







Increasing the QoS and Lifespan in Wireless Sensor Networks Using Cluster Formation and Mobile Sink (IQLWS-MC)

Bo-Jiun Huang , Chen-Min Tsai , Hsi Chen , and Lei Wang 

Feng Chia University, Taichung 40724, Taiwan
joeliuiane2@gmail.com

Abstract. Wireless Sensor Networks (WSNs) are used to monitor temperature, humidity and gas concentrations in warehouses to ensure product quality. In the transportation industry, WSNs track the location and number of passengers on public transport to provide real-time data for the optimization of routes and schedules. WSN technology is beneficial but the energy in sensor nodes (SNs) is limited, which is similar to a battery. As WSN applications grow, an efficient routing protocol that minimizes SNs' energy consumption must be developed.

This study proposes a routing scheme that maintains service quality (QoS) in terms of coverage and extends the lifespan of a SN. The aggregation points (APs) is determined based on SN density and the area is divided accordingly. The base station (BS) uses the GPS coordinates of the SNs to calculate the greatest communication range overlap density for AP designation. Each AP uses a SN as a cluster head (CH) and a Particle Swarm Optimization (PSO) algorithm is used to form clusters.

To reduce the high energy consumption of CHs, mobile sinks (MSs) collect data from CHs and return it to the BS. This reduces energy consumption, increases scalability and stability and meets the requirements for various applications. The proposed method outperforms advanced algorithms in terms of the lifecycle, stability period and coverage QoS.

Keywords: Wireless sensor networks · particle swarm optimization · mobile sink · routing protocol · cluster formation

1 Introduction

WSNs are affordable and disposable and use numerous wireless sensor nodes to gather critical data from areas to which access is difficult. The collaborative sensor nodes establish networks and are deployed to monitor environments and terrain for applications such as fire detection [1], traffic management [2], healthcare [3], toxic gas emissions [4], industrial processes [5], construction [6] and space exploration [7], where WSNs monitor environmental changes. SNs are interconnected and integrated with Internet of Things (IoT) technology to provide continuous environmental and phenomenon monitoring for

smart home systems and to allow remote oversight [8]. However, a large number of sensors are required and these are inaccessible so the sensors are often non rechargeable and non-replaceable and energy consumption must be optimized to extend the lifespan of wireless sensor networks [9].

The energy model for wireless communication exhibits a direct correlation between communication distance and energy consumption. The energy that is required by the sensor increases with distance so longer communication distances result in higher energy usage. To reduce energy consumption, communication distances must be reduced and long-range transmission must be eliminated by optimizing the network's topology and routing protocols.

Traditional wireless sensor networks are segmented into clusters, each of which contains a designated CH [10]. The cluster head gathers data from members of its cluster and forwards the aggregated data to a base station (BS) or gateway node (GN). This structure minimizes long-distance transmission of data from all nodes so the lifespan of the network is increased. However, cluster heads that act as relays to handle more data and which communicate over extended distances with the base station consume energy faster than other nodes because they manage data transmission from or through sensor nodes that are far from the receiver. This creates a hotspot [11] or an energy hole [12, 13], which results in early network partitioning and compromises network functionality. Solutions typically involve rotating cluster heads to mitigate energy consumption, but this increases the network overhead and delays so overall efficiency decreases.

Mobile sinks (MS) are used for sensor networks. A MS travels along a predetermined path to collect data from deployed sensor nodes (SNs) and then returns this data to the base station (BS). A MS may recharge during its return trip, which significantly reduces the energy that is consumed between the CH and the BS and prolongs the network's overall lifespan.

Conventional MS methods involve collecting data from each sensor node, which results in significant time delays, so aggregation points (APs) are established within the network, at which the MS pauses and gathers data from nearby cluster heads (CHs). This reduces time delays and ensures that energy is consumed efficiently.

This study introduces an increased routing protocol for APs. MS's are recharged to reduce the load on sensor nodes and extend the network's lifespan. The key contributions of the study include optimizing the number of APs based on node density, identifying high-density communication areas to establish APs, balancing intra-cluster energy by assigning Cluster Heads appropriately, using Particle Swarm Optimization to create shortest-distance clusters and developing an optimal routing strategy for the MS. Simulations to determine the network's stability, lifespan and coverage for various conditions are used to ensure that the network performance meets the demands of practical applications.

2 Study Background

2.1 Related Work

Many studies of WSNs increase energy efficiency and data aggregation [14–16]. With the rapid development of WSN and Internet of Things (IoT) technologies, traditional data collection methods have become inadequate for increasingly complex demands so methods that use mobile sinks are used to reduce energy consumption for the overall network. This method decreases energy use and increases the efficiency with which data is collected [17]. The path for a MS is planned based on the deployed SNs and advanced routing algorithms are used to determine the optimal clusters for the efficient collection of data from CHs. Methods that use a mobile sink strategy are used to address the evolving needs of Wireless Sensor Networks.

The RRP method [18] uses a ring structure within the sensor field. Nodes within this ring monitor the receiver's location and share this information with the source nodes, which detect specific events. A mobile sink (MS) that moves randomly denotes a neighboring node as an anchor node (AN) and updates the ring nodes with the location of the AN. This AN acts as the representative receiver for the entire sensor field. Source nodes first retrieve the AN's location from the ring and then use a greedy geographic routing method to send data to the AN. However, this single-ring design is not suitable for large sensor fields. Boundary nodes in a ring with a smaller radius require more energy and time to locate the receiver. A ring with a larger-radius ring creates similar challenges for nodes that are located nearer the center.

Wen et al. [19] used an Energy Aware Path Construction (EAPC) algorithm to optimize network routing. This method uses the Prim algorithm to organize nodes into a minimum spanning tree (MST) with the base station as the root. The mobile sink (MS) is restricted to a fixed movement range of movement and the algorithm removes the high-benefit convergence points (CPs) from the MST. A counter-clockwise path generation method is then used to establish routing paths between the removed CPs. The MS follows this route to collect data from these CPs. This technique creates a less complex route for the MS but the network becomes fragmented if nodes fail or batteries deplete. This fragmentation creates isolated network segments that cannot communicate with each other, so data is lost, communication delays are increased, network efficiency is decreased and maintenance costs are increased for practical applications.

Youxi Lee et al. [20] proposed Virtual Grid-Based Data Collection Using a Mobile Sink (VDGC). This method segments sensor nodes (SNs) into predefined grid areas and assigns collection points (CPs) within each grid. Within each CP, the sensor node that is closest to the current mobile sink (MS) is denoted as the central node. The other nodes then form a minimum spanning tree around this central node. As the clusters are established, the mobile sink traverses in a zigzag pattern along the lower edge of the monitored zone to collect data. This method consumes less energy than traditional methods and other methods that use a mobile sink-based algorithm, reception delays are increased because the mobile sink uses a longer path. These delays increase as the number of collection points increases.

Vaibhav Agarwal et al. [21] developed the Energy Efficient Mobile Sink Based Intelligent Data Routing Scheme for Wireless Sensor Networks. This method uses a

Particle Swarm Optimization (PSO) routing protocol to establish a minimum spanning tree to form clusters, which significantly increases the longevity of WSNs. It also uses a path model for the mobile sink that maintains a consistent path length and minimizes network delays that are created by the mobile sink's route. However, this method places significant demands on the cluster heads (CHs) so energy is distributed unevenly across the network and overall energy efficiency is reduced. In conclusion, current methods that use a mobile sink frequently fail to extend the lifespan of the network or create significant latency. This study proposes a routing strategy that uses wireless networks to increase the topology structure and increases overall network stability and the usable coverage.

2.2 Environmental Framework

WSN's feature diverse environmental architectures so this study uses the framework that was proposed by Vaibhav Agarwal et al. [21] to ensure consistent simulation results. The sensor nodes SNs, which are represented as dots, are randomly distributed and divided into different numbers of regions based on the number of SNs, as shown in Fig. 1. Each region denotes a coordinator as the aggregation point (AP), which is represented as a star label, to establish the path for the MS. A suitable number of nodes near the AP that meet specific criteria are then denoted as CHs and these collect and transmit data to the MS.

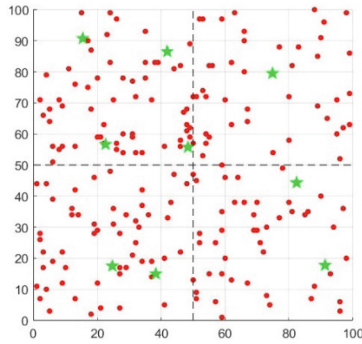


Fig. 1. Partitioning the network into appropriately sized areas

For this architectural method, the network is conceptualized as a connectivity graph $G(S, E)$, with $S = \{s_1, s_2, \dots, s_n\}$ representing an array of sensor nodes, and E symbolizing the links between them. These nodes are scattered randomly across a 2D space with dimensions of $Z * Z$. Nodes are deemed to be connected if the Euclidean distance between them is less than their communicative range (R). The connection is defined as Eq. (1):

$$E_{ij} = \begin{cases} 1, & e_{ij} \leq R \\ 0, & e_{ij} > R \end{cases} \quad (1)$$

where e_{ij} represents the distance between two connected points and R is the communication radius for the sensors.

For this study, the energy that is consumed to transmit data is represented as $E_{Tx}(k, d)$ and is calculated using Eq. (2) [22]:

$$E_{Tx}(k, d) = \begin{cases} E_{ele} \times k + \epsilon_{fs} \times k \times d^2, & d \leq d_0 \\ E_{ele} \times k + \epsilon_{mp} \times k \times d^4, & d \geq d_0 \end{cases} \quad (2)$$

where k represents the amount of data in k -bits, d is the distance between the transmitting and receiving units and E_{elec} is the energy that is consumed by the sensing circuitry to transmit or receive each bit of data. ϵ_{fs} denotes the energy that is lost during short range transmissions in free space and ϵ_{mp} is the energy that is dissipated during long distance transmissions in a multi-path environment. The threshold distance d_0 is calculated as Eq. (3):

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (3)$$

The energy that is consumed when data is received, $E_{Rx}(k)$, is calculated as Eq. (4):

$$E_{Rx}(k) = E_{agg}(k) + k \times E_{ele} \quad (4)$$

where k denotes the amount of data in k -bits and E_{elec} is the energy that is dissipated per bit to operate the receiver circuit.

The total energy E_{Total} that is consumed by the sensor network (SN) in the system is calculated using Eq. (5):

$$E_{Total} = E_{Tx} + E_{Rx} \quad (5)$$

3 Proposed Method

A mobile intelligent data routing scheme includes network partitioning, cluster formation, optimal path planning for the MS and data collection and transmission. When the network is partitioned into suitably sized segments, the BS calculates the known GPS positions to determine the area with the highest energy accumulation and this is designated as the AP. The optimal number of CH's is then determined using the Particle Swarm Optimization (PSO) algorithm to form the best clusters. When all clusters are established, the optimal path for the MS is determined.

3.1 Calculating the Number of Access Points (APs)

The number of APs is calculated based on the number of nodes that each AP represents and the length of path for the MS. If there are too many APs, each AP represents fewer nodes, which increases the likelihood of a node becoming a CH so the MS must move to more areas. This reduces the efficiency of the energy balance and increases delays. If

there are too few APs, the rate at which the MS collects data increases but the CHs must channel more data so the network's lifespan is reduced.

It is assumed that all SNs are equipped with GPS and a function is simulated to partition the network into M equally sized smaller regions. This method ensures a path for the MS that is not too long and balances energy consumption. M is calculated using Eq. (6):

$$M = i^2, (i - 1) < \frac{1}{5}\sqrt{s} \leq i \quad (6)$$

where i is the number of sensor nodes (SNs) in the current network and M is the number of regions. Equation (7) is used to calculate the number of boundaries K :

$$K = \frac{Z}{\sqrt{M}} \quad (7)$$

where Z is the boundary length that is established during the simulation. All SNs are equipped with GPS so their GPS Grid Cell Segmentation (GGCS) is determined using their coordinates (x, y) for Eq. (8):

$$\begin{cases} GGCS_x = \frac{x}{K} \\ GGCS_y = \frac{y}{K} \end{cases} \quad (8)$$

3.2 Selecting AP Locations

When the regions are divided, the proposed scheme determines the optimal locations for the APs. In WSN simulations, energy consumption increases closer to the inner layers so this study determines the points with the highest communication density (i.e., the positions where the most SNs can communicate) using GPS and the communication radius for the SNs. This method allows the numerous SNs near the RP to alternate as cluster heads CHs so the likelihood that APs change is reduced. This increases energy balance in the inner layers and minimizes the need to recalculate the MS path if an AP is replaced. Algorithm 1 shows the pseudocode for the proposed method to assign AP locations.

Algorithm 1

Input: X, Y coordinates , communication radius of SNs

Output: AP coordinates

```

1: for (i = 1 to  $\sqrt{M}$ )
2:     for (j = 1 to  $\sqrt{M}$ )
3:         for each node
4:             if distance to other nodes < 2 communication radius
5:                 Store intersection coordinates;
6:             end if
7:         end for
8:         Count = 0;
9:         for each stored intersection:
10:            for each node:
11:                if distance to intersection < communication radius then
12:                    Count++;
13:                end if
14:            end for
15:        end for
16:        if Count > max_count then
17:            max_count = Count;
18:        end if
19:    end for
20: end for
21: Store max_point as AP coordinates (i, j);
22: Return AP coordinates;

```

Count represents the number of SNs located near a given AP. After determining the locations of the APs, we prioritize selecting an appropriate number of nearby SNs as CH candidates. To optimize the energy balance of the CHs, we must select the candidate with the highest threshold value τ in each round. The threshold value takes into account each candidate's residual energy ($E_{\text{residual-}i}$) and their respective distance (D_i) to the AP follows Eq. (9):

$$\tau_i = \text{Max} \frac{E_{\text{residual}_i}}{D_i} \quad (9)$$

The actual node distribution may not be uniform, as calculated using Eq. (6) and the number of nodes in each partitioned region varies so additional calculations to address extreme scenarios are necessary. A large number of CHs more effectively distribute the data load but excessive use of CHs increases the number of clusters so computational complexity increases and it is less viable to use CHs to manage the majority of the nodes. Reducing the number of CHs mitigates this issue and reduces computational complexity.

Equations (10) and (11) are used to calculate the number of CHs:

$$\begin{cases} d_{num} = \text{int}\left(\frac{40}{\text{num}_{\text{node}(i,j)}}\right) \\ d_{num} = 2, \text{ if } \text{num}_{\text{node}(i,j)} \geq 20 \end{cases} \quad (10)$$

$$CH_{num} = \text{floor}\left(\frac{\text{max_count}}{d_{num}}\right) \quad (11)$$

In terms of Eqs. (10) and (11), as the overall number of nodes in the sensor network increases, a higher proportion of CHs are allocated. Therefore, a simulation-based method is used to calculate the number of CHs that allows effective use of the nodes. If the number of nodes in any block ($\text{num}_{\text{node}(i,j)}$) exceeds 20, d_{num} has a value of 2. Half of the CH candidates (max_count) must serve as CHs in each round. If there are too few, using half of the CH candidates is impractical so the use of CHs is restricted using Eqs. (10) and (11).

3.3 Cluster Formation

When the CHs are assigned, the Particle Swarm Optimization (PSO) algorithm is used to create the minimum spanning tree with the CHs as the roots. The PSO algorithm, which was proposed by Kennedy and Eberhart in 1995 [19], simulates the movement of particles in a search space to determine the optimal solution. PSO is more easily implemented, has stronger global search capabilities, is better suited to continuous optimization problems and is less influenced by the initial solution than other nature-inspired algorithms. The processes to update the motion and position of individual particles are conducted independently and simultaneously.

In a previous study [20], ZHU Xia et al. compared the PSO algorithm with a Genetic Algorithm (GA) and demonstrated that the former has better training performance and convergence behavior so it is more adaptable to specific problems. In another study [17], Vaibhav Agarwal et al. used a PSO algorithm for MS-type WSNs to significantly increase network lifespan. This study uses this algorithm and improves the mutation rate and fitness value. The movement patterns for the particles are changed to escape local minima and to create the smallest and most reasonable clusters. The pseudocode for Algorithm 2 is shown in the following:

Algorithm 2

Input: Complete Graph $G(S, E)$

Output: MST

```

1: for each particle i
2:   for each dimension d
3:     Initialize position  $X_{id}$  randomly within
       permissible range;
4:     Initialize velocity  $V_{id}$  randomly within per-
       missible range;
5:   end for
6: end for
7: Iteration  $t = 1$ ;
8: do
9:   for each particle i
10:    Calculate fitness value;
11:    if the fitness value is better than  $p_{id\_best}$ 
        in history
12:      Set current fitness value as the  $p_{id\_best}$ ;
13:    end if
14:  end for
15:end do
16: Choose the particle having the best fitness value as
    the  $g\_best$ ;
17:for each particle i
18:  for each dimension d
19:    Calculate velocity according to the equation;
20:     $V_{id}(t+1) = w * V_{id}(t) + c_1 * r_1 (p_{id\_best} - x_{id}(t)) +$ 
        $c_2 * r_2 (g\_best - x_{id}(t));$ 
21:    Update particle position according to the
       equation;
22:     $X_{id}(t+1) = x_{id}(t) + V_{id}(t+1);$ 
23:  end for
24:end for
25:  $t = t + 1$ ;
26:WHILE maximum iterations or minimum error criteria are
    not attained

```

The algorithm uses six parameters:

1. X_{id} : Position of the i -th particle, which is represented as $X_{id} = (x_{i1}, x_{i2}, \dots, x_{id})$.
2. V_{id} : Velocity of the i -th particle, which is represented as $V_{id} = (v_{i1}, v_{i2}, \dots, v_{id})$.
3. p_{id_best} : Personal best position (individual best solution) for the i -th particle, which is represented as $p_{id_best} = (p_{i1}, p_{i2}, \dots, p_{id})$.
4. g_best : Global best position (global best solution) in the swarm, which is represented as $g_{best} = (p_1, g_{best}, p_2, g_{best}, \dots, p_d, g_{best})$.
5. f_p : Fitness value for the best position that is achieved by the i -th particle.
6. f_g : Fitness value for the best position that is achieved in the swarm.

The velocity and position of each particle in each iteration are adjusted based on the results of the previous iteration, using Eqs. (12) and (13):

$$\begin{aligned} \text{Vid}(t+1) = & w \times \text{Vid}(t) + c1 \times r1 \times (\text{pid}_{\text{best}} - \text{xid}(t)) + c2 \times r2 \\ & \times (\text{gbest} - \text{xid}(t)) \end{aligned} \quad (12)$$

$$\text{Xid}(t+1) = \text{xid}(t) + \text{Vid}(t+1) \quad (13)$$

In Eq. (12), $c1$ is the cognitive learning factor, $c2$ is the social learning factor and $r1$ and $r2$ are random numbers between $[0, 1]$ that are used to create a random search. The maximum fitness value is determined, which typically represents the total path length (L_{total}) inverse. The calculation uses Eq. (14):

$$F = \frac{1}{L_{\text{total}}} \quad (14)$$

3.4 MS Path

The MS path, which is similar to cluster formation, is an NP-hard problem. Therefore, many studies use algorithms to calculate the optimal path. However, the MS is rechargeable so the MS path for this study is designed to reduce delay, rather than to minimize the distance that is travelled. The method of the EAPC paper [16] is used to calculate the MS path, as shown in Fig. 2. The algorithm is divided into the following two stages:

Connecting the Edges of APs. Two sets are assigned: P_{initial} and P_{final} . P_{final} is initially empty and P_{initial} contains the base station (B0) and aggregation points (APs), which are represented as $\{B0, RP1, RP2, \dots, RPM\}$. B0 is placed into P_{final} , $P_{\text{final}} = \{B0\}$ and is defined as the starting point and the line L , which is assumed to be infinitely extended, is rotated clockwise/counterclockwise. When line L touches an RP, AP is added to P_{final} as shown in Eqs. (15) and (16):

$$P_{\text{final}} = P_{\text{final}} \cup AP_j \quad (15)$$

$$P_{\text{initial}} = P_{\text{initial}} - AP_j \quad (16)$$

Connecting the Missed APs If M is greater than 4, when the first step is executed, APs in the middle region may not be connected so the two APs in P_{final} that are closest to this AP are selected. The distance between these is $d(AP_i, AP_{i+1})$. This connection distance is removed and the new AP_j is added. The new path (P_l) is determined using Eqs. (17) and (18):

$$P_l = \{B0, RP1, RP2, \dots, RPM, B0\} \quad (17)$$

$$P_l = \min[d(AP_i, AP_j) + d(AP_j, AP_{i+1}) - d(AP_i, AP_{i+1})] \quad (18)$$

When AP_j is added to P_{final} , it must be removed from P_{initial} . B0 is then established as the endpoint and the MS path is defined.

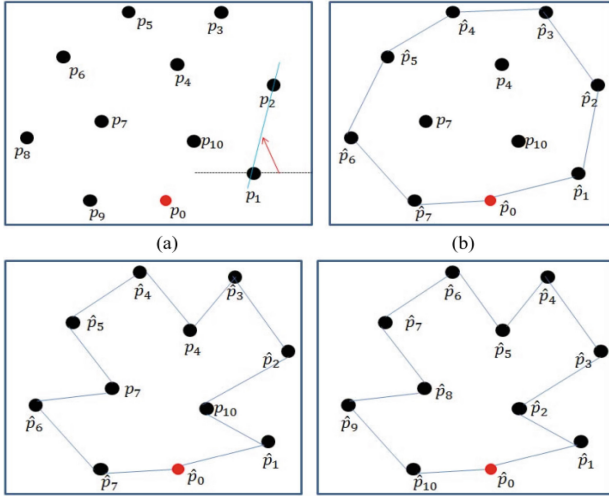


Fig. 2. MS Path [12]

4 Simulation Result

4.1 Simulation Parameters

This study uses IQLWS-MC to calculate the performance of the protocol using two types of simulations. Scenario 1 compares IQLWS-MC with EEMS [21] by varying the number of APs and maintaining a constant overall network density and determines the difference in network stability and survival rates when the network density changes. To validate the algorithm's results, simulations used MATLAB R2023a and each dataset was verified more than five times, so there were more than 100 simulations.

Scenario 2 determines the differences in maintaining the coverage rate between IQLWS-MC and EEMS for identical conditions in terms of node placement and network size. The simulation parameters are shown in Table 1.

The stability period is the cycle until the first node failure. The WSN network decays rapidly following the death of the first node so some regions are isolated. Increasing the stability period increases the overall network lifespan. The SP is calculated using Eq. (19):

$$SP = \begin{cases} i \exists SN_{re} = 0 \\ otherwise \end{cases} \quad (19)$$

4.2 Performance Comparison

This study respectively uses 100, 400, and 900 nodes in networks of 100×100 , 200×200 and 300×300 to maintain an overall network density of 0.01. The results are compared with those for EEMS and are shown in Fig. 3. The first scenario determines the performance of IQLWS-MC and EEMS as the network scale increases and the results

Table 1. x

Parameters	Value
Deployment range	100*100, 200*200, 300*300 m ²
Number of Nodes	100 to 900
QoS(Expected Coverage Ratio)	70%
Transmission Range	25 m
Sensing Range	7 m
Power initiated	0.5 J
E_{ele}	50 nJ/bit
ϵ_{fs}	10 pj/bit/m ²
ϵ_{mp}	0.0013 pj/bit/m ⁴
E_{agg}	5 nJ/bit
BS Coordinate	(50,0)
Packet size	240 bits

show that both protocols feature degradation. As the number of nodes increases, the amount of data that is transmitted per area also increases so transmission costs increase.

Figure 3 shows that IQLWS-MC maintains greater stability and the SP value decreases from 1905 to 1787 and 1711 for the three scenarios, which is a decrease of approximately 6% to 10%. If EEMS uses 400 and 900 nodes, only 16 and 9 nodes per area alternate as CH to minimize energy consumption. Therefore, EEMS experiences a significant decrease in the SP value from 1612 to 1393 if 400 nodes are used, which is a decrease of about 13%.

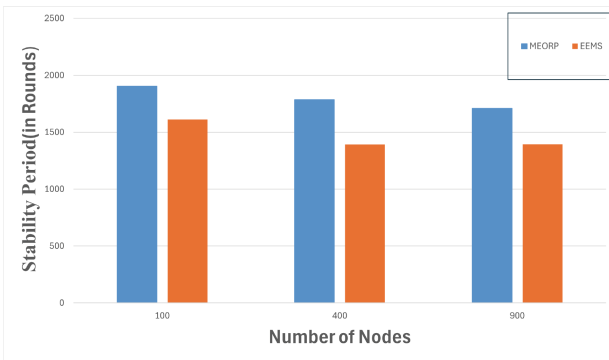


Fig. 3. Stability period (same densities)

To determine the survival rate after the simulation stability period (SP), changes in survival rates were measured when the remaining nodes were farther from their respective APs. The results for environments with 100 nodes, 400 nodes and 900 nodes are respectively shown in Figs. 4, 5, and 6, IQLWS-MC consistently outperforms EEMS in terms of survival rate and SP. The curves for survival rates for the three scenarios are very similar. If the survival rate is approximately 60%, EEMS performs comparably to IQLWS-MC because IQLWS-MC's allocates energy more efficiently within clusters if the node count exceeds 60%, so the rate at which nodes die increases. However, if there are significantly fewer nodes, coverage may be insufficient and the network can fail, so EEMS experiences a slower decline in the later stages but these issues can persist.

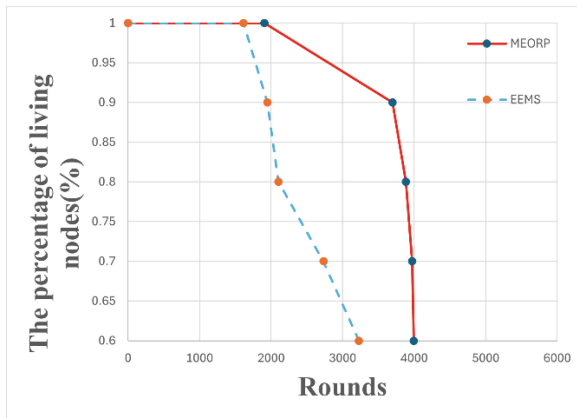


Fig. 4. Stability period (SP) with 100 nodes

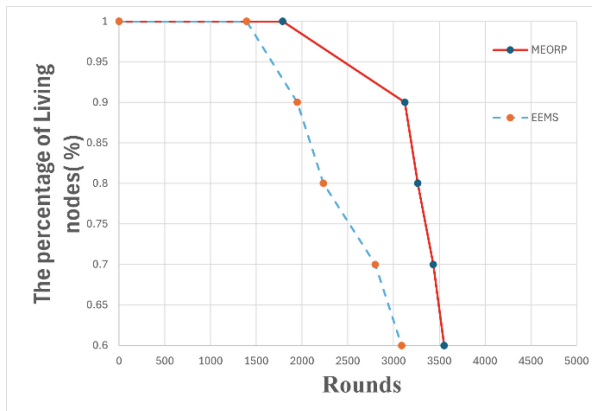


Fig. 5. Stability period (SP) with 400 nodes

To determine the survival rate after the simulation stability period (SP), changes in survival rates are measured when the remaining nodes are farther from their respective

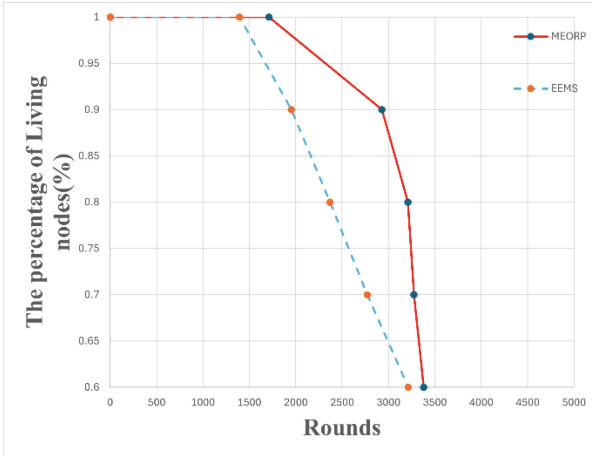


Fig. 6. Stability period (SP) with 900 nodes

APs. The results for environments with 100 nodes, 400 nodes and 900 nodes are shown in Figs. 4, 5 and 6, IQLWS-MC consistently outperforms EEMS in terms of survival rate and SP. The curve for survival rates for the three scenarios are very similar. If the survival rate is approximately 60%, EEMS performs comparably to IQLWS-MC because IQLWS-MC more efficiently allocates energy within clusters if the node count exceeds 60%, so the rate at which nodes die increases. However, using fewer nodes may give insufficient coverage and the network can fail, so EEMS experiences a slower decline in the later stages but these issues can persist.

To maintain a stable density within any network region, the extreme scenario using 900 nodes is avoided and the node count is maintained within a certain range. Figure 7 shows the simulation results for IQLWS-MC and EEMS for different densities. The simulations were conducted in a 100×100 area using node counts of 100, 199, 200, 299, 300 and 399. The results show that for different node densities and a fixed area, IQLWS-MC maintains a SP value that is within a stable range until around 400 nodes, after which performance slightly deteriorates. EEMS performs best for a node density of 0.0299 (nodes per area of $100 \times 100 \text{ m}^2$) but its overall performance varies. IQLWS MC consistently maintains stable and good performance because the number of nodes is constant if the overall network density changes.

This study also maintains effective coverage. The results of previous studies [25, 26] show that coverage decreases as nodes fail during transmission. Wireless Sensor Networks (WSNs) generally provide good coverage if the coverage exceeds 90% but if coverage is less than 70%, data integrity or quality of service are insufficient so network performance is significantly decreased and the network fails. This study determines the variation in coverage for IQLWS-MC and EEMS using 400 nodes that are distributed in a 100×100 unit area and an initial coverage of 100%. The variation in coverage after 6000 rounds was measured and the results are shown in Fig. 8.

QoS (Quality of Service) refers to the performance standards that a network achieves for different dimensions, such as coverage, latency, bandwidth, and reliability. In the

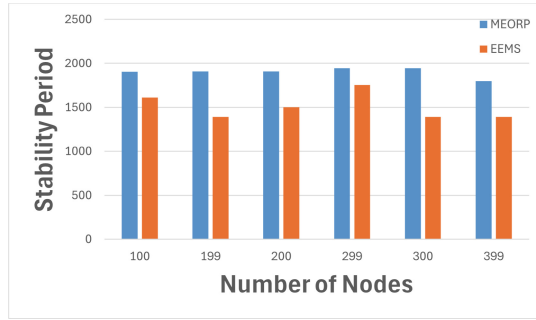


Fig. 7. Stability period (different densities)

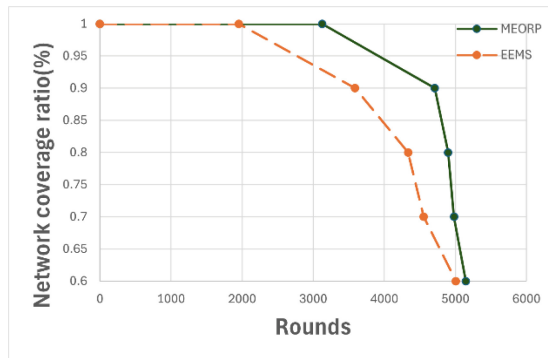


Fig. 8. Coverage

context of coverage, QoS specifically denotes the expected minimum coverage that is required for the network to provide necessary services. If coverage is less than this expected level, the network is considered to have failed. For this study, the QoS value is 70%.

Figure 6 shows that IQLWS-MC maintains 100% coverage for approximately 1000 more rounds than EEMS. Coverage decreases to less than 90% at around the 4700th round and rapidly decreases to 70% by the 5000th round, at which point it is considered to have failed. EEMS begins to deteriorate at around the 1900th round, fails to maintain adequate coverage (below 90%) at the 3500th round and completely fails at the 4500th round. EEMS is more stable in the later stages (below 90%) but its coverage is less than that for the proposed method before network failure, so it is not considered to be acceptable. The trend in coverage is also similar to that for previous node lifetime performance graphs.

5 Conclusion

This study proposes a network energy-saving topology algorithm that uses mobile base stations. To simulate real world conditions, network nodes are randomly distributed and extensive simulations are conducted for each data set to verify the effectiveness of the

algorithm. The use of mobile base stations reduces the effect of the distance to the base station on the energy that is consumed by cluster heads (CHs), so the topology structure significantly affects energy consumption within clusters.

Network partitioning is calculated for stable node counts and each area's maximum transmission range is designated as access points (APs). Nodes are then allocated as cluster heads (CHs) and a Particle Swarm Optimization (PSO) algorithm is used to generate a minimum spanning tree. The path for the mobile sink (MS) is then planned based on the locations of the APs.

The performance of the proposed algorithm is compared with that of the EEMS [21] algorithm. Nodes that are closest to the APs experience a higher energy load and are more likely to fail first, so IQLWS-MC uses multiple alternating cluster heads to ensure that the energy in the inner layers is sufficient. This method ensures a uniform stability period (SP) for various parameter values and a comparison of overall network lifespan shows that IQLWS-MC extends the lifespan. Lifespan only declines rapidly when the overall network lifespan decreases significantly or when failure is imminent, so IQLWS-MC distributes energy more effectively and creates a more stable network.

The coverage that is provided by the two algorithms are also compared. IQLWS-MC ensures more balanced energy consumption so premature node failure is prevented and energy consumption is reduced so the network does not fail because transmission distances are excessive. Therefore, lifespan and coverage increase, so IQLWS-MC is more adaptable to various environments.

In practical applications, differences in node distribution, sensor design, and fault issues affect the performance of the algorithm. Network dynamics, data security, energy efficiency, fault detection, the optimization of network topology and cost issues are also important. Future research should use adaptive algorithms, encryption technologies, efficient energy management, fault recovery mechanisms and optimization of network topology and cost-benefit analysis to increase system performance and application value. Applying the proposed topology algorithm to practical scenarios, such as environmental monitoring, smart cities and healthcare, may yield better results.

References

1. Yu, L., Wang, N., Meng, X.: Real-time forest fire detection with wireless sensor networks. In: International Conference on Wireless Communications, Networking and Mobile Computing, pp. 1214–1217. IEEE, Wuhan, China (2005)
2. Elmriani, A., Amrani, A.G.: Wireless sensors network for traffic surveillance and management in smart cities. In: 5th International Congress on Information Science and Technology (CiSt), pp. 562–566. IEEE, Marrakech, Morocco (2018)
3. Shelar, P., Gogate, U.: Performance evaluation of fmac protocol in healthcare monitoring system based on wireless sensor network. In: International Conference on Smart Innovations in Design, Environment, Management, Planning and Computing (ICSIDEMPC), pp. 100–104. IEEE, Aurangabad, India (2020)
4. Vidhya Sree, A., Sudarmani, R., Vaisali, S., Aishwarya, K.: Development of manhole cover detection and continuous monitoring of hazardous gases using WSN and IoT. In: 6th International Conference on Computing Methodologies and Communication (ICCMC), pp. 202–206. IEEE, Aurangabad, India (2020)

5. Saadaoui, S., Tabaa, M., Monteiro, F., Chehaitly, M., Dandache, A., Oukaira, A.: IWSN under an industrial wireless channel in the context of Industry 4.0. In: 29th International Conference on Microelectronics (ICM), pp. 1–4. IEEE, Beirut, Lebanon (2017)
6. Dahmane, W.M., Brahmia, M.-e.-A., Dollinger, J.-F., Ouchani, S.: A BIM-based framework for an Optimal WSN Deployment in Smart Building. In: 11th International Conference on Network of the Future (NoF), pp. 110–114. IEEE, Bordeaux, France (2020)
7. Mejias-Morillo, C.R., Gbaguidi, A., Kim, D.W., Namilae, S., Rojas-Nastrucci, E.A.: UHF RFID-based additively manufactured passive wireless sensor for detecting micrometeoroid and orbital debris impacts. In: 2019 IEEE International Conference on Wireless for Space and Extreme Environments (WiSEE), pp. 41–47. IEEE, Ottawa, ON, Canada (2019)
8. Assim, M., Al-Omary, A.: Design and implementation of smart home using WSN and IoT Technologies. International Conference on Innovation and Intelligence for Informatics. Comput. Technol. (3ICT) **2**(5), 1–6 (2020)
9. Cheng, C., Tse, C.K., Lau, F.C.M.: A delay-aware data collection network structure for wireless sensor networks. IEEE Sens. J. **11**(3), 699–710 (2011)
10. Kaur, G., Chanak, P., Bhattacharya, M.: Memetic algorithm-based data gathering scheme for IoT-enabled wireless sensor networks. IEEE Sens. J. **20**(19), 11725–11734 (2020)
11. Mehto, A., Tapaswi, S., Pattanaik, K.K.: Rendezvous point based delay-efficient trajectory formation for mobile sink in wireless sensor networks. In: Proceedings of the 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), pp. 1–6. IEEE, Kanpur, India (2019)
12. Bagga, N., Sharma, S., Jain, S., Sahoo, T.R.: A cluster-tree based data dissemination routing protocol. Procedia Comput. Sci. **54**, 7–13 (2015)
13. Mehto, A., Tapaswi, S., Pattanaik, K.K.: A review on rendezvous based data acquisition methods in wireless sensor networks with mobile sink. Wireless Netw. **26**, 2639–2663 (2019)
14. Heinzelman, W. R., Chandrakasan, A., Balakrishnan, H.: Energy-efficient communication protocol for wireless microsensor networks. In: 33rd Annual Hawaii International Conference on System Sciences, vol. 2, p. 10. IEEE, Maui, HI, USA (2000)
15. Ye, W., Heidemann, J., Estrin, D.: An energy-efficient MAC protocol for wireless sensor networks. In: Twenty-First Annual Joint Conference of the IEEE Computer and Communications Societies, pp. 1567–1576. IEEE, New York, NY, USA (2002)
16. Manuel, E.M., Pankajakshan, V., Mohan, M.T.: Efficient strategies for signal aggregation in low-power wireless sensor networks with discrete transmission ranges. IEEE Sensors Lett. **7**(3), 1–4 (2023)
17. Wang, Z.M., Basagni, S., Melachrinoudis, E., Petrioli, C.: Exploiting Sink Mobility for Maximizing Sensor Networks Lifetime. In: 38th Annual Hawaii International Conference on System Sciences, pp. 287a. IEEE, Big Island, HI, USA (2005)
18. Tunca, C., Isik, S., Donmez, M.Y., Ersoy, C.: Ring routing: an energy-efficient routing protocol for wireless sensor networks with a mobile sink. IEEE Trans. Mobile Comput. **14**(9), 1947–1960 (2015)
19. Wen, W., Zhao, S., Shang, C., Chang, C.-Y.: EAPC: energy-aware path construction for data collection using mobile sink in wireless sensor networks. IEEE Sens. J. **18**(2), 890–901 (2018)
20. Lee, Y., Chang, C.-Y., Lin, J.: Virtual grid-based data collection using mobile sink in wireless sensor networks. In: 2020 IEEE International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan), pp. 1–2. IEEE, Taoyuan, Taiwan (2020)
21. Agarwal, V., Tapaswi, S., Chanak, P.: Energy-efficient mobile sink-based intelligent data routing scheme for wireless sensor networks. IEEE Sensors J. **22**(10), 9881–9891 (2022). <https://doi.org/10.1109/JSEN.2022.3164944>
22. Behera, T.M., Mohapatra, S.K., Samal, U.C., Khan, M.S., Daneshmand, M., Gandomi, A.H.: Residual energy-based cluster-head selection in WSNs for IoT application. IEEE Internet of Things J. **6**(3), 5132–5139 (2019). <https://doi.org/10.1109/JIOT.2019.2897119>

23. Kennedy, J., Eberhart, R.: Particle swarm optimization. In: Proceedings of the International Conference on Neural Networks, pp. 1–5. IEEE, Piscataway, NJ, USA (1995)
24. Zhu, X., Zhang, Y.: Wireless sensor network path optimization based on particle swarm algorithm. In: IEEE International Conference on Computer Science and Automation Engineering, pp. 534–537. IEEE, Shanghai, China (2011)
25. Liu, Y., Liang, W.: Approximate coverage in wireless sensor networks. In: IEEE Conference on Local Computer Networks 30th Anniversary (LCN'05), pp. 68–75. IEEE, Sydney, Australia (2005)
26. Bai, H., Chen, X., Ho, Y.C., Guan, X.: Percentage coverage configuration in wireless sensor networks. In: Pan, Y., Chen, D., Guo, M., Cao, J., Dongarra, J. (eds.) ISPA 2005. LNCS, vol. 3758, pp. 780–791. Springer, Heidelberg (2005). https://doi.org/10.1007/11576235_78