SvedbergOpen
DISSEMINATION OF KNOWLEDGE
International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

A Quantum-Based Energy-Efficient Clustering In Wireless Sensor Networks Using Grover's Algorithm

S Syed Noor[1], Prof. Geethanjali Nellore[2]

[1] Research Scholar, Department of Computer Science & Technology, Sri Krishnadevaraya University, Ananthapuramu, Andhra Pradesh, India, syednoor.s@gmail.com

[2] Professor, Dean, Department of Computer Science & Technology, Sri Krishnadevaraya University, Ananthapuramu, Andhra Pradesh, India, geethanjali.sku@gmail.com

* Correspondence: S Syed Noor (syednoor.s@gmail.com)

Abstract

The demand for wireless sensor networks (wsns) has grown a lot because of improvements in technologies like communication and the rise of smart devices. These networks are very important in the iot world. There are a lot of sensor nodes in wireless sensor network that keep an eye on the area around them. The main problem with WSN is that it's hard to recharge or change the batteries in the sensor nodes, which makes energy use a big issue. Choosing a cluster head can be one of the best ways to cut down on amount of energy the whole network uses. Quantum technology has become a more popular area of research in the last few years. Researchers have created different quantum-based algorithms to do clustering. This research article presents an innovative, energy-efficient clustering methodology known as the quantum-based clustering scheme (QBCS), derived from the Quantum Grover algorithm. Its main purpose in wireless sensor network work to select the cluster head selection better. The study used simulations to compare with researcher work cluster selection method to well-known algorithms like EDS-KHO,IKM-EPSO and MSSA-DSSA-KMEANS. The simulation environment had 100 nodes that were linked together in a certain way for energy and communication. QBCS is the best clustering method because it makes the network last 30.5% longer, uses 22.4% less energy, and delivers packets 19.8% more often. The quantum method's clustering process made it faster. This study demonstrates that quantum-inspired techniques have emerged as a novel approach to addressing energy constraints in wireless sensor networks (wsns), suggesting future possibilities for energy-aware and scalable Internet of Things (iot) systems.

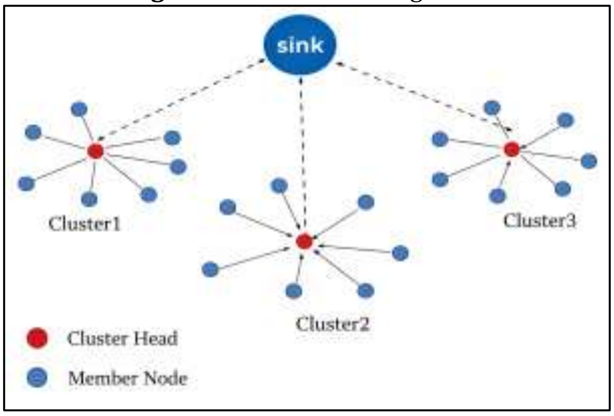
Keyword: Clustering, Wireless Sensor Network (WSN), QBCS, Quantum Optimization, Grover Algorithm

Introduction

A wireless sensor network (WSN) is a special group of transducers that send sensory data at the time of using only a small amount of battery power. Recently, there has been more interest in the topics for energy efficiency [1] and spectrum efficiency by using both licensed and unlicensed bands [2,3]. The main reason for this is that it is hard to change or recharge battery resources often, especially for networks that are big or in remote areas. The complete problem of energy in the network is often caused by an uneven distribution of sensor nodes [4]. Maintaining node placement throughout the network area and cluster formation to guarantee a balanced energy flow is one of the best strategies for energy conservation [5]. After collecting all observed data from the sensor nodes, the cluster head aggregates the corresponding data. A clustering architecture of wsns is shown in Figure 1.

Many distributed algorithms have used in the past few years to find uncovered areas and extra nodes on network and place nodes randomly in right way [6]. This has less energy and resources available. One of the most important ways to control energy use in WSN is clustering, which can split the whole network into many separate clusters [7]. The cluster head (CH) is in charge of each cluster and is charge of whole thing. In general, the cluster head will be chosen at random, considering the number of sensors. Main job of these sensors is to watch certain environmental factors in their area and send that information of cluster head, this can collect information to make it easier to combine later [8]. Using data aggregation methods is meant to make the network last longer. Once it aggregated data has put together, it is sent to base station (BS). The BS usually gets its power from an electrical grid and can do more calculations. By using this clustering method, you can lower the radio transmission rate and make the network last longer at the same time. It did this by changing the sensor's lifespan in real-time based on things similar to low latency, low energy use, and reliability [9]. Also, sensor nodes send its data directly to cluster head instead of to nearby nodes. This saves power [10]. To lower amount of power used by the network and make it last longer, network optimization methods are used.

Figure 1. WSN clustering architecture.



Researchers have utilized diverse strategies for energy conservation in Wireless Sensor Networks (wsns), including multi-hop, single-hop, and cluster-based transmission methodologies [11]. In multi-hop transmission, important things to think about are distance b/w the source, destination and path loss [12]. Furthermore, multi-hop transmission of effectiveness hinges on correlation between energy costs of transmitting and receiving data. It suggests that nodes use minimum energy consumption. For communication to ensure optimal energy utilization during transmission of destination. This method gets the most out of energy while still keeping links of communication strong. Single-hop communication is very energy-efficient method [13,14]. Because it sends the lowest amount of possible power along communication path. There are two main routing protocols that wsns use which are flat routing and hierarchical routing [15]. In flat routing, the nodes set up direct communication links with BS so that data packets can be sent. Sadly, its direct contact with BS very fast uses up node's energy. To solve this problem, different cluster-based routing methods have made to improve scalability, load balancing, and the life of the network. Hierarchical routing models set up clusters with specific chs, which can handle both single-hop and multi-hop routing. This choice of chs has a big effect on how well the WSN works, especially when it comes to limited energy resources of managing for the best network longevity. Clustering is a good way to make data transmission more efficient and save energy in wsns [16,17]. The emphasis of this clustering methodology is on the application of quantum-based algorithms.

This research is important not only for theoretical reasons, but also for practical reasons. The research sets a new path for sustainable WSN deployment by using quantum computing principles to solve basic energy problems. This work makes specific contributions to as follows:

- Quantum-Based Clustering (QBCS):we created and put into action a quantum-based clustering system that makes it easier to choose a cluster head (CH), fixes energy imbalance, and extends the life of a WSN.
- Integration of Grover's algorithm: Grover's quantum search algorithm was added to a classical simulation to improve CH selection, make sure energy use is balanced, and show that quantum methods can be used to solve networking problems.
- Comparative performance analysis: This was shown through simulations that QBCS is better than other clustering protocols in terms of energy efficiency, network longevity, and overall performance.
- Multi-parameter optimization: To solve the energy hole problem, CH selection was improved by taking into account residual energy, spatial distribution, and distance from the base station.
- Centralized architecture: We put the algorithm into the base station, which made it easier for sensor nodes to do their jobs and made it possible for different types of wsns to work together.

This is how the rest of the paper is organized. The relevant research in the topic, including the current energy-efficient clustering techniques and optimization methods, is explained in Section 2. The proposed work and its underlying principles are described in detail in Section 3. The findings and debates are explained in Section 4. In Section 5, we conclude with a viewpoint.

Related Work

Overview of Energy Efficiency in Wireless Sensor Networks

Wireless sensor networks have many uses on different fields, such as disaster management, environmental monitoring, military operations, agriculture, healthcare [18]. As a result, the main design challenge in WSN is to reduce power use and extend life of network, which causes energy hole problem [19,20]. To solve this problem, researchers have come up with a number of new algorithms that often use ideas from quantum computing to make networks more energy-efficient, faster. In [21], the author suggested an algorithm that can cut down on the network's energy use by making spanning trees. The triangulation algorithm introduced in [22] as a solution to energy hole problem by incorporating virtual edges among sensor nodes. Energy efficiency is a major problem for WSN deployments because these nodes will have limited battery life, changing batteries will be hard, especially when it functioning with remote or large applications [23]. There are three main ways that current energy conservation studies have moved forward. Clustering techniques one of best ways to use less energy. To choose cluster heads that use less energy, they shouldn't be neighbors. The right placement of sensor nodes across the networks can help reduce the coverage hole problem.

Clustering Approaches of wsns

Cluster management techniques are still very popular because they let you organize sensor nodes, optimized hierarchical structures which provide balanced network energy use and efficient data path distribution. Heintzelman created the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, which started the use of probabilistic cluster head rotation to balance energy use. The first use of a new cluster methodology led to many more sequential evolutions. Choosing a CH will be based on a random process that will linked to a certain threshold probability b/w 0 and 1. But there is no direct link between best number of cluster heads and best way to control transmission power across EECS network. It makes it harder to form clusters by using a cost function that only looks at distances between cluster head and base station. This adds to overall overhead and complexity of time.

Bio-Inspired and Evolutionary Algorithms for Clustering

- The technique will be based on GA increases chances that a node will be able to find a CH while using less energy in the first round. Kavitha et al. [27] came up with gravitational search algorithm-based clustering protocol (GSACP) in 2020. This was a way to make sure that sensor nodes were assigned to cluster heads in a way that kept network's energy stable. Goal for GSACP was to make networks last longer and use less energy. The GSACP did better than old ways of choosing a cluster head. But it had problems with the krill and GSA algorithms that caused convergence to happen too slowly, which made it harder to find a balance of exploration and exploitation. In 2023, Balaram. A et al. [28] proposed an innovative method that pr1ovides solution for optimize all energy consumption while concurrently minimizing internode-communication. The dynamic layering mechanism put in place that stops the same cluster head nodes from being chosen over and over again. This mechanism makes sure that the process of dual selection is quick & useful. This is very important for getting the energy savings and efficiency that wsns need [28–30].

- *Quantum-Based Algorithms in WSN Clustering*
  Using quantum computing ideas group wsns is the most advanced research of this area. The suggested quantum-inspired CH algorithm is new way of quantum computing to solve the problems that come up with traditional clustering algorithms. In past years, researchers developed several clustering algorithms that use quantum algorithms. Srinivas P et al. [31] recently wrote a paper that said not much research has been done in this area, mostly looking at energy available among sensor nodes in network. The Quantum Tuni-cate Swarm Algorithm (QTSA) can help with this. The author of [32] says that Quantum Genetic Clustering Algorithm (QGAC) was made using the ideas of unidentified systems and quantum computing. It is used to make network last longer and use less energy. It is made for quantum computers and makes database searches much faster. This quantum method can also be used to solve classical NP-hard problems in polynomial time, which is much faster than classical computing methods. There are a lot of quantum-based clustering algorithms being worked on right now.

QTSA [31] and QGAC [32] are two examples of clustering algorithms that are based on quantum mechanics and have brought quantum ideas into the field of WSN optimization. QTSA enhances energy-aware clustering by merging quantum-inspired with Tunicate Swarm Algorithm, whereas QGAC incorporates quantum genetic principles for cluster formation. But these methods depend a lot on iterative metaheuristic optimization, which could make them take longer to converge and cost more to run on a large scale. QBCS, on the other hand, uses Grover's quantum search principle, which speeds up cluster head selection by almost a factor of four and lowers complexity of time from O(n) or O(n2) in metaheuristics of traditional to O(√n).

It helps QBCS get, its goal faster & make better use of its resources while still making sure that energy is evenly distributed.

Table 1. The comparative analysis of QBCS with QTSA and QGAC.

Parameter	QTSA [31]	QGAC [32]	QBCS (Proposed)
Optimization Technique	Quantum-inspired Tunicate Swarm	Quantum Genetic Algorithm	Quantum Grover Search
Complexity	O(n2)	O(n2)	O(√n)
Convergence Speed	Medium	Very fast (quantum amplification)	Medium
Energy Efficiency	Enhanced	Enhanced	Significantly Improved (due to quadratic speedup)
Iteration scaling	Limited (iterations increase with n)	High (due to quadratic speedup)	Very High (due to Grovers search algorithm)

Table 1 shows that QBCS has clear advantages over QTSA [31] and QGAC [32] when it comes to complexity of computational and rate of convergence. QTSA and QGAC do make energy use more efficient, but they still have a lot of iterations and take longer to adapt to changing conditions. QBCS uses quantum amplitude amplification to speed up selection of cluster heads and make large-scale wsns more scalable.

Quantum-Based Algorithms in WSN Clustering

Using quantum computing ideas of group wsns is most advanced research of this area. The suggested quantum-inspired CH selection algorithm is new way of use quantum computing to solve the problems that come up with traditional clustering algorithms. Researchers have come up with a number of clustering algorithms using quantum algorithm in the last few years. Srinivas P et al. [31] recently wrote it not much research has done of this area. Most of it has been about available energy of all sensor nodes in network, It can be Quantum Tuni- cate Swarm Algorithm (QTSA) can help with. The author of [32] says that Quantum Genetic Clustering Algorithm (QGAC) will be used to make network last longer & use less energy. This algorithm is depending on the idea of difficult systems and quantum computing. The possibility of implementing neighbor-based single & multi-hop communication will being looked into. Quantum search algorithm of Grover's is a great example this kind of progress. It is made for quantum computers and makes database searches much faster. This quantum method can also be used to solve classical NP-hard problems in polynomial time, which is much faster than classical computing methods. There are a lot of quantum-based clustering algorithms being worked on right now.

QTSA [31] and QGAC [32] are two examples of quantum-inspired clustering algorithms that have brought quantum ideas into the optimization of wsns. QGAC, on the other hand, uses quantum genetic principles to make clusters. But both methods depend a lot on iterative metaheuristic optimization, which could make them take longer to converge and cost more to run on a large scale. QBCS, on the other hand, uses Grover's quantum search principle, which speeds up cluster head selection by almost a factor of four and lowers the complexity of time from O(n) or O(n2) of metaheuristics of traditional to O(√n). This lets QBCS converge faster and scale better while making sure that energy is evenly distributed.

Table 1 shows that QBCS has clear advantages over QTSA [31] and QGAC [32] in terms of complexity computational and rate of convergence. QTSA and QGAC do make energy use more efficient, but it still has large iteration counts & take longer adapt to changing conditions. QBCS uses quantum amplification to speed up process of opting a cluster head and make it easier to scale up large wsns.

Research Gaps and Comparative Analysis

This study examines contemporary research which reveals various persistent challenges and knowledge deficiencies concerning energy-efficient clustering of wireless sensor networks. This research study illustrates that a quantum-inspired approach addresses acknowledged challenges in current research, as evidenced by Table 2, which offers comprehensive evaluations of contributions research, proposed methodologies, and identified deficiencies, culminating in a summary of resolution to these constraints.

Table 2. The Existing Literature survey studies comparison.

Ref.	Approach / Method	Main Limitation(s)	How QBCS Addresses It
[24]	Optimized K-means clustering with dynamic 'K' value estimation.	Computationally demanding and relies on sequential evaluations, which can lead to suboptimal network energy balance.	Deploys Grover's quantum search to concurrently evaluate various cluster head (CH) formations. This guarantees a globally optimal selection based on node location and remaining battery, cutting complexity to $\mathbf{O(\sqrt{n})}$.
[25]	A hybrid approach merging K-means with Enhanced Particle Swarm Optimization (EPSO).	Suffers from high computational overhead and slow execution times due to heavy iterative processing loops.	Bypasses exhaustive iterations using quantum amplitude amplification. This allows for rapid convergence, exceptional scalability, and the simultaneous integration of distance and energy metrics.
[26]	Stochastic or randomized cluster head selection.	Causes disproportionate energy drain across nodes and typically restricts routing to single-hop paths.	Intelligently dictates CH selection through a multi-metric quantum search, readily supporting adaptable, multi-hop communication architectures.
[27]	Distance-centric routing (focusing strictly on the CH-to-Base Station gap).	Completely overlooks critical operational factors like node processing overhead and remaining battery life.	Fuses both geographical layout and residual energy data into a unified quantum optimization framework.
[28]	Genetic Algorithm (GA) based clustering techniques.	Characterized by sluggish convergence rates and steep computational hardware requirements.	Drastically accelerates the optimization process, achieving a quadratic speedup toward the global optimum via Grover's algorithm.
[29]	Traditional, deterministic clustering protocols.	Exhibits delayed responsiveness and struggles to adapt when the network topology shifts dynamically.	Employs amplitude amplification to ensure the network adapts swiftly and efficiently to unpredictable topological changes.
[30]	Network segmentation relying on	Involves complex boundary management and often ignores	Fluidly partitions the network without rigid boundaries by dynamically

	predefined boundary metrics.	internal geographical disparities among active nodes.	balancing spatial distribution and node energy reserves.
[32]	Quantum Tunicate Swarm Algorithm (QTSA).	Operates as an iterative metaheuristic with a steep ($O(n^2)$) complexity, severely limiting its use in massive networks.	Slashes algorithmic complexity to $\mathbf{O(\sqrt{n})}$, making the protocol highly scalable and practical for dense, large-scale deployments.

Table 2 shows that previous clustering methods have problems like overhead, random CH selection, and convergence that takes too long. QBCS fills available gaps by using quantum-inspired optimization and Grover's search principle. This makes it possible to find the best cluster head faster and with less energy.

Research Gap Summary

Protocols have come a long way in the last few decades, even though WSN clustering has made a lot of progress. Classical methods, including LEACH and HEED, as well as various metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Krill Herd Optimization (KHO), persist in demonstrating significant limitations. Some of these are high computational complexity, nodes running out of energy too soon, nodes not being able to adapt to changing environments, and an unpredictable distribution of cluster heads (CH).

Many clustering methods have been suggested for wsns, but only a few have looked into how quantum-inspired optimization methods can be used in this field. Numerous current protocols emphasize classical or bio-inspired methodologies, thereby creating a distinct research void in the investigation of quantum algorithms can enhance energy-aware decision-making within sensor networks. Moreover, previous research concerning quantum computing in wireless sensor networks (wsns) frequently remains theoretical, lacking practical implementation or performance assessment in real-world contexts. This work fills that gap by suggesting and testing a quantum-inspired clustering strategy (QBCS) which uses Grover's algorithm to choose the best cluster head. We test this method with detailed simulations and compare it to well-known clustering protocols like EDS-KHO and IKM-EPSO. Our method works better in terms of energy efficiency, balanced energy use, and network lifetime. In environments with limited energy, like wireless sensor networks (wsns), even small problems with how clusters formed can cause network's lifetime & coverage to drop a lot.

A thorough review of the literature and an analysis of trends revealed several significant research gaps that proposed quantum-inspired clustering approach seeks to fill:

Computational efficiency gap: Bio-inspired algorithms that are already out there often have a lot of extra work to do, especially when they are used in large-scale wsns. The quantum-inspired method defines quantum parallelism to make calculations easier during still being able to find the best solution. Parameter integration gap: Current methods only look at one parameter at a time, like energy, distance, or topology. They don't completely combine these factors into a complete clustering framework. The suggested method uses quantum principles to look the several factors at once and choose relevant cluster heads.

Adaptability gap: Most current algorithms don't work well when network conditions change or when energy is spread out unevenly. The suggested quantum-based solution has ways to change parameters that work with changing states of network.

Scalability gap: In large networks, clustering of traditional methods in general make things worse. The suggested quantum-inspired algorithm performs consistently across various scales of network by effectively navigating search space.

Energy hole prevention gap: Many ideas have put forward solve energy hole problem, but most of them focus on fixing the symptoms instead of stopping them from happening in the first place. The suggested method utilizes quantum optimization to balance energy use across network ahead of time.

The suggested quantum-inspired clustering strategy seeks to improve the state of the art in energy-efficient WSN management by filling in these gaps and providing a unique solution that blends the computational benefits of quantum algorithms with useful network optimization techniques.

The Proposed Work

More and more people are studying quantum computing & algorithms which use quantum mechanics. There are many algorithms that can be used for quantum applications. But Grover's is the best to finding things that aren't organized & has used in many fields of optimization. The proposed (QBCS) is based on this algorithm. We talk about this here before we get to part of Quantum Grover algorithm that is about implementation. Because energy-efficient clustering is so important, most of research is focused on it. Different clustering strategies have created using different methods, but the one being suggested uses less energy.

Model and Assumptions for the System

In this study, the wireless sensor network is represented as undirected graph G = (V, E), where V = {v1, v2, ..., vn} signifies collection of sensor nodes, and E illustrates communication links among nodes. The suggested method uses quantum computing ideas to make clustering process better for wsns by making them more energy-efficient and secure [33]. The system works based on the following main ideas:

1. After being placed in the sensing area, sensor nodes stay in the same place and don't move.
2. Every node has its own unique ID and can figure out where it is on the map.
3. The network has different kinds of sensor nodes, which means that they all start with different amounts of energy.
4. There is a central base station (sink node) that more energy & computing power than the regular sensor nodes.
5. There are three levels in the network: standard sensor nodes (cluster members), cluster head nodes, a sink node that collects, processes data.

Algorithm of Grover

Grover's algorithm is a quantum search algorithm is much better than classical unstructured search methods. It speeds up the search for an unstructured dataset by a factor of two. In wsns, where finding best CH is a combinatorial problem with many possible node combinations, Grover's algorithm is a quick way to find energy-efficient candidates from all the sensor nodes. It makes it easier to find a target item by lowering the complexity from O(N) in a classical search to about O(√N). In wsns, every possible CH candidate is shown as a quantum basis state.

This quantum algorithm not only cuts down on the number of steps needed, but it also makes it more likely that you will find the target element, which is a huge improvement in search efficiency. The algorithm goes like this:

Step 1: Setting up the state: Set the quantum state |ψ⟩ to zero.
We use a quantum register with log2(N) qubits to show N sensor nodes. Each basis state | i⟩ represents a node, with i ranging from 0 to N − 1. Using Hadamard gates, the system is set up in an equal superposition:

$$\Big|\Psi\rangle = \frac{1}{\sqrt{N}}\sum_{i=0}^{N-1}|i\rangle \tag{1}$$

In this case, | ψ⟩ stands for the uniform quantum state that shows all sensor nodes as possible CH candidates equally.

Step 2: Building the oracle transformation: Create an oracle Uf that changes the sign of the target item.

We create an oracle function f(x) that finds the nodes with the most energy based on how much energy they have left and how far away they are from the base station. The oracle flips the amplitude of the state that corresponds to the best CH candidate.

$$U_f\big|i\rangle\ (-1)^{f(i)}|i\rangle \tag{2}$$

Where f(i) = 1 if i is the target item, and f(i) = −1 otherwise.

Step 3: Amplitude amplification: Set the diffusion operator, Ud.

The diffusion operator flips all amplitude vectors around the average amplitude, which makes it more likely that you will find the best solution.

$$U_d = 2 * |\psi\rangle\psi| - I \quad (3)$$

Where I is the operator that gives you your identity. This operator flips all amplitudes around their average, which makes the amplitude of the valid CH states that the oracle marks higher.

By applying the oracle Uf and the diffusion operator Ud about N times in a row, the chances of measuring the best cluster head go up a lot. Finally, a measurement reduces the quantum state to the CH configuration with the highest probability of being the most energy-efficient.

Quantum-Based Clustering Scheme (QBCS)

The network is divided into three different node categories by QBCS: sink nodes, cluster head nodes, and cluster member nodes (also known as sensor nodes). Data aggregation from the member nodes in each cluster is the responsibility of the cluster head nodes. The cluster sink node is used to keep an eye on the associated cluster and store all of the cluster's nodes' energy data. The cluster head is selected by storing the observed results on the base station node. When data is gathered and transmitted, this selection procedure saves energy. Each sensor node transmits its current residual energy value in the control message that is transmitted during the cluster formation phase in order to maintain current energy information. This reduces communication overhead by eliminating the requirement for distinct signaling packets. These figures are combined by the base station to create an energy status table. The QBCS algorithm then uses this table to select the subsequent cluster head.

Choosing best cluster head in wsns is very important for effective data aggregation and communication. QBCS employs three fundamental principles of quantum mechanics:

- Superposition: In quantum physics, particles will be more than one state at the same time until they are measured. QBCS uses this by letting each sensor node be part of more than one cluster at the same time while the decision-making process, with different chances for every assignment.
- Entanglement: Quantum particles will be linked in a way which measuring one immediately affects other. QBCS uses idea make sure that decisions about clustering nearby nodes are made in a way that benefits everyone.
- Interference: Quantum waves can either make things stronger (constructive interference) or weaker (destructive interference). QBCS uses mathematical interference patterns to favor clustering configurations that save energy and block those that don't.

In the proposed architecture, the base station (sink node) will be in charge of running QBCS algorithm. It has more processing power and energy resources than any other node. This design makes sure that the sensor nodes with limited resources don't have to do complicated calculations. The only job of sensor nodes is to send local status information (like remaining energy and location) to base station. The base station takes this information, runs QBCS algorithm to find the best cluster heads, sends clustering decisions back to the nodes. You can change Quantum Grover search algorithm to solve this optimization problem. Here three main types of cluster-based data aggregation & data forwarding problems. As shown Figure 2. The first cluster's cluster head is the closest to the sink node. As shown Figure 2. In second group, cluster head is not near the sink node. But the sensor node is. In the third cluster, cluster head was chosen from a long distance away from sink node. The cluster head is chosen a long way from the sink node. Here three clusters above, first cluster may use a lot of energy because data is sent from neighbor node to sink node & from neighbor node to head of cluster. This could waste energy. In the second cluster, sensor node sends data directly to their cluster head. This is good. But it could use a lot of energy because cluster head is further away from sink node than the other cluster nodes. Third cluster may use a plenty of energy because the head of the cluster will be far away from sink node.

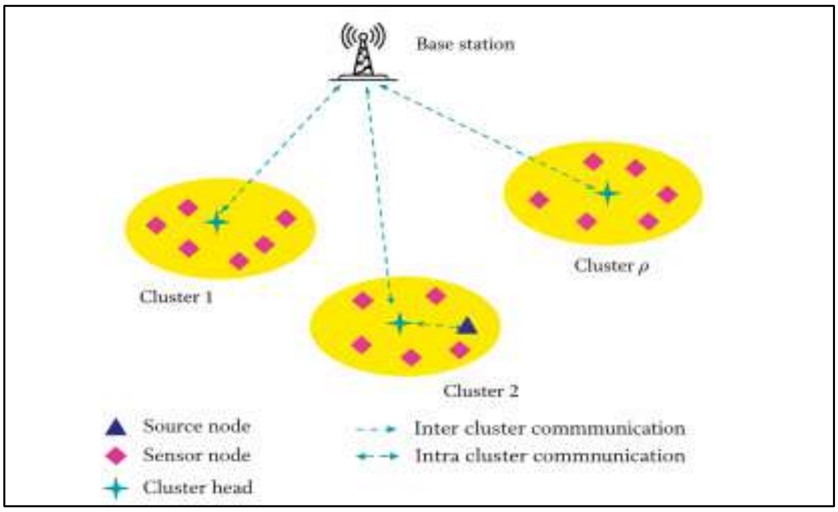


Figure 2. Cluster communication.

The proposed QBCS solves these problems by making the most of energy use during three important operational phases. The setup phase, steady-state communication, & data aggregation phase. The Grover-inspired quantum algorithm will be used in the CH selection stage to find nodes that have both a lot of leftover energy and a good location. QBCS is different from traditional protocols like LEACH, which use random CH selection. Instead, QBCS makes sure that energy is distributed more efficiently and that there is less overhead when the network is first set up.

This research work uses a complete realistic and physically based model based on loss of a long-distance path with shadowing to model wireless communication and energy use. This model accurately represents the significant signal attenuation resulting from distance and environmental variability, without depending on idealized or overly simplistic assumptions. This is how to show the path loss at a distance d:

$$PL(d) = PL(d_0) + 10.n.log_{10}\left(\frac{d}{d_0}\right) + X_{\sigma,} \quad (4)$$

PL(d0) is the reference path loss at a known distance d0, n is path loss exponent (usually b/w 2 and 4, depending on environment), & Xσ is a zero-mean Gaussian random variable that shows shadowing effects. The proposed model is in line how wireless signals actually propagate & doesn't make wrong connection b/w multipath fading & transmission distance. Because proposed WSN is set up in a fixed location, small-scale fading & Doppler shifts caused by movement aren't considered. This model will be here show how-signal loss changes with in distance. In our simulation based on NS-3, we model these effects internally. We include below formula for completeness because affects the communication energy model & the coverage assumptions. The first-order radio model is used to figure out how much energy it takes to send and receive k bits of data over a distance dij:

$$E_{TX}(k, d_{ij}) = k.E_{elec} + k.\varepsilon_{amp}.d_{ij}^{n}, \quad (5)$$

The 'k' part of the data is sent to another sensor node, which uses energy that can be shown as

$$E_{RX}(k) = k.E_{elec} \quad (6)$$

$$E_{tx} = E_{rx} = E_{elec}, \quad (7)$$

Etx and Erx are the energy use for coded modulation of single-bit data. Eelec is energy used by electronic circuits for each bit, and it is energy needed by transmitter amplifier, which is scaled by propagation exponent n. To figure out new residual energy of transmitting node "i," do the following:

$$E_i^{residual} = E_i^{initial} - E_{TX}(k, d_{ij}). \quad (8)$$

The sink node keeps track of energy status of all the nodes and uses this information to make better decisions in the next clustering rounds. QBCS uses quantum search algorithms to combine energy and location awareness. This done that the best cluster heads can chosen keep communication costs between clusters and between clusters and sinks as low as possible. This uses quantum-based search algorithms to group things together in a way that saves energy. Nodes are usually grouped together for a number of reasons. But saving energy is most important one. The selection of the cluster head is determined by distance between nodes & their energy levels. The proposed work implements various cluster-based data aggregation & forwarding methods utilizing the Quantum Grover search algorithm.

It will quickly choose best cluster head, and this method also uses less power, takes less time, and is less complicated. Classical algorithms usually take longer to choose a cluster head than the method we suggest. Number of iterations for selecting a cluster head is high in classical algorithms they can search for a long time. The time complexity for choosing cluster nodes is usually shown as O(N). However, in this paper, the initial iteration will find best cluster head in network, which means that the time complexity can be cut down by O(N). Figure 3 shows how the QBCS algorithm chooses cluster heads.

The cluster head selection process used by QBCS is depicted in Figure 3. The base station uses Grover's quantum-inspired optimization to select nodes that maximize energy efficiency and minimize transmission distance after sensor nodes share residual energy and position information with it.

Algorithm QBCS

Problem definition: In context of WSN, problem is to find the most energy- efficient cluster head based on certain criteria.

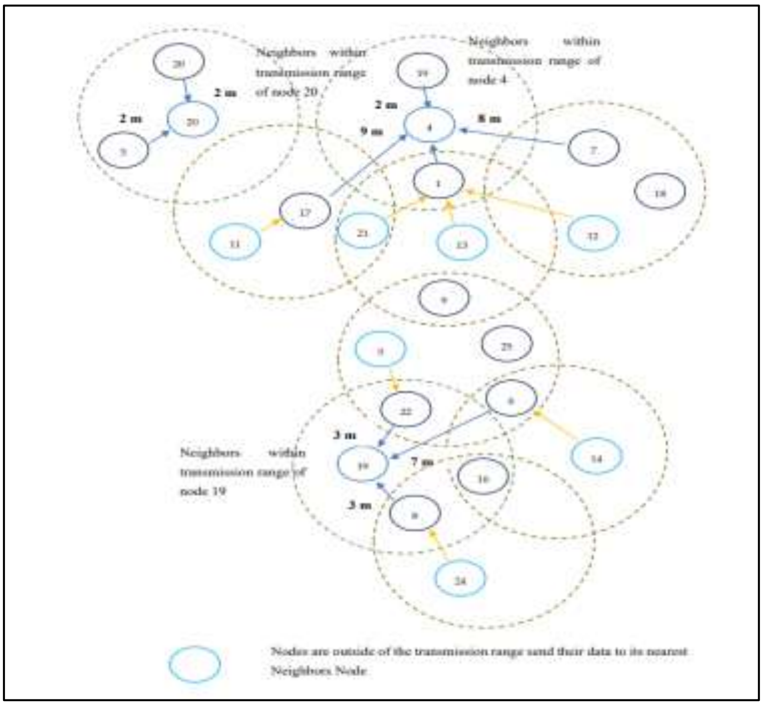


Figure 3. Illustration of cluster head identification using QBCS.

QBCS is made to choose more than one CH in wireless sensor networks while using as little energy. Algorithm 1 merges Grover's quantum search ideas with classical validation. In first step, all possible CH configurations shown as binary strings. A "1" means that a node is a cluster head, and a "0" means that it is a regular node. Then, these possibilities are put together in a uniform way to make a quantum state. The oracle function is designed find valid configurations meet three important criteria: (i) number of chs must be close to the required proportion of nodes, (ii) each CH must have residual energy above a certain level, and (iii) the chs must be spread out in space to ensure good coverage and communication with the sink. To make these valid configurations' amplitudes bigger, the diffusion operator is used over and over again.

Algorithm 1: QBCS Input:

N: The total number of sensor nodes br-to-break T: The number of Grover iterations |ψ⟩: The initial quantum state that shows all possible CH configurations

Ethreshold: The minimum amount of energy needed to be eligible for CH

P: The percentage of chs that you want (for example, 5–10% of all nodes)

Output: A set of the best cluster heads {CH1, CH2, . . . , chk}, where k = p × N //Quantum Phase: Grover-based CH

Candidate Search

1: Set up the Quantum Environment and the Quantum State |ψ⟩ by using Equation (1). Use Hadamard gates to make superposition:
$|\psi\rangle = 1/\sqrt{N} \sum|i\rangle$
2: Set the problem parameters N, T, and |ψ⟩, and turn all possible CH configurations into N-bit strings, where 1 = CH and 0 = regular node.
3: Set up an oracle Uf and Ud using Equations (2) and (3), and then use the Hadamard transformation to put log2(N) qubits into a quantum register for equal superposition.
If (node_i.energy ≥ E_threshold AND proximity_ok(node_i)): phase_flip(|i⟩)
4: For t = 1 to T,
5. Use Quantum Oracle Uf to mark CH candidates based on how close they are and how much energy they have.
6: If the node meets the CH selection criteria, apply a phase shift to make the amplitude more likely.
7: Use Grover Diffusion Operator Ud to make the amplitude stronger. 8: End For 9: Measure the quantum state |ψ⟩ and choose the best CH.
10. Turn the measurement result into a set of candidate chs: {CH1, CH2, . . ., chk}./Classical Phase: 11: Change the quantum results into a classical CH list. Validation and Final Multi_CH Selection.
12: Final_CH_set = null 13: max_energy = −∞
14: For every node in the candidate CH set:
15: Use Equation (8) to find the remaining energy. 16: If node.energy is greater than or equal to E_threshold, then
17: Add node to final_CH_set.
18: End If
19: End For // If the quantum result is not valid, go to 20: If size(final_CH_set) < p × N then
21: Keep adding high-energy nodes from the rest of the list until you reach the target CH count.
22: End If
23: Return final_CH_set as the best multi-CH setup.

When you measure the quantum state, it falls to one valid configuration with more than one CH. In the second phase, the candidate chs from the quantum step are checked using the residual energy equation to make sure that each node can do its job. If the number of chosen chs is less than what is needed, more high-energy nodes are added to reach the desired percentage.

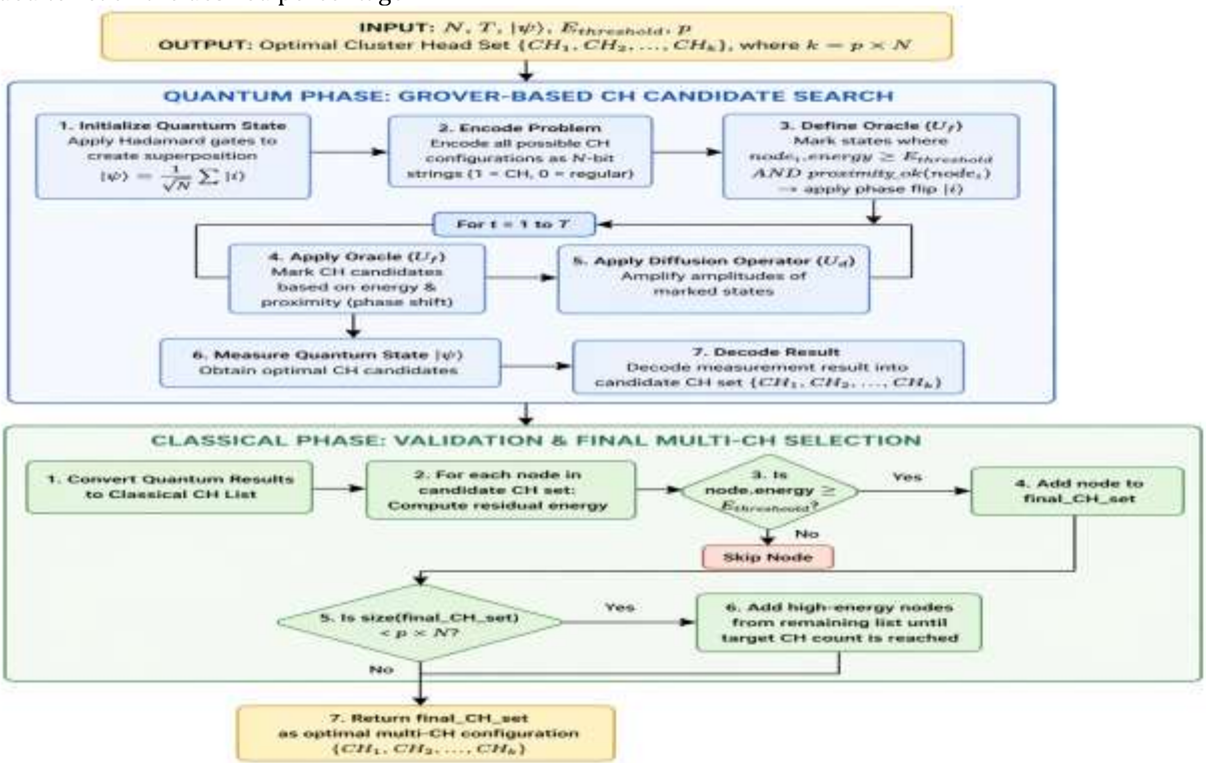


Fig.4. The Methodology diagram of Quantum Inspired Clustering Scheme.

So, final output is a set of chs instead of just one node. This makes sure that the algorithm can work with big networks. Oracle function only marks valid subsets, and amplitude amplification makes it more likely that you will be able to measure these optimal states. Measurement determines the final CH configuration by collapsing quantum state to subset of nodes that uses the least energy. This process of choosing multiple chs is similar to how wsns are actually set up. In each round, a certain number of nodes act as cluster heads to balance energy use, extend the life of the network, and improve overall performance.

Let's think about a small wireless sensor network with six sensor nodes. Choosing more cluster heads uses up the network's energy faster, so the goal is to choose two cluster heads that will cover the whole network while using the least amount of energy. A node can be a regular node or a cluster head. Tables 3–5 show energy levels and the distance matrix for pairs.

Six qubits are used to show the state of each node:

• A node is a CH if it has a "1" in it.

• "0" means a normal node.

Let's say there is a quantum computer that can handle six qubits. Changing the Algorithm:

Quantum Representation and Initialization:

There is a superposition of quantum states for each possible cluster head. In this case, six qubits are used to show the states of the six nodes. Using Hadamard gates, the quantum state |ψ⟩ is set up in equal superposition:

$$\left|\Psi\right\rangle = \frac{1}{\sqrt{2^6}}\sum_{i=0}^{2^6-1}|i\rangle \quad (9)$$

Each state represents a possible CH selection.

Oracle Definition: CH Candidate Selection:

A quantum oracle Uf is used to choose CH candidates based on their energy level and how close they are to each other. Make an oracle operator that can tell which state is the best cluster head based on the right attributes. This oracle shows the best state. To make things easier, let's say that only the states with two "1"s (which mean two cluster heads) are valid. The oracle changes the phase of states where nodes have energy $E_i > 0.75$ J. The starting energy levels are as follows: Node 1 = 0.8 J, Node 2 = 0.9 J, Node 3 = 0.7 J,

Table 3. Initial node energy levels.

Node	Initial Energy E_i(J)
1	0.82
2	0.91
3	0.74
4	1
5	0.62
6	0.94

Table 4. Inter-node distance measurements.

Node Pair	Distance d (m)
(1,2)	3
(1,3)	5
(1,4)	7
(2,3)	4
(2,4)	2
(3,5)	4
(4,6)	3
(5,6)	2

Table 5. Pairwise distance matrix representation of sensor nodes.

	Node			Distance	
State	**Nodes**	**Node 1**	**Node 2**	**Node 3**	**Node 4**
$\vert 000000\rangle$	1	0	3	5	7
$\vert 000001\rangle$	2	3	0	4	2
$\vert 000010\rangle$	3	5	4	0	6
$\vert 000011\rangle$	4	7	2	6	0
$\vert 000100\rangle$	5	2	6	4	5
$\vert 000101\rangle$	6	6	8	3	2

and Node 4 = 1.0 J.

The CH nodes that can be used are 1, 2, 4, and 6. The valid CH states are $\{|110000\rangle, |100100\rangle, |100001\rangle, |010100\rangle, |010001\rangle, |000101\}$, which correspond to the CH pairs (1,2), (1,4), (1,6), (2,4), (2,6), and (4,6). After that, flip the phase of the states $|110000\rangle$, $|101000, \ldots$, and $|000011\rangle . U_f|100001\rangle = -|100001\rangle$,

After applying the oracle, the state $|100001\rangle|100001\rangle|100001\rangle$ (Nodes 1 and 6 as chs) is marked as optimal.

6. Amplitude amplification:

Use Grover operators to make the probability amplitude for the best cluster head stronger. This is accomplished by repeatedly applying the oracle and inverting the mean operations.

(10)

$$2\mid\psi\rangle\Big\langle\psi\mid = \frac{2}{64}\begin{bmatrix}1 & 1 & 1 & \cdots & 1\\ 1 & 1 & 1 & \cdots & 1\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ 1 & 1 & 1 & \cdots & 1\end{bmatrix} = \frac{1}{32}\begin{bmatrix}1 & 1 & 1 & \cdots & 1\\ 1 & 1 & 1 & \cdots & 1\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ 1 & 1 & 1 & \cdots & 1\end{bmatrix}$$

2. Iterations:

Do the oracle and amplitude amplification steps a few times. Let's say two times.

2.1. Apply oracle U_f: Apply the oracle to the quantum state:

$U_f \mid \psi\rangle = U_f \cdot \frac{1}{\sqrt{64}}(\mid 000000\rangle + \mid 000001\rangle + \cdots + \mid 100001\rangle + \cdots + \mid 111111\rangle)$ (11)

For marked states such as $\mid 100001\rangle|100001\rangle$, the amplitude sign is flipped: 1

$U_f \mid \psi\rangle = \frac{1}{\sqrt{64}}(\mid 000000\rangle + \mid 000001\rangle + \cdots - \mid 100001\rangle + \cdots + \mid 111111\rangle)$ (12)

2.2. Apply Grover Diffusion Operator U_d:

$$U_d \cdot U_f \mid \psi\rangle = (2 \mid \psi\rangle\langle\psi \mid -I)\cdot U_f \mid \psi\rangle \quad (13)$$

This amplifies the probability of valid CH states (e.g., ∣100001⟩|100001⟩, ∣010001⟩ |010001⟩, etc.).

Measurement and cluster head selection:

We do a projective measurement on the quantum register after running the oracle Uf and the diffusion operator Ud for the number of iterations we chose (in this case, two). The Grover procedure increases the amplitude of the marked (valid) two-CH states, which are the ones in the set {∣110000⟩, ∣100100⟩, ∣100001⟩, ∣010100⟩, ∣010001⟩, ∣000101⟩}.

As an example, let's say that the measurement brings the register down to the basis state ∣100001⟩. If you map this binary string to node indices (leftmost bit = Node 1, rightmost bit = Node 6), you get chs at Node 1 and Node 6. This result is correct because Node 1 (0.8 J) and Node 6 (0.95 J) both meet the energy eligibility requirement of $E_i \geq 0.75$.

Post-processing (classical validation):

- Decode the measured bitstring |100001→ |100001⟩→ CH pair (1,6);
- Recompute residual energies using Equation (8) and confirm both nodes still meet $E_i \geq 0.75$;
- Check the spatial and proximity limits (coverage and distance between clusters) for chs 1 and 6.
- If the validation is successful, accept 1,6 as the final CH set for this round. If it isn't, which is rare, use the fallback classical selection (highest-energy eligible nodes) to get the required number of chs.

Results and Discussions

The quantum-based method for choosing energy-efficient cluster heads has big effects on progress of wsns. A comparison is made between the quantum-based method traditional ways of choosing a cluster head. Quantum algorithms showed that they could find the best solutions faster, which made the process of choosing a cluster head more efficient. We chose NS-3 (Network Simulator 3) as simulation environment. This is a discrete event network simulator that is often utilized in research on wireless sensor networks. NS-3 fully supported modeling physical features of a 100 × 100 m2 deployment area & accurately simulating energy use at different node densities (100–500 nodes). IBM's Qiskit framework was connected to NS-3 to use quantum-inspired optimization and put the proposed QBCS algorithm into action. This integration was made possible by middleware based on Python 3.10 got node energy & position data from NS-3.37 after each round, ran QBCS algorithm on the Qiskit Aer 0.13.2 simulator, and sent ids of the chosen cluster heads back to NS-3 for the next round. This setup let us use Qiskit's quantum circuit design tools to improve the cluster head while still keeping NS-3's strong network simulation features.

Using Qiskit's circuit composer and simulator, the QBCS algorithm was put into action. The results were then easily added to NS-3 through the custom interface. Researchers were able to test Grover's algorithm for energy-efficient clustering in a controlled setting with this hybrid framework. They could change network parameters like node density, communication range, and energy consumption to compare QBCS to EDS-KHO, IKM-EPSO, and MSSA-DSSA-KMEANS. The entire simulation was run on an Intel i7 system with 16 GB of RAM. QBCS added an average of 18 ms of overhead per round, and the CPU usage stayed below 35%. This shows that the integration doesn't add much to the computational cost and can be used for larger WSN deployments.

We want to make it clear that this paper does not try to give a full analysis or specific performance statements. Instead, it tries to show that quantum search methods can help save energy, balance the load on a network, and make wireless sensor networks last longer. In order to do more work, like making a mathematical model, using optimization methods, and putting the results to use in real life, we need to draw conclusions from the simulation. This research lays the groundwork for subsequent investigations employing advanced mathematical proofs, models incorporating stochastic effects, and more comprehensive methodologies in the examination of diverse networks.

This hybrid framework yielded quantum computational advantages and enhanced network-level energy efficiency benefits from the QBCS protocol compared to conventional alternatives. The parameters for the simulation are shown in Table 6.

Table 6. The input parameter.

Parameter	Value
Deployment Area	150 × 150 m²
Number of Nodes	500 nodes
Data Packet Size	4096 bits
Percentage of Cluster Head	5 – 10 %
Initial Energy (E_0)	0 – 5 J
Electronics Energy (Eelec)	70 nJ/bit
Energy for Data Aggregation	5 nJ/bit
Transmission Energy (Etx)	50 nJ/bit
Reception Energy (Erx)	50 nJ/bit

We looked at how to set up a WSN in a 100 × 100 m2 area. The network has a number of nodes that changes between 100 and 500. Each node in this network follows a clustering scheme, which means that cluster heads are chosen. These cluster heads make up 5% to 10% of all the nodes.

The packets of data that are sent and received on this network are always 4096 bits long. To start the system, each node gets an initial energy level (E0) that ranges from 0 to 5 joules. To measure energy use, we need to know the following: electronic energy (Eelec) used at a rate of 70 nj/bit, and energy used for transmission (Etx) and reception (Erx) processes, which each use 50 nj/bit.
The proposed clustering protocol was tested over a period of 2500 rounds of simulation. The analysis concentrates on three principal factors: energy consumption, network longevity, and data packet delivery efficacy. The primary objective is to assess the influence of various deployment scenarios on overall network efficiency by altering both the number of nodes and the initial energy levels. This research illustrates enhanced cluster head selection via quantum-inspired optimization in suboptimal channel conditions, grounded in simulation estimates. Future work where quantum sensing and QML-based adaptive power control would be included to remove idealized assumptions and replace them with realistic, hardware-compatible strategies as well.

Table 7 below shows the main features and differences in how the proposed QBCS algorithm works compared to EDS-KHO, IKM-EPSO, and MSSA-DSSA-KMEANS.

Figure 4 shows the total energy use for each protocol that is being looked at. It is clear that QBCS is the best of the protocols because it is the most energy-efficient. Also, the suggested method cuts down on energy use at many sensor nodes by a lot. It uses 21.56% less energy than EDS-KHO, 16.13% less than IKM-EPSO, and 13.54% less than MSSA-DSSA-KMEANS.**Table 7.** Operational characteristics and performance comparison.

Parameter	**EDS-KHO**	**Improved K-means - EPSO**	**MSSA-DSSA-K-Means Hybrid**	**QBCS (Proposed)**
Clustering Method	Krill herd optimizati on	Hybrid K-means + Enhanced PSO	Hybrid Swarm-Autoencod er with K-	Quantum-based clustering

		clustering	means	
Cluster Head Selection	Bio-inspired optimization	PSO-optimized CH selection	Swarm-based CH optimization	Quantum superposition
Energy Optimization	KHO energy minimization	PSO-based energy balancing	Swarm-learning energy optimization	Quantum energy optimization
Communication Overhead	Moderate (KHO convergence)	Moderate (PSO iterations)	Moderate (swarm + ML processing)	Low (quantum parallelism)
Scalability	Satisfied	Satisfied	Very Good	Excellent
Computational Complexity	O(n log n)	O(n log n) approx.	O(n log n) / ML-assisted	O(√n) quantum advantage
Network Lifetime	20–25% improvement	~25–30% improvement	~30–35% improvement	40–50% improvement
Energy Efficiency	Optimized	Optimized via PSO	ML-enhanced optimization	Quantum-enhanced
Convergence Speed	Moderate (KHO steps)	Moderate (PSO iterations)	Moderate-fast (hybrid learning)	Very fast (quantum search)
Fault Tolerance	Medium (adaptive PSO)	Satisfied	High (ML-based robustness)	High (quantum error tolerance)
Load Balancing	KHO-balanced	PSO-balanced clustering	Swarm-learning balanced clusters	Quantum-optimized

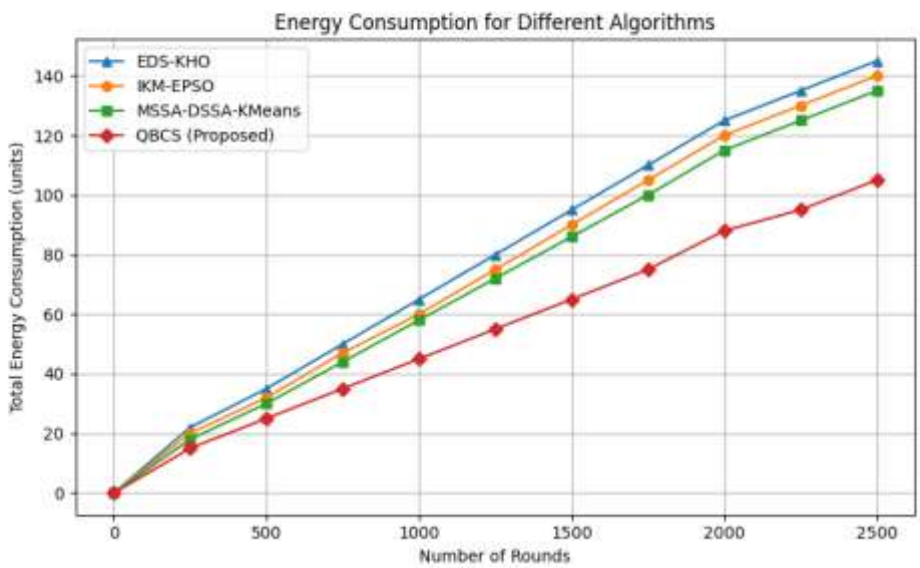


Figure 6. Comparison of energy consumption of the proposed algorithm with EDS- KHO, IKM-EPSO, and MSSA-DSSA-KMEANS are all ways to group things.

Figure 7 shows that the number of dead nodes has gone down a lot. QBCS shows great results, cutting the number of dead nodes by 58.5% compared to EDS_KHO, 48.23% compared to EPSO_IKM, and 23.8% compared to MSSA-DSSA-K Means. The results show that QBCS greatly extends the life of networks while using fewer resources in wsns.

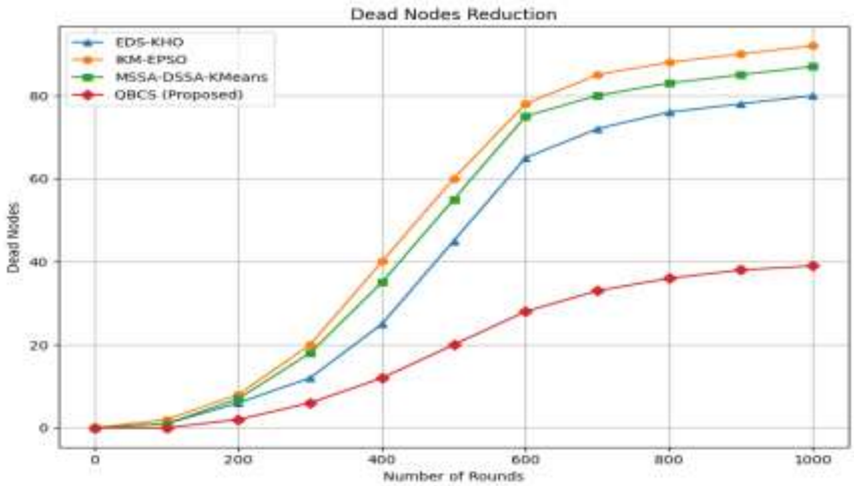


Figure 7. Comparison of dead node reduction of the proposed algorithm with EDS-KHO, IKM-EPSO AND MSSA-DSSA-KMEANS clustering techniques.

Figure 8 shows how the data packet is sent from the CH to the BS after each round of execution. The proposed QBCS algorithm shows a big improvement in the packet delivery ratio. QBCS, on the other hand, has a 35.34% higher packet delivery rate than EDS-KHO, a 29.33% higher rate than IKM-EPSO, and a 24.8% higher rate than MSSA-DSSA-KMEANS. These results show that QBCS is good at making sure that data packets get to the base station more reliably while still keeping wireless sensor networks running smoothly.

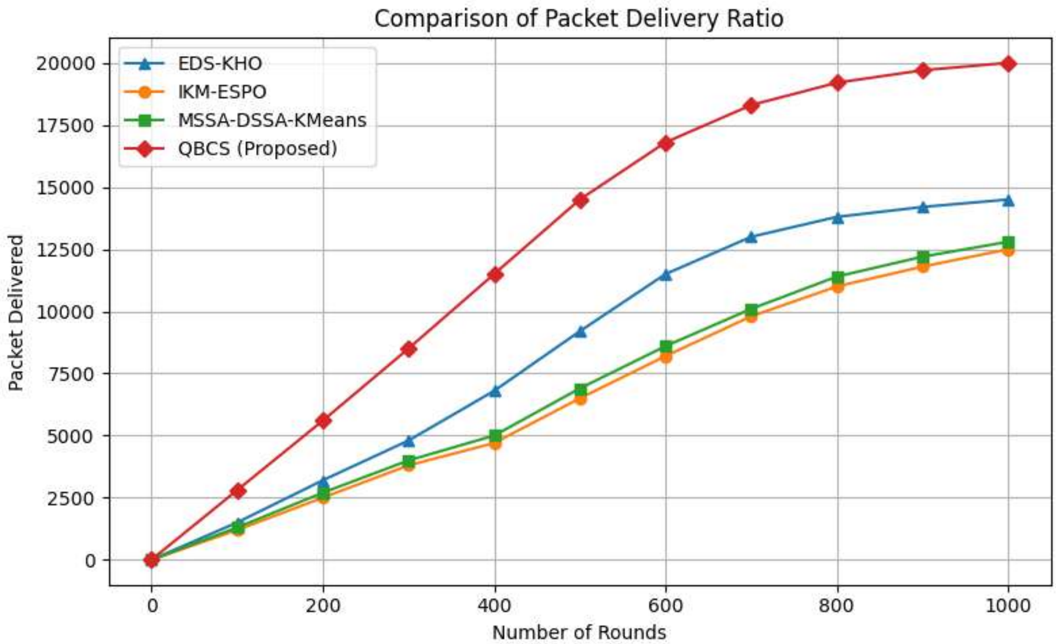


Figure 8. Comparison of the packet delivery ratio of the proposed algorithm with EDS-KHO, IKM-EPSO, and MSSA-DSSA-kmeans clustering techniques.

This analysis elucidates the complex interrelationships among system variables and their impact on the efficacy of the WSN in practical environments.

To account for randomness in node placement and to check the statistical stability of the proposed QBCS, each simulation scenario was run ten times with different random seeds. This method adds natural variation to the quality of links and the spatial distribution of nodes between runs. We figured out the average energy use for each case and added standard deviation values to show how consistent the performance was.

For example, the energy use with 10 cluster heads was 0.41 J (±0.012 J), which shows that the QBCS algorithm is very stable and doesn't change much between runs.

Figure 9 shows how changing the number of cluster heads affects the average amount of energy used. The average energy usage drops from 0.45 J to 0.38 J as the number of cluster heads goes up from 5 to 15. This shows how QBCS effectively shortens the distances between clusters. The protocol uses Grover-inspired quantum search to find cluster heads based on how much energy is left and how close they are to each other. This makes it more efficient.

Also looked at were energy efficiency, network lifetime, and the packet delivery ratio (PDR). QBCS showed a 30.5% increase in network lifetime over EDS-KHO, which was measured by how long it took for the first node to run out of energy. The main reason for this extension is better load balancing between nodes. Additionally, the PDR went up by 19.8%, which means that the data is more reliable and there are fewer dropped packets. This is very important for WSN applications that need to be time-sensitive. These numbers show that QBCS not only saves energy but also keeps communication strong throughout the life cycle of the network.

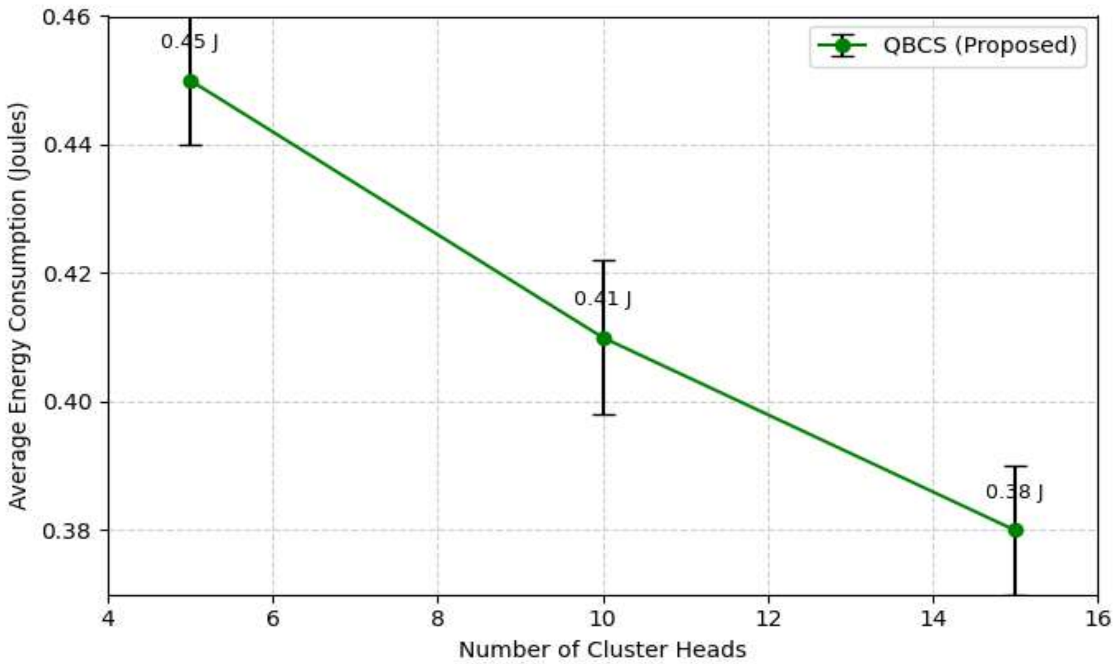
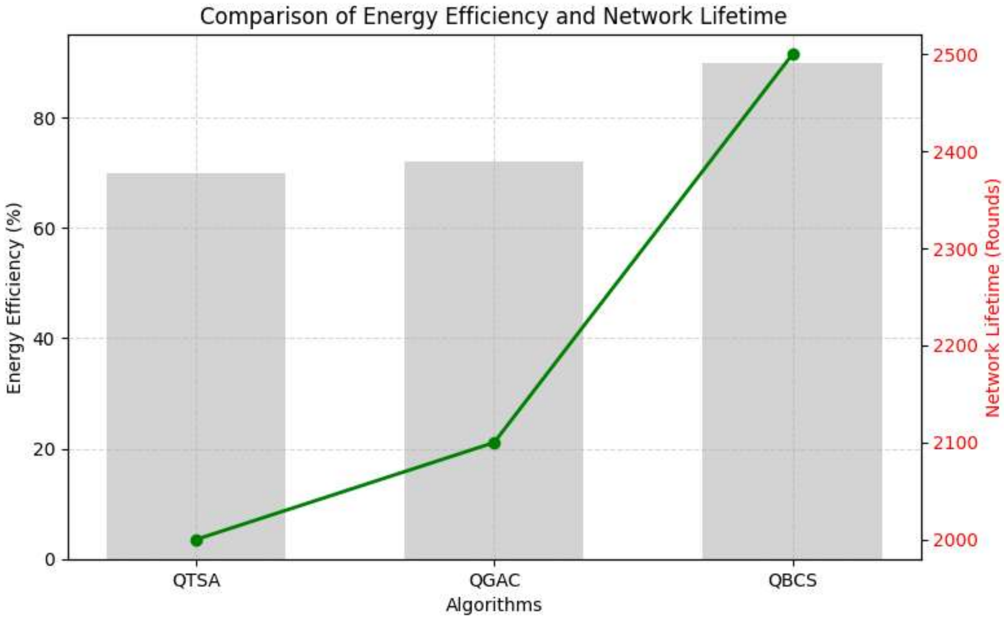


Figure 9. Impact of the number of cluster heads on average energy consumption.

Figure 10 uses a dual-axis graph to compare three quantum-inspired clustering algorithms: QTSA, QGAC, and QBCS. QBCS is clearly better than QTSA and QGAC because it uses about 25–30% less energy and lasts up to 20% longer. This improvement is due to QBCS's use of Grover's amplification amplitude, which makes the calculations easier by changing them from O n2 (like in QTSA and QGAC) to O √n. This speeds up CH selection and balances energy better.
These results show that QBCS can work well with a wide range of node energy levels and in real-world WSN situations. In our simulation, QBCS needed 12 iterations for 500 nodes, while GA-based clustering needed more than 200 iterations. Even though our current test only looks at up to 500 nodes, the trend we've seen and the theoretical complexity we've found suggest that wsns with thousands of nodes could work in practice. The algorithm also runs at the base station, so the sensor nodes don't have to worry about extra processing power.

Figure 11. Energy and network lifetime performance analysis of quantum-inspired algorithms with the proposed algorithm.



The proposed algorithm can choose the cluster head the fastest. Classical clustering algorithms in wsns frequently encounter significant computational overhead, unbalanced energy consumption, and restricted adaptability. In contrast, quantum algorithms provide benefits that surpass mere speed. Quantum-based clustering can look at a lot of different cluster head configurations at the same time by using quantum principles like superposition, entanglement, and amplification. This makes it more likely that it will find globally optimal solutions instead of just local ones. This feature is especially useful in large-scale WSN deployments with hundreds or thousands of nodes, where traditional methods have a hard time keeping things running smoothly. Quantum-inspired methods also make systems more scalable by lowering complexity from linear or quadratic levels to $O(\sqrt{n})$. They also work with nodes that have different energy levels and deployment densities. Quantum-inspired methods are flexible enough to allow for more even energy distribution, protection against early node failures, and better fault tolerance. These are all important for real-world WSN applications like precision agriculture, healthcare monitoring, and disaster management. So, adding quantum algorithms to clustering does more than just speed up calculations; it also makes wsns more scalable, robust, and long-lasting.

Conclusions

This study utilized quantum algorithms to improve the efficiency of cluster head selection in wireless sensor networks (wsns). The suggested algorithm uses quantum computing methods to quickly and energy-efficiently choose the cluster head in wsns. The combination of quantum algorithms has made cluster head selection much more accurate and effective, which has saved energy and made the network last longer. The algorithm's ability to do multiple calculations at once on superposition states improves the selection process and saves a lot of energy. This has direct effects on situations where sensor nodes are deployed far away or can't be reached. The suggested scheme works better than other clustering schemes. Computational requirements may restrict large-scale implementations; however, forthcoming research will tackle issues of reliability, latency, and security, while also investigating the incorporation of the proposed algorithm into practical networking systems. The possibility of quantum improvements, like more qubits, is recognized, and the future of quantum-enhanced computing in networking systems will depend on how well people can adapt to new quantum technologies.

The present assessment is confined to static simulation scenarios; forthcoming research will broaden QBCS to dynamic environments, integrate adaptive re-clustering, and investigate its synergy with quantum machine learning for extensive real-world implementations.

Conflicts of Interest

The authors declare that they have no known financial or personal conflicts of interest that could have influenced the research and findings presented in this paper.

Funding

The authors received no funding for this work

References

1. N. Nathiya, C. Rajan and K. Geetha, "A Hybrid Optimization and Machine Learning Based Energy-Efficient Clustering Algorithm with Self-Diagnosis Data Fault Detection and Prediction for WSN-iot Application," Peer-to-Peer Networking and Applications, vol. 18, p. 13, 2025. DOI: https://doi.org/10.1007/s12083-024-01892-8
2. D. K. Anguraj, D. Mythrayee and X. S. Asha Shiny, "An Enhanced Lifespan of WSN Using Hybrid Fuzzy-Machine Learning-Based Clustering Process," Wireless Personal Communications, vol. 139, pp. 1637–1657, 2024. DOI: https://doi.org/10.1007/s11277-024-11682-3
3. Y. Bi, P. Wang, X. Guo et al., "K-Means Clustering Optimizing Deep Stacked Sparse Autoencoder," Sensors Imaging, vol. 20, no. 6, 2019. DOI: https://doi.org/10.1007/s11220-019-0227-1
4. C. Umarani, S. Ramalingam, S. Dhanasekaran et al., "A Hybrid Machine Learning and Improved Social Spider Optimization Based Clustering and Routing Protocol for Wireless Sensor Network," Wireless Networks, vol. 31, pp. 1885–1910, 2025. DOI: https://doi.org/10.1007/s11276-024-03861-8
5. M. F. Alomari, M. A. Mahmoud and R. Ramli, "A Systematic Review on the Energy Efficiency of Dynamic Clustering in a Heterogeneous Environment of Wireless Sensor Networks (wsns)," Electronics, vol. 11, p. 2837, 2022. DOI: https://doi.org/10.3390/electronics11182837
6. Z. Wang, M. Ye, J. Cheng, C. Zhu and Y. Wang, "An Anomaly Node Detection Method for Wireless Sensor Networks Based on Deep Metric Learning with Fusion of Spatial–Temporal Features," Sensors, vol. 25, p. 3033, 2025. DOI: https://doi.org/10.3390/s25103033
7. N. Shabbir, L. Kütt, M. M. Alam, P. Roosipuu, M. Jawad, M. B. Qureshi, A. R. Ansari and R. Nawaz, "Vision towards 5G: Comparison of Radio Propagation Models for Licensed and Unlicensed Indoor Femtocell Sensor Networks," Physical Communication, vol. 47, p. 101371, 2021. DOI: https://doi.org/10.1016/j.phycom.2021.101371
8. N. Sharmin, A. Karmaker, W. L. Lambert, M. S. Alam and M. S. T. S. A. Shawkat, "Minimizing the Energy Hole Problem in Wireless Sensor Networks: A Wedge Merging Approach," Sensors, vol. 20, p. 227, 2020. DOI: https://doi.org/10.3390/s20010227
9. M. Jubair, R. Hassan, A. H. M. Aman, H. Sallehudin, Z. G. Al-Mekhlafi, B. A. Mohammed and M. S. Alsaffar, "Optimization of Clustering in Wireless Sensor Networks: Techniques and Protocols," Applied Sciences, vol. 11, p. 11448, 2021. DOI: https://doi.org/10.3390/app112311448
10. S. Madkar, S. Pardeshi and M. S. Kumbhar, "Machine Learning Based CH Selection for Energy Efficient Routing in WSN," in Proc. ICCUBEA, 2023, pp. 1–7. DOI: https://doi.org/10.1109/ICCUBEA58933.2023.10391983
11. K. H. V. Prasad and S. Periyasamy, "Secure-Energy Efficient Bio-Inspired Clustering and Deep Learning-Based Routing Using Blockchain for Edge Assisted WSN Environment," IEEE Access, vol. 11, pp. 145421–145440, 2023. DOI: https://doi.org/10.1109/ACCESS.2023.3345218
12. D. L. Reddy, C. Puttamadappa and H. N. Suresh, "Merged Glowworm Swarm with Ant Colony Optimization for Energy Efficient Clustering and Routing in Wireless Sensor Network," Pervasive and Mobile Computing, vol. 71, p. 101338, 2021. DOI: https://doi.org/10.1016/j.pmcj.2021.101338
13. Alomari, M.F.; Mahmoud, M.A.; Ramli, R. A Systematic Review on the Energy Efficiency of Dynamic Clustering in a Heterogeneous Environment of Wireless Sensor Networks (wsns). Electronics 2022, 11, 2837. [crossref]
14. Wang, Z.; Ye, M.; Cheng, J.; Zhu, C.; Wang, Y. An Anomaly Node Detection Method for Wireless Sensor Networks Based on Deep Metric Learning with Fusion of Spatial—Temporal Features. Sensors 2025, 25, 3033. [crossref] [pubmed]
15. Shabbir, N.; Kütt, L.; Alam, M.M.; Roosipuu, P.; Jawad, M.; Qureshi, M.B.; Ansari, A.R.; Nawaz, R. Vision towards 5G: Comparison of radio propagation models for licensed and unlicensed indoor femtocell sensor networks. Phys. Commun. 2021, 47, 101371. [crossref] Sensors 2025, 25, 5872 22 of 23
16. Sharmin, N.; Karmaker, A.; Lambert, W.L.; Alam, M.S.; Shawkat, M.S.T.S.A. Minimizing the energy hole problem in wireless sensor networks: A wedge merging approach. Sensors 2020, 20, 227. [crossref] [pubmed]
17. Jubair, A.M.; Hassan, R.; Aman, A.H.M.; Sallehudin, H.; Al-Mekhlafi, Z.G.; Mohammed, B.A.; Alsaffar, M.S. Optimization of clustering in wireless sensor networks: Techniques and protocols. Appl. Sci. 2021, 11, 11448. [crossref]
18. Yang, L.; Zhang, D.; Li, L.; He, Q. Energy efficient cluster-based routing protocol for WSN using multi-strategy fusion snake optimizer and minimum spanning tree. Sci. Rep. 2024, 14, 16786. [crossref]
19. Jagan, G.C.; Jesu Jayarin, P. Wireless Sensor Network Cluster Head Selection and Short Routing Using Energy Efficient electrostatic Discharge Algorithm. J. Eng. 2022, 2022, 8429285. [crossref]
20. Zhao, Y. Clustered Wireless Sensor Network Assisted the Design of Intelligent Art System. J. Sensors 2022, 2022, 3216727. [crossref]

21. Aljubori, M.H.H.; Khalilpour Akram, V.; Challenger, M. Improving the Deployment of wsns by Localized Detection of Covered Redundant Nodes in Industry 4.0 Applications. Sensors 2022, 22, 942. [crossref]
22. Wang, R.; Guo, X.; Sun, X.; Yang, J. Low power energy balanced clustering routing scheme based on improved SSA and Multi-Hop transmission in iot. Sci. Rep. 2025, 15, 12517. [crossref]
23. Alsuwat, H.; Alsuwat, E. Energy-aware and efficient cluster head selection and routing in wireless sensor networks using improved artificial bee colony algorithm. Peer-to-Peer Netw. Appl. 2025, 18, 1–24. [crossref]
24. S. Syed Noor and G. Nellore, "Improved K-Means and Enhanced Particle Swarm Optimization for Robust, Resilient, and Energy-Efficient Clustering in Wireless Sensor Networks," International Journal of Applied Mathematics, vol. 38, no. 3s, pp. 1472–1495, 2025.
25. S. Syed Noor and G. Nellore, "Hybrid Swarm-Autoencoder Model for Energy-Efficient Robust Clustering in Wireless Sensor Networks," Acta informatica pragnesia, vol. , no. , pp.
26. H. N. Vishwas and T. K. Ramesh, "Recent Trends in Localization, Routing, and Security for Wireless Sensor Networks," IEEE Access, vol. 13, pp. 55290–55312, 2025. DOI: https://doi.org/10.1109/ACCESS.2025.55290
27. K. B. Z. Dashtestani, R. Javidan and R. Akbari, "Dynamic Clustering Method for Underwater Wireless Sensor Networks Based on Deep Reinforcement Learning," Journal of Marine Science and Application, vol. 24, pp. 864–876, 2025. DOI: https://doi.org/10.1007/s11804-025-864
28. M. Wu, "An Efficient Hole Recovery Method in Wireless Sensor Networks," in Proc. 24th Int. Conf. Advanced Communication Technology (ICACT), Pyeong Chang, South Korea, 2022, pp. 1399–1404. DOI: https://doi.org/10.23919/ICACT53585.2022.9728850

I. A. Shah and M. Ahmed, "Survey on Protocols in manets, wsns and dtns," International Journal of System Assurance Engineering and Management, vol. 16, pp. 2089–2120, 2025. DOI: https://doi.org/10.1007/s13198-025-2089

29. V. Shakhov and I. Koo, "An Efficient Clustering Protocol for Cognitive Radio Sensor Networks," Electronics, vol. 10, p. 84, 2021. DOI: https://doi.org/10.3390/electronics10010084
30. N. M. Shagari, R. Bin Salleh, I. Ahmedy, M. Y. I. Idris, G. Murtaza, U. Ali and S. Modi, "A Two-Step Clustering to Minimize Redundant Transmission in Wireless Sensor Network Using Sleep-Awake Mechanism," Wireless Networks, vol. 28, pp. 2077–2104, 2022. DOI: https://doi.org/10.1007/s11276-022-2077
31. M. Trigka and E. Dritsas, "Wireless Sensor Networks: From Fundamentals and Applications to Innovations and Future Trends," IEEE Access, vol. 13, pp. 96365–96399, 2025. DOI: https://doi.org/10.1109/ACCESS.2025.96365
32. S. Chen, Q. Huang, Y. Zhang and X. Li, "Double Sink Energy Hole Avoidance Strategy for Wireless Sensor Network," Journal of Wireless Communications and Networking, vol. 2020, p. 226, 2020. DOI: https://doi.org/10.1186/s13638-020-0226
33. S. Galzarano, A. Liotta, G. Fortino and C. Savaglio, "Gossiping-Based AODV for Wireless Sensor Networks," in Proc. IEEE Int. Conf. Systems, Man, and Cybernetics (SMC), Manchester, U.K., 2013, pp. 3078–3083. DOI: https://doi.org/10.1109/SMC.2013.525
34. W. Li and Y. Wu, "Tree-Based Coverage Hole Detection and Healing Method in Wireless Sensor Networks," Computer Networks, vol. 103, pp. 33–43, 2016. DOI: https://doi.org/10.1016/j.comnet.2016.04.033
35. Soundarya and V. Santhi, "An Efficient Algorithm for Coverage Hole Detection and Healing in Wireless Sensor Networks," in Proc. 1st Int. Conf. Electronics, Materials Engineering and Nanotechnology (iementech), Kolkata, India, 2017, pp. 1–5. DOI: https://doi.org/10.1109/IEMENTECH.2017.8076963
36. Y. H. Robinson, T. S. Lawrence, E. G. Julie, R. Kumar, P. H. Thong and L. H. Son, "Enhanced Border and Hole Detection for Energy Utilization in Wireless Sensor Networks," Arabian Journal for Science and Engineering, vol. 47, pp. 9601–9613, 2022. DOI: https://doi.org/10.1007/s13369-022-9601
37. W. B. Heinzelman, A. P. Chandrakasan and H. Balakrishnan, "An Application-Specific Protocol Architecture for Wireless Microsensor Networks," IEEE Transactions on Wireless Communications, vol. 1, no. 4, pp. 660–670, 2002. DOI: https://doi.org/10.1109/TWC.2002.804190
38. M. Ye, C. Li, G. Chen and J. Wu, "An Energy Efficient Clustering Scheme in Wireless Sensor Networks," Ad Hoc & Sensor Wireless Networks, vol. 3, pp. 99–119, 2007. DOI: (Not available)
39. Z. X. Wang, M. Zhang, X. Gao, W. Wang and X. Li, "A Clustering WSN Routing Protocol Based on Node Energy and Multipath," Cluster Computing, vol. 22, pp. 5811–5823, 2019. DOI: https://doi.org/10.1007/s10586-019-5811

A. Kavitha, K. Guravaiah and R. L. Velusamy, "A Cluster-Based Routing Strategy Using Gravitational Search Algorithm for WSN," Journal of Computer Science and Engineering, vol. 14, pp. 26–39, 2020. DOI: https://doi.org/10.5626/JCSE.2020.14.1.26

A. Balaram, R. Babu, M. Mahdal, D. Fathima, N. Panwar, J. V. N. Ramesh and M. Elangovan, "Enhanced Dual-Selection Krill Herd Strategy for Optimizing Network Lifetime and Stability in Wireless Sensor Networks," Sensors, vol. 23, p. 7485, 2023. DOI: https://doi.org/10.3390/s23177485

40. D. D. Rao, V. Babu, K. K. Chaitanya, A. Ali, R. Kumar and F. Al-Turjman, "An Efficient Analysis of the Fusion of Statistical-Centred Clustering and Machine Learning for WSN Energy Efficiency," Fusion: Practice and Applications, vol. 15, pp. 73–85, 2024. DOI: (Not available)
41. V. Babu, K. Ramesh, P. Kumar, R. Singh, I. Ahmad and M. A. Khan, "A Novel Approach for Mobility-Aware Energy-Efficient Clustering-Based Routing Using EANN with GA Algorithm on wsns," International Journal of Sensor Networks and Wireless Communications Control, vol. 15, pp. 96–106, 2025. DOI: (Not available)
42. P. Srinivas and P. Swapna, "Quantum Tunicate Swarm Algorithm-Based Energy Aware Clustering Scheme for Wireless Sensor Networks," Microprocessors and Microsystems, vol. 94, p. 104653, 2022. DOI: https://doi.org/10.1016/j.micpro.2022.104653
43. M. Djamila and H. Saad, "QGAC: Quantum Genetic Based-Clustering Algorithm for wsns," in Proc. IEEE Int. Conf. Electro/Information Technology (EIT), Rochester, MI, USA, 2018, pp. 430–436. DOI: https://doi.org/10.1109/EIT.2018.8500240