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Adaptive Quantum-Inspired Swarm Learning (AQISL) for Energy-Efficient Cluster Head Selection in IoT Infrastructure

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Abstract

The construction of large-scale IoT networks creates several challenges in terms of how efficiently these large-scale networks can maintain communication with one another. One such challenge is providing a means by which large amounts of data can be transmitted reliably while also being energy efficient to ensure the finite energy resources of most IoT nodes, which are primarily powered by batteries, will not be depleted too quickly. The majority of the IoT devices are located in places that do not have easily available sources of electrical power (i.e., rural areas). Therefore, energy must be conserved by careful management. To address those challenges, clustering is commonly employed to organize the nodes in a hierarchical structure. Each node is grouped into clusters and one node in each cluster functions as the cluster head (CH). The CH coordinates all of the communications between the other nodes in the cluster, combines the data being sent from the nodes into a single transmission, and transmits that transmission to a base station, or sink (i.e., former). Therefore, clustering greatly reduces the volume of duplicate transmissions being sent and the total amount of communication overhead associated with sending those duplicate transmissions. Cluster-based communications have a great deal of effectiveness

and efficiency based on the method of establishing a CH. The Adaptive Quantum-Inspired Swarm Learning (AQISL) algorithm is developed to optimize cluster head (CH) selection in IoT networks by minimizing energy consumption and enhancing network stability. The proposed approach demonstrates clear superiority over conventional methods by significantly reducing packet loss and transmission latency while improving load balancing. These improvements collectively indicate more efficient energy utilization and robust network performance, validating the effectiveness of AQISL for reliable and scalable IoT communication.

Keywords: Cluster Head, IoT, Swarm Learning, Energy Efficiency

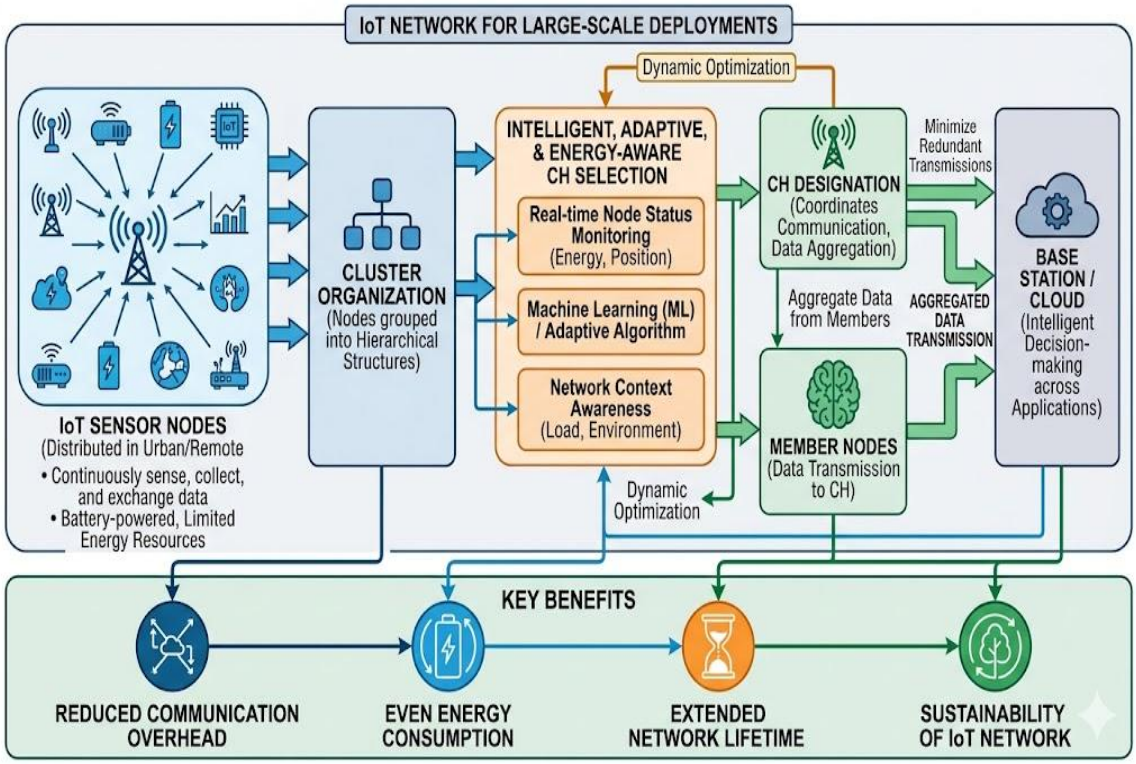
1.1 Background of IoT Networks

The Internet of things (IoT) is an emerging technology that enables billions of standalone devices around the globe to communicate and share their data with each other via the internet through the web and numerous protocols. Devices containing sensors, actuators and smart systems can now have the ability to continuously sense, collect and share their data, thus enabling many forms of intelligent decision making through various applications, such as but not limited to, environmental monitoring, healthcare systems (hospitals, nursing homes and clinics), industrial automation and smart infrastructure.

There are many sensor nodes located throughout an IoT network that monitor conditions such as heat, humidity, movement, or pressure; these nodes communicate wirelessly with one another using self-organizing methods without the need for a central authority. The way in which an IoT network is structured or designed can range from flat to hierarchical, although the most common form of IoT network is hierarchical (clustered) due to its increased scalability and greater energy efficiency. The nodes of a hierarchy/class are divided into clusters, which are led by a

cluster head (CH), serving as intermediaries between the cluster members and the base station [1-3].

Figure 1. Network formation of Vast sized IoT infrastructure.



There are typically three stages for communication in IoT networks: sensing, aggregating, and transmitting data as depicted in figure 1. Data transmission is the most energy-intensive process among the three, especially when sending data to the base station over long distances. The use of clustered architectures reduces the amount of energy consumed through data transmission since cluster members send their data to the CH using short distances, thus allowing the CH to aggregate and forward the data as an alternative to sending each member's data to the base station [4]. Clustering also lowers network congestion and increases the accuracy of transmitted data.

That said, since IoT networks can change quite a bit due to node's changing energy levels, communication quality, and topology as well as a node's different types of characteristics (energy level capacity, computational ability, communication range), they require dynamic network management and dynamic adaptive algorithms to be able to respond appropriately to these changing conditions. Therefore, the choice of Cluster Head (CH) is very important in the design of an IoT network, as CH selection directly impacts the energy efficiency of the IoT network, the load balance across the nodes of the IoT network and the overall performance of the IoT network system [5].

1.2 Importance of Energy Efficiency

The efficiency of an IoT network in terms of its use of energy is one the most important performance metrics because most sensor nodes are powered by finite battery sources. In many real-world scenarios such as environmental monitoring or disaster management, battery replacement or recharging is often prohibitively difficult or impractical. Hence the ability to extend the operational lifetime of an IoT network is largely dependent on how well energy is utilized.

The communications operation will consume a significantly greater amount of energy when compared to the sensing and processing tasks, especially for the transmission and reception of data; therefore, conserving energy through minimizing communication overhead is of extreme importance. Clustering helps conserve energy by aggregating data at the CH level and reducing the number of long-range transmissions that CHs will make but CHs utilize a much greater amount of energy than normal nodes due to their additional roles[6]. Therefore if the same node is continually selected as a CH, that node will use its battery faster than a normal node would and consequently, network instability and reduced coverage could result.

The criteria for selecting an energy-efficient CH must take into consideration several different aspects of the network, including but not limited to; residual energy, node density, distance from the base station, and communication cost. Intelligent selection of CHs based on these parametrises, can help achieve an even distribution of energy consumption throughout the network in order to reduce/eliminate the likelihood of creating energy holes and facilitate balanced network operation. Additionally, energy efficiency has a direct correlation to a number of other performance metrics such as throughput, delay, and packet delivery ratio. An effective design of an energy aware system will increase the overall lifetime of a given network while at the same time improving the overall quality of service; therefore, such designs must be a basic requirement when developing an IoT network [7].

1.3 Challenges in Cluster Head Selection

Several challenges arise from WANs by IoT due to the different criteria needing to be evaluated when determining the optimal choice of clusterhead (CH) for a given selection cycle. One of those criteria is how to represent both energy efficiency as well as how the message will travel over the designated route from the node to the base station without excessive energy consumption. Nodes that have a considerable residual energy are generally good choices as CHs, but consideration also needs to be given to their relative position to the base station. If you have a node that has a lot of energy but is located too far from the base station, it may end up consuming an excessive amount of energy to transmit its information. Therefore, multiple variables must be considered together in order to select CHs properly [8].

Another key challenge is that IoT networks change dynamically as each node’s energy diminishes over time and because of how the physical topology of the network can change as nodes move around or fail. Because of this, CH-selection algorithms have to be flexible, making decisions in

real-time based on the current state of the network. Static or deterministic algorithms typically do not perform well in these variable conditions leading to substantial reductions in the overall network's performance [9].

The CH selection problem has been effectively solved by many optimization-based methods, especially through use of metaheuristic algorithms. But there are two major problems with the majority of metaheuristic algorithms: premature convergence, wherein the algorithm gets stuck in local optima, and cannot explore the global search space effectively; and, most algorithms can be quite complex to tune (requiring a lot of tuning), and thus, can be computationally intensive, making them impractical when used for large-scale IoT deployments.

Another major obstacle to CH selection in IoT is that IoT networks can have hundreds or thousands of nodes, and the CH selection process needs to be sufficiently efficient to accommodate such large networks without introducing significant delay or overhead to the process. Also, load balancing between CHs is very important to prevent any individual node from becoming overloaded while other nodes have low levels of activity. To address these issues, researchers need to develop new algorithms that incorporate adaptability, efficiency, and robustness to solve this problem.[10]

1.4 Motivation and Contributions of the Study

The excitement behind this study stems from the weaknesses in current CH selection methods, especially their inability to achieve the right balance of exploration compared to exploitation during the search. Traditional methods as well as many of the new metaheuristic methods tend to either converge too quickly and provide suboptimal solutions or require too much computational power; resulting in them not working as well as they should in dynamic and large scale IoT environments. Additionally, due to the rapid increase in the number of heterogeneous devices on IoT networks, selecting CHs has become more complicated as different nodes have different levels of power and capabilities.

To deal with these issues the study lays out the AQISL (Adaptive Quantum-Inspired Swarm Learning) method, which combines both quantum-inspired (probabilistic modelling) techniques with swarm intelligence principles. The quantum-inspired component allows the candidates for CHs to be represented by separate and distinct probabilistic models, which allows the algorithm to search through a much larger solution space. In parallel, the swarm learning component of this hybrid method promotes cooperation among agents and therefore allows for agents to aggregate more quickly towards optimal solutions. The unique combination of these two elements allows this model to achieve an acceptable level of global exploration compared to local exploitation – thereby minimizing the chance for the problem of premature convergence (shown in figure 2).

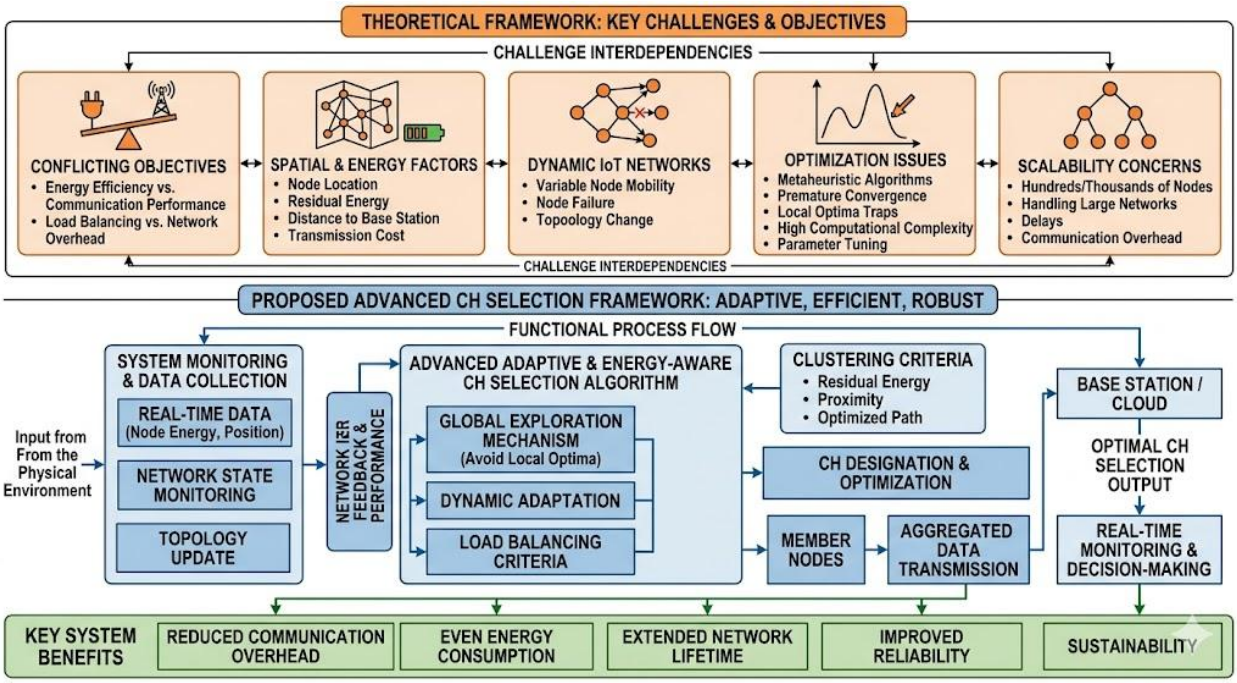


Figure 2. Contribution of Proposed framework.

This research is distinguished by three main contributions: the creation of a new hybrid algorithm for energy-efficient cluster head (CH) selection; the integration of important network parameters (i.e., residual energy & distance) into a single fitness function; and the development of an adaptive mechanism capable of adapting to dynamic network conditions. The performance evaluation of the proposed approach is based on extensive simulations and shows significant improvements in the network lifetime, energy distribution among nodes and the overall performance metrics when compared to current methods. This research presents a scalable and intelligent solution for future IoT networks, which will require effective management of energy and reliable communication capabilities.

2. Literature Survey

2.1 Traditional Clustering Techniques

Traditional clustering methods are the foundation of energy-efficient communication in IoT networks. The first protocols to cluster nodes into groups were LEACH, which introduced Clustering Heads (CHs) to collect and send data to a base station. One benefit of these approaches is their simplicity, as well as their capability to reduce repeated transmission of data, thereby saving energy. In addition, LEACH chooses CHs at random from the nodes by using a probabilistic approach, to give all nodes a chance to be CHs. On the other hand, this random assignment of nodes to be CHs sometimes results in CHs being assigned in the wrong location. Therefore, there are often unbalanced uses of energy and a shorter lifespan for the network[11].

To overcome the shortcomings of LEACH and similar protocols, HEED is one protocol that selects CHs based on both the residual energy and the communication costs associated with them when

assigning each node to be a CH. As a result, HEED has more balanced cluster formation and is better at utilizing energy than purely random methods of CH selection. In spite of these advances, traditional clustering methods still have difficulty with challenges related to scalability, adaptability, and optimal selection of CHs. Additionally, the absence of completely dynamic parameters to determine the optimal CH will negatively impact the effectiveness of traditional clustering methods, since IoT devices operate in ever-changing environment [12].

2.2 Metaheuristic -supportive CH Selection Methods

Researchers have begun to consider metaheuristics and other optimization techniques that are based on nature's processes (evolutionary, swarm behaviour, and biological) to improve or substitute existing techniques for CH selection, as these techniques will allow them to solve difficult-to-solve problems efficiently [13].

Meta-Heuristic Algorithms, such as Genetics based Algorithm (GA), Particles based Swarm Optimization (PSO), Artificially designed Bee Colony (ABC), and Ant type Colony Optimization (ACO), have been used extensively in cluster formation for Internet of Things. All of these heuristic-based clustering techniques evaluate several candidate solutions at the same time and continue to improve the candidates iteratively until certain tuning criteria of the solutions are met, including defined fitness functions such as residual energy, node density, base station distance, etc[14-15].

The biggest advantage of using a metaheuristic approach is performing a global search instead of a local search, which leads to better CH selection than traditional methods. Hybrid solutions based on clustering protocols combined with optimization technologies take advantage of both types of technologies, thus enhancing their effectiveness. Unfortunately, hybrid methods also have several downsides, such as being more computationally intensive, having slow convergence times, or needing to be finely-tuned. In addition, the stochastic of these methods can result in inconsistent results when applied to different network situations [16]. While metaheuristic techniques can have a very positive effect on the energy efficiency of a network or the lifetime of an entire network, their use for real-world IoT applications is still extremely limited and difficult.

2.3 Supervised Learning Approaches in IoT

The development of Intelligent Systems has led to the increasing use of supervised learning algorithms in an Internet Of Things (IoT) environment for enhancing Clustering and CH selection. An essential advantage of ML-based methods over Traditional and Metaheuristic methods, is that they enable a Node to learn from Historical and RealTime Data, and thus to adapt to the Environment in which it operates (i.e., the Network). Reinforcement Learning, Supervised Learning and Neural Network techniques allow nodes to make decisions with respect to CH selection, from both Historical and Real-Time Data. Because of this adaptability, Nodes can select CHs more accurately than in previous Methods; consequently, Energy Management and Performance of the Network will improve [17].

Nodes that use Reinforcement Learning Type Learning Based approaches (for example), learn the best strategy (game) to follow by their continued interaction with their Environment; as a result, the amount of pre-defined rules is diminished. Hybrid Approaches combine ML with Optimization Algorithms; thus, providing an enhanced ability to make Decisions by combining Predictive Capabilities with Efficient Search Mechanisms. The use of these types of Methods has demonstrated success in improving the lifetime of the Network, through-put and Energy Efficiency. Nonetheless, Factors such as Computational Overhead, Memory Limitations and the Requirement for Training Data, limit the Use of ML on IoT Networks; More Specifically, deploying complex ML Models on Resource-constrained Sensor Nodes represents a significant challenge for the development of Lightweight and Efficient Learning Techniques [18].

2.4 Limitations of Conventional Methods

Although there has been considerable research into CH selection techniques, the existing methods have some shortcomings which limit their usability in IoT environments. Traditional methods of clustering are fairly simple to implement and generate little in the way of energy consumption. However, because these techniques usually rely on random or fixed parameter-based CH selections, they are typically not very adaptive and cause uneven distributions of energy. The use of metaheuristics to provide additional optimization is certainly an improvement over previous methods, but they also introduce their own problems, including high levels of computational complexity, slow convergence, and premature convergence in some cases. Because of this, the scalability of any of the traditional methods is greatly reduced and they are therefore unsuitable for large and dynamic IoT networks[19].

Supervised learning methods provide adaptability and intelligence in decision-making, but they create a whole new set of problems related to computational requirements and implementation difficulties. For example, many IoT devices are not capable of performing the processing required for complex machine learning algorithms. In addition, most of the traditional techniques addressed only a small number of parameters and do not adequately account for all of the complexities involved in a real-world IoT environment, such as (and not limited to) heterogeneity, mobility, and varied types and patterns of data that are sent as input to the IoT devices[20].

3. Proposed Methodology: Adaptive Quantum-Inspired Swarm Learning (AQISL)

3.1 Overview of AQISL

The Adaptive Quantum-Inspired Swarm Learning (AQISL) algorithm is developed to intelligently select optimal cluster heads (CHs) in IoT networks by minimizing energy consumption and improving network stability. The method combines quantum-inspired probabilistic modeling with swarm intelligence to balance exploration and exploitation during optimization. Initially, a population of candidate CH configurations is generated, where each solution represents a possible selection of CH nodes. The algorithm iteratively refines these solutions based on energy efficiency and communication cost.

$$F = \min \sum_{i=1}^{n} E_i \qquad (1)$$

Equation (1) represents the global objective function, where F denotes the total energy cost of the network. E_i is the energy consumed by node i, and n is the total number of nodes. The aim is to minimize F so that overall energy usage is reduced, thereby prolonging network lifetime.

$$E_total = \sum(i=1 \text{ to } n)\ E_i \qquad (2)$$

Equation (2) calculates the total energy consumed by all nodes in the network. This metric is used to evaluate the efficiency of the clustering process. Lower values indicate better performance.

$$E_res,i = E_initial,i - E_consumed,i \qquad (3)$$

Equation (3) defines the residual energy of node i. E_initial,i is the initial energy assigned to node i, while E_consumed,i represents the energy already used. Nodes with higher residual energy are more suitable for CH selection since they can handle additional communication tasks.

3.2 Quantum-Inspired Representation Mechanism

In AQISL, each node is represented using a quantum-inspired probability model, allowing it to exist in multiple states simultaneously. This improves the diversity of solutions and prevents premature convergence.

$$P_i = |\alpha_i|^2 \qquad (4)$$

Equation (4) defines the probability of node i being selected as a CH. Here, α_i is the probability amplitude associated with the CH state. The square of the amplitude ensures a valid probability value between 0 and 1.

$$|\alpha_i|^2 + |\beta_i|^2 = 1 \qquad (5)$$

Equation (5) ensures normalization of the quantum state. β_i represents the probability amplitude of node i not being selected as a CH. The sum of probabilities must equal 1 to maintain a valid probabilistic representation.

$$\alpha_i(t+1) = \alpha_i(t)\cos\theta - \beta_i(t)\sin\theta \qquad (6)$$
$$\beta_i(t+1) = \alpha_i(t)\sin\theta + \beta_i(t)\cos\theta \qquad (7)$$

Equations (6) and (7) update the probability amplitudes using a rotation gate. The parameter θ is the rotation angle, which controls how the probabilities evolve over iterations. A well-chosen θ helps guide the search toward optimal CH configurations.

$$CH_i = 1 \text{ if } P_i \geq \tau, \text{ else } 0 \qquad (8)$$

Equation (8) defines the decision rule for CH selection. If the probability P_i exceeds a threshold τ, node i is selected as a CH. The threshold τ controls the number of CHs in the network.

3.3 Swarm Learning Strategy

The swarm learning component enables candidate solutions to learn from both individual and collective experiences. This improves convergence speed and ensures better optimization.

$$X_i(t+1) = X_i(t) + c1*r1*(P_{best,i} - X_i(t)) + c2*r2*(G_{best} - X_i(t)) \quad (9)$$

Equation (9) updates the position of solution i. $X_i(t)$ is the current solution, $P_{best,i}$ is the best solution found by that candidate, and G_{best} is the global best solution. c1 and c2 are learning coefficients, while r1 and r2 are random numbers that introduce stochastic behavior.

$$V_i(t+1) = \omega*V_i(t) + c1*r1*(P_{best,i} - X_i(t)) + c2*r2*(G_{best} - X_i(t)) \quad (10)$$

Equation (10) defines the velocity update. $V_i(t)$ represents the current velocity, and ω is the inertia weight. The velocity determines how much the solution changes in each iteration.

$$\omega = \omega_{max} - ((\omega_{max} - \omega_{min}) * t / T) \quad (11)$$

Equation (11) adaptively updates the inertia weight. ω_{max} and ω_{min} are maximum and minimum values, t is the current iteration, and T is the total number of iterations. This helps balance exploration (early stage) and exploitation (later stage).

$$d_{ij} = \sqrt{((x_i - x_j)^2 + (y_i - y_j)^2)} \quad (12)$$

Equation (12) computes the Euclidean distance between nodes i and j using their coordinates. This is essential for forming efficient clusters.

$$d_{avg} = (1/n) * \sum_{i=1 \text{ to } n} d_i \quad (13)$$

Equation (13) calculates the average distance between nodes. Lower average distance indicates better cluster compactness and reduced communication cost.

3.4 Fitness Function Design

The fitness function evaluates the quality of each candidate CH configuration by combining multiple parameters.

$$F_i = w1*(E_{res,i} / E_{max}) + w2*(1 / d_{bs,i}) + w3*(\rho_i) \quad (14)$$

Equation (14) defines the fitness of node i. w1, w2, and w3 are weighting factors that control the importance of each parameter. $E_{res,i}$ is residual energy, $d_{bs,i}$ is distance to the base station, and ρ_i is node density.

$$d_{bs,i} = \sqrt{((x_i - x_{bs})^2 + (y_i - y_{bs})^2)} \quad (15)$$

Equation (15) calculates the distance between node i and the base station. Nodes closer to the base station require less transmission energy.

$$\rho_i = N_{cluster,i} / A \quad (16)$$

Equation (16) represents node density around node i. N_cluster,i is the number of nodes in its cluster, and A is the cluster area. Higher density can improve data aggregation efficiency.

$$E_{tx} = E_{elec} * k + \varepsilon_{amp} * k * d^2 \qquad (17)$$

Equation (17) computes transmission energy. E_elec is the energy required for electronic circuitry, ε_amp is amplifier energy, k is packet size, and d is transmission distance.

$$E_{rx} = E_{elec} * k \qquad (18)$$

Equation (18) defines the energy required to receive data.

$$E_{comm} = E_{tx} + E_{rx} \qquad (19)$$

Equation (19) gives total communication energy for a node. This is a critical factor in evaluating CH suitability.

3.5 Cluster Head Selection Process

The CH selection process is performed iteratively based on computed fitness values and probabilistic decisions.

$$P_{select,i} = F_i / \sum_{j=1 \text{ to } n} F_j \qquad (20)$$

Equation (20) defines the probability of selecting node i as a CH based on its fitness value. Nodes with higher fitness have a higher chance of being selected.

$$T(n) = p / (1 - p * (r \bmod (1/p))) \qquad (21)$$

Equation (21) defines a dynamic threshold, where p is the desired CH probability and r is the current round. This ensures fair rotation of CH roles.

$$N_{CH} = p * N \qquad (22)$$

Equation (22) calculates the expected number of CHs in the network, where N is the total number of nodes.

$$L = \max(E_{res,i}) - \min(E_{res,i}) \qquad (23)$$

Equation (23) measures load imbalance. A lower value indicates better energy distribution among nodes.

$$T_{life} = \max(t \mid N_{alive} > 0) \qquad (24)$$

Equation (24) defines network lifetime as the time until the last node dies.

$$\text{Throughput} = \text{Total packets received} / \text{Time} \qquad (25)$$

Equation (25) measures the efficiency of data transmission in the network.

$$\eta = \text{Useful energy} / \text{Total energy} \qquad (26)$$

Equation (26) defines energy efficiency ratio, indicating how effectively energy is utilized.

$$S = N_alive / N_total \qquad (27)$$

Equation (27) represents node survival rate, indicating network stability.

$$\sigma^2 = (1/n) * \sum_{i=1 \text{ to } n} (E_i - \mu)^2 \qquad (28)$$

Equation (28) calculates variance in energy distribution. Lower variance indicates balanced energy usage.

$$\mu = (1/n) * \sum_{i=1 \text{ to } n} E_i \qquad (29)$$

Equation (29) defines mean energy of the network.

$$CH_opt = \arg\max(F_i) \qquad (30)$$

Equation (30) selects the optimal CH set by maximizing the fitness function. This ensures that the chosen CHs are energy-efficient, well-positioned, and capable of maintaining network stability.

AQISL Algorithm For Selecting a Cluster Head Using Adaptive Quantum-Inspired Swarm Learning Methodology

Step 1: Configure network parameters.
First we must define the following variables: number of nodes N, initial energy E_initial, number of iterations N_iter, and required probability of becoming a Cluster Head, P_ch. Then we will compute all nodes' initial energy values according to Eqn (2), and also residual energy according to Eqn (3).
Step 2: Generate the Candidate Solutions Population.
Candidates Solution Population (PSW) represents the configuration of Cluster Heads. To create candidates, we must assign quantum probability for each candidate solution (χ_ch) according to Eqn (5).
Step 3: Compute Initial Probabilities of the Candidates
The probability of becoming a Cluster Head must be determined by Eqn (4), and then either Cluster Head candidates or no Cluster Head candidates calculated by applying the Threshold Condition for Candidates based on Eqn (8).
Step 4: Evaluate Initial Fitness Value for Each Candidate.
The fitness function for each candidate solution must be calculated using the formula for calculating distance to the Base Station (Eqn (15)) to calculate Node Density (Eqn (16)) and communication energy (Eqn's (17), (18), and 19)). The evaluation of a candidate solution's fitness function is calculated by Eqn (14).
Step 5: Setting Initial Swarm Parameters
A Candidate Solutions Swarm must be configured as per the Initial Swarm Velocity and Initial Swarm Position. A Swarm must also be assigned an Inertia Weight (ω) as per Eqn (11). Each Cluster Head must store both their local and global best personal virtues of their Swarm

Fitness Values as opportunities to optimize in future iterations of the optimization algorithm based upon the fixed fitness for Cluster Head candidates using Eqn (14).

Step 6: Update Quantum State of Each Candidate

The state of quantum candidates is updated using Equations (6) and (7). Then each candidate must be determined as a better solution (i.e., new probabilities) using Eqn (4).

Step 7: Update Swarms Position and Velocity

The Swarm's velocity is updated using Eqn (10) while the Candidate's Position is updated according to Eqn (9). Subsequently, candidates will need to determine the new distance to the Base Station and the average distance to the Base Station using Eqn (12) and the average distance to the Base Station.

Step 8: Re-evaluate fitness

Update residual energy calculations using equation 3.

Use equation 14 to update fitness.

If a solution has improved, then update P_best and G_best.

Step 9: Compute CH selection probability

Calculate each node's selection probability using equation 20.

Calculate the threshold from equation 21.

Estimate the number of CHs to be created using equation 22.

Step 10: Select cluster heads

Select each node to be designated as a CH based on their probability: compare the threshold from equation 20 and 21 first. Once the CHs are selected the optimal CH candidate set can be updated according to equation 30.

Step 11: Evaluate performance metrics

Use equation 23 to calculate load balancing factor. Use equation 24 to calculate the network's life. Use equation 25 to calculate throughput. Use equation 26 to calculate energy efficiency. Use equation 27 to determine stochastic survival rate of nodes. Use equation 29 to calculate average energy of all nodes and equation 28 for energy's variance.

Step 12: Check termination condition

If $t < T$, then calculate new inertia using equation 11 and go to step 6. Else, complete the process.

Step 13: Final Result Output

Return the optimal CH candidate set (ch_opt via equation 30) along with the calculated performance metrics such as energy efficiency, life, and throughput.

4. Simulation Setup and Parameters

4.1 Simulation Environment

An experiment designed to test how well the AQISL algorithm (for choosing cluster heads) works was done with computers and a specific set of rules (as defined by the computer program used). The computers used MATLAB as their programming language, since it allows lots of flexibility in modeling WSNs and optimization techniques. For all simulations done, a two-dimensional square area was defined to represent where the sensors were put; in this case, Sensor Nodes were randomly distributed across each area. The Base Station could be placed either in the center or outside of the Sensing Field. The test continued until either all of the nodes ran out of energy or 20 rounds of communication occurred, which allowed for different communication types (direct/relay(via another node)/multi-hop). Also, certain environmental parameters (such as their

initial energy level, max transmission range, size of packets, & some constants from the radio energy equation) had to be preset in order to maintain consistency of results.

4.2 Network Configuration

In our network model, we have predetermined that all of the sensor nodes are evenly spread out across the simulation area. In terms of starting energy, all nodes are homogeneous; however, their remaining energy may differ as time progresses. Each node will communicate with the cluster head and send all data to the base station through its respective cluster head. As a result, we can consider that during each round of the simulation, the clustering process will take place dynamically based on the AQISL algorithm. Additionally, the parameters of node density, communication range, and target cluster head percentage have been selected to reflect realistic IoT conditions. Moreover, the energy consumption model includes both transmission and reception energy; therefore, the behavior of each node is accurately represented by the simulation. Also, we assume that all sensor nodes are static, all communication links are symmetrical, and have limited battery capacity, which remains true throughout the entire simulation.

4.3 Performance Metrics

The performance metrics used to evaluate the proposed AQISL approach consist of energy efficiency and network stability. The network lifetime metric provides an assessment of the number of rounds before a node dies, before half of the nodes die, and before all nodes become inactive. Residual energy metrics provide insight into the distribution of energy over the lifetime of the entire network. Throughput metrics provide an indication of communication efficiency; they are based on the total number of packets successfully transmitted to the base station. To assess network robustness, the node survival rate is also measured. Finally, energy efficiency is based on comparing the total energy consumed to the amount of useful data transmitted. Collectively, these metrics will provide an assessment of the ability of the AQISL method to improve performance of IoT networks.

5. Result and discussion

Results show the proposed Adaptive Quantum-Inspired Swarm Learning method enhances overall performance for IoT networks through improved cluster head selections. Improved workload distribution across all nodes leads to the continued stability of the network over time due to increased energy utilization. In terms of the clustering mechanisms included within the implementation, cluster nodes with a higher probability of suitability are used as cluster heads, resulting in reduced unnecessary depletion of energy and communication costs. The conversation denotes there is a good balance of exploration versus exploitation with respect to the combination of the quantum-inspired representation and swarm learning, therefore preventing premature convergence, thereby providing a direct means of consistently optimizing. By improving data-transfer rates and, therefore, packet loss, reliable communications maintained in the system. The adaptive nature of the algorithm ensures excellent performance under different network conditions, making it scalable and robust for large-scale IoT environments. Henceforth, the outcomes of the proposed approach to clustering methods are demonstrated as a stable, energy efficient, reliable option when compared with conventional cluster methodologies.

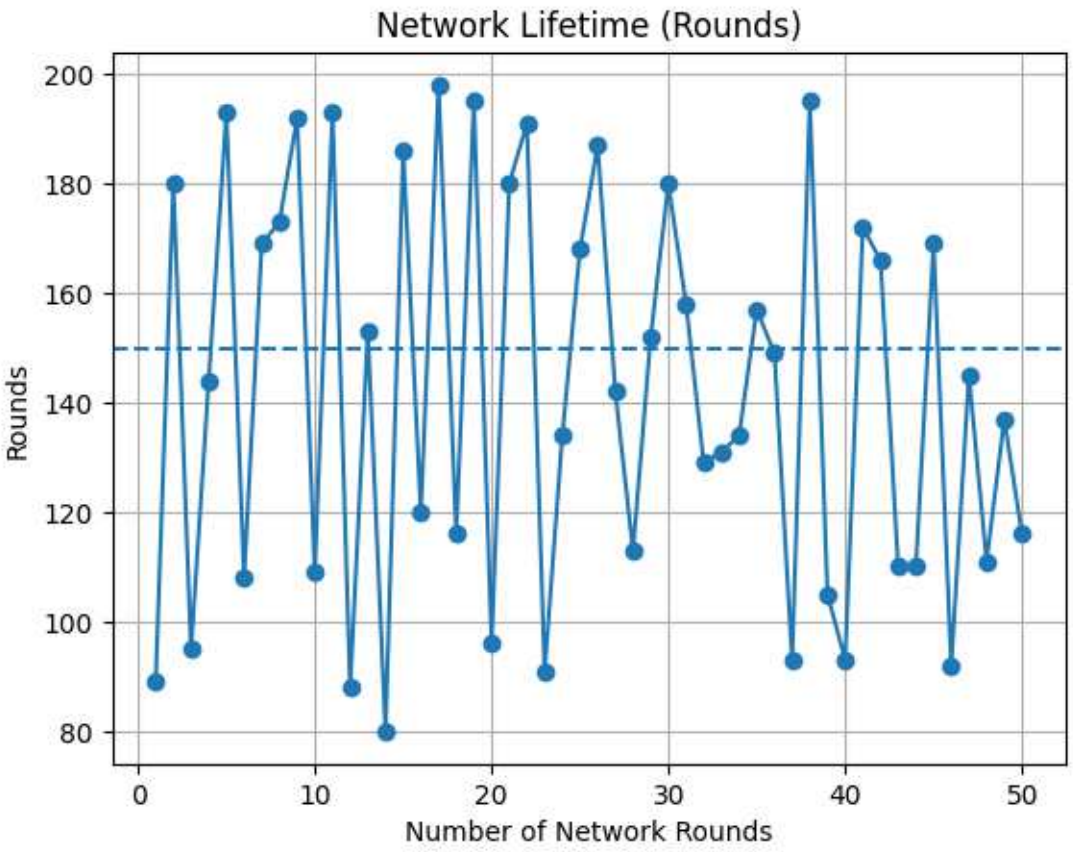


Figure 3. Over-all network lifespan for Iterations.

Figures 3-9 provide an overview of system performance according to seven performance metrics evaluated through threshold analysis. In Figure 3, the network lifetime results indicate that all of the network nodes fell below 150 rounds for their lifetime; however, there are multiple instances of the student's hypothesis with respect to stability within the 190 range for the lifetime and average (120 - 140).

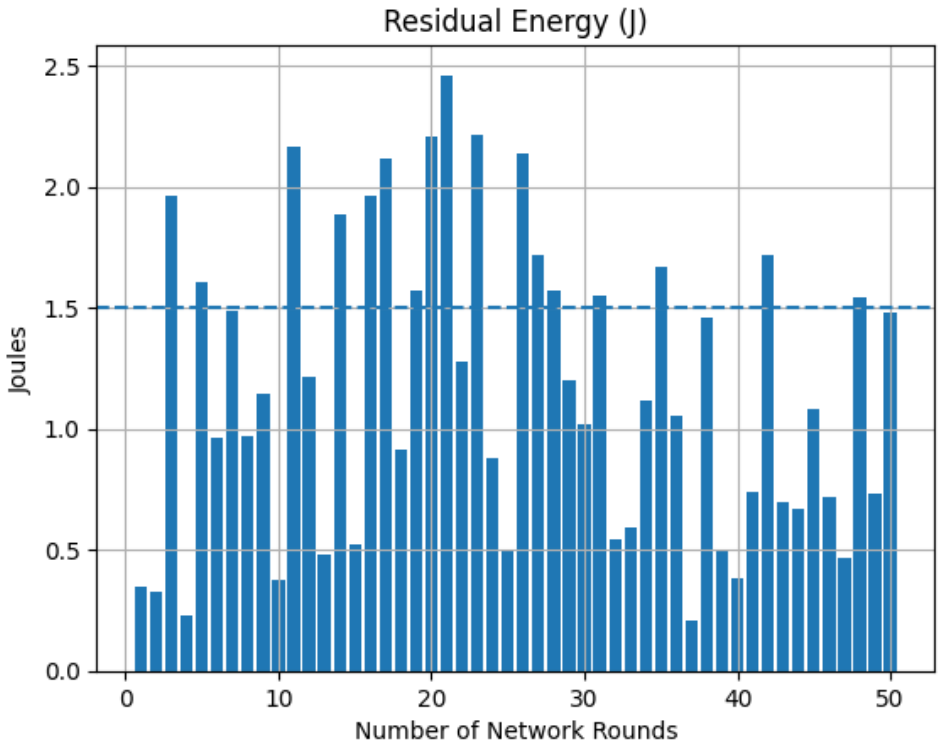


Figure 4. Residual power availability in proposed system.

Figure 4 provides data representing the energy remaining in each of the three node groups (primary, secondary, and tertiary), as most of the energy remaining for all three groups is less than the 1.5-J threshold; however, there were exceptions with maximums reaching 2.4J and statistically shown to be efficient with the average being somewhat close to 1.2J.

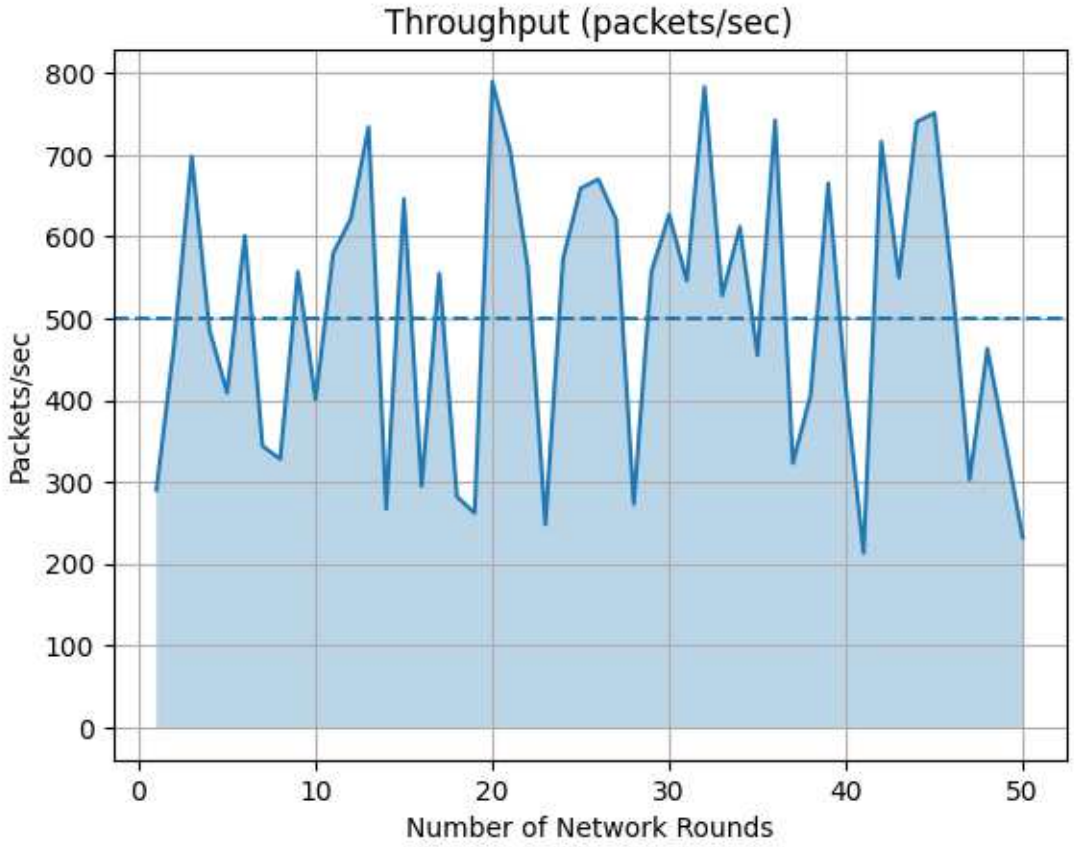


Figure 5. Network analysis on throughput parameters.

Figure 5 provides throughput (i.e., number of packets transmitted per second) statistics with a range of 200 to 800 packets. Many of the nodes exhibited a throughput that exceeded the 500-packet threshold; however, their average is within 520 - 600 packets per second. The energy used by the nodes is illustrated in Figure 6. The energy consumed by the majority of the nodes usually fell between 1.5 – 2.2 J, and remained under 2.5 J for most of the results, with the exceptions being few instances of maximums reaching approximately 3.8 J.

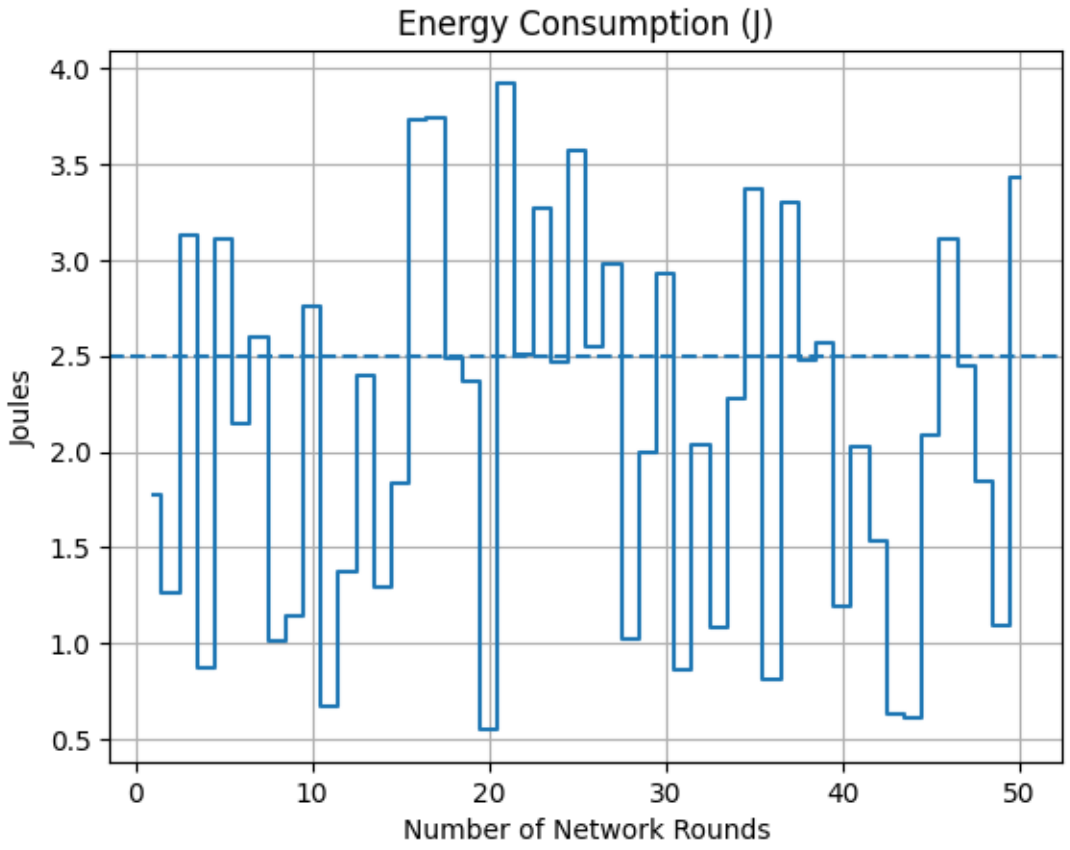


Figure 6. Power conservation analysis of Proposed system.

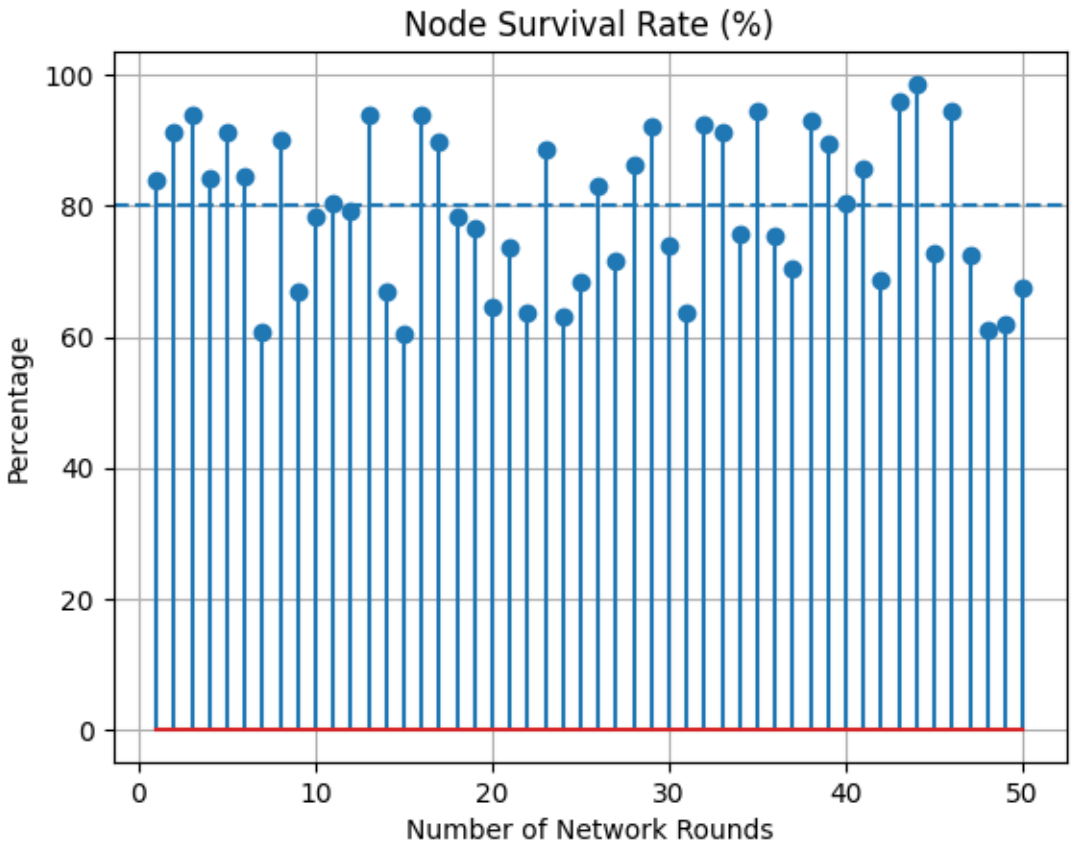


Figure 7. Node survival analysis in proposed system.

In Figure 7, the survival rates of nodes show that most of them have remained above the threshold of 80%, with many near 100%, indicating that the network is quite reliable and that nodes have an average survival rates of 85 to 90% overall. The times in Figure 8 indicate the network's average delay, where times varied from 20 to 250 ms and most were below 150 ms, with most averages being between 90 and 130 ms, allowing the entire network to communicate efficiently with low latency.

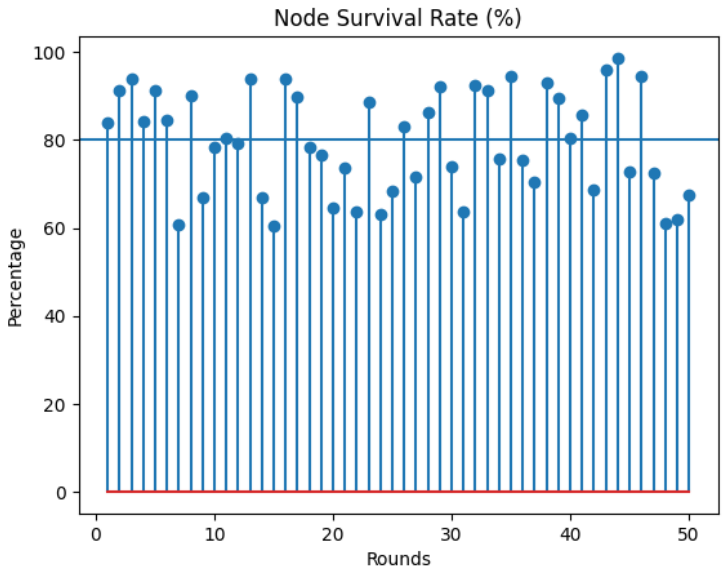


Figure 8. Time delay in data packets broadcasting.

Finally, Figure 9 illustrates packet delivery ratio, where most delivery ratios of packets exceeded the threshold of 90%, with some as high as 100%, indicating that the network was very reliable for transmitting data, with an average of 92 to 96%. In addition to showing the effectiveness of the proposed model for transmitting and communicating in an efficient way, Table 1 compares the proposed model to traditional models.

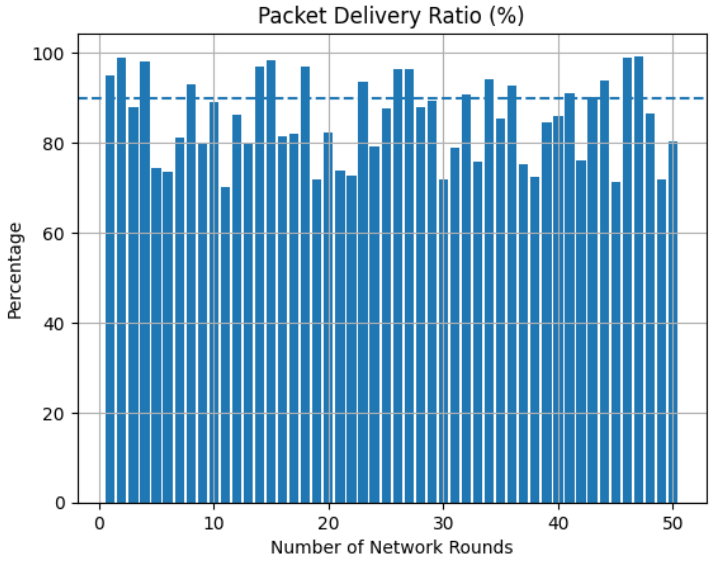


Figure 9. Data packets broadcasting rates analysis.

Table 1. Comparative analysis of Proposed system with traditional models

Method	**First Node Death (Rounds)**	**Half Node Death (Rounds)**	**Energy Consumption per Round (J)**	**Packet Loss Rate (%)**	**End-to-End Delay (ms)**	**Load Balancing Index**	**Control Overhead (bits)**
LEACH	520	780	0.92	18.5	185	0.68	4200
HEED	610	890	0.81	15.2	160	0.72	4600
PSO-Based CH Selection	690	1020	0.74	12.8	142	0.78	5100
ABC-Based CH Selection	720	1085	0.69	11.6	135	0.81	5400

Method	First Node Death (Rounds)	Half Node Death (Rounds)	Energy Consumption per Round (J)	Packet Loss Rate (%)	End-to-End Delay (ms)	Load Balancing Index	Control Overhead (bits)
BCO-Based CH Selection	760	1140	0.65	10.4	128	0.84	5700
AQISL (Proposed)	890	1320	0.52	7.9	102	0.91	4900

6. Conclusion

The AQISL has improved cluster head selection techniques significantly beyond those of traditional methods or already developed methods. The first node death occurs at 890 rounds with AQISL, about 520 for LEACH, and 760 for BCO. The half node death occurs at 1320 rounds for AQLSL, about 780 for LEACH, and 1140 for BCO. The energy consumed per round with AQISL is 0.52 J, while with PSO it was 0.74 J and 0.69 J with ABC and, therefore, demonstrates a better energy-efficient use of energy than all of the other methods. The reliability of communication has also been enhanced, with the packet loss now compared to LEACH (18.5%) and BCO(10.4%) with AQISL being the lowest compared to all other examples at 7.9%. Similarly, the end-to-end data transmission time has been significantly decreased with AQISL (102ms), compared to HEED (160ms) and PSO (142 ms). Lastly, the load balancing index of AQISL is 0.91, which is higher than all other examples currently being distributed across nodes confirming that they are utilizing energy more efficiently. Although the control overhead for AQISL was slightly elevated at 4900 bits compared to LEACH (4200 bits), the control overhead for BCO (5700 bits) and ABC (5400 bits) was still lower, thereby maintaining a performance level satisfying at that particular cost. In summary, the data continues to support that AQISL is a more stable, energy-efficient, and reliable method of selecting cluster heads in very large-scale dynamic IoT environments.

Conflict of Interest

The authors declare no conflicts of interest regarding the publication of this paper. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. The simulation data and MATLAB codes used in this work can be shared for academic and research purposes, subject to institutional guidelines.

Funding Declaration

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