Aware Node Localization in Wireless Sensor Networks Using Harris Hawks Optimization

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https://doi.org/10.26636/jtit.2025.4.2285

Abstract — Precise and efficient localization is a key enabler for context-aware operations in emerging 6G cognitive semantic communication (CSC) systems. In AI-native and semantic-aware networks, precise node positioning improves semantic compression, context-driven routing, and adaptive spectrum allocation, positively affecting communication reliability and resource utilization efficiency. This paper addresses the problem of localization in wireless sensor networks (WSNs) in the broader context of 6G CSC, formulating it as an optimization task. Based on the previous research, we explore the application of bio-inspired metaheuristic algorithms to achieve robust and high accuracy positioning. Specifically, we propose the use of the Harris hawks optimization (HHO) algorithm to develop a semantic-aware, stable, and efficient localization framework. The proposed approach is implemented and tested within the Matlab simulation environment. Performance evaluation is conducted through comparative experiments with two widely used optimization algorithms: particle swarm optimization (PSO) and cuckoo search optimization (CSO). The simulation results demonstrate that the proposed HHO-based localization method not only improves positioning accuracy by up to 25% compared to the benchmarks, but also provides enhanced stability, enabling its integration with CSC architectures for intelligent resource management in next-generation networks.

Keywords — 6G cognitive semantic communication, context-aware resource management, Harris hawks optimization, node positioning, semantic-aware localization, WSN

1. Introduction

Wireless sensor networks (WSNs) are composed of a large number of sensor nodes which are densely distributed and interconnected via a wireless medium. Their primary mission is to collect and transmit environmental information in real time to support the observation and monitoring of various physical phenomena, such as meteorological data, health status, as well as security- and surveillance-related parameters. In the context of 6G cognitive semantic communication (CSC) systems, precise node localization becomes even more important, as spatial context directly enhances semantic-aware data processing, context-driven routing, and intelligent spectrum allocation [1], [2].

Installation of GPS receiver sensors on each sensor node is often impractical and costly. Therefore, alternative localization methods have been developed under the assumption that only a subset of nodes, called anchors, is equipped with GPS and knows its exact position [3]. In 6G WSNs, localization also plays a role in reliable and efficient communication, where intelligent transmission strategies rely on positional knowledge to optimize the lifetime of the network and improve data relevance [4].

Over the last decade, optimization-based localization methods have received much attention due to their ability to improve sensor positioning accuracy and reduce estimation errors. These methods reformulate localization as an optimization problem which requires the definition of an objective function [5].

The localization process generally consists of two stages: estimation of distance between sensors and subsequent calculation of their position. Recent research favors nature-inspired metaheuristic algorithms to address localization challenges. These algorithms randomly generate an initial solution and iteratively refine it by optimizing the difference between the measured distance from an unknown node to the anchors and the Euclidean distance computed from the estimated node position and anchor coordinates.

The first metaheuristic approach applied to localization was simulated annealing (SA) [6], followed by particle swarm optimization (PSO) [7] and genetic algorithms (GA) [8]. These early successes spurred extensive experimentation with other metaheuristics, including the chicken swarm optimization algorithm (CSO) [9] and cuckoo search optimization (CSO) [10]. The authors of [11] introduced two localization approaches based on the fruit fly optimization algorithm (FOA). These studies collectively demonstrated the adaptability of metaheuristics to WSN localization, making them suitable candidates for integration into next-generation semantic-aware, energy-efficient, and context-driven 6G WSN architectures.

This study addresses the problem of accurate node localization in wireless sensor networks (WSNs) by introducing a novel localization framework based on the Harris hawks optimization (HHO) algorithm. Taking advantage of the dynamic balance between exploration and exploitation offered by HHO, the proposed method, termed HHO-L, formulates the localization task as a non-linear optimization problem, minimizing the discrepancy between the estimated and actual distances from the anchor nodes.

The main contributions of this work can be summarized as follows.

- Novel application of HHO to WSN localization. This is among the first attempts to adapt Harris hawks optimization to the node localization problem, demonstrating its potential in handling complex and high-dimensional search spaces.
- Robust formulation of the objective function. The localization problem is modeled to minimize the localization error by integrating the estimated distances from the signal strength indication (RSSI), the time of arrival (TOA), and other range-based metrics with Euclidean distance calculations.
- Performance benchmarking. A comprehensive comparative analysis is conducted against two well-established metaheuristics, particle swarm optimization (PSO) and cuckoo search optimization (CSO), to evaluate localization accuracy, convergence behavior, and stability.
- Simulation-driven validation. Matlab-based experiments are performed under varying network densities, anchor ratios, and deployment scenarios to prove the accuracy and robustness of the approach.
- Alignment with next-generation networks. The study situates HHO-L within the context of emerging 6G cognitive semantic communication (CSC) paradigms, highlighting its potential for integration into location-aware, metaheuristic-driven network optimization frameworks.

The remainder of this article is structured as follows. Section 2 presents an overview of localization in WSNs, reviews the related literature, and highlights the limitations of existing methods. Section 3 describes the Harris hawks optimization algorithm and details the proposed HHO-L localization framework, including its mathematical formulation and implementation steps. Section 4 reports and discusses the experimental results, including a comparative evaluation with PSO and CSO. Finally, Section 5 concludes the paper and outlines potential directions for future research.

2. Related Works

Localization in WSNs has been studied over the past two decades, as it plays a crucial role in enabling context-aware operations such as routing, monitoring, and environmental sensing. Several techniques have been proposed to estimate the positions of unknown nodes, ranging from traditional range-based and range-free methods to more advanced optimization-based approaches. An excellent review of this topic is presented in article [12].

Among the most well-known metaheuristics applied to the localization problem is PSO [7], which simulates the social behavior of flocks of birds. PSO has been widely adopted due to its simplicity and fast convergence. However, it often suffers from premature convergence and becomes trapped in local optima when dealing with complex, high-dimensional search spaces. To overcome these limitations, more recent approaches have turned to nature-inspired algorithms with stronger exploration and exploitation capabilities.

Cuckoo search optimization (CSO) is one such algorithm that mimics the behavior of cuckoo birds. CSO has shown promising results in WSN localization [10], offering better performance than PSO in several studies due to its Lévy flight-based search mechanism which enhances global exploration. However, while CSO improves convergence and avoids local optima more effectively, it can still exhibit instability under specific deployment scenarios or sparse anchor configurations.

More recently, bio-inspired metaheuristics, such as bat algorithm, whale optimization algorithm (WOA), and gray wolf optimizer (GWO) have also been adapted for node localization [13], with varying degrees of success. These algorithms aim to balance the trade-off between exploration and exploitation by simulating specific natural behaviors like echolocation or pack hunting. While these techniques offer improved robustness and adaptability, they still face challenges in terms of accuracy, convergence speed, and sensitivity to parameter tuning.

In addition to single-algorithm approaches, hybrid and improved localization strategies have emerged. For example, the authors of [14] proposed a regularized least squares DV hop method to enhance multihop localization accuracy, while in [15], DV hop using RSSI-based distance estimation and recursive computation, significantly reducing localization errors, was improved. In parallel, UAV-assisted approaches have been explored to enhance network connectivity and reduce localization error in large-scale or complex deployments.

In [16], an energy efficient UAV flight path model with metaheuristic optimization for cluster head selection in next generation WSNs was proposed, demonstrating the benefits of UAV mobility for improving network lifetime and coverage. Similarly, a Java macaque algorithm for optimizing VANET routes based on the IoT was presented in [17], illustrating the adaptability of meta-heuristic frameworks to various wireless network contexts, including localization.

In this context, the Harris hawks optimization (HHO) algorithm has emerged as a novel and powerful optimization tool [18]. HHO mimics the cooperative hunting behavior of Harris' hawks and dynamically adjusts its search patterns between soft and hard besiege strategies. Although HHO has shown success in various domains such as feature selection, machine learning, and engineering design, its application to WSN localization remains relatively underexplored. The current study contributes to bridging this gap by adapting and evaluating HHO for node localization and comparing its performance against PSO and CSO under various network configurations.

Beyond traditional WSNs, recent research has highlighted the importance of accurate localization in the emerging field concerned with 6G cognitive semantic communication (CSC).

In AI-native 6G networks, precise node localization is not merely a positioning task, but a foundational enabler for semantic-aware and context-driven communication. Accurate location information supports semantic compression by providing spatial context that determines which sensing data are relevant, thereby reducing unnecessary transmissions and improving network efficiency in applications such as V2X, UAV swarms, and IoT deployments for the metaverse [19]–[21].

The authors of [22] analyzed localization performance using a channel knowledge map (CKM) in a 3D environment, integrating angle-of-arrival, angle-of-departure, and path-loss information to achieve submeter accuracy. Their CRLB-based analysis demonstrated the impact of propagation paths and grid resolution on positioning performance, offering valuable information on optimizing localization accuracy in 6G communication contexts.

Similarly, in [23], a reconfigurable intelligent surface (RIS) system assisted by UAVs was proposed for vehicle positioning in dense urban environments, using the snake optimization algorithm to dynamically adjust the placement of RIS. This work illustrates how metaheuristic-driven localization can be embedded in integrated sensing and communication (ISAC) frameworks, directly aligning with the 6G CSC goals for intelligent transportation and dynamic network optimization.

Localization is also crucial for intelligent routing and dynamic spectrum allocation in CSC, where location-aware decisions improve robustness, reduce latency, and enhance resource utilization [20], [24], [25]. In advanced 6G infrastructures, such as those leveraging intelligent surfaces or edge-based semantic processing, localization enables adaptive beamforming and spectrum reconfiguration to maintain high-quality links [20], [24]. Moreover, semantic-aware frameworks increasingly integrate location data into multimodal resource prioritization strategies for scenarios such as smart traffic systems, immersive environments, and mission critical industrial IoT [26]–[28].

Parallel to these developments, AI and meta-heuristic algorithms are playing a central role in multi-task/multimodal optimization for CSC. Machine learning, reinforcement learning, and evolutionary optimization have been applied to semantic spectrum allocation, channel selection, and joint localization–communication design, allowing adaptive and context-aware resource management in highly dynamic 6G environments [19], [20], [29], [30].

Metaheuristics such as HHO, GA, and swarm intelligence methods offer the advantage of handling high-dimensional optimization problems with non-convex constraints, making them suitable for integrated CSC tasks involving spectrum management, edge computing, and secure semantic data delivery [31]–[33]. Joint optimization frameworks that combine localization with semantic-aware transmission have been shown to improve end-to-end performance under latency, utility, and security constraints [33]–[35].

This body of work, including recent advances in CKM-based positioning [22] and UAV-assisted RIS metaheuristic optimization [23], suggests that integrating high-accuracy localization algorithms into CSC frameworks could directly improve semantic compression efficiency, adaptive spectrum allocation, and network resilience.

2.1. Research Gap

Despite significant progress in WSN localization, several challenges remain, particularly when positioning is viewed through the lens of next-generation wireless networks and CSC paradigms. Traditional range-based and range-free algorithms, as well as classical metaheuristics such as PSO and CSO, have demonstrated effectiveness in moderate-scale, relatively stable network conditions. However, these methods often struggle with:

- Balancing exploration and exploitation in high-dimensional search spaces. Many existing algorithms converge prematurely, becoming trapped in local optima, which limits their accuracy in complex and irregular deployments.
- Robustness under dynamic and sparse-anchor conditions. Localization accuracy tends to degrade significantly when anchor nodes are sparse, network topology changes, or environmental noise increases.
- Integration into next-generation semantic-aware networks. Most existing localization studies focus on accuracy within traditional WSN deployments and overlook integration into AI-native, 6G ready infrastructures where location data must also serve real-time semantic compression, context-driven resource allocation, and cross-layer optimization.
- Underexplored potential of advanced metaheuristics. Although bio-inspired algorithms such as bat algorithm, GWO, and WOA have been applied to WSN localization, newer approaches like HHO, with adaptive transition strategies between exploration and exploitation, have not been extensively evaluated.

Given these limitations, there is a clear need for a localization method that not only improves accuracy and stability over existing metaheuristics, but also aligns with the multi-objective demands, where node positioning directly impacts semantic communication efficiency, spectrum utilization, and network resilience.

The proposed HHO-based localization framework addresses this gap by combining high-dimensional optimization capability with adaptability to varying deployment conditions, making it a candidate for integration into future intelligent and semantic-aware WSN architectures.

3. Methodology

Harris hawks optimization (HHO) is a nature-inspired metaheuristic optimization algorithm that simulates the cooperative hunting behavior of Harris' hawks, a predatory bird species known for their intelligent and collaborative strategies in capturing prey. Originally introduced in [18], HHO mimics the social hierarchy and dynamic tactics employed by these raptors, such as surprise pounce and perching strategies, to explore and exploit the search space effectively. The algorithm adaptively balances exploration and exploitation phases, making it suitable for solving complex and non-linear optimization problems.

The HHO algorithm begins with an initial population of candidate solutions, represented as a set of individuals. These individuals are considered "hawks" in the algorithm. Each hawk represents a potential solution to the optimization problem.

The algorithm iteratively updates the positions of the hawks in search of better solutions. It employs various operators inspired by the behavior of Harris' hawks, such as exploration, exploitation, and flight. These operators allow the hawks to explore the search space, exploit promising regions, and escape from local optima.

During the optimization process, the hawks communicate and cooperate with each other to improve the overall performance. They exchange information, share knowledge, and learn from their experiences to guide the search toward optimal solutions. The main objective of the HHO algorithm is to find the best solution that optimizes a given fitness function. This approach can be applied to a wide range of optimization problems, including engineering design, planning, data mining, and many others [18].

Exploration is the initial phase of the hunting process, which involves observing, tracking, and locating the prey. In the context of the HHO algorithm, this step is referred to as the exploratory mechanism. In nature, Harris' hawks may spend several hours searching for prey. Similarly, in the algorithm, the probability of spotting the prey (target solution) depends on the quality of the hawks (candidate solutions). Therefore, the best candidate solution is the one closest to the prey.

Harris' hawks adopt two strategies while waiting for their prey. They either position themselves near other family members to initiate a group attack, or they choose random vantage points such as high trees. Both strategies are modeled and represented by Eq. (1).

$$\begin{aligned} &X(t+1) = \\ &X_{rand}(t) - r_1\big|X_{rand}(t) - 2\,r_2 X(t)\big| \;\text{ for }\; q \geqslant 0.5 \\ &X_{rabbit}(t) - X_m(t) - r_3\big(LB + r_4(UB - LB)\big) \text{ for } q < 0.5 \end{aligned} \tag{1}$$

where $X(t+1)$ represents the new positions of the hawks at iteration t, X_{prey} corresponds to the location of prey, denotes a hawk selected randomly in the search space, and X (t) indicates the initial locations of the hawks, which are calculated according to Eq. (2). Variables r_2, r_3, r_4, r_5 and q are random values between 0 and 1. It is important to note that these random numbers are updated at each iteration t.

$$X_m(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t)\;, \tag{2}$$

where X_i represents the position of the hawk in iteration t and N is the total number of hawks.

The HHO algorithm can move from the exploration phase to the exploitation phase by adapting its exploitation behaviors according to the escape energy of the prey. During the escape phase, the energy of prey decreases significantly. To take this reduction into account, the energy of prey is modeled as follows:

$$E = 2\,E_0\left(1 - \frac{t}{T}\right)\,. \tag{3}$$

After discovering the prey during exploration (i.e. extended search), the next phase marks the start of exploitation. Harris' hawks then attempt to swoop down on their prey suddenly. On the other hand, the prey attempts to escape, which is commonly called the seven escapes.

Optimization of Harris' hawks proposed four potential approaches for modeling hunting strategies and escape behaviors. A random number r is used to represent the probability of success of the prey in the fight ($r < 0.5$) or its failure ($r \geqslant 0.5$). Additionally, Harris' hawks use either a soft block or a hard block to capture the prey, depending on the strength of the prey E. For example, if the block is soft, the condition will be $E \geqslant 0.5$, otherwise $E < 0.5$.

In the soft siege phase, when the values of E are greater than or equal to 0.5 with r greater than or equal to 0.5, this means that the prey has sufficient energy to defend itself against Harris' hawks by following random paths and performing deceptive jumps. Unfortunately, the prey will fail because Harris' hawks exhaust their energy by circling them and then launching a surprise attack. Eq. (4) shows the modeling of this behavior.

$$\begin{aligned} X(t+1) =& \Delta X(t) - E\big|JX_{rabbit}(t) - X(t)\big| \text{ or} \\ &\Delta X(t) = X_{rabbit}(t) - X(t)\;, \end{aligned} \tag{4}$$

$$J = 2 \times (1 - r_6)\,. \tag{5}$$

In the soft siege phase, X represents the difference in position between the prey and their initial position in iteration t. The value r_6 is chosen randomly within the interval $0 \ldots 1$. For J, it refers to the random jump of the prey, and its value changes randomly to imitate the nature of the prey's movements.

In the hard phase $t < 0.5$ and $r < 0.5$. Therefore, the pray does not have enough energy to escape. In addition, Harris's hawks are ready to surround the prey and carry out a surprise attack, with difficulty. Equation 6 illustrates the update of current positions in this situation.

$$X(t+1) = X_{prey}(t) - E\big|\Delta X(t)\big|\,. \tag{6}$$

The third case, soft seat with progressive rapid dips, is more complicated than the one described above, because it is used when $|E| \geqslant 0.5$ and $r < 0.5$. Thus, the prey has enough power to escape successfully. On the other hand, Harris' hawks continue to perform numerous rapid dives to force the prey to change trajectory and distract it. The process continues until the best time to catch the prey is chosen. The following equation describes the decision to move to implement soft encirclement.

$$Y = X_{prey}(t) - E\big|JX_{prey}(t) - X_{(t)}\big|\,. \tag{7}$$

If Harris' hawks notice that the prey is making deceptive movements and is about to escape, they will intensify their sharp, irregular, and rapid dives. The new technique of the hawks is based on the Levy fights (LF) as:

$$Z = Y + S \times LF(D)\,. \tag{8}$$

where D indicates the dimension of the problem, S refers to a random vector of size $1 \times D$, and LF is calculated according to:

$$LF(x) = 0.01 \, \frac{u \, \sigma}{|v|^{\frac{1}{\beta}}} \,, \tag{9}$$

$$\sigma = \frac{\Gamma(1+\beta) \, \sin(\frac{\pi\beta}{2})}{\Gamma \, \frac{1+\beta}{2} \, \beta \, 2^{\frac{\beta-1}{2}}} \,, \tag{10}$$

where u and v refer to a random value in the interval $0 \ldots 1$, β indicates the fixed variable defined in Eq. (10).

Therefore, the mathematical model for updating the positions of hawks in the soft circling stage is given by the following equation.

$$X(t+1) = \begin{cases} Y \;\text{ for } F(Y) < F\big(X(t)\big) \\ Z \;\text{ for } F(Z) < F\big(X(t)\big) \end{cases} . \tag{11}$$

In the case given by Eq. (11), Y represents the value calculated according to the specified formula, while Z represents the value calculated according to Eq. (8).

The rigid seat with progressive rapid dips is the last case, when the values of $r < 0.5$ and $|E| < 0.5$. This means that the prey does not have enough strength to escape. At the same time, hawks seek to reduce the space between themselves and the prey before surprising and attacking it. Equation (12) describes the updating of the hawks' positions.

$$Y = X_{prey}(t) - E\big|JX_{prey}(t) - X_m(t)\big| \,. \tag{12}$$

The summary of the HHO algorithm-based procedures is presented in pseudo-code form as Algorithm 1, where the value of $X_m(t)$ is calculated using Eq. (2).

3.1. Proposed Algorithm

The goal of the localization process in WSNs is to calculate the coordinates of N unknown sensors based on the known position of sensors. It is assumed that all sensors are deployed in a two-dimensional area of interest, all sensors have similar hardware characteristics, particularly in terms of their ability to send and receive information (similar connectivity radius R), and that each sensor is equipped with a similar radio interrogator which allows sensors in the neighborhood to estimate the distance between them.

The localization process based on the Harris hawks optimization algorithm is illustrated as Algorithm 1.

Furthermore, localization consists in calculating the coordinates of unknown nodes (target nodes) using the inter-node distance information managed by the anchors.

The basic steps of the positioning process are described below.

1. The network sensors (N known nodes and M unknown nodes) are randomly deployed within the area of interest.

2. Known nodes (considered anchors during this process) frequently broadcast their positions until the localization process is completed.

3. Each unknown node receives an RSSI radio signal through three or more anchors, so it is considered a localizable sensor.

Algorithm 1 Harris hawks optimization (HHO) [18]

```
Inputs: The population size N and maximum number of iterations T
Outputs: The location of rabbit and its fitness value
Initialize the random population X_i, i = 1, 2, ..., N
while stopping condition is not met do
    Calculate fitness values of hawks
    Set X_rabbit as the location of rabbit (best location)
    for each hawk X_i do
        Update the initial energy E_0 and jump strength J
        E_0 = 2 rand() − 1,  J = 2 (1 − rand())
        Update the E using Eq. (3)
        if |E| ⩾ 1 then
            Update the location vector using Eq. (1)
        end if
        if |E| < 1 and r ⩾0.5 and |E| ⩾ 0.5 then
            Update the location vector using Eq. (4)
        else if r ⩾0.5 and |E| < 0.5 then
            Update the location vector using Eq. (6)
        else if r <0.5 and |E| ⩾ 0.5 then
            Update the location vector using Eq. (11)
        else if r <0.5 and |E| < 0.5 then
            Update the location vector using Eq. (12)
        end if
    end for
end while
Return X_rabbit
```

Furthermore, we assume that the distance measurement between neighboring captures can then be transferred to equivalent distances based on the RSSI technique.

The real distance d_{ij} between target node x_i, y_i and the j-th anchor x_j, y_j is defined by the following Euclidean distance as:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \,. \tag{13}$$

The measured distance d_{ij} between target node x_i, y_i and the j-th anchor x_j, y_j is formulated as follows:

$$\hat{d}_{ij} = [d_{ij} \pm n_{ij}] \,, \tag{14}$$

where n_{ij} represents the error between target node x_i, y_i, and its neighboring anchor x_j, y_j.

4. The objective function of the localization problem represents the mean-square difference between a target node and the corresponding anchors. It is formulated by the following equation:

$$f(x,y) = \frac{1}{N} \sum_{i=1}^{N} \left(\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} - \hat{d}_{ij} \right)^2 , \tag{15}$$

where N ($N \geqslant 3$) represents the number of anchors in the unknown communication range, the target node can calculate its geographic coordinates by running the HHO algorithm, represented by the flow diagram given in Fig. 1.

The objective function $f(x_i, y_i)$ is minimized, then (x_i, y_i) represents the coordinate of the ith localizable node.

5. The sensors located during this process act as anchors during the next iterations, so that the number of anchors

increases with the iterations and the number of unknown nodes decreases. But this will only be used to locate nodes initially considered non-localizable, i.e. those that do not have three or more anchors in their transmission range.

6. Steps 2 to 5 are repeated until all unknown nodes are localized.

7. Now we can calculate the average localization error as the average Euclidean distance between the real positions and the estimated coordinates of all unknown sensors. Thus, the average localization error can be calculated using the following equation:

$$E_L = \frac{1}{N_L} \sum \sqrt{(X_{real} - X_{rabbit})^2 - (Y_{real} - Y_{rabbit})^2}\,, \tag{16}$$

where N_L is the number of unknown nodes, X_{rabbit}, Y_{rabbit} are the coordinates of the calculated node and X_{real}, Y_{real} is the position of the real node, $L = M - N$, M is the number of unknown nodes, and N is the number of anchors.

The smaller the average error, the higher the localization accuracy. Therefore, the challenge is to reduce the average error, and in this way to transform the localization problem into an optimization problem.

4. Results

In this section, the performance of the proposed HHO-L optimization algorithm was evaluated based on the density of anchor nodes, the density of unknown nodes, communication range and population size.

At the same time, a comparative study was carried out between the proposed approach and two recent similar works which use one of the most popular metaheuristic algorithms: PSO [7] and CSO [9], noting that comparative tests are performed using the same network configuration.

Simulations are performed using the Matlab environment, with their parameters summarized in Tab. 1.

To facilitate parameter modification and to generate multiple results for evaluating the performance of our proposed approach, a simulation interface was developed for flexible experimentation and analysis. It is illustrated in Fig. 2.

The large white square in the interface shows the deployment of nodes within a two-dimensional area. The orange lozenges represent anchor nodes, while the black squares correspond to unknown nodes. The blue circles indicate the estimated

Tab. 1. Configuration of WSN during simulation.

Parameter	Value
Number of sensor nodes	30 – 60
Number of anchors nodes	5 – 20
Deployment area	50 m × 50 m
Transmission range	$\sum_{i=6}^{i=12} 5 \times i$ [m]
Maximum iterations	10 – 30
Population size	15 – 30

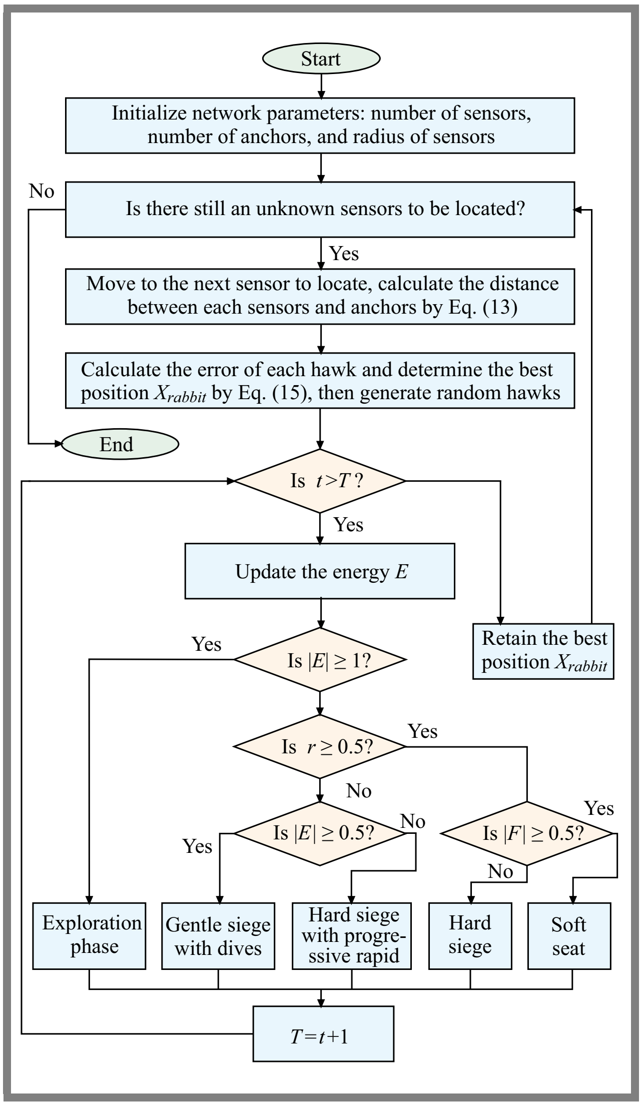

Fig. 1. Node localization by proposed method.

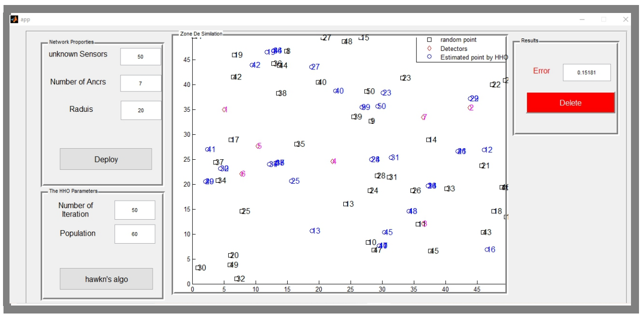

Fig. 2. Example of a localization process relying on the proposed algorithm.

positions of the unknown nodes. The network parameters selected for this deployment are presented in the side panels, shown in the small boxes adjacent to the simulation area.

4.1. Effect of Anchor Density

The number of anchor nodes is one of the most important parameters that influences the localization accuracy in WSNs. In this experiment, the objective is to evaluate the impact of

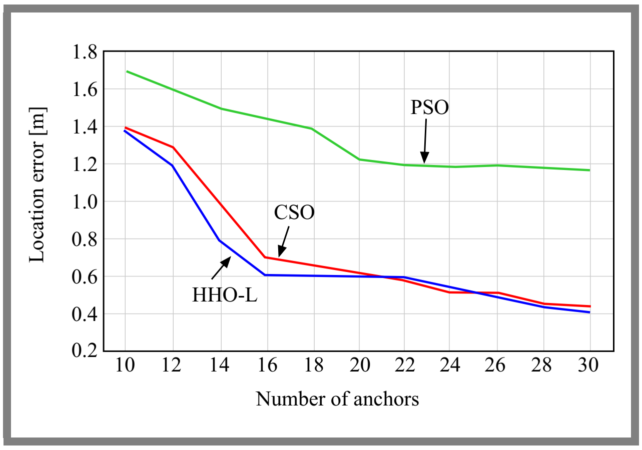

Fig. 3. Anchor effect on localization error.

a varying the number of anchors on localization performance. To achieve this, several experiments were conducted in which the number of anchors varied from 10 to 30. All other network parameters remained unchanged, as detailed in Tab. 1.

Figure 3 presents the localization error obtained as the number of anchors changes, using the HHO algorithm, along with the two other metaheuristic algorithms employed for comparison. This evaluation allows to assess the sensitivity of each algorithm to the density of anchor nodes in the network.

The average localization error was evaluated by varying the number of anchors in the network at different node densities. The results clearly show that as the number of anchors increases from 10 to 30, the localization accuracy improves significantly across all algorithms used in this comparative study. The proposed approach (HHO-based localization) consistently outperforms other methods, demonstrating its effectiveness.

This improvement is attributed to the fact that, as the number of anchor nodes increases, the number of unknown nodes that can estimate their positions based on these reference anchors also increases. Anchors are typically deployed manually or are equipped with GPS receivers, making them reliable reference points.

However, it is observed that beyond a certain threshold, a further increase in the number of anchors yields diminishing returns in terms of localization accuracy. The improvement becomes minimal or negligible, suggesting that an excessive number of anchors may not be effective, especially considering the additional hardware (GPS modules) required or the need to manually place the anchors.

Furthermore, the results also indicate that as the density increases, the average localization error decreases, reinforcing the importance of the network structure in localization performance. Therefore, selecting an optimal anchor-to-node density ratio is essential to balance performance and cost in real-world wireless sensor network deployments.

4.2. Effect of Unknown Sensor Density

Localization performance is also impacted by the density of unknown sensor nodes. In this experiment, we varied the number of sensor nodes, while keeping all other parameters unchanged, as specified in Tab. 1. The results of this experiment are illustrated in Fig. 4.

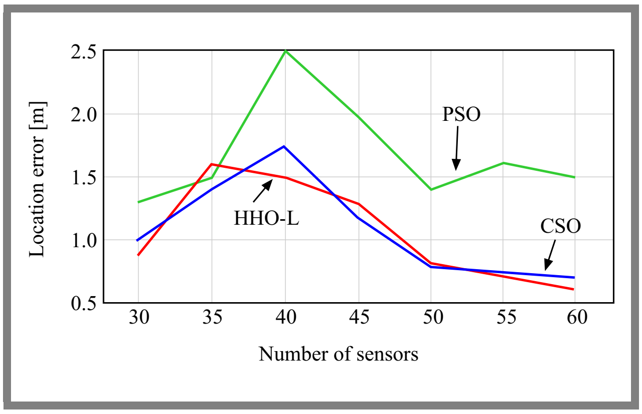

Fig. 4. Effect of unknown sensors on localization error.

One may notice that the localization error decreases gradually as the number of nodes increases. This improvement is attributed to the fact that a higher density of unknown sensors enhances the connectivity of the network. Consequently, the likelihood that each unknown node has multiple anchor nodes within its communication range increases. This means that nodes are more evenly and densely distributed throughout the network, allowing them to form connections with several neighbors and effectively participate in the localization process.

Furthermore, in the proposed approach, once unknown nodes are successfully localized, they can be reused as additional anchor nodes to assist in the localization of other nodes that lack at least three anchors in their vicinity. This dynamic anchor promotion strategy significantly contributes to the superiority of our approach, even with different node densities, as confirmed by experimental results.

4.3. Effect of Connectivity Radius

Connectivity radius is another key parameter that significantly affects the accuracy of node localization in WSNs. The influence of the connectivity radius on the performance of the HHO algorithm for localization is illustrated in Fig. 4. This evaluation verifies localization error, considering different network settings, and includes a comparison with two alternative metaheuristic approaches.

In this experiment, the connectivity radius is varied within the 5 – 20 m range. As shown in Fig. 5, when the connectivity radius is less than 10 m, the internode communication is relatively weak, leading to poor connectivity across the network. As a result, the average localization error is slightly higher, mainly due to the fact that many unknown nodes cannot access a sufficient number of anchor nodes to perform an accurate localization.

However, as the connectivity radius increases above 18 m, the localization error begins to decrease. This improvement is due to the fact that more unknown nodes are able to detect multiple anchors within their communication range, providing more distance-based information to accurately estimate their positions. Nevertheless, the decrease in error becomes more

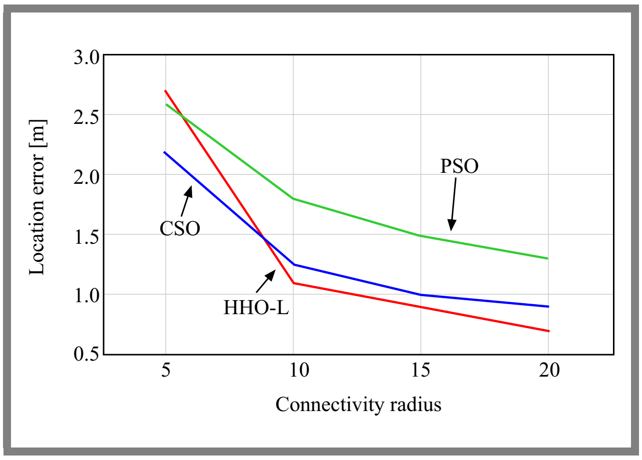

Fig. 5. Effect of connectivity radius on localization error.

gradual beyond a certain point, indicating a saturation effect, where further increases in radius yield marginal improvements only.

These results confirm that the selection of an appropriate connectivity radius is essential for maintaining sufficient network connectivity and achieving high localization accuracy while avoiding unnecessary energy consumption or communication overhead.

4.4. Effect of Population Size

The population size, i.e., the number of individuals in the swarm, plays an important role in the convergence behavior of metaheuristic algorithms, particularly during the exploration phase of the search space. In addition, the size of the population directly influences the execution time of the algorithm. Similarly, variations in the number of iterations can have a comparable effect on performance and computational cost.

The relationship between localization error and population size is illustrated in Fig. 6. The results show that when the number of individuals in the population is small, the localization accuracy is relatively low.

However, as the population size increases, accuracy improves as well. This improvement is attributed to the algorithm's ability to better exploit the search space during the exploitation phase. A larger population allows the algorithm to explore the neighborhood of each solution more effectively in search of the optimal coordinates of the unknown nodes.

In essence, a larger population enhances the algorithm's ability to avoid premature convergence and reduces the risk of falling into a local optimum. Therefore, an adequately large number of individuals is necessary to ensure effective localization and to improve the robustness of the solution, especially in complex or high-dimensional problem spaces.

5. Conclusions

The proposed method leverages the dynamic transition between the exploration and exploitation phases inherent to HHO, enabling robust performance under varying deployment conditions. Simulation experiments demonstrated that HHO-L achieves approximately 25% higher localization accuracy compared to other bio-inspired techniques. Specifically, it reached an average accuracy of approximately 0.4 m, outperforming CSO (0.5 m) and significantly surpassing PSO (1.2 m). The study relies on Matlab simulations without any physical testbeds. In real deployments, RSSI fluctuations may be more severe, which could degrade accuracy.

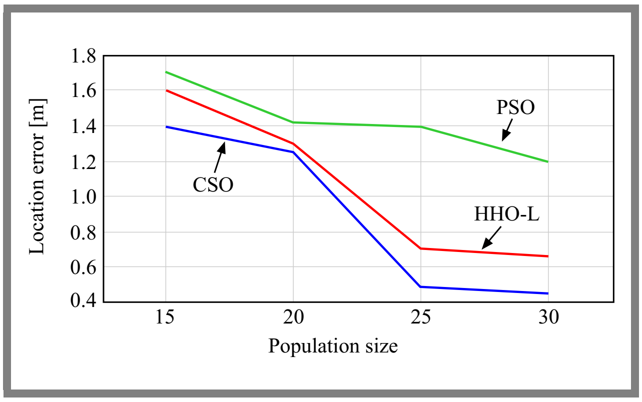

Fig. 6. Effect of population size on localization error.

These results not only confirm the algorithm's superiority in classical WSN contexts but also highlight its potential for integration into emerging 6G CSC environments, where precise localization improves semantic compression, spectrum utilization, and adaptive communication in intelligent transportation.

Future research can build on this work in several directions:

- Adaptive and hybrid strategies – dynamically adjusting hawk population size, escape energy parameters, or integrating HHO with complementary metaheuristics (e.g., grey wolf optimizer, whale optimization algorithm) could further improve convergence speed and resilience against environmental noise.
- Cross-layer integration in 6G CSC – embedding HHO-L within semantic-aware network architectures, enabling joint optimization of localization, routing, and spectrum allocation for applications such as V2X, UAV-assisted sensing, and RIS-enabled communication.
- Scalability and real-world deployment – extending the framework to large-scale heterogeneous WSNs with irregular topologies and mobility patterns, and validating its performance on physical testbeds.
- Real hardware experiments, study of environmental noise, energy consumption, and scalability.
- Energy-aware localization – combining HHO-L with energy-efficient communication protocols to minimize localization overhead in resource-constrained next-generation sensor deployments.

By addressing these aspects, HHO-L can evolve from a high-accuracy localization algorithm into a core enabler for intelligent, semantic-driven wireless sensor networks in the era of 6G and beyond.

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