

# A Niche Quantum Ant Colony Multifaceted Routing Algorithm for WSN-based IoT Networks in the Emerging Quantum Industry

P. Suseendhar<sup>1\*</sup>, and Capt. Dr.K.P. Sridhar<sup>2</sup>

<sup>1\*</sup>Research Scholar, Department of ECE, Karpagam Academy of Higher Education, Coimbatore, Tamilnadu, India. suseendhar.p@gmail.com, <https://orcid.org/0000-0002-4775-4593>

<sup>2</sup>Professor, Department of ECE, Karpagam Academy of Higher Education, Coimbatore, Tamilnadu, India. sridhar.kp@kahedu.edu.in, <https://orcid.org/0000-0001-9377-7182>

Received: July 19, 2024; Revised: August 27, 2024; Accepted: September 30, 2024; Published: November 30, 2024

## Abstract

Quantum computing (QC) is an important area of technological study. The ever-growing network size and complexity in quantum computation research are the cause of evolutionary dynamics in QC. The Internet of Things (IoT) is a paradigm shift in thinking; it advances many forms of communication that rely on WSNs to gather data, and it has the potential to be even more effective with the help of quantum computing. Network congestion results in lost packets, delayed transmissions, and wasted effort during recovery. In an attempt to improve the efficiency and velocity of the route, the proposed method considers a number of objectives. Since quantum computers leverage the characteristics of quantum states to do certain computations at orders of magnitude quicker than classical computers, this is an exciting new direction to investigate. This study introduced the Niche Quantum Ant Colony Multifaceted Routing Algorithm (NQAC-MRA), a method for optimizing wireless distributed networks in IoT routes that combines quantum computation, an optimization function for several objectives, and monitoring. Producing cost-effective routing that is congestion-aware for alarm message transmission over WSN-IoT and for alert message transmission utilizing IoT devices to their respective destinations with the lowest latency is the primary goal of this study. To be more specific, the quantum bits stand in for the node pheromone, and turning quantum gates modifies the search path's pheromone. Nodes' power consumption, communication delay, and degree of network load-balancing serve as fitness metrics to find the best communication path. According to the results of the performance analysis, the suggested scheme is both lightweight and more effective than the alternatives. The performance research showed that the proposed approach outperformed the alternatives while being significantly lighter. The suggested NQAC-MRA beat its competitors in terms of total simulation results thanks to its reduced energy usage and enhanced performance.

**Keywords:** Ant Colony Multifaceted Routing Algorithm, Wireless Sensor Networks, IoT.

## 1 Introduction

The advent of QC has sparked renewed enthusiasm for several fields of study, particularly communication, all around the globe (Dayana & Kalavathy, 2022). The ability to remotely transmit

---

*Journal of Internet Services and Information Security (JISIS)*, volume: 14, number: 4 (November), pp. 418-435.  
DOI: 10.58346/JISIS.2024.14.026

\*Corresponding author: Research Scholar, Department of ECE, Karpagam Academy of Higher Education, Coimbatore, Tamilnadu, India.

and manipulate quantum bits is one way in which QC technology can enhance ICTs (Ghorpade et al., 2021). Even though QC is still in its infancy as a field of study, it shows great promise for bolstering national and business competitiveness through the development of new technologies in areas such as quantum communications, quantum encryption, quantum optics, etc (Liu et al., 2022). When optimizing routing, a key function is to direct data streams between network nodes along the best possible end-to-end paths, taking into account specific network conditions (Rivero-Angeles, 2021). Any network type can have its general efficiency negatively impacted by an ineffective forwarding scheme. One or more pathways are defined as part of a routing strategy, which allows endpoints to communicate with each other via a network (Roy & Kim, 2022).

The base stations (BSs), node sensors, and endpoint structures make up the WSN, which is an autonomous communication system (Jannu et al., 2022). Quantitative QC can enhance the IoT, which stands for forward-thinking ideas and advances several communication structures that rely on WSNs to gather data. Thus far, a number of IoT services and applications facilitate the transmission of data packets (Hosseini Shirvani & Akbarifar, 2020). Insufficient sensor techniques could lead to an issue with energy exploitation during the routing phase. It is possible to assess the vast potential by transferring many nodes in the land portion across a few kinds of wireless equipment (Srinivas & Swapna, 2022). A key component of the IoT, WSN has expanded into numerous distinct practical implementations (Alamer & Shadadi, 2023). The widespread usage of WSNs and IoTs in non-critical and potentially dangerous activities has prompted efforts to extend their service life (Vijayan et al., 2024). In battery-driven methods, WSN nodes are negligible; however, the cost-effective approach increases the network lifetime, which is critically important. Concepts for energy efficiency in WSN-based IoT architectures have so far made use of a variety of techniques and procedures (Khudair Madhloom et al., 2023). In addition, communication congestion causes packet loss and longer latency times. Because of the limited capacity of the channels, congestion develops (Sathish & Babu, 2021).

The primary goal of conventional wireless networks like WSN and Ad hoc is to minimize transmission congestion and maximize network throughput by determining the shortest path from one node to another with the least amount of latency (Maharajan et al., 2021). As a result of the lengthy lifespan demands and restricted node energy, the routing strategy prioritizes energy efficiency. When it comes to industries that demand outstanding results in terms of energy consumption and lifespan, WSNs aren't a good fit for traditional WSN routing methods due to the network's limited power and resources (Liu et al., 2021). This paper explores the idea of combining Ant colony optimization (ACO) with specialized quantum-inspired adaptive algorithms. The goal is to improve ACO-based routing methods in IoT networks by addressing their limitations, such as slow harshness and earlier sluggishness (Suvarna & Deepak, 2024; Sujanthi & Nithya Kalyani, 2020). The Multifaceted Routing Algorithm would then balance demand, actual time delivery, and energy usage. Niche Quantum Ant Colony Multifaceted Routing Algorithm (NQAC-MRA), a new and effective method for transporting WSNs, is thus suggested. When dealing with a significant issue, this method can greatly improve search navigation and resolution speed (Xu et al., 2024). In contrast, NQAC-MRA uses the niche methodology to guarantee a variety of species in a huge ant population. Because there are consistent variations among individuals in the colony, NQACO is able to solve the early challenge that other approaches have and provide better local searching capacities.

The main contributions of the article include:

1. The NQAC-MRA optimizes IoT routes for wireless distributed networks by combining monitoring with quantum computation and an optimization function for multiple objectives for reduced energy consumption.

2. Quantum bits represent the node pheromone, while quantum gates change the search path pheromone. Fitness parameters for the optimum routing path include node power consumption, communication delay, and network load balancing.
3. The performance analysis shows that the proposed approach is lightweight and more effective than alternatives.

Here is the outline for the paper. The second section compared and contrasted the most current studies. Moving on from Section 3's introduction to NQAC-MRA, the next step is to cover WSN fitness functions and routing. Section 4 discusses the outcomes of the experiments, and Section 5 presents the final thoughts.

## 2 Literature Survey

Khan et al., (2023) proposed a novel architecture that improves network interaction by smartly adjusting to the ever-evolving Internet of Things (IoT) environment and the upcoming 6G network architecture. In particular, it introduced BACO-6G-IoT, an Adaptive Biomimetic Ant Colony Optimization with 6G Integration for Internet of Things Network Communication, which takes advantage of and improves upon the Ant Colony Optimization (ACO) algorithm in a way that is specifically tailored to the difficulties caused by the combination of 6G and IoT. The foundation for future advancements in wireless communication technology is laid by this methodological synthesis, which creates a comprehensive strategy that could transform network performance.

Venkatasubramanian, (2022) discuss RSL-MRP, a method for selecting cluster heads in MANETs that incorporates multipath routing protocol, as a means of addressing quality of service. In this article, we see how to construct an optimizer algorithm based on a Randomized Selected Leader (RSL) that selects a cluster head for each cluster. Based on criteria including energy usage, delay, and traffic index prices, the proposed method uses Cluster Heads to choose dependable channels for data transmission. Results from simulations show that the proposed protocol outperforms state-of-the-art protocols with regard to network life and throughput.

Alolaiwy et al., (2023) introduced electric and flying vehicles (EnFVs); the transport sector has made great strides in sustainability, congestion, and mobility. This meta-analysis examines genetic algorithms' (GAs) EnFV route optimization in multiple case studies. The study suggests combining hybrid methods with other optimization methods, improving energy efficiency and environmental sustainability in routing, adaptability for large-scale distribution problems, uncertainty and risk management, and real-time data and dynamic route updates (Salem & Sulaiman, 2024). By exploring these areas, researchers can improve EnFV routing algorithms and integrate them into modern transportation systems.

Sathiamoorthy et al., (2022) present the OEEFCP framework, which stands for an optimal and energy-efficient UWCN routing protocol based on cluster communication. In the first stage, a robust cluster head (CH) can efficiently choose a data carrier. Data transmission via efficient channels will be the primary emphasis of Phase 2, which employs an efficient multipath energy model. From the best possible CHs, a gateway node is selected based on the RSSI (Received Signal Strength Indicator) value. The NS2 simulator is used to compare the proposed OEEFCP to current systems, including OC-TARE-TOPSIS and TARE-TOPSIS protocols. The results show that the suggested OEEFCP can achieve good performance in terms of throughput, energy conservation, maximum PDR, and prolonged network lifespan.

Rathee et al., (2020) offer a routing in big networks known to be NP-Hard. Hence, Meta heuristic techniques are used to address this issue. Quantum-inspired algorithms are novel metaheuristic techniques that have demonstrated superior performance compared to their conventional counterparts. The study introduces the Quantum-inspired Ant-Based Energy-Balanced Routing (QBER) algorithm to tackle the issue of energy-balanced routing in Wireless Sensor Networks (WSNs). The simulation findings validate that the proposed QBER algorithm outperforms other quantum-inspired routing methods for WSNs.

Abas et al., (2024) introduced a groundbreaking algorithm called QIGA, which is inspired by quantum computing for effective optimization of WSNs. In the first step of the method, candidate routes are quantum encoded using qubits, which can represent numerous routes concurrently using concepts like entanglement and superposition. To tackle the complex problems of WSN network optimization, the suggested approach presents a paradigm influenced by quantum computing, which shows potential. This research adds to the growing body of literature on quantum computing's potential networking applications. It paves the way for more advanced algorithms inspired by quantum theory that are better suited for use in WSN settings.

Chen et al., (2022) demonstrate proof-of-principle for swiftly finding optimal or nearly optimal solutions by replacing conventional processors with quantum annealing ones. Both academic and business academics have taken an interest in energy-efficient routing in WSNs, spurred on most recently by the possibility of applying methods inspired by software-defined networks. Algorithms for solving these NP-hard problems need computing time that grows at a rate greater than that of polynomials as the problem size increases. In practice, heuristic algorithms are utilized despite their inability to ensure optimal performance. Based on the early findings with smaller networks, this quantum computing strategy seems to be quite promising. It might pave the way for more substantial enhancements to the efficiency of network algorithms and Literature Survey shown in Table 1.

Table 1: Literature Survey

Author	Method	Application	Limitation
(Khan et al., 2023) [16]	Adaptive Biomimetic Ant Colony Optimization with 6G Integration for Internet of Things Network Communication	Adapts to the changing Internet of Things (IoT) environment and 6G network architecture to improve network interaction.	Adds complexity to a large network.
(Venkatasubramanian, 2022) [17]	RSL-MRP	An RSL-based optimizer that chooses a cluster head for each cluster.	Router-specific dependency.
(Alolaiwy et al., 2023) [18]	EnFV route optimization	Using hybrid approaches with other optimization methods to improve routing energy efficiency and sustainability, flexibility for large-scale distribution difficulties	Request ongoing trust monitoring and real-time application latency.
(Sathiamoorthy et al., 2022) [19]	OEEFCP framework, which stands for an optimal and energy-efficient UWCN routing protocol based on cluster communication	The first stage requires a reliable cluster head (CH) that can efficiently choose a data carrier. Phase 2, using an efficient multipath energy model, will focus on data transfer over efficient routes.	Higher computational resource needs.
(Rathee et al., 2020) [20]	Quantum-inspired Ant-Based Energy-Balanced Routing (QBER)	Addressing energy-balanced routing in Wireless Sensor Networks	Lack of real-world validation
(Abas et al., 2024) [21]	QIGA	Quantum computing for effective optimization of WSNs	Scalability issues
(Chen et al., 2022) [22]	Heuristic algorithms are used despite their incapacity to optimize performance.	Algorithms for solving these NP-hard problems need computing time that grows at a rate greater than that of polynomials as the problem size increases.	High Implementation complexity, Less focus on energy efficiency

The analysis of the literature showed that latency, security, and dependability are problems that NQAC-MRA designers face. The suggested approaches offer novel approaches to these issues by showcasing energy savings and quick network response times, all the while boosting security, average trust, system efficacy, and network performance. These methods show how improved quality control is necessary for optimum routing paths.

### 3 System Methodology

#### 3.1 Overall Structure of the Proposed Model

The primary goal of the study is to develop energy-efficient and cost-effective routing algorithms that are congestion-free when sending urgent notifications over the WSN-IoT. Additionally, find ways to send alarm signals using IoT devices to their respective destinations as quickly as possible. Figure 1 shows the proposed Niche Quantum Ant Colony Multifaceted Routing Algorithm (NQAC-MRA) model. Reducing contact over long distances is the goal of a multi-tier structure that uses the subdividing technique for node placement, which improves the network lifetime. Adaptability and distribution of load are capabilities of the suggested multi-tier architecture. When designing a systematic routing system for WSN-IoT, scalability must be a top priority. A good transmission method should be available and able to adjust to changes in the network's setup.

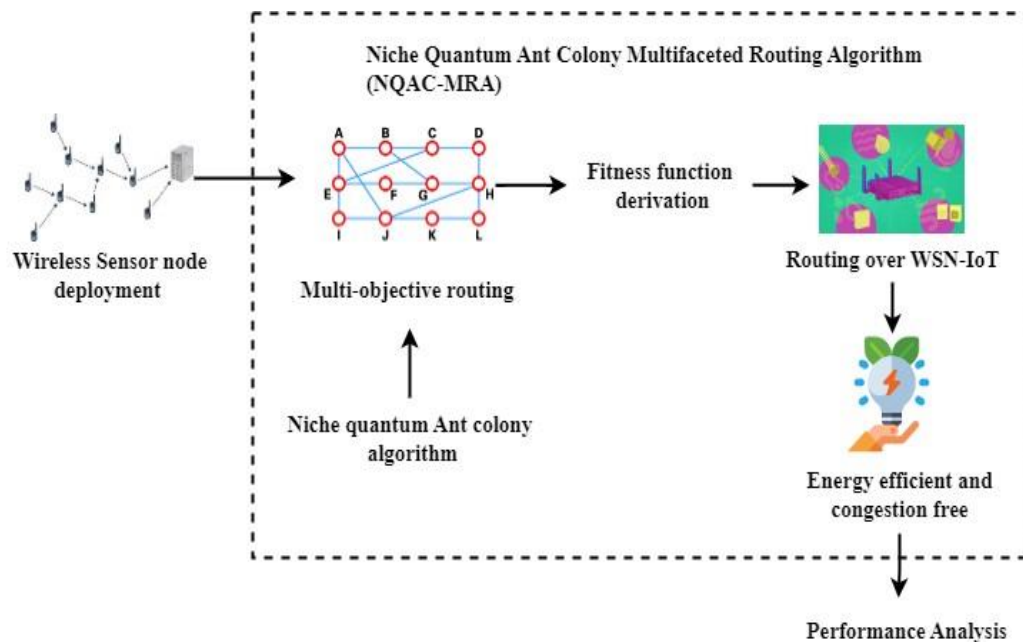


Figure 1: Structure of NQAC-MRA

It all starts with deploying the sensor node. After that, the sensor nodes and the multi-objective routing model are both built. Next, the fitness function is computed using the suggested NQAC-MRA. After that, the NQAC-MRA-based routing via WSN-IoT moves on, and cluster head selection takes place. The data transmission is examined for collision-free status after the routing phase. The primary components of wireless transmission nodes' energy consumption in NQAC-MRA are detecting, data transmission, and processing. More than half of the overall energy consumption of NQAC-MRA is attributable to the energy consumption of wireless connection nodes used for data communication, according to numerous recent research results.

On top of that, optimizing to lower the sensing energy use and the processor's energy usage is challenging because they are relatively fixed. So, to achieve energy savings in the network, this research mainly examines a reasonable routing approach and evaluates the energy loss of each communications node in NQAC-MRA. To minimize congestion and maximize energy efficiency, the next section discusses the basic and proposed Ant colony optimization for WSN in terms of optimal routing.

### 3.2 Multifaceted Routing for WSN-based IoT

Figure 2 shows the various stages that the data goes through in a multifaceted routing IoT system that WSN helps. Wireless Sensor Networks (WSNs) play a pivotal role in the Internet of Things (IoT), providing the essential infrastructure for data collection, monitoring, and communication across various applications. Effective routing in WSN-based IoT is crucial to ensure efficient data transmission, prolonged network lifetime, and robust performance. Multifaceted routing approaches address these needs by integrating multiple strategies to optimize various aspects of the network. Groups of networks called aggregators or cluster members gather data from the WSN-IoT network, which is subsequently combined into a base station (BS). Data is sent to the cloud for additional processing through a gateway device. Pre-processing or post-processing the data is possible depending on the network type (centralized vs. distributed). There is a cloud server that receives data from the IoT system, stores it, and then sends it on to the user. The processing unit is composed of hardware that executes algorithms as programmed into it. Based on data collection techniques, the program can maximize the network lifetime settings using a combination of optimization algorithms.

Typically, a large number of cheap and unimportant sensor nodes make up the WSN. There are a lot of different presentations that make use of these nodes. Some examples are ecological inquiry, gravity's pull and humidity, weather prediction, identifying geologic shakes, vehicle operations, and military inquiry. It is also considered that the node with the most load traffic is the primary factor that needs fixing in order to make WSN better. It is usual practice to place a sink node in the middle of an identification zone so that the network structure can understand sensor nodes.

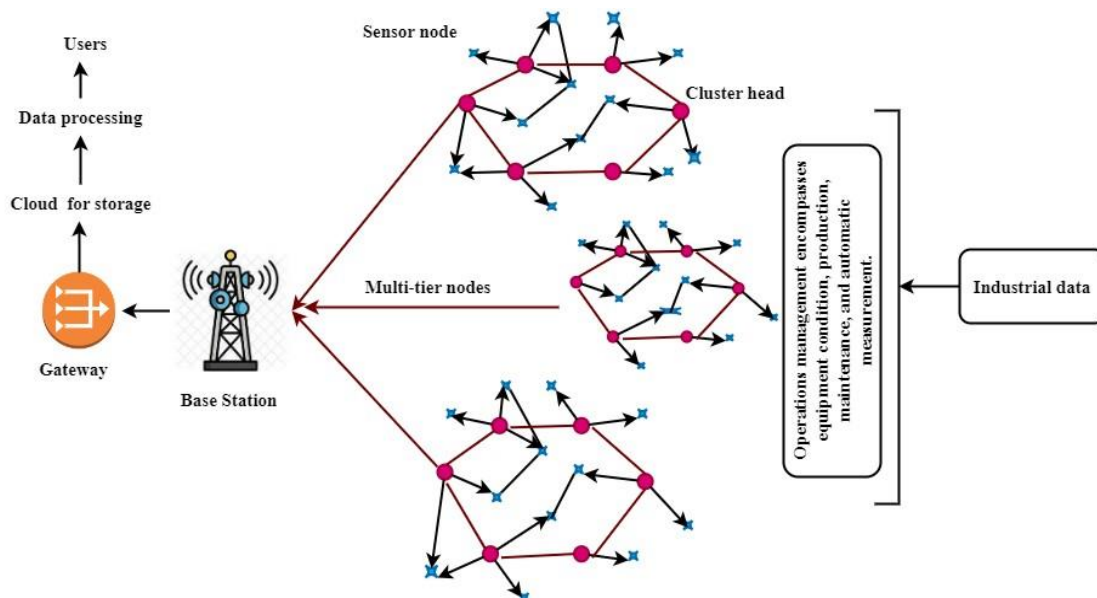


Figure 2: Structure of Multifaceted Routing for WSN-based IoT

A new WSN routing technique, niche quantum ant colony, is going to be covered in the next session. It incorporates quantum technology and a multifaceted fitness component into a routing research approach. Surveillance in such industrial environments may involve the use of a multifunctional routing algorithm for WSN-based IoT. Every node's pheromone is replaced with quantum bits, and the pheromone is refreshed along the hunt route by switching on quantum gates. Optimal search paths are achieved by using fitness procedures that consider the underpinning network's load-balancing capability, data transmission delay, and node energy consumption. While discussing the ins and outs of commercial continual manufacturing, this paper looked at two performance metrics: lifespan of networks and rate of convergence.

The majority of energy use in WSNs occurs during the interaction, which plays a significant role in multi-objective routing in the WSN-based IoT-based energy model, as shown in Figure 3. It is assumed that the following: all nodes can receive data from their adjacent molecules; data includes data on separation and remaining energy; the sensor's broadcast circuit has a power regulator and can use the least amount of energy needed to reach its users; and the wireless circuit can be turned off to prevent obtaining unwanted communication. Figure 2 illustrates that when a sensor node sends  $n$ -bit packets to neighbouring nodes at an interval of  $d$  meters, the energy expenditure from the sending node is denoted by  $n, m$  comprising primarily of communication energy  $T_e(n, m)$  and  $T_{rec}(n, m)$ . Here,

$T_{e_{trans}}(n, m)$  denotes the energy dissipation from the signal-transmitting circuit unit when sending data information.  $T_{e_{rec}}(n, m)$  represents the energy consumption produced by the signal power amplifier circuit unit when amplifying the flow of power.

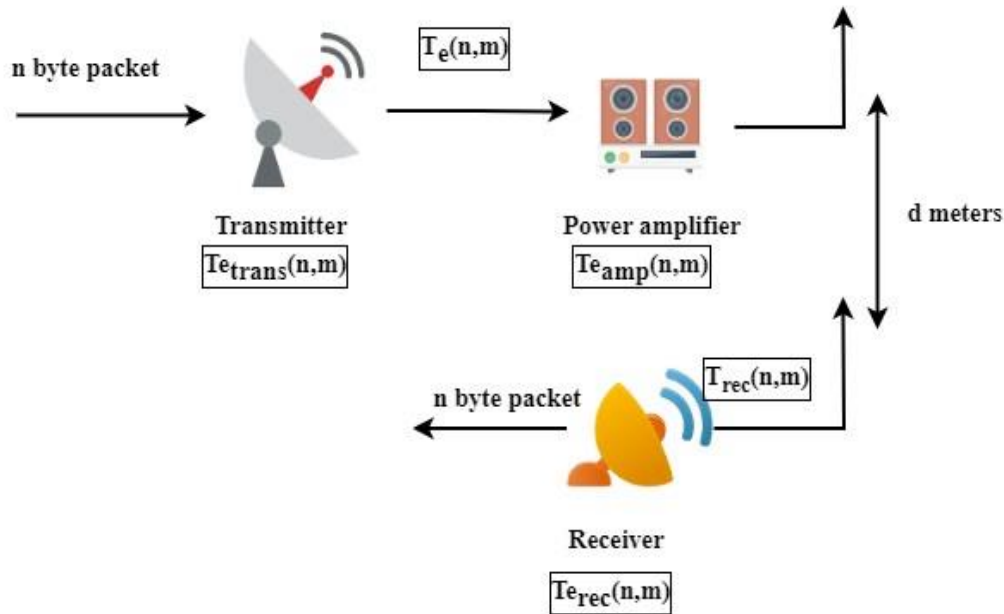


Figure 3: Model for Utilization of Energy in WSN

Here are the energy expenses of sending and receiving an  $n$ -bit message at a specific distance. Equations (1 – 3) show the transmitting, receiving, and total cost energy is given by,

$$T_e(n, m) = T_{e_{trans}}(n) + T_{e_{amp}}(n \times m^2) \quad (1)$$

$$R_e(n) = T_{e_{elect}} \times n + e_{bf} \times n \quad (2)$$

$$T_{EC} = T_e(n, m) + R_e(n) \quad (3)$$

Where,  $e_{elect} = 60nJ/bit$ ,  $e_{amp}=100pj/bitm^2$  for the transmitter amplifier and  $e_{bf}=5nJ/bit$  when using beam shaping,  $n$  is the distance between two nodes, and  $m$  represents the message bit. Reducing the communication bandwidth and the information volume for transmission allows for energy savings.

### 3.3 NQAC-MRA for WSN-IoT

The beneficial feedback concept is that an ant colony operating under ACO will be more likely to choose a route with a dense concentration of pheromones for data transmission. Create ant-based sequencing for WSNs from scratch using this optimization method. Starting at the origin node and progressing toward the desired location, the forward-moving ant  $k$  moves at periodic times. Each forward ant avoids going through a node that another ant has already visited by keeping track of the addresses of each node it stays in a list called  $x_n$ . Equation (4) shows information transmission from node  $x$ . Advancing ants follow a predetermined dispersion to choose the next hop node  $y$ .

$$H_k(x, y) = \begin{cases} \frac{[t(x,y)]^\alpha \cdot [E(y)]^\beta}{\sum [t(x,y)]^\alpha \cdot [E(y)]^\beta} & \text{if } y \in x_k \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Where,  $H_k(x, y)$  denotes the probability of the individual ants  $k$  that moves from node  $x$  to node  $y$   $t$  is the pheromone concentration on every connection and the routing tables at each node( $x, y$ ) nodes and  $E$  stands for the empirical data.  $\alpha$  and  $\beta$  the relevance of heuristics relative to the weight variables that represent pheromones. A reverse ant follows the same paths that an ahead ant took to get to its objective. The ant calculates the quantity of pheromone  $\Delta t_k$  It will drop before it moves, which is given in Equation (5), and its routing table is calculated based on Equation (6).

$$\Delta t_k = \frac{1}{x - Fd_k} \quad (5)$$

in which  $x$  is the overall count of nodes and  $Fd_k$  is the marching frequency of the advancing ant  $k$ —nodes  $x$  modify their routing tables whenever they receive inbound ants from neighbouring nodes.

$$t_k(x, y) = (1 - \mu)t_k(x, y) + \Delta t_k \quad (6)$$

Where  $(1 - \mu)$  represents the pheromone's evaporation. When an ant that has gone backwards makes it to the node from where it started, the following cycle starts. Each node will discover the optimal neighbours to transmit data packets to after a number of cycles. Sluggish sharpness and initial stagnation are still possibilities despite the ACO-based technique's capability and durability, qualifying it to discover an effective remedy for the proposed model.

The goal of developing the proposed method was to facilitate the automated and effective search for Internet routing by nodes in WSN. The discharging phase made use of a technique that drastically cut down on the additional work that portals had to do as a result of command signal broadcasting in reaction to nodes seeking new pathways or maintaining existing ones. The reactive step involved using the NQAC-MRA approach to find gateways, both new and existing. The proactive phase included keeping an eye on existing paths, looking into new ones, and fixing any issues with the ones that were already in place.

The suggested NQAC-MRA is an enhanced version of the classic ACO that utilizes quantum evolutionary and niche technology. Using qubit programming to store data, it explains the theory and notion of QC and finishes updating quantum programming with a quantum rotational gateway. Meanwhile, quantum evolution guarantees that the algorithm's performance will be unaffected and can even significantly boost the algorithm's convergence speed. The qubit is the most compact data unit in quantum electromechanical systems, in contrast to the binary bits used in traditional computers for memory.



In addition, NQAC-MRA employs the niche process to partition the ant colony into many niches to discover an ideal solution throughout the entire solution space, as shown in the flow chart representation in Figure 4. The species variety of an ant colony is a result of the reduced gene exchange that occurs as a result of the relative isolation of various niches. As a result, there are some variations in the genes of the different species present in the colony. Swarm intelligence optimization techniques like NQAC-MRA are able to improve local search capabilities and avoid the early problems that other algorithms have exhibited. The following are the specific steps to take while utilizing NQAC-MRA to optimize multi-objective routing in WSN-based IoT:

1. Community size, maximum iterations, transparency parameters, pheromone fluctuation factor, congestion factor, number of communication nodes in the network, and pheromone trajectory intensity are some of the settings that should be initialized with NQAC-MRA.
2. Ant colonies using quantum computing based on qubit states, the knowledge carried by individual ants encoded using quantum encoding and activation by chaotic mapping.
3. The NQAC-MRA algorithm addresses the traffic congestion issue in WSN forwarding by utilizing quantum coding and state measurement. The binary bits, whose states are 0 or 1, are the most common method for data storage. However, qubits—a narrow-minded complicated vector space—are used for storing data in QC. The qubit is the unit of data storage in QC. Express every qubit state using a linear blend of two overlapping elements  $\alpha$  and  $\beta$ . The following is the process used to calculate the qubit state  $\psi$  in equation (7), which is utilized to portray the qubit state.

$$\varphi = \alpha(0) + \beta(1) \quad (7)$$

The "0" and "1" states, as well as the linear combination of the two, are possible for the qubit, which is denoted as  $\alpha(0)+\beta(1)$ , where 0 and 1 represent the quantum states. This has two times the number of possible states for a qubit of size x. In NQAC-MRA, a cluster of qubits stands in for the data carried by an ant colony. This set of qubits codes for a clustering scheme is required to solve the clustered optimization issue. Pretend that the MRA consists of n WSN nodes, with p nodes chosen to serve as cluster heads and the other n-Q nodes serving as member nodes. As a result, n is the maximum length of encoding that a single ant can carry out. An ant's encoded data can be represented by a specific equation (8).

$$Q_i = \left( \frac{\alpha_1}{\beta_1} \mid \frac{\alpha_2}{\beta_2} \mid \dots \mid \frac{\alpha_n}{\beta_n} \right) \quad (8)$$

For an n-nodes population, a qubit stands in for the pheromone in NQAC-MRA. For every qubit,  $Q_i$  contains the likelihood that two stacked vectors, representing its state, will exist in a given row. Changing quantum encoding to binary programming is essential since the coding technique cannot directly retrieve the clustering algorithm. To make the process of convergence a reality, this study employs the approach for determining the qubit's state. One way to establish a wireless communication node as a cluster head is to look at the state of the associated quantum bitcount. This is done by first numbering all of the WSN networks in the IoT network from 1 to n. In this study, Equation (9) is used to determine the i qubit's condition. In WSN, node i is component node multifaceted routing; the i qubit in a code has a state detection value of 0.

Ants are part of NQAC have a workable plan for getting around. It is necessary to initialize a population with number pop size during the first iteration of population evolution. This article explains how NQAC-MRA creates the initial data code that each ant in the colony carries using a tent map. Tented projection produces a more evenly distributed and faster iteratively-paced unpredictable

succession in the period [0, 1] than the more popular logistical projection. The mapping function's computation approach is as follows:

$$q_{i+1} = \begin{cases} 2q_0 & 0 \leq q_i \leq 1/2 \\ 2(1 - q_i) & 1/2 \leq q_i \leq 1 \end{cases} \quad (9)$$

The variable  $q$  in the given Equation can take on any value between zero and one. The initial setup of a sample begins with the distribution of an arbitrary number  $q_0$ , which can take on values between zero and one. Tent maps are employed to produce  $n$  variables that are chaotic on this foundation.

**Fitness Function Derivation:** The overarching objective of this paper's optimization of the NQAC-MRA is to maximize the network's lifetime by minimizing energy dissipation throughout the transfer of data. Since this is an optimization problem, the best candidates for cluster heads should be WSN nodes that have large leftover energy, a short distance to communicate inside the group, and proximity to the base station (BS). The fitness function is a crucial part of predictive optimization techniques for finding the best selection of routing path schemes, as it allows us to quantify how efficient the method is at finding the ideal route scheme. Suppose  $c$  is the estimated amount of cluster members in multifaceted routing algorithm. In that case,  $n$  is the number of nodes from node  $x$  to node  $y$ , and  $D(c,BS)$  and  $D(m,c)$  are the distances from the  $y^{\text{th}}$  node to the BS and  $i^{\text{th}}$  member node to the  $y^{\text{th}}$  cluster head, respectively. Therefore, the following is the definition of the fitness purpose in NQAC-MRA is represented in equation (10):

$$F_{func} = f_c + f_m \quad (10)$$

$f_c$  the power used by the  $y$ th node in the network during a single data distribution,  $f_m$  this stands for the amount of energy that each node in the network uses. Include all nodes in the routing table, as well as their neighbours. To create a forward ant, data from source nodes—which also serve as sinks and pass-through nodes—is transmitted. Create the path for the routing. Randomly assign  $m$  people to the source nodes—the rule for state transitions that determine these people's routing. Find the optimal solution and save it in  $B(t)$ . Here is the routing tree's evaluation function in equations (11 to 14).

$$f(t) = \frac{1}{[z_1(t)][z_2(t)][l_n(t)][\sigma_n(t)]} \quad (11)$$

Where the energy consumption factor is given in Equation with the weight parameters.

$$z_1(t) = \sum_{x=0}^x kd_{xy}(xy) \in T \quad (12)$$

The time delay factor for the routing tree is given in the Equation.

$$z_2(t) = Fd_t(t) \quad (13)$$

The distance travelled by the forward ant to find the optimum path for routing to make the transmission collision-free and energy efficient is represented as  $F(t)$ .

$$F(t) = \max (F_{func}) \quad (14)$$

$[l_n(t)][\sigma_n(t)]$  denotes the load balancing factors of the optimum routing in the algorithm, which represents the average value and mean of the nodes  $n$ . Refresh the pheromone according to the quantum gateway regulations once the ant is back. If the number of iterations is fewer than the maximum, go back to the previous step.

This research primarily focuses on how to categorize ant colony members using niche technology that depends on the congestion process to produce a good routing scheme. It all starts with the reality that different kinds of life have to fight for the same few assets in a confined space. The congestion factor picks one-fifth of the ant colony's members at random to act as overcrowding individuals and then figure out how those people's numbers compare to the other unselected ant individuals. The code that each ant carries is a quantum code, which may be thought of as a matrix.

Thus, by computing the relationship between the encoding matrices depicting the two individuals, one can derive the relationship between two people in an ant community. According to the excluding system, the person with the lowest fitness level of the two ants will be substituted with the one with the higher fitness value if the correlation between the two individuals is larger than the mean of the connection between individuals in the colonies. At the end of the specified maximum amount of repetitions, the method for routing will produce the routing scheme used by the individual with the highest fitness value. In that case, the process of iterative optimization will keep on.

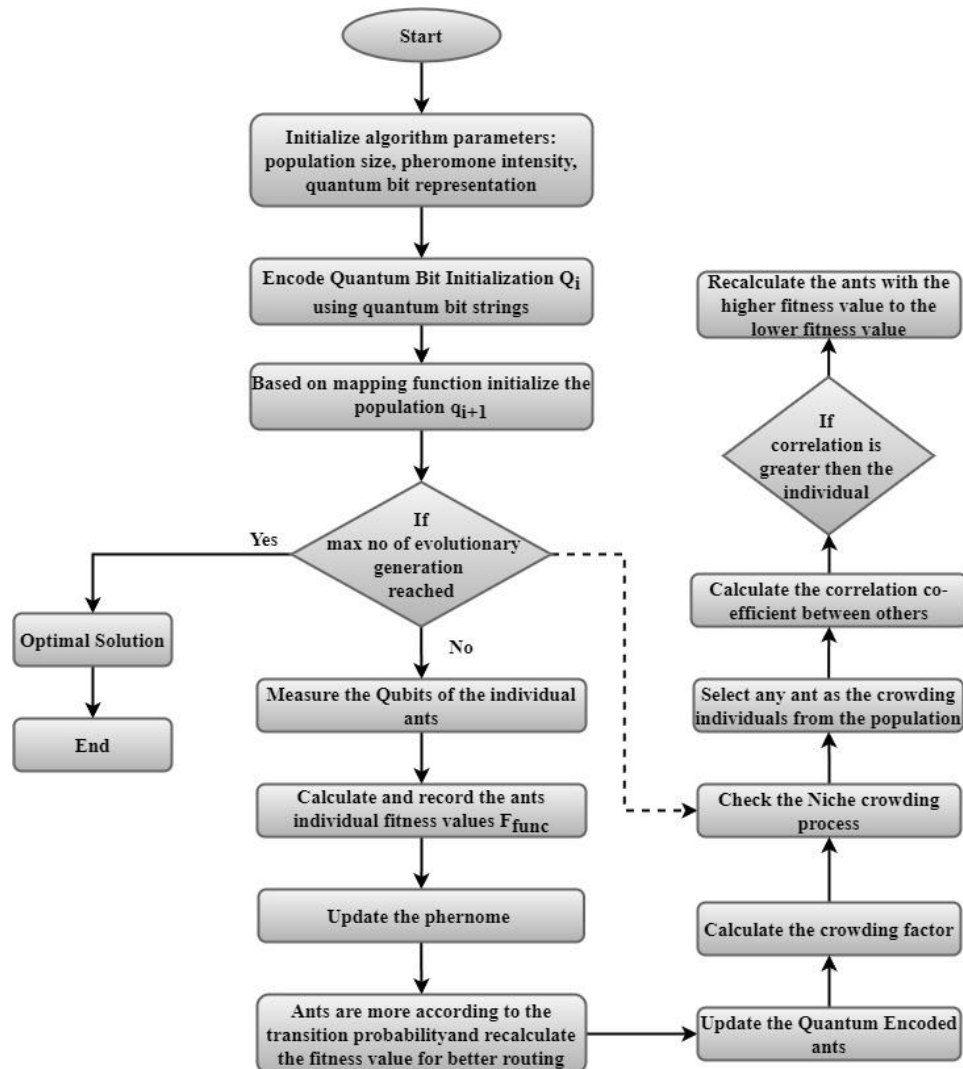


Figure 4: Flowchart Representation of NQAC-MRA

Although the suggested method relies on quantum computing techniques on WSN-based IoT, it is important to remember that NQAC-MRA is really an evolutionary algorithm and not a quantum algorithm. It is possible to address certain issues with basic ACO in NQAC. Adjusting the extent of the path can make resolution rates quicker, and the modelling of qubit adds a likelihood research method, which makes balancing between discovery and extraction simpler than the usual ACO algorithm. To avoid algorithmic traps like local resolution or inappropriate stagnation, it's important to provide population variety by exploring unoccupied nodes using heuristic data, updating the local pheromone, and upgrading the global pheromones with the quantum routing path.

## 4 Experimental Results

In these models, building the routing strategy using the MATLAB 9.1 modelling program (R2016B). An Intel Core i7-11700K microprocessor working at 3.6 GHz, 16 GB of RAM, and the 64-bit UBUNTU software distribution (Linux) are the requirements for executing the experiment. As a routing protocol with multipath routing, AntHocNet is able to deal with the constantly shifting characteristics of ad hoc networks thanks to its biological foundation in ACO.

With many performance variables to consider in WSNs on the IoT, energy efficiency and routing become critical processes. Routing decisions affect network lifetime, discovery time for different routing algorithms, transmission rates, and end-to-end packet delays are the metrics compared with RSL-MRP [17], OEEFCP [19], QBER [20] and QIGA [21]. When comparing routing methods in WSNs, various performance criteria can be utilized. This paper primarily uses the following measures to verify the effectiveness of the suggested algorithm. The arrangement of sensor nodes is completely arbitrary. Think of a scenario where there were 400 nodes, and the network range was 1000 m<sup>2</sup>. Table 2 shows the parameters of the network model. The NQAC-MRA optimum path had source nodes designated 2–60 and a sink node assigned 1. Keep in mind that in order for the method to reach a consensus,  $t_{max}$  must be larger than the total variety of repetitions.

Table 2: Experiment Parameter Settings

Parameter	Experiment 1	Experiment 2
Number of nodes	400	400
Area	1000m <sup>2</sup>	1000m <sup>2</sup>
Data rate	2mbps	2mbps
Maximum iterations	400	400
Packet size	512	512
Simulation time(s)	100	100

### Energy Consumption Performance

Table 3 displays the results of an examination of the proposed NQAC-MRA's energy performance in relation to other systems, such as RSL-MRP [17], OEEFCP [19], QBER [20] and QIGA [21], in an energy consumption scenario. Table 3 shows that compared to the other three traditional methods, the suggested NQAC-MRA uses less energy. There are fewer nodes involved in the routing in the NQAC-MRA technique. Table 2 displays the results of the comparison regarding the performance of energy usage. When compared to current methods, the suggested NQAC-MRA uses less energy, as shown in the table. By consistently establishing the optimal path from baseline to endpoint while using the least amount of energy, the NQAC-MRA technique outperforms the other three methods in terms of energy usage in the suggested model. Effectiveness energy usage also reveals that the setup's energy consumption increases with the number of nodes. In addition, more energy is wasted because nodes go through the highest and greatest efficiency factor, which increasingly matters for data packet progress. In contrast, traditional methods involve sending out an additional node for the same data packet, which means more energy is wasted in the current methods.

Table 3: Energy Consumption Performance

Number of Nodes	Energy usage(J)				
	RSL-MRP	OEEFCP	QBER	QIGA	NQAC-MRA
100	2.4	3.8	4.43	1.72	0.8
150	5.29	7.2	7.5	3.58	1.46
200	8.39	9.19	8.38	4.98	3.29
250	13.13	19.8	15.23	14.39	10.47
300	25.29	26.84	22.3	20.39	15.34
350	37.48	33.45	30.92	26.53	24.57
400	45.35	41.13	40.23	37.86	31.34

### Optimum Path for the Routing Algorithm

Figure 5a illustrates the results of the first test, which compared the optimal routing function  $F(t)$  based on equation 11 for scenarios with 10–200 nodes using standard techniques. In Figure 6, the two algorithms have identical initial values for  $F(t)$ , and then their values decrease as the total amount of nodes grows. There is a more gradual decline in the NQAC-MRA curve as compared to the BABR curve. This is because energy conservation, load equilibrium, and duration delay are among the additional features that NQAC-MRA considers.

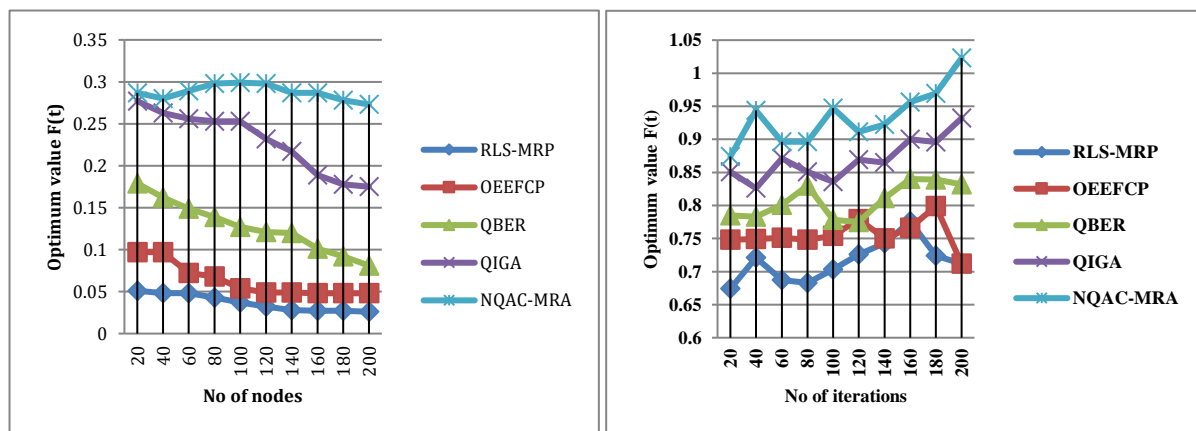


Figure 5a & 5b: Optimum Path for Routing Algorithm

Figure 5b assesses how long NQAC-MRA's network convergence property. Carrying out the experiment is contingent upon an increase in the number of iterations. The y-axis shows the total network lifetime, while the x-axis indicates the number of nodes. The lifespan value for NQAC-MRA is always greater than that for BABR; this disparity widens as the number of nodes increases, and it remains constant at 36 nodes.

### Packet Delivery Ratio

When evaluating ACO routing protocol, the percentage of packets delivered is a crucial metric to consider. A number of simulated settings affect the protocol's performance. Packet size, number of nodes, transmission range, and network architecture are the key parameters. By dividing the entire number of data packets transmitted from sources by the total amount of data packets that arrived at destinations, obtain the packet delivery ratio. A higher packet delivery ratio improves performance.

Mathematically, it is expressed in Equation (15). Figure 6 displays the results of an evaluation of the proportion of packets delivered using NQAC-MRA in comparison to other approaches, such as RSL-MRP, OEEFCP, QBER, and QIGA. Figure 6 shows that compared to the current methods, NQAC-MRA yields a superior Packet Delivery ratio. Not only that, when the associated communication only uses binary and single values, the PDR ratio becomes very high. The graph clearly shows that, in comparison to current methods, the suggested NQAC-MRAs provide more data packets to a given node.

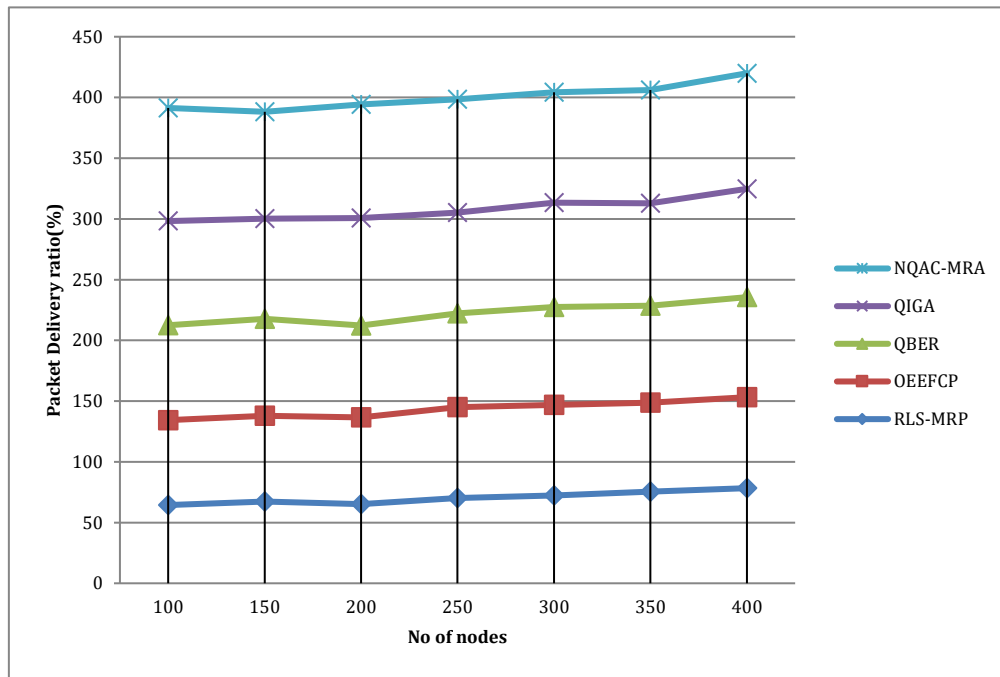


Figure 6: Packet Delivery Ratio

### Network Lifetime-based on Routing Performance

Figure 7 shows the results of comparing NQAC-MRA's efficiency with that of other methods for calculating network lifetimes, including RSL-MRP, OEEFCP, QBER and QIGA. Results compared to the current approaches show that NQAC-MRA performs better. As an example of a WSN, consider a collection of sensors placed in a capture zone that monitors environmental variables like pressure, moisture, and temperature. Sensors often run on changeable batteries that have a limited capacity. All of the WSN's functionality is dependent on the sensors' energy levels. Due to this characteristic, energy is a vital resource that must be saved if the WSN is to have a longer lifespan. Numerous techniques for routing have been suggested to guarantee data delivery in WSN and prolong the WSN lifetime. Existing approaches such as RSL-MRP, OEEFCP, QBER and QIGA transport data packets randomly as the number of nodes in the network increases.

On top of that, the node can have a time limit. By identifying the most suitable node to transmit the packets, the NQAC-MRA approach extends the life of both the network's hardware and the energy source. Figure 7 shows that when compared to existing methods, the proposed NQAC-MRA increases the overall network longevity at a specific node.

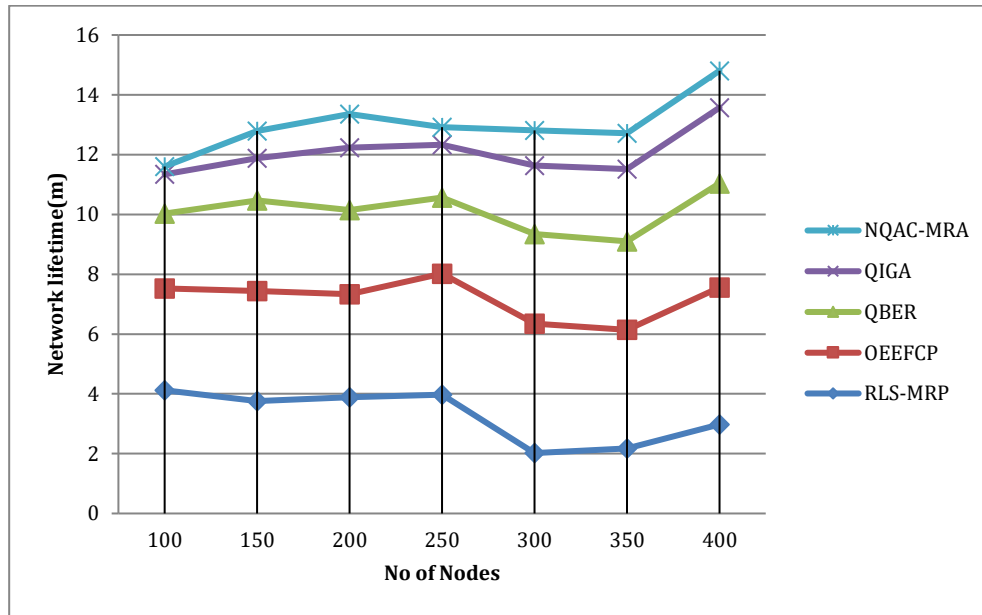


Figure 7: Network Lifetime based on Routing Performance

According to the results of the performance research, the suggested method was much lighter and more effective than the alternatives. Because of its superior performance and decreased energy consumption, the proposed NQAC-MRA topped the competition in terms of overall simulation results. In addition, both the network lifetime and PDR increased when compared to the previous method.

## 5 Conclusion

The suggested approach takes a variety of goals into account in an effort to enhance the route's efficiency and speed. This is a fascinating new area to explore since quantum computers use the properties of quantum states to outperform classical computers in certain operations significantly. In order to optimize the routes of wireless distributed networks in the IoT, this study presented the Niche Quantum Ant Colony Multifaceted Routing Algorithm (NQAC-MRA). This algorithm combines monitoring with quantum computation, an optimization function for several purposes. This project aims to produce congestion-aware, cost-effective routing for sending warning messages via WSN-IoT and using IoT devices to send them to their destinations with the least amount of latency possible. To be more precise, quantum bits represent the node pheromone, and the motion of quantum gates alters the pheromone along the search path. Fitness indicators for determining the optimal communication path include nodes' power consumption, communication delay, and degree of network load-balancing. The results of comparing NQAC-MRA's efficiency with that of other methods for calculating network lifetimes, including RSL-MRP, OEEFCP, QBER and QIGA. Results compared to the current approaches show that NQAC-MRA performs better. As an example of a WSN, consider a collection of sensors placed in a capture zone that monitors environmental variables like pressure, moisture, and temperature. The performance research showed that the proposed approach outperformed the alternatives while being significantly lighter. The suggested NQAC-MRA beat its competitors in terms of total simulation results thanks to its reduced energy usage and enhanced performance. Plus, in comparison to the old way, both the network lifetime and PDR went up. The next challenge for this research is to incorporate hybridization optimization methods to boost the network's efficiency.

## References

- [1] Abas, S. M., Noori, S. F., Yuvaraj, D., & Priya, S. S. (2024). Quantum Computing-Inspired Genetic Algorithm for Network Optimization in WSN. *International Journal of Intelligent Systems and Applications in Engineering*, 12(15s), 188-194.
- [2] Alamer, L., & Shadadi, E. (2023). DDoS Attack Detection using Long-short Term Memory with Bacterial Colony Optimization on IoT Environment. *Journal of Internet Services and Information Security*, 13(1), 44-53. <https://doi.org/10.58346/JISIS.2023.I1.005>
- [3] Alolaiwy, M., Hawsawi, T., Zohdy, M., Kaur, A., & Louis, S. (2023). Multi-objective routing optimization in electric and flying vehicles: a genetic algorithm perspective. *Applied Sciences*, 13(18), 10427. <https://doi.org/10.3390/app131810427>
- [4] Chen, J., Date, P., Chancellor, N., Atiquzzaman, M., & Sreenan, C. (2022). Controller-based energy-aware wireless sensor network routing using quantum algorithms. *IEEE Transactions on Quantum Engineering*, 3, 1-12. <https://doi.org/10.1109/TQE.2022.3217297>
- [5] Dayana, R., & Kalavathy, G. M. (2022). Quantum Firefly Secure Routing for Fog Based Wireless Sensor Networks. *Intelligent Automation & Soft Computing*, 31(3), 1511-1528. <https://doi.org/10.32604/iasc.2022.020551>
- [6] Ghorpade, S. N., Zennaro, M., Chaudhari, B. S., Saeed, R. A., Alhumyani, H., & Abdel-Khalek, S. (2021). A novel enhanced quantum PSO for optimal network configuration in heterogeneous industrial IoT. *IEEE access*, 9, 134022-134036. <https://doi.org/10.1109/ACCESS.2021.3115026>
- [7] Hosseini Shirvani, M., & Akbarifar, A. (2020). Anomaly-based Detection of Blackhole Attacks in WSN and MANET Utilizing Quantum-metaheuristic algorithms. *Journal of Communication Engineering*, 9(1), 77-92. <https://doi.org/10.22070/jce.2020.5466.1160>
- [8] Jannu, S., Dara, S., Thuppari, C., Vidyarthi, A., Ghosh, D., Tiwari, P., & Muhammad, G. (2022). Energy efficient quantum-informed ant colony optimization algorithms for industrial internet of things. *IEEE Transactions on Artificial Intelligence*, 5(3), 1077-1086. <https://doi.org/10.1109/TAI.2022.3220186>
- [9] Khan, S., Awan, K. A., Din, I. U., Almogren, A., & Seo-Kim, B. (2023). An Adaptive Biomimetic Ant Colony Optimization with 6G Integration for IoT Network Communication. *IEEE Access*, 11, 95584-95599. <https://doi.org/10.1109/ACCESS.2023.3310273>
- [10] Khudair Madhloom, J., Abd Ali, H. N., Hasan, H. A., Hassen, O. A., & Darwish, S. M. (2023). A quantum-inspired ant colony optimization approach for exploring routing gateways in mobile ad hoc networks. *Electronics*, 12(5), 1171. <https://doi.org/10.3390/electronics12051171>
- [11] Liu, Y., Li, C., Xiao, J., Li, Z., Chen, W., Qu, X., & Zhou, J. (2022). QEGWO: Energy-efficient clustering approach for industrial wireless sensor networks using quantum-related bioinspired optimization. *IEEE Internet of Things Journal*, 9(23), 23691-23704. <https://doi.org/10.1109/JIOT.2022.3189807>
- [12] Liu, Y., Li, C., Zhang, Y., Xiao, J., & Zhou, J. (2021, December). IQWOA: improved quantum whale optimization algorithm for clustering in industrial wireless sensor network. In *2021 IEEE 2nd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA)* (Vol. 2, pp. 337-340). IEEE. <https://doi.org/10.1109/ICIBA52610.2021.9688107>
- [13] Maharajan, M. S., Abirami, T., Pustokhina, I. V., Pustokhin, D. A., & Shankar, K. (2021). Hybrid Swarm Intelligence Based QoS Aware Clustering with Routing Protocol for WSN. *Computers, Materials & Continua*, 68(3), 2995-3013. <https://doi.org/10.32604/cmc.2021.016139>



- [14] Rathee, M., Kumar, S., & Dilip, K. (2020). Quantum-inspired ant-based energy balanced routing in wireless sensor networks. *Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science)*, 13(6), 1292-1301. <https://doi.org/10.2174/2213275911666180724110706>
- [15] Rivero-Angeles, M. E. (2021). Quantum-based wireless sensor networks: A review and open questions. *International Journal of Distributed Sensor Networks*, 17(10), <https://doi.org/10.1177/15501477211052210>
- [16] Roy, K., & Kim, M. K. (2022). Applying quantum search algorithm to select energy-efficient cluster heads in wireless sensor networks. *Electronics*, 12(1), 63. <https://doi.org/10.3390/electronics12010063>
- [17] Salem, B., & Sulaiman, A. M. G. (2024). Intrusion Detection System Using Chaotic Walrus Optimization-based Convolutional Echo State Networks for IoT-assisted Wireless Sensor Networks. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, 15(3), 236-252. <https://doi.org/10.58346/JOWUA.2024.I3.016>
- [18] Sathiamoorthy, J., Usha, M., Ravichandran, S., & Nishanth, R. B. (2022). OEEFCP—an optimal energy efficient framework employing cluster communication based routing protocol for UWCNs. *Wireless Networks*, 28(4), 1389-1409. <https://doi.org/10.1007/s11276-022-02901-5>
- [19] Sathish, A., & Babu, L. A. (2021). A Novel Quantum Beetle Swarm Optimization based Route Selection and Hybrid Data Transmission in Wireless Sensor Networks. *Annals of the Romanian Society for Cell Biology*, 2434-2448.
- [20] Srinivas, P., & Swapna, P. (2022). Quantum tunicate swarm algorithm based energy aware clustering scheme for wireless sensor networks. *Microprocessors and Microsystems*, 94, 104653. <https://doi.org/10.1016/j.micpro.2022.104653>
- [21] Sujanthi, S., & Nithya Kalyani, S. (2020). SecDL: QoS-aware secure deep learning approach for dynamic cluster-based routing in WSN assisted IoT. *Wireless Personal Communications*, 114(3), 2135-2169. <https://doi.org/10.1007/s11277-020-07469-x>
- [22] Suvarna, N.A., & Deepak, B. (2024). Optimization of System Performance through Ant Colony Optimization: A Novel Task Scheduling and Information Management Strategy for Time-Critical Applications. *Indian Journal of Information Sources and Services*, 14(2), 167–177. <https://doi.org/10.51983/ijiss-2024.14.2.24>
- [23] Venkatasubramanian, S. (2022, August). Improvement of QoS and selection of cluster head using RSL algorithm with multipath routing protocol in MANET. In *2022 3rd international conference on electronics and sustainable communication systems (ICESC)* (pp. 569-576). IEEE. <https://doi.org/10.1109/ICESC54411.2022.9885318>
- [24] Vijayan, K., Kshirsagar, P. R., Sonekar, S. V., chakrabarti, P., Unhelkar, B., & Margala, M. (2024). Optimizing IoT-enabled WSN routing strategies using whale optimization-driven multi-criterion correlation approach employs the reinforcement learning agent. *Optical and Quantum Electronics*, 56(4), 568. <https://doi.org/10.1007/s11082-023-06269-4>
- [25] Xu, M., Zu, Y., Zhou, J., Liu, Y., & Li, C. (2024). Energy-efficient secure QoS routing algorithm based on Elite Niche Clone evolutionary computing for WSN. *IEEE Internet of Things Journal*. 11(8), 14395–14415. <https://doi.org/10.1109/JIOT.2023.3342091>

## Authors Biography



**P. Suseendhar**, pursuing his PhD degree in the area of wireless sensor networks. He obtained his M.E Degree in Embedded Systems in the year 2012. Currently he is working as an Assistant Professor in the Department of ECE, in Sri Manakula Vinayagar Engineering College, Madagadipet, Puducherry. His research interest includes Embedded Systems, Wireless Sensor Networks and Signal Processing. He has Received 2 granted patents and received fund from NSTEDP (National Science and Technology Entrepreneurship Development Board). He published more than 5+ SCI and Scopus Indexed article



**Capt. Dr.K.P. Sridhar**, Professor & Head, Centre for Interdisciplinary Research, Karpagam Academy of Higher Education Coimbatore, Tamil Nadu, India. He obtained his Ph.D. degree in Robotics from Karpagam Academy of Higher Education. His research interest includes Robotics, Artificial Intelligence, IoT and Deep learning. He received research grants of More than 2 Crore from the Department of Science and Technology, New Delhi, India. He published 42 patents and has 52 granted patents. He published more than 35+ SCI, SCIE and Scopus Indexed articles. He is the reviewer of IEEE Access, Wiley Black and Springer Journals. He is the Prime Minister Awardee for start-up grants.