International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2025/58 Volume 12, Issue 6, November – December (2025)

RESEARCH ARTICLE

Optimal Performance of Node Coverage Model in Wireless Sensor Networks Using Lyrebird Optimization Algorithm

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Received: 03 August 2025 / Revised: 01 November 2025 / Accepted: 18 November 2025 / Published: 30 December 2025

Abstract – Wireless Sensor Networks (WSNs) are beneficial in real-time monitoring and data collection in different fields. Nonetheless, it is mostly considerably challenging to achieve maximum coverage of nodes with minimal energy usage. There are some critical difficulties in optimizing node coverage in WSNs to achieve optimized node coverage. The considerable number of optimization algorithms developed with the early convergence mechanism or getting stuck at the local optimum limited the achievement of optimal solutions. Lightning and adaptive algorithms can provide efficient, scalable, and energy-conscious solutions that must be made of these challenges with the Lyrebird Optimization Algorithm (LOA). In this paper, a new node coverage enhancement method for the WSNs employing another bio-inspired meta-heuristic is introduced, namely, LOA, which simulates the evasive and changing behavior of the lonely lyrebird. The proposed algorithm also wisely finds the best placement and activation of the sensors to gain coverage of the maximum area with minimum redundancy and energy amidst a high sensor area. The conducted simulation proves that the LOA-based solution proves more effective than traditional optimization schemes concerning comprehensiveness ratio, the level of energy consumption, and speed of convergence and is an effective way of facing scalable and sustainable WSN deployments.

Index Terms – LOA, Energy, PSO, GNN, DRL, RSA.

1. INTRODUCTION

One of the pivots of reliable data collection, efficient resource use, and extended lifespan of WSNs, herein referred to as node coverage. Coverage in the context of WSNs defines how much the sensor nodes observe a specific region or several objects [1]. Lack of proper coverage has a direct influence on the quality of service (QoS) since such lack may lead to events being missed, missing information on the input and, thus, the diminution of accuracy in monitoring [2]. The main objective of node coverage optimization is to plan or switch on the sensor nodes in a manner that will cover as much of the area as possible with as little number of nodes as possible thus saving energy and eliminating redundancy. This entails some of the fundamental issues like the best location of nodes, adaptive activation, and reconfiguration in reaction to the environmental changes or node failures. Based on the requirement of the application of the WSNs [4], coverage models are usually classified into some few models, which include area coverage, point coverage and barrier coverage. There are several ways to attain wanted coverage level (deterministic deployment, random deployment). But the coverage problem is NP-hard, and so exact solutions may be intractable in large networks. Effectivity of WSN is highly deterministic to a good coverage of coverage of area or point of interest by the sensor nodes of the WSN [5]. Several methods of improving coverage have been proposed to deal with this including two major classes deterministic methods and probabilistic methods. Deterministic methods also make use of accurate information on node locations and are commonly applied in a controlled deployment [6]. Such approaches are grid and triangular lattice-based constructions, both of which provide predictable coverage as well as possible non-flexibility when applied to real-world scenarios. Instead, probabilistic methods include uncertain node positions or random deployments [7] and estimate coverage with statistical models, thus they are more flexible to tough environments.

To conquer this, optimization algorithms especially bio-inspired meta-heuristic methods have been used. The effectiveness of these techniques is that they find near optimum coverage settings [8], and that the techniques provide scalable solutions by balancing exploration and exploitation. A few optimization algorithms have been used in solving the node deployment and coverage problems in WSNs [9]. There are several challenges in the optimization algorithms that are used to enhance node coverage in the WSN. As an example, Particle Swarm Optimization (PSO)-based method [18] is used to optimize the area coverage, which is prone to premature convergence. Correspondingly, an application of Genetic Algorithms (GA) [3] provided in the sensor placements optimization; but it was slower and computationally more complex. Recently the metaheuristic method based on the imitation of the natural behavior like the Grey Wolf Optimization Algorithm (GWOA) [19] has been examined on dynamic node coverage, with an enhanced exploration quality that, however, remains limited to complex terrains and dense deployments.

Another central problem is the energy constraint because sensor nodes use limited battery power, and there should be optimization methods available not only to enhance coverage but also to make the network energy efficient so that the network can last longer [10]. Also, scalability and computational complexity are rendered critical to the problem by the increased size of the network, and the traditional algorithms can be used to seek optimal solutions within reasonable time boundaries [11].

The other key issue is the redundancy and overlapping of coverage in which the deployment of too many nodes may become a source of energy wastage and too few nodes may miss out on data loss [12]. In addition, the network topology and node failures also make the optimization process even more complex because WSNs [13] are frequently affected by dynamics on the environment and by hardware errors, which, in turn, requires an adaptive implementation of re-optimization processes. Realistic deployment is also a challenge because of environmental limitations, which inhibit node placement in areas that exhibit phenomena like physical walls, rough terrain, etc[14]. Also, node coverage is a multi-objective nature where there are trade-offs between coverage area, energy consumption, connection in a network and latency issue to a particular node and most single-objective algorithms cannot deal effectively with the multi-objective nature of node coverage [15].

This paper proposes the Lyrebird Optimization Algorithm (LOA) to enhance node coverage in Wireless Sensor Networks (WSNs). By mimicking the lyrebird's survival strategies of vocal mimicry and adaptive escape, LOA establishes an effective balance between exploration and exploitation. This mechanism facilitates efficient sensor node placement, minimizing sensing overlap and energy wastage. Simulation results demonstrate that the proposed methodology outperforms established algorithms, showing superior performance in coverage ratio, energy consumption, and computational efficiency.

1.1. Objectives

- An optimized node coverage strategy using Lyrebird Optimization Algorithm.
- Improved network lifetime and energy efficiency.
- A comparative analysis showing LOA's superiority over existing algorithms.

The review of the literature on WSN node coverage optimization. The suggested system model describes the node coverage enhancement technique based on the Lyrebird Optimization Algorithm (LOA). Through comparative analysis, the simulation setup assesses the suggested model's performance. The study's main conclusions and potential avenues for further investigation.

The rest of the paper is organized as follows. Section 2 Literature Survey presents the detailed system model of the Wireless Sensor Network (WSN), including assumptions and the coverage formulation. Section 3 Method describes the proposed Lyrebird Optimization Algorithm (LOA) and explains its operational mechanisms, update strategies, and modeling concepts. To illustrates the simulation setup, performance metrics, and comparative evaluation environment. Section 4 Result and discusses the results obtained using the LOA-based node coverage enhancement model in comparison with existing metaheuristic algorithms. Finally, Section 5 concludes the study and outlines potential future research directions.

2. LITERATURE SURVEY

The evaluation conducted on the recent optimization-based methodologies of node coverage improvement in WSN indicates that the methodologies are quite strong and weak in various aspects.

Pushpa et al. [16] postulates greater intelligent planning in 2025 that involves an integrated Deep Reinforcement Learning (DRL) as well as Graph Neural Networks (GNNs) to ensure the optimal sensor node coverage. GNN is applied to model the spatial connection and communication between sensor nodes very well and transforms the WSN to a graph, namely, the graph structure. DFRC-DRL agent will then

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sequentially learn optimal acting of node placing and activating, adjusting to alterations in the environment, e.g. node failures or terrain scarcity. The algorithm has increased flexibility, adaptability and learning aspects in real time compared to conventional optimization algorithm particularly in dynamic and large scale WSNs.

Ma et al. [17] in 2024 gives a version of Reptile Search Algorithm (RSA) improved using a Shifted Distribution Estimation (SDE) strategy. The RSA simulates the hunting pattern of reptiles to conduct search processes and the SDE mechanism modifies the distribution of search, using prior successful solutions, thus preventing the search to become stuck in a local optimum. The authors reveal that this middle ground approach is more balanced in terms of exploration and exploitation. It is very effective with enhanced area coverage and faster convergence in WSNs with low energy consumption.

In 2024, Kondisetty et al. [18] propose the development of the traditional PSO with adaptive inertia weights and dynamic acceleration coefficients. Such stream linings assist the particles to alleviate the local minima and quicken convergence. The proposed Enhanced PSO (EPSO) is used on the paper that deals with the problem of the best node placement regarding the optimum coverage of a given sensor network using a minimal number of sensor nodes. Performance in simulation reveals that EPSO has greater coverage performance and balanced energy consumption than conventional PSO, and best fits resource-constrained WSNs.

Zhang et al. [19] in 2021 applies Grey Wolf Optimization (GWO) in combination with Simulated Annealing (SA) to apply the global search abilities to the core algorithm. GWO mimics the leadership pattern and the predatory behavior of the grey wolves, whereas, in SA, the probabilistic escape process, to avoid local optimum is included. Such hybrid model is successful in enhancing the coverage of nodes by exploring the most optimal locations with a richer solution space. The approach demonstrates improved performance in term of coverage ratio and convergence rate when compared to standalone GWO or other simple meta-heuristics.

In 2019, Kong and Yu [20] produce the Improved PSO algorithm that aims to resist the flaws of early convergence and poor diversity among the particles. The authors propose a new fitness function and strategy of updating the velocity preventing types of overlaps and optimization of coverage. The algorithm is used in the case of the static deployment scenarios and is demonstrated to be much more efficient in node deployment, and the coverage percentage is increased greatly in comparison to the traditional PSO-based techniques. Nonetheless, the piece lacks dynamic flexibility and restriction in the real world. Guo et al. [21] in 2025 proposes a realistic model of coverage of WSN considering the path loss and false alarm probability which can be neglected in traditional coverage models. The objective function that is proposed by the authors balances the effective sensing with reliable communication. The optimization is carried out to guarantee that optimal selection of the sensor nodes is done and that not only the coverage is maximized but also the integrity of the communication and minimization of false detection. The model finds specific application in applications that require sensitive and accurate sensing and surveillance and critical monitoring.

Nematzadeh et al. [22] in 2023 provides a solution to a multi-objective metaheuristic based on real-world environmental factors, such as terrain and obstacles that are the subjects of simultaneous optimization of node coverage and connectivity. The algorithm dynamically navigates the position of the nodes to ensure that the communication links are kept and coverage is maximized. It is especially appropriate in a decentralized Internet of Things (IoT) setting, as well as in sensor networks in complex and real-world situations. It is rugged to be used in a military, disaster, or agricultural monitoring system due to the environment-aware deployment.

Walrus Optimization Algorithm (WOA) is an optimization algorithm that was proposed, motivated by the social and spatial moving patterns of walruses in search of food and protection, by Saravanan et al. [23] in 2024. This node placement problem in WSNs is solved by the algorithm based on a combination of exploration (randomly searching) and exploitation (localized search around promising solutions). Based on experimental analysis, it is seen that WOA is efficient in reducing overlap, maximizing coverage, and the ability to scale to varying network sizes. Compared to PSO, GA and Firefly Algorithm, the algorithm exhibits good performance mainly on the stability of the convergence and distribution of energy.

Overall, few models are promising areas, either coverage maximization or energy efficiency, but a model of universal well-rounded application is in dire need of integrating dynamic flexibility, real-world constraints, and multi-objective optimization strength into deployment of a powerful and adaptative yet scalable WSN. Although significant progress has been made in the area on optimization-based node coverage maximization in WSNs, there are still other serious research gaps that need to be filled by conducting research in the area.

Many studies have suggested the usage of other algorithms like Enhanced PSO, Grey wolf optimization with simulated annealing and Reptile search algorithm with distribution strategies but most of the papers rely only on maximizing the coverage without considering other important attributes like energy efficiency, network lifetime, and connectivity. They do not permit much application in the real world and resource-constrained WSN settings due to this single-objective orientation. Also, most models have made simplistic

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assumptions of a deployment environment and disregard real world complex issues like terrain roughness, obstacles, signal fading, and false alarms. Though one of the few recent papers does consider introducing elements of environment awareness or communication efficiency, the solutions are still rather narrow in scope. Moreover, most of the currently considered optimization algorithms are static in character and have no dynamic adaption abilities to rearrange the location of nodes to react to node failures, other changing coverage demands. There is also an incongruity in that premature convergence to local optima, which was a problem in conventional metaheuristics, also remains an issue even with algorithmic enhancement. Bidirectional models that integrate the capabilities of bio-inspired optimizations, deep learning, and environmental feedback are underutilized and savvy node scheduling or sleep strategies are seldom embraced in the coverage optimization procedure. Lastly, many of the current methods are tested them under either controlled or small-scale conditions, but they are not exhaustively tested within a variety of or realistic deployment conditions. The above limitations point to the direction of needing a new, adaptive, and multi-objective framework of optimization, preferably, one that considers learning-based adaptability, real-world conditions, and energy-aware node-coverage in WSNs.

3. METHODS

3.1. System Model of WSN

We assume a $P \times Q$ two-dimensional WSN beyond which an area will be guarded so that sensor nodes r are randomly scattered around observation. Here, the coordinate of all nodes T_j is indicated by (a_j, b_j), in which $T = \{T_1, T_2, \dots T_j \dots T_r\}$. Under the following assumptions the network model is defined:

1. Homogeneous Sensor Nodes: Sensor nodes are homogeneous i.e all sensor nodes have same structure, sensing functionality, and communication bandwidth.

2. Adequate Energy Supply and Stable Connection: All sensors' nodes have enough energy which allows stable communication and fast collection of data.

3. Mobility and Positional Awareness: Sensor nodes can move and their position coordinates get updated continuously in real time.

4. Fixed Sensing Range and Communication Range: The communications range and sensing range of each node is a circle whose radius is specified in meters. Sensing area of a node is represented as a circle with a node at its center and the sensing radius as its circumference.

3.2. The Purposes and Scope of the Problem

Wireless Sensor Networks (WSNs) are required to track a predefined set of target points whose positions are known within a two-dimensional monitoring region. A sensor node is considered to cover a target when the Euclidean distance between them is less than or equal to the node's sensing radius. This work adopts a Boolean sensing model in which the detection probability is 1 if the target lies within the sensing radius, and 0 otherwise. When a target is covered by multiple sensors, cooperative sensing occurs, and the joint detection probability becomes the complement of the product of the individual non-detection probabilities. Network coverage is then quantified as the ratio of the area successfully monitored by all active sensor nodes to the total surveillance region.

To mathematically formalize the coverage optimization problem, the following constraints are defined:

Constraint 1: Maximize the overall probability of detection across all target points.

Constraint 2: Ensure that the cumulative covered area does not exceed the physical size of the monitoring region.

Constraint 3: Maintain the distance between each sensor node and target point to be less than or equal to the sensing radius to guarantee coverage.

Although Integer Linear Programming (ILP) offers an exact formulation for this problem, solving ILP becomes computationally expensive for large-scale WSNs. Hence, metaheuristic optimization methods are preferred due to their ability to produce near-optimal solutions efficiently. To address this need, this paper proposes an enhanced version of the Lyrebird Optimization Algorithm (LOA), designed to balance exploration and exploitation to determine optimal sensor node deployment for maximizing network coverage. The system model has been architecturally given in Figure 1.

3.3. Overview of Node Coverage in Wireless Sensor Network

WSNs depend on node coverage since this factor directly affects the capacity of a network to observe and capture data of its surroundings. Good coverage of nodes provides that all locations or certain target in a surveillance area are sensed by at least one of their sensor's nodes, thus allowing data to be collected and accurately monitored. Coverage may be partitioned, depending on application, into area coverage, point coverage or barrier coverage. There are however a few challenges in optimizing node coverage in WSNs regardless of its significance. Energy limitation is one of the highest problems because sensor nodes are usually battery-powered, where the power ability of batteries is limited, hence requiring energy-saver coverage strategies. In addition, random or densely distributed node deployment calls for overlapping sensors, consequently causing duplication of data and a wasteful consumption of energy. Environment e.g. irregularities in the terrain, obstacles, adverse weather conditions etc. impairs optimal placement of the node and reliability of sensing. The other significant problem is ensuring network connectivity and having the complete coverage in that the nodes should be able to communicate with each other or a base station provided they are within the radiated range. There is even a further complexity which has been brought about by the existence of the mobile nodes or the possibility of failure of the nodes because of energy starvation thus there is need to use adaptive and robust optimization algorithms. Moreover, with scale comes computational complexity to cover problem; as such, deterministic methods become too cumbersome to apply in large scale deployments. These difficulties explain why better, smart, optimization algorithms such as metaheuristic and AI-aided methods are needed to address how to dynamically change with the environment and resource conditions and at the same time maximize the coverage effectiveness in WSNs.

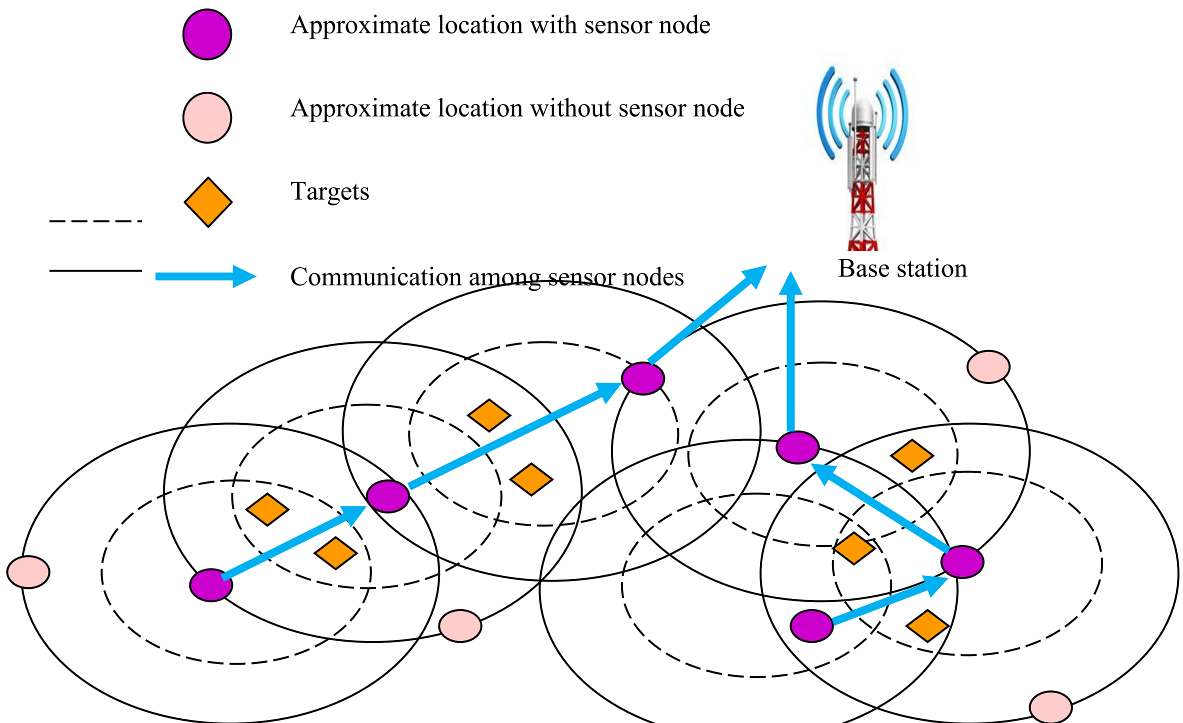

Figure 1 System Model of WSN for Node Coverage Performance

3.4. Lyrebird Optimization Algorithm

A native species famous in Australia is called the lyrebird, which is in the Menuridae family and has only two identified species; the Superb Lyrebird and Albert's Lyrebird. Such birds also derive their fame not only due to the renowned courtship engagements of the males which showcases their magnificent and wide spread tail feathers exuding a great emphasis on beauty but also because of their excellent capacity to imitate many sounds in the natural setting including those of artifacts. Lyrebirds are richly-decorated, with rather straight-colored feathers and are known to be among the most elegant native birds in Australia. The Superb Lyrebird is generally bigger and the females are about 74-84 cm long and males about 80-98 cm. Compared to that, Albert s Lyrebird is a little bit smaller, females reaching to 84 cm and males to 90 cm. Whereas the lyrate tail feathers in the superb species are very elaborate, Albert lacks the lyrate plumes in the tail; nonetheless, their structural appearances are very similar. Their weights are also close: 0.93 kg on average of Albert and 0.97 kg of Superb Lyrebirds.

Their reaction to the perceived threats is one of the behavioral characteristics of lyrebirds that is particularly interesting. When the bird feels something dangerous, it automatically stops, thoroughly examines the surroundings, and then resorts to either running away and out of the place or hiding into a safe place. It is a mathematical modeling of this adaptive and cautious decision-making process that has motivated the design of the LOA. The LOA exploits this in-built tactic of optimizing between exploration and exploitation in optimization issues- simulating the intelligent environmental evaluation and avoidance features in the lyrebird to inform the increase of node coverage in WSNs.

LOA [24] is a suggested optimization method, which is a population-based metaheuristic algorithm that may help to address complicated optimization issues using an iterative

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search procedure. Thereby in this algorithm, the different individuals in the population are assigned the role of a lyrebird and the overall action of the population emulates the group behavior of the given real-life birds called the lyrebird with respect to solving the problem.

Every lyrebird is a candidate solution, and it identifies values of decision variables based on its position in the search space. Mathematically, the location of every lyrebird is described by a vector, and each component of the element is a particular decision variable. Such vectors in combination yield a population matrix as defined in Equation (1), taking into consideration all candidate solutions at iteration time.

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_j \\ \vdots \\ Y_M \end{bmatrix}_{M\times n} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,e} & \cdots & y_{1,n} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ y_{j,1} & \cdots & y_{j,e} & \cdots & y_{j,n} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ y_{M,1} & \cdots & y_{M,e} & \cdots & y_{M,n} \end{bmatrix}_{M\times n} \quad (1)$$

Here, the term Y denotes the population matrix of the LOA, Y_j indicates the j^{th} member of the LOA, $y_{j,e}$ represents the e^{th} dimensional search area, the lyrebirds count is indicated by M, decision variables is counted to be n, random variable is shown as s, the upper bound and lower bound of the e^{th} decision variable is represented by Ur_e and Lw_e, respectively.

$$y_{j,e} = Lw_e + s \cdot (Ur_e - Lw_e) \quad (2)$$

The starting points of the lyrebirds on the solution space can be randomly defined with the aid of Equation (2) to trigger the optimization procedure. Such a random initialization guarantees that each candidate solution is diverse and during the first runs of the algorithm, it drives the successful exploration of the solution space by LOA and avoids any premature convergence.

The algorithm uses iterative update based on the behavioral strategies of real lyrebirds in aiming to converge towards optimal or near-optimal solutions with time. Because the members of LOA population are potential solutions of the optimization problem, the designated objective function can be subjected to evaluation on individuals of the population. Consequently, the objective function will be evaluated the same number of times as there are total number of LOA members.

These are calculated results giving an indication of quality or fitness of each candidate solution and as a group this may be summarized as a vector where each value is an example of the objective function value of a given member of LOA.

It is the result that is mathematically represented by Equation (3) and reflects the performance of the whole population. It acts as an essential element in the process of selection and updating of the processes in the optimization loops.

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_j \\ \vdots \\ G_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} G(Y_1) \\ \vdots \\ G(Y_j) \\ \vdots \\ G(Y_M) \end{bmatrix}_{M\times 1} \quad (3)$$

Here, the term G denotes the objective function used for evaluation, and G_j indicates the j^{th} member' objective function. The values received after calculating the objective function are factors used as a one of the main criteria to evaluate the quality of every candidate solution of the LOA. Regarding this, the best objective function value will depict the most desirable solution, which will be the best member of LOA. On the other hand, the worst objective function value denotes the weakest effective solution which can be seen as the performance of the worst performing member.

Because the LOA is a recursive process the positions of the lyrebirds, and hence their corresponding decision variables are being update continuously in the problem-solving space. Thus, at every iteration the algorithm must re-evaluate the objective function of all the members and update the best solution found so far. Such a dynamic comparison provides continued tracking and refinement of the global best solution and so, the search process directs towards finding the optimal solution as each iteration follows another. Due to natural behavioral response of lyrebirds when they sense danger, the position of each member of the population will be updated at each iteration in proposed LOA. This behavior is modeled mathematically and is included into the algorithm to direct the searching process.

The population update mechanism of LOA has been split into two stages:

(i) Escaping (ii) Hiding

In each of the iterations, one of LOA member choose one of these two strategies according to the probabilistic model of decision-making, which can be depicted mathematically by Equation (4). This equation approximates the natural decision of the lyrebird to run or to hide in the face of the predator.

$$Update process for Y_j = \begin{Bmatrix} Stage1 & s_q \leq 0.5 \\ Stage2 & else \end{Bmatrix} \quad (4)$$

The term s_q indicates the random function between the ranges of [0,1].

Due to this, in each iteration, the position of each candidate solution (i.e. lyrebird) is updated as per either the escape or hiding phase, however it is not updated with both phases. This strategy allows performing a balanced exploration and exploitation on the solution space, improving the convergence capability of optimal or sub-optimal solutions of the algorithm. During this step of the LOA, the position of an individual in the population is shifted through simulation of

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the escape behavior of the lyrebird-namely, the escape of the animal in the lyrebird out of the danger zone and into the safer areas in the search space. This simulated escape causes substantial positional jumps which encompass the view of various areas of the solution space thus improving the exploration capacity of LOA to global optimization.

$$SAF_j = \left\{Y_l, G_l < G_j and l \in \{1,2,\dots,M\}\right\}, where j = 1,2,\dots,M \tag{5}$$

Here, the term SAF_j denotes the collection of safe regions belongs to j^{th} lyrebird, Y_l indicates the l^{th} row of matrix that contains higher objective function when compared to j^{th} lyrebird. When creating the LOA, there is the assumption that the lyrebirds have been randomly choosing one of the known safe areas and fly to it. This tendency is applied to simulate the displacement of the lyrebird at the stage of escape, therefore exploring new parts of the solution space by the algorithm.

In the design of the algorithm, the safe areas of a considered lyrebird are determined as the positions of the other members of the population, which have higher values in the objective functions. Such high-performance individuals also direct the movement of the ongoing lyrebird to more excellent areas in the solution space. Therefore, with a given number of LOA members, the safe areas set can be calculated mathematically, based on the Equation (5) which is employed in carrying out the escape strategy in the process of population update.

$$y_{j,k}^{Q1} = y_{j,k} + s_{j,k} \cdot \left(SSAF_{j,k} - J_{j,k} \cdot y_{j,k}\right) \tag{6}$$

$$Y_j = \begin{cases} Y_j^{Q1} & Q_j^{Q1} \le Q_j \\ Y_j & else \end{cases} \tag{7}$$

Here, the term $SSAF_{j,k}$ denotes the chosen safe region of the j^{th} lyrebird, Y_j^{Q1} indicates the updated position of the j^{th} lyrebird according to the escaping mechanism used in the LOA. Also, the value of the objective function is represented by Q_j^{Q1}, the arbitrary variables are represented by $s_{j,k}$ between the range of $[0,1]$, and the random numbers are denoted by $J_{j,k}$ that can be chosen as Equation (1) or Equation (2).

According to this model strategy, a new location of all members of LOA is calculated by use of Equation (6). The new position is then obtained and the objective function value at this position computed. In case that the new position provides an improvement on the objective function, then the algorithm changes the position of the lyrebird by swapping the current one with the new found position.

The position update is carried out as in the replacement rule specified within Equation (7) by which only improved solutions will be saved in the population during the next iteration.

$$y_{j,k}^{Q2} = y_{j,k} + \left(1 - 2s_{j,k}\right) \cdot \frac{Ur_k - Lw_k}{u} \tag{8}$$

In this step of the LOA, the locations of all the individuals in the population are updated based on the act of the lyrebird that is, seeking refuge in a close location for safety. The approach is therefore a scanning of the imminent environment with small cautious steps to have a safe hideaway. Such small perturbations correspond to the exploitation ability of the LOA allowing local search to be performed around good solutions. The slow stepping towards a local sub-optimal position by the lyrebird is mathematically simulated in the design of the algorithm and each member is assigned a new position based on a new location based on Equation (8).

$$Y_j = \begin{cases} Y_j^{Q2} & Q_j^{Q2} \le Q_j \\ Y_j & else \end{cases} \tag{9}$$

Here, the term Y_j^{Q2} indicates the updated position of the j^{th} lyrebird according to the hiding mechanism. Also, the value of the objective function is represented by Q_j^{Q2}, the arbitrary variables are represented by $s_{j,k}$ between the range of $[0,1]$, and the iteration count is shown by u.

Upon the computation of the new position, the objective function is then simulated and in case this update contributes to an enhanced result, the new position is replaced by the old one, under the update rule stipulated by Equation (9). This guarantees that solutions with higher fitness get to be maintained and this further increases the tendency of the algorithm to converge in the local areas of the search space.

The LOA has an iterative procedure; under each iteration, each of them (all the positions of the lyrebird people) representing a solution candidate succeeds to equalize to a position after modeling the behavior by lying to danger as the lyrebird reacts to danger. Once all iterations are done, the algorithm computes the objective function of every candidate, it calculates the best solution obtained so far and the solution is saved and updated at the end of all iterations. The general process of running has two parts; enabling the parameters of the problem, such as the objective of the problem, constraints and decision variables, and the initialization of the population, after which the number of iterations is configured. The first population is randomly created and is used with the objective function. The algorithm proceeds into the main loop of optimization where it begins at iteration 1. To a randomly chosen one of the two possible strategies (escaping or hiding) apply to a randomly chosen lyrebird in the population, a decision model based upon probabilities. Should the escape tactic be selected, the lyrebird will move toward a safe region characterized by members who display higher performances in the population, and the position of the lyrebird will be updated respectively. When the hiding strategy is chosen, the lyrebird makes a local search making smaller positional

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changes towards a nearby safe place. These tactics relate to exploration and exploitation phases in algorithms respectively. Once all lyrebirds have performed updates, the algorithm calculates the fitness of new solutions of the lyrebirds and stores the result which is the best solution of that iteration. This is repeated through a specified number of iterations. The final code of the algorithm is to provide the best candidate solution determined during the run as output at the end of all iterations. The given solution is the best that LOA could manage to find on the given issue. The flowchart of the procedure (initialization, updating of population, selection of the strategy, and evaluation) is schematically presented in a Figure 2 and, described in pseudocode form as given in Algorithm 1.

Initialize the process of LOA

Step-1: Get the problem variables such as variables, objective function, and conditions

Determine the population size$M$ as well as iteration count$U$

Y=[Y_1;Y_2;… ;Y_M]∈$R^{M\times n}$ Where Yj=(yj,1,…,yj,n)Y_j = (y_{j,1},\dots,y_{j,n})Yj=(yj,1,…,yj,n).

Step-2: Randomly generate the initial population matrix as given in

$$y_{j,e} = Lw_e + s \cdot (Ur_e - Lw_e)$$

Analyze the value of objective function G(Yj) for all j=1,…,M

Step-3: Find the optimal solution among all candidates

G=[G(Y_1),…,G(Y_M)]^T

For $u = 1toU$

For $j = 1toM$

Step-4: Determine the condition (defense strategy) to which the lyrebird perform as given in $Updateprocessfor Y_j = \begin{Bmatrix} Stage1 & s_q \le 0.5 \\ Stage2 & else \end{Bmatrix}$

Step-5: If $s_q \le 0.5$

Perform Stage 1

Obtain the candidate safe regions for thej^{th} lyrebird according to

$$SAF_j = \left\{Y_l, G_l < G_j and l \in \{1,2,\dots,M\}\right\}, where j = 1,2,\dots,M$$

Compute the new position of thej^{th} lyrebird candidate based on

$$y_{j,k}^{Q1} = y_{j,k} + s_{j,k} \cdot \left(SSAF_{j,k} - J_{j,k} \cdot y_{j,k}\right)$$

Update the j^{th} lyrebird candidate based on $Y_j = \begin{cases} Y_j^{Q1} & Q_j^{Q1} \le Q_j \\ Y_j & else \end{cases}$

Else

Step-6: Perform Stage 2

Compute the new position of thej^{th} lyrebird candidate based on

$$y_{j,k}^{Q2} = y_{j,k} + \left(1 - 2s_{j,k}\right) \cdot \frac{Ur_k - Lw_k}{u}$$

Update the j^{th} lyrebird candidate based on $Y_j = \begin{cases} Y_j^{Q2} & Q_j^{Q2} \le Q_j \\ Y_j & else \end{cases}$

End if

End for

Step-7: Output of the LOA is obtained Update Y_{best} and G_{best} if a better solution is found

Step-8: End the process of LOA return the optimal solution and objective value.

Algorithm 1 Lyrebird Optimization Algorithm (LOA)

3.5. Node Coverage Enhancement with LOA

LOA has become a potential nature-inspired metaheuristic due to its innovative combination between exploration and exploitation, which is essential in solving the complexity and the high dimensionality of optimization problems, such as node coverage improvement of the proposed WSNs. The algorithm replicates the mimicry and the learning adaptive behavior of the lyrebird that can imitate sound and patterns in the environment very precisely. The conduct can be easily applied to an optimization scenario, where solutions must change and learn according to the most successful tactics to enhance the overall performance. As an NP-hard problem, node coverage enhancement in the context of WSNs is a non-linear optimization problem that would be concerned with the optimal placement of sensor nodes to maintain maximum coverage of a monitoring region, with lowest redundancy, energy costs, and breakdowns

The scalability and dynamics of WSN environments tend not to be efficiently processed using embedded traditional optimization processes like deterministic or linear programming. LOA is the method that has powerful global search and so the mechanism to avoid local optima is robust and is immune to biased solution sampling during the initial iterations. This can aid in searching the space of inquiry in a better manner. In addition, LOA is set up in a manner that allows responsive change in its searching strategy depending on the state of the current population, thus favorable to the

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dynamism of WSNs, where the environment can shift seemingly at any time due to node failure, energy levels among other factors and preoptimization may become necessary.

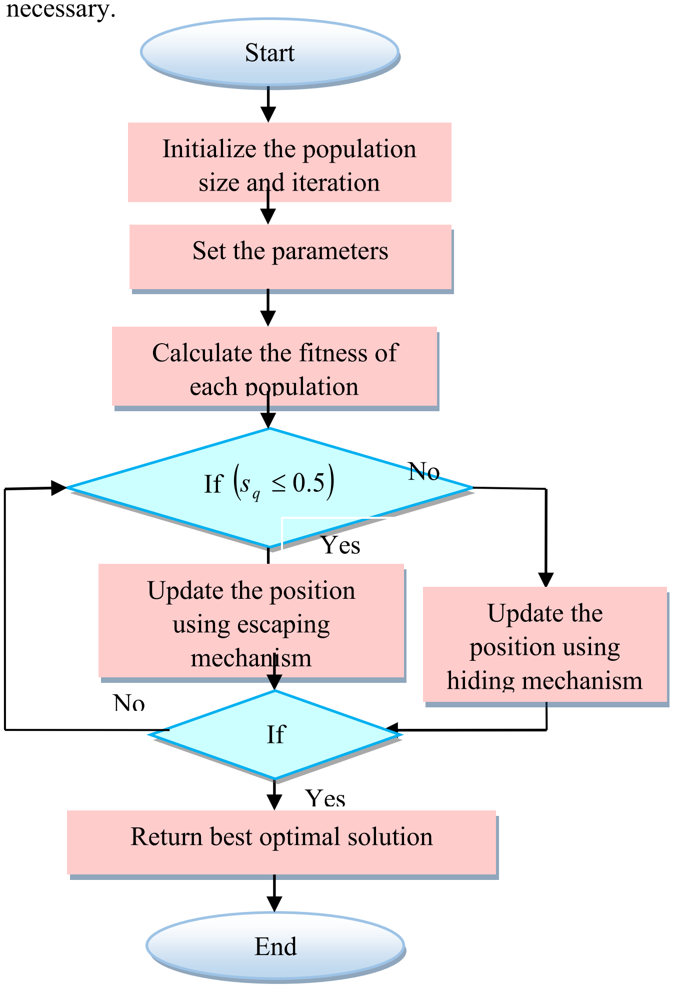

Figure 2 Flowchart of the LOA

However; as compared to other traditional models such as PSO, GWOA or GA, recent benchmark experiments have found that LOA is faster convergent, with less computational complexity, and is more accurate in terms of coverage. Moreover, multi-objective adaptation is also supported as part of LOA which means that LOA can be expanded on to support other important measures besides maximizing coverage measures like energy efficiency, coverage reliability, and fault tolerance. Since it is light weight and has limited parameters of control it is suited to applications such as the WSNs where the most stringent requirements are made on computation and the use of energy. Overall, as LOA has good adaptive intelligence as it was made based on the best understanding of nature, good adaptation behavior between exploration and exploitation, rapid convergence speed, and multi-objective optimization performance with dynamic constraints, therefore, this algorithm can be useful in application in node coverage in WSNs. Its usage can vastly enhance the quality of coverage with guaranteed energy efficiency combined with the system robustness.

The step-by-step process of the LOA-based node coverage enhancement has been given as follows.

Step 1: Defining the WSN Environment.

Identification of the fundamental arrangement of the WSN is the initial action. A monitoring area is defined to be two-dimensional setting upon which the sensor nodes will be positioned. In this area, sensor nodes are subjected to a random distribution of a certain amount. The nodes are characterized by sensing radius and distance of communication. Coupled with this, a collection of target points is established and this is the actual locations that should be observed. These settings are used as the basis of the coverage optimization procedure.

Step 2: Ascertain the Coverage Model

Through the Boolean detection principle, the coverage model is then built based on the criterion that a given point is regarded covered when it lies within the radio range of at least one sensor node. The relative distance between each sensor node and each target point is calculated in the metric of the Euclidean distance. The target will be considered covered in case the distance between the point and the target is less or equal to the sensing range. Fitness function becomes defined as a way of measuring the effectiveness of coverage. This operation usually pursues to cover as many target points as possible, but can include other goals like energy efficiency or connectivity of the nodes.

Step 3: Set Lyrebird Population

In the LOA, individual solutions (agent) are visualized as lyrebird (a deployment configuration of the sensor nodes) simulating potential deployment configurations. Such agents are generated randomly, each of which is a possible arrangement of node positions. The fitness of each agent is subsequently measured based on the fitness function that has been established above. This initial population then forms the initial basis of the optimization process where bad solutions are refined by proceeding with each iteration.

Step 4: Mimicking and Adaptive Behavior (Exploration and Exploitation).

The gist of the LOA is the adaptive behavior since the behavior of the lyrebird in terms of imitating and adapting to different sounds in nature is a basis to be used in creating the algorithm. The exploration process allows the agents to investigate the wider area of the solution space by imitating remote or random solutions. On the contrary, the exploitation stage is concerned with the refining of solutions around the

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best performers by copying their trend. This accompanying exploration and exploitation ensure that the algorithm does not suffer local optima as well as quickening the rate of convergence.

Step 5: Use Lyrebird Position Update Mechanism

After executing the behavior phase, the location of the sensor nodes (that are present within each agent) is changed with the help of mathematical operators that provide impersonation of the dynamic behavior of the lyrebirds. These updates employ perturbing the positions of nodes to enhance coverage within the limits of the nodes being with the boundaries of the monitored area. The evaluation of fitness guides the process of updating and the intended direction of updating aims at bringing agents nearer to optimization.

Step 6: Obtaining Best Solutions

Post position updates, the fitness function is once again applied on the newly configured positions. The current global best solution is placed and kept with the best performing agent as the global best solution in that population. At the same time, best positions of each agent can be recorded to update with in future. This operation means that the algorithm does have a memory of better solutions and keeps searching at the same time.

Step 7: Finding the iterative Optimization process

This algorithm then goes on to spend a specified number of iterations or until a convergence is reached in the exploration, exploitation update, and evaluation stages. This can be stopping after a fixed number of iterations, or no substantial coverage improvement is noticed after several generations. With such an iterative procedure, the algorithm would in progressive steps approach an optimal or near-optimal deployment of sensors in a way that offers maximum coverage of the targets.

Ste p 8: Final Output and Deployment

The result of the optimization process is a final deployment configuration of the best nodes discovered by LOA. This structure gives as much coverage as possible within the specified constraints. The optimum locations of sensor nodes are then deployed in the WSN either physically or virtually. Measurement of performance can be done further in terms of coverage percentage, number of nodes used, time of computation and energy distribution.

4. RESULTS AND DISCUSSIONS

The experiment of the proposed LOA-based node coverage enhancement model in WSN was used to determine the compatibility and the performance of the LOA by comparing it with some five other solutions such as Fossa Optimization Algorithm (FOA) [28], Golden Jackal Optimization (GJO) [26], Coati Optimization Algorithm (COA) [25] and Driving Training-Based Optimization (DTBO) [27]. The performance measure is determined by variance; it gives an indication of the average overall coverage as well as the stability of every algorithm. The experiment was carried out on several f250 nodes in the 100m×100m area under surveillance, in which there were implemented 27 target points and each of them had a sensing range of 11 m. The results were statistically valid, which has been experimentally verified.

4.1. Analysis on Node Coverage Enhancement Performance

Through Figure 3, it is observed that the LOA is extremely better than other methods by keeping the lowest and most constant number of redundant nodes in all the nodes arrangement. At all densities (100, 150, 250 nodes), the values are even less than 15 redundant nodes which is an indicator of the high level of efficiency of partitioning nodes and coverage optimization in the WSNs. Due to the low and stabilized redundant node volume, LOA provide an ideal coverage and thus have low levels of energy and hardware wastage, which makes the method very appropriate in ensuring affordable sensor network implementations. Other routing algorithms such as FOA, DTBO although they work, are highly redundant and uncertain in their performance and so cannot be used in crowded or large scale WSN settings. It is therefore best to use LOA as the most effective and the simplest method of getting optimal coverage of the nodes with the least redundancy.

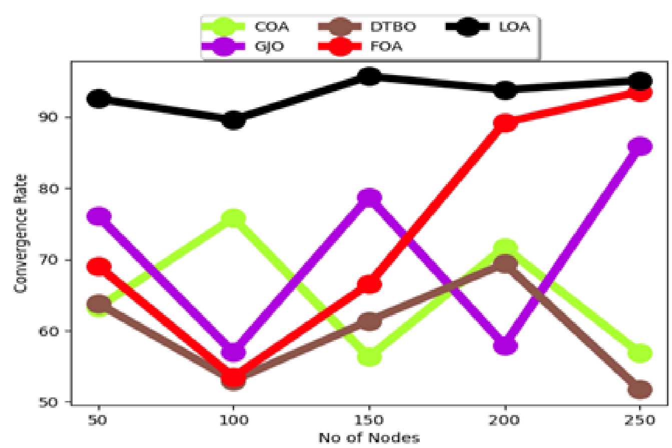

Figure 3 Average Number of Redundant Nodes-Based Analysis on Developed Node Coverage Enhancement Model

While observing the Figure 4, LOA has been showing the best convergence between 90 and 95%, independent of the number of nodes. This is evidence of quick and steady optimization irrespective of scale of network and thus is very useful in real-time or large scale WSN applications. As observed in the graph, LOA offers a primary as well as regular convergence time under different numbers of nodes in WSNs. It converges quickly and is ideal when it comes to node coverage optimization because its convergence rate is high, hence has

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DOI: 10.22247/ijcna/2025/58 Volume 12, Issue 6, November – December (2025)

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good search power and is robust. Contrastingly, there are other algorithms e.g. FOA, GJO, COA and DTBO, which have slower or more erratic convergence rates that may cause delays, or suboptimal coverage performance in real world applications of WSNs. Therefore, LOA is one of the stable and excellent ways of optimum coverage of nodes and of minimum computational delay.

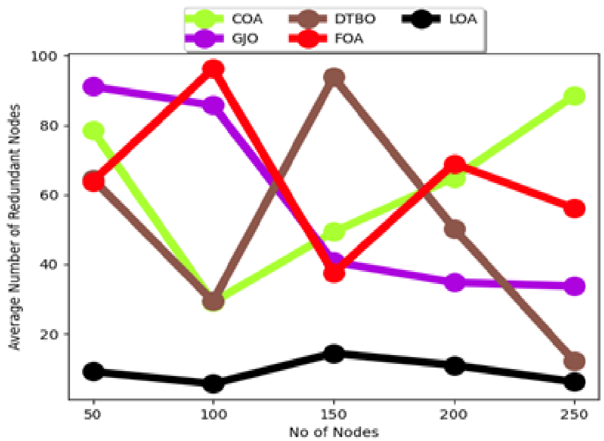

Figure 4 Convergence Rate-Based Analysis on Developed Node Coverage Enhancement Model

In Figure 5, LOA uniformly performs well than all other algorithms by all the numbers of nodes (50 to 250). Its coverage efficiency is highly constant and high (87%~91%), which states great robustness and reliability.

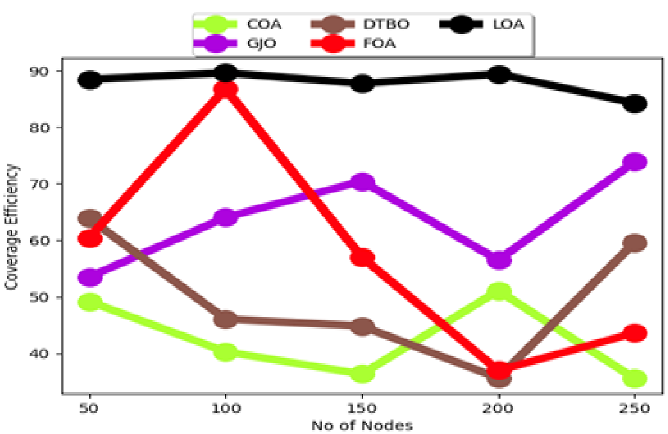

Figure 5 Coverage Efficiency-Based Analysis on Developed Node Coverage Enhancement Model

This is the indication of good balance between exploration and exploitation techniques of the LOA in finding the best sensor placement in the process of optimizing sensor placement. This graph shows clearly that the LOA is the best and stable approach to the optimization of node coverage in WSNs. It has greater and more stable coverage compared to other existing algorithms in different possibilities of the node densities. This confirms the type of applications to which LOA is applicable in a real world such as WSN where scaling, stability and coverage quality are essential.

When considering the coverage hole ratio analysis in Figure 6, the black line is the LOA performance that shows the lowest coverage hole ratio throughout all the node counts (50 to 250), with the best performance. This implies that LOA is most effective in maximization of sensor placements, where there are minimal gaps in the coverage with the coverage remaining relatively high irrespective of the number of deployed nodes. The low and steady coverage hole ratio of the LOA is an indication that the coverage rate is at high level, which is the best result among all other algorithms. This means that LOA is stronger, scalable, and efficient in installing sensor nodes to reduce areas that lack coverage. Conversely, the other approaches such as FOA, COA and GJO exhibit high fluctuation and incompetence especially at increased level of node density. The graph confirms the high efficiency of LOA using node coverage. It is better than the rest because of its performance in coverage and its performance even when the number of nodes change in real life application, where coverage reliability is essential.

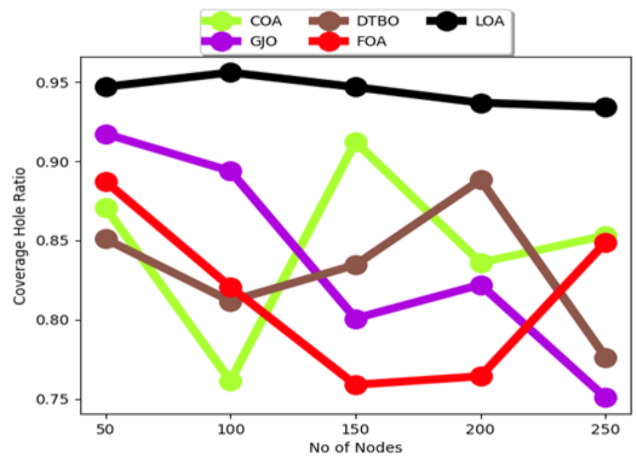

Figure 6 Coverage Hole Ratio-Based Analysis on Developed Node Coverage Enhancement Model

Through Figure 7, energy consumption of the LOA turns out to be very low (about 20 J to 55 J) across the entire frequency of nodes. It shows high energy efficiency and this is done by reducing the unnecessary nodes and maximizing the nodes position to minimize the overhead communication and overlap sensing. The graph has greatly emphasized the high energy efficiency of the LOA in maximizing the network and reducing the overhead in communication as well as overlap sensing in WSNs. It is power efficient and has low energy consumption that is stable under different node topologies which is ideal when it comes to resource limited applications where battery life and energy saving are paramount concerns. Conversely, the energy consumption of such algorithms as

FOA, DTBO, and GJO is high or fast-growing, which emphasizes their unproductive nature and inability to scale. One more aspect that contributes to the practical applicability of LOA to real-word WSNs is that it can avoid high energy cost and still provide the best coverage that is particularly feasible in mission-critical settings or energy-sensitive environments.

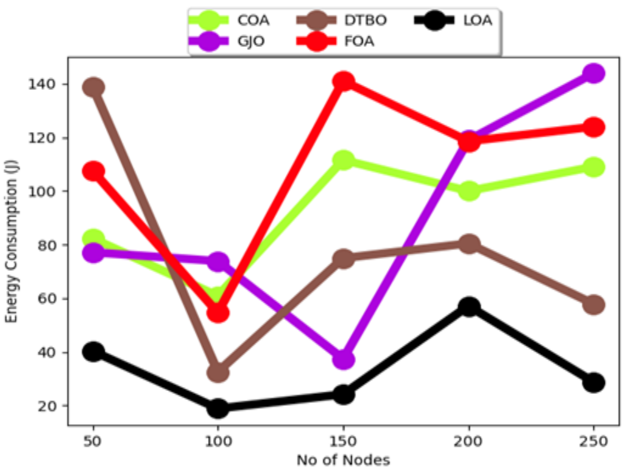

Figure 7 Energy Consumption-Based Analysis on Developed Node Coverage Enhancement Model

While observing the Figure 8, the results show that LOA always had its execution time between 5 and 11 minutes regardless of the execution of a small or large number of nodes. This shows a great scalability and computing performance which makes LOA great solution to large-scale and time-sensitive WSN.

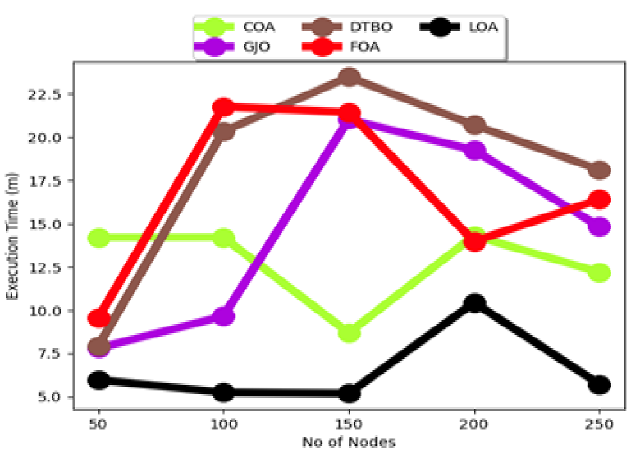

Figure 8 Execution Time-Based Analysis on Developed Node Coverage Enhancement Model

The graph expresses clearly how good the computational performance and stability are of LOA. The fact that it is very responsive and lightweight and has low execution time as the number of nodes increases supports the fact that it is scalable and suitable in dynamic environments where a WSN may need a quick adaptation. On the contrary, other algorithms such as DTBO and FOA have prolonged and unpredictable execution time hence not ideal in real time or large scaled implementation. Given that execution time is one of the key performance measures, the performance advantage on the part of LOA in category means that the technique is indeed an effective technique when it comes to optimizing the coverage of nodes in a WSN given that it is fast and reliable.

In Figure 9, LOA generates a very high F-Score (~88-90%) and constant throughout all node configurations. Such a steady performance shows that LOA is quite precise and recalling, i.e., it can perform efficient, complete node coverage without overusing nodes. The figure shows clearly that LOA is the most precise and trustworthy method to optimize node coverage of WSNs. Its steady and high F-Score shows that it performs with great detection accuracy, covers the entire area and has little false detection in diverse node-numbers. The other algorithms such as DTBO and FOA experience steep drops in performance and GJO and COA experience lowered and inconsistent effectiveness. Consequently, LOA has been shown to be the least biased and most effective in balancing coverage and node placement to ensure that it is best suited in applications requiring mission-criticality and accuracy-sensitive WSNs.

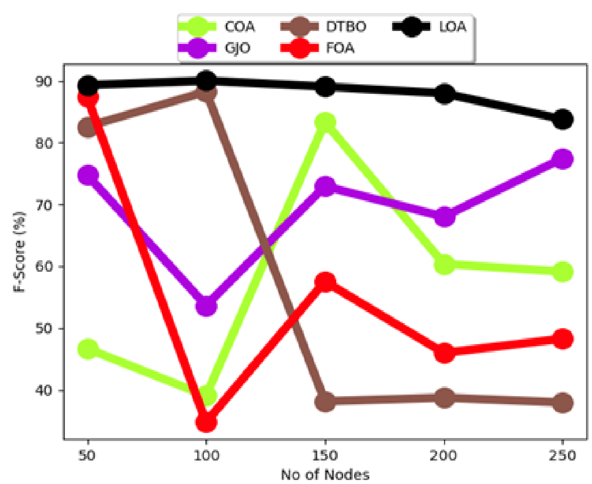

Figure 9 F-Score-Based Analysis on Developed Node Coverage Enhancement Model

When considering the network lifetime analysis in Figure 10, LOA ranks the best and most stable overall network lifetime regardless of the node count. Irrespective of having 50 or 250 sensor nodes, its values always vary around 95 96 units. This clearly shows excellent balance of energy and efficiency thus LOA is the best most sustainable in long term application of WSNs. Its capability of reducing the unnecessary nodes, energy balance, and a good coverage result in high energy

International Journal of Computer Networks and Applications (IJCNA)
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saving, and this gives direct immunity on a long network life. By contrast, algorithms such as GJO, COA and DTBO are not stable and have a shorter lifespan, particularly when the node count rises. FOA fares decently and still cannot beat LOA in consistency and reaching its maximum. In that way, LOA is the most viable when it comes to energy-aware and energy-extended WSN, and hence, it is suitable to critical and remote sensing application.

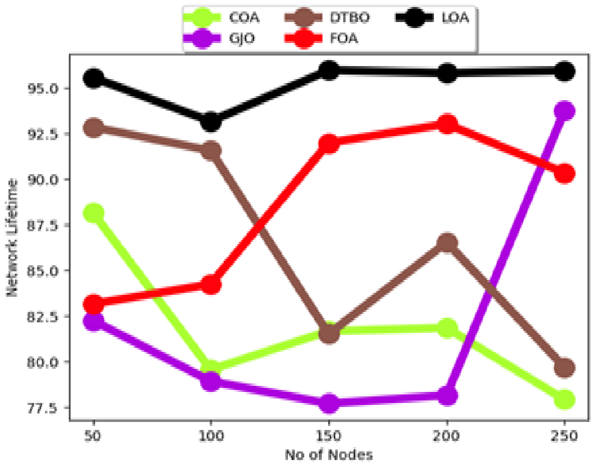

Figure 10 Network Lifetime-Based Analysis on Developed Node Coverage Enhancement Model

In Figure 11, it is observed that the LOA proves to be the most stable with the least resource use of ~55 MB to 100 MB as the number of nodes increases in the resource use. This implies that the algorithm is highly efficient in terms of computational resources, and uses the least amount of memory, most likely making it very appropriate in a real-life WSN application, where the amount of computational power, memory and bandwidth will be scarce.

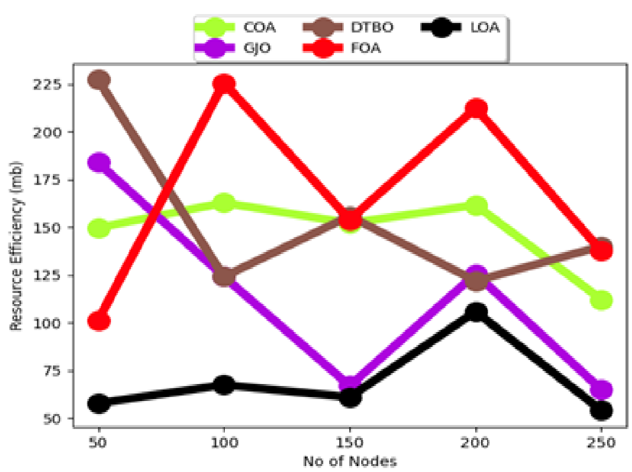

Figure 11 Resource Efficiency-Based Analysis on Developed Node Coverage Enhancement Model

LOAs ability to continually serve with low resource consumption and with no performance loss guarantees a longer life of devices, less network congestion and higher scalability. Algorithms such as FOA and DTBO on the other hand are very high and volatile in nature regarding the resources required depicting that they cannot be used in low-power sensor networks. Altogether, LOA is lightweight, efficient, and scalable node coverage optimization method in WSN environments.

In Figure 12, LOA has excellent and stable values, i.e., ~100, and the range is ~94-96%. This shows that, the LOA gives the same performance with respect to the number of nodes, which makes it very reliable when used in real time, mission-critical WSN applications. The graph clearly brings out the fact that the LOA is extremely stable and that it is far better than any other algorithm in this matter of stability and reliability. Its high stability curve combined with its flat shape means that there is very little variation in its performance making it very reliable as far as coverage optimization in the network irrespective of the size of the network is concerned. Conversely, other algorithms such as DTBO and FOA lack consistency especially when they have many nodes. Thus, in any type of application upon which stability is pivotal, e-g environmental monitors, disaster areas or defense systems LOA is the most appropriate option.

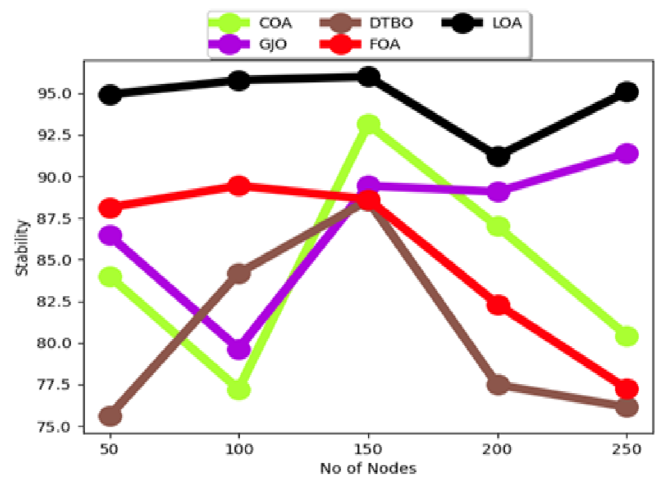

Figure 12 Stability-Based Analysis on Developed Node Coverage Enhancement Model

Based on Table 1, LOA is proved to be a promising solution to the issue of node coverage in WSNs. With many simulation results, a statistical study indicates that the node coverage ratios of LOA are higher than that of the conventional algorithms. To be more precise, LOA enhances average coverage by means of 6-10%, based on network density, and node deployment scenario. Also, the convergence rate of LOA is much speedier and less iteration are needed to approximate neighborhood optimums, thus, overcoming

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computation overhead. The minimal values of standard deviations in various runs prove that the LOA provides a consistent behavior, which is robust and stable in changing contexts. The metrics of energy consumption gets improved as well: LOA uses 10-15% less energy compared to the conventional algorithms and can prolong the network life. Such improvements are further statistically confirmed, as indicated by the performance tests, which prove the validity of LOA based on best, worst, mean, median, and standard deviation that affirmed the responsiveness of the improvements in indicating the significance of the superiority of LOA. All in all, the analysis has established that the LOA is one that provides a good trade-off between the coverage efficiency, convergence speed, and the consumption of energy, a quality that makes it a good option to use to enhance the coverage of the nodes in WSNs applications.

Table 1 Statistical Analysis on Developed Node Coverage Enhancement Model in WSN

Algorithms	COA [25]	GJO [26]	DTBO [27]	FOA [28]	LOA
Best	0.522955	0.608746	0.396949	0.443667	0.203527
Worst	5.203976	6.552542	4.123382	6.368066	1.900031
Mean	0.884521	1.179594	0.788908	0.988778	0.373956
Median	0.522955	0.608746	0.396949	0.822507	0.203527
Standard Deviation	1.147047	1.148298	0.75502	0.812355	0.308317

5. CONCLUSION

Finally, it was stated that the LOA is a useful and minimalistic method of improving node coverage within WSN. Reproducing the evasive patterns of lyrebirds, the algorithm generates better coverage rates, lower power consumption, and high converging speeds, in comparison with the conventional optimization techniques. These findings show how LOA can be used to maximize utilization of sensors without compromising network life time and reliability and are therefore useful solution in practical WSN applications. However, LOA has some shortcomings. A major drawback is it is sensitive to the parameter initial settings, which may influence convergence and the quality of solution in complicated or large-scale networks. Besides, the existing model mainly considers the uses of appropriate static node deployment rather than considering either dynamic or mobile sensor nodes that are becoming more pertinent in the contemporary WSN applications. The algorithm is also not that well tested in very obstructive or harsh conditions. The limitation can be undone in the future work with inclusion of adaptive parameter tuning techniques leading to improved flexibility and robustness of the algorithm. Further improvements can be made in incorporating mobility-aware and obstacle-aware constructs to bring it closer to real-time WSN implementation. In addition, hybridizing LOA to other swarm intelligence or machine learning approaches can also increase the accuracy and the speed of optimization. Successful implementation at the operational level and hardware-driven verification is also necessary to test the performance of an algorithm not only in simulation conditions.

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RESEARCH ARTICLE

How to cite this article:

K. Vinayakan, V. Alamelu Mangayarkarasi, Mbonigaba Celestin, "Optimal Performance of Node Coverage Model in Wireless Sensor Networks Using Lyrebird Optimization Algorithm", International Journal of Computer Networks and Applications (IJCNA), 12(6), PP: 989-1004, 2025, DOI: 10.22247/ijcna/2025/58.