Enhancing network lifetime in wireless sensor networks through coverage-aware optimized sensor activation

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ABSTRACT

Wireless sensor networks (WSNs) are a pivotal technology in the modern era, enabling the monitoring and sensing of environmental conditions across vast areas with unprecedented precision and flexibility. At the heart of WSNs lie crucial challenges such as optimizing coverage, extending network lifetime, and strategizing node deployment to ensure efficient operation while conserving energy. This paper introduces the coverage-aware optimized sensor activation and deployment (CAOSAD) Strategy, a novel methodology designed to address these challenges. By integrating advanced node placement algorithms and scheduling techniques, the EcoNet lifespan maximization (ELM) strategy significantly enhances area and target coverage, minimizes energy consumption, and thereby prolongs the network's operational lifespan. We present a comprehensive framework that dynamically adjusts node activity based on a predictive model, ensuring robust coverage and connectivity with minimal energy expenditure. Through a series of simulations, the ELM strategy demonstrates a substantial improvement in network sustainability compared to existing methodologies, offering a promising approach for the development of future WSNs. By focusing on the synergy between coverage optimization, energy-efficient node deployment, and innovative scheduling algorithms, this paper contributes a ground-breaking perspective to the research and application of WSNs, setting a new benchmark for the design of eco-friendly and durable sensing infrastructures.

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1. INTRODUCTION

Ad-hoc network technology has attracted huge volumes of research throughout time [1], Ad-hoc networks fall into two primary categories: mobile Ad-hoc networks (MANETs) and wireless sensor networks (WSNs). It is crucial to compare the hardware costs and power consumption of MANETs and WSNs. It is acknowledged that WSNs are economical and energy-efficient [2]. WSN nodes are often used to sense and monitor a variety of environmental parameters, including wind, air quality, humidity, pressure, vibration, gas and chemical levels, earthquakes, and more. These nodes are equipped with integrated CPUs and refined sensors. Mobile devices made for MANET applications can move in any direction. WSNs entrust sensor nodes with the task of monitoring the assigned region [3]. In real-time applications encounter an ordered or disordered network within a WSN [4]. A spontaneous WSN is dispersed throughout the sensor field in a concentrated sensor region. Complex problems with connection management and failure detection can occur [5]. The efficiency of communication between nodes is influenced by the connection level [6]. Conversely, a coverage issue might be classified as a target coverage issue or an area coverage issue. Information gathering for a whole area of interest is the primary goal of the area coverage problem. To solve the issue of target coverage, it is important to monitor certain locations within a given region [7]. Three forms of covering are discussed in [5]: blanket, barrier, and sweep coverage. It is important to establish a pre-configured network of sensor nodes throughout the sensing region to guarantee total coverage and boost the target detection rate. In a similar vein, barrier coverage lessens the possibility of covert infiltration.

Before deployment, two crucial components of the network function are confirmed known as the distinctions between connection and coverage. When analyzing the efficacy of sensor field monitoring in WSNs, coverage assessment is an essential measure to take into account [8]. It falls into two distinct categories. Determining target coverage is the process of calculating the total number of targets that can be covered given particular target assumptions. Area coverage is the whole of the sensing field’s covered territory [9]. Connectivity is key to evaluating the performance of networks between active sensor nodes and the communication capability of WSNs.

Establishing the necessary WSN requires installing wireless nodes in the monitoring region. Handling this problem in WSN may be difficult and have a big impact on a network’s efficiency. During deployment, nodes can be dropped at random or placed in a certain sequence [10]. The primary objective of deployment is to locate nodes and diagnose connectivity problems, as shown in [11]. Because deployed nodes in WSNs have limited capacity and changing their batteries is a challenge, energy saving is a major concern. In WSNs, designing protocols to reduce energy consumption and increase network longevity is a major problem, particularly when preserving the required coverage. It is essential to monitor these networks to observe different physical or environmental aspects [12]. Placement of the sensors might be done systematically or at random. If deterministic deployment is being used, strategically placing sensor nodes is essential to optimizing coverage. Utilizing random deployments is advised when the location information is unknown. There might be a lot of sensor nodes in certain places and not so many in others. Because WSN communication is multi-hop in nature, establishing a full connection is necessary to guarantee dependable data transmission [13]. When every node in a network can exchange data and interact, the network is said to be completely linked. It is possible to communicate directly between nodes as well as through intermediaries. Taking into account the significance of connection. The two techniques for increasing transmission range are the use of directional antennas and collaborative transmission [14].

The impetus for this research is centered on the pivotal challenge of maximizing network lifetime through strategic node deployment and coverage optimization in WSNs. The limited and non-renewable energy resources of sensor nodes necessitate a design that ensures efficient energy consumption while maintaining continuous and comprehensive network coverage. This paper is motivated by the potential to significantly extend the operational lifespan of WSNs through the introduction of advanced deployment strategies and coverage techniques. By focusing on these critical aspects, our work endeavors to present a novel approach that can lead to substantial improvements in the sustainability and efficacy of sensor networks, particularly in applications where the longevity of the network is paramount. Our goal is to contribute a methodology that enhances coverage without compromising the longevity of the network, thereby setting a new benchmark for energy-efficient WSN design:

- Novel deployment strategy for optimized coverage: this paper introduces a cutting-edge deployment technique designed to enhance area and target coverage in WSNs. By integrating a sophisticated node placement algorithm, we can significantly reduce coverage holes and overlap, leading to a more uniform distribution of sensor nodes across the monitoring area. This strategy not only ensures comprehensive coverage but also contributes to the extension of the network’s lifetime by conserving energy that would otherwise be wasted in redundant sensing.
- Optimized sensor activation algorithm for prolonged network longevity: we present an innovative scheduling algorithm that judiciously activates sensor nodes, thereby minimizing idle listening and unnecessary energy expenditure. By selectively powering nodes and employing a predictive model to forecast the required active periods for data transmission, our approach effectively balances the trade-off between maintaining robust network coverage and conserving energy, substantially enhancing the overall lifetime of the network.
- Efficient energy utilization through strategic node deployment: the paper contributes a novel framework for node deployment that accounts for the energy profile of each sensor. By considering the initial energy, consumption rates, and the potential for energy harvesting, the proposed method strategically positions nodes to capitalize on their energy efficiency. This approach leads to an optimized network where the longevity of individual nodes is maximized, resulting in an overall increase in network lifetime and reliability.

This paper is organized into four sections; the first section gives a brief overview of the WSNs, challenges in WSNs related to coverage, network lifetime, and energy-efficient node deployment. The second section discusses the related work. The third section discusses the proposed methodology and the fourth section discusses results in the form of graphs.

2. RELATED WORK

A memetic algorithm to address the SET K-COVER problem and extend the lifespan of WSN. This method is very efficient for segmenting a group of nodes into smaller subgroups and ensuring that each subgroup includes all necessary targets before activating them one by one [11]. Maximizing coverage and extending the lifetime are the main objectives of the SET K-COVER problem, much like how sensors are organized for efficient coverage. A proposed strategy utilized a method combining particle swarm optimization (PSO) and ant colony optimization (ACO) to choose a sensor with the most remaining energy to cover all target locations [12]. We resolved this issue by applying the Boolean disk model and probabilistic sensor model to tackle the minimal weight sensor coverage (MWSCP) problem. Three pheromones ACO (TPACO) solves the energy-efficient coverage (EEC) issue as mentioned [13]. Energy efficient multi-parameter approach inspired by biological procedure introduced in [14], the energy efficient multi-parameter reverse glowworm swarm optimization (EEMRGSO) algorithm addresses coverage and energy concerns at the same time. To achieve the best coverage, nodes need to be mobile, which results in increased energy usage. Coverage and energy are closely connected topics. By moving sensor nodes to specific grid positions, you can reduce overlapping coverage. Each node symbolizes a single glowworm. Because nodes are randomly placed, there is a chance that their coverage regions may overlap. A new deployment technique to address the gaps in the sensing field coverage [15]. The system proposed uses a binary sensing model and is developed based on the multi-objective immune algorithm (MIA) to tackle the coverage whole issue resulting from conventional deployment approaches. Nodes are adjusted to improve coverage and reduce energy consumption during transit by limiting how far they can move. Limiting the movement of nodes within the communication range ensures a stable node connection.

The study cited in [16], [17] highlights the importance of optimizing average energy cost, average sensitivity area, and network reliability in tackling the relay node placement problem. This task is proving to be quite difficult. We delved into and implemented various multi-objective meta-heuristics, such as the trajectory algorithm. Another approach described in reference [18] outlines how the metaheuristic algorithm can be utilized to tackle the WSN deployment problem. Search economics is the commonly accepted term for this concept. Metaheuristic algorithms may converge to the local optimum due to their limited short-term memory. Introduces bio-inspired self-organizing network (BISON), a novel adaptation of the Voronoi algorithm designed to tackle specific challenges in sensor networks [19], [20].

This method is characterized by its constraints on node capabilities: firstly, nodes gather information exclusively from their immediate surroundings, and secondly, their communication is affected by noise. The effectiveness of BISON is evaluated based on several criteria: the extent of area coverage achieved, the nodes' total movement distance, overall energy expenditure, and the evenness in the spatial distribution of the nodes. A new meta-heuristic technique that combines a novel meta-heuristic (ARSH-FATI) with a multi-population approach is shuffled ARSH-FATI [21]. By breaking down the lifetime maximization of range adjustable sensors (LM-RAS) problem, shuffled ARSH-FATI successfully solves it as two smaller problems. First, develop energy-efficient coverage schemes, and then schedule them. For optimal outcomes, the performance of ARSH-FATI relies heavily on the quality of the coverage schemes. Utilizing a linear programming (LP) model to generate the optimal schedule for coverage strategies. The memorial mixed-response algorithm (MMRA), is available for synchronous or distributed implementation. Viewed as a component of a system, every sensor node initiates the procedure by refreshing its memory with a temporary action based on a predefined response guideline [22]. Each participant randomly selects an action from memory with an equal chance to start the iteration. Emphasizes enhancing coverage quality in battery-free WSNs (BF-WSNs) rather than solely extending network lifespan [23]. Studies show that the coverage problem recently identified falls under the category of NP-hard. This study highlights two crucial elements for efficiently reaching the optimal solution to the problem. In addition, three approximation methods are suggested to ensure optimal coverage if the required conditions are not met [20].

3. PROPOSED METHOD

The study focuses on implementing energy-efficient methodologies in WSNs to maintain connectivity while maximizing coverage. These methodologies typically involve intelligent routing algorithms, adaptive power management techniques, and clustering approaches to ensure efficient data transmission and sensor node operation. By carefully balancing energy consumption with network performance, these strategies enable prolonged network lifetime and improved coverage in resource-constrained environments.

3.1. Network modelling and preliminaries

Consider a WSN that is static and has $V = \{V_1, \dots \dots, V_o\}$ that are static destination points, sets of $U = \{U_1, \dots., U_p\}$ that are sensors and $D = \{D_1, \dots, D_g\}$ that represent sinks while o, p, g are the dimension of V, U, D respectively. The sensing tasks are performed by a node used for sensing. These nodes produce data packets that are sent to a minimum of one sink through communication performed over the radio. These packets are relayed using a relay node. It is assumed that the rate of generating these packets at all the sensory nodes is similar which is represented as ω. A sensory node is termed active if it is chosen as a relay or sensory node or chosen as both. If the node is not active, it enters into a state of sleep to conserve energy. It is also assumed that once the energy of a node is depleted, it cannot be recharged. The lifetime of the network is described as the period for which the network is set till one of the given constraints is true: one of the sensory nodes is unable to be linked to any of the sinks through the relay nodes j, in which case j is expressed as a parameter that is defined prior such that $j\ belongs\ to\ \mathbb{P}$. And one of the destination nodes is unable to be covered by any of the sensory nodes.

In this study, the factors that affect delay in packets are studied and analyzed, the count of hops is one such important factor that contributes to the delay. Adding to this factor is the re-transmission as well as the period for queuing. Hence, the condition of delay is described as well and the sensor information is needed to be sent to the connections by j hops. The sensory nodes are deployed in a dense manner where for each target at least one of the sensory nodes is covered. While taking into account these constraints and assumptions, the main focus in this paper is for these nodes to be scheduled while their energy is conserved which ensures the target is connected and covered. Consider u is a node, the destination targets that are within the range to be sensed u are given as $\mathbb{O}(u)$, all of the nodes are expressed as $\mathbb{E}(u)$ as well as the sinks where u can send the information. If the model on the basis for the disk is used, in this case, $\mathbb{O}(u)$ is made up of the targets whose length to u is limited to the sensory radius of u. The relay nodes are $\mathbb{E}(u)$ and the sink's length does not exceed the radius of the linked nodes. Here, the energy at the start of the node is expressed as $G_0(u)$ for the node u.

The algorithm that is used for the process of scheduling is performed in a centralized manner at the sink. This sink is one of the many sinks and is determined before the initialization of the network, which is termed the control sink. Before the performance of the algorithm, this sink gathers data via the sensory nodes, once complete the control sink has to transfer the schedule to the sensory nodes. The control sink ID is installed in the nodes prior. At the initialization of the network, each node is used to determine to list of neighbors at the first hop, and the location, and transfers its data along with the data of starting energy to the control sink. This process is executed once and the nodes are free to use any protocol for routing that could include a greedy algorithm for routing as well as the shortest path first for routing and this data is transferred. However, it is also noted that the paths of routing at the initial stage are not the routes used for sending sensory information. Since these paths do not satisfy the condition of the hop bound. However, the use of fixed paths for routing for transferring sensory information results in imbalance across the network as well as reduces the lifetime of the network. Considering the data of the nodes, the control sink executes the algorithm for the schedule as well as determines the nodes that are used for the scheduling. This schedule is then transferred back to all of the nodes. The control sink is also responsible for the gathering of information relating to tasks as the other sinks. As the schedule is being executed, every node is occupying its location data only once.

3.2. Network energy modelling

The consumption of energy for a node consists of three elements: energy sense for operations, energy received during receiving packets of data as well as energy transmission while sending packets of data. The transmitter disperses the energy to use the amplifier as well as the radio, where the receiver uses energy to work the radio. While the distance that is between the receiver as well as the transmission unit that is expressed as f is lesser in comparison to the threshold f_0, the power loss denoted as f^2 along with the free space is used. Else, the channel with a power loss of f^4 is used. The energy that is transmitted for node u per bit is formulated as given (1).

$$G_v(u) = \begin{cases} g_v(u) + g_{he}(u) \times f^2 & if\ f\ is\ lesser\ than\ f_0(u) \\ g_v(u) + g_{or}(u) \times f^4 & if\ f\ is\ greater\ than\ or\ equal\ to\ f_0(u) \end{cases} \tag{1}$$

In this case, $g_v(u)$ is expressed as the energy that is consumed by the transmitter for every bit of data. $g_{he}(u)$ and $g_{or}(u)$ are used to denote the consumption of energy by the amplifier for every bit of data as well as a mode of fading channel, respectively. A constant f_0 is expressed as $f_0(u) = \sqrt{g_{he}(u) / g_{or}(u)}$. The energy that is used in the transmission namely, sending and receiving of data bit for the node u is constant and is given as $g_u(u)$ and $g_t(u)$, respectively.

3.3. Coverage aware sensor activation and deployment (CAOSAD) technique

In this study, the active state as well as the sleep state is scheduled for the sensory nodes for the maximum lifetime of the network, which is achieved by attaining the given conditions. The first condition includes coverage, where every destination node is covered using one sensory node at the least. Secondly, the Link condition, where every sensory node is linked to one sink at least through the relay j nodes. And lastly, the energy condition, where the complete consumption of energy U_k does not overseed the starting energy $G_0(U_k)$.

Linked cover route for a destination node V_k is described as a set having at most of $j+1$ sensory nodes that satisfy the given constraints: $V_k\ belongs\ to\ \mathbb{O}(U_{k1})$, implying that V_k is inside the sensory range of the first node. The other two conditions, $U_{k_{s+1}}\ belongs\ to\ \mathbb{E}(U_{k_s})$ and $\{D_1, \ldots, D_g\} \cap \mathbb{E}(U_{k_y}) \neq \emptyset$ express the sensory nodes forming a path for routing that can transfer the data from U_{k1} to sink. For consumption of energy for linked cover route, let us assume r is the linked cover route, the arbitrary node is given as u and the energy consumed for one unit of time is given as $ec(r,u)$ where the energy used by u while r is active for one unit of time. Particularly, $ec(r,u)\ is\ equal\ to\ zero, if\ u\ does\ not\ belong\ to\ r$. This is formulated as given in (2).

$$ec(r,u) = t(r) \times g_{uv}(u) + t(r) \times \begin{cases} g_v(u) + g_{he}(u) \times f^2 iffislesserthanf_0(u) \\ g_v(u) + g_{or}(u) \times f^4 iffisgreaterthanorequaltof_0(u) \end{cases} \tag{2}$$

Considering the (2), if u is the sensory node in r and $g_{uv}(u) = g_t(u)$, then $g_{uv}(u) = g_u(u)$. In this case, f is the distance from u to the closest sink while u is the node of r. The rate of information generation is $t(u)$ at the sensory node r. For the linked cover set, we assume V_C is the set of all destination nodes that are within or on the edge of C, then a linked cover set for C is set to linked cover routes of the destination nodes that belong to V_C, where at least one of the linked cover routes belongs to V_C. For the consumption of energy in the linked cover set, we assume z is a linked cover set that includes $r_1, \ldots, r_y$ and u is the arbitrary node, then the consumed energy per time unit of u in z is described as the energy used by u when z is in an active state for the unit time. The linked final coverage schedule is described as a linked final coverage schedule for C that is made up of a set of linked cover sets for C and their respective active times.

The challenge that is resolved in this paper includes maximization and increasing the lifetime of the network. Let us consider, V, U, D are the set of destination nodes, sensory nodes as well and sinks that are present in the network. The maximization of lifetime for network challenge involves the determination of the constraint for energy schedule for the entire network for the longest lifetime. This problem is formulated as given in (3) and (4).

$$Max \sum_{l=1}^{w} v_l \tag{3}$$

While v_l is greater than or equal to 0,

$$\sum_{l=1}^{w} gu(Z_l, U_k)\, v_l\ is\ lesser\ than\ or\ equal\ to\ G_0 \tag{4}$$

Considering these equations, the active state of the node is given as v_l for $Z_l(l = \overline{1,w})$. Therefore, the (3) depicts all the active state periods for the lifetime of the network. The (4) gives the active state time for every network lifetime that is not negative. An active state equal to zero means the related network lifetime is not active. This equation also implies that the energy utilization of each sensory node does not cross its starting energy. The linked cover routes as well as the network lifetime are not affected by the location accuracy of the sensory node. The dimension of w which includes the problem of maximization of network lifetime is observed as the product of linked cover routes for the destination nodes that increase exponentially while the dimension of the network increases.

The complexity of the period to resolve the maximizing network lifetime challenge is dependent on the destination nodes as well as the sensory nodes. Therefore, a natural method is utilized for increasing the speed of the scheme. We propose an approximation algorithm based on the splitting and moving method.

The main aim of it is to make several splits on the network region, each splits the network as smaller regions using a grid. Further, the ideal solution for the small regions is determined and then concatenated to obtain the entire network. For the partial maximization of network lifetime, consider an area $\mathcal{C}$ for a network, where the problem on partial maximization of network lifetime determines the energy schedule constraint of $\mathcal{C}$ having the best network lifetime. Figure 1 shows the flow of the proposed algorithm. Algorithm 1 shows the proposed algorithm. Algorithm 2 shows the CAOSAD phase 2 Algorithm.

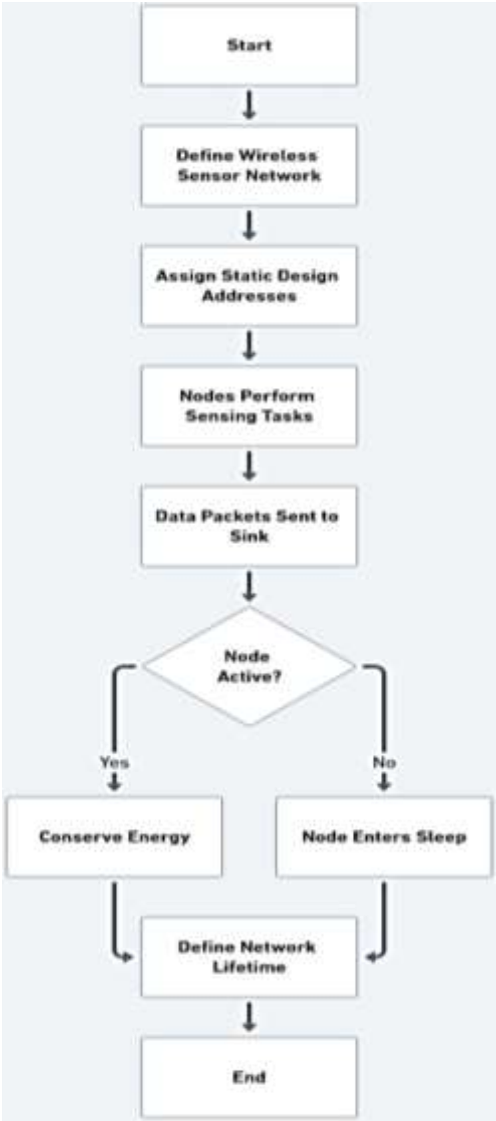

Figure 1. Workflow of the proposed algorithm

Algorithm 1. CAOSAD phase 1 algorithm

Step 1: The ideal solution for the partial maximization of the network lifetime is determined for every node and the ideal resolution is given as $\vartheta^{(k,l)}$ relating to $F_{k,l}(k=\overline{1,p_y}; l=\overline{1,p_j})$

Step 2: Let $\sigma_r^{(k,l)}(r=\overline{0,s_{kl}})$ that expresses the combined active time in a set of active periods of ϑ

Step 3: Sort $\sigma_r^{(k,l)}(k=\overline{1,p_y}; l=\overline{1,p_j}; r=\overline{0,s_{kl}})$ in ascending order and represent $W=\sum_{k=1}^{p_y}\sum_{l=1}^{p_j} w_{kl}$

Step 4: For every $k,l\left(k=\overline{1,p_y}; l=\overline{1,p_j}\right)$, let $s_{k,l}$ be the integer that is used to satisfy $\sigma_{s_{k,l}-1}^{(k,l)}$ *is lesser than or equal to* σ_{s-1}^* *is lesser than or equal to* σ_s^* *is lesser than*

Step 5: the maximum utilization of energy is determined using all the nodes ϑ'that is given as $\hat{G}=\max energy(\vartheta',u)$

Step 6: the output for the algorithm is schedule ϑ that is resulted from ϑ' obtained by multiplication of the elements of $\mathbb{V}(\vartheta')$ with ${energy_{min}}/{energy}$

Algorithm 2. CAOSAD phase 2 algorithms

Step 1: The Algorithm 1 is applied for every split and is expressed as ϑ'_{za} as the resolution that resulted from the $za-th$ split ($z=\overline{0,M-1}; a=\overline{0,M-1}$)
Step 2: A schedule is built ϑ' as given. The linked cover set for ϑ' is given as $\mathbb{Z}(\vartheta')=\bigcup_{z=0}^{M-1}\bigcup_{a=0}^{M-1}\mathbb{Z}(\vartheta'_{za})$
Step 3: The active time for all the z *belongs to* $\mathbb{Z}(\vartheta')$ that is described by the summation of the active state periods for all the ϑ'_{za}
Step 4: We assume $\hat{G}$ is the highest utilization of energy for all sensory nodes in ϑ'
Step 5: The output for this algorithm is the ϑ schedule that results from ϑ' by the multiplication of all elements of $\mathbb{V}(\vartheta')$ with ${energy_{min}}/{energy}$.

3.4. Network lifetime enhancement

However, the designing and development of linear programming can attain the ideal resolution, evaluation of all the linked cover sets is not possible while the count of destination nodes as well as sensory nodes are very huge in number. Further in the study, an approximation equation for linear programming is proposed that has the dimension of the variable polynomial for the nodes considering their numbers. Therefore, an algorithm is proposed for the conversion of the ideal approximation formation into a resolution that is feasible for the challenge of the maximization of network lifetime. Here, the minimum life of the target node is to be maximized. Consider V, U, D are the target nodes, sensory nodes as well as sinks that are present in the network. This challenge required the linked cover route to be determined as well as the related active state periods to maximize the shortest life for all target nodes while assuring the constraint on the energy. Algorithm 3 shows the network lifetime enhancement algorithm.

Algorithm 3. Network lifetime enhancement

Step 1: Input: $\vartheta_2=\{\mathcal{A},\mathcal{N}\}$
Step 2: Output: $\vartheta_1=\{\mathcal{Z},\mathcal{V}\}$ an ideal resolution for the minimum life of the target node to be maximized
Step 3: For $k=\overline{1,o}$
do
Step 4: $R_k=\{a_{k1},\ldots,a_{kx_k}\}$ is the set containing $\mathcal{A}$ elements where n_{kl} *is greater than zero*
O_{kl} denotes the target nodes that the sensory node covers
Step 5: end
Step 6: $m\leftarrow 1$ while R_k *is not equal to* $\emptyset$ do
Step 7: $Z_m\leftarrow\emptyset$; $E_m\leftarrow 1$ while E_m *is not equal to* V do
Step 8: $y_{maximum}\leftarrow 0$; $c_{maximum}\leftarrow 0$; $k^*\leftarrow 0$; $l^*\leftarrow 0$
Where V_k *does not belong to* E_m do
Step 9: For a_{kl} *belongs to* R_k do
Step 10: $\mathbb{E}(a_{kl})\leftarrow$set of target nodes that the sensory node a_{kl} covers
Weight of $a_{kl}\leftarrow {\left|\mathbb{E}(a_{kl})\cap\left\{\frac{V}{E_m}\right\}\right|}/{\mathbb{E}(a_{kl})\cap E_m}$
Step 11: End
Step 12: If Weight of a_{kl} *is greater than or equal to* $y_{maximum}$ and c_{kl} *is greater than* $c_{maximum}$ then
Step 13: $y_{maximum}\leftarrow$ Weight of a_{kl}; $c_{maximum}\leftarrow c_{kl}$; $k^*\leftarrow k$; $l^*\leftarrow l$
Step 14: End
Step 15: End
Step 16: $Z_m.add(a_{k*l*})$; $E_m.add(all\ targets\ that\ k*l*cover)$
Step 17: End
Step 18: $V.add(v_m)$ for $k=\overline{1,s}$ do
Step 19: If $c_{m_k p_k}=0$, then r_{m_k}.
Step 20: End
Step 21: $m\leftarrow m+1$
End
Step 22: Return $\vartheta_1=\{\mathcal{Z},\mathcal{V}\}$

4. PERFORMANCE EVALUATION

The study presents the EcoNet lifespan maximization (ELM) strategy, an approach designed to optimize WSNs. The strategy aims to extend the network lifetime, reduce energy consumption, and minimize node movement. Performance evaluations show that the ELM strategy significantly outperforms existing methods, achieving longer network lifetimes across various node sizes, maintaining complete area coverage, and enhancing energy efficiency. The results suggest that the ELM strategy is a highly effective solution for sustainable WSN deployment and management. The proposed model CAOSAD is compared with the existing model minimum overlapped full area coverage using hybridized genetic algorithm-PSO (MOFA-CA-PSO O) [24], along with critical optimized connected coverage heuristic (OCCH-critical), most likely cell-time (MLCT), greedy connected set covers (CSC) [25]. Table 1 shows the simulation parameters.

Table 1. Simulation parameters

Parameter	Values
Dimension of area of interest (AOI)	225×260 m²
Initial energy per WSN node	1 J
Total number of WSN nodes	25
Permissible "data packet size" (k)	4096 bits
Total initial energy	0.25E+14 J

4.1. Network lifetime across various nodes

Figure 2 illustrates the comparative lifetimes, measured in hours, of different methodologies when applied to a scenario represented by 150 nodes. The proposed model outperforms the other methodologies, with a lifetime significantly exceeding 14 hours, suggesting it is the most robust or efficient approach among those tested. In contrast, DC has the shortest lifetime, at just over 2 hours, indicating it may be the least effective method in this context. The remaining methodologies OCCH-critical MLCT, greedy CSC, and MOFA-CA-PSO exhibit a range of effectiveness, with MOFA-CA-PSO being the second most effective, though still falling short of the proposed model by a notable margin.

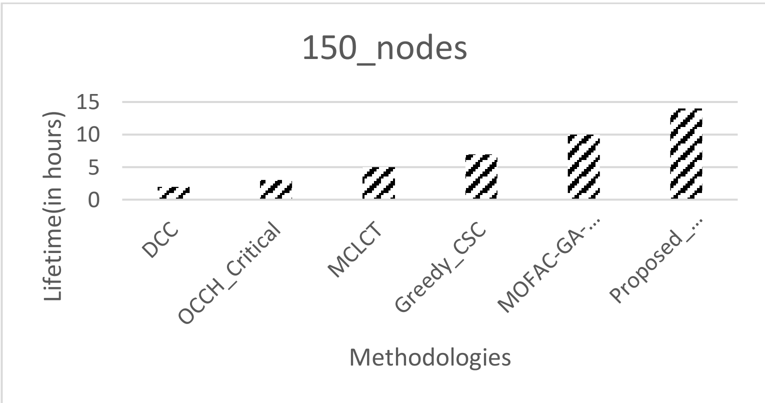

Figure 2. Network lifetime comparison for 150 nodes

Figure 3 displays a comparison of various methodologies based on their 'lifetime in hours' for a system or network comprised of 200 nodes. Observing the data, the 'proposed model' methodology shows the highest lifetime, suggesting it is the most efficient or durable among those compared. It is followed closely by MOFA-CA-PSO, which also exhibits a high lifetime, indicating effective performance. The greedy CSC and MLCT methodologies show moderate lifetimes, while OCCH-Critical has a slightly better performance than the least effective DC methodology. The chart indicates that the proposed model and MOFA-CA-PSO are superior in maintaining the system's lifetime when scaling to 200 nodes, which could be crucial for applications where longevity and sustained operation are critical.

Figure 4 illustrating 250 nodes compares the lifetimes, in hours, of different methodologies when applied to a network of 250 nodes. The proposed model stands out with the highest lifetime, significantly outperforming the other methodologies, which suggests it may offer the most robust solution for larger networks. MOFA-CA-PSO and greedy CSC show moderate lifetimes, indicating satisfactory performance. MLCT follows closely behind, while OCCH-Critical has a lower lifetime, albeit better than the DC methodology, which has the shortest lifetime. This visualization underscores the scalability of the proposed model, potentially making it a preferred choice for maintaining operational longevity in systems with a node count of 250.

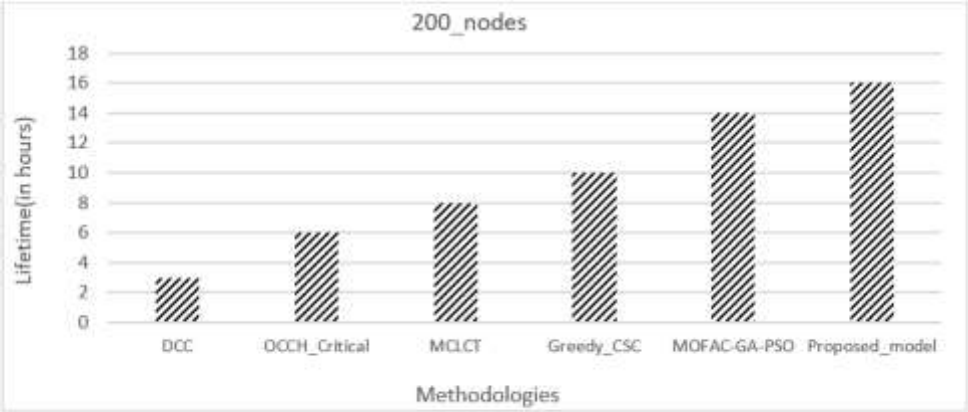

Figure 3. Network lifetime comparison for 200 nodes

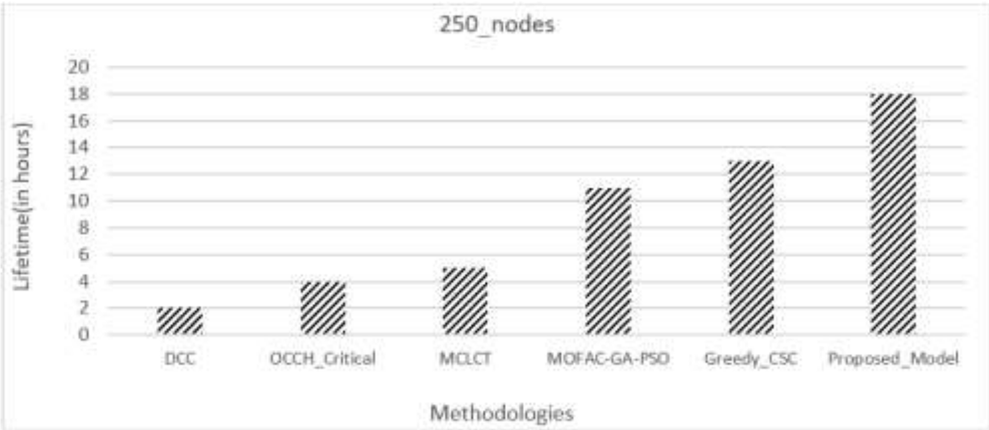

Figure 4. Network lifetime comparison for 250 nodes

Figure 5 illustrates a graph for 300 nodes that compares the lifetimes of different methodologies within a network consisting of 300 nodes. In this comparison, the proposed model once again exhibits the highest lifetime, suggesting it is most effective or optimized for networks of this size. The MOFA-CA-PSO methodology shows a strong performance, with a lifetime that is significantly higher than MLCT and Greedy CSC, which display moderate lifetimes. The OCCH-Critical methodology, while better than the least effective DC methodology, still lags behind the others. This chart reinforces the notion that the ‘proposed model’ consistently provides superior performance across varying network sizes, maintaining its lead as the network scales to 300 nodes. It also illustrates the varying degrees of scalability and efficiency among the methodologies, which is critical information for network design and management, particularly in large-scale systems where longevity is paramount.

Figure 6 shows the comparison of various methodologies based on the lifetime of 350 nodes, expressed in hours. The DCC methodology shows the lowest lifetime, just over 2 hours, followed by OCCH-critical, which is slightly better yet still under 5 hours. The MLCT and greedy CSC methodologies demonstrate a substantial increase in lifetime, both hovering around 10 hours, indicating they are relatively comparable in prolonging node lifetime. MOFAC-PSO [21] falls between the aforementioned methodologies with a lifetime between 5 and 10 hours. However, the proposed model stands out significantly, showcasing a lifetime of approximately 23 hours, more than doubling the performance of MLCT and greedy_CSC. This suggests that the proposed model is markedly superior in enhancing the node lifetime, which could be critical for applications where extended operational periods are desirable, such as in network systems requiring high durability and minimal maintenance.

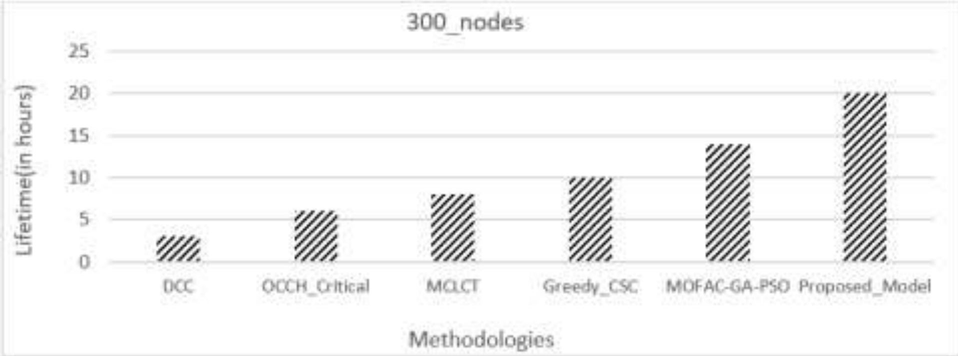

Figure 5. Network lifetime comparison for 300 nodes

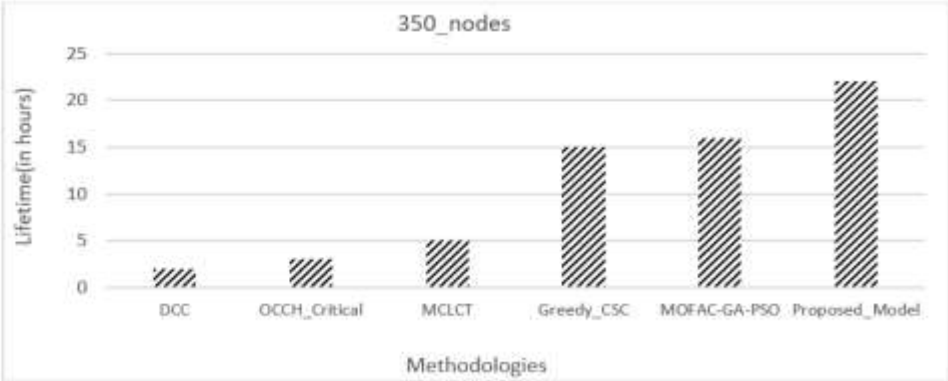

Figure 6. Network lifetime comparison for 350 nodes

4.2. Average moving distance per node

Figure 7 presents a comparison of the average moving distance per node between two methods: existing MOFCA_GA_PSO and the proposed. This comparison suggests that the proposed method is far more efficient in terms of the average moving distance per node, potentially indicating a more stable or energy-efficient approach depending on the context, such as in mobile networks where movement consumes resources. If the goal is to minimize movement to conserve energy, prolong operational time, or reduce wear and tear, the proposed method would be the superior choice according to the data shown in the graph.

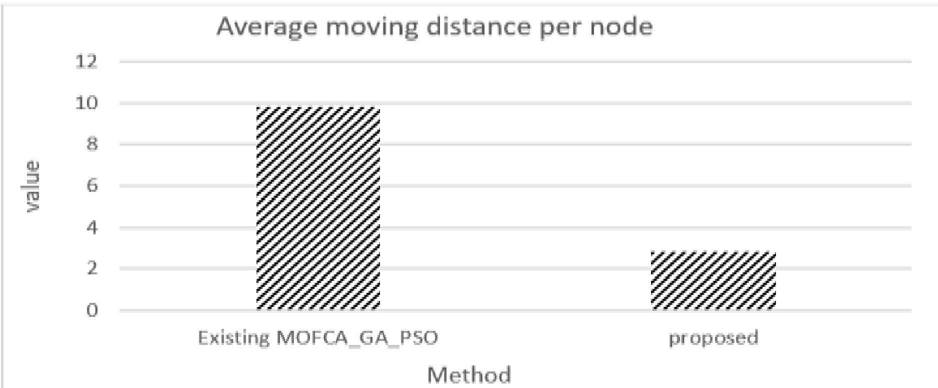

Figure 7. Comparison of average moving distance per node of the existing system with the proposed

4.3. Total energy consumed per sec

Figure 8 illustrates a comparison between two methods, existing MOFCA_GA_PSO and proposed, regarding the total energy consumed per second. The existing MOFCA_GA_PSO method shows a substantially higher energy consumption, with the value extending to roughly 25,000,000. On the other hand, the proposed method exhibits a significantly reduced energy consumption, with a value that appears to be slightly above 5,000,000. The stark contrast between the two methods indicates that the proposed method is much more energy-efficient, consuming approximately one-fifth the energy per second compared to the existing MOFCA_GA_PSO method.

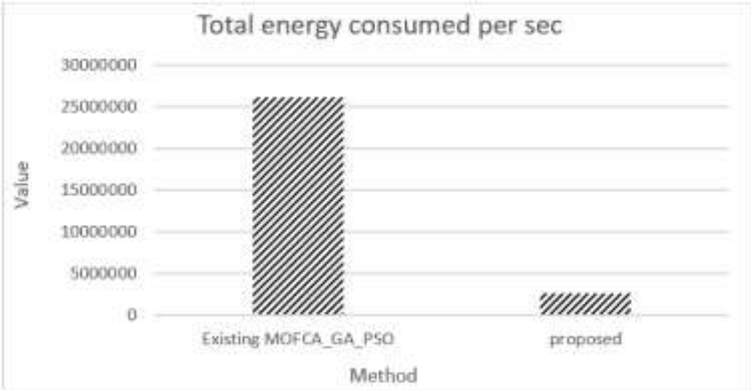

Figure 8. Comparison of total energy consumed per sec of the existing system with the proposed system

5. CONCLUSION

In conclusion, the proposed ELM strategy marks a significant advancement in the field of WSNs, offering a robust solution to the challenges of coverage optimization, network longevity, and energy-efficient node deployment. Through the innovative integration of a sophisticated node placement algorithm and a predictive scheduling model, the ELM strategy ensures comprehensive area and target coverage while significantly reducing energy consumption, thus extending the operational lifespan of WSNs. The empirical results underscore the efficacy of the ELM strategy in enhancing network performance and sustainability, surpassing existing methodologies in both coverage efficiency and energy utilization. This research not only sets a new standard for WSN design but also paves the way for future advancements in sensor network technologies, emphasizing the importance of eco-friendly and sustainable practices in the digital age.

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