# A Combined Approach Based on Antlion Optimizer with Particle Swarm Optimization for Enhanced Localization Performance in Wireless Sensor Networks

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***Abstract*—Wireless sensor networks play essential role in daily life scenarios due to their wide range of applications. These networks are widely adopted in to accomplish several tasks such as smart cities, smart transportation, weather monitoring etc. These networks have limited resources and suffer from various challenges which impact their performance. Moreover, these networks collect the event information and if the location of information is not known then the data becomes meaningless. Therefore, localization is considered as the important aspect of these networks. Initially, Global Positioning System (GPS) based localization was considered as solution for localization but these networks consist huge number of nodes which increases the cost of network deployment. GPS won't deliver accurate localization outcomes in an indoor environment. In dense network, manually establishing location reference for each sensor node is also a tedious task. This creates a situation where the sensor nodes must locate themselves without any specialised hardware, such as GPS, or manual configuration. Utilizing localization methods, Wireless Sensor Networks (WSNs) may be deployed with reduced cost. Localization accuracy and complexity still remains the challenging issue for traditional methods. Therefore, in this work, we introduce optimization-based method where we consider antlion optimization as base method and incorporate particle swarm-based position and velocity update method to increase the localization performance. The experimental study shows that the average localization error is obtained as 0.06525 m, 0.08125 m, 0.1175 m, 0.3 m, and 0.575 m using proposed model, Cat Swarm Optimization (CSO), Penguins Search Optimization Algorithm (PeSOA), Particle Swarm Optimization (PSO), and Binary Particle Swarm Optimization (BPSO), respectively.**

***Keywords*—Wireless Sensor Networks (WSNs), Sensors Nodes (SN), localization, Received Signal Strength Indicator (RSSI), Distance Vector-Hop (DV-Hop) algorithm, antlion optimization, Particle Swarm Optimization (PSO)**

## I. INTRODUCTION

Current advancements and development in miniaturization of machine and communication technologies has led to emergence of micro-sensors. These micro sensors have revolutionized the contemporary communication strategies. In the view of this technological growth, the wireless sensor networks have gained huge attention from various domains of real-time applications [1]. Nowadays, Internet of Things (IoT) is one of the fastest growing and promising technology in the field of information technology. The Wireless Sensor Network (WSN) is considered as the core technology of IoT [2, 3]. As IoTs play important role to create smart environment such as smart building [4], smart cities [5], smart transportation etc. However, WSN is a crucial component of this smart environment. It serves as a mediator between the outside world and intelligent systems.

The number of Sensors Nodes (SN), which make up a WSN, can range from a few to hundreds of thousands [6, 7]. An SN can be as little as a dust particle or as large as a shoe. The cost of SNs varies from a few cents to hundreds of dollars depending on how complicated each node is. SNs perform several tasks, including monitoring and sensing, processing, information collecting, and communication [8]. They are utilised in a variety of monitoring applications due to their low cost and independence from human influence, including environmental monitoring [9, 10], health monitoring [11, 12], underground and underwater systems [13, 14], industrial equipment, and surveillance [15].

These applications demonstrate the AdHoc behaviour of the network but generally, these networks suffer from various challenges such as small size, deployment in hostile environment, limited battery life, less and smaller bandwidth, minimized communication range and transmission capabilities [16]. In order to deal with these issues, several methods have been discussed such which

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include sensor node localization to know the location of nodes, routing is used for efficient data transmission from source to destination [17], security management considers preventing various attacks on the network, etc.

WSN typically comprises of several sensor nodes placed throughout the monitoring region. These nodes can take measurements of the physical characteristics in their immediate environment, carry out basic computations and store the sensed information, and send information to the base station wirelessly. Sensing data must be integrated with location data in many WSN applications. Since these unknown nodes are dispersed at random throughout the monitoring area, it is vital to locate them beforehand. Since many applications require the knowledge of source positions and data without location content is frequently meaningless [18], node localization becomes a significant challenge for WSN. In this work, we focus on location estimation of sensor nodes to ensure the appropriate communication among nodes.

Generally, the localization is a process to acquire the coordinate of some node (anchor nodes) with the help of Global Positioning System (GPS) or manual deployment [19]. Later, employing some specific approach to obtain the coordinate of other nodes (unknown nodes). This is a widely faced problem in sensor networks and numerous procedures have been presented to tackle the issue of localization. In this context, unknown sensor node equipped with the GPS is the easiest and reliable way to accomplish the localization task. However, the GPS installation leads to increasing the cost of the network. Moreover, the GPS systems do not provide adequate performance for indoor and complex sensor network deployment environments. Thus, GPS based localization is not considered as universal solution for sensor node localization. Similarly, manual deployment of these sensor nodes and storing the coordinate information is another solution but it is not considered as a practical solution for large scale networks and some of the monitoring areas are not accessible to human for deployment of sensor nodes.

Generally, the localization schemes are classified in two main categories as range based and range-free localization where distance measurement is required for localization [20, 21]. According to the range-based methods, the distance between unknown and anchor node is estimated to estimate the location coordinates. On the other hand, the range free methods use the network density and network connectivity as the important parameter of whole network to estimate the localization of nodes. Therefore, the range-based localization provides better localization performance when compared with the range-free localization algorithms. Several methods have been discussed based on these methods such as Angle of Angle (AOA), Time of Arrival (TOA), and Received Signal Strength Indicator (RSSI) [22, 23].

On the other hand, anchor node movement-based methods are also introduced which are divided into static and dynamic anchor node localization. As discussed, these methods are based on the network connectivity therefore the static anchor node localization scheme require specific node density to ensure the connectivity. Similarly, the dynamic anchor node-based methods can help to reduce the need of static sensor nodes, reduce the operational cost of network, and improves the localization.

The process of WSN localization refers to determine the spatial coordinates of the individual sensor nodes to carry out the communication efficiently. Therefore, localization plays an important role in improving the performance of WSN. Several motivations are present to obtain the efficient localization such as localization schemes helps to improve the tracking and monitoring. By knowing the exact location of each sensor node, it becomes possible to gather and analyze data with spatial context, enabling more accurate and targeted decision-making. Similarly, it helps to optimize the deployment and utilization of sensor nodes. With the help of this precise location of sensor nodes helps network planners can strategically position them to achieve maximum coverage and connectivity with minimum redundancy. This leads to efficient utilization of network resources, such as battery power, bandwidth, and computational capabilities. On the other hand, the Localization aids in detecting and diagnosing faults or failures in a WSN. By knowing the expected locations of sensor nodes, deviations from their expected positions can indicate issues such as node failures, malicious attacks, or physical tampering. Localization data can be used to trigger appropriate recovery mechanisms or reconfigurations in the network to maintain its functionality and reliability. Moreover, it enables data fusion from multiple sensor nodes. When the precise location of each node is known, the collected sensor data can be combined based on their spatial relationships, leading to improved accuracy and reliability of the sensed information. Context-awareness is also enhanced as the location information can be used to correlate the sensed data with specific environmental conditions or events occurring in the physical space.

Localization information assists in optimizing routing and communication protocols within a WSN. By considering the spatial relationships between nodes, routing decisions can be made based on factors such as energy consumption, hop count, or proximity to the sink node. This leads to more efficient data transmission, reduced latency, and improved overall network performance.

Similarly, localization can enhance security and privacy in WSNs. By localizing the sensor nodes, it becomes easier to detect and prevent unauthorized node insertions or intrusions. Furthermore, location-based authentication mechanisms can be employed to enhance security in data transmission. Localization also helps in preserving privacy by allowing nodes to estimate their location without revealing it to other nodes in the network.

Overall, WSN localization plays a crucial role in enhancing the efficiency, effectiveness, and reliability of wireless sensor networks across a wide range of applications, ultimately enabling better decision-making, and improving the overall performance of the network.

Generally, the localization accuracy of these models is affected due to angle and distance measurement. Moreover, signal variations due to switching of signal propagation environment and presence of obstructions. Along with these issues, degree of connectivity also has an impact on localization accuracy. The increasing degree of connectivity leads to increase the localization accuracy and vice versa. Similarly, the amount of energy consumed by nodes during localization is also considered as an important factor which depends on the computational complexity and message exchanged between nodes. Therefore, there is a trade-off in WSN localization in terms of coverage, localization accuracy, connectivity, and energy consumption. in this work, we consider these issues and focus on increasing the localization accuracy for WSNs.

The main objectives of the proposed approach are listed as follows:

- To present a localization error-based problem formulation model
- To incorporate RSSI based path loss model to incorporate the hop error correction to minimize the ranging error
- To present Antlion based optimization model and improve the elite operator with the help of particle swarm optimization.

Rest of the article is organized as follows: Section II describes the details of existing localization schemes for WSNs, Section III presents proposed solution for range-based localization, Section IV presents the experimental analysis and comparative study, Section V is concluding this paper.

## II. Literature Review

This section presents the brief discussion about recent localization techniques for wireless sensor networks. This section includes range-based, range-free, static, and dynamic methods of localization. In a broader view, the localization algorithms are classified as distributed and centralized schemes. The centralized approaches perform all computations with the help of central entity however it increases the cost of communication of the network and poor localization accuracy [24]. These techniques are not suitable for low density networks. Therefore, less studies are present on this technique.

On the other hand, the distributed localization algorithms perform all computation at the sensor node itself. Since only inter-node communication takes place here instead than in centralised schemes, therefore, there is less energy consumption. The distributed algorithms are classified as range based and range free methods [20, 21]. In range-based localization procedures, the location of a sensor node is estimated using trilateration or triangulation using estimates of the angles or distances between Bayesian Networks (BNs) and the sensor node. The TOA, Time Difference of Arrival (TDOA), and RSSI of beacons broadcast from BNs and the sensor node are used to calculate the distance estimates. However, the main drawback of these methods is the requirement of additional hardware to estimate the range or angle. Luomala *et al*. [24] considered outdoor scenarios for WSN localization and developed adaptive range-based method which uses trilateration and reference node selection methods. This method uses Geometry of Reference Triangle (GRT) to analyse the effect of ranging error. The GRT values are computed for 3 combination of reference nodes, further, this value is used to identify the best node. Acoustic communication has a smaller bandwidth and longer propagation latency than radio transmission. This imposes further limitations on any localization algorithm. Therefore, Nain *et al.* [25] considered the localization problem for underwater scenario because traditional algorithms suffer from latency and localization error issue. However, some methods focused on incorporating the optimization strategy but proliferation in energy depletion and computational complexity degrade the overall performance. Moreover, the existing schemes lead to increasing the localization latency and error therefore, authors suggested to incorporate optimization strategies and introduced a new fitness function while considering the number of hops, ToA distance estimation error and delay.

Sabbella *et al*. [26] focused on developing the energy efficient localization and adopted Meta heuristic Krill Herd inspired optimization approach to estimate the location of non-anchors by using mobile anchor nodes. This optimization approach considers crossover and mutation operators to analyse the behaviour of mobile anchor nodes. The location is estimated based on the foraging motion of anchor nod, random diffusion of all sensor nodes and movement generated by thee all sensor nodes in the neighbourhood range. Similarly, Rabhi *et al*. [27] introduced Fruit Fly Optimization for Localization (FOA-L). According to this method, the localization process is initialized where random direction and distance values are assigned to the group of flies. The fitness function considers the highest smell value using fitness function to identify the location of target node. Phoemphon *et al.* [28] discussed that range-based methods are based on the distance measurement where RSSI converts the signal into distance. However, the obstacle between nodes affects the direct communication, therefore, multihop relay-based schemes need to be considered for distance estimation. Moreover, authors suggested to apply clustering.

Chuku *et al*. [29] reported the advantages of RSSI approach for distance estimation to localize the sensor nodes. However, the localization performance is affected due to impediments caused by natural and man-made hindrances which lead to signal attenuation and localization error. Thus, authors introduced a novel approach to detect the outlier in distance measurement to minimize the error. This method uses spatial correlation analysis to obtain the location which is supported by majority of beacon signals. The outlier detection method uses a simple clustering method which only considers the most effective candidate location and finally, mean shift clustering is applied for outlier detection.

Zhang *et al.* [30] suggest an enhanced RSSI- Least Square Support Vector Regression in order to maximize the location estimate accuracy and to reduce the localization cost. The experimental outcome of this method demonstrates the proposed technique reduce the localization cost and ensures the localization reliability. Yu *et al.* [31] introduced a new algorithm-triangle centroid localization strategy which is based on the weighted feature points along with RSSI based measurements are also incorporated to obtain the better localization. Researchers are particularly focused on two positioning-related problems: the accuracy of the RSSI value and the localization algorithm's optimization. Similarly, Mahapatra *et al*. [32] focused on RSSI based method and presented a localization approach. Along with this, authors incorporated average filter and Gaussian filter to estimate the distance for localization where trilateration and least square methods were used to obtain the final coordinates. Ding *et al*. [33] also adopted RSSI method to estimate the location for unknown node. This work reported that the larger difference between actual and real distance affects the localization accuracy. Therefore, authors presented a ZigBee based mechanism for location estimation. Further, maximum likelihood and Mini-Max positioning methods are also incorporated to ensure that the distance estimated by RSSI is less than 10 m or not.

By employing RSSI measurement in WSNs based on ZigBee, Zhang *et al.* [30] suggest a unique method of device-free human detection. The effectiveness of the suggested detection method is demonstrated by simulation results [30]. Many improved DV-Hop algorithms use the RSSI measuring method. By employing RSSI measurement in WSNs based on ZigBee, Wang *et al*. [34] suggest a unique method of device-free human detection. The effectiveness of the suggested detection method is demonstrated by simulation results [34]. Many improved DV-Hop algorithms use the RSSI measuring method, such as proposed in [35], where the authors suggest a localization method based on RSSI and an improved artificial immune algorithm. In their study, they apply a correction coefficient using the RSSI data provided by the node in order to update the Hop Count value. Then, an improved artificial immune technique was also implemented which uses Gaussian mutation in position estimation [36].

Optimization based methods are also widely adopted in this field. Dao *et al*. [37] presented antlion optimization where fitness function is designed based on the distance estimation of sensor nodes. Further, the obtained solutions are updated based on the node density and communication range of nodes. Singh *et al*. [38] developed Particle Swarm Optimization (PSO) based node positioning method and improve the performance of DV-Hop. Shayokh *et al.* [39] also adopted optimization method and presented chicken swarm optimization scheme. Below given table summarizes the challenges faced by these methods (see Table I).

TABLE I. HIGHLIGHTING RELATED WORK OF PREVIOUS LOCALIZATION SCHEMES

| **Article** | **Challenges** |
|---|---|
| Luomala and Hakala [24] | The algorithm works for certain localization scenarios therefore adaptability is a major challenge in this work |
| Nain *et al.* [25] | This method uses CSO and PSO based optimization strategies to obtain the optimal number of hops from anchor nodes. However, poor convergence of PSO affects the optimization performance. |
| Phoemphon *et al.* [28] | This approach suffers from scalability and robustness to dynamic environments |
| Chuku *et al.* [29] | Limited accuracy of RSSI, moreover, RSSI-based localization schemes often require calibration and training phases to establish a relationship between RSSI values and distances. |
| Zhang *et al.* [30] | Localization accuracy and robustness to noise interference and the main challenging issue for this research |
| Yu *et al.* [31] | susceptible to errors caused by non-line-of-sight conditions, Dependency on Network Density and sensitivity to signal variations |
| Mahapatra and Shet [32] | This method achieves desired performance for indoor environments |

## III. METHODOLOGY

This section presents the proposed solution for WSN localization by using RSSI based distance estimation method. The first phase of this section describes the traditional method of distance estimation where least square based models are used to measure the distance between sensor nodes. Based on this, we find the ranging error parameter which affects the localization accuracy. Here, our main aim is to minimize the ranging error therefore, we adopt RSSI based measurement which measures the distance based on the signal strength. However, the traditional distance measurement model miscalculates the hop distance which leads to increase the error of average distance. To handle this issue, we use average hop distance model to consider the appropriate distance between nodes. Later, we incorporate ALO optimization and improve its position update process by combining PSO model in it.

Generally, the traditional algorithms use least square method to estimate the distance and this information is used further to estimate the node positions. The obtained cumulative error is used for measuring the localization accuracy. The localization error for any obtained coordinates can be expressed as:

$$\begin{cases} d_1 = \sqrt{(x_1 - x)^2 + (y_1 - y)^2} \\ d_2 = \sqrt{(x_2 - x)^2 + (y_2 - y)^2} \\ \vdots \\ d_n = \sqrt{(x_n - x)^2 + (y_n - y)^2} \end{cases} \tag{1}$$

where $(x, y)$ represents the location of unknown sensor nodes in the considered network area, $(x_i, y_i)$ represents the coordinates of reference nodes, $d$ is the distance between reference node and unknown node deployed in the given region. The relation between reference and unknown node can be represented as:

$$\mathrm{A} \times \mathrm{X} = \mathrm{b} \tag{2}$$

where $A$ denotes the matrix of least square, which is expressed as:

$$A = -2 \times \begin{bmatrix} (x_1 - x_n) & (y_1 - y_n) \\ (x_2 - x_n) & (y_2 - y_n) \\ \vdots & \vdots \\ (x_{n-1} - x_n) & (y_{n-1} - y_n) \end{bmatrix} \tag{3}$$

Similarly, $X$ is a vector which denotes the $x$ and $y$ coordinates of the nodes, given as:

$$X = \begin{bmatrix} x \\ y \end{bmatrix} \tag{4}$$

Similarly, $b$ is the coefficient matrix which is denoted as:

$$b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 - d_1^2 + d_n^2 \\ x_2^2 - x_n^2 + y_2^2 - y_n^2 - d_2^2 + d_n^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 - d_{n-1}^2 + d_n^2 \end{bmatrix} \tag{5}$$

However, these localization theories are constructed under the ideal conditions but real-time scenarios suffer from various aforementioned challenges such as incorrect distance measurement, and obstacles etc. let us consider that $N$ is a vector with dimensions, thus, the linear equation can be expressed as Specifically, to increase the accuracy, the error $N$ must be minimized. The $X$ can be given as:

$$X = (A^T A)^{-1} A^T b \tag{6}$$

In order to reduce the complexity in distance calculation, the node localization problem can be expressed in the form of constrained optimization problem and therefore, distance measurement can be updated as:

$$\begin{cases} d_1^2 = (x - x_1)^2 + (y - y_1)^2 \\ d_2^2 = (x - x_2)^2 + (y - y_2)^2 \\ \vdots \\ d_n^2 = (x - x_n)^2 + (y - y_n)^2 \end{cases} \tag{7}$$

Based on this, the distance error measurement between nodes is modeled as:

$$|r_i - d_i| < \epsilon_i \tag{8}$$

where $\epsilon$ denotes the error variable for ranging node $r_i$ and the actual distance between reference node and unknown node is expressed as:

$$\begin{cases} d_1^2 - \epsilon_1^2 \le (x - x_1)^2 + (y - y_1)^2 \le d_1^2 + \epsilon_1^2 \\ d_2^2 - \epsilon_2^2 \le (x - x_2)^2 + (y - y_2)^2 \le d_2^2 + \epsilon_2^2 \\ \dots \\ d_n^2 - \epsilon_n^2 \le (x - x_n)^2 + (y - y_2)^2 \le d_2^2 + \epsilon_2^2 \end{cases} \tag{9}$$

Here, we consider ranging error $(f_i)$ [36] which is computed between unknown and reference node. This is given as:

$$f_i(x, y) = \sum_{i=1}^{n} \sqrt{(x - x_1)^2 + (y - y_1)^2 - d_i^2} \tag{10}$$

The small value of $f(x, y)$ denotes that the coordinate values are closer to the actual cost.

During the localization process, each sensor node obtains a certain number of hop between two nodes by applying distance vector routing. Here, we focus on determining the average hop distance because distance measurement plays important role in localization process. The average distance is computed as:

$$D = \frac{\sum_{i \ne j} \sqrt{(x - x_1)^2 + (y - y_1)^2}}{\sum_{i \ne j} Hop\ Count} \tag{11}$$

Here,$(x_i, y_i)$ and $(x_j, y_j)$ are the coordinates of beacon node $i$and $j$. As a correction value, the estimated average hop distance is broadcast to the network. Further, when the node to be measured receives three or more beacon nodes, then the coordinates of nodes are estimated with the help of trilateral, triangulation or maximum likelihood methods. Generally, the traditional methods face hop error problem. This process of hop error problem, every hop in the communication range of beacon nodes is considered as a hop even if has different range. This can lead to huge error cumulatively. Belo given Fig. 1 shows the example of this error.

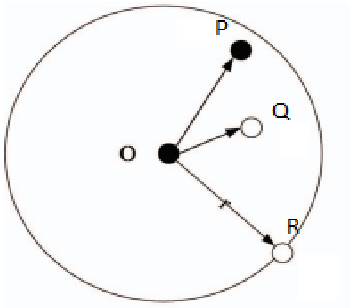


Fig. 1. Example of hop error problem.

In Fig. 1, node O and node P are the beacon nodes whereas node Q and R are the unknown nodes. Due to the error, the OP, OQ, and OR are considered as one hop whereas the actual hops are OP, OQ, and OR with different length.

In order to deal with these issues, we incorporate RSSI based measurement. This is a logarithmic path loss model and it is also considered as function of distance. Moreover, it is useful in describe the characteristics of signal attenuation. The path loss model for this can be explained as follows:

$$PL(d)dB = PL(d_0) + 10\, n \log\left(\frac{d}{d_0}\right) + a \tag{12}$$

Here $d$ is the distance between sender and receiver node, $d_0$ is the reference distance, $PL(d)$ is path loss at distance$d$, $PL(d_0)$ is the path loss distance at distance$d_0$, and $a$ is the random variable subjected to Gaussian distribution. The RSSI model is used to minimize the hop error. In this approach, we compare the RSSI value of unknown node and RSSI value when distance between beacon and unknown node is known. In this way, the hop values are updated by adding the current hop values to the previous hops. With the help of this, we obtain a correction coefficient$\omega$, expressed as:

$$\omega = \frac{RSSI_i}{RSSI_r} \quad (13)$$

Similarly, the final hop is updated as:

$$Hoplist = Hoplist_{i-1} + \frac{RSSI_i}{RSSI_r} \quad (14)$$

Step 1. Initialize variables:

- RSSI_threshold: Threshold value to filter out weak RSSI signals
- RSSI_distances: Array to store RSSI-distance pairs
- Coordinates: Array to store coordinates of sensor nodes

Step 2. For each sensor node in the network:

- Measure the RSSI value from the target node.
- If the RSSI value is below the RSSI_threshold, skip to the next node.
- Calculate the estimated distance based on the RSSI value (using a calibration model).
- Store the RSSI-distance pair in the RSSI_distances array.

Step 3. Select a subset of nearby sensor nodes (e.g., K-nearest neighbors) based on the estimated distances.

Step 4. apply antlion optimization to identify the best sensor node based on the distance.

Step5. Apply a localization algorithm (e.g., trilateration) using the RSSI-distance pairs and the coordinates of the selected sensor nodes to estimate the target node's location.

Step 6. Output the estimated coordinates of the target node.

The larger RSSI values denote that the node to be measured is close to beacon node. Thus, it minimizes the hop error problem and reduces the error. Random nature of sensor nodes and deployment affects the overall localization process. Therefore, several researchers have suggested to adopt optimization strategies. However, these optimization schemes suffer from local optimal solution, slow convergence, and computational cost. Therefore, we adopt the Ant Lion Optimization for localization [37].

The ALO is a nature inspired approach used in optimization tasks. This approach works based on the behavior of Antlion for their food hunting process. This optimization is performed into five different steps which are as follows: random walk of ants, trap building, entrapping ants in the formed trap, prey catching and rebuilding traps. The initial positions of ant and Antlion are given below as $M_{Ant}$and $M_{antlion}$, respectively

$$M_{Ant} = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1d} \\ A_{21} & A_{22} & \dots & A_{2d} \\ \dots & \dots & \dots & \dots \\ A_{n1} & A_{n2} & \dots & A_{nd} \end{bmatrix} \quad (15)$$

$$M_{Antlion} = \begin{bmatrix} AL_{11} & AL_{12} & \dots & AL_{1d} \\ AL_{21} & A_{L22} & \dots & AL_{2d} \\ \dots & \dots & \dots & \dots \\ AL_{n1} & AL_{n2} & \dots & AL_{nd} \end{bmatrix} \quad (16)$$

For the given Ants and Antlions, the objective function during optimization is given as follows:

$$M_{OA} = \begin{bmatrix} f([A_{11}, A_{12}, .., A_{1d}]) \\ f([A_{21}, A_{22}, .., A_{2d}]) \\ \dots \\ f([A_{n1}, A_{n2}, .., A_{nd}]) \end{bmatrix} \quad (17)$$

$$M_{OAL} = \begin{bmatrix} f([AL_{11}, AL_{12}, .., AL_{1d}]) \\ f([AL_{21}, AL_{22}, .., A_{L2d}]) \\ \dots \\ f([AL_{n1}, AL_{n2}, .., AL_{nd}]) \end{bmatrix} \quad (18)$$

Based on these parameters, the different stages of ALO are given as follows:

**Random Walk of Ant:** In each step of optimization process, ants are allowed to update their positions. A random walk function for ants can be defined as:

$$X(t) = [0, cumsum(2s(t_1) - 1), cumsum(2s(t_2) - 1), .., cumsum(2s(t_n) - 1)]$$

$$X_i^t = (X_i^t - a_i) \times (d_i - c_i^t) / (d_i^t - a_i) \quad (19)$$

where $s$ is the stochastic function which is expressed as.

$$s(t) = \begin{cases} 1 \; if \; rand > 0.5 \\ 0 \; if \; rand \le 0.5 \end{cases} \quad (20)$$

Here, consume is used for cumulative sum, $t$ is the present iteration, $n$ denotes the maximum number of iterations, and $rand$ is a random number generator, generating random number in the interval of [0,1]. In each search space, a certain boundary is assigned which keeps the random walk of ants in the defined search space. This is obtained by using min-max normalization before updating the positions of ants:

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i - c_i^t)}{(d_i^t - a_i)} + c_i \quad (21)$$

where $a_i$ denotes the minimum value of random, $d_i$ denotes the maximum of random walk, $c_i^t$ represents the least value and $d_i^t$ denotes the maximum values at $t^{th}$ iteration.

**Trapping:** The aforementioned random walk of ants is affected due to traps of Antlions, which is expressed as:

$$c_i^t = Antlion_j^t + c^t$$

$$d_i^t = Antlion_j^t + d^t \quad (22)$$

This shows the random walk of ants follow the hyper spherewhich is defined by the vector $c$and $d$, $Antlion_j^t$ denotes the position of $j^{th}$ Antlion at $t^{th}$ iteration.

**Trap building:** In order to filter the Antlion for catching the ants, this method uses a roulette wheel in ALO which uses fitness function during optimization process.

**Ants sliding towards Antlion:** Once the ants are in the trap of Antlion, the Antlions shoot the sandoutward from the center of pit. This leads to sliding down of trapped ants and radius of hyperspace also decreases.

**Prey catching:** After reaching to the final stage of pit, the Antlion catches the ant and updates its position as follows:

$$Antlion_j^t = Ant_i^t \text{ if } f(Ant_i^t) > f\left(Antlion_j^t\right) \quad (23)$$

**Elitism:** it is considered as an important characteristic in optimization process which is helpful in maintaining the best solution in any given stage of optimization. In ALO, every ant follows random walk around the selected Antlion and elite. This is expressed as:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (24)$$

where $R_A$ the random is walk around Antlion and $R_E$ is the random walk around the elite $E$

However, the dynamic nature of sensor nodes affects the local and global optimal solutions. Therefore, we incorporate particle swarm optimization strategy to increase the stability in achieving the optimal solution. The PSO follows velocity update and position update of particles to find the solution. The velocity and position update can be expressed as:

$$v_i^{t+1} = wv_i^t + c_1 rand()(pbest^t - x_i^t) + c_1 rand()\,(gbest^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (25)$$

where $x_i^t$ is the current position, $v_i^t$ is the current velocity of $i^{th}$ particle at $t^{th}$ iteration, $c_1$ and $c_2$ are the constant denoted as acceleration coefficient which are used to monitor the impact of $pbest$ and $rand()$ is the random number generator which generates random number in range [0,1] and $\omega$ is the inertial weight which is nonnegative and less than 1. This process of velocity update is incorporated in elitism operation of ALO and improved operator can be expressed as:

$$Ant_i^t = \omega \frac{R_A^t + R_E^t}{2} + c_1 rand()(R_A^t - elite) + c_2 rand()(R_E^t - elite) \quad (26)$$

Thus, the combined ALO-PSO considers the local and global best solutions to find the best position of node. Below given table shows the algorithm for antlion optimization for WSN localization.

Step 1. Initialize variables:

- Population: Set of Antlions representing potential solutions
- N: Number of Antlions in the population
- MaxIterations: Maximum number of iterations
- D: Number of dimensions (coordinates) for the target node's location
- Bounds: Bounds for each dimension

Step 2. Randomly initialize the positions of Antlions within the given bounds.

Step 3. For each Antlion, evaluate its fitness based on localization accuracy.

Step4. Set the $best\_antlion$ as the Antlion with the highest fitness.

Step 5. Randomly initialize the positions of Antlions within the given bounds.

Step 6. For each Antlion, evaluate its fitness based on localization accuracy.

Step 7. Set the $best\_antlion$ as the Antlion with the highest fitness.

Step 8. Repeat the following steps until the maximum number of iterations is reached:

- For each Antlion in the population:
- Perform local search around the current position to improve the solution.
- Update the fitness of the Antlion based on the improved localization accuracy.
- Sort the Antlions in descending order based on their fitness.
- Update the $best\_antlion$ if a new Antlion with higher fitness is found.
- Perform global update to adjust the positions of Antlions towards the $best\_antlion$.
- Apply bounds enforcement to ensure the Antlions' positions are within the defined bounds.

Step 9. Output the coordinates of the $best\_antlion$ as the estimated location of the target node.

## IV. RESULT AND DISCUSSION

This segment presents the detailed discussion about outcome of proposed approach of sensor node localization. The obtained performance is compared with the state-of-art schemes to prove the robustness of proposed approach in terms of localization accuracy for varied simulation scenarios. This approach is implemented by using MATLAB simulation tool. We measure the performance in various terms such as:

- Localization error versus transmission range: in this parameter, we vary the range of transmission of the nodes and find the localization error. Generally, increasing the transmission range reduces the localization error.
- Anchor nodes versus error: here, we vary the number of anchor nodes and measure the error in localization. Moreover, we measured the average localization error and computation time for varied anchor nodes.

Finally, we compared the performance with existing techniques such as Particle Swarm Optimization (PSO), Binary Particle Swarm Optimization (BPSO), Cat Swarm Optimization (CSO), and Penguins Search Optimization Algorithm (PeSOA). Table II shows the considered parameter for simulation.

TABLE II. SIMULATION PARAMETER

| Simulation Parameter | Considered Parameter |
|---|---|
| Network area | 100×100 $m^2$ |
| Number of anchor nodes | 10, 20, 30, and 40 |
| Maximum number of iterations | 150 |
| Transmission range | 25–40 |
| Initial energy | 0.5J |
| Radio elec energy | 50nJ/bit |
| Radio propagation | Free space |
| $\in fs$ | 10 pJ/bit/m |
| $\in mp$ | 0.0015 pJ/bit/$m^4$ |

According to this experiment, we deployed nodes randomly in the 100×100 $m^2$ area where 10–40 nodes are deployed as anchor nodes. Initially we set the transmission range as 25 which is considered as default for the other simulations. However, we have varied transmission range as 25–40 m. we have considered energy parameters but these parameters are not used during localization because our main aim is to improve the localization performance.

### *A. Localization Error vs Transmission Range*

In this section we present the comparative study for varied transmission range. Below given figure shows the localization error performance.

The average localization error is obtained as 0.06525 m, 0.08125 m, 0.1175 m, 0.3 m, and 0.575 m using proposed model, CSO [39], PeSOA [39], PSO [38] and BPSO [39], respectively. This experiment shows that the increasing the transmission range reduces the localization error because of its coverage maximization. Moreover, the proposed approach reduces the hop error which cumulative decrease the localization error. Increasing the transmission range can potentially reduce the localization error in certain scenarios. The relationship between transmission range and localization error depends on various factors and considerations, some of the important factors are as follows:

- Signal Strength and Quality: Increasing the transmission range can improve the signal strength and quality at greater distances. With a stronger and more reliable signal, the accuracy of localization techniques that rely on signal strength, such as RSSI (Received Signal Strength Indicator), can improve. This can lead to a reduction in localization error.
- System Geometry: The arrangement of reference points and the localized device’s geometry can impact the localization accuracy. Sometimes increasing the transmission range helps to resolve this issue, especially in complex environments or when there are limited reference points.
- Increased transmission range helps to consider more number of relay node thus increases the reliability by collecting the various information about network.

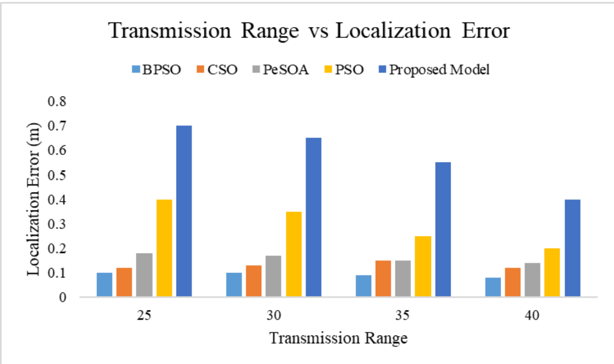


Fig. 2. Localization error performance.

Fig. 2 shows a comparative performance for varied number of anchor nodes. As we increase the number of nodes, the localization rises. The proposed approach achieves an average performance as 0.0625, whereas CSO [39], PeSOA [4], PSO [38], and BPSO [39] achieves the average localization error as 0.09, 0.1075, 0.3725, and 0.555, respectively. According to this experiment, the increased number of anchor nodes reduce the localization error because it leads to improve the communication in the presence of appropriate amount of data (see Fig. 3).

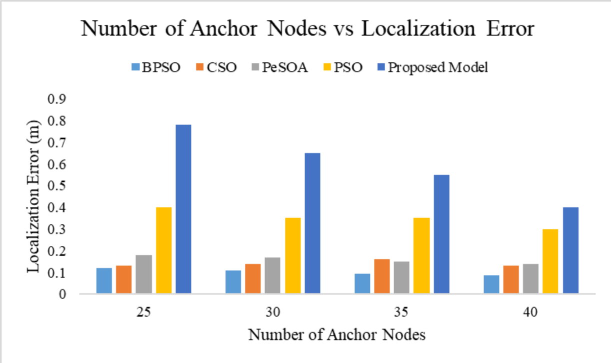


Fig. 3. Number of anchor nodes versus localization error performance.

### *B. Localization Error vs Anchor Nodes*

Similarly, we have compared the localization error performance for varied ratio of anchor nodes where we have considered the communication range as 30 m and number of nodes are 200. Fig. 4 shows a comparative study for varied anchor nodes. The obtained performance is compared with existing techniques such as DV-Hop [40], enhanced PSO [40], weighted DV-Hop [40], and DANS D-Hop [40].

In this experiment, we obtain the average localization error as 0.121, 0.361, 0.286, 0.163, and 0.1422 using aforementioned techniques respectively. However, the network arrangement with anchor node ratio 0.3 and 0.4 achieves similar performance due to similar configuration and network density. Moreover, the DANSD-Hop follows the dynamic anchor node process and it doesn’t rely on centralized infrastructure for localization similar to proposed approach. Moreover, the proposed approach is also based on finding the optimal node set by employing ALO whereas the DANS D-Hop simply uses the hop-count information to improve the localization accuracy without optimizing the hop-count.Though, average performance shows significant reduction in localization error. Further, we measure the computational time required to obtain the node localization (see Table III).

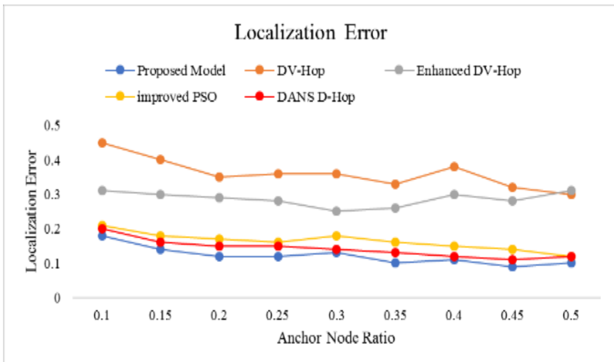


Fig. 4. Localization error performance for varied ratio of anchor nodes.

TABLE III. COMPARATIVE PERFORMANCE FOR THIS EXPERIMENT

| Algorithm | Time taken (150 iterations) |
|---|---|
| PSO [38] | 874.24 |
| BPSO | 649.293 |
| PeSOA | 409.6816 |
| CSO | 255.0341 |
| Proposed Approach | 156.0834 |

The proposed approach consumes 156.0834 s for 150 iterations to complete the localization process which is comparatively very low when compared with other techniques. This is achieved due to the faster convergence and proposed fitness function.

## V. CONCLUSION

The increasing demand of wireless sensor networks has gained huge attention in real-time applications such as monitoring, tracking, surveillance etc. However, these networks collect the information when there is any event or activity. The collected information is transmitted to the destination node. However, combining the localization with even is extremely important otherwise the data becomes meaningless. In order to overcome these issues, researchers have focused on localization schemes to find the coordinates on the sensor nodes. Several methods are introduced during last decade such as centralized and distributed localization where range based and range free algorithms are widely adopted for daily life scenarios. However, range-based localization systems provide better accuracy but computational complexity, localization error and resource consumption in localization remains a challenging task. In this work, we present a novel localization scheme which considers antlion optimization strategy for error minimization. Further, we incorporate PSO based velocity and position update method to improve the localization accuracy. The outcome of proposed approach is compared with other existing schemes where proposed approach outperforms when compared with state-of-art optimization-based localization techniques.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

S.G.R. has conducted the research, performed experiment, generated data, and wrote the paper; M.S.V.N. has analyzed and verified the data. All authors have read and agreed to the published version of the manuscript.

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