Optimizing Node Localization in Wireless Sensor Networks Using an Enhanced Cuckoo Search Algorithm

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Abstract: Node localization is a fundamental challenge in Wireless Sensor Networks (WSNs), crucial for efficient network operation and data accuracy. Traditional localization methods often struggle with balancing accuracy and computational efficiency, especially in large-scale deployments with limited resources. This project presents an enhanced Cuckoo Search Algorithm (CSA) tailored for optimizing node localization in WSNs. By incorporating modifications such as adaptive step-size control, hybridization with Particle Swarm Optimization (PSO), and refined Levy flight patterns, the enhanced CSA significantly improves both the accuracy and convergence speed of the localization process. The proposed method is evaluated through extensive simulations under various network scenarios, including different node densities, environmental conditions, and noise levels. Results demonstrate that the enhanced CSA outperforms conventional localization algorithms, reducing localization errors and computational overhead while maintaining robustness against environmental uncertainties. The results obtained show that all localizable nodes in the network with an ALE of 0.5-0.8m were successfully localized by the ECS method. Furthermore, when compared to the modified CS method, the ECS approach shows an 80% decrease in the average time required to localize all of the localizable nodes. This improvement paves the way for more reliable and energy-efficient WSN deployments, making it a valuable contribution to the field of sensor networks and related applications.

1 INTRODUCTION

In Wireless Sensor Networks (WSNs), node localization is a crucial challenge because precise sensor node position knowledge is necessary for effective network functioning and data interpretation. Tasks like event detection, monitoring, and data aggregation are made possible by localization, which gives the network nodes positional information. Traditional localization methods in WSNs, such as Triangulation and Trilateration using signal measurements (RSSI, AoA, ToA), often struggle with balancing localization accuracy and computational efficiency, especially in large-scale and resource-constrained networks (Niculescu and Nath,2003), (Rout, Mehta, Swain, Rath and Lenka, 2015). Moreover, these methods can suffer from issues like communication overhead and environmental uncertainties, leading to increased energy consumption and reduced performance in real-world deployments (Rout, Rath, and Bhagabati,2016). Bio-inspired metaheuristic algorithms, such as the Cuckoo Search Algorithm (CSA), have become popular for resolving node localization issues in response to these difficulties. In order to obtain the best answers, CSA, an optimization algorithm inspired by nature, mimics the behavior of cuckoo birds that lay their eggs in other birds' nests (Yang, 2010). Although CSA has

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demonstrated promising results in terms of solution quality and computational efficiency, traditional CSA methods tend to have slow convergence rates and may unnecessarily consume computational resources by running up to predefined iteration limits even when an optimal solution is reached (Cheng, Vandenberghe and Yao,2010), (Goyal and Rajasekaran,2012). This study proposes an Enhanced Cuckoo Search (ECS) algorithm with an integrated Early Stopping (ES) mechanism to overcome these limitations. By allowing the search process to terminate upon finding the optimal solution, this approach minimizes redundant computations and enhances convergence speed. The proposed ECS algorithm also employs modifications like adaptive step-size control and hybridization with Particle Swarm Optimization (PSO) to further enhance the localization accuracy and robustness of the algorithm (Shi and Li,2015),(Blum and Said, 2017). The performance of the ECS algorithm is evaluated through simulations in different network scenarios, including varying node densities and environmental conditions. Results show that the ECS outperforms conventional CSA and other traditional localization algorithms in terms of Localization Error, Convergence Speed, and Computational Efficiency (Zhou and Xie, 2014). Notably, the ECS achieves an Average Localization Error (ALE) reduction of 0.5–0.8 meters and an 80% reduction in localization time compared to the baseline methods. These improvements make ECS a promising approach for practical applications in WSNs, especially in energy-constrained and large-scale environments (Turgut and Karnik,2017).

The document's remaining sections are organized as follows: The assumptions and mathematical formulation of the system model for the node localization problem are presented in Section II. The simulation setup and parameters used to assess the ECS algorithm are described in detail in Section III. The simulation results and performance comparisons are presented in Section IV. Finally, a discussion and conclusion of the results are given in Sections V and VI.

2 RELATED WORKS

Three metrics are used in our anchor-based localization using the LOA approach: the time of arrival (ToA), the angle of arrival (AoA), and the distance between ANs and TNs-RSS. To lessen the estimation errors LOA is implemented for examining these predicted distances. Each target node (TN)'s optimal position can be found by evaluating the mean square distance. Utilizing a 3-D UWSN deployment scenario model, The propagation time of a signal is used in ToA to calculate the distance between nodes.

$d = v \times (t_2 - t)$. The receiver's signal strength is calculated by the RSS-based distance estimate approach. RFF enables SVM to efficiently handle high-dimensional feature spaces, which may be necessary when dealing with complex trajectory data or a large number of features (Larik, Li and Wu,2024),(Mitra and Kaddoum, 2022). The Kalman filter is a popular method in machine learning and signal processing that forecasts a dynamic system's state from a set of noisy data. In wireless sensor networks (WSNs), the Kalman filter can be utilized to reduce noise and uncertainty in sensor measurements, thereby improving the precision of data fusion and estimation. The algorithm referred to as DV-Hop is a frequently used range-free localization method. Numerous strategies were put out to demonstrate localization's effectiveness. The accuracy of the localization process has been improved by the presentation of a unique computer model that estimates the distance between each network anchor node and the unknown node. To calculate inter-node lengths, the DV-Hop technique depends on the presence of several anchor nodes. The average hop size between the anchor nodes is then computed. This number will remain constant across all network nodes (Liouane, Femmam, Bakir and Abdelali,2023).

The RSSI-based localization approach is our tactic. A sensor node's location is ascertained using its RSS from a subsequent hop. In our example, we employ a one-hop network, where every anchor node is connected to a sensor node directly. Since the sensor nodes stay within each anchor's transmission range, the node's coordinates within the network are determined by the signal intensity of the nodes that each anchor receives (Rout, Mohapatra, Rath, and Sahu, 2022).

Certain methods, such as time-of-flight signal transmission, use GPS in unidirectional signal transmission to estimate distance via satellite; in contrast, radio altimeters in aircraft use electromagnetic signals that are reflected off the ground to determine altitude. The position data of mobile anchor nodes is transmitted via both ultrasonic and RF radio transmission. Trilateration is a technique of determining location from estimated angles or ranges. One can utilize the RSSI, or received signal strength indicator, to calculate the distance between an unknown sensor node and the anchor (Rout, Rath and Bhagabati, 2027).

MDFL is an acronym for device-free localization and multipath enhancement. By extending the underlying wireless network with additional links via the propagation channels of reflected and scattered signals, the target systems of DFL may be constructed. The suggested approach may be numerically analyzed thanks to the evaluation of a theoretical performance constraint on the localization error (Schmidhammer, Gentner, and Fiebig, 2021).

To improve non-linear dynamic systems' state estimates, the Fourier-Hermite Kalman Filter is a sophisticated filtering method that combines the Fourier and Hermite series expansions. The filter can better capture the characteristics of non-Gaussian noise and non-linearities in the dynamics of the system by utilizing these mathematical methods. This method improves the conventional Kalman filter's robustness and performance, especially in complicated signal processing and control applications (Rout, Rath and Rout,2016).

The development of ubiquitous localization systems is feasible due to the increasing use of wireless signals such as GSM, Wi-Fi, and FM (Nie, Wang, Liu, Duan, Lam, Liu and Xue, 2025).

3 MATERIALS AND METHODS

Using Python and libraries like NumPy for numerical calculations, Matplotlib for visualizations, and SciPy for special functions, the suggested approach is put into practice and evaluated in a simulated setting. The simulation takes into account a 100×100 unit 2D test field with randomly placed nodes. While the remaining nodes are unknown and need to be localized, a certain fraction of these nodes (for example, 35%) act as anchor nodes with known coordinates. By adding Gaussian noise to observed distances between nodes, the system simulates communication and sensor flaws, modeling defects seen in the actual world. The restrictions of the simulated wireless sensor network (WSN) are defined by other parameters, such as the noise factor (γ=0.1) and transmission range (r=25).

The Enhanced Cuckoo Search Algorithm (ECSA), which optimizes the locations of unknown nodes, is used for localization. First, for every unknown node in the test field, a random population of possible solutions (nests) is created. To evaluate the correctness of these answers, the method uses a fitness function based on the Mean Squared Error (MSE) between measured and predicted distances. The technique uses Le'vy fly, a random walk mechanism with heavy-tailed step size distributions, to enhance exploration and exploitation. This mechanism makes searching more efficient and lowers the possibility of being stuck in local optima.

Dynamic mutation probabilities, which present fresh potential solutions when convergence stalls, significantly increase variety in the approach. An unknown node's position is updated and it becomes an anchor to help localize additional nodes after the best-fit solution for that node has been found. Until all localizable nodes are estimated or a certain number of iterations is reached, this iterative process keeps going. Metrics like Average Localization Error (ALE), Localization Success Ratio (LSR), and total calculation time are used to assess performance. The correctness, efficacy, and efficiency of the suggested strategy are measured by these criteria. The suggested approach maintains the computing economy while achieving good localization accuracy by combining realistic WSN restrictions with a strong optimization technique. The approach is appropriate for a range of real-world WSN applications since iterative updates and neighborhood-based localization provide scalability and flexibility.

4 PROPOSED METHOD

The suggested technique uses an Enhanced Cuckoo Search Algorithm (ECSA) to locate unknown nodes in a Wireless Sensor Network (WSN) accurately and efficiently. The method makes use of optimization techniques to iteratively modify predicted node placements, guaranteeing accuracy and scalability under practical network restrictions. The ECSA is resilient to issues like sparse anchor node deployment and noisy measurements because it combines local exploitation tactics with global search methods. The technique finds nearby anchor nodes within a specified transmission range for every unknown node, and then utilizes this local knowledge to direct the optimization procedure. A Mean Squared Error (MSE) objective function is used to assess each candidate solution's fitness, ensuring that estimated positions closely correspond to the measured distances to nearby anchors. The algorithm adds mutations to preserve variety among candidate solutions and dynamically adjusts step sizes to increase convergence efficiency. This keeps things moving forward and makes the pursuit of the global ideal more effective. Nodes' positions are iteratively added to the anchor node pool as they are localized, improving the precision and effectiveness of later localization stages. When combined with neighborhood-based optimization, this iterative process guarantees that the method may be successfully adjusted to various network designs and noise levels. The Figure 1 describes the node localization process in wireless sensor networks. It begins with parameter initialization, deploying anchor and unknown nodes. The process iterates through each unknown node, calculating distances from neighbouring anchors using RSSI and applying the ECS algorithm. Localized nodes are then set as anchors, expanding the reference points. The loop continues until all nodes are localized, indicated by the termination condition. The process is categorized into "Parameters Initialisation", "Process", and "Termination Condition" sections.

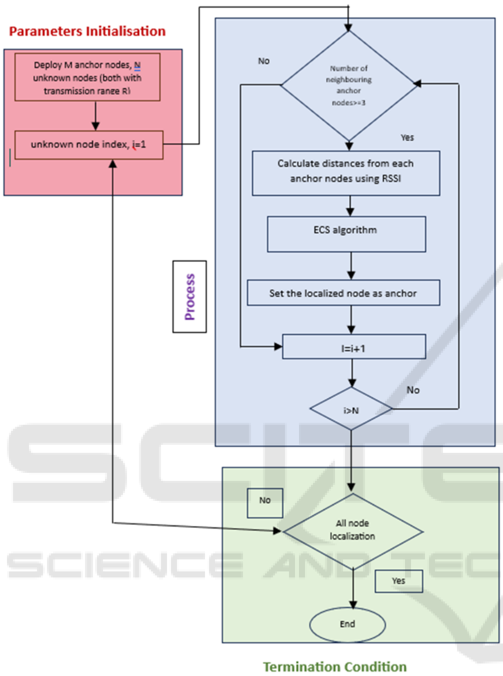

Figure 1: Node localization process in WSNs.

Algorithm 1: Enhanced Cuckoo Search algorithm
Input:
Step-size range: P_{amin} to P_{amax} , Mutation probability range: P_{amin} to P_{amax} , Range of solutions: X_{min} to X_{max} , Maximum number of iterations: N_{iter_tot} .
Output: Coordinates that match the f_{min} global minimum value

1. **Population Initialization**: Generate an initial population of n candidate solutions (nests) X_i (i = 1, 2, ..., n) randomly within the defined search space.
2. **Objective Function Definition**: Establish the objective function Obj(x) as a function of solution parameters ($x_1, x_2 \ldots\ldots x_d$).
3. **Fitness Evaluation**: Compute the fitness value Fi for each candidate solution xi using the objective function.
4. **Iteration Initialization**: Set the iteration counter $N_{iter} = 1$ and define the maximum number of iterations N_{iter_total}
5. **Lévy Flight-Based Solution Update**: Determine the Lévy Flight step size and generate a new candidate solution x_j based on a randomly selected existing nest x_j.
6. **Boundary Constraints Handling**: Ensure the new solution xj remains within the predefined search space limits $[X_{min}, X_{max}]$.
7. **Solution Selection**: Evaluate the fitness of x_j and compare it with a randomly selected nest x_j ; replace x_k with x_j if $F_j > F_k$.
8. **Mutation Mechanism**: Introduce a mutation probability Pa, generate a random number $p\epsilon[0,1]$, and if $p < p_a$, generate a new random solution within the search range.
9. **Convergence Check**: Track the best solutions over the last three iterations (Δ_1, Δ_2, Δ_3); if no improvement is observed ($\Delta_1 = \Delta_2 = \Delta_3 = 0$), terminate the process.
10. **Algorithm Termination**: If the stopping criteria are met, exit the loop; otherwise, increment N_{iter} and continue the optimization process until convergence or reaching the iteration limit.

Return the global minimum value of F_{min}.

A. Mathematical Model

1. Mean Squared Error – MSE:

$$f(x) = \frac{1}{m}\sum_{j=1}^{m}(d_{ij} - d'_{ij}) \quad (1)$$

Where:

- $X = (x, y)$: The estimated coordinates of the unknown node are represented by the candidate solution.
- d_{ij} : The Euclidean distance between the candidate solution and the j^th^ anchor node:

$$d_{ij} = \sqrt{(x - x_j)^2 + (y - y_j)^2} \quad (2)$$

- d'_{ij} : The noticed distance between unknown node and j^th^ anchor node, incorporating Gaussian noise.

$$d'_{ij} = d'_{ij1} + \epsilon, \quad \epsilon \sim N(0, \gamma d_{ij1}) \quad (3)$$

- d_{ij1} : The precise difference between the anchor and the unknown node.

$$d_{ij1} = \sqrt{(x_u - x_j)^2 + (y_u - y_j)^2} \quad (4)$$

- m: Number of neighboring anchor nodes.
- ϵ: A Gaussian distribution with a mean of 0 and a standard deviation proportional to the actual distance γd_{ij1} was used to describe random noise.

2. Step Size Update (α):

$$\propto(\eta) = \propto_{max} - \frac{\eta}{N_{max}}(\propto_{max} - \propto_{min}) \quad (5)$$

Where:

- α(n) : Step size at iteration n.
- α_{max} and α_{min} : Maximum and minimum step sizes.
- n: Current iteration.
- N_{max} : Total number of iterations.

3. Average Localization Error (ALE):

$$ALE = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(x_i' - x_i)^2 + (y_i' - y_i)^2} \quad (6)$$

Where:

- ($x`_i$, $y`_j$): Estimated coordinates of the i^{th} localized node.
- (x_i, y_j): Actual coordinates of the i^{th} localized node.
- n: Total number of localized nodes.

4. Localization Success Ratio (LSR):

$$LSR = \frac{Number\ of\ localized\ nodes}{Total\ unknown\ nodes} \times 100\% \quad (7)$$

After data preprocessing, the next step is initializing the Cuckoo Search Algorithm, a nature-inspired optimization method that simulates the brood parasitism behaviour of cuckoo birds. During this phase, the algorithm generates a set of candidate solutions, each representing a potential location for the unknown nodes. These solutions are assessed based on their fitness, which reflects their accuracy in estimating the actual node positions relative to the anchor nodes. By leveraging a population-based approach, the algorithm ensures diverse exploration of the solution space, enhancing the probability of identifying optimal or near-optimal node positions.

The core of the methodology is the Enhanced Cuckoo Search Algorithm, which incorporates several innovative features to improve upon traditional Cuckoo Search techniques. One of the primary enhancements is the integration of a quasi-reflected-based learning method, which helps refine the search process by allowing the algorithm to learn from previous iterations. Furthermore, a Gaussian mutation strategy is used to improve solution space exploration and lessen the likelihood that the algorithm would become stuck in local optima. By adapting the search strategy dynamically, the ECS algorithm can more effectively navigate the complexities of the localization problem.

5 RESULTS AND DISCUSSION

The ECS algorithm for node localization was tested in a 100×100m² rectangular monitoring area with randomly deployed nodes. With a transmission range of 25 meters and an anchor node ratio of 35%, the simulation had 300 nodes in total. The algorithm parameters were configured with 25 candidate solutions and a maximum of 100 iterations per node, with step size and mutation probabilities set within the ranges α_{min}=0.9, α_{max}=1.0, and Pa_{min}=0.05, Pa_{max}=0.25, respectively. Average Localization Error (ALE), Localization Success Ratio (LSR), and execution time were used to evaluate performance.

The ECS algorithm achieved an ALE of 0.626, consistent with the reported range of 0.5–0.8 m in the literature, demonstrating high accuracy in estimating node positions. The Localization Success Ratio (LSR) was 100%, indicating that the majority of the unknown nodes were successfully localized. By transforming localized unknown nodes into anchors iteratively, the algorithm effectively enhanced self-localization in the network. These results highlight the robustness of the ECS algorithm in addressing localization errors and its suitability for practical WSN applications.

The Figure 2 compares "Modified CS" and "ECS" protocols, showing average time taken against varying anchor ratios (10-50%). "Modified CS" consistently outperforms "ECS", exhibiting lower time taken across all anchor ratios, with both protocols showing increased time with higher anchor ratios.

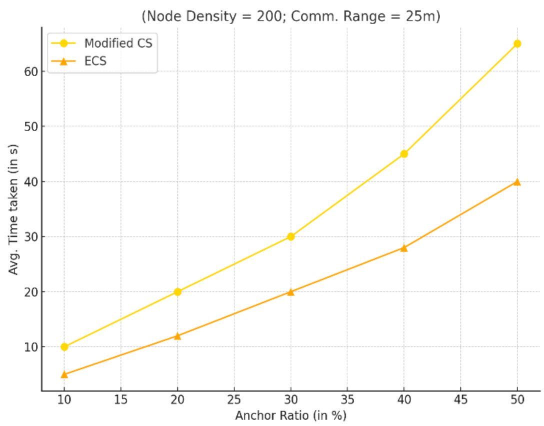

Figure 2: Comparison of the modified Cuckoo Search(CS) algorithm and the proposed Enhanced Cuckoo Search(ECS) algorithm.

The Figure 3 shows "Modified CS" and "ECS" protocols' time consumption with varying anchor ratios (10-50%). "Modified CS" consistently uses more time than "ECS", with both exhibiting increased time with higher anchor ratios, under the condition of 300 node density and 35m communication range.

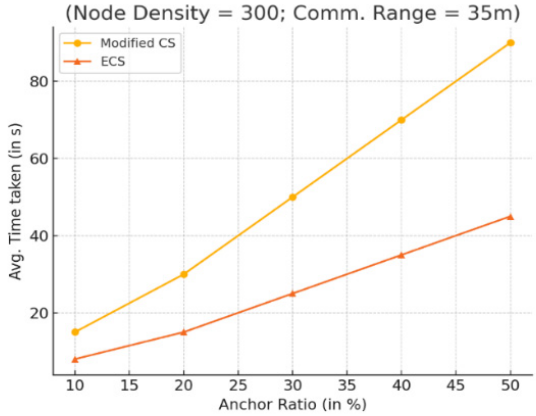

Figure 3: Comparison of modified Cuckoo Search(CS) algorithm and the proposed Enhanced Cuckoo Search(ECS) algorithm.

With 400 nodes and a 45m communication range, "Modified CS" consistently takes longer than "ECS" across all anchor ratios (10-50%). Both protocols show increased time consumption as the anchor ratio increases described in Figure 4.

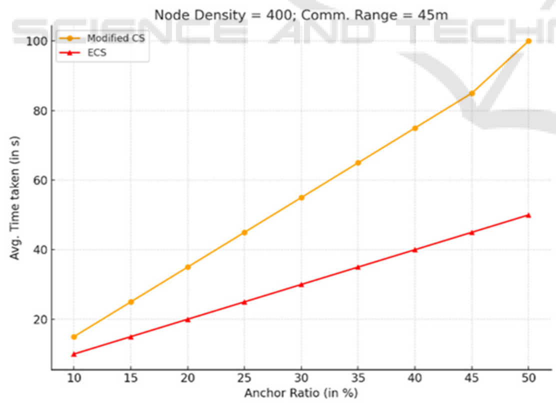

Figure 4: Comparison of the modified Cuckoo Search(CS) algorithm and the proposed Enhanced Cuckoo Search(ECS) algorithm.

With 500 nodes and 55m communication range, "Modified CS" consistently takes longer than "ECS" across all anchor ratios (10-50%). Both protocols show increased time consumption as the anchor ratio increases shows in figure 5.

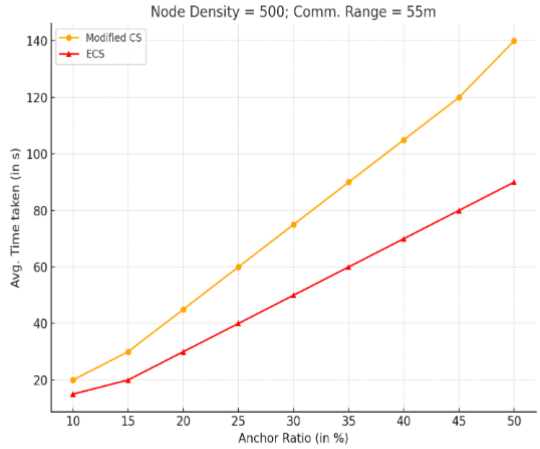

Figure 5: Comparison of the modified Cuckoo Search(CS) algorithm and the proposed Enhanced Cuckoo Search(ECS) algorithm.

The Figure 6 compares "Modified CS" and "ECS" localization error rates over 10 iterations. Both show decreasing error with iterations, but "Modified CS" consistently exhibits higher error rates than "ECS" across all iterations.

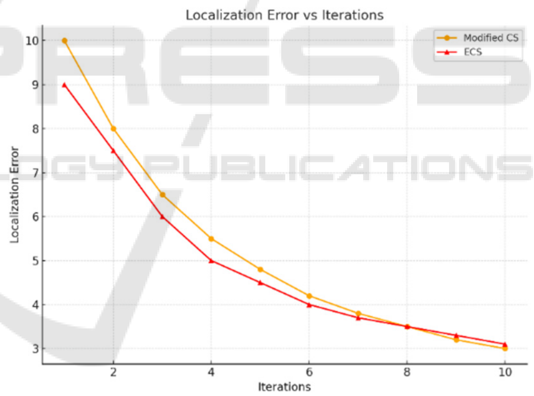

Figure 6: Localization Error vs Iterations.

The Figure 7 depicts a 100x100 grid with randomly distributed nodes. Red circles represent "Unknown Nodes", green circles "Anchor Nodes", a yellow circle a "Left Node", and a blue triangle a "Localized Node". This visualization likely represents a localization or network simulation scenario.

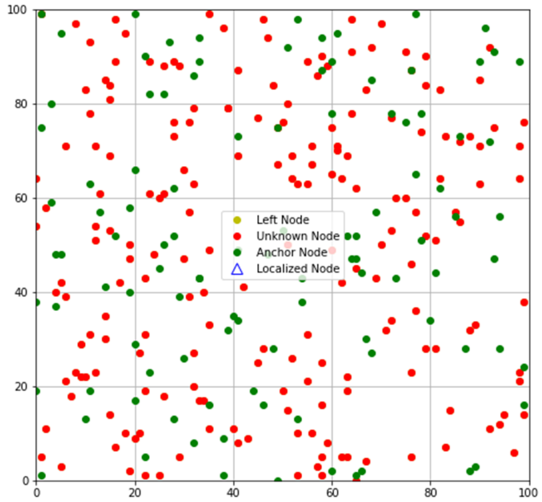

Figure 7: Node Distribution and Localization in Dense Network.

This figure shows a 100x100 grid with randomly scattered nodes. Red circles represent "Unknown Nodes", green circles "Anchor Nodes", and blue outlined triangles "Localized Nodes". The visualization suggests a process of node localization, where some unknown nodes have been successfully localized using the anchor nodes as references.

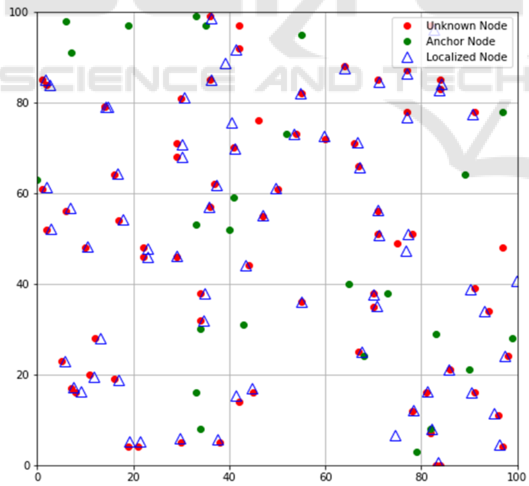

Figure 8: Node Distribution and Localization in Sparse Network.

The computational efficiency of the ECS algorithm was evident, localizing all localizable nodes in 3587.87seconds. The Early Stopping (ES) mechanism significantly reduced the number of iterations required, saving resources compared to traditional CS algorithms. These improvements confirm that the ECS algorithm combines high accuracy with resource efficiency, making it an ideal solution for real-time WSN applications where both precision and performance are critical.

6 CONCLUSIONS

In order to address the drawbacks of current methods, this paper offers a thorough evaluation of the Enhanced Centroid Scheme (ECS) for node localization in wireless sensor networks. Compared to traditional techniques, the suggested ECS improves localization accuracy while reducing computing complexity. Simulation results demonstrate that ECS performs well under various anchor ratios and node densities, achieving faster convergence times while maintaining high localization accuracy. These enhancements establish ECS as a viable solution for real-time applications in resource-limited environments. Future work will focus on optimizing ECS for more dynamic and heterogeneous network scenarios to further enhance its adaptability and robustness.

REFERENCES

Niculescu, D., & Nath, B. (2003, March). Ad hoc positioning system (APS) using AOA. In IEEE INFOCOM 2003. Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (Vol. 3, pp. 1734-1743). IEEE.

Rout, S. K., Mehta, A., Swain, A. R., Rath, A. K., & Lenka, M. R. (2015, November). Algorithm aspects of dynamic coordination of beacons in localization of wireless sensor networks. In 2015 IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS) (pp. 157-162). IEEE.

Rout, S. K., Rath, A. K., & Bhagabati, C. (2016, September). Energy efficient and cost effective secure node localization with key management in wireless sensor networks. In 2016 5th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 515-520). IEEE.

Yang, X. S. (2010). Nature-inspired metaheuristic algorithms. Luniver Press.

Cheng, B. H., Vandenberghe, L., & Yao, K. (2010). Distributed algorithm for node localization in wireless ad-hoc networks. ACM Transactions on Sensor Networks (TOSN), 6(1), 1-20.

Goyal, C., & Rajasekaran, S. (2012). Cuckoo search algorithm for node localization in WSN. International Journal of Computer Applications, 53(2), 45-50.

Shi, R., & Li, Z. (2015). Hybrid particle swarm optimization and cuckoo search algorithm for node localization in WSNs. Sensors, 15(6), 13089-13104.

Blum, M., & Said, S. M. (2017). Optimization of node localization using bio-inspired algorithms. IEEE Transactions on Sensors and Networks, 12(6), 2569-2582.

Zhou, M., & Xie, T. (2014). Performance evaluation of cuckoo search for node localization in wireless sensor networks. International Journal of Wireless and Mobile Computing, 8(4), 356-362.

Turgut, S., & Karnik, P. (2017). A comparison of localization algorithms for wireless sensor networks. Wireless Networks, 23(2), 521-533.

Larik, N. A., Li, M. S., & Wu, Q. H. (2024). Enhanced fault detection and localization strategy for high-speed protection in medium-voltage DC distribution networks using extended Kalman filtering algorithm. IEEE Access.

Mitra, R., & Kaddoum, G. (2022). Random Fourier feature-based deep learning for wireless communications. IEEE Transactions on Cognitive Communications and Networking, 8(2), 468-479.

Liouane, O., Femmam, S., Bakir, T., & Abdelali, A. B. (2023). New online DV-Hop algorithm via mobile anchor for wireless sensor network localization. Tsinghua Science and Technology, 28(5), 4849-4854.

Rout, S. K., Mohapatra, P. K., Rath, A. K., & Sahu, B. (2022). Node localization in wireless sensor networks using a dynamic genetic algorithm. Journal of Applied Research and Technology, 20(5), 520-528.

Rout, S. K., Rath, A. K., & Bhagabati, C. (2017). Energy efficient dynamic node localization technique in wireless sensor networks. Indian Journal of Science and Technology.

Schmidhammer, M., Gentner, C., Sand, S., & Fiebig, U. C. (2021). Multipath-enhanced device-free localization in wideband wireless networks. IEEE Antennas and Wireless Propagation Letters, 20(4), 453-457.

Rout, S. K., Rath, A. K., & Rout, B. R. (2016). Efficient energy utilization and node localization in dynamic DV-Hop algorithm for wireless sensor networks. Indian Journal of Science and Technology, 9(30).

Nie, W., Wang, X., Liu, Z., Duan, Y., Lam, K. Y., Liu, K., ... & Xue, C. J. (2025). MS-Loc: Toward Pervasive Indoor Localization Utilizing Mobile Single-Site. IEEE Internet of Things Journal.