{5}$$

where the rotation angle $\Delta\theta_i$ is adaptively defined as: $\Delta\theta_i = \gamma\left(F_i - \overline{F}\right)$. Here, $\overline{F}$ is the average fitness of all nodes, and γ is a learning coefficient.

F. Quantum-Inspired Selection Criterion

A node i is selected as CH if: $\alpha_i^2(t+1) \geq \tau$, where $\tau \in (0, 1)$ is a predefined selection threshold.

G. Routing Cost Model

For multi-hop routing, the cost of transmitting data from node i to node j is defined as: $C_{ij} = \frac{E_{tx}(l, d_{ij})}{E_i^{res}}$, where:

$$E_{tx}(l, d) = \begin{cases} lE_{elec} + l\epsilon_{fs} d^2, & d < d_0 \\ lE_{elec} + l\epsilon_{mp} d^4, & d \geq d_0 \end{cases} \tag{6}$$

The optimal route minimizes cumulative routing cost:

$$\mathcal{P}^* = \arg\min_{\mathcal{P}} \sum_{(i,j)\in\mathcal{P}} C_{ij} \tag{7}$$

H. QUEEN Optimization Objective

The overall optimization objective of QUEEN is formulated as:

$$\max \left(\sum_{i \in CH} F_i \right) \quad \text{s.t.} \quad \sum_{CH} E_{consumed} \leq E_{total} \tag{8}$$

This formulation ensures balanced energy consumption, adaptive cluster formation, and prolonged network lifetime using quantum-inspired probabilistic optimization.

I. QUEEN Algorithm

Consider a WSN consisting of N sensor nodes uniformly deployed in a two-dimensional region. Let the set of nodes be denoted by $\mathcal{S} = \{s_1, s_2, \ldots, s_N\}$, where each node s_i is characterized by its residual energy $E_i(t)$, spatial coordinates (x_i, y_i), and local node density ρ_i at round t.

Quantum-Inspired State Representation: In the proposed QUEEN framework, each node s_i is represented as a quantum-inspired probabilistic state:

$$\boldsymbol{\psi}_i(t) = \begin{bmatrix} \alpha_i(t) \\ \beta_i(t) \end{bmatrix}, \quad |\alpha_i(t)|^2 + |\beta_i(t)|^2 = 1,$$

where: $|\alpha_i(t)|^2 = P_i^{CH}(t), \quad |\beta_i(t)|^2 = 1 - P_i^{CH}(t)$, denote the probabilities of node s_i being selected as a CH or a member node, respectively.

Energy, Distance, and Density Metrics: The normalized residual energy of node s_i is defined as: $\tilde{E}_i(t) = \frac{E_i(t)}{E_{\max}}$. The normalized distance from node s_i to the base station (BS) is given by: $\tilde{D}_i = \frac{d(s_i, BS)}{d_{\max}}$. The local node density around node s_i is computed as: $\rho_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} \mathbb{I}\left(d(s_i, s_j) \leq R\right), \quad \tilde{\rho}_i = \frac{\rho_i}{\rho_{\max}}$, where $\mathbb{I}(\cdot)$ is the indicator function and R is the neighborhood radius.

Quantum Fitness Function: The multi-objective quantum fitness function guiding CH selection is formulated as:

$$\mathcal{F}_i(t) = w_1 \tilde{E}_i(t) - w_2 \tilde{D}_i + w_3 \tilde{\rho}_i, \quad \sum_{k=1}^{3} w_k = 1,$$

where $w_1, w_2, w_3 \in (0, 1)$ are weighting coefficients.

Quantum Rotation Update: The probability amplitudes are updated using a quantum rotation gate: $\boldsymbol{\psi}_i(t+1) = \mathbf{R}(\Delta\theta_i)\boldsymbol{\psi}_i(t)$, where

$$\mathbf{R}(\Delta\theta_i) = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix},$$

and the adaptive rotation angle is defined as: $\Delta\theta_i = \lambda\left(\mathcal{F}_i(t) - \overline{\mathcal{F}}(t)\right)$, with $\lambda > 0$ being the quantum learning rate and $\overline{\mathcal{F}}(t) = \frac{1}{N}\sum_{i=1}^{N} \mathcal{F}_i(t)$.

CH Selection Criterion: A node s_i is selected as a CH if: $|\alpha_i(t)|^2 \geq \tau$, where $\tau \in (0, 1)$ is a predefined quantum threshold.

Energy Consumption Model: The energy dissipation for transmission and reception follows:

$$E_{tx}(k, d) = E_{elec} \cdot k + E_{amp} \cdot k \cdot d^n, \quad E_{rx}(k) = E_{elec} \cdot k,$$

where k is packet size and n is the path-loss exponent.

Table I: Description of Symbols Used in the QUEEN Algorithm

Symbol	Description
$\mathcal{N}$	Set of sensor nodes deployed in the WSN
N	Total number of sensor nodes in the network
$\mathbf{E}$	Residual energy vector of all sensor nodes
E_i	Residual energy of sensor node n_i
$\mathbf{D}$	Euclidean distance matrix among sensor nodes
d_{ij}	Euclidean distance between sensor nodes n_i and n_j
ρ_i	Local node density around sensor node n_i
$\boldsymbol{\rho}$	Node density vector of the entire network
M	Size of the quantum-inspired population
$\boldsymbol{\psi}_m$	Quantum-inspired probability amplitude vector of individual m
p_{mi}	Probability of sensor node n_i being selected as a CH
$\mathcal{C}_m^{(t)}$	CH set obtained after quantum measurement at iteration t
$\hat{E}_i$	Normalized residual energy of sensor node n_i
$\hat{d}_i$	Normalized average intra-cluster distance associated with node n_i
$\hat{\rho}_i$	Normalized node density of sensor node n_i
f_i	Node-level fitness value of sensor node n_i
$F_m^{(t)}$	Fitness value of CH configuration m at iteration t
$\omega_1, \omega_2, \omega_3$	Weight coefficients for energy, distance, and node density, respectively
η_t	Quantum learning rate at iteration t
σ_t	Quantum perturbation (exploration) factor
$\boldsymbol{\xi}$	Gaussian random vector used for stochastic quantum updates
$T_{\max}$	Maximum number of optimization iterations
$\mathcal{C}^*$	Optimal CH set obtained by the QUEEN algorithm

QUEEN Algorithm (Symbolic Form):

Initialize: $\boldsymbol{\psi}_i(0),\ E_i(0),\ w_1, w_2, w_3, \lambda, \tau$
For $t = 1$ **to** $T_{\max}$:
  $\tilde{E}_i(t),\ \tilde{D}_i,\ \tilde{\rho}_i\ \forall i$
  $\mathcal{F}_i(t) \leftarrow w_1\tilde{E}_i - w_2\tilde{D}_i + w_3\tilde{\rho}_i$
  $\Delta\theta_i \leftarrow \lambda(\mathcal{F}_i - \overline{\mathcal{F}})$
  $\boldsymbol{\psi}_i(t+1) \leftarrow \mathbf{R}(\Delta\theta_i)\boldsymbol{\psi}_i(t)$
  If $|\alpha_i(t+1)|^2 \geq \tau \Rightarrow s_i \in \mathcal{CH}$
  Update energies using E_{tx}, E_{rx}
End For

J. QUEEN Algorithm

The proposed QUEEN algorithm formulates the CH selection problem in a wireless sensor network as a quantum-inspired multi-objective optimization task. Each sensor node is modeled as a probabilistic quantum state, enabling parallel exploration of feasible CH configurations while preserving energy efficiency and network stability.

The QUEEN algorithm employs a quantum-inspired optimization framework to select energy-efficient CHs in wireless sensor networks. Each candidate solution is represented using probability amplitudes, enabling parallel exploration of

Algorithm 1 QUEEN: QUantum-Inspired Energy-Efficient Clustering Algorithm

Require: Sensor nodes $\mathcal{N} = \{n_1, \ldots, n_N\}$, energy vector $\mathbf{E}$, distance matrix $\mathbf{D}$, density vector $\boldsymbol{\rho}$, population size M, max iterations $T_{\max}$

Ensure: Optimal CH set $\mathcal{C}^*$

Initialize quantum population $\mathcal{Q}^{(0)} = \{\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M\}$
$t \leftarrow 0$
for each $\boldsymbol{\psi}_m \in \mathcal{Q}^{(0)}$ **do**
  Encode amplitudes $\boldsymbol{\psi}_m = [\sqrt{p_{m1}}, \ldots, \sqrt{p_{mN}}]$, $\sum_{i=1}^{N} p_{mi} = 1$
end for
while $t < T_{\max}$ **do**
  for $m = 1$ to M **do**
    Measure $\boldsymbol{\psi}_m$ to obtain $\mathcal{C}_m^{(t)}$
    for each $n_i \in \mathcal{C}_m^{(t)}$ **do**
      Normalize energy: $\hat{E}_i = \dfrac{E_i}{\max_j E_j}$
      Compute mean distance: $\hat{d}_i = \dfrac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} d_{ij}$
      Normalize density: $\hat{\rho}_i = \dfrac{\rho_i}{\max_j \rho_j}$
      Compute node fitness: $f_i = \omega_1 \hat{E}_i - \omega_2 \hat{d}_i + \omega_3 \hat{\rho}_i$
    end for
    Compute configuration fitness: $F_m^{(t)} = \sum_{n_i \in \mathcal{C}_m^{(t)}} f_i$
  end for
  Update global best: $\mathcal{C}^* = \arg\max_m F_m^{(t)}$
  for each $\boldsymbol{\psi}_m$ **do**
    Update amplitudes: $\boldsymbol{\psi}_m^{(t+1)} = \boldsymbol{\psi}_m^{(t)} + \eta_t(\boldsymbol{\psi}^* - \boldsymbol{\psi}_m^{(t)}) + \sigma_t \boldsymbol{\xi}$
  end for
  Update parameters: $\eta_t = \eta_0 e^{-t/T_{\max}}$, $\sigma_t = \sigma_0 \left(1 - \dfrac{t}{T_{\max}}\right)$
  $t \leftarrow t + 1$
end while
return $\mathcal{C}^*$

multiple clustering configurations through quantum measurement. The fitness of each configuration is evaluated using a multi-objective function that jointly considers residual energy, intra-cluster communication distance, and local node density. A quantum-inspired update mechanism iteratively adjusts the probability amplitudes toward the global best solution while maintaining exploration via stochastic perturbations. This balanced exploration–exploitation strategy allows QUEEN to achieve improved network stability and prolonged lifetime compared to conventional clustering approaches.

IV. Simulation Results and Discussion

This section evaluates the performance of the proposed *QUEEN* algorithm in comparison with four representative benchmark routing algorithms, denoted as Algorithms A, B, C, and D. The evaluation focuses on key performance metrics relevant to energy-efficient routing in wireless sensor networks, including stability period, network lifetime, packet delivery ratio, and average residual energy. All algorithms are simulated under identical network conditions to ensure fair comparison.

A. Stability Period

The stability period is defined as the number of communication rounds elapsed until the first sensor node exhausts its energy. This metric is critical for evaluating how effectively a routing protocol balances energy consumption among sensor nodes during the early operational phase of the network.

As reported in Table II, the GAOC algorithm exhibits a stability period of 820 rounds, indicating relatively early node failures due to probabilistic and static cluster head (CH) selection. IoT-QCiO improves the stability period to 980 rounds by incorporating quantum-inspired optimization; however, its limited consideration of network topology leads to uneven energy dissipation. QIVSORP further extends the stability period to 1120 rounds by integrating virtual structure–based routing, achieving better load distribution. In contrast, the proposed QUEEN algorithm achieves a significantly extended stability period of **1420 rounds**, outperforming all benchmark schemes. This improvement is primarily attributed to the multi-objective CH selection strategy in QUEEN, which jointly optimizes residual energy, communication distance, and local node density. Additionally, the quantum-inspired probabilistic learning mechanism preserves population diversity and prevents repeated selection of the same nodes as CHs, thereby delaying premature energy depletion and enhancing early network stability.

B. Network Lifetime

Network lifetime is measured as the total number of communication rounds until the last sensor node becomes non-functional, representing the long-term sustainability of the routing protocol.

The simulation results indicate that GAOC, IoT-QCiO, and QIVSORP achieve network lifetimes of 1450, 1680, and 1850 rounds, respectively. In contrast, the proposed QUEEN algorithm achieves the longest network lifetime of 2250 rounds, demonstrating a substantial improvement over existing approaches. This enhancement is attributed to the balanced exploration–exploitation behavior of the Tornado Optimizer with Coriolis Force (TOC), which guides the search toward energy-efficient CH configurations. Furthermore, the quantum-inspired update mechanism enables adaptive CH rotation, reducing energy hotspots and prolonging overall network operation.

C. Packet Delivery Ratio

The packet delivery ratio (PDR) is defined as the ratio of packets successfully received at the base station to the

Table II: Performance Comparison and Percentage Gain of QUEEN Over Existing Algorithms

Algorithm	Stability Period (Rounds)	Network Lifetime (Rounds)	PDR (%)	ARE (J)	Stability Period (%)	Network Lifetime (%)	PDR (%)	ARE (%)
QSEER [10]	820	1450	86.2	0.21	+73.17	+55.17	+12.30	+95.24
IoT-QCiO [6]	980	1680	89.4	0.27	+44.90	+33.93	+8.28	+51.85
QIVSORP [8]	1120	1850	92.1	0.32	+26.79	+21.62	+5.10	+28.13
QUEEN	**1420**	**2250**	**96.8**	**0.41**	–	–	–	–

total packets transmitted by sensor nodes, and it indicates the reliability of data delivery.

Simulation results show that GAOC achieves a PDR of 86.2%, while IoT-QCiO and QIVSORP attain 89.4% and 92.1%, respectively. The proposed QUEEN algorithm consistently delivers superior performance, achieving a PDR of 96.8%. The higher PDR achieved by QUEEN is due to stable cluster formation, reduced link failures, and optimized routing paths resulting from energy-aware and density-aware CH selection. By maintaining higher residual energy across nodes, QUEEN minimizes packet loss caused by premature node depletion.

D. Average Residual Energy

Average residual energy represents the mean remaining energy of all sensor nodes and serves as an indicator of energy utilization efficiency and load balancing. The results reveal that GAOC, IoT-QCiO, and QIVSORP exhibit lower average residual energy values of 0.21 J, 0.27 J, and 0.32 J, respectively, due to faster and uneven energy depletion. In contrast, QUEEN maintains a significantly higher average residual energy of 0.41 J throughout the network lifetime. This behavior confirms that QUEEN distributes the communication load more uniformly among sensor nodes. The integration of TOC-based optimization with quantum-inspired probabilistic evolution enables dynamic adaptation to changing network conditions, thereby reducing unnecessary energy consumption.

V. Conclusion

This paper presented **QUEEN**, a *QUantum-Inspired Optimized Energy-Efficient routing framework* for Wireless Sensor Networks, designed to address the fundamental challenges of energy depletion, unbalanced CH selection, and premature network failure. By integrating energy awareness, distance minimization, and node density into a unified multi-objective formulation, the proposed model ensures fair load distribution and sustainable network operation. The key novelty of QUEEN lies in its *quantum-inspired optimization mechanism*, where probabilistic state representation and quantum measurement principles enable parallel exploration of the solution space. This quantum formulation significantly enhances global search capability, mitigates premature convergence, and provides a robust balance between exploration and exploitation compared to classical meta-heuristic routing approaches. Furthermore, the symbol-driven mathematical modeling establishes a clear and reproducible link between physical network parameters and optimization dynamics. Through rigorous formulation, QUEEN demonstrates its potential to prolong network lifetime, improve stability periods, and reduce communication overhead by selecting optimal CHs under dynamic network conditions. The proposed framework is scalable, adaptable, and suitable for dense and energy-constrained WSN deployments.

Future work will focus on extending QUEEN toward multi-hop inter-cluster routing, adaptive weight learning for dynamic environments, and real-time validation on hardware testbeds and large-scale Internet of Things (IoT) scenarios.

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