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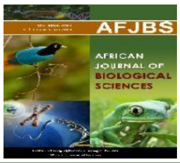


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# Secure and Accurate Node Localisation and Route Optimization for Wireless Sensor Network (WSN)

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**Abstract:** Wireless sensor networks are becoming more and more capable of transporting information as computer and communication technology continue to advance. Wireless sensor networks may not be able to handle a high number of data transfer requests as the demand for information transmission rises. Finding solutions to lower energy consumption during wireless sensor network information transmission is critical for improving the operational efficacy of wireless sensors. Energy carried by the sensor takes precedence in this process. In order to emphasize the significance of the predicted model, security among the sensor nodes is also crucial. The preliminary study examines wireless sensor network clustered routing and begins by looking at cluster creation using the LEACH protocol and analyzing its benefits and drawbacks. The modified bat algorithm is used in this article to assess the nodes' operational status in light of network node usage. The work improves how the localization accuracy between anchor and neighbor nodes is evaluated. Once the modified bat algorithm has determined the node optimization for the best localization accuracy, the Q-learning algorithm is used to locate nodes using its state-action-reward mechanism. For the coverage issue of WSNs, an modified bat algorithm with Q-learning is suggested. This technique can speed up the process of obtaining the ideal solution point set and efficiently extend the life of the system. The simulation revealed some useful benefits of the Modified BAT-Q-learning technique (MBQ), which can be used for later wireless sensor network coverage optimization. The experimental evaluation indicates the proposed MBQ outperforms the existing state-of-art techniques.

**Keywords:** Localisation, optimisation, routing, security, Q-learning, bat algorithm, and sensor nodes.

## 1. Introduction

A Wireless Sensor Network (WSN), a technique that permits the evaluation of the physical atmosphere, disperses several sensor nodes at random throughout an area or region. Each sensor node is equipped with a radio unit, an integrated detecting circuit, and a computer processor (Ghosh et al. 2019). As a result, it uses air media to prepare information and correspondence skills over a short distance in addition to completing the detecting responsibilities. Nodes that are part of the network are frequently installed without thorough preparation in many applications. Particularly, nodes should be able to run for a respectable period on battery (Abhishek et al. 2019).

Modifying or even powering their batteries in a hostile environment is very challenging. WSNs have a denser deployment of nodes than conventional wireless networks, a higher degree of sensor node unreliability, and strict power, calculation, and memory constraints. Numerous obstacles stand in the way of WSNs being improved because of their special qualities and restrictions. 1) A network of several sensors that are randomly placed in various locations is referred to as a sensor network (Hassanien et al. 2019). 2) As depicted in Figure 1, Base Stations (BSs) or data sinks are situated either inside or outside the network.

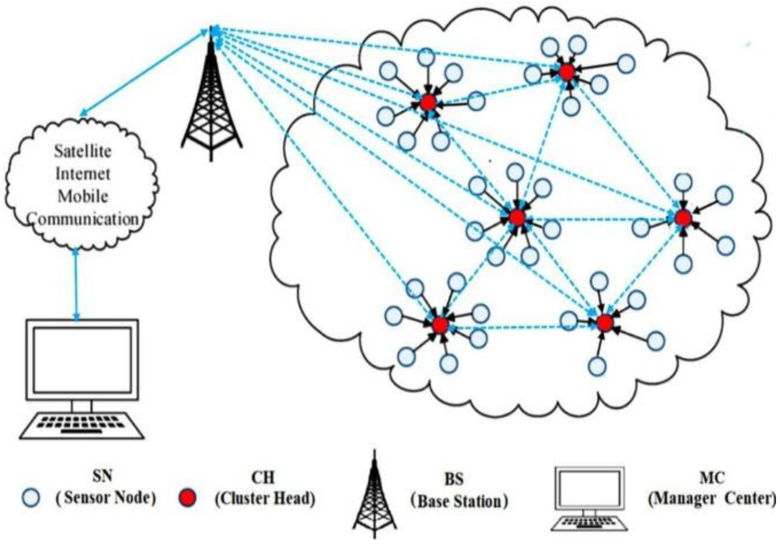


Figure 1. WSN Architecture

There is a trade-off between sensor coverage and network longevity in WSNs. More sensors would need to be active simultaneously in order to obtain better coverage, consuming more energy and shortening the network lifetime. Conversely, the coverage would degrade if more sensors were turned off to lengthen the network lifetime. The trade-off between sensor coverage and network lifetime cannot be easily resolved at the deployment stage because the network lifetime requirement, which depends on the application and may change as the mission unfolds, is difficult to anticipate (Kumar et al. 2015). When the sensor density is insufficient to meet the requirements for both lifetime and coverage, coverage must be traded for lifetime. The sensors must do their best efforts in this situation to provide coverage while staying within the lifetime constraint.

The majority of current research studies take random node deployment into account. On clustering, many energy-efficient coverage protocols are built. These protocols allow for the partitioning of the network field into different clusters. These techniques are not without issues, though. Nodes in a clustered network do not spend energy at the same rate since the cluster head uses more energy than a cluster member. As a result, a network coverage gap could result from losing a crucial node for coverage. In order to pick the best cluster heads and cluster sizes while balancing energy consumption and maintaining enough network coverage, a better mechanism could be proposed (Li et al. 2015).

Localization is one of the most common problems faced by WSNs, since data cannot be obtained from a specific location unless it has been found the information that the SNs collect is useless. The locations of the nodes in WSNs are chosen at random and their earlier locations are unknown. Predicting the positions of each SN in WSNs is the goal of the localization issue. Global Positioning System (GPS) is another option for node localization, although it takes more time, uses more power, and raises network costs. Many researchers plan to present a novel localization technique using optimization and encryption algorithm to address these problems (Bharathi et al. 2020).

*Research Motivation*

WSN offer the best opportunity to link with data from the actual environment. The main components of WSNs are data evaluation, deployment, lifetime, scheduling, routing, and localisation. It is made up of a number of nodes that have diminished battery life that may detect and reveal the presence of sensor fields. Although it is a difficult task, location detection is regarded as essential in many WSN applications (Li et al. 2015). The difficult task of SN localization is to determine the previous place of occurrence. Applications that require accurate location determination include those for tracking moving objects, detecting forest fires, and monitoring animals. Numerous localization algorithms are examined in the literature to address the difficulties in WSN localization. The goal of this study is to offer a practical solution to the location problems.

The remainder of the article is organised as follows: the overview of WSN and research motivation is detailed in Section 1, the related works are discussed with research gap is given in Section 2, the secure energy aware routing is explained in Section 3, the experimental investigation, illustration, and discussion is accomplished in Section 4, and the article is concluded in Section 5.

## 2. Related Works

The three research papers focus on improving node localization accuracy in wireless sensor networks (WSNs). Aroba et al. (2023) compare different algorithms for node localization, highlighting the superiority of the DEEC-Gaussian Gradient Distance Elimination Algorithm (DGGDEA) in minimizing localization error. Yu et al. (2023) propose a quantum annealing bat algorithm (QABA) for 2D and 3D node localization, demonstrating significantly improved convergence speed and solution accuracy compared to other heuristic algorithms. Agarwal et al. (2023) present the Intelligent Aquila Optimization Algorithm Based Node Localization Scheme (IAOAB-NLS), inspired by the behavior of Aquila birds, which effectively determines node coordinates in WSNs. These studies collectively contribute to advancing node localization techniques, crucial for various applications from military to commercial sectors.

Mohanta et al. (2021) Controlled Layer Deployment (CLD), a technique that has been developed, proposes deterministic node placement and makes use of the PEAS algorithm. In CLD, the cascade effect is minimized by deterministic node deployment. The cascading impact is investigated regarding the nodes employed on data transfer paths to the sink. A battery drains faster on many pathways to the sink nodes than others. This shows that there will be a cascade effect. The network coverage benefits function determines the optimal coverage set or the smallest sensor nodes with the greatest energy left over. To create the dominant coverage sets, which are then utilized to guarantee network access to the sink, a select few nodes assemble the best coverage sets from across the network. Using 1-hop and 2-hop nodes to ensure connectivity, the dominant coverage sets are constructed from the optimal coverage sets (Poongodi et al. 2021).

The coverage contribution is then calculated between each working node and its nearby working nodes. Similar to DCCA, coverage contribution is calculated. Working nodes go into a sleeping state if their coverage contribution is independent or if they become unnecessary. In that case, it changes to working mode. Based on connectivity and coverage conditions, nodes attempt to switch between working and sleeping states during the second phase of CESS. Periodically, nodes in the sleeping state awaken and enter the checking state. If the neighbouring checking node has a higher level of remaining energy, the working node goes into sleep mode (Shanmuganathan et al. 2021).

In CTCk, the failure of the central entity may lead to a breakdown in network communication. A node can serve as a relay node for several rounds. This could cause this node to use more energy, which can cause it to die sooner. As the number of targets rises, a little bit smaller coverage sets are required (Qin et al. 2021). Many models can be used to account for the probabilistic character of sensing models, such as the exponential, polynomial or staircase (Rabhi et al. 2021). Each technique relies on Computational geometry, based on the idea that nodes are deployed in a static manner and remain there after that. Additionally, these methods presumptively use identical node characteristics. Each node is supposed to have positional information, a fixed sensor coverage area, and a fixed radio coverage area. Any existing geometric pattern in the network that can be identified may help to increase coverage and energy efficiency. Below, we go over coverage protocols that make use of this geometric data to improve coverage and energy efficiency.

The research gap addressed by the modified bat algorithm and the Q-learning algorithm lies in the need for more efficient and accurate node localization techniques in wireless sensor networks (WSNs). Existing methods, such as Controlled Layer Deployment (CLD) and other coverage protocols, focus on node deployment strategies and energy management but may lack in terms of localization accuracy. The introduction of the modified bat algorithm aims to optimize node placement for improved localization accuracy, leveraging the unique characteristics of bat behavior to enhance the search process. Similarly, the utilization of the Q-learning algorithm introduces a state-action-reward mechanism to efficiently locate nodes, addressing the need for more intelligent and adaptive localization approaches in WSNs. By incorporating these novel algorithms, the research contributes to filling the gap in existing localization techniques by providing more accurate and efficient solutions tailored to the specific challenges of WSNs.

**Proposed - Secure and Accurate Node Localisation and Route Optimization**

A WSN is often made up of numerous sensor nodes dispersed around an area and whose primary function is jointly monitoring the area. However, sensor nodes are also constrained by a limited sense range and inadequate processing power. The following two performance indicators should normally be considered when evaluating the deployment of sensor nodes in

WSNs: the sensor's ability to cover a certain area and the network's overall life cycle. Area and target coverage are the two subtypes of the sensor node deployment's coverage issue. Unlike the target coverage problem, which focuses on a small number of specified locations in the monitoring zone, the area coverage problem monitors the entire area. Coverage rate, which measures the wireless sensor networks' service quality, is the primary indicator of area coverage. The target coverage problem, also known as the sensor coverage problem, is being studied it is occasionally necessary to maintain a watch on several specific sites besides the standard coverage, which consists of Q-coverage and basic coverage. In the straightforward coverage problem, each target just requires one sensor to cover itself. Bat optimization is used in this work to address the current problems.

***Sensor Network and Energy Model***

The research consider a monitoring region a two-dimensional plane to meet sensor placement problems in diverse scenarios best. The wireless sensor nodes use a boolean sensing model, where the probability that the target point is within the sensing range is 1, and the probability that it is not is 0, to simplify the coverage issue. It is difficult to use a formula to figure out the total coverage rate of all nodes in the monitoring region when there are many sensors involved. As a result, the area is divided into equal-sized grid points, which may also be compared to pixels with a discrete precision of 1. The sensor node's placement is the centre of the common sensing range, which resembles a disk. The coordinates of the sensor node $s_i$ = ($x_i$ , $y_i$) and the sensing radius $R_i$ in the current arrangement of Euclid space are the formal definitions of the Boolean sensing model. The likelihood of seeing pixel point an at (x, y) coordinates is as follow in Equation 1.

$$P(a, s_i) = \{ \begin{matrix} 1 & s(a, s_i) \leq R_i \\ 0 & otherwise \end{matrix} \quad (1)$$

S(a, $s_i$) = a - $s_i^2$ is the Euclidean distance in this case. The likelihood that the sensor set S = $s_i$,i=1,2,…,M. All conceivable sensors will observe pixel point a, as shown in Equation 2.

$$P(a, S) = 1 - \prod_{s_i \in S}[1 - p(a, s_i)] \quad (2)$$

The following Equation 3 can be used to express the sensor deployment area's coverage ratio *f* presuming that the monitoring area is similar to $u \times v$ pixel points:

$$f = \frac{\sum_{x=1}^{m} \sum_{y=1}^{n} p(a, s_i)}{u \times v} \quad (3)$$

The best sensor deployment's basic objective function is described above as the coverage rate. The only limits that must be added for K-coverage problems with different criteria are specific ones. When K = 0, the issue is one of optimization with no constraints on coverage; When K is equal to 1, it means that certain important targets must be covered; when K is equal to 2, it can have K-coverage limitations with particular network lifespan conditions, meaning that each important point must be within the coverage range of K sensor nodes.

The main resources of the nodes are the converter, power amplifier, and radio receiver. The design uses the free space and fading flow depending on how close or far apart the transmitter and receiver. A sensor node's energy usage is linearly correlated with the square of the distance between them. If the propagation distance d is smaller than the threshold d0, this condition is met. On contrary, the distance is proportional to the distance of $d^4$.

The maximum energy expended for the supply of a l-bit packet by a reference length from the transmitter to the receiver is determined by Equation (4).

$$E_r(l,d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2 & d < d_o \\ lE_{elec} + l\varepsilon_{mp}d^4 & d < d_o \end{cases} \quad (4)$$

$E_{elec}$, is the amplifier coefficient of the free-space model and mp is the amplifier coefficient of the multi-path fading model, is defined as the energy consumed by the node for transmitting or receiving it via a 1-bit message. Therefore, the threshold distance $d_0$ between the two sensor nodes is estimated by Equation (5).

$$d_o = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (5)$$

The energy usage of the sensor nodes when $d > d_0$ is calculated using the Free-space model, where the amplifier parameter in this case is εfs. The energy consumption of the sensor nodes when $d \geq d_0$ is calculated using the multi-path fading model, and the amplifier parameter employed in this calculation is $\varepsilon_{mp}$. This section does not regulate the total node transmission length to reach $d_0$, meaning that the transmission span of the recommended uneven dynamic clustering procedure includes nodes in the same cluster.

***Clustering and Node Localisation using Modified Bat Algorithm***

The lifespan of a WSN can be shortened by energy conservation, depending on the network model. The network's routing protocol has an impact on how long the network will last. In order for the network's nodes to receive the greatest amount of coverage from other nodes, node deployment plays a crucial role. For the deployment of the moving nodes in the proposed system, the route parameters have been optimized using the LEACH routing protocol based on the sensing domain signal intensity. Before the nodes are deployed, there is a setup phase during which the sensor nodes are organised into groups, and all data is sent from the cluster head to the appropriate cluster nodes via a sink node. Data from the nodes is collected by the cluster head, which then delivers it to the network's anchors and nearby nodes. It is assumed that each node's energy usage is under control at every stage of the sensor selection procedure. The energy consumption is predicated on the cluster assumptions when using balance analysis to reach threshold values. The LEACH procedure and an interval range of [1,0] are used to track the energy. Using Equation (5), the network's threshold value is calculated.

$$TSN(i) = \begin{cases} \frac{probability\ of\ percentage\ in\ clustter\ head\ (pr_{ch})}{1-probability\ of\ percentage\ in\ clustter\ head\ (pr_{ch})} if\ m\ \in \\ 0 \end{cases} \quad (6)$$

Where, TSN(i) displays the network's threshold values. $Pr_{ch}$ for the probability of percentage in the cluster head. The most nodes that may communicate among themselves in a cluster is m. The group of sensor nodes that could be utilized to estimate the sensor nodes' framework is indicated by the letter N.

The leach routing protocol calculates the Euclidean distance between sensor nodes and nearby nodes in the suggested system. The Euclidean distance formula utilized in the suggested system is given in Equation 6.

$$E_D(N_i, D_j) = \sqrt{((N_i, D_j)^2 - (y_i, D_y)^2)} \quad (7)$$

The sensor nodes and nearby nodes are used to compute the distance using the obstruction of values that have been examined using probability estimation. The LEACH protocol is being used by the nodes to describe the task of forecasting the defined, in Equation 7.

$$I_{ri} \leq E_D(N_i, D_j)$$
$$pr_{ch}(N_i, D_j) = \{e^{-y \frac{E_D(N_i,D_j) - I_{ri} - I_{re} \leq E_D(N_i,D_j) < I_{re}}{I_{re} - E_D(N_i,D_j)}} \quad (8)$$
$$I_{ri} - I_{re} \geq E_D(N_i, D_j)$$

Ire and Iri are used to calculate the radius and determine the sensor node's sensing inaccuracy, respectively. It demonstrates the attenuation $\gamma$ coefficient and sensing parameter. The probability evaluation's assumptions lead to the target coefficient being veiled, which is specified as $\mathrm{Pr_{ch}}$ $(N_i, N_i)$, as indicated in Equation 8.

$$P_{sn} = 1 - \prod_{i==1}^{N} Prch\,(N_i, D_j) \quad (9)$$

To illustrate the sensor node's node coverage, the characteristics of the received signal strength in each cluster node, as described in Equation 9, are employed.

$$E_{s(i)} = (\sum_{i=1}^{num} \sum_{Src \in CH} E_{source}\, SN_{ch} + E_{RSSI} + E_{DA}) + \sum_{i=1}^{num} E\, SN_{ch}, dest + E_{Final} \quad (10)$$

Equation (9) displays the presumptions used to anticipate a sensor node's energy in a network utilizing the LEACH protocol. where $E_{source}$ denotes the energy supply node for a cluster's sensor nodes. The energy of the received signal strength is predicted by $E_{RSSI}$ , and the information used to predict the transmission range of the network is known as $E_{DA}$ . The destination is taken into account to be within the mean values, and the nodes' final energy is taken into account to be within the range of the cluster head selection's number values. The provided values offer estimations denoting the operational state and roles within a sensor network:

- A value of -1 signifies an assumption that both the route and the sensor node are inactive or malfunctioning.
- A value of 0 indicates that both the route and sensor node are presumed to be fully operational, either in a static state or functioning optimally.
- A value of 1 suggests assumptions regarding the sensor node's role as a cluster head and its relationship to the route.
- Values exceeding 1 represent the sensor node's active role as a cluster head within the network.

The optimum coverage is used to estimate the amount of energy used in the proposed work. The factors for the best coverage are listed in Equation (10).

$$E_{Src,dest} = \begin{cases} E_{consum}\, X\, Z + E_{dissip}\, X\, Z\, X\, E_D(N_i, D_j) \\ \quad if\ E_D(N_i, D_j) < E_{DO} \\ E_{consum} X\, Z + E_{utilised}\, X\, Z\, X\, E_D(N_i, D_j) \\ \quad if\ E_D(N_i, D_j) \geq E_{DO} \end{cases} \quad (11)$$

where, The energy used by the network's source and destination nodes is expressed as $E_{Src,dest}, E_{consum}$ is the total energy utilized to transmit 'z' bits of data by all nearby sensor nodes and dissipation nodes in a wireless communication environment. Data in wireless communication are forecasted using a model is used to identify the estimations using Euclidean distance measurements. The distance calculated using the Euclidean assumption is displayed as $E_{(DO)} = \sqrt(E_{dissip} \backslash E_{utilised})$ in terms of energy dissipated and energy used. The sensor nodes are used in the data transfer because the analysis below allows the data to be transmitted.

Based on the node energy wasted and the energy consumed in the estimation, the received energy is approximated. Equation (11) gives the received signal strength in terms of Z bits, which creates a receipt of node location in the WSN. As a result, the 'Z' number of bits is employed to calculate the energy used.

$$RX_{\boldsymbol{E}} = E_{utilised}\ X\ Z = \frac{E_{dissip}\ X\ Z}{E_{RSSI}} \qquad (12)$$

The sensor nodes and their related nodes use the strongest node reception. Equation (11) satisfies the energy allotted for use in the cluster analysis-based node optimisation. The ultimate average energy is presumptively the total of the energy consumed by active sensor nodes and inactive nodes, as shown in Equation (12).

$$E_{Final} = \sum E_{IN} + SN_a \qquad (13)$$

The $SN_a$must have descended for the nodes to be ideal in the active region, as stated by Equation (13) from the ultimate sensor nodes in the active zones.

$$SN_a = \{ \begin{matrix} 1, if\ E_{Src,dest} \in\ Src_{CH}\ orE_{Src,dest} \in\ Src_{non\ CH} \\ 0, otherwise \end{matrix} \qquad (14)$$

The node coverage rate has been calculated using the prospective energy outcome, and it is projected that the majority of the energy will be consumed by the sensor nodes in the local node upgrade. Equation (3.19) determines the node technique with the highest coverage accuracy. Using a coverage node with the target of ($SN_i$) and $I'$ parameters, Equation (14) calculate the target node coverage rate:

$$T(i) = \sum_{i=}^{m} T_c(SN_i) \qquad (15)$$

The average task carried out at each node, which is presumptively in the sensor nodes' highest coverage region, is shown in Equation (15):

$$SN_a = \{ \begin{matrix} 1, if\ if\ E_D \in\ SN_{inactive}\ and\ E_D\ \leq r_i \\ 0, otherwise \end{matrix} \qquad (16)$$

Identify the coordinates of the nodes to find the average localization error (Avg.LE), the coordinates of neighbour nodes ($Avg.LE$ ) and the sensor nodes ($S_i, N_i$ ) , which is outlined as below Equation (16).

$$Avg.LE = \frac{1}{Tn}\sum_{i=1}^{Tn} \sqrt{(S_i - s_i)^2 + (N_i - n)^2} \qquad (17)$$

By utilising optimisation techniques, it is calculated that the node localization is enhanced by inclined values of the average LE at and unknown node (U) as in Equation (17).

$$U = S_n - T_n \qquad (18)$$

$S_n$ Sensor Nodes and $T_n$ Available number of nodes Mean Localization Error(LE) is calculated by the normalized Average LE and the range of sensor nodes transmission ($R_t$ ) in Equation (18).

$$Mean.LE = \frac{\frac{1}{Tn}\sum_{i=1}^{Tn} \sqrt{(Si-si)^2+(Ni-ni)^2}}{Rt} \qquad (19)$$

| Algorithm 1. Modified Bat Optimisation Algorithm |
| --- |
| 1. InitializeSensorNodes()<br>2. DefineParameters()<br>3. FormAdjacentNodes() |

```
4. ModifiedBatAlgorithm():
   4.1. InitializePopulation()
   4.2. while (termination criteria not met):
      4.2.1. for each bat in population:
         4.2.1.1. UpdateBatPosition()
         4.2.1.2. EvaluateFitness()
         4.2.1.3. UpdatePulseRate()
         4.2.1.4. UpdateLoudness()
      4.2.2. SelectBestSolution()
5. OptimizeNodePositions():
   5.1. UseBestSolution()
   5.2. AdjustNodePositions()
   5.3. EvaluatePerformance()
6. OutputFinalConfiguration()
```

***Q-Learning based Secure Communication***

In wireless communication systems where secure nodes are scarce, Reinforcement Learning leverages neighboring nodes to predict sensor node pairs using reliable ones. The agent 'a' in the Wireless Sensor Network (WSN) takes actions based on the environment's state using the Q-learning algorithm. Node optimization is achieved through the bat algorithm within the WSN environment. Q-learning is utilized to propose a mapping context, addressing various axioms such as the diverse operating environments of sensor nodes and the comparison of agent tasks with the operational status of sensor nodes. The RL model learns the operational environment as the task set activates the agent. The event space, reward, and network outcome are crucial measures in the WSN technique, where jamming in node communication is represented by WSN process events, and rewards aid in analyzing communication growth prospects. The Q-learning characteristics are applied to determine the action and state space in the functional sensor paradigm, with the largest positive reward guiding Q-value determination. Additionally, the cumulative reward from sensor node $SN_i$ for the collection of action spaces serves as the benchmark for the best action in the given environment.

## 3. Result and Discussion

The simulation in this section was carried out using the energy-saving MBQ algorithm, and the outcomes are contrasted with other two optimization techniques. The simulation is performed using NS2. As shown in Table 1, the simulation coverage for various L-form, T-shape, Z-shape, and U-shape networks was performed. In an L shape network, nodes are arranged in the form of the letter "L", with one vertical line connected to a horizontal line at a right angle. This shape is useful in scenarios where communication needs to occur along two perpendicular axes, such as in building corridors or road intersections. A T shape network consists of nodes arranged in the shape of the letter "T", with a vertical line intersected by a horizontal line at its midpoint. This shape is commonly employed in scenarios where communication needs to occur along a main axis with branches extending from it, such as in transportation networks or pipeline systems. In a U shape network, nodes are arranged in a U-shaped pattern, resembling the letter "U". This shape is suitable for scenarios where communication needs to occur along a curved or semi-circular path, such as in river monitoring systems or perimeter surveillance. A Z shape network features nodes arranged in the shape of the letter "Z", with diagonal lines connecting alternating nodes. This shape is useful in scenarios where communication needs to occur along a zigzagging or alternating path, such as in mountainous terrain or zigzagging road networks.

Table 1. Simulation Settings

| Simulation Parameter | Network Setup |
|---|---|
| Simulation Area | 250 X 250 m |
| Sensor Nodes | 1000 Nodes |
| Band of frequency | 700 MHz |
| The unknown nodes anchor and others | 250 |
| A packet's size (Control) | 150 bit |
| Channel efficiency | 4 MHz |
| Size of a data packet | 4Kbytes |
| Power used in transmission | 10j |
| Receiver energy | $40 \times 10^{-8}$ |
| Send out energy | $40 \times 10^{-8}$ |
| Maximum lifetime | $6 \times 10^{-8}$ |

The performance of the proposed energy preserving cluster based routing is analysed in terms of packet delivery rate, latency, energy consumption and network lifetime.

- Packet Delivery Rate (PDR): The PDR indicates the proportion of successfully delivered packets out of all transmitted data. A reliable routing algorithm should exhibit a satisfactory PDR, striving for maximum efficiency. The PDR can be calculated using the following Equation.

$$PDR = \frac{Number\ of\ Successfully\ Delivered\ Packets}{Total\ Number\ of\ Transmitted\ Packets}$$

- Latency (Lat): Latency represents the average time taken for data transmission from the source node to the destination node. It's crucial for latency to be minimized to ensure efficient communication. The average latency can be computed using the following Equation.

$$Lat = \frac{\sum_{i=1}^{n}(T_i - T_o)}{n}$$

  where $T_i$ denotes the time when the $i^{th}$ packet reaches the destination, $T_0$ is the time when the first packet is transmitted, and $n$ is the total number of packets transmitted.

- Energy consumption (EC): The energy consumption of sensor nodes is assessed concerning the simulation duration. It involves calculating the remaining energy of the nodes at specific intervals, usually measured in joules. The energy consumption is given in Equation.

$$E_{remaining} = E_{initial}(P \times \Delta t)$$

  where $E_{remaining}$ is the remaining energy of the sensor nodes, $E_{initial}$ is the initial energy of the sensor nodes, $P$ is the power consumption rate of the sensor nodes, and $\Delta t$ is the simulation time interval.

- Network lifetime (NL): Network lifetime refers to the duration of network operation throughout the simulation. An extended network lifetime is indicative of improved sensor node longevity. It's evaluated based on the total number of active nodes within specific time intervals, with a higher count signifying enhanced efficiency. The Network lifetime is given in Equation.

$$Network\ Lifetime = \frac{1}{Active\ Node\ Rate}$$

where Active Node Rate is the rate of active nodes within specific time intervals, typically measured as the ratio of active nodes to the total number of nodes. All these performance measures are utilized for evaluating the performance of the proposed approach and the experimental results are presented as follows.

Table 2. Comparison of PDR

| No of Nodes | DEEC | IAOAB-NLS | MBQ |
|---|---|---|---|
| 200 | 81 | 88 | 91 |
| 400 | 82 | 89 | 93 |
| 600 | 83 | 89.5 | 94 |
| 800 | 84 | 90 | 95 |
| 1000 | 85 | 90.5 | 95.6 |

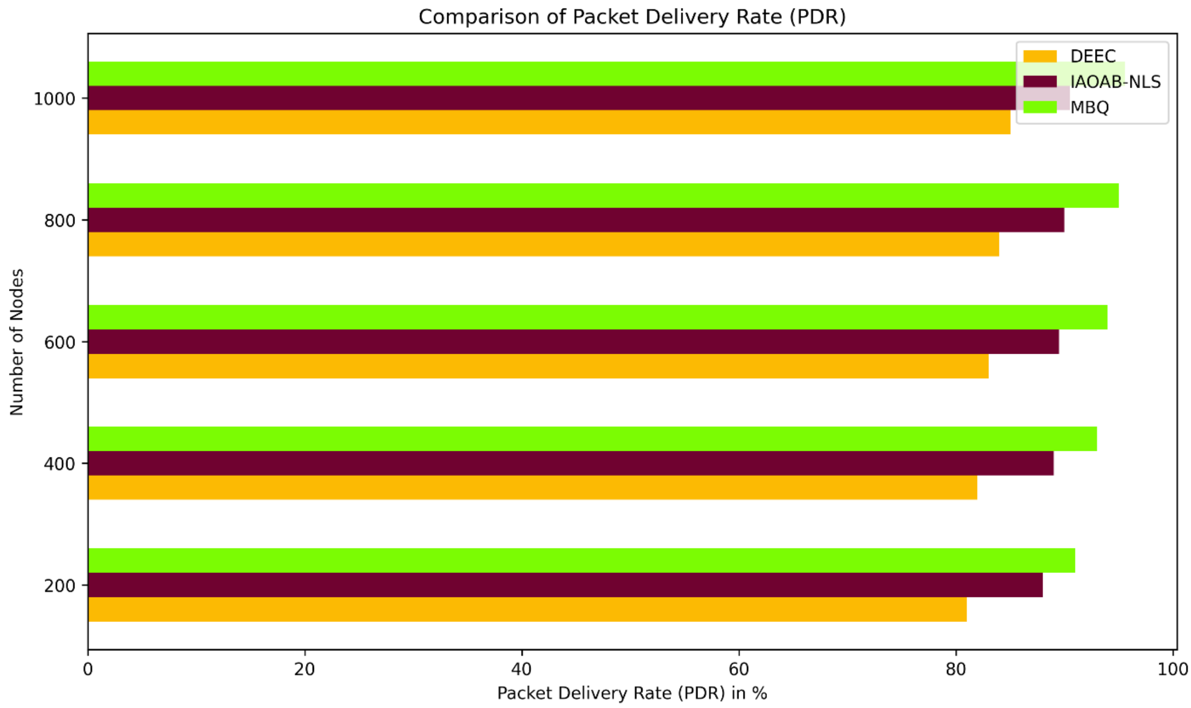


Figure 2. Comparison of PDR

Table 3. Comparison of Latency

| No of Nodes | DEEC | IAOAB-NLS | MBQ |
|---|---|---|---|
| 200 | 465 | 415 | 312 |
| 400 | 481 | 398 | 325 |
| 600 | 491 | 387 | 333 |
| 800 | 534 | 381 | 349 |

| | | | |
|---|---|---|---|
| 1000 | 556 | 376 | 358 |

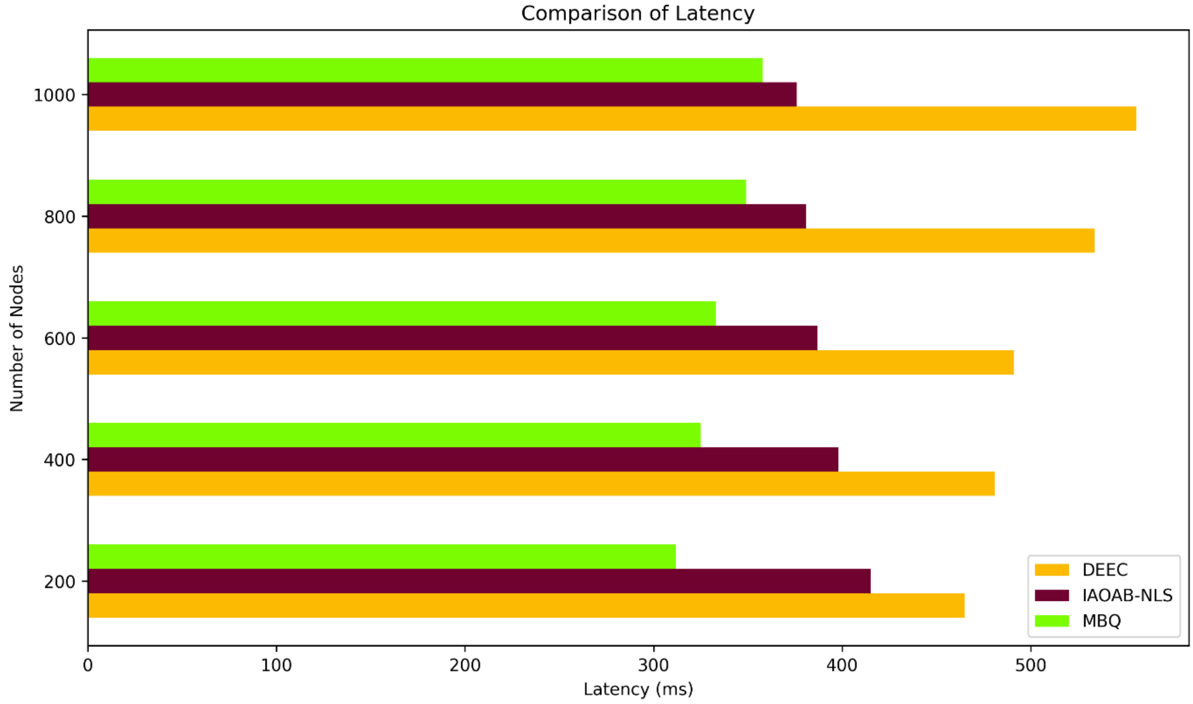


Figure 3. Comparison of Latency

Table 4. Comparison of Energy consumption (EC)

| No of Nodes | DEEC | IAOAB-NLS | MBQ |
|---|---|---|---|
| 200 | 3.687 | 3.123 | 2.572 |
| 400 | 3.982 | 3.423 | 2.672 |
| 600 | 4.178 | 3.672 | 2.912 |
| 800 | 4.892 | 3.891 | 3.013 |
| 1000 | 5.123 | 3.923 | 3.112 |

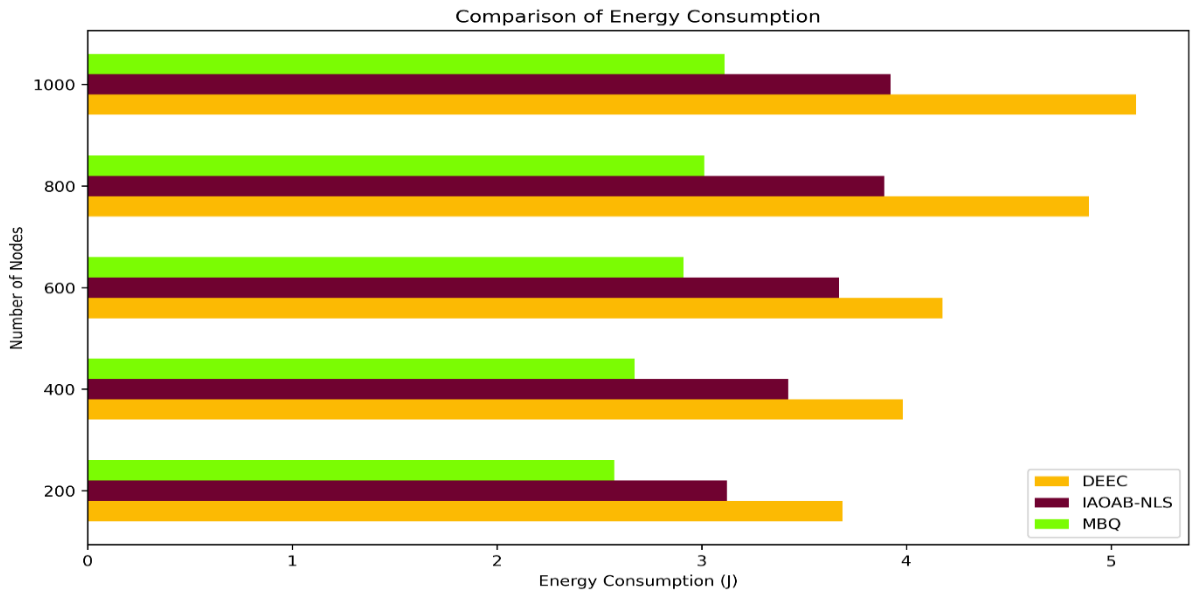


Figure 4. Comparison of Energy consumption (EC)

Table 5. Comparison of Network Lifetime in ms

| No of Nodes | DEEC | IAOAB-NLS | MBQ |
|---|---|---|---|
| 200 | 3.132 | 4.233 | 5.465 |
| 400 | 3.234 | 4.324 | 5.672 |
| 600 | 3.435 | 4.542 | 5.892 |
| 800 | 3.678 | 4.672 | 5.982 |
| 1000 | 3.782 | 4.782 | 6.231 |

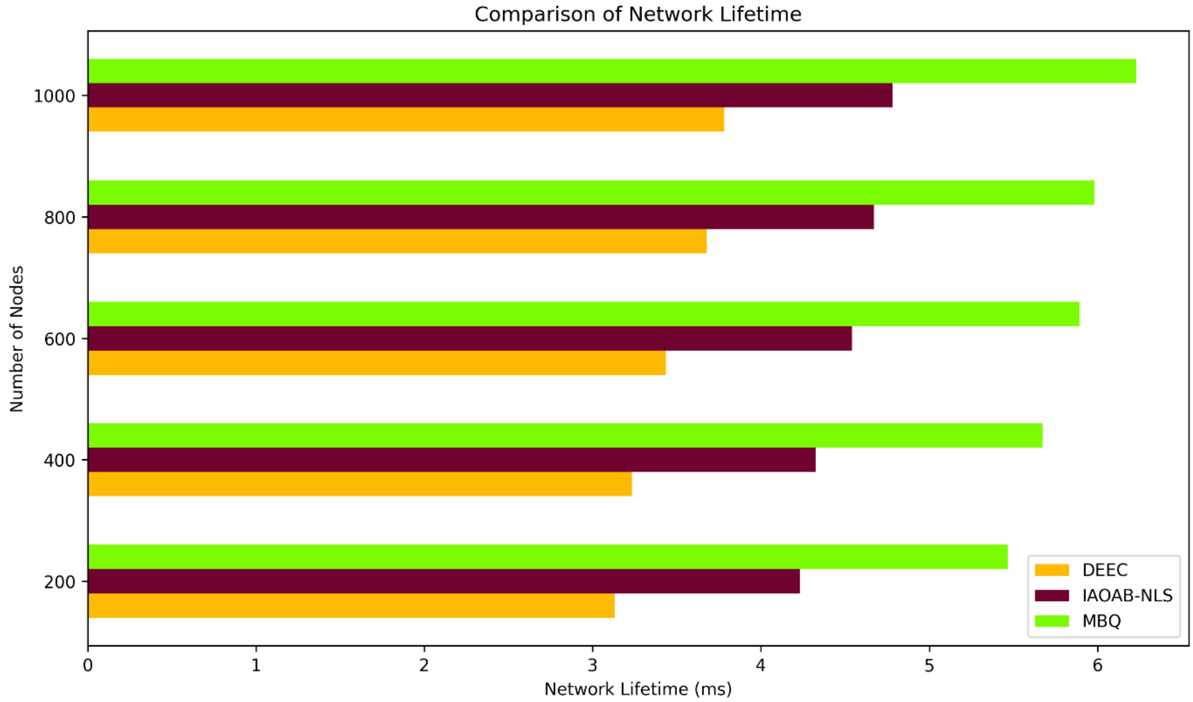


Figure 6. Comparison of Network Lifetime

The comparative analysis of three routing protocols, DEEC, IAOAB-NLS, and MBQ, reveals significant disparities in Packet Delivery Rate (PDR), Latency, Energy Consumption (EC), and Network Lifetime. Across varying node counts, MBQ consistently outperforms DEEC and IAOAB-NLS in terms of PDR, with MBQ achieving the highest PDR at 95.6% at 1000 nodes. Regarding Latency, MBQ demonstrates the lowest latency across all node counts, indicating faster data transmission compared to DEEC and IAOAB-NLS. In Energy Consumption, MBQ exhibits superior energy efficiency, consuming the least energy at 3.112 J at 1000 nodes. Moreover, MBQ also showcases the longest Network Lifetime, indicating prolonged network operation, with a network lifetime of 6.231 ms at 1000 nodes. Overall, MBQ emerges as the most efficient routing protocol, offering high PDR, low latency, minimal energy consumption, and extended network lifetime compared to DEEC and IAOAB-NLS.

## 4. Conclusion

The localised sensor nodes and other node clusters are used in this chapter to improve node optimisation. Numerous situations allow for the observation of the received signal intensity. The network has been assessed utilising three alternative network designs as the suggested model obtained a tuned node optimisation, including L-form, T-shape, Z-shape, and U-shape networking architectures. In order to find the best optimum solution for node optimisation, the proposed MBQ technique examines the sensor nodes. The outputs much surpassed the best outcomes of the DEEC and IAOAB-NLS approaches. The Q learning performs secure communication with the best nodes in order to enhance the secured connectivity based on the working environment. The developed nodes are efficiently optimised by the MBQ and Q learning algorithms, which also help those nodes save energy. The key Parameters settings play a major role in the algorithm‟s convergence and performance in the BAT Algorithms. This improved node optimization Efficiency is beneficial for many real-world applications, one of the application is Infrastructure Monitoring: that is in Bridge, tunnel, and other critical infrastructure sensor networks can find wear and tear on the structure. Energy-efficient nodes prolong the life of these networks and offer affordable infrastructure repair.

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