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RESEARCH ARTICLE

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COMPARATIVE ANALYSIS OF BIO-INSPIRED ENHANCEMENT TECHNIQUES FOR LOCALIZATION IN 2D WIRELESS SENSOR NETWORKS

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ABSTRACT

Accurate node localization is crucial for optimizing the performance of Wireless Sensor Networks (WSNs), which are widely used in applications such as environmental monitoring and smart city infrastructure. This study conducts a comparative evaluation of three bio-inspired optimization algorithms for node localization: Particle Swarm Optimization (PSO), Fruit Fly Optimization Algorithm (FOA), and Drop Mongoose Optimization Algorithm (DMOA). The algorithms are assessed based on their localization accuracy and precision, which are key performance metrics for WSN applications. PSO, inspired by the collective movement of particle birds, is a well-established meta-heuristic technique, while FOA simulates the foraging behavior of fruit flies to determine optimal locations. The recently introduced DMOA, modeled after the hunting and movement strategies of mongooses, represents a novel approach in optimization. Simulation results indicate that while PSO and FOA perform well under specific conditions, DMOA outperforms them in terms of accuracy and precision, making it a promising solution for improving node localization in WSNs. This study underscores the effectiveness of bio-inspired algorithms in enhancing the reliability and efficiency of WSN deployments.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have garnered significant attention in recent years due to their wide-ranging applications and the increasing demand for low-cost, energy-efficient solutions. These networks rely on the deployment of numerous inexpensive sensors over a designated area, which necessitates the development of appropriate routing protocols and efficient algorithmic implementations. These factors open promising avenues, particularly in monitoring and target-tracking applications [1]. One of the fundamental challenges in WSNs is the accurate estimation of each sensor node's location, which is crucial for the network's overall performance. Due to cost constraints, each sensor device typically has limited bandwidth, power, memory, and energy reserves. Furthermore, their detection and communication capabilities are bounded by a maximum range. In terms of network structure, WSNs can be viewed as a graph, where each node represents a sensor and each edge models a neighborhood between two devices-i.e., a reciprocal detection and potential communication link [2].

The Global Positioning System (GPS), a free service, theoretically solves the localization problem for each node in the network. However, equipping every sensor with a GPS receiver is often impractical due to the prohibitive costs, limited energy reserves, and the poor performance of GPS technology in indoor environments. Instead, each sensor is equipped with a transmitter-receiver module that enables wireless communication with neighboring sensors, allowing the estimation of inter-node distances [3].

The primary goal of the localization algorithm is to calculate the relative coordinates of each sensor based solely on proximity measurements. Initial approaches to solving the localization problem were centralized, but it became clear that this strategy conflicts with the energy constraints of WSNs. Local data processing, which is energy-efficient, was not prioritized, while energy-intensive wireless transmission drained the already limited batteries of the sensors (the energy cost of wireless transmission is approximately 100 times higher than local processing [4]). Additionally, centralized approaches lack robustness, as the failure of the central processing unit could lead to the collapse of the entire system. Therefore, an alternative strategy is required to improve the network's lifespan compared to centralized approaches. A distributed implementation of the algorithm across the network, where each sensor contributes through local preprocessing, presents an effective solution to meet these demands. One of the most effective methods that researchers have recently used to solve complex problems is the nature-inspired methods, and similarly, localization researchers have used it to address this complex problem in WSN. The paper by [5] presents a comprehensive review of various meta-heuristic localization methods in these networks. These include, but are not limited to, the following: Particle Swarm Optimization (PSO) is one of the first algorithms bio-inspired that was used to improve localization, and this is in [6], Cuckoo Search Algorithm-based WSN Localization by [7], Chicken Swarm Optimization for WSN Localization by [8], Moth Flame Optimization Algorithm is utlised by [9],[10] used Fruit Fly Optimization Algorithm for enhance localization and taking into account the reduction of energy use due to the low cost of calculation in FOA. Very recently in 2024 I present a hybrid model by bio-inspired algorithms in [11]. Then I noticed recently that every bio-inspired algorithm appeared, researchers used it to solve the problem of localization in a wireless sensor network.

This paper explores bio-inspired optimization algorithms as a promising approach for node localization in WSNs. By comparing three algorithms—Particle Swarm Optimization (PSO), Fruit Fly Optimization Algorithm (FOA), and the novel Drop Mongoose Optimization Algorithm (DMOA)—we aim to identify the most effective method for improving the precision and accuracy of node localization, ultimately enhancing the robustness and efficiency of WSN deployments. The remainder of the paper is organized as follows: Section 2 provides the mathematical model for the localization problem in Wireless Sensor Networks (WSNs). Section 3 presents an overview of the three bio-inspired optimization algorithms used in this study. Section 4 discusses the results of the comparative analysis and the localization performance of each algorithm. Finally, the conclusion of the paper is presented in Section 5.

II. MATHEMATICAL MODELING OF LOCALIZATION PROBLEM

The main objective of localization in WSN is to accurately localize statically placed sensors that are randomly distributed within a two-dimensional (2D) area. To achieve this, the bio-inspired Algorithms are used alongside a set of anchors with known positions. The goal is to estimate the positions of several unknown nodes that have similar communication radius. The coordinates (x, y) of the target node are estimated, and the distance d_{ij} between the target node and each anchor is calculated using the following equation:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (1)$$

The measured distance dj obtained via RSSI measurement techniques is adjusted by adding a normal error noise ($dj = d_j + noise$). The aim is to minimize the difference between the measured distance and the distance calculated by the following objective function:

$$f(x, y) = \frac{1}{M} * \sum_{j=1}^{M} \left| \sqrt{\left(x` - x_j\right)^2 + \left(y` - y_j\right)^2} - d_j \right| \quad (2)$$

Where M≥3 is the number of anchor nodes within the target node's radius, (x′,y′) represents the estimated coordinates of the node, (x_j,y_j) are the coordinates of the j^{th} anchor, and d_j is the actual distance between the unknown sensor and the anchor.

III. BIO-INSPIRED OPTIMIZATION ALGORITHMS FOR NODE LOCALIZATION IN WSN

Researchers have used hundreds of nature-inspired meta-heuristic algorithms, but their application to positioning in a wireless sensor network is uniform in general idea, but each algorithm has its own way of moving from one step to the next using equations inspired by The behaviors of insects, animals, and even humans sometimes, such as neural networks. The following Flowchart of Figure 1, explains the general steps for applying any Bio-inspired algorithm to solve the localization problem.

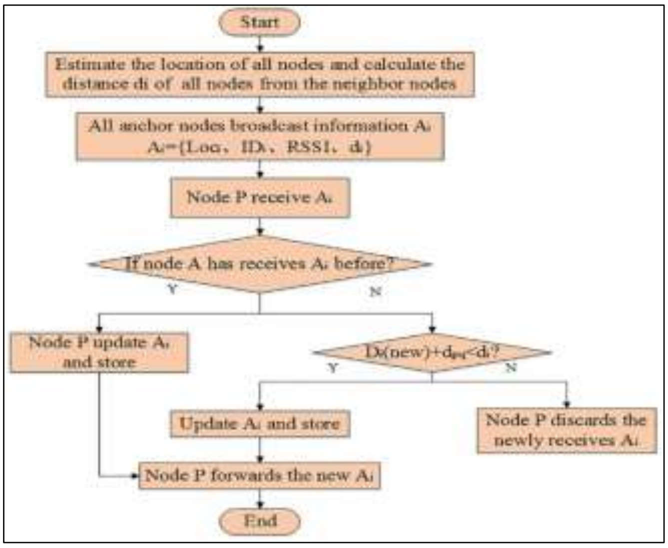

Figure 1: Flowchart of implementing meta-heuristics algorithms to locate nodes.
Source: Authors, (2025).

III.1 PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization (PSO) is one of the most well-known bio-inspired algorithms, modeled after the social behavior of bird flocks or fish schools, this algorithm was proposed by Russel Eberhart (electrical engineer) and James Kennedy (socio-psychologist) in 1995 [12]. In PSO, a group of particles (potential solutions) moves through the search space, adjusting their positions based on their own experience and that of neighboring particles. Each particle has a velocity that is updated by considering both its personal best position and the best-known position within the swarm. For node localization in WSNs, PSO is particularly attractive due to its ability to explore a wide search space and converge quickly towards an optimal solution. This algorithm's inherent parallelism and simplicity make it suitable for distributed processing, which is crucial in WSNs where energy efficiency is a key concern. However, PSO may sometimes get trapped in local optima, which can affect the precision of node localization, particularly in more complex network topologies. In this comparative study we use the localization results obtained in our work presented in [13] the article entitled: An Improved approach for localization in wireless sensor networks Using PSO algorithm.

PSO models swarm behavior, where particles (solutions) iteratively adjust their positions based on personal and global best positions. The algorithm follows these update rules:

$$v_{i,j}^{t+1} = wv_{i,j}^{t} + c_1 r1_{i,j}^{t}\left[pbest_{i,j}^{t} - x_{i,j}^{t}\right] + c_2 r2_{i,j}^{t}\left[gbest_{i,j}^{t} - x_{i,j}^{t}\right], j \in \{1,2,\dots,D \tag{3}$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + v_{i,j}^{t+1}, j \in \{1,2,\dots,D\} \tag{4}$$

Where, v_i is velocity, x_i is position, p_i is local best, g is global best, and c_1, c_2, r_1, r_2 are acceleration coefficients with random weights. PSO's strength lies in fast convergence but risks local optima trapping.

III.2 FRUIT FLY OPTIMIZATION ALGORITHM (FOA)

The Fruit Fly Optimization Algorithm (FOA) is another bio-inspired approach proposed by [14], based on the foraging behavior of fruit flies. In FOA, fruit flies search for food by first locating it through smell and then refining their position based on visual cues. In the context of WSNs, FOA uses a similar strategy where nodes adjust their positions to minimize localization errors by iteratively refining their distance estimates relative to their neighbors. The simplicity of FOA, combined with its relatively low computational complexity, makes it a viable option for WSN node localization. However, FOA can sometimes suffer from slower convergence compared to PSO, especially in larger networks. Despite this, it is still considered effective in networks where the number of nodes is moderate, and energy resources need to be preserved. In this work we use the localization results obtained in our work presented in [10] the article entitled: An improved method for distributed localization in WSNs based on FOA.

FOA mimics fruit fly foraging behavior using an iterative process where flies locate an optimal position based on smell and sight. The key equations are:

$$X_{new} = X_{current} + step * Random() \tag{5}$$

$$Y_{new} = Y_{current} + step * Random() \tag{6}$$

After each iteration the best-smelling position is chosen. FOA is computationally efficient but may suffer from slow convergence in complex environments

III.3 DROP MONGOOSE OPTIMIZATION ALGORITHM (DMOA)

The Drop Mongoose Optimization Algorithm (DMOA) is a novel bio-inspired algorithm introduced specifically for optimization problems like node localization in WSNs, DMO is introduced 2022 by [15]. This algorithm is inspired by the mongoose's hunting and evasion techniques, which involve rapid, unpredictable movements to evade predators or catch prey. DMOA applies this dynamic behavior to the search process by enabling nodes to make both large exploratory moves and fine-tuned adjustments in their position, mimicking the mongoose's strategic shifts. In WSNs, this translates into a balance between exploration and exploitation of the search space, which allows DMOA to escape local optima and achieve higher precision compared to more traditional methods like PSO or FOA. The adaptability and robustness of DMOA make it particularly well-suited for complex network environments, offering superior accuracy in node localization while maintaining energy efficiency.

These bio-inspired algorithms provide diverse strategies for tackling the node localization problem in WSNs, with each offering unique strengths and trade-offs depending on the specific network configuration and energy constraints. The comparative study of these algorithms will offer valuable insights into their relative performance, particularly in terms of localization precision and accuracy, key factors for the success of WSN applications. Here we use the obtained results of our latest work entitled: WSN localization based on DMOA, and presented in [16].

DMOA is inspired by the dynamic movement of mongooses when hunting. The algorithm balances exploration and exploitation through sudden directional changes:

$$X_{new} = X_{current} + \alpha\ (Random() - 0.5) \tag{7}$$

$$Y_{new} = Y_{current} + \beta\ (Random() - 0.5) \tag{8}$$

Where *α, β* are control step size variations. DMOA enhances search diversity and avoids local optima, making it robust for localization.

IV. COMPARISON OF EXPERIMENTAL RESULTS

İn this part of paper we will compares the results of the three bio-inspired algorithms: PSO, FOA, and DMOA. The experiment takes place in a 50 × 50 m² area and involves two types of nodes: anchor nodes with known coordinates and unknown nodes whose coordinates need to be estimated. All nodes have a communication range of 25 meters, and all metaheuristics having the same swarm size with 25 individuals. The experiment is performed under various scenarios, varying the number of nodes with a fixed number of anchor equal 25 nodes.

In Figure 2, we give an example of a random distribution of 200 unknown nodes represented by black squares and 25 known nodes or anchors represented by red Rhombus. To ensure a fair comparison we used the same network properties mentioned above for all algorithms used in this comparison part.

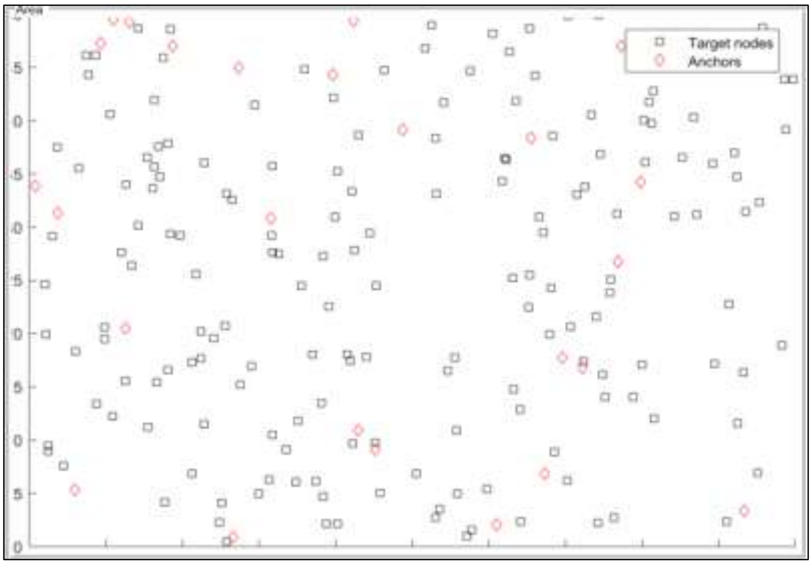

Figure 2: Example of random deployment.
Source: Authors, (2025).

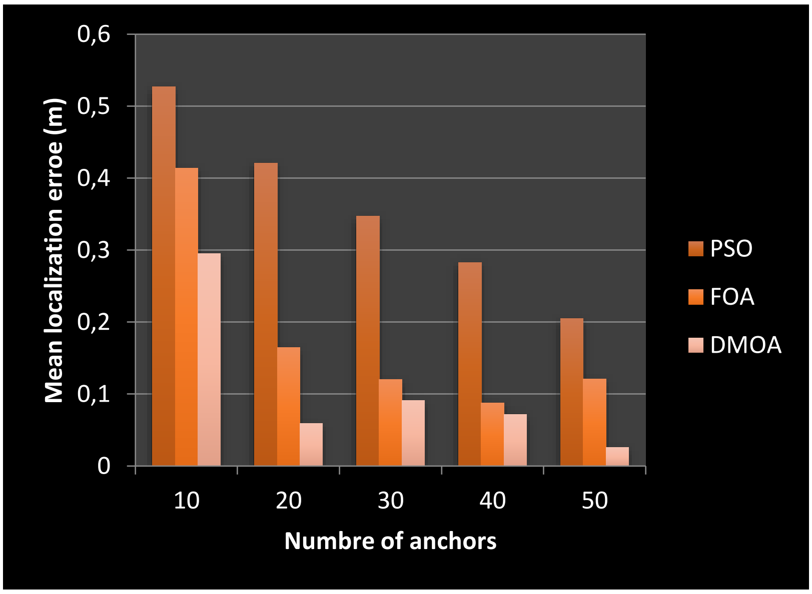

Figure 3: Localization error of various approaches Vs Numbre of nodes.
Source: Authors, (2025).

The graphs of Figure 3 shows the comparison of the mean localization error for three bio-inspired algorithms when we change the number of anchors between 10 and 50. DMOA consistently performs the best, with the lowest mean error rates in all scenarios, starting below 0.295 meters for 25 anchor nodes and decreasing to under 0.105 meters at 50 anchor nodes. FOA performs moderately, starting around 0.378 meters for 10 anchor nodes and gradually decreasing to 0.175 meters for 50 nodes. PSO has the highest localization error, beginning around 0.592 meters and reducing to approximately 0.199 meters. Overall, the localization accuracy improves for all algorithms as the number of anchor nodes increases, with DMOA showing the most significant improvement.

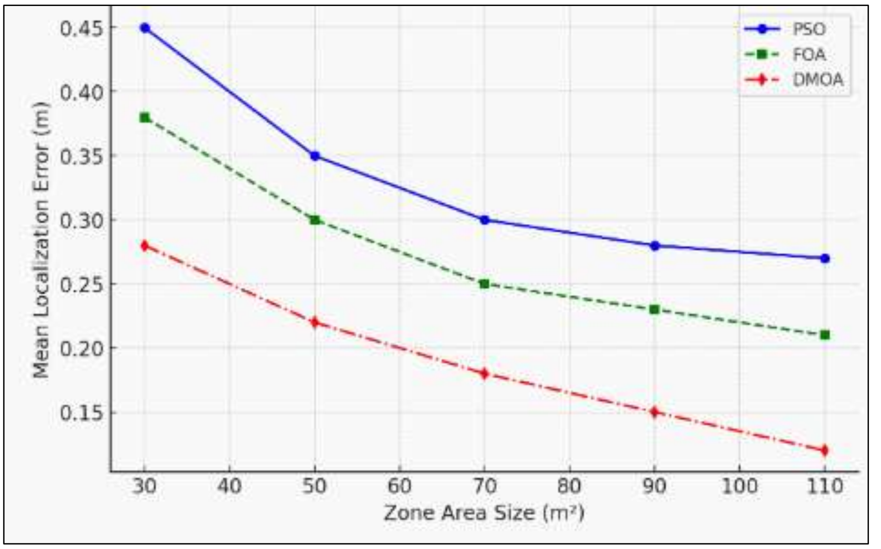

Figure 4: Comparison of positioning accuracy with different area sizes.
Source: Authors, (2025).

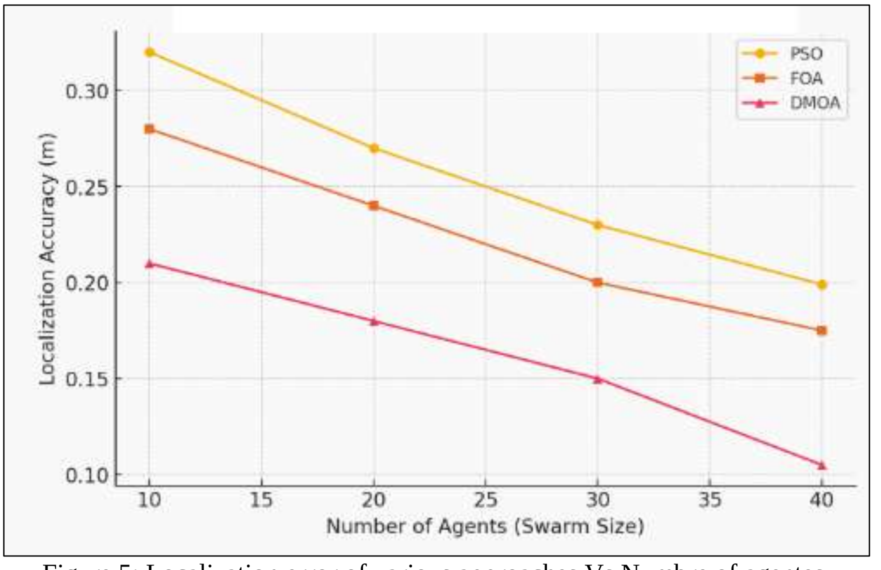

Figure 5: Localization error of various approaches Vs Numbre of agentes.
Source: Authors, (2025).

The graphs of Figure 4, illustrates how the localization accuracy of PSO, FOA, and DMOA changes with varying zone areas. The key observations are as the zone area increases, localization accuracy tends to degrade for all three algorithms. This is expected since a larger area introduces more uncertainty and greater distances between nodes, making accurate position estimation more challenging. For small to medium-sized areas, all three algorithms can achieve reasonable accuracy. For large zones, DMOA is the most reliable, making it the preferred choice for scalable WSN deployments. Hybrid approaches integrating multiple techniques may help mitigate accuracy loss in larger environments.

The Figure 5 presents a comparative analysis of localization accuracy for PSO, FOA, and DMOA when varying the number of agents (swarm size) in the optimization process. The x-axis represents the number of agents involved in localization, while the y-axis denotes the mean localization error. Each algorithm's performance trend is plotted to show how increasing the number of agents impacts accuracy.

As the number of agents increases, the localization error decreases for all three algorithms. This is expected, as a larger swarm size generally leads to better exploration and more accurate positioning. DMOA consistently outperforms both PSO and FOA, achieving the lowest localization error across all agent counts. This suggests that DMOA effectively balances exploration and exploitation, allowing for more precise node localization. FOA shows moderate improvement with increasing swarm size, but its convergence rate is slower compared to DMOA. This indicates that while FOA is effective, it may require more iteration to achieve optimal results. PSO has the highest localization error, even with an increasing number of agents. This suggests that it struggles with local optima, limiting its accuracy improvements despite having more agents.

The diminishing returns effect is visible, where adding more agents beyond a certain threshold leads to minimal improvement. This suggests that an optimal number of agents exist for efficient localization without unnecessary computational overhead. DMOA's superior performance makes it the best candidate for accurate localization in WSN applications. FOA can be a viable alternative but requires careful parameter tuning to enhance its convergence. PSO's higher error rates suggest that modifications (such as hybridizing with other algorithms) may be needed to improve its effectiveness.

V. CONCLUSIONS

Accurate node localization is crucial for ensuring optimal performance in WSNs, which are widely used in applications such as environmental monitoring and smart cities. This paper presents a comparative analysis of three bio-inspired optimization algorithms—Particle Swarm Optimization (PSO), Fruit Fly Optimization Algorithm (FOA), and Drop Mongoose Optimization Algorithm (DMOA)—to assess their effectiveness in node localization. PSO, inspired by bird flocking behavior, is a popular heuristic method, while FOA is based on the foraging behavior of fruit flies. DMOA, a novel algorithm, draws from the movement and attack strategies of the mongoose, introducing a new approach to optimization. Simulation results reveal that while PSO and FOA perform well in certain scenarios, DMOA consistently achieves the highest localization precision and accuracy. This makes DMOA a highly effective option for improving node localization in WSNs. The study underscores the potential of bio-inspired algorithms to enhance the efficiency and reliability of WSN deployments.

VI. REFERENCES

[1] Amal Gulati, and all, A review paper on wireless sensor network techniques in Internet of Things (IoT), Materials Today: Proceedings, Volume 51, Part 1, 2022, Pages 161-165, ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2021.05.067.

[2] Cardone, G., Corradi, A., & Foschini, L. (2011). Cross-network opportunistic collection of urgent data in wireless sensor networks. *The Computer Journal*, *54*(12), 1949-1962. https://doi.org/10.1093/comjnl/bxr043.

[3] Enge, P. K. (1994). The global positioning system: Signals, measurements, and performance. International Journal of Wireless Information Networks, 1, 83-105. https://doi.org/10.1007/BF02106512.

[4] Cook, B. W., Lanzisera, S., & Pister, K. S. (2006). SoC issues for RF smart dust. Proceedings of the IEEE, 94(6), 1177-1196. DOI: 10.1109/JPROC.2006.873620.

[5] Ahmad, R., Alhasan, W., Wazirali, R., & Aleisa, N. (2024). Optimization Algorithms for Wireless Sensor Networks Node Localization: An Overview. IEEE Access. DOI: 10.1109/ACCESS.2024.3385487.

[6] Gopakumar, A., & Jacob, L. (2008, January). Localization in wireless sensor networks using particle swarm optimization. In *2008 IET international conference on wireless, mobile and multimedia networks* (pp. 227-230). IET. DOI: 10.1049/cp:20080185.

[7] Goyal, S., & Patterh, M. S. (2014). Wireless sensor network localization based on cuckoo search algorithm. Wireless personal communications, 79, 223-234. https://doi.org/10.1007/s11277-014-1850-8.

[8] Al Shayokh, M., & Shin, S. Y. (2017). Bio inspired distributed WSN localization based on chicken swarm optimization. Wireless Personal Communications, 97, 5691-5706. https://doi.org/10.1007/s11277-017-4803-1.

[9] Miloud, M., Abdellatif, R., & Lorenz, P. (2019). Moth flame optimization algorithm range-based for node localization challenge in decentralized wireless sensor network. International Journal of Distributed Systems and Technologies (IJDST), 10(1), 82-109. DOI: 10.4018/IJDST.2019010106

[10] Rabhi, S., Semchedine, F., & Mbarek, N. (2021). An improved method for distributed localization in WSNs based on fruit fly optimization algorithm. Automatic Control and Computer Sciences, 55, 287-297. https://doi.org/10.3103/S0146411621030081.

[11] Rabhi, S., Semchedine, F., & Mbarek, N. (2024). Localization in Wireless Sensor Networks by Hybridization between Optimization Algorithms of Particle Swarms and Fruit Flies. Automatic Control and Computer Sciences, 58(2), 177-184. https://doi.org/10.3103/S014641162470007X.

[12] Kennedy, J., and Eberhart, R.: 'Particle swarm optimization'. Proc. IEEE Int. Conf. Neural Networks, Perth, Australia, Jan 1995, pp. 1942-1948. DOI: 10.1109/ICNN.1995.488968.

[13] Rabhi, S., Belbali, M. S., & Haissoune, M. (2021). An Improved approach for localization in wireless sensor networks Using PSO algorithm. African Review of Science, Technology and Development, 6(1), 10-23.

[14] Cho, H. H., Lee, R. H., & Park, J. G. (2011). Adaptive parameter estimation method for wireless localization using RSSI measurements. Journal of Electrical Engineering and Technology, 6(6), 883-887. https://doi.org/10.5370/JEET.2011.6.6.883.

[15] Agushaka, J. O., Ezugwu, A. E., & Abualigah, L. (2022). Dwarf mongoose optimization algorithm. Computer methods in applied mechanics and engineering, 391, 114570. https://doi.org/10.1016/j.cma.2022.114570.

[16] Rabhi, S. (2024). Wireless sensor network localization based on Drop Mongoose Optimization Algorithm. *Studies in Engineering and Exact Sciences*, *5*(2), e8845-e8845. DOI: https://doi.org/10.54021/seesv5n2-300.