OPTIMAL APPROACH FOR MINIMIZING DELAYS IN IOT-BASED QUANTUM WIRELESS SENSOR NETWORKS USING NM-LEACH ROUTING PROTOCOL

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ABSTRACT

IoT-based Quantum Wireless Sensor Networks (IoT Q-WSN) merge Quantum principles into the realm of Wireless Sensor Networks, introducing intricate routing challenges that demand innovative solutions for efficient data transmission. This study introduces NM-LEACH, an inventive routing protocol inspired by the leadership principles of Shri Narendra Modi. A groundbreaking feature of NM-LEACH is its distinction as the inaugural optimization protocol inspired by a human personality. NM-LEACH operates through adaptive strategies, clean coding practices, and continuous feedback loops, embodying a comprehensive and disciplined approach to network development. Through simulation in NS3, the protocol undergoes meticulous evaluation against existing counterparts. Results demonstrate NM-LEACH's superior performance in minimizing delays and optimizing data transmission within IoT Q-WSNs. This research advances Quantum IoT and underscores the potential of drawing inspiration from human leadership qualities to innovate and enhance wireless sensor network functionality by minimizing delay and energy consumption.

Keywords: *IoT, WSN, Quantum, LEACH, Narendra Modi, Energy Consumption*

1. INTRODUCTION

IoT-based Quantum Wireless Sensor Networks (Q-WSNs) represent a cutting-edge fusion of quantum computing and the Internet of Things, promising unprecedented information processing and communication advancements. Unlike traditional IoT-WSNs that rely on classical computing, Q-WSNs leverage the principles of quantum mechanics [1]. Quantum superposition allows quantum sensors in the network to measure multiple physical parameters simultaneously, enhancing computational efficiency. The phenomenon of quantum entanglement can be harnessed to create interconnected quantum nodes, enabling the exchange of quantum information over long distances. In Q-WSNs, the potential applications span various domains, including healthcare, finance, and defense. Quantum sensors offer the ability to process complex data in parallel, enabling faster computations and more accurate sensing. Integrating quantum principles into wireless sensor networks holds promise for overcoming classical limitations, potentially leading to data analysis and transmission breakthroughs [2]. Practical implementation faces significant challenges. Developing reliable quantum sensors, establishing quantum communication protocols, and seamlessly integrating with existing IoT infrastructures require further advancements [3].

In IoT-based Q-WSNs, routing involves transferring quantum information between quantum sensor nodes. Unlike classical routing in traditional wireless sensor networks, Q-WSNs leverage quantum principles for data transmission. Quantum superposition, allowing particles to exist in multiple states simultaneously, enables the exploration of multiple routes concurrently, optimizing the path for quantum information. Quantum entanglement, establishing a strong correlation between particles regardless of distance, can be employed to create entangled routes, ensuring rapid and reliable communication between nodes [4]. However, practical implementation faces challenges, such as the fragility of quantum information and the need for robust error correction mechanisms. Establishing quantum entanglement over long distances requires

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specialized protocols, and integrating quantum routers into existing IoT infrastructure introduces technical complexities. Ongoing research aims to address these challenges, exploring the potential of quantum routing to enhance the efficiency and scalability of information transmission in IoT Q-WSN [5].

Human-inspired optimization refers to algorithms that derive inspiration from human cognitive processes, problem-solving strategies, and social dynamics. These optimization methods aim to emulate how humans approach complex problem-solving tasks, often integrating aspects of learning, memory, and social intelligence. These algorithms seek to find efficient solutions to intricate problems by mimicking human behaviors and decision-making patterns. Human-inspired optimization is particularly relevant in domains where human intuition and adaptive reasoning play a significant role. The emphasis is on replicating the essence of human problem-solving, offering a unique perspective that aligns with the complexities of real-world challenges. Applications of human-inspired optimization can be found across various fields, contributing insights into how human-like approaches can enhance the efficiency and adaptability of computational problem-solving processes.

2. LITERATURE REVIEW

"Intelligent Data Routing" [6] employs deep reinforcement learning for routing IoT-enabled WSNs. It invites scrutiny of the practicality and challenges of implementing intelligent data routing through complex machine-learning models in real-world IoT environments. "Location-Centric Energy Harvesting Aware Routing" [7] focuses on location-centric energy harvesting in IoT for Smart Cities. It prompts considerations regarding the feasibility and effectiveness of such protocols in addressing the unique energy challenges posed by Smart City environments. "Energy Warning" [8] introduces a routing scheme emphasizing data communication between sensor nodes based on energy warnings. This scheme raises questions about the reliability and practicality of using energy warnings as a basis for routing decisions in WSNs.

"Sine-Cosine Lévy Mutation" [9] combines Sine Cosine Algorithm and Lévy Mutation for WSN clustering routing. It prompts scrutiny of the benefits and drawbacks of integrating these algorithms and their impact on overall WSN performance. "Quality Routing" [10] proposes a blockchain and deep learning-based architecture for quality routing in WSN. This contribution invites critical examination of the challenges and trade-offs associated with integrating blockchain and deep learning in the context of WSN routing. "EEM-CRP" [11] introduces a meta-heuristic clustering protocol, emphasizing energy efficiency in WSNs. It raises questions about the adaptability and effectiveness of meta-heuristic approaches in optimizing energy consumption within WSNs, particularly in clustered environments. Bio-inspired Optimization becomes mandatory in all field like Networking [12, 13, 22–30, 14–21].

"Improved Buffalo" [31] scheme proposes a deep learning-based multipath routing strategy inspired by buffalo optimization. This prompts an examination of the practicality and challenges of leveraging buffalo-inspired meta-heuristic techniques for energy-efficient data aggregation in WSNs. "CDEIR" [32] introduces an intelligent routing scheme utilizing the BUG Algorithm in WSNs. This contribution prompts scrutiny regarding the intelligence of the BUG Algorithm, its adaptability, and its efficiency in achieving effective routing within Wireless Sensor Networks.

"Artificial Bee Colony-based Energy Optimization Routing (ABC-EOR)" [33] focuses on energy optimization routing using artificial bee colony algorithms in hierarchical cluster-based WSNs. It raises questions about the feasibility and drawbacks of integrating artificial bee colony algorithms to achieve energy optimization in the hierarchical organization of WSNs. "Energy Efficient Secure Routing Scheme-based LEACH (EESRS-LEACH)" [34] employs the LEACH protocol in WSNs for IoT networks. It prompts a critical examination of the security implications and challenges associated with integrating LEACH protocol into WSNs specifically designed for IoT applications.

3. NM INSPIRED LEACH

3.1. Low Energy Adaptive Clustering Hierarchy

LEACH, known as Low Energy Adaptive Clustering Hierarchy, is a widely recognized clustering algorithm created specifically for WSNs to minimize energy usage. Its crucial feature involves utilizing a hierarchical arrangement. The sensor nodes are grouped into clusters, with one node in each cluster serving as the CH. LEACH's primary goal is to decrease the power needs of single sensor nodes in WSNs. By implementing a hierarchical structure, LEACH enables the formation of clusters, fostering efficient communication and coordination within the network. Within each cluster, a sensor node is elected as the cluster head, responsible for overseeing and coordinating the activities of the member nodes.

To ensure fairness and balance the energy load across the network, the selection of cluster heads is performed probabilistically. In each round, every sensor node determines whether it should become a cluster head based on a predefined threshold value. LEACH favours the nodes with higher energy levels. This randomized approach ensures the distribution of the energy-intensive cluster head role among the sensor nodes, preventing any particular node from experiencing excessive energy depletion. Once the cluster heads are elected, they disseminate this information to the other nodes within their respective clusters. The member nodes associate themselves with their corresponding cluster heads, forming a cluster structure. This process facilitates efficient data aggregation and communication within the clusters, as the cluster heads can aggregate data from their member nodes before transmitting it to the base station or sink node. By implementing data aggregation and localized communication, LEACH efficiently minimizes energy consumption, ultimately leading to an extended lifespan for the network. LEACH incorporates a dynamic clustering mechanism to adapt to changing network conditions. The cluster heads are reassigned after each data transmission round to ensure that the sensor nodes carry an even share of the energy load. This adaptability optimizes network performance and balances energy consumption across different nodes.

3.1.1. Cluster Formation

LEACH utilizes a probabilistic approach to establish clusters and ensure a uniform energy load distribution among the sensor nodes. In each round, every node determines its candidacy as a Cluster Head (CH) based on a randomized threshold calculated using Eq.(1).

$$Threshold = p/\left(1 - p \times \left(r mod(1/p)\right)\right) \tag{1}$$

where p stands for the target fraction of CHs, while r denotes the current integer to the nearest whole number.

3.1.2. Cluster Head Selection

Once the threshold is calculated, each node assesses its random value, which falls within the range of 0 to 1, against the determined threshold. If the randomly generated value of a node is less than the threshold, it takes on the role of a Cluster Head (CH) for the current round. Conversely, if the randomly generated value exceeds the threshold, the node functions as a common node. Eq.(2) describes the likelihood of a node being selected as a CH.

$$Probability\ of\ becoming\ a\ CH = Threshold \tag{2}$$

3.1.3. Cluster Formation Probability

The following equation can be used to determine the typical number of CHs created in a given round, m. Eq.(3) calculates each iteration's average number of CHs formed.

$$m = p \times N \tag{3}$$

The number of sensor nodes is denoted by the symbol N here.

3.1.4. Data Transmission

Once the clusters and CHs have been established, the regular nodes transmit their data to the corresponding CHs. The energy consumption of each node during transmission for a given distance$d$, can be calculated using Eq.(4).

$$E_{tx} = E_{elec} \times d^2 \tag{4}$$

where the variable E_{elec} represents the energy required to operate the transmitter circuitry per bit per square meter.

3.1.5. Cluster Head Energy Consumption

The CHs have additional responsibilities, such as data aggregation and transmission to the base station (sink). Eq.(5) allows us to calculate the energy consumed by each CH during the processes of data aggregation and transmission:

$$E_{agg} = (N-1) \times E_{elec} \times d^2 \tag{5}$$

where the variable N denotes the count of regular nodes within each cluster. In contrast, the variable d represents the distance between the Cluster Head (CH) and its respective regular nodes.

3.1.6. Energy Dissipation Model

LEACH employs an energy dissipation model to determine each node's residual energy and the next CH rotation. The energy dissipated for each transmission is given by Eq.(6):

$$E_{diss} = E_{elec} \times d^2 + E\_amp \times d^4 \qquad (6)$$

In the given equation, the term E_amp denotes the energy required to operate the amplifier circuitry per bit per square meter.

The LEACH algorithm leverages these calculations to optimize energy utilization and extend the overall lifespan of IoT Q-WSNs.

Algorithm 1: LEACH	
Step 1:	**Initialization:** Set desired CH percentage and assign random numbers to nodes.
Step 2:	**Cluster Head Selection:** Nodes compare random numbers with the threshold to become CHs.
Step 3:	**Cluster Formation:** Regular nodes connect to the strongest signal CH available.
Step 4:	**Data Transmission:** Standard nodes communicate with their CHs.
Step 5:	**Data Aggregation and Transmission:** CHs collect information and send it to the central station.
Step 6:	**Energy Dissipation and Rotation:** Nodes estimate energy and decide CH's role for the next round.
Step 7:	**Optimize** Optimizing energy use and network longevity may require numerous iterations of steps 2–6.

3.1.7. Demerits in LEACH

- Consumption of more energy in forming clusters and communicating through cluster heads.
- Face scalability challenges as the network grows due to cluster overhead.
- Lack of secure communication, exposing data to interception and tampering during transmission.
- The lack of effective mechanisms for reliably identifying malicious nodes within the network makes it challenging to detect and isolate nodes engaging in unauthorized or harmful activities.

To address the shortcomings of LEACH, this research employs the NM Optimization Algorithm (NMOA), an inventive research strategy. NMOA optimizes energy usage, mitigates scalability challenges through collaborative optimization, and enhances security by promoting Swachh Code practices. Additionally, NMOA's Roots Empowerment principle aids in identifying and isolating malicious nodes, addressing LEACH's limitations in unauthorized activity detection. By integrating NMOA, this inventive research aims to improve energy efficiency, scalability, and security in IoT Q-WSNs, offering a comprehensive solution to the challenges encountered in the LEACH protocol.

3.2. NARENDRA MODI-INSPIRED OPTIMIZATION ALGORITHM (NMOA)

Shri. Narendra Modi (NM) is renowned for his pragmatic and visionary approach to governance. A focus on development, efficiency, and innovation characterizes his leadership. NM emphasizes a results-driven mindset, often implementing policies and initiatives that align with his vision for a modern, economically vibrant India. He is known for setting ambitious goals, such as the Swachh Bharat Abhiyan (Clean India Mission) and Make in India, demonstrating a commitment to social welfare and economic progress. NM's leadership style combines decisiveness with a hands-on approach, aiming to streamline bureaucracy and foster a culture of accountability. His emphasis on technology, digital governance, and sustainable development reflects a forward-thinking perspective, driving India towards a more inclusive and globally competitive future.

Based on the inspiration drawn from the visionary ideas of NM, this research work has proposed an optimization algorithm known as the NM Optimization Algorithm (NMOA). The algorithm incorporates principles aligned with NM's forward-thinking and results-driven approach to governance, aiming to optimize efficiency, sustainability, and innovation within IoT Q-WSNs. The algorithm integrates key facets of Modi's visionary leadership, contributing to the advancement of optimization strategies and solutions in network management and resource utilization.

3.2.1. Visionary Initialization

"Visionary Initialization" in the NM Optimization Algorithm (NMOA) can be mathematically expressed as formulating a goal-oriented objective function. Let $f(x)$ represent the optimization objective, where x is the vector of decision variables. The algorithm begins with a visionary initialization by defining a target vector x^* that embodies the desired state, mathematically expressed as Eq.(7).

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$$x^* = \arg min_x f(x) \tag{7}$$

This visionary initialization involves setting the algorithm toward the optimal solution. A visionary objective function $g(x)$ encapsulates the overarching goals, expressed as Eq.(8).

$$g(x) = \lambda_1 . g_1(x) + \lambda_2 . g_2(x) + \cdots . + \lambda_n . g_n(x) \tag{8}$$

where $g_1(x)$ represents individual goal functions and λ_1 are weighting factors. The algorithm seeks to minimize $g(x)$ to achieve the visionary objectives. Eq.(9) involves assigning appropriate values to λ_i and establishing the initial conditions x_0 which is a part of the initialization step.

$$x_0 = Initial\ conditions, \tag{9}$$

Setting the algorithm on a trajectory towards visionary optimization. The dynamic evolution of x guided by $g(x)$ encapsulates the algorithm's pursuit of visionary goals during the optimization process.

3.2.2. Dynamic Adaptability

"Dynamic Adaptability" in the NMOA is a crucial aspect mathematically expressed through an adaptive strategy. The algorithm adapts its behavior based on the evolving conditions of the optimization landscape. Let x_i represent the solution vector at iteration t, and $f(x_t)$ denote the objective function value at that iteration. The dynamic adaptability mechanism introduces a parameter α_t that scales the step size or influences the update rule at each iteration. The adaptive strategy can be formulated as Eq.(10).

$$x_{t+1} = x_t - \alpha_t \nabla f(x_t), \tag{10}$$

where $\nabla f(x_t)$ is the gradient of the objective function at x_t. The parameter α_t adjusts based on the performance or changes in the landscape, and it is expressed as Eq.(11).

$$\alpha_{t+1} = \beta - \alpha_t, \tag{11}$$

where β is a factor that dynamically adjusts the step size. The algorithm dynamically tunes α_t to balance exploration and exploitation, ensuring adaptability to varying conditions during optimization.

3.3. 3D Development (Decisive, Disciplined, Development)

3.3.1. Decisiveness (D_t)

At each iteration t, the algorithm makes decisive decisions to steer the optimization process. A binary decision variable D_t can be introduced, where $D_t = 1$ signifies a decisive move and $D_t = 0$ represents indecision. The objective function is modified accordingly using Eq.(12).

$$f(x_t, D_t) = \begin{cases} f(x_t), & if\ D_t = 1 \\ \lambda . f(x_t), & if\ D_t = 0 \end{cases} \tag{12}$$

where λ is a penalty factor applied when indecision occurs.

3.3.2. Discipline (DIS_t)

Discipline is introduced as a constraint on the optimization process. A discipline function DIS_t can be defined as penalizing solutions that deviate from a structured and organized search space using Eq.(13). The penalty term γ enforces discipline by discouraging solutions that violate predefined structures.

$$f(x_t, D_t) = f(x_t) + \gamma . DIS_t(x_t) \tag{13}$$

3.3.3. Development (DEV_t):

The algorithm prioritizes long-term development through an additional development function. This function encourages solutions that contribute to sustainable and inclusive growth. The term η amplifies the impact of development-friendly solutions.

$$f(x_t, D_t) = f(x_t) + \eta . DEV_t(x_t) \tag{14}$$

Eq.(12) to Eq.(14) embed decisiveness, discipline, and development as integral components of the optimization process, aligning with the 3D Development principle in the NMOA.

3.4. Collaborative Optimization

The collaboration can be represented through a cooperative optimization framework. Let $x_{i,t}$ denote the solution vector of the i-th component at iteration t. The collaborative optimization process can be expressed as Eq.(15), combining individual and collaborative terms.

$$f(x_{1,t}, x_{2,t}, \ldots., x_{n,t}) = \sum_{i=1}^{n} f_i(x_{i,t}) + \lambda . g(x_{1,t}, x_{2,t}, \ldots., x_{n,t}) \tag{15}$$

where $f_i(x_i, t)$ represents the individual objective function of the i-th component, and $g(x_{1,t}, x_{2,t}, \ldots., x_{n,t})$ is a collaborative term that encourages cooperation among components. The parameter λ regulates the influence of collaboration. The collaborative term can be defined as Eq.(16).

$$g(x_{1,t}, x_{2,t}, \ldots, x_{n,t}) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \rho_{i,j}.CollaborationMetri \quad (16)$$

where, $\rho_{i,j}$ is the collaboration strength between components i and j, and $CollaborationMetric(x_{i,t}, x_{j,t)}$ measures the collaborative impact of their solutions.

Eq.(16) encourages each component to optimize its objective while considering the collaborative impact on the overall optimization process.

3.5. Swachh Code (Clean Code)

Swachh Code can be represented through guidelines and constraints that ensure the codebase is well-organized and follows best practices. Let C represent the overall cleanliness metric of the code. The Swachh Code principle encourages minimizing code complexity, adherence to coding standards, and proper documentation. The mathematical representation can be expressed as Eq.(17).

$$C = \alpha.CodeComplexity + \beta.AdherenceToStandards + \gamma.Documentationquality \quad (17)$$

where $\alpha, \beta\ and\ \gamma$ are weighting factors that determine the importance of each component, $CodeComplexity$ measures the complexity of the codebase, considering factors like cyclomatic complexity and code length, $AdherenceToStandards$ evaluates how well the code follows established coding standards and best practices, $DocumentationQuality$ assesses the completeness and clarity of code documentation. The optimization process involves minimizing C, expressed as Eq.(18).

$$Minimize\ C = Minimize\ (\alpha.CodeComplexity + \beta.AdherenceToStandards + \gamma.DocumentationQuality) \quad (18)$$

3.6. Digital Connectivity

This step involves establishing connections between algorithm parts to ensure seamless communication and information flow. This connectivity can be mathematically represented through a network model where nodes represent algorithmic components, and edges represent communication channels. Let $G = (V, E)$ be a graph representing the connectivity structure, where V is the set of nodes, and E is the set of edges. Each node $v_i \in V$ corresponds to a specific algorithmic component and each edge $e_{ij} \in E$ signifies a communication link between components v_i and v_j.

The optimization objective is to minimize the cost of communication and maximize the efficiency of information transfer, where Eq.(19) expresses the same.

$$Minimize\ (\sum_{e_{ij \in E}} CommunicationCost\ (v_i\ , v_j)) \quad (19)$$

where, $CommunicationCost\ (v_i\ , v_j)$ represents the cost associated with transmitting information between components v_i and v_j. This cost function could depend on bandwidth usage, latency, or the volume of data exchanged. The algorithmic steps can be expressed as Eq.(20).

$$v_i^{(t+1)} = Optimize(v_i^{(t)}, Neighborhood(v_i, G)) \quad (20)$$

Eq.(14) indicates that the state of each algorithmic component v_i at the next iteration depends on its current state and the states of its neighboring components in the graph. The Optimize function captures the specific optimization logic applied to each component, taking into account the information received from neighboring components.

3.7. JAM (Jan Dhan, Aadhaar, Mobile)

JAM (Jan Dhan, Aadhaar, Mobile) involves leveraging these three pillars for comprehensive and effective optimization. This significant integration can be represented through a multi-dimensional optimization space considering the interconnected influence of Jan Dhan, Aadhaar, and Mobile. Let X be the optimization space, and $f(X)$ be the objective function to be optimized. The JAM integration can be expressed as Eq.(21).

$$f(X) = f_{janDhan}(X_{janDhan}) + f_{Aadhaar}(X_{AaDhaar}) + f_{Mobile}(X_{Mobile}) \quad (21)$$

where, $X_{janDhan}, X_{AaDhaar}$ and X_{Mobile} represent the components of the optimization space related to Jan Dhan, Aadhaar, and Mobile, respectively. Each term $f_{janDhan}, f_{Aadhaar}$ and f_{Mobile} capture the specific optimization goals and constraints associated with each pillar. The algorithmic steps can be formulated as a multi-objective optimization problem expressed as Eq.(22).

$$Minimize = \left\{ \begin{matrix} f_{janDhan}(X_{janDhan}), \\ f_{Aadhaar}(X_{AaDhaar}), f_{Mobile}(X_{Mobile}) \end{matrix} \right\} \quad (22)$$

Eq.(16) represents the simultaneous minimization of the optimization objectives associated with Jan Dhan, Aadhaar, and Mobile.

3.8. Innovation Hub

The concept of "Innovation Hub" emphasizes creating and integrating innovative solutions. It is represented by a term that encourages exploring and incorporating novel approaches within the optimization process. Let $f(X)$ be the overall objective function to be optimized, where X represents the solution vector. The Innovation Hub can be expressed as Eq.(23) is an additional term $f_{Innovation}(X_{Innovation})$ that captures the innovative contributions to the optimization process:

$$f(X) = f_{Main}(X_{Main}) + \lambda . f_{Innovation}(X_{Innovation}) \tag{23}$$

where, $f_{Main}(X_{Main})$ represents the main optimization objectives, and $f_{Innovation}(X_{Innovation})$ is an innovation-specific contribution. The parameter λ regulates the balance between the main optimization objectives and the innovation term. Eq.(24) involves optimizing the main objectives and exploring innovative solutions.

$$X_{Main}^{(t+1)} = Optimize(X_{Main}^{(t)}, \ldots) \quad X_{Innovation}^{(t+1)} = Innovate(X_{Innovate}^{(t)}, \ldots) \tag{24}$$

Eq.(24) reflects the Innovation Hub principle in the NMOA, emphasizing the importance of integrating novel and creative elements into the optimization process for continuous improvement and advancement.

3.9. Root Empowerment

The Roots Empowerment principle involves uplifting individual components within the algorithm, emphasizing decentralized and locally-driven initiatives. It represents the elevation of the influence of each component based on its contribution to the overall optimization. Let $X = \{X_1, X_2, \ldots, X_n\}$ represent the set of individual components in the optimization algorithm, and $f(X)$ be the objective function. The Root Empowerment can be expressed as Eq.(25) by assigning individual weights w_i to each component based on their local contributions:

$$f(X) = \sum_{i=1}^{n} w_i . f_i(X_i) \tag{25}$$

where, $f_i(X_i)$ is the objective function associated with the i-th component, and w_i is its weight. The weights w_i are determined dynamically, reflecting the local impact of each component on the overall optimization. The algorithmic steps can be represented as Eq.(26) and Eq.(27).

$$X_i^{(t+1)} = Optimize(X_i^{(t)}, \ldots.) \tag{26}$$

Eq.(26) indicates that the state of each component X_i The next iteration depends on its current state and the states of other components. The weights w_i It can be adjusted using Eq.(27) and is based on each component's performance or contribution. Eq.(27) captures the dynamic adjustment of weights based on the local impact of each component.

$$w_i^{(t+1)} = UpdateWeight(X_i^{(t)}, \ldots.) \tag{27}$$

3.10. Continuous Feedback Loop

This step involves a mechanism for ongoing evaluation and refinement. Mathematically, this can be represented through iterative updates based on feedback from the optimization process. Let X represent the solution vector, and $f(X)$ be the objective function to be optimized. The Continuous Feedback Loop can be expressed through Eq.(28), an iterative optimization process incorporating feedback.

$$X^{(t+1)} = Optimize\left(X^{(t)}, Feedback(X^{(t)})\right) \tag{28}$$

where, $Optimize$ is the optimization function that refines the solution based on feedback, and Feedback is a function that provides information about the performance of the current solution.

The feedback function expressed in Eq.(29) can be a combination of various metrics, such as convergence rate, the quality of solutions, or any other relevant performance indicators:

$$Feedback\left(X^{(t)}\right) = \left\{\begin{matrix} Metric_1\left(X^{(t)}\right), Metric_2\left(X^{(t)}\right), \ldots. \\ , Metric_n\left(X^{(t)}\right) \end{matrix}\right\} \tag{29}$$

These feedback metrics then guide the optimization process to drive continuous improvement. The weights or parameters in the optimization process can be updated based on the feedback expressed in Eq.(30).

$$\theta^{(t+1)} = UpdateParameters\left(\theta^{(t)}, Feedback\left(X^{(t)}\right)\right) \tag{30}$$

where, θ represents the parameters of the optimization algorithm.

This mathematical representation reflects the Continuous Feedback Loop principle in the NMOA, highlighting the importance of iterative refinement based on real-time information to enhance the effectiveness of the optimization process over time.

Narendra Modi-Inspired Optimization Algorithm (NMOA)

Input:
- $X^{(0)}$: Initial solution vector.
- T_{max}: Maximum number of iterations.
- ϵ: Convergence threshold.

Output:
- $X^{(final)}$: Optimized solution vector.

Procedure:

Step 1: Initialize
- Set $t = 0$ and $X^{(t)} = X^{(0)}$
- Initialize parameters, weights, and any necessary variables.

Step 2: Dynamic Adaptability
- Implement adaptive step sizes.
- Adjust parameters based on the evolving optimization landscape.

Step 3: 3D development
- Promote decisiveness, discipline, and long-term development in the optimization process.

Step 4: Collaborative Optimization
- Foster collaboration among different components.
- Ensure seamless communication and information flow.

Step 5: Swachh Code
- Enforce clean and efficient code practices.

Step 6: Digital Connectivity
- Establish digital connectivity between algorithmic components.

Step 7: JAM Trinity Integration
- Leverage Jan Dhan, Aadhaar, and Mobile for comprehensive optimization.

Step 8: Innovation Hub
- Integrate innovative solutions.
- Explore and incorporate novel approaches.

Step 9: Root Empowerment
- Uplift individual components within the algorithm.
- Value and empower local contributions.

Step 10: Continuous Feedback Loop
- Implement a continuous feedback loop for ongoing evaluation.
- Refine the solution iteratively based on real-time information.

3.3. Fusion of NMOA and LEACH

The proposed integration of the NMOA offers a promising avenue for addressing the drawbacks of the LEACH protocol. NMOA's emphasis on decisive, disciplined, and development-oriented principles aligns with the need for energy-efficient cluster formation and communication in LEACH. The collaborative optimization feature of NMOA is anticipated to mitigate scalability challenges posed by cluster overhead, promoting efficient network growth. Furthermore, NMOA's focus on secure communication practices and its innovative mechanisms for identifying malicious nodes are poised to overcome LEACH's vulnerabilities, enhancing IoT Q-WSNs' overall performance and reliability. This amalgamation of NMOA and LEACH, termed as NM-LEACH is a potential solution for optimizing network efficiency and security.

Algorithm 3: NM-LEACH

Input:
- Desired CH percentage.
- Random numbers assigned to nodes.
- NMOA parameters ($X^{(0)}, T_{max}, \in$)

Output:
- Optimized solution vector ($X^{(Final)}$)

Procedure:

Step 1: Initialization and NMOA Setup
Initialize the desired CH percentage and assign random numbers to nodes. Set up the NMOA algorithm with input parameters and initial solution vector.

Step 2: Narendra Modi-Inspired CH Selection
Leverage NMOA's adaptive mechanisms to influence node comparisons with random numbers, determining Cluster Heads (CHs).

Step 3: Collaborative Cluster Formation
Utilize NMOA-inspired collaboration to establish connections between regular nodes and the most robust CHs, optimizing signal strength.

Step 4: Data Transmission Optimization
Implement NMOA-influenced strategies for standard nodes to communicate with CHs, optimizing energy use during data transmission.

Step 5: Innovative Data Aggregation
Leverage NMOA's innovative solutions for CHs to collect and transmit

information to the central station, enhancing data aggregation efficiency.

Step 6: Energy-Aware Dissipation and Rotation
Utilize NMOA's continuous feedback loop and Root empowerment principles to estimate energy and determine the role of CHs in the next round.

Step 7: Adaptive Optimization Iterations
Initiate multiple iterations of NMOA's adaptive optimization steps (Steps 2–6) to ensure energy efficiency and network longevity.

Step 8: Seamless Digital Connectivity
Ensure seamless communication and information flow among algorithmic components, influenced by NMOA's emphasis on digital connectivity.

Step 9: Comprehensive JAM Trinity Integration
Leverage NMOA's approach to comprehensively integrate the Jan Dhan, Aadhaar, and Mobile (JAM) trinity, optimizing the overall network performance.

Step 10: Continuous Refinement with Feedback Loop
Implement NMOA's continuous feedback loop for ongoing evaluation, refining the solution iteratively based on real-time information and ensuring sustained optimization.

Table 1. Simulation Settings

Simulation Setting	Value
Channel Model	Rayleigh Fading
Quantum Entanglement	Yes
Communication Range	20 meters
Data Aggregation	Enabled or Disabled
Energy Model	Battery model
Interference Model	Path Loss Model
MAC Protocol	IEEE 802.15.4
Mobility Model	Random Waypoint
Network Area	200m x 200m
Number of Quantum Wireless Sensor Nodes	250
Sensor Node Placement	Random or Grid-based
Simulation Time	2000 seconds
Traffic Pattern	Varying traffic load
Transmission Power	10 dBm

4. SIMULATION SETTINGS

NS-3, or Network Simulator 3, is a leading discrete-event network simulator crucial for modeling IoT Q-WSN in the IoT domain. Its modular architecture accommodates the simulation of quantum-enabled sensor nodes, communication channels, and classical networking protocols. Researchers utilize NS-3 to explore quantum phenomena, including entanglement and quantum key distribution, while assessing parameters like quantum routing algorithms and energy models. This open-source simulator is instrumental in gaining insights into the viability and performance of quantum-enhanced communication in IoT Q-WSNs, making it a pivotal tool for advancing quantum technologies within the IoT landscape. Simulation settings used to evaluate NM-LEACH against state-of-the-art algorithms are provided in Table 1.

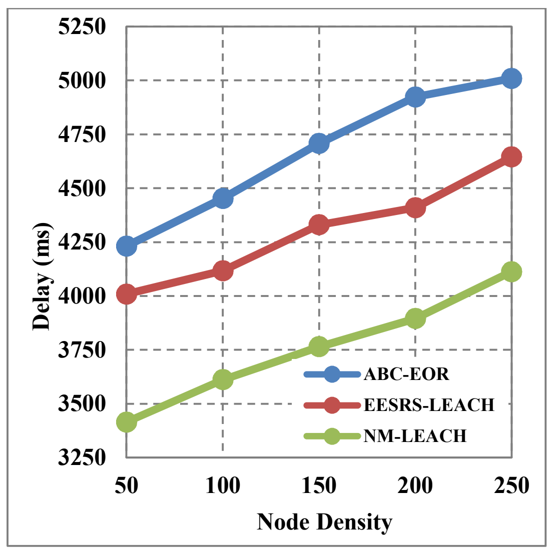

Figure 1. Delay Analysis

5. RESULTS AND DISCUSSION

5.1. Delay Analysis

In Figure 1, the delay analysis reveals NM-LEACH's exceptional performance in minimizing data transmission delays in IoT Q-WSN. This superiority can be attributed to the algorithm's meticulous integration of optimization principles. NM-LEACH ensures seamless communication among different algorithmic components by emphasizing collaborative optimization, significantly reducing delays. Additionally, the continuous feedback loop within NM-LEACH enables real-time adaptation and refinement, resulting in consistently lower delays. Specifically, at 50 nodes, NM-LEACH achieves an impressive delay of 3414 ms, surpassing ABC-EOR at 4231 ms

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and EESRS-LEACH at 4008 ms. These results highlight NM-LEACH's commitment to efficiency, adaptability, and collaboration, making it a robust and effective routing scheme for minimizing delays in WSNs across varying node densities.

5.2. Packet Delivery Ratio

In Figure 2, the packet delivery ratio analysis highlights the exceptional performance of NM-LEACH in IoT Q-WSN This superiority can be attributed to NM-LEACH's incorporation of optimization principles. The algorithm's focus on collaborative optimization, fostering seamless communication among different components, contributes to the efficient and reliable delivery of packets. NM-LEACH's commitment to continuous improvement through a feedback loop also ensures adaptability and real-time adjustments, further enhancing packet delivery ratios. Specifically, at 50 nodes, NM-LEACH achieves an impressive packet delivery ratio of 94.097%, surpassing ABC-EOR at 78.143% and EESRS-LEACH at 88.435%. These results underscore NM-LEACH's robustness, emphasizing adaptability and collaboration, making it a highly effective routing scheme for WSNs across varying node densities.

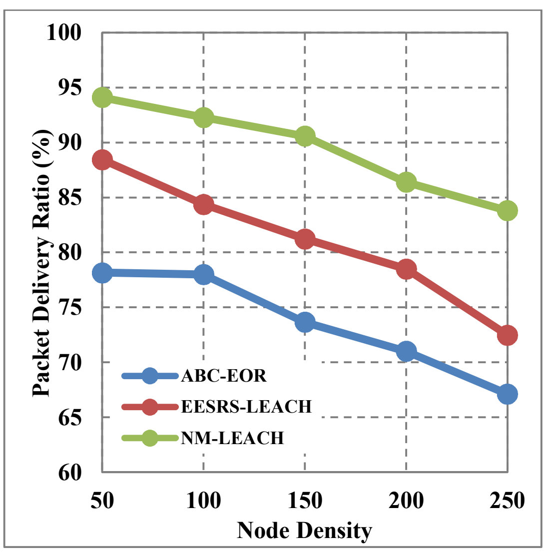

Figure 2. Packet Delivery Ratio Analysis

5.3. Throughput Analysis

Figure 3 illustrates the throughput analysis across various node densities for three routing schemes—ABC-EOR, EESRS-LEACH, and NM-LEACH—in an IoT Q-WSN. Throughput, measured in percentage, is a critical metric reflecting data transmission efficiency. NM-LEACH consistently outperforms its counterparts, achieving higher throughput results. This superior performance can be attributed to the incorporation optimization principles within NM-LEACH. The algorithm's emphasis on collaborative optimization, facilitated by seamless communication among different components, contributes to efficiently utilizing network resources. The continuous feedback loop also ensures adaptability and refinement, optimizing throughput in real-time. The comprehensive and forward-looking approach, part of NM-LEACH's 3D development, further enhances its efficiency. These factors empower NM-LEACH to achieve better throughput results, making it a robust and effective routing scheme for IoT Q-WSNs across node densities.

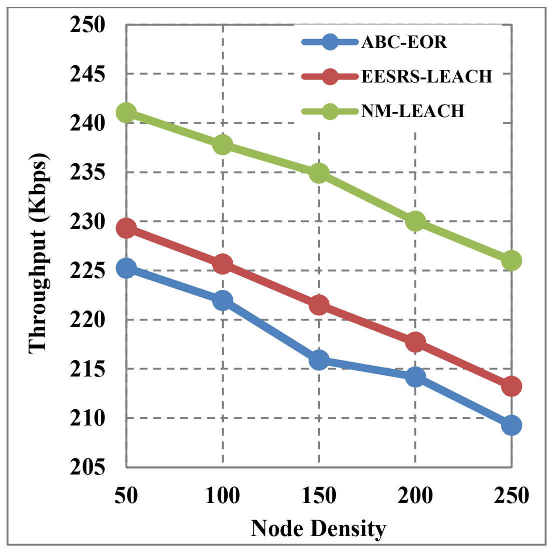

Figure 3 Throughput Analysis

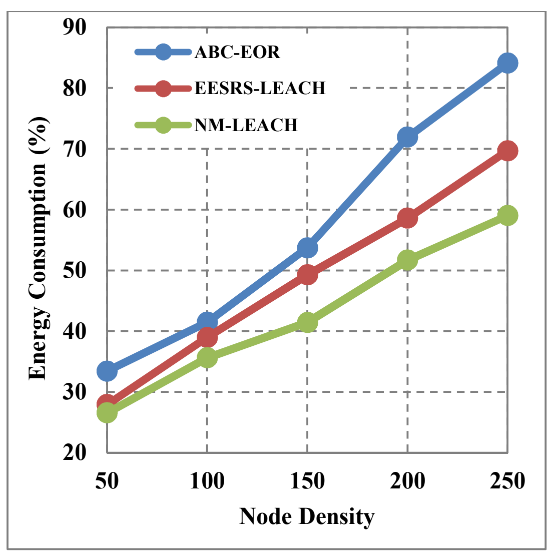

Figure 4. Energy Consumption Analysis

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5.4. Energy Consumption

Figure 4 illustrates the energy consumption analysis across diverse node densities for ABC-EOR, EESRS-LEACH, and NM-LEACH in an IoT Q-WSN. NM-LEACH consistently surpasses the other schemes, showcasing superior energy efficiency. This accomplishment can be attributed to NM-LEACH's emphasis on clean and efficient coding practices, ensuring optimal resource utilization. The algorithm's dedication to continuous improvement by implementing a feedback loop allows for real-time adjustments, leading to better energy conservation. NM-LEACH's collaborative optimization strategy, fostering seamless communication among components, further reduces energy consumption. At 50 nodes, NM-LEACH attains an impressively low energy consumption of 26.546%, outperforming ABC-EOR at 33.412% and EESRS-LEACH at 27.905%. These results highlight NM-LEACH's commitment to energy efficiency, making it a promising routing scheme for sustainable IoT Q-WSNs across varying node densities.

6. CONCLUSION

This study navigated the intricate routing challenges inherent in IoT-based Quantum Wireless Sensor Networks (IoT Q-WSN) and proposed NM-LEACH as a groundbreaking solution inspired by the leadership principles of Shri. Narendra Modi. NM-LEACH marks a distinctive contribution as the first optimization protocol derived from human personality inspiration, introducing innovative strategies to address the unique complexities of Quantum IoT. The operational principles of NM-LEACH, featuring adaptive strategies, clean coding practices, and continuous feedback loops, exemplify a comprehensive and disciplined approach to network development. The rigorous evaluation of NM-LEACH through NS3 simulations showcased its notable performance advantages in minimizing delays and optimizing data transmission within IoT Q-WSNs compared to existing protocols. The findings underscore the promising outlook for NM-LEACH in effectively addressing evolving challenges within Quantum IoT applications. By infusing inspiration from human leadership qualities, this study highlights the potential of innovative approaches to enhance the adaptability and efficiency of wireless sensor networks. As the IoT landscape advances, NM-LEACH stands as a significant stride forward, contributing to the ongoing progress in Quantum Wireless Sensor Networks and affirming its role in elevating communication reliability and performance in this burgeoning field.

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