Mitigating Dead Node Impact on Coverage and Connectivity in Wireless Sensor Networks Using a Hybrid Approach

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***Abstract*—Wireless sensor networks' coverage and efficient connectivity are pivotal for reliable data collection and communication. However, dead nodes, resulting from hardware failure or power depletion, can affect coverage and connectivity, leading to information loss and degraded performance. Previous research in the same context indicates the need for further investigation to achieve optimal trade-offs in network resource allocation. This research introduces a hybrid Artificial Bee Colony-Sequential Re-connectivity and Coverage Algorithm (ABC-SRCA) approach, combining the ABC algorithm with a developed SRCA. The ABC algorithm adjusts sensor node placement to maximize the coverage and minimize holes, while the SRCA algorithm restores connectivity by reconnecting the network when nodes fail. The approach uses probabilistic selection to explore various solutions, making the approach adaptive to diverse scenarios. The simulation outcomes indicate that the ABC-SRCA method enhances coverage accuracy by up to 30% compared to ABC and SRCA when they are used separately. In addition, the rate of connectivity error detection decreases by about 25%, highlighting the method's effectiveness in dynamic network conditions. The approach also surpasses existing methods, including Genetic Algorithms and Sensing Radius Adaptive Coverage Control (SRACC), by achieving coverage level up to 98% while conserving resources. The ABC-SRCA achieves better energy consumption than Particle Swarm Optimization (PSO) and PSO Voronoi Diagram and achieves competent energy when compared with SRACC. The hybrid approach provides an effective solution for ensuring efficient and reliable network operations, supporting the successful deployment of WSNs in diverse applications.**

***Index Terms*—ABC algorithm, Coverage optimization, Dead nodes, Hybrid approach, Re-connectivity, SRCA algorithm, Wireless sensor networks.**

I. Introduction

Wireless sensor networks (WSNs) have gained considerable interest across diverse applications, including environmental monitoring, surveillance, and smart systems. A WSN is often defined as a group of interconnected wireless sensor nodes that capture the surroundings at a region of interest, communicate with each other, and send information to the end user (Bhat and Santhosh, 2022). One of the characteristic features of WSNs is that many nodes can be placed in a definite area to guarantee coverage. However, sensor nodes are prone to frequent failure due lack of power, physical harm, or environmental interferences (Adu-Manu, et al., 2022). However, a relatively congested network results in numerous problems like node overlap (Ling, et al., 2020) and failure of a group of nodes that reduce the multi-hop paths in the network (Baradaran and Navi, 2020), which can bring about a "disconnection" that isolates a subset of non-failed nodes from the other nodes. If no path exists between two nodes, they are considered disconnected (Zhang, et al., 2020a). Therefore, sensor node non-existence or failure can affect coverage and connectivity, which, in turn, influences sensor network performance and the quality of service of the entire WSN (Wang, et al., 2022). Ensuring complete coverage and maintaining connectivity is a vital challenge in WSNs (Zeng, et al., 2023), however, dead nodes, which no longer function can affect coverage and connectivity, leading to information loss and reduced network performance. Network coverage can be improved by addressing optimal node locations that managing the sensing range, identifying alternative paths, and adjusting transmission ranges, and ensuring sustained connectivity. This guarantees the network operation's dependability and resilience. To tackle coverage and re-connectivity issues, this study proposes an approach combining the Artificial Bee Colony (ABC) optimization algorithm with a developed sequential re-connectivity and coverage algorithm (SRCA) to achieve efficient coverage and re-connectivity, with a specific focus on dead nodes. The approach optimizes the deployment of sensor nodes, ensuring maximum coverage range and facilitating re-connectivity in the presence of dead nodes or connectivity gaps. The two algorithms are run sequentially, the ABC algorithm first optimizes the placement of sensor nodes within the network, ensuring coverage requirements are met and minimizing coverage gaps. Then, the SRCA algorithm re-establishes connectivity, reconnecting the network in the

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presence of dead nodes. By adapting to dynamic changes in network topology, ABC-SRCA achieves greater resource efficiency than existing techniques. Amalgamating the ABC and SRCA algorithms, the hybrid approach offers several benefits. It enhances network coverage by selecting optimal node locations that maximize the sensing range. In addition, it resolves dead nodes by identifying alternative paths and adjusting transmission ranges to ensure sustained connectivity. This results in a more dependable and resilient network operation.

The remainder of this paper is organized as follows: Section 2 provides the related work. Section 3 demonstrates the problem statement. Section 4 presents the ABC-SRCA approach. Section 5 highlights the results and discussions, while Section 6 concludes and offers future directions for the study.

II. Related Work

Many techniques have been proposed for deployment to avoid node failures and enhance the coverage of WSNs. (Lu, et al., 2025) proposed an approach to optimize the deployment strategy of heterogeneous WSNs concentrating on balancing network coverage, connectivity, and deployment costs. The authors present an improved Secretary Bird Optimization Algorithm (ISBOA) integrating Gaussian Cuckoo Mutation and a smooth exploitation mechanism. Simulation results indicate that the ISBOA attains higher accuracy and faster convergence compared to other algorithms. The authors suggest a minimum spanning tree domain reduction strategy for large-scale issues to enhance efficiency with minimum loss of accuracy. However, the research does not utilize dynamic adaptive and fault recovery mechanisms to maintain the network efficiency and stability in a long-term operation. (Guo, et al., 2025) introduced a perception model incorporating path loss and false alarm probability to optimize coverage problems in WSNs using an intelligent optimization algorithm and longevity. The model includes a logarithmic-based path loss model and the Neyman–Pearson criterion for maximizing detection probability. The simulation results indicate that the model attains full coverage with fewer nodes than traditional models, hence, improving network performance and longevity. However, the research does not explain whether the algorithm adapts to changing parameters or conditions during execution. (Velavalapalli, Ramamurthy and and Satyanarayana, 2024) proposed a wholly distributed approach for enabling each node of delay tolerant networks to rapidly determine if its sensor generates faulty data. A continuous-time state equation is used to model the approach's dynamic behavior. The research also considers the effect of misbehaving nodes to deactivate the fault detection. The research evaluates the detection and false alarm rates by comparing theoretical predictions with simulation results. The simulations show that the packet reception delay metric beats the expected transmission count metric and also energy consumption and end-to-end delay metrics, while still preserving a high packet delivery ratio. However, the proposed approach encounters complexity in implementation, and challenges in handling misbehaving nodes and network resource constraints. (Khedr, Osamy and Salim, 2018) suggested a design that involves random provisioning of Heterogenous WSNs (HWSNs) and a distributed algorithm for detecting holes that result from node failures. Accordingly, nodes in this new scheme can work together to detect and predict any possible coverage gaps. Alternatively, (Yan, et al., 2020) proposed a connectivity-based k-coverage hole detection algorithm for WSNs, utilizing homology theory and Rips complex to effectively identify and reduce coverage holes. The simulation results indicate that the proposed algorithm can reliably detect over 95% of non-triangular K-coverage holes. The algorithm reduces the energy consumption, as fewer nodes are active at any given time, which helps in extending the network's operational lifetime. However, the algorithm can only detect non-triangular coverage holes because the Rips complex cannot capture triangular holes, leading to missing some coverage holes.

A coverage hole patching algorithm is proposed by (Lu, et al., 2022). Depending on the size of the coverage holes, the algorithm prioritizes patching to reduce node redundancy, improve network coverage, and balance resource allocation. The results show that the proposed algorithm coverage rate and node redundancy reduction are better than the conventional coverage hole patching algorithms. A localization and deployment model using the Arithmetic Optimization Algorithm is presented in (Khatir, et al., 2021). By implementing this algorithm, a deployment model is developed to achieve a fully connected network. Considering the average localization error within 5 m, the algorithm demonstrates its accuracy in localizing nodes and identifying coverage holes in different fields. Based on the simplified Rips complex, (Zhang, Chu, and Feng, 2020b) proposed an efficient algorithm to detect coverage holes. The algorithm decreases the computational efficiency and enhances the detection accuracy. The results indicate that the proposed algorithm exhibits reduced complexity and achieves higher accuracy, reaching 99.03%, when compared to other algorithms. The algorithm enhances energy consumption by implementing redundant node sleeping and edge deletion, which help simplify the network structure, reducing the number of active nodes and edges required to communicate and process data. However, the algorithm may face challenges in dense or highly dynamic networks where node locations and network topology change continually. An improved Coverage Hole Patching Technique (CHPT) based on tree algorithms is proposed by (Das and Debbarma, 2020). The Delaunay triangle and void circle properties are used to detect hole patching. A hole's location is estimated using the inner empty circle property. The results of the experiments show that CHPT increases the coverage percentage to 98.6% compared to other techniques. (Al-Fuhaidi, et al., 2020) proposed a deployment model based on probabilistic sensing models (PSM) and Harmony Search Algorithms (HSA) to balance network coverage and cost in HWSNs. The HSA optimizes the deployment of nodes by balancing coverage and cost, while the PSM is utilized to solve the overlapping problem among sensors. Based on the simulation results, the proposed deployment model achieves maximum coverage and minimum sensor number, and it attains superior results when compared with other algorithms. (Amer, et al., 2024) introduced a hybrid algorithm, CFL-PSO, combining an enhanced Fick's Law algorithm with comprehensive learning and Particle Swarm Optimization (PSO) to enhance connectivity and coverage by optimizing router node placement in WSNs. The simulation results show that CFL-PSO improves network performance, attaining up to 66.5% better connectivity, 16.56% better coverage, and a 21.4% improvement in the objective function value compared to several algorithms including the standard FLA. However, the research does not address the network scalability and does not consider energy consumption. Accordingly, (Aljubori, Khalilpour Akram, and Challenger, 2022) developed a distributed algorithm based on 2-hop local neighborhood information to identify redundant nodes. In the proposed algorithm, nodes are classified as redundant based on their connections with their neighbors. An Artificial Hydrocarbon Network Technique is presented by (Gutiérrez and Ponce, 2019) to detect sensor failures at a remote location. The method can predict the temperature and detect malfunctions at remote sensors utilizing information from a web service and comparing it with data from the field temperature sensor. In discussing the automatic detection of coverage holes, (Jain, 2020) proposed a four-step architecture that includes cluster formation, coverage hole detection, Cluster Head (CH) selection, recovery, and routing for dynamic clustering, focusing on coverage hole detection and recovery to enhance energy efficiency in IoT applications. The results show that the architecture reduces energy consumption, increases network lifetime, and improves the WSN's overall efficiency. However, the complexity of cluster maintenance and the time-consuming of using fuzzy logic for coverage holes should be considered. (Lai, et al., 2022) introduced a method for tracing coverage holes in WSNS known as Force-Directed and Transfer Learning. It depends on the layout generation capabilities of force-directed algorithms and the image recognition capabilities related to convolutional neural networks. Similarly, (Satyanarayana, et al., 2023) developed a fault detection model to improve the coverage area by establishing relay nodes for positioning sensor nodes in the environment and simulating the entire module with different analyses including transmission range, sensing range, and distance traveled to compare its performance with existing techniques. The simulation results reveal the effectiveness of the proposed algorithm in enhancing the coverage area and energy efficiency of the WSN. However, the proposed algorithm suffers from implementation complexity and computational resources. Moreover, it faces challenges in preserving connectivity and performance in the existence of multiple node failures. (Siamantas and Kandris, 2024) presented a new algorithm based on Particle Swarm Optimization (PSO) to improve WSNs coverage and connectivity by placing a predefined number of sensor nodes within a square target area. The research introduced a new objective function obtained from circle-packing geometric problems. The simulations and statistical tests revealing the algorithm effectiveness compared to other algorithms. However, the research focuses on attaining only 1-connectivity, which may not provide adequate network robustness and fault tolerance compared to m-connectivity. In (Kuthadi, et al., 2021), an Optimized Energy Management Model for Data Dissemination is proposed to enhance transmission links and energy consumption. The model utilizes a non-adaptive routing approach to disperse data efficiently from a single source to several points, integrating a dispersed collaboration system and priority task planning to improve energy usage. The results show that the model enhances the data transmission rate and reduces energy consumption by 20.11% in WSNs. However, the model may be complex to implement and need substantial computational resources due to the mathematical calculations. (Abdulzahra, Al-Qurabat and Abdulzahra, 2023) proposed an energy-efficient fuzzy-based unequal clustering with a sleep scheduling (EFUCSS) protocol for IoT that uses WSN to extend the network lifetime and reduce energy. The results show that the proposed protocol conserves energy by 26.92–213.4% and network lifespan by 39.58–408.13%. The network lifespan shows significant improvement compared to other algorithms. However, the protocol may increase the implementation complexity and require more computational resources due to clustering, CH selection using fuzzy logic, and sleep scheduling.

The literature proposed several techniques to improve coverage and connectivity in WSNs. However, there is still a significant gap in repairing and reconnecting dead nodes, dynamic adaptation, and energy efficiency, which are critical to maintaining network reliability and robustness. Existing research has suggested methods meant to maintain coverage and connectivity; there remains a notable gap in the literature regarding the proper repair and re-connection of non-functional sensor nodes, as well as the effective remediation of coverage holes yet. Many approaches lack mechanisms for dynamic adaptation to changing network conditions, such as node failures or varying environmental factors, which can impact network reliability. Accordingly, we integrate the ABC algorithm with a developed SRCA algorithm to develop range and connectivity for coverage hole detection formations between two nodes. The approach ensures continuous monitoring and adaptation to dynamic changes within the system. A comparison between the research is introduced in Table I below:

Table I shows a comparison of several research in the literature, underscoring their strengths and limitations, which help understand the gaps that the proposed hybrid ABC-SRCA approach aims to handle.

III. Problem Statement

Ensuring robust network coverage and connectivity in WSNs is a critical but unresolved problem due to several challenges. These include dynamic environments, energy

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TABLE I
Comparing of Research

Research	Approach	Strengths	Limitations
Lu, et al. (2025)	Improved Secretary Bird Optimization Algorithm	Higher accuracy, faster convergence, efficient for large-scale issues	Lacks dynamic adaptive and fault recovery mechanisms
Guo, et al. (2025)	Perception model with path loss and false alarm probability	Full coverage with fewer nodes, improved network performance	Does not adapt to changing parameters or conditions during execution
Velavalapalli, Ramamurthy and Satyanarayana (2024)	Distributed approach for detecting faulty data	High packet delivery ratio, effective fault detection	Implementation complexity, challenges in handling misbehaving nodes and resource constraints
Khedr, Osamy and Salim (2018)	Random provisioning design for HWSNs	Detects and predicts coverage gaps	Does not address dynamic adaptation
Yan, et al. (2020)	Connectivity-based k-coverage hole detection algorithm	Reliable detection of non-triangular holes, reduced energy consumption	Miss triangular holes, limited effectiveness
Lu, et al. (2022)	Coverage hole patching algorithm	Improved coverage rate, reduced node redundancy	Does not address dynamic network conditions
Khatir, et al. (2021)	Localization and deployment model using Arithmetic Optimization Algorithm	Accurate localization, identification of coverage holes	Challenges in dense or highly dynamic networks
Zhang, Chu and Feng (2020b)	Efficient algorithm based on simplified Rips complex	High accuracy, reduced complexity	Struggles in dynamic networks with changing node locations
Amer, et al. (2024)	Hybrid CFL-PSO algorithm	Improved connectivity and coverage, better network performance	Does not address network scalability and energy consumption
Al-Fuhaidi, et al. (2020)	Deployment model using PSM and HSA	Maximum coverage with minimum sensors, balanced coverage, and cost	Does not consider dynamic adaptation
Kuthadi, et al. (2021)	Optimized energy management model	Enhanced transmission links, reduced energy consumption	Complex implementation, substantial computational resources required
Abdulzahra, Al-Qurabat and Abdulzahra (2023)	Fuzzy-based unequal clustering with sleep scheduling protocol	Conserves energy, extends network lifespan	Increased implementation complexity, requires more computational resources

limitations, and irregular sensor deployment. The irregular distribution of nodes, often resulting from random sensor deployment, aggravates coverage gaps and makes repairing dead nodes a significant challenge. Existing solutions usually fail optimally to balance coverage and energy efficiency trade-offs while adapting to various conditions. In addition, the complexities of sensor networks and their operating environments have prevented the development of a universally accepted solution. Moreover, the lack of scalable and generalizable approaches ensures this issue remains an open research area. The previous research underscores different approaches to enhance coverage and connectivity in WSNs. Many approaches focus on optimizing deployment, catching coverage holes, and handling energy consumption. However, there is a significant gap in dynamic adaptation and fault recovery mechanisms, which are essential for preserving network dependability and robustness. The hybrid ABC-SRCA approach combines the strengths of the SRCA and ABC algorithms to manage these gaps by incorporating dynamic adaptation, energy-aware optimization, and scalable re-connectivity, presenting a more thorough solution for WSNs.

IV. The Proposed Approach

The hybrid ABC-SRCA approach combines two techniques: the ABC algorithm and a developed SRCA. The proposed approach integrates the strengths of both algorithms to tackle coverage and re-connectivity issues. The ABC algorithm is a nature-inspired optimization algorithm that simulates bees' foraging behavior. It is easy to implement, and there are fewer parameters to adjust. Moreover, it utilizes exploration and exploitation mechanisms to adjust the placement of sensor nodes in the network iteratively (Wang, et al, 2023). Thus, this algorithm can optimize network resource utilization and maximize the coverage area. However, it may obtain a local minimum and can achieve the global optimum with relative computational simplicity (Wang, et al, 2023). On the other hand, the SRCA algorithm is developed by the author to establish connectivity among deployed nodes by manipulating their transmission ranges. The SRCA has two main functions. First, it identifies disconnected nodes and adjusts their transmission ranges sequentially to establish connectivity with neighboring nodes. Second, the SRCA algorithm identifies coverage holes and constructs coverage by adjusting node positions. To achieve these functions, several steps are performed including (1) initialization of nodes sensors positions, (2) node distance estimation, (3) coverage hole detection, and (4) re-connectivity to dead nodes. All these steps are explained in the following sections B and C. The algorithm iteratively refines the positions of nodes by evaluating their fitness and generating new solutions. This process ensures the network remains connected even with dead nodes, enabling seamless data transmission and communication, thereby addressing the local optima problem effectively. Therefore, integrating these algorithms provide a robust solution for optimizing network coverage and connectivity, thereby addressing the local optima problem effectively. Moreover, improving coverage and facilitating re-connectivity in the presence of dead nodes can indirectly contribute to energy efficiency by reducing the need for redundant nodes and minimizing communication overhead. In addition, maintaining connectivity and coverage can help in efficient network operations, which may lead to better energy utilization.

The proposed approach can improve the coverage and re-connecting to the dead node in WSNs and considers that all sensor nodes are heterogeneous randomly deployed in the ROI. All nodes are assumed to be capable of sensing the environment to detect physical constraints. All sensors are presumed to uphold a synchronization protocol, enabling consistent time synchronization across the network. This allows them to make informed decisions about maintaining reconnection with their neighbors. Presumably, the sensing range (Rs) and communication range (Rc) of each node are (Rc > 2RS), with no conflict likely to occur after deployment. It is used in the proposed approach to optimize the deployment and routing of sensor nodes and to estimate distance among nodes. In this algorithm, new solutions are produced, where the iteration for the node searching process is to find a new position and apply a distance estimation process. This procedure is started by selecting the start node and then generating the distance for the next node (from the start node to the end node) in ROI after the sensor node is randomly deployed using a post-deployment algorithm. The SRCA algorithm prioritizes creating connections between deployed nodes by adjusting their transmission ranges. It identifies disconnected nodes and gradually modifies their transmission ranges to link up with neighboring nodes, aiming to establish connectivity.

This approach can be customized based on prioritizing coverage holes or dead nodes which are two common challenges in WSNs Prioritization depends on the approach focus. If the approach strategy focuses on sustaining network functionality, re-connectivity for dead nodes should be carried out first. Moreover, handling coverage holes might be preferable if the focus is on accurate monitoring or data collection. The ABC-SRCA approach involves three main steps shown in Fig. 1, and explained in the following sections.

A. Node Distance Estimation

The step related to node distance estimation involves the utilization of the ABC algorithm to calculate the node distance estimation and adjust sensor node positions. The ABC algorithm is a metaheuristic optimization algorithm commonly utilized for solving optimization problems but is not explicitly designed for distance estimation. To use the ABC algorithm for estimating distances, there is a need for distance-based objective function or fitness measure. The ABC algorithm is customized to estimate the node distance and adjust sensor nodes' positions. The ABC algorithm iteratively refines a population of node sources (representing solutions in a multi-dimensional space) by evaluating their fitness, creating neighbor solutions, selecting better solutions, and recording the best-found solution until evaluations up to a maximum. The algorithm procedure is introduced in the following:

Input: Number of node sources SN (solution), number of dimensions D, lower bounds x_{min}, upper bounds x_{max}, max evaluations MaxEval, abandonment limit L

1. Initialization:
for i = 1 to SN:
for j = 1 to D:

$$x_i^j = x_{min}^j + rand[0,1]\left(x_{max}^j - x_{min}^j\right) \tag{1}$$

end for
evaluate fitness (fi) for each solution xi.
set EvalCount = SN
bestSolution = best(xi)
2. Repeat until EvalCount ≥ MaxEval:
/Employed Bee Phase:
for each employed bee associated with solution xi:
choose a random neighbor index k (k ≠ i) and a random dimension j ∈ {1,…, D}
generate new solution (neighbor) vi:
vij = xij + ϕij * (xij - xkj) (2)
where ϕij ∈ [-1, 1] (random)
evaluate fitness f(vi)
evalCount = EvalCount + 1
if f(v_i) is better than f(xi):
update xi = v_i
reset trial counter for xi
else:
increment trial counter for xi
end for
//Onlooker Bee Phase:
calculate selection probabilities for each solution:
for i = 1 to SN:

$$p_i = \frac{fitness_i}{\sum_{n=1}^{SN} fitness_n} \tag{3}$$

end for
for each onlooker bee:
select a solution xi based on probability pi (e.g., using roulette wheel selection)
choose a random neighbor index k (k ≠ i) and a random dimension j ∈ {1,…, D}
generate new solution vi using:
vij = xij + ϕij * (xij - xkj) (2a)
evaluate fitness f(vi)
evalCount = EvalCount + 1
if f(v_i) is better than f(xi):
update xi = vi
reset trial counter for xi
else:
increment trial counter for xi
end for
//Scout Bee Phase:
for each solution xi:
if trial counter for xi exceeds limit L:
//Abandon current solution and generate a new one randomly
for j = 1 to D:

$$x_i^j = x_{min}^j + rand[0,1]\left(x_{max}^j - x_{min}^j\right) \tag{1a}$$

end For
evaluate fitness f(xi)
evalCount = EvalCount + 1

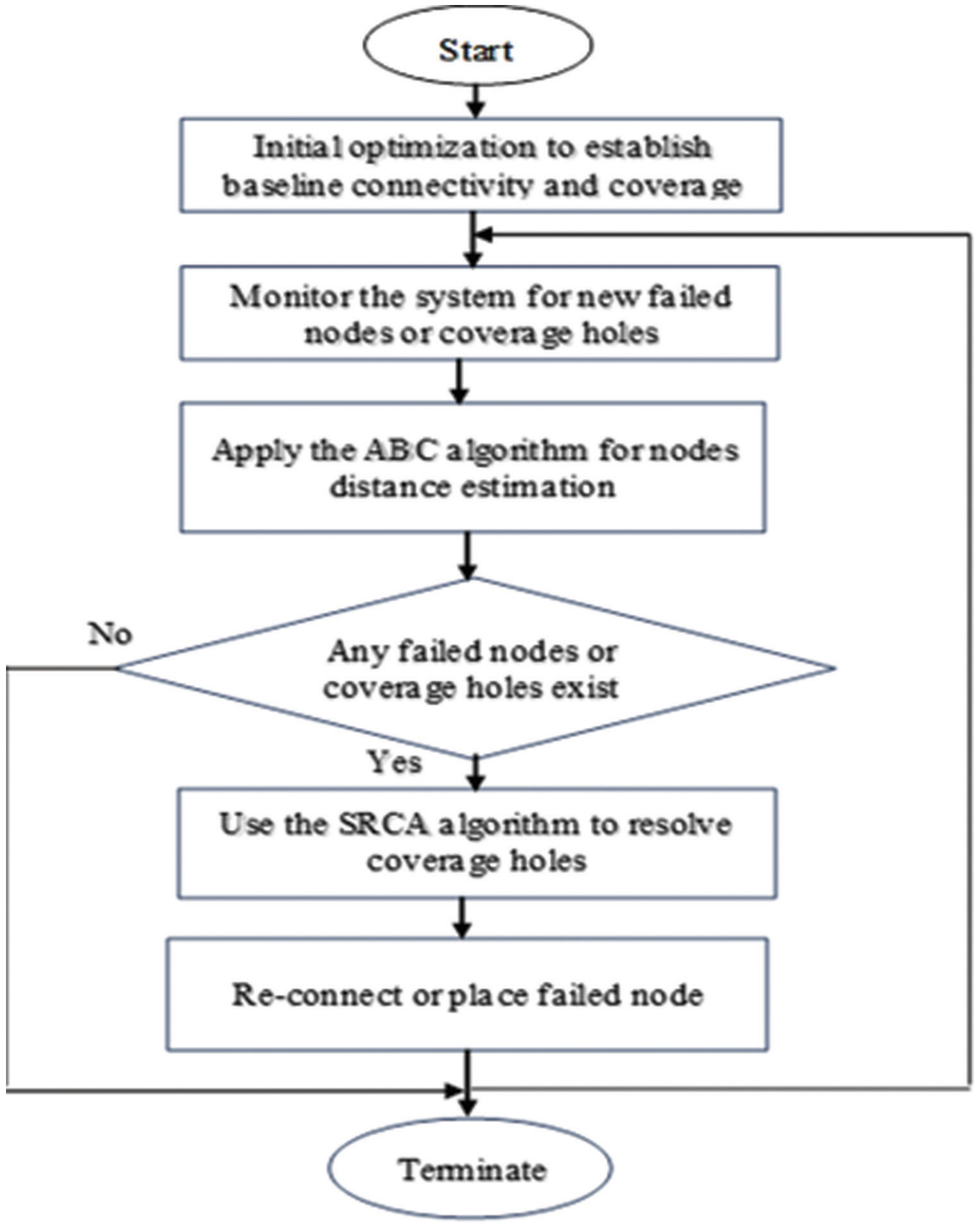

Fig. 1. Flow chart for the combined artificial bee colony-sequential re-connectivity and coverage algorithm algorithms proposal/approach.

reset trial counter for xi
end For
//update the best solution found so far:
bestSolution = best (BestSolution, {xi})
end Repeat
Output: BestSolution

Overall, this procedure resembles a population-based optimization algorithm inspired by the behavior of bees in a colony. It aims to iteratively refine the solutions (node sources) and introduce new random solutions to improve the overall performance or fitness of the nodes based on defined parameters and fitness evaluations. The algorithm evaluates solutions based on their “fitness” or performance, giving a higher probability to solutions that perform better rather than randomly choosing solutions. Moreover, the algorithm avoids getting stuck in local optima by continuously exploring new areas. In general, the algorithm provides efficient, scalable, and adaptive methods for optimizing problems, making it particularly appropriate for WSN optimization, where maintaining connectivity and coverage is crucial.

B. Coverage Hole

The coverage hole step includes the usage of the SRCA algorithm, whose function is to determine and construct the coverage holes. The SRCA initializes the sensor node position and calculates the coverage area by saving distance estimation and node location information. It usually updates its position through the node-finding process to determine the coverage area in the ROI. The selected backup node must maintain a one-hop information table corresponding to the critical node. The node degree represents the number of communication links it has with other nodes in the ROI, which is equivalent to the number of its neighboring nodes. A higher node degree indicates a more significant number of surrounding dead nodes. The proposed approach selects node positions from start to end to reconnect to the dead node as a new position. When a node dies, the backup node is chosen from its neighbor to minimize dead nodes, messages, and time. During the initialization of the node table, each node sends a broadcast message containing its ID and coordinates. All nodes within the communication range receive the message. After exchanging information, each node determines whether it is nearest to the dead node through the node table neighborhood list. However, live/active nodes must not break network connectivity. Therefore, a backup node must be selected only for the dead node. Selecting backup nodes depends on the minimum distance between the dead node and the nearest node and the node degree.

C. Re-Connectivity to Dead Nodes

This step includes recovering the dead node and re-connecting to it using the connectivity algorithm to the dead node. The SRCA algorithm establishes connections among deployed nodes by fine-tuning their transmission ranges. It detects isolated nodes and systematically adjusts their transmission ranges, striving to connect them with neighboring nodes and ultimately achieve network connectivity. Sensor nodes are deployed randomly, resulting in highly connected networks in some areas while leaving others only partially connected. This uneven distribution can compromise coverage. To address this, sensor nodes must be able to adjust their positions to achieve uniform distribution and maximize coverage. Typically, the sink node oversees this distribution, processing data and making decisions. However, this approach increases communication overhead and incurs delays, as decisions must be transmitted across the entire network. As a result, self-organizing nodes are recommended to reduce overall network message traffic. The effects of node failure are pretty different in highly interconnected networks where all nodes are placed close to each other. Any loss of one or more nodes can affect connectivity, splitting the network into several disjoint segments. Furthermore, numerous nodes cannot send data to the sink node [30]. The SRCA and dead node reconnection in WSNs work, assuming all sensor nodes are heterogeneous sensors placed randomly in the ROI. Hence, all nodes are supposed to be aware of the environment and physical limitations. The SRCA selects the backup (alternative) node to each dead node from its neighbor nodes through a neighborhood list (NL). The SRCA algorithm procedure for re-connectivity is introduced as follows:

1. If node position is not found, the algorithm terminates the condition, or else it turns up to step 8
2. The node position is often regarded as the current best location
3. Start re-connectivity sensor node in the coverage hole area
4. Select node position from start to end to re-connect to the failed node
5. If re-connectivity fails (SRCA), it is highly recommended to return to step 4
6. Optimize the result of the SRCA algorithm to re-connect the start and end nodes
7. Calculate each node position's value (this value is supposed to be the current best new node position)
8. In case of reaching max iteration, the algorithm must be terminated; if not, go to step 3.

When a dead node is detected, the pre-established backup node will execute the restoration strategy and initiate cooperation with the nearest node. If the backup node itself is dead, the restoration algorithm will move to the next backup node until a functional one is found. Before selection a backup node, it sends a message to its neighboring nodes, updating their neighbor information tables. When choosing the location for backup nodes, the communication areas of the backup node and its neighboring nodes should be considered. The goal is to optimize the backup node's position to maximize effective connectivity while estimating the presence of dead nodes. On detecting a dead node (failure) within its monitoring area, the backup node calculates the optimal destination coordinates to maximize local connectivity. This involves minimizing overlapping areas, and the coordinates corresponding to the minimum overlapping area function are determined. These calculated coordinates are considered the optimal position for the dead node, ensuring necessary connectivity for lifetime coverage. The SRCA algorithm supposes that heterogeneous nodes can decide their location with their neighbors. If the heterogeneous node is not equipped before the dead, it will need some time to react. In this way, the SRCA algorithm yields an ongoing relocation of mobile nodes if the failure occurs, guaranteeing connectivity and coverage with no wasted time. In general, the algorithm iterates the reconnection attempts for improved efficiency and systematically iterates different node positions. In addition, the algorithm provides robust failure handling by retrying alternative paths and positions when connectivity fails.

D. The ABC - SRCA Approach Pseudo Code

The ABC-SRCA approach outlines a multi-step process primarily focused on optimizing node deployment, coverage, and connectivity within a sensor network. The ABC-SRCA algorithm is designed to optimize the sensor nodes deployment in WSNs by iteratively refining node positions. Initially, nodes are randomly deployed, and their coverage areas are calculated based on a uniform detection range. A set of preliminary solutions is generated and evaluated, with bees performing neighborhood searches to improve solution quality. Solutions are selected based on fitness values, with a roulette selection method used to determine the probability of selection. In addition to optimizing coverage, the algorithm considers potential issues such as failed nodes and coverage holes by incorporating mechanisms to detect and address neglected solutions. Throughout the iterative process, the algorithm updates the best solution found so far, aiming to enhance WSN coverage and efficiency while mitigating deployment challenges. Termination occurs when a predefined criterion is met, at which point the best result is outputted. The pseudo code of this approach is introduced in the following:

Input: area covered by sensor node i. (A_covi), detection range of the sensor node (R), Set of all sensor nodes in the network (S), A sensor node in the set S (n), A candidate solution in the neighborhood search (new solution) (xij), modified candidate solution in the domain search (vij) Probability of selecting a solution, calculated based on its fitness (pi).

Step 1: initialize running time measurement

start_timer ()

record start time T_{start}

Step 2: random deployment Nodes using the post-deployment algorithm.

The optimal deployment distance selection is originally related to the plane area intensity. The following equation illustrates this intensity:

$$\varphi_i = \frac{N^2}{\sum_{i=1}^{n}\sum_{m=1}^{N} d_{im}} \tag{4}$$

Step 3: Nodes normally share their information with other sensor neighbors

Step 4: Sensor nodes usually communicate with each other

Step 5: Sensor field as accounted for in 2D

Step 6: Sensor nodes possess the same detection range

Step 7: Sensor Si is located at a particular point (x_i, y_i), for each point P the node coverage ratio is counted using

$$XR = \frac{A_{covi}}{R},\ n \in S \tag{5}$$

Step 8: For any point, the Euclidean distance

$$d\left(s_i, N\right) = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{6}$$

Step 9: Randomly create (bee colony size) to perform as preliminary solutions, then match half of them with bees, calculate each solution's fitness value, and finally record the best solutions.

Step 10: repeat = 1.

Step 11: The honeybee performs a neighborhood search to yield a new solution v_{ij}, calculates its fitness value, *then do* the SRCA selection of x_{ij} and v_{ij}.

Step 12: Calculate the probability of selection pi related to xi.

Step 13: Select the solution with probability p_i using the roulette selection method, and then do a domain search to yield a new solution, calculate the fitness value, and *then do* the SRCA choice of x_{ij} and v_{ij}.

Step 14: Determine if a solution to be neglected is available. If so, use equation (3) to do a random search to produce a new solution that will be used instead of the old one.

Step 15: Determine the best of all solutions yet.

Step 16: Repeat = repeat + 1, if $cycle$ < SRCA; after that go to step 8 or output the best result.

Step 17: The ABC-SRCA algorithm normally updates its location under the node-finding process.

Step 18: running time measurement

end_timer (), record end time T_{end}, compute and record running time for current sensor node count

Step 19: output the best solution and running_time for the current sensor node configuration

This approach incorporates deployment and optimization, guaranteeing robust coverage and connectivity by starting with a random deployment and then using ABC and SRCA algorithms to optimize node positions. It uses probabilistic selection to explore various solutions, making the approach adaptive to diverse scenarios. Moreover, it can handle many nodes (scalable) due to ABC's iterative and probabilistic nature.

V. Performance Metric

Evaluation of the proposed approach requires covering more aspects and provides better insight into its overall performance. This study used the following performance metrics:

- Energy Consumption

Efficient energy use is vital for extending the network's operational lifetime. Since the sensor energy is limited, it is required to reduce sensor motion. The following equation is used to calculate the energy consumption for sensor n moving from point a to point b is calculated by (Guo and Jafarkhani, 2019):

$$En\ (a,b) = \theta n\ \|\ b\text{-}a\| \tag{7}$$

Where θn is the energy cost per unit distance for moving node n to a new position. The term ‖b-a‖ denotes the Euclidean distance between the initial locations and the final destination, which represents the energy needed to move or communicate between the nodes.

- Connectivity

The WSNs connectivity refers to the ability of each sensor node to find a path to reach the selected sink node. If no route is available, the sink node cannot process the data collected by that node. The connectivity represents the ability of nodes to communicate.

- Coverage

The sensor network coverage refers to the ability of sensors to monitor the field of interest. The metric measures network sensing capability. Coverage in ABC-SRCA is the measure of the duration and extent for which the sensors can monitor the field of interest.

- Scalability

The approach's performance is tested on two different area scales with varying numbers of nodes, which may reflect its efficiency in larger or real-world deployments.

- Running Time

Running or processing time in WSNs denotes the duration for algorithms to perform tasks such as node deployment, coverage optimization, and energy management. It relies on the sensor node number, network size, and algorithm complexity. Evaluating the running time of the research approach is done using the MATLAB.

VI. Results And Analysis

The experimental procedure is performed by installing MATLAB version R2020 on a pc with Intel@ Core i7-3770 CPU@3.40GHz and 16GB RAM. A WSN square area 100 m × 100 m is considered, where 50 wireless sensor nodes were deployed to monitor the area. The sensing radius is 10m. The overall performance concerning coverage, and connectivity of ABC algorithms and the ABC-SRCA approach is compared. The outcomes are recorded in Tables II-IV. MATLAB is used for implementing and simulating the ABC-SRCA optimization approach because it can address complex mathematical calculations and algorithms, making it well-suited. Simulation is a necessary first step in evaluating the approach's feasibility and outcomes in a controlled environment before testing it in real-world conditions.

Table II and Fig. 2 display the results of the connectivity between sensor nodes that employ an isolated node localization model considering different node numbers. The results show that the actual connectivity error detection rates using the proposed ABC-SRCA approach are better for the different number of deployment nodes regardless the inconsistency in the error detection rate of the approach. An increased error detection rate with more nodes indicates improved network coverage and monitoring capabilities. However, it may indicate inefficiencies such as false positives, network congestion, or redundancy in error reporting (Adday, et al., 2022) The SRCA and ABC-SRCA dynamically adjust reallocation and transmission power based on node density. A higher node count leads to reducing errors per node probability, increasing the approach ability to correct coverage gaps and optimize deployment. This leads to a lower percentage of errors despite a larger network. However, increased sensor numbers can increase interference and data collisions, overlapping, communication overhead, scalability challenges, and sudden node failures, which may negatively affect the overall error detection rate.

Table III and Fig. 3 show that the proposed approach achieves better coverage accuracy (how accurately nodes deployed with how much coverage) on different sizes of ROI for various node numbers compared with the ABC and SRCA. The proposed approach revealed promising results in optimizing sensor node placement, leading to improved coverage of the target area. However, the approach's coverage accuracy can vary depending on problem formulation, network topology, and implementation details; additionally, proper parameter tuning and optimization strategy selection are critical for optimal results.

Table IV introduces a comparison between the proposed approach and previous studies in similar scenario including the same number of nodes and the same deployed area. The first study was (Yue, Cao, and Luo, 2019), who presented an improved ABC algorithm (IABC) and compared its coverage performance with GA and the Random Distribution Algorithm (RDA). The study deployed different sensor nodes within a 200 m × 200 m area. The second study is the study of (Wang, et al., 2018), who introduced a sensing radius adaptive coverage control algorithm (SRACC) and compared it with the particle swarm optimization and Voronoi diagram (PSO-VD). The study deployed different sensor nodes within a 100 m × 100 m area. The ABC-SRCA approach combines the strengths of the ABC and SRCA algorithms to enhance network coverage and connectivity. The efficacy of this combination is shown through the comparative analysis with other hybrid approaches, such as ABC-GA and ABC-PSO. Table IV reveals that the ABC-SRCA approach accomplishes the best coverage accuracy, reaching up to 97.89% in a 200 m × 200 m area and 98.05% in a 100 m ×100 m area. These results demonstrate that the ABC-SRCA approach exceeds the Improved ABC Algorithm (IABC), Genetic Algorithm (GA), Random Distribution Algorithm (RDA), SRACC, and PSO-VD in terms of coverage accuracy. The higher coverage accuracy attained by ABC-SRCA underscores its efficacy in optimizing sensor node placement and sustaining network

TABLE II
Connectivity Error Detection of the Proposed Approach

No. of nodes considered	Error detection rate		
	ABC (%)	SRCA (%)	ABC-SRCA (%)
10	16.6	19.6	26.9
20	15.85	18.85	27.61
30	14.8	16.8	26.41
40	13.69	15.69	25.9
50	12.98	14.98	27.93

ABC: Artificial bee colony, SRCA: Sequential re-connectivity and coverage algorithm

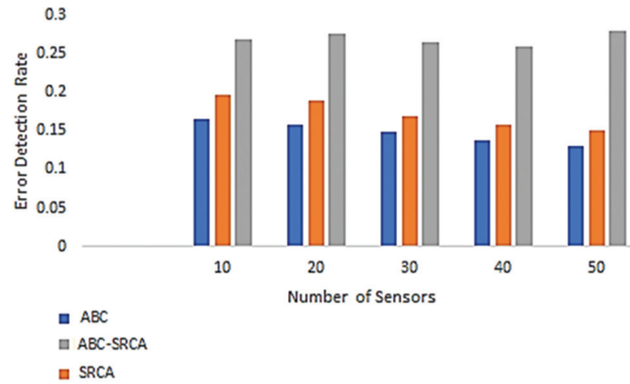

Fig. 2. Error detection rate.

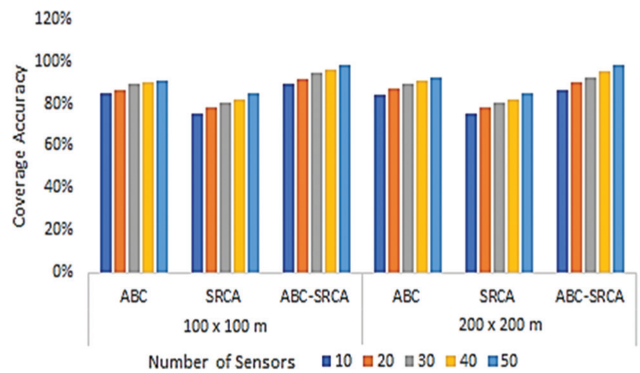

Fig. 3. Coverage accuracy of artificial bee colony-sequential re-connectivity and coverage algorithm in different areas.

TABLE III
Coverage Accuracy of the Proposed Approach

Number of deployed nodes	Research approach					
	100×100 m			200×200 m		
	ABC (%)	SRCA (%)	ABC-SRCA (%)	ABC (%)	SRCA (%)	ABC-SRCA (%)
10	85	75	89	84.00	75.00	86.44
20	86	78	91.23	87.00	78.00	90.33
30	89	80	94.12	89.00	80.00	92.42
40	90	82	96.10	91.00	82.00	95.22
50	91	85	98.05	92.00	85.00	97.89

ABC: Artificial bee colony, SRCA: Sequential re-connectivity and coverage algorithm

TABLE IV
Comparison of Coverage Accuracies

Deployed nodes number	Coverage accuracy				Coverage accuracy		
	Research approach 200×200 m	(Yue, Cao and Luo, 2019) 200×200 m			Research approach 100×100 m	(Wang, et al., 2018) 100×100 m	
	ABC-SRCA approach (%)	Improved ABC algorithm (%)	Genetic algorithm (%)	Random distribution algorithm (%)	ABC-SRCA algorithm (%)	SRACC (%)	PSO-VD (%)
10	86.44	54	54	43	89.00	-	
20	90.33	76	67	57	91.23	-	
30	92.42	85	76	64	94.12	37	34
40	95.22	93	86	67	96.10	77	69
50	97.89	96	91	72	98.05	85	80

ABC: Artificial bee colony, SRCA: Sequential re-connectivity and coverage algorithm, SRACC: Sensing radius adaptive coverage control, PSO-VD: Particle Swarm Optimization Voronoi Diagram

connectivity, making it a proper solution for WSNs compared to other hybrid combinations.

The comparison results in Fig. 4 reveal that the ABC-SRCA significantly outperforms the other algorithms in attaining better coverage by employing various node numbers deployed in area 200 m × 200 m. The ABC-SRCA steadily attains the highest coverage accuracy, starting at 86.44% (10 nodes) and reaching 97.89% (50 nodes), outperforming all other approaches.

The comparison results in Fig. 5 show that the ABC-SRCA achieves better coverage accuracy for various nodes number deployed in Area 100 m × 100 m. The ABC-SRCA achieves the highest accuracy in this smaller area, reaching 98.05% at 50 nodes.

Table V and Fig. 6 show that the energy consumption scales linearly with the number of nodes due to the complexity of interactions and connectivity maintenance. The 200 m × 200 m area consumes more energy due to higher transmission distances and communication overhead.

To evaluate the energy efficiency of the research approach, it is compared with other algorithms in 100 m × 100 m area and the results are introduced in the Table VI.

Table VI and Fig. 7 show that the ABC-SRCA approach consumes 11J of energy, which is lower than PSO (14J) and PSO-VD (12J) but slightly higher than SRACC (10J). The ABC-SRCA approach consumes slightly more energy (I J) because it ensures high coverage and connectivity and manages dead nodes, which is not considered by other algorithms. This indicates the extra processes conducted by the hybrid algorithm do not cause extra resource consumption. The approach attains its objectives without

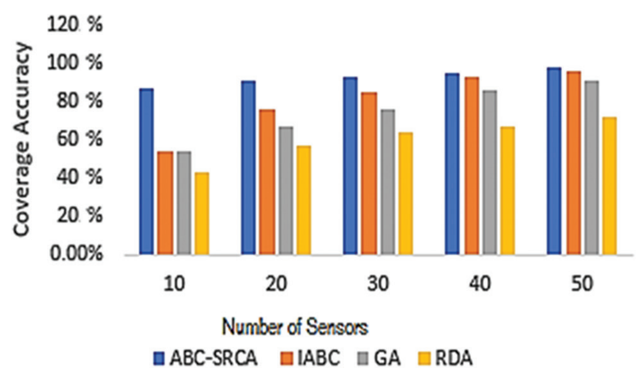

Fig. 4. Comparison of coverage accuracy in area 200 m × 200 m.

significantly increasing energy usage, as energy efficiency is a critical factor in WSN design and operation.

The ABC-SRCA can be considered real-time if the computation time for determining node placement and maintaining network connectivity is evaluated. Table VII introduces the computation times for different numbers of deployed nodes.

Table VII and Fig. 8 show that the running time increases as the number of sensor nodes increases, which is expected. The larger area (200 m × 200 m) consistently shows a longer running time compared to the smaller area (100 m × 100 m). This indicates that the size of the area impacts the running time, even with the same number of sensor nodes. The growth in running time appears to be roughly linear for both areas, but the larger area exhibits a slightly higher rate of increase. This is due to several reasons. First reason is due increases the number of sensor nodes, which increases the complexity

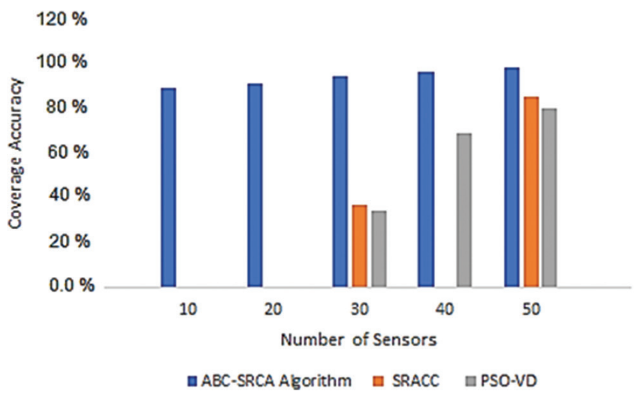

Fig. 5. Comparison of coverage accuracy in area 100 m × 100 m.

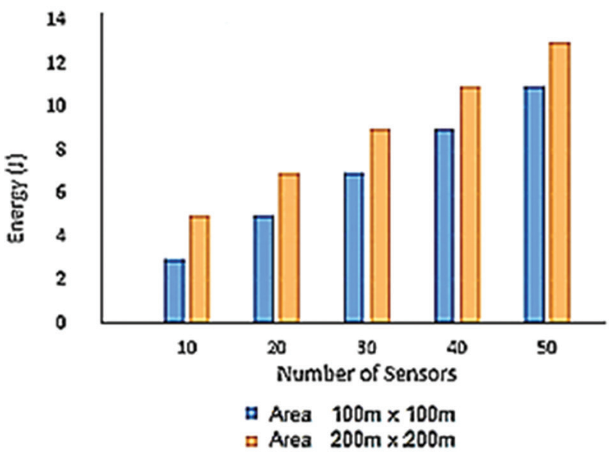

Fig. 6. Artificial bee colony-sequential re-connectivity and coverage algorithm energy consumption.

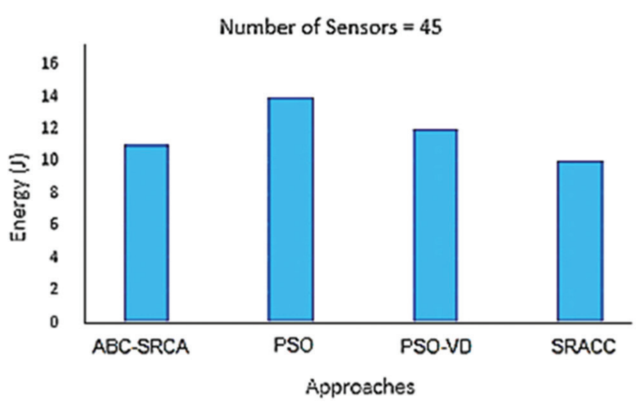

Fig. 7. Energy consumption comparison.

of managing and coordinating these nodes. Second reason is increasing distance between nodes leading to longer communication paths and increased latency. Third reason is the propagation of signals. As signals are transmitted over longer distances, their strength can decrease, requiring more time and possibly causing them to be retransmitted. Forth reason is the increase volume of data which requires more processing time.

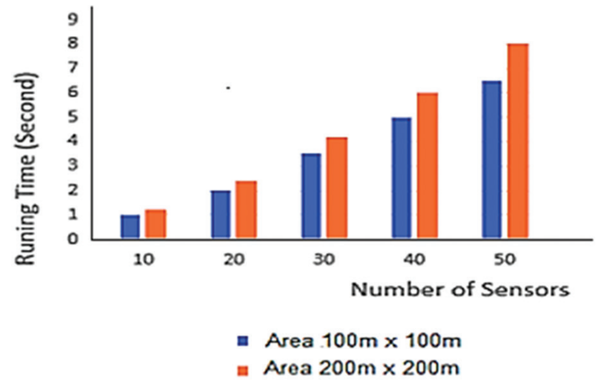

Fig. 8. Running time of artificial bee colony-sequential re-connectivity and coverage algorithm.

TABLE V
Energy Consumption for ABC-SRCA

Number of nodes	Hybrid ABC-SRCA energy (J) 100 m×100 m	Hybrid ABC-SRCA energy (J) 200 m×200 m
10	3	5
20	5	7
30	7	9
40	9	11
50	11	13

ABC: Artificial bee colony, SRCA: Sequential re-connectivity and coverage algorithm

TABLE VI
Energy Consumption Comparison for Area 100 m×100 m

Number of Nodes	Research approach	Wang, et al., 2018		
	ABC-SRCA energy (J)	PSO Energy (J)	PSO-VD energy (J)	SRACC energy (J)
45	11	14	12	10

ABC: Artificial bee colony, SRCA: Sequential re-connectivity and coverage algorithm, PSO-VD: Particle Swarm Optimization Voronoi Diagram

TABLE VII
ABC-SRCA Running Times

Number of sensor nodes	Running time (Second)	
	Area 100 m×100 m	Area 200 m×200 m
10	1	1.2
20	2	2.4
30	3.5	4.2
40	5	6
50	6.5	8

ABC: Artificial bee colony, SRCA: Sequential re-connectivity and coverage algorithm

VII. Discussion

The research approach integrates ABC's strength for coverage optimization and SRCA's strength for connectivity recovery. This integration ensures that the network remains robust and adaptive to dynamic changes, such as node failures or environmental interference. The ABC algorithm performs well in exploration and exploitation, making it well-suited to optimizing sensor node placement. However, it can get stuck in local optima. By integrating SRCA, this limitation is handled by introducing a sequential mechanism to dynamically adjust transmission ranges and reconnect nodes, ensuring global optimization. The study results indicate the efficacy of the hybrid ABC-SRCA approach in improving coverage and connectivity in WSNs compared to other techniques. The GA often suffers from slow and slow convergence to local optima, particularly in dynamic environments like WSNs. The SRACC is focuses on energy and coverage but lacks reliable mechanisms for handling dead nodes or dynamic network changes. The PSO is simple and has fast convergence but does not cope with maintaining a diversity of solutions, leading to suboptimal coverage in complex WSNs. The ABC-SRCA approach, with its adaptive nature and sequential re-connectivity mechanism, addresses these issues by dynamically adjusting node positions and transmission ranges, ensuring better performance in real-time scenarios.

The results show that the research approach consistently surpassed the ABC and the SRCA algorithms, as well as other existent techniques such as GA and SRACC. The approach attained up to 98% coverage accuracy, particularly higher than other algorithms, which implies its robustness in optimizing sensor node placement and sustaining network performance. In addition, the ABC-SRCA approach reduced the connectivity error detection rate by approximately 25%, underscoring its ability to keep reliable communication paths even in dead nodes' presence. The analysis of energy consumption showed that while the ABC-SRCA approach consumes slightly more energy than SRACC, it is more efficient than PSO and PSO-VD. The approach exhibits a balanced trade-off between network performance and energy efficiency. The approach linear scalability concerning the node number and area size further highlights its usefulness for large-scale deployments. In general, the hybrid ABC-SRCA approach significantly contributes to the WSN field by proposing a vigorous, adaptive, and efficient solution for confirming optimal coverage and connectivity, thereby reinforcing the WSN's successful deployment in various applications.

VIII. Conclusion and Future Direction

Sensing and connectivity are crucial and essential features of WSN. The quality of a sensor's coverage is known through how well it monitors the area of interest where the sensors are placed. Nodes' connectivity measures their capability to communicate with each other. The proposed ABC-SRCA approach has been employed to maintain the sensing range and monitor the movement of deployed nodes to prevent failed nodes from re-connecting and jointly enhance coverage connectivity. The proposed approach has shown promise in addressing optimization challenges in WSNs, particularly regarding coverage and re-connectivity with dead nodes. The approach offers optimization capabilities, adaptability to changing network conditions, and scalability for large-scale sensor networks. The advantage of this approach lies in its capacity to calculate the distance and value of neighboring nodes, coverage, and connectivity to control the message between the sensing range and the newly covered area. Finally, the suggested approach can efficiently maintain the detection of coverage sensing nodes within the radius by expanding the sensing range of the selected node. To evaluate the performance of the proposed approach, we compare its performance results with algorithms in terms of accuracy, average energy consumption, and running time, and it shows promising results. However, there are limitations regarding parameter tuning, convergence speed, and sensitivity to problem formulation. Future directions include more research to improve the efficiency and performance of the approach. Researchers' contribution to this collaborative effort is highly valued.

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