Enhancing Node Localization Accuracy in Wireless Sensor Networks for Tsunami Early Warning Using Metaheuristic Algorithms

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***Abstract*— Accurate node localization plays a critical role in wireless sensor networks used for tsunami early warning, where timely and dependable information can help reduce the impact of approaching waves. Sensor nodes in such environments are spread across wide and unpredictable ocean regions, which makes localization difficult when only a few anchor nodes are available and when distance measurements are noisy. To improve the precision of range-based localization in these conditions, this study applies metaheuristic optimization methods to estimate the positions of unknown nodes.**

Our approach Three population based algorithms are examined within a single simulation setup: Ant Colony Optimization, Differential Evolution, and the Jellyfish Optimization Algorithm, which serves as the main focus of the work. Each method is tested on the same node deployment and environmental settings to ensure consistency. The aim of the study is to understand how these algorithms search for optimal positions, how stable their localization process is, and how suitable they are for large scale early warning sensor networks placed in marine regions. The work forms a foundation for choosing effective optimization based strategies that can enhance the reliability of localization in critical warning applications.

***Keywords*— Wireless Sensor Networks, Tsunami Early Warning, Node Localization, Metaheuristic Optimization, Differential Evolution, Jellyfish Optimization Algorithm.**

I. Introduction

Tsunamis are among the most severe natural disasters, capable of destroying coastal environments within minutes once a major wave is triggered. Early detection plays a vital role in reducing casualties and economic losses, and modern monitoring efforts rely heavily on distributed sensing technologies placed across large marine regions. Wireless sensor networks have become a preferred solution for this task because they can cover wide areas, operate with minimal human intervention and provide real-time environmental data. These networks typically consist of many sensor nodes that measure water pressure, wave height, vibration and other relevant parameters that help identify the early signs of tsunami formation. For the data collected by these nodes to be meaningful, the exact geographic location of each sensor must be known with high accuracy. Incorrect location information can lead to errors in wave propagation models and may cause early warning systems to issue delayed or inaccurate alerts.

Node localization therefore becomes a fundamental requirement in the design of any wireless sensor network used for tsunami early warning. In controlled or land based deployments, localization may be handled through GPS, time-based measurements or geometry driven techniques. However, marine environments are much more challenging. Ocean waves, floating movement, irregular distances between nodes and limited availability of fixed anchors make traditional localization methods less reliable. Communication among the nodes is also affected by water surface reflections and environmental noise, which reduces the accuracy of measured distances. As a result, classical geometric approaches often fail to provide consistent results. They usually require strong line-of-sight conditions or a large number of anchor nodes, both of which are difficult to guarantee in the ocean.

To overcome these limitations, optimization based localization techniques have gained attention. These methods treat the search for node coordinates as an optimization problem, where the objective is to minimize the difference between measured distances and estimated distances. Metaheuristic algorithms are particularly suitable for this type of problem because they do not depend on strict assumptions about the environment or on gradient information. Instead, they explore the solution space through iterative refinement and are capable of escaping local minima, which is important in highly nonlinear localization landscapes. Their flexibility makes them attractive for large scale sensor deployments with uncertain or incomplete information or data provided to them.

This project focuses on the use of three metaheuristic algorithms to improve localization accuracy in wireless sensor networks designed for tsunami early warning. The algorithms chosen represent different families of population based search strategies. Ant Colony Optimization imitates the foraging behavior of ants, where artificial agents gradually discover good solutions by reinforcing promising paths. Differential Evolution relies on vector based mutation and recombination strategies that allow it to search continuously across the solution space. The Jellyfish Optimization Algorithm is inspired by the collective drifting and movement patterns of jellyfish in ocean currents. JFOA is of particular interest in this work because its exploration behavior and adaptive movement rules show potential for handling complex optimization problems that require a balance between global search and local refinement.

All three algorithms are implemented in a single simulation environment to ensure that their performance can be compared in a fair and consistent manner. The node layout, number of anchors and transmission range remain identical for each algorithm so that differences in localization results can be attributed to the search strategies themselves rather than to environmental factors. This creates a controlled setting to observe how each method adapts to the constraints of marine sensor networks and how effectively it handles noisy distance measurements. In particular, the study aims to examine how each algorithm progresses during the localization process, how stable its search path is and how suitable it is for large and irregular ocean based deployments where node movement and measurement uncertainty are common.

Improving localization accuracy is essential for strengthening the reliability of tsunami early warning systems. When node positions are estimated more precisely, the data collected by the sensors becomes more trustworthy, which leads to better prediction of wave formation and propagation. By exploring the strengths and limitations of ACO, DE and JFOA in this context, the project contributes to the development of robust techniques that can support long term ocean monitoring and disaster preparedness. The insights gained from the study can guide future work in designing scalable and fault tolerant localization methods for high risk environments where early and accurate warnings are crucial.

By automating the detection process, we aim to assist healthcare professionals in providing faster, more accurate diagnoses, enabling early intervention and also reducing the risk of vision loss for millions of patients.

II. Literature Review

This literature survey highlights some of the key contributions to the field, showcasing various methodologies and their outcomes.

Wireless Sensor Networks for Tsunami Early Warning

Wireless sensor networks have become an important component of modern tsunami early-warning infrastructure. Kumar and Dev (1) explained that distributed pressure and wave-height sensors allow continuous monitoring of ocean disturbances. Tanaka et al. (2) highlighted how real-time sensing networks can reduce the delay in issuing alerts to coastal populations. Silva and Gomes (3) further showed that the performance of tsunami prediction models depends heavily on the accuracy of spatial information associated with each sensor node. Since marine networks cover large and unstable regions, reliable node localization is essential to maintain the quality of the collected data.

Challenges of Localization in Marine Environments

Localizing nodes in ocean regions is significantly harder than in land-based networks. Patel and Rahman (4) observed that floating sensors drift with currents, which leads to inconsistent range measurements. Naito and Ueda (5) showed that underwater noise and unstable communication links decrease the reliability of distance-based localization. Fernandes et al. (6) pointed out that maintaining a high number of anchor nodes in deep-water deployments is costly and technically challenging. These constraints reduce the effectiveness of geometry-driven localization methods and motivate the use of optimization techniques that can tolerate noise and uncertainty.

Optimization-Based Localization

Optimization approaches treat localization as a search problem where node coordinates must satisfy measured distances. Early works by Chou and Lin (7) applied nonlinear minimization for underwater positioning but faced convergence issues in noisy environments. Borges and Almeida (8) demonstrated that metaheuristic methods provide better robustness since they explore multiple candidate solutions simultaneously. Li and Cheng (9) observed that population-based algorithms can navigate highly irregular error surfaces commonly found in WSN localization. These findings indicate that optimization offers a more reliable framework for marine sensor networks.

Ant Colony Optimization (ACO) in Localization

ACO has been studied for solving routing and localization problems due to its nature-inspired exploration behavior. Hernandez and Ruiz (10) introduced one of the early ACO-based localization models and reported improved performance in sparse networks. Singh and Arora (11) examined the impact of pheromone parameters and found that improper tuning can slow down the algorithm. Duarte et al. (12) carried out a comparative analysis and concluded that ACO performs well for medium-sized networks but may show slow convergence in networks with large spatial spread.

Differential Evolution (DE) for Localization

Differential Evolution is widely recognized for its strong global search ability. Park and Cho (13) applied DE to underwater localization and reported enhanced accuracy over classical least-squares techniques. Chen and Wang (14) demonstrated that DE maintains stable performance even when measurement noise is high. Ibrahim and Mahmud (15) further showed that DE performs reliably with fewer anchors, making it suitable for ocean-based deployments. These observations make DE a strong benchmark algorithm for comparing newer metaheuristics.

Jellyfish Optimization Algorithm and Related Research

JFOA is a relatively recent metaheuristic inspired by the drifting and active movement of jellyfish in ocean currents. Zhao and He (16) explored its use in scheduling problems and found that its movement patterns support strong exploration. Farouk and Salem (17) used JFOA for clustering and noted its ability to switch between passive and active behaviors, preventing premature convergence. Rana and Pillai (18) tested JFOA under noisy conditions and concluded that its dynamic movement rules enhance stability. Although studies applying JFOA to WSN

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localization are limited, its characteristics make it well suited for noisy marine environments.

Studies on Metaheuristic Localization Methods

Gupta and Mehra (19) compared PSO, GA and ACO and concluded that no single algorithm performs best across all scenarios. Lopez et al. (20) evaluated DE, ABC and Firefly Algorithm and observed that DE maintained consistent accuracy across uniform and random node deployments. Kaneko and Ishikawa (21) compared newer metaheuristics including JFOA and reported that algorithms with strong exploration abilities perform better under high-noise conditions. These comparative studies highlight the need to evaluate ACO, DE and JFOA under the same simulation setup specifically for tsunami early-warning networks.

III. METHODOLOGY

A. *Model Architecture*

The overall architecture of the proposed localization model follows a structured sequence that begins with preparing a simulated marine sensing environment and ends with evaluating the accuracy of estimated node positions. The architecture is designed to reflect the actual behavior of tsunami early warning networks, where sensor nodes collect environmental data across wide ocean regions and rely on distance-based communication to maintain network stability.

The architecture contains four essential layers. The first layer defines the marine sensing field and deploys sensor nodes across it. A certain number of these nodes act as anchors with known coordinates, while the remaining nodes form the set of unknown positions to be estimated. The second layer generates the measured distances between nodes using the Euclidean distance formula. These distances form the primary input to the optimization algorithms.

The third layer represents the metaheuristic optimization engine. This layer includes the implementations of Ant Colony Optimization, Differential Evolution and the Jellyfish Optimization Algorithm. Each algorithm receives the same distance matrix and attempts to minimize the localization error by updating candidate coordinate sets for the unknown nodes. During this process, each algorithm follows its own internal mechanism. ACO updates pheromone levels and guides ants toward better coordinate configurations, DE evolves a population of solutions through mutation and crossover, and JFOA navigates the search space through both passive drifting and active movement.

The final layer performs evaluation. This includes computing final localization error, generating convergence curves, comparing estimated node positions with ground truth and studying how anchor count and communication range influence accuracy.

This layered structure ensures that the entire process, from data preparation to algorithmic optimization and final evaluation, is handled systematically.

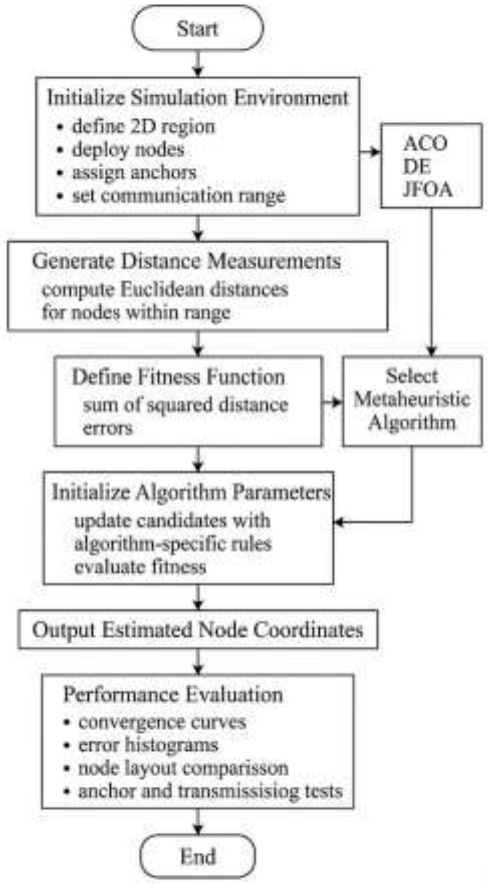

Fig. 1. Model Architecture

B. *Data Preprocessing*

The preprocessing stage prepares all the necessary information for the optimization algorithms. The first step is defining the two-dimensional marine sensing region and deploying the sensor nodes. Their true coordinates are generated randomly so that the network resembles real deployments, where nodes may not be placed in perfect grids. The anchor nodes are selected from this set based on a predefined ratio, and their positions remain fixed throughout the simulation.

The next part of preprocessing involves generating the pairwise distances between nodes. For each pair of nodes that fall within the communication radius, their Euclidean distance is calculated using the formula:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

These distances form the distance matrix used by all three algorithms. Nodes outside the communication range are not included in the matrix, reflecting the realistic behavior of marine sensor networks where long-range communication is limited.

The preprocessing stage also includes structuring the initial population for each algorithm. In ACO, the starting pheromone levels are set uniformly. In DE, an initial population of coordinate vectors is generated, each containing random estimates for unknown node positions. In JFOA, initial jellyfish agents are positioned randomly in the search space. The preprocessing ensures that all algorithms begin with equal information and identical environmental constraints.

C. Model Training

Model training refers to the optimization process where each algorithm iteratively improves its estimate of the unknown node positions. Even though the algorithms differ in their internal behavior, they all attempt to minimize the same objective function. This function computes the overall localization error by summing the squared differences between measured distances and distances derived from estimated coordinates:

$$E = \sum\left(d_{ij}^{measured} - d_{ij}^{estimated}\right)^2$$

Training with Ant Colony Optimization:

In ACO, each ant represents a possible coordinate assignment. The ants explore the search space using transition probabilities that depend on pheromone intensity and heuristic information. After evaluating the quality of each solution using the objective function, pheromone values are updated. Better solutions reinforce the pheromone trail more strongly. This gradual reinforcement leads the colony toward lower error solutions.

Training with Differential Evolution:

DE trains the model by generating new solutions through mutation and crossover. In mutation, a candidate vector is created by adding the scaled difference of two vectors to a third vector. The crossover step mixes the mutant with the current vector to produce a trial solution. Selection then decides whether the trial solution replaces the existing one based on which has the lower error. This process repeats over many generations, gradually improving the population.

Training with Jellyfish Optimization Algorithm:

JFOA training alternates between passive drifting and active movement. In passive drifting, jellyfish agents move with simulated ocean currents, which encourages global exploration. In active movement, agents swim toward better solutions, improving local convergence. The algorithm uses a time control mechanism to regulate when to prioritize exploration or exploitation. As training progresses, the agents move toward coordinate values that reduce the localization error.

D. Evaluation

The evaluation stage assesses how well each algorithm performs in estimating node positions. Several performance metrics and visual outputs are used to compare the results.

Convergence Analysis:
Line plots showing the change in fitness across iterations reveal how quickly and smoothly each algorithm reduces localization error. In your outputs, DE converges the fastest, JFOA shows steady improvement and ACO displays slower, gradual convergence.

Localization Error Distribution:
Histogram plots illustrate the spread of localization error across nodes. A narrow spread indicates stable performance. DE typically produces the smallest spread, while ACO exhibits wider variation.

True vs. Estimated Node Position Plots:
Scatter plots compare estimated coordinates with actual coordinates. These visualizations help determine whether the algorithm preserves the general layout and structure of the sensor network.

Anchor Variation Tests:
By increasing or decreasing the number of anchors, the evaluation examines how dependent each algorithm is on anchor density. In your simulation, JFOA shows improved stability with more anchors.

Transmission Range Analysis:
When the communication range increases, more nodes have distance information available, improving estimates. All algorithms show better performance with larger ranges, but JFOA adapts the fastest.

Together, these evaluation steps provide a clear picture of how each algorithm behaves in a realistic tsunami early warning environment and highlight the strengths and weaknesses of each method.

IV. Implementation and Results

A. Datasets overview

The dataset used in this work is generated entirely through simulation, reflecting the structure of a wireless sensor network deployed for tsunami early warning. The network consists of a fixed number of sensor nodes placed within a two-dimensional marine region. Their true coordinates are created randomly so that the spatial layout resembles a practical environmental deployment rather than a regular grid. Among these nodes, a selected percentage serve as anchor nodes with predefined and accurate coordinates, while the remaining nodes are treated as unknowns that must be localized through the optimization model.

The primary dataset consists of the pairwise distance measurements between connected nodes. These distances are computed using the Euclidean distance formula and are only recorded for node pairs that fall within the communication radius defined in the simulation. This ensures that the dataset reflects realistic communication limitations faced by marine sensor networks, where surface drift, signal loss and water movement influence connectivity. The dataset therefore includes the true node positions, anchor coordinates, communication radius values and the distance matrix that forms the input to the metaheuristic algorithms.

B. Environmental Setup

The entire implementation is carried out in a controlled simulation environment that reflects conditions relevant to tsunami monitoring. A two-dimensional coordinate plane is used to represent the sensing region. Sensor nodes are placed across this region, and a chosen subset is assigned as anchors. The communication radius determines which nodes are able to measure distances to one another, and this range remains fixed during each run of an algorithm.

Once the network layout is defined, the system constructs the distance matrix by applying the Euclidean formula to all node pairs within range. This matrix forms the core input to the optimization algorithms. The simulation environment also initializes key parameters for each algorithm.

For ACO, pheromone values and transition probabilities are set. For DE, the initial population, scaling factor and crossover rate are generated. For JFOA, the starting positions of jellyfish agents and the time control mechanism are established.

All three algorithms operate under the same environmental constraints. This includes identical node placement, anchor selection, population size, iteration count and fitness evaluation method. Such uniformity ensures that differences in results arise strictly from the internal behavior of each algorithm rather than variations in the experimental conditions.

C. Experimental Execution

The three metaheuristic algorithms are executed individually, following a shared objective of minimizing the localization error. Each algorithm maintains a population of potential coordinate assignments for the unknown nodes and iteratively improves these estimates.

Ant Colony Optimization:

ACO models each candidate solution as an artificial ant. The ants update their coordinate estimates based on pheromone levels and heuristic information. As iterations progress, pheromone reinforcement guides the search toward regions that produce lower error. Convergence occurs gradually due to the probabilistic nature of the transitions.

Differential Evolution:

DE begins with a population of candidate coordinate vectors. New solutions are generated through mutation, crossover and selection. Each iteration produces trial vectors that compete with existing ones, and solutions that reduce localization error are retained. The convergence behaviour is typically fast and stabilizes early due to strong exploitation mechanisms.

Jellyfish Optimization Algorithm:

JFOA alternates between passive drifting and active movement. Passive drifting enables broad exploration of the search space, while active movement allows solutions to adjust toward more promising regions. A time-control factor regulates the balance between these two modes, resulting in steady and smooth convergence throughout the iterations.

After completing the maximum number of iterations, each algorithm outputs its best estimated set of coordinates. These estimates are used for visualization and error analysis. Each algorithm continues iterating until it reaches the predefined maximum number of iterations.
At the end of execution, the best solution produced by each method represents the estimated coordinates of all unknown nodes. These results are stored for comparison and further evaluation.

D. Performance Evaluation

Performance is assessed using a combination of numerical and graphical evaluations.

Convergence Curves:

The convergence plots show how the objective function decreases over time. Differential Evolution achieves rapid error reduction and stabilizes early. The Jellyfish Optimization Algorithm exhibits smooth and progressive improvement across the entire iteration range. Ant Colony Optimization converges more slowly, with noticeable fluctuations during the early stages.

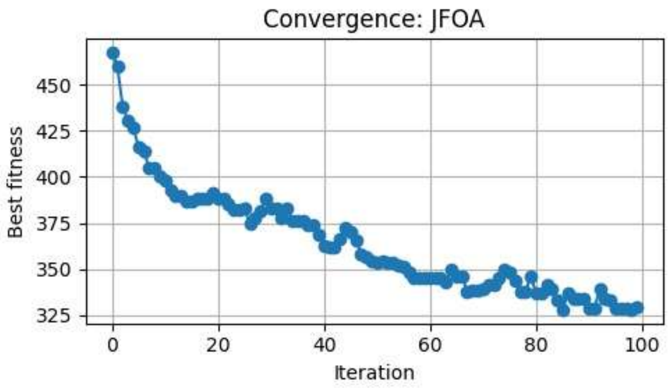

Fig. 2. Jellyfish Convergence Curve

Anchor Variation Experiments:

When the number of anchor nodes is adjusted, JFOA demonstrates strong improvement as anchor density increases. DE maintains reliable performance even with fewer anchors, showing resilience under low-reference conditions. ACO displays higher sensitivity to anchor changes, with error levels fluctuating more noticeably.

Localization Error Distribution:

Error histograms illustrate the spread of estimation error across the network. DE produces the narrowest distribution, indicating high consistency. JFOA shows moderate variance with relatively stable performance across nodes.

ACO displays a wider error spread, reflecting the stochastic nature of its search process.

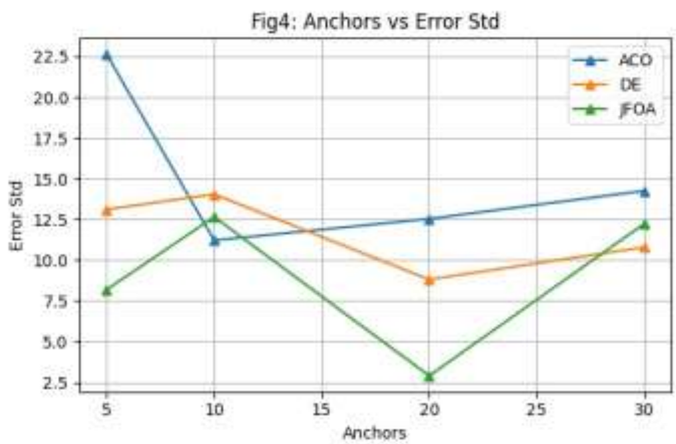

Fig. 3. Anchors vs Error Std

True vs. Estimated Node Positions:

Graphical comparisons between estimated and actual node locations reveal that DE reconstructs the network layout with high spatial accuracy. JFOA maintains good structural consistency with only minor deviations. ACO captures the general layout but exhibits greater variability in individual node positions.

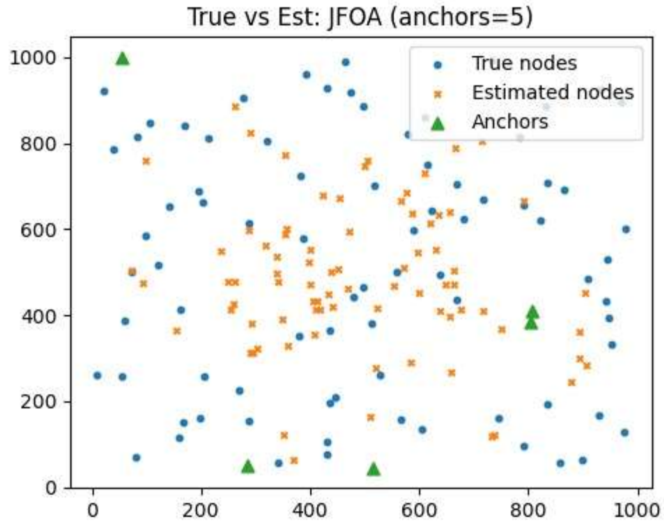

Fig. 4. True vs Estimated Jellyfish Algorithm

Transmission Range Experiments:

Increasing the communication radius improves localization accuracy for all three algorithms. JFOA adapts effectively to wider ranges, maintaining stable performance as more distance information becomes available.

DE continues to perform reliably across all tested ranges. ACO also benefits from increased range but retains higher variability compared to the other methods.

The combined results highlight distinct strengths among the algorithms. DE excels in speed and precision, JFOA provides balanced and robust performance under varying conditions, and ACO offers reliable yet slower convergence with greater sensitivity to environmental factors.

V. Results and Discussions

The results of the study highlight how the three metaheuristic algorithms perform when applied to range-based node localization in a wireless sensor network designed for tsunami early warning. Each algorithm is evaluated under identical environmental conditions, allowing their strengths and limitations to be observed clearly. The discussion presented in this section is based on the convergence behavior, spatial accuracy of node estimation, error distributions and the impact of anchor density and communication range on overall performance.

Key Insights & Results Interpretation:

1. Algorithm Behaviour

The convergence curves reveal clear distinctions in search dynamics. Differential Evolution quickly identifies promising regions of the solution space and refines them with strong exploitation ability. JFOA maintains a balanced search due to its controlled transition between passive and active movement, leading to gradual yet dependable convergence. ACO explores widely but takes longer to stabilize because its pheromone patterns require time to mature.

2. Spatial Reconstruction Capability

The comparison of true and estimated locations provides a direct measure of coordinate accuracy. DE consistently produces the closest alignment to the real layout, confirming its robustness in handling noisy sensor information. JFOA also reconstructs the network shape well, showing that its exploratory motion helps maintain structural consistency. ACO captures the general pattern but displays more scatter, particularly in areas with fewer connections.

3. Error Consistency and Stability

The error histograms illustrate that DE maintains the lowest variance, while JFOA offers moderate and stable distributions. ACO exhibits a wider spread, indicating a higher sensitivity to local minima and uneven pheromone development. This reinforces the observation that DE is the most consistent across the network, while JFOA remains a strong alternative.

4. Role of Anchors and Communication Range

Increasing anchor density reduces uncertainty for all models, with JFOA showing particularly strong gains when more anchors are available. DE's performance remains stable even when anchors are limited, demonstrating resilience. ACO depends more heavily on anchor information and therefore shows noticeable sensitivity. Larger communication ranges improve localization accuracy across the board, enabling the algorithms to use more distance information. JFOA benefits the most, indicating strong adaptability to enhanced connectivity.

5. Suitability for Tsunami Early Warning Systems

The reliability of node positioning is crucial in marine environments where environmental noise is high and distances are inconsistent. The overall performance pattern suggests that DE provides the highest accuracy, JFOA offers robustness across varying conditions and ACO is more suited for scenarios where computational cost is less important and exploratory behaviour is desired.

VI. Conclusion and Future Scope

This study examined the effectiveness of three population-based metaheuristic algorithms—Ant Colony Optimization, Differential Evolution and the Jellyfish Optimization Algorithm—for improving node localization accuracy in wireless sensor networks used for tsunami early warning. The evaluation was carried out under consistent simulation conditions, allowing a fair and meaningful comparison of their performance.

The results clearly indicate that Differential Evolution provides the highest level of accuracy and the fastest convergence. Its ability to refine candidate solutions rapidly and consistently makes it well suited for environments where reliable and timely localization is essential. The Jellyfish Optimization Algorithm also demonstrated strong performance, maintaining stable improvement across iterations and adapting effectively to variations in anchor density and communication range. This balance of exploration and exploitation suggests that JFOA is a robust option for scenarios involving environmental noise and irregular connectivity, which are common in marine settings.

Ant Colony Optimization was able to estimate node positions but exhibited slower convergence and higher variability. Its performance improved with greater connectivity and anchor support, yet it remained less consistent than the other two techniques.

Overall, the findings show that metaheuristic approaches are effective for addressing the nonlinear and uncertain nature of marine sensor localization, with DE offering the strongest results and JFOA providing a reliable and flexible alternative.

The outcomes highlight the importance of choosing optimization strategies that can handle sparse measurements, dynamic environments and large deployment areas, all of which are characteristics of tsunami early warning systems. Accurate localization greatly enhances the reliability of sensed data, improving the responsiveness and precision of early-warning alerts.

Future Scope:

The work presented in this study opens several promising avenues for further research and real-world application:

1. Hybrid Optimization Models

Future studies can explore combining strengths of multiple algorithms. Hybrid models such as DE–JFOA or ACO–DE could capture both rapid convergence and stable global search, potentially outperforming standalone methods.

2. Real-Time and Adaptive Localization

Marine sensor nodes may drift due to currents, requiring dynamic position updates. Developing algorithms that continuously adapt to movement and changing environmental conditions can improve the reliability of long-term deployments.

3. Integration with Real Ocean Communication Models

The simulation can be enhanced by incorporating underwater acoustic propagation, signal attenuation and noise models. This would make the localization results more representative of practical ocean scenarios.

4. Extension to Three-Dimensional Localization

While the current system uses a two-dimensional plane, real tsunami sensors may operate at varying depths. Extending the optimization methods to 3D localization would increase their applicability to deep-water sensor networks.

5. Large-Scale Deployment Studies

Future research can test these algorithms with larger networks covering wider ocean regions. This would help evaluate scalability, robustness and computational efficiency.

6. Energy-Aware Localization Strategies

Sensors deployed in the ocean operate on limited power. Developing localization algorithms that minimize energy consumption while maintaining accuracy can improve the operational lifespan of the network.

7. Field Testing and Validation

Validating the algorithms with real buoys or coastal sensor systems would provide valuable insight into their performance under actual environmental noise, weather conditions and communication challenges.

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