International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I4P112
Volume 73 Issue 4, 120-129, April 2025


*Original Article*

# LS-FCS-DV Hop Least Square Fuzzy Chicken Swarm Optimization-based approach for WSN Localization

Kavitha Narayan B M[1], Smitha Elsa Peter[2], Siddesha K[3]

[1]*Department of Power Electronics, Ponnaiyah Ramajayam Institute of Science and Technology (PRIST) Deemed to be University, Tamil Nadu, India.*
[2]*Department of Electronics and Communication Engineering, Ponnaiyah Ramajayam Institute of Science and Technology (PRIST) Deemed to be University, Tamil Nadu, India.*
[3]*Department of Electronics and Communication Engineering , Dr. Ambedkar Institute of Technology, Karnataka, India.*

[1]*Corresponding Author : kavithanarayan.et@drait.edu.in*

Received: 07 August 2024 Revised: 13 January 2025 Accepted: 18 March 2025 Published: 26 April 2025

***Abstract** - Wireless Sensor Network (WSN) has drawn plenty of interest from the general public and experts lately. Utilization of it crosses traditional bounds in various scientific applications such as military observation, regulating temperatures, humidity tracking, and observing the weather. WSNs comprise several nodes, all of which serve as sensors and are primarily liable for data collection. Energy, electricity, performance, and deployment challenges are some of the limitations that these nodes must work within. The strategic placement of nodes significantly impacts the effectiveness of data transmission. Furthermore, due to the absence of location information, the information becomes worthless. Therefore, localization plays a crucial role in WSN applications. Several methods have been introduced for localization; however, localization error impacts the performance of these methods. To overcome the drawbacks of existing methods, this article introduces a novel hybrid approach where least square and DV hop localization schemes are used as base localization models. Further, combined chicken swarm optimization and the fuzzy logic-based model were also incorporated to improve the overall performance. The experimental analysis demonstrates that the proposed has reported the average localization error as 0.0644, 0.085 and 0.125 for varied transmission range, anchor node and the ratio of anchor nodes, respectively, showing a significant improvement in localization accuracy.*

***Keywords** - Chicken swarm optimization, DV-hop, Fuzzy logic, Localization, Wireless sensor networks.*

## 1. Introduction

During the last two decades, the world has noticed tremendous growth in various technological domains, facilitating connectivity through networks using both wired and wireless networks. This connectivity allows us to share information and establish communication across the globe. However, the excessive use of these advanced communication technologies poses several challenges in adopting them for different applications. Currently, WSNs have fascinated scholars due to their versatile range of functionalities in various real-world applications [1]. Generally, the WSN is a collection of small, tiny, low-cost sensor nodes placed in a certain region and connected by a wireless connection medium to formulate the sensor field. A battery powers the sensor nodes to perform certain computations according to the given task. These networks are used in numerous real-world scenarios, such as environment tracking [2], battlefield surveillance [3], habitat monitoring, health monitoring and target tracking [5] etc. Despite their diverse applications, the sensor networks face several challenges due to the dynamic nature of deployment region, limited processing power, limited storage, etc. As discussed before, these networks are used in various applications; therefore, the collected information is transferred to the desired location with the help of other sensor nodes. The location data of these sensory devices plays a significant role in efficiently analyzing the information. On the other hand, these networks follow a geographical routing model, which also relies on the location information of the nodes for packet transmission [6]. The WSN's work depends on the occurrence of the event, and if the location of the event occurrence is not identified, then the complete network may lead to inaccurate analysis. Therefore, spatiotemporal context becomes an important aspect in WSN to detect and identify the geolocation and timestamp of the incident. The precise identification of event location can be identified if the position of the sensory device is known accurately. Moreover, the WSN model applications request precise location information to facilitate accurate information collection and processing. Thus, location identification becomes an important aspect. To achieve this, sensor node localization schemes have been introduced. Generally, the localization methods are carried out either manually or by using GPS modules. Manual localization involves complex computations and human interaction, whereas GPS localization relies on satellite assistance. The drawback of GPS is its inability to function in densely forested areas, mountains, or other obstacles obstructing the line-of-sight to GPS satellites. Localization utilizes reference nodes, neighbour nodes, and anchor nodes (whose positions are known through GPS) for the localization process [7]. Typically, localization algorithms operate on a 2-dimensional plane, specifically the $x$ and $y$ plane, where the coordinates align with the actual surface position, and the altitude remains constant. A 2D localization system is less intricate, demanding lower energy and time resources. It delivers accurate results on flat terrains but struggles with accuracy in challenging terrains. The system excels in providing precise distances when more nodes are present, along with anchor nodes. In a 3D plane, an additional plane (z plane) is introduced, enhancing accuracy by incorporating height. This configuration proves beneficial in rugged and hilly terrains [8]. While mapping estimated positions to the real world, errors may occur due to the involvement of all three planes. The utilization of a 3D localization system effectively eliminates this issue.

Several localization methods have been introduced, classified as centralized, distributed [9, 10], anchor-based, anchorless, range-based and range-free localization algorithms [11,12]. As per the concept of centralized localization, the network comprises a central base station to perform certain required computations for location purposes. As discussed before, the sensory devices are fortified with limited resources; therefore, the central servers help mitigate the issues of computational limitations. However, the nodes communicate to BS, which consumes excessive energy and impacts the network lifetime. Moreover, it leads to an increase in the communication overhead. In contrast, the distributed localization methods use nodes to communicate with each other and guess the position of sensors in the network.

The distributed algorithm can decrease the error but uses mobile nodes and acoustic energy for distance approximation. Similarly, anchor-based methods have also been adopted for localization, such as anchor-based and anchor-less location methods. The anchor-based methods are adopted as an initial reference for any localization method. According to the anchor-based methods, the average localization error exhibits an inverse association with the density of anchor nodes. An increased count of anchor nodes results in more precise reference points. However, augmenting these nodes comes at the expense of increased system costs and additional resources. To date, distance measurement techniques have not achieved optimal accuracy. In many applications, global coordinates take precedence over local coordinates, underscoring the recent emphasis on anchor-based localization. On the other hand, the anchor-less localization methods assess the distance between the sensory devices and produce a local map of sensor nodes. This local map of the sensor node can be employed for any coordinate system by using rotation, translation or flipping methods. Similarly, the range-based localization approaches use distance estimation by using sensors. Moreover, these methods can adopt several different techniques, such as triangulation, to identify the absolute position of non-anchor nodes. The accuracy of these methods is higher, but they require additional hardware, thus increasing the implementation cost. The literature review section describes the most recent techniques of localization based on these approaches. Despite several advanced localization methods, these methods face several challenges, such as limited resources and the reliability of existing methods on several factors such as range measurement, number of anchor nodes, network uncertainty, scalability, energy consumption, and limited energy resources. Therefore, this work focuses on developing a novel localisation approach for WSNs. Major contributions of this work are:

- To adopt DV Hop localization and least square-based localization
- To present a combined Least Square and DV-Hop localization for improved accuracy
- To incorporate Fuzzy logic with chicken swarm meta heuristic optimization approach for improved decision making.

The remaining manuscript is organized into the following sections: Section II presents the detailed literature review about existing methods and reports their drawbacks, section III presents the implementation details and methodology of proposed localization approach, section IV presents the detailed result of suggested model and its comparative analysis with existing localisation methods, and finally, section V presents the conclusion and future scope of the research work .

## 2. Literature Review

This part of the article presents a short review about existing methods for sensor node localization. Various localization algorithms have been discussed for sensor node localization, and some recent methods are discussed here. Kumar et al. [13] reported that the Distance Vector Hop approach has been adopted widely for range-free localization systems, but its performance is affected by the inappropriate measurement of hop count and hop size. Consequently, rather than relying on hop parameters, authors have presented an optimized localization approach for large heterogeneous networks and exploited the property of irregular communication range. This approach divides the nodes into two different sets where one set is known as the antecedent set, and the second set is known as the descendent set. Further, the centre of AS discloses the position that is additionally optimized to reduce the localization error. Mani et al. [14] focused on refining the estimated position in sensor node localization and introduced an iterative bounding box algorithm, which is enhanced by employing the Kalman filter to improve the localization performance. This method replaces the GPS-equipped anchors with single mobile anchors to reduce the implementation cost. The complete model is based on the range-free method of localization. Moreover, this model reported promising performance for varied parameters such as communication range, the position of mobile anchor nodes and varied network deployment topology.

Cao et al. [15] developed a DV hop based localization approach and focused on improving the localization accuracy in WSN localization tasks. To achieve this, the authors introduced optimum anchor node subsets based on the optimal approach for localizing the sensor nodes. According to this approach, in the first phase, the anchor node performs self-localization with the help of another node, and later, a binary PSO approach is used to obtain the optimal subset of anchor devices. In the next stage, the proposed optimized approach, i.e. OANS, helps to compute the required average hop size and transmits the updated hop size to the adjacent node. Finally, a new fitness function is obtained using PSO to improve the localization accuracy.

El Khediri et al. [16] adopted a K-means clustering approach for localization. This approach structures the network as a simple space partition because the wireless channels lack stability, and the node placement is coarse. In the next stage, this method evaluates the overall network energy consumption and performs the cluster head selection depending on the network magnitude. The objective function is formulated based on the space from CH to node, and membership weight is considered to design the objective function. Further, improved K Means clustering, i.e., the optimal K means clustering approach, is introduced where "single hop and multi-hop communication" modes are employed for inter-cluster and intra-cluster communication.

Similarly, range-based localization methods have been adopted widely for localization where RSSI is considered a promising technique. Chuku et al. [17] developed an RSSI-based localization approach for sensor networks. It is a cost-effective approach for estimating the distance. However, RF-based systems are widely adopted for the deployment of sensor networks where the communication performance of these models is affected due to the shadowing caused due to natural and man-made obstacles, which affect the performance of RSSI-based distance estimation due to signal attenuation and shadowing. In order to overcome this issue, authors have introduced an outlier detection-based method to discard the impact of erroneous distance estimation by using RSSI. Ou et al. [18] reported the importance of localization because, without the location information, its source may be worthless. Currently, optimization-based strategies are widely adopted to improve localization performance; therefore, authors have introduced an improved cuckoo search algorithm with fuzzy logic combined with fuzzy logic and Gauss-Cauchy strategy. This approach is a combination of both meta-heuristic and traditional approaches.

Tagne et al. [20] reported the importance of optimization methods in sensor node localization and suggested a new approach based on particle swarm optimization and tabu search method. The tabu search helps to determine the best neighbour, which improves convergence performance and leads to the best solution. Moreover, it also uses RSSI based method to estimate the inter-sensor distance. Similarly, Lakshmi et al. [21] introduced a combined range-free and hybrid DV-Hop optimization approach to improve localization accuracy. It also uses 2D and 3D measurements with Kalman filter linked with DV Hop. Finally, a new ensemble PSO model is introduced to reduce the localization error.

## 3. Proposed Model

This section highlights the suggested strategy for sensor node localization. The complete work is based on the combination of DV hop, least square with meta-heuristic optimization method along with DV hop localization method. First, a network model is designed for the experiment, and later, a general overview is presented about these methods. Finally, the suggested combined model is introduced to enhance localization by improving localization accuracy.

### *3.1. Network Model*

The assumed sensor network model comprises of $n$ no. of sensory nodes where $m$ number of the anchors, and total $u$ no. of unidentified nodes present in the sensing field. The anchors are equipped with the GPS; thus, the anchor nodes know their location. The $(x_i, y_i)$ represents the location axis of $i^{th}$ anchor device and the location of the unknown sensor node is denoted as $(x, y)$ . Each sensor node has $R$ as the communication radius. Figure 1 depicts deploying a sensor network where the total distribution area is 500m x 500m.

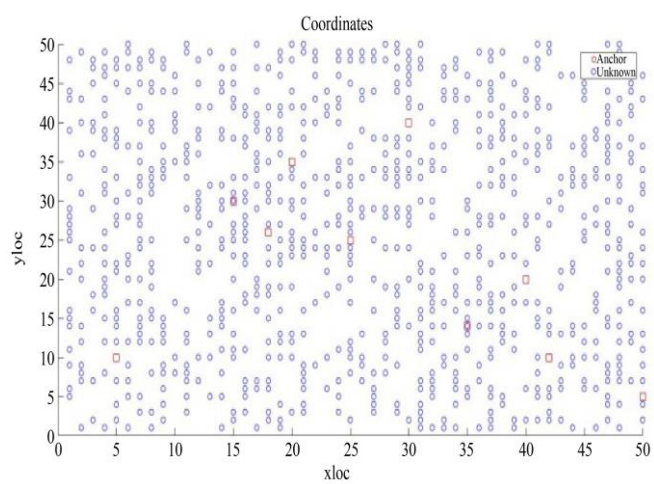


**Fig. 1 Random deployment of sensor nodes in the squared region**

### *3.2. Localization by using Combined Least Square and DV-Hop*

This section describes the process of DV Hop for localization tasks in sensor networks. The basic idea behind DV-Hop is to evaluate the distances between nodes based on the number of hops (transmissions) required to reach from one node to another. Various steps of this approach are as follows:

Step 1: Distance Measurement: Initially, each node in the network broadcasts a signal. Neighbouring nodes receive the signal and measure the distance based on signal strength or time of flight.

Step 2: Minimal hop count collection: generally, the $AN$ broadcasts the data packets, including the location axis information and no. of hops. The hop count is set to 0 initially and incremented by 1 at every subsequent hop; if the obtained value is smaller from the previous one, the sensor updates and stores this min. hop value. Upon completion of the transmission cycle, all sensors obtain the min. hop count information.

Step 3: Average hop distance computation: during the initial stage, the minima hop, count, and anchor node coordinates are obtained from any two anchor devices as per step 1. The avg. hop distance can be expressed as $H_i$ can be obtained as:

$$H_i = \frac{\sum_{i\neq} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i\neq j} h_{ij}} \tag{1}$$

Where $h_{ij}$ denotes the minimal hop count value from the anchor node $i$ to. Based on this, the avg. hop, all the distance info gets broadcast to the overall n/w.

Step 4: Coordinate computation of unknown nodes: as discussed before, the entire network is equipped with numerous unknown nodes; these nodes compute the distance $d_{ik}$ from $i^{th}$ anchor to $k^{th}$ unidentified node with the help of average hop distance computed in step. This distance between these nodes can be expressed as:

$$d_{ik} = H_i \times h_{ik} \tag{2}$$

This process helps to obtain the distance data of three or more anchor nodes distance data and based on these data, the least square technique can be employed to attain the location axis of unknown nodes. In the context of localization, the least square technique is used to assess the location axis of an object or sensor by minimizing the sum of the squared differences between the observed and predicted measurements. According to the working of the least square method, it is assumed that there is a total $N$ number of reference points with known coordinated. $(x_i, y_i)$ are present in the given field, and their distance measurement values are also known. The distance-based relationship can be expressed as:

$$(x_i - x)^2 + (y_i - y)^2 = d^2 \tag{3}$$

Based on this equation, the distance for all $m$ anchor nodes can be expressed as:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = d_1^2 \\ (x_2 - x)^2 + (y_2 - y)^2 = d_2^2 \\ \vdots \\ (x_i - x)^2 + (y_i - y)^2 = d_i^2 \\ \vdots \\ (x_{m-1} - x)^2 + (y_{m-1} - y)^2 = d_{m-1}^2 \\ (x_m - x)^2 + (y_m - y)^2 = d_m^2 \end{cases} \tag{4}$$

With the help of this, the last equation is subtracted from previous $m-1$ equations, and the following relations can be obtained:

$$\left.\begin{aligned} &(x_i - x)^2 - (x_m - x) + (y_i - y)^2 - (y_m - y)^2 = d_i^2 - d_m^2 \\ &2(x_i - x_m)x + 2(y_i - y_m)y = x_i^2 - x_m^2 + y_i^2 - y_m^2 + d_m^2 - d_i^2 \end{aligned}\right\} \tag{5}$$

Let us consider that the final coordinates are obtained as $X = [x, y]^T$, according to the least square method, the coordinate estimation relationship requires $AX = b$ where A and $b$ can be represented as

$$\left.\begin{aligned} A &= \begin{bmatrix} 2(x_1 - x_m) & 2(y_1 - y_m) \\ 2(x_2 - x_m) & 2(y_2 - y_m) \\ \vdots & \vdots \\ 2(x_i - x_m) & 2(y_i - y_m) \\ \vdots & \vdots \\ 2(x_{m-2} - x_m) & 2(y_{m-2} - y_m) \\ 2(x_{m-1} - x_m) & 2(y_{m-1} - y_m) \end{bmatrix} \\ b &= \begin{bmatrix} x_1^2 - x_m^2 + y_1^2 - y_m^2 + d_m^2 - d_1^2 \\ x_2^2 - x_m^2 + y_2^2 - y_m^2 + d_m^2 - d_2^2 \\ \vdots \\ x_i^2 - x_m^2 + y_i^2 - y_m^2 + d_m^2 - d_i^2 \\ \vdots \\ x_{m-2}^2 - x_m^2 + y_{m-2}^2 - y_m^2 + d_m^2 - d_{m-2}^2 \\ x_{m-1}^2 - x_m^2 + y_{m-1}^2 - y_m^2 + d_m^2 - d_{m-1}^2 \end{bmatrix} \end{aligned}\right\} \tag{6}$$

With the help of these estimations, the least square technique helps to assess the coordinates of unidentified nodes as follows:

$$\hat{X} = (A^T A)^{-1} A^T b \tag{7}$$

The location axis of the unidentified node can be expressed as:

$$\begin{cases} x = \hat{X}(1) \\ x = \hat{X}(2) \end{cases} \tag{8}$$

The combined model has several advantages over traditional DV hop and least square methods, such as the DV-hop approach facilitating initial estimates, but its performance is affected due to several factors, such as varied communication range and obstacles. The combination of least squares helps to refine the initial estimate to ensure accuracy. Generally, the DV Hop alone is sensitive to measurement errors in hop distances, whereas the Least square method can be beneficial in this context. Moreover, systematic errors inherent in DV-Hop, such as anchor placement biases, can be mitigated by the iterative optimization process of LSL, reducing the impact of such errors on final position estimates.

| **Algorithm 1**: Least Square Approach. | **Algorithm 2**: Combined Least square and DV Hop algorithm. |
|---|---|
| **Input**: $M$ Number of anchor nodes with known positions, $N$ Number of unidentified nodes to be localized, $p_i$ denotes the identified location axis of anchors, where $i = 1,2, \dots M$, $d_i$ is the measured distance between the anchor and the unknown node. | **Input**: $M$ Number of anchor nodes with known positions, $N$ Number of unidentified nodes to be localized, $p_i$ denotes the identified location axis of anchors, where $i = 1,2, \dots M$, $d_i$ is the measured distance between the anchor and the unknown node. |
| **Output:** Approximated location axis of unidentified nodes $x_j$ where $j = 1,2, \dots, n$ | **Output**: Estimated location axis of unknown nodes $x_j$ where $j = 1,2, \dots, n$ |
| Step 1: Initialization:<br>• Define a matrix $A$ of size $M \times 2$ to store the anchor node positions.<br>• Define a vector $b$ of size $M$ to store the measured distances.<br>Step 2: construct $A$ and $b$<br>For each anchor node $i$ from 1 to $M$:<br>• Store the coordinates of anchor node $i$ in row $i$ of matrix $A$.<br>• "Store the measured distance $\boldsymbol{d}_i$ between anchor node $i$ and unidentified nodes in the $i^{th}$element of vector $b$."<br>Step 3: Solve the least square problem<br>• Compute the pseudo-inverse of the matrix<br>$A = A^+$<br>• Compute the approx... position of unidentified nodes as<br>$x = A^+ . b$<br>where $x$ is a vector containing the estimated $x$ and $y$ coordinates of the unidentified nodes.<br>Step 4: Output**:** return the approx. location axis $x_j$ of unidentified nodes | Step 1: DV-Hop Distance Estimation:<br>• "Use DV-Hop algorithm to estimate the distances $d_i$ between anchor nodes and unknown nodes.<br>Step 2**:** Least Squares Localization:<br>• Apply the least squares localization algorithm using the estimated distances $\boldsymbol{d}_i$ obtained from DV-Hop.<br>• Obtain the estimated location axis $x_j$ of the unidentified nodes.<br>Step 3: Output:<br>• Return the estimated location axis $\boldsymbol{x}_j$ of the unidentified nodes obtained from the least squares localization step. |

### *3.3. Optimizing the Localization Performance*

To make it more adaptive, this paper introduces an optimization-enabled localization model; therefore, a combined fuzzy Chicken Swarm Optimization (CSO) model is presented, which is the combination of CSO and Fuzzy Logic. This section presents a brief overview of these algorithms, and finally, a combined model is presented to obtain better convergence and accuracy.

#### *3.3.1. Chicken Swarm Optimization*

The CSO approach has three main entities such as roosters, hens and chicks, where each of them has diverse behavioural specifications. The basic assumptions of CSO are as follows:

- The CSO algorithm organizes a chicken swarm into distinct groups, each consisting of a rooster, several hens, and a limited chick count.
- The assignment of roles (roosters, hens, and chicks) is based on individual fitness values, with the highest-ranked individuals becoming roosters, the lowest-ranked becoming chicks, and the rest selected as hens. Every chick picks a hen at random to be its mother, and every hen chooses a rooster to be its mate and join his flock.
- Throughout the populace, distinct roles, spousal connections, and parent-child relationships remain constant for G generations (G represents the reiterative cycle). Only after G generations do these roles and relationships undergo an update.
- Within each cluster of the overall population, hens accompany their mate roosters in foraging for food, engaging in random competitions with other group members. The likelihood of obtaining food is influenced by the individuals' fitness values, favouring those with superior fitness.

According to this model, RN, HN, CN and MN represent the rooster, hens, chicks and mother hens respectively. The position of $i^{th}$ chicken in $j^{th}$ dimensional space of $i^{th}$ iteration is expressed as $x_{i,j}^t$ where $\in \{1, \dots, N\}$ , $j \in \{1, \dots D\}$ and $t = \{1, \dots, T\}$ signifies the overall count of chickens, dimensions and maximum iterations. The positions of these entities are updated regularly, which can be expressed as:

Roosters follow the expression mentioned below to describe their recurrent position

$$x_{i,j}^{t+1} = x_{i,j}^{t+1} * (1 + Randn(0, \sigma^2))$$

$$\sigma^2 = \begin{cases} 1, if\ f_i \leq f_k \\ \exp\left(\frac{f_k - f_i}{|f_i| + \epsilon}\right), otherwise\ k \in [1, RN], k \neq i \end{cases} \quad (9)$$

$Randn(0, \sigma^2)$ represents the random number following Gaussian distribution with a variance of $\sigma^2$, $k$ is a rooster selected randomly, $f_i$ and $f_k$ represents the fitness value of $i^{th}$ and $k^{th}$ rooster, respectively. Similarly, the position of the hen can be expressed as:

$$x_{i,j}^{t+1} = x_{i,j}^t + C_1 * Rand * \left(x_{r_1,j}^t - x_{i,j}^t\right) + C_2 * Rand * \left(x_{r_2}^t - x_{i,j}^t\right) \quad (10)$$

$$C_1 = \exp\left(\frac{(f_i - f_{r_1})}{(abs\ (f_i) + \epsilon)}\right) \text{ and } C_2 = \exp\left(f_{r_2} - f_i\right)$$

Where $C_1$ and $C_2$ are the learning factors, $Rand$ is the random number following the uniform distribution. Finally, the position of the chick can be expressed as:

$$x_{i,j}^{t+1} = x_{i,j}^t + FL * \left(x_{m,j}^t - x_{i,j}^t\right) \quad (11)$$

Further, this model is combined with the fuzzy logic approach [19]. Fuzzy logic is a computing paradigm that deals with uncertainty and imprecision, allowing for a more flexible approach to decision-making and control systems. Fuzzy logic algorithms use linguistic variables and rules to emulate human-like decision processes.

A fundamental aspect of implementing the fuzzy method involves its application in adjusting the parameters of CSO algo.

The primary goal is to intuitively incorporate human knowledge into the parameter manipulation process, thereby enhancing the convergence and precision of the algorithm.

In essence, the procedure starts by fuzzifying the parameter values so that a knowledge-based evaluation of how to change them may be conducted. The knowledge library, which contains the parameter scales, is then used to identify the values that need to be adjusted.

The method then moves on when the fuzzy values for the parameters are de-fuzzified. In order to dynamically adjust the CSO parameters in response to changing population circumstances, the suggested FCSO algorithm incorporates a fuzzy framework.

These parameters include the total number of chickens in the population (N) and random variables. In order to overcome the limitations of CSO, this dynamic mechanism uses the fuzzy technique for adaptive parameter modification in an iterative process. Figure 2 demonstrates the combined fuzzy logic and LS-CSO approach.

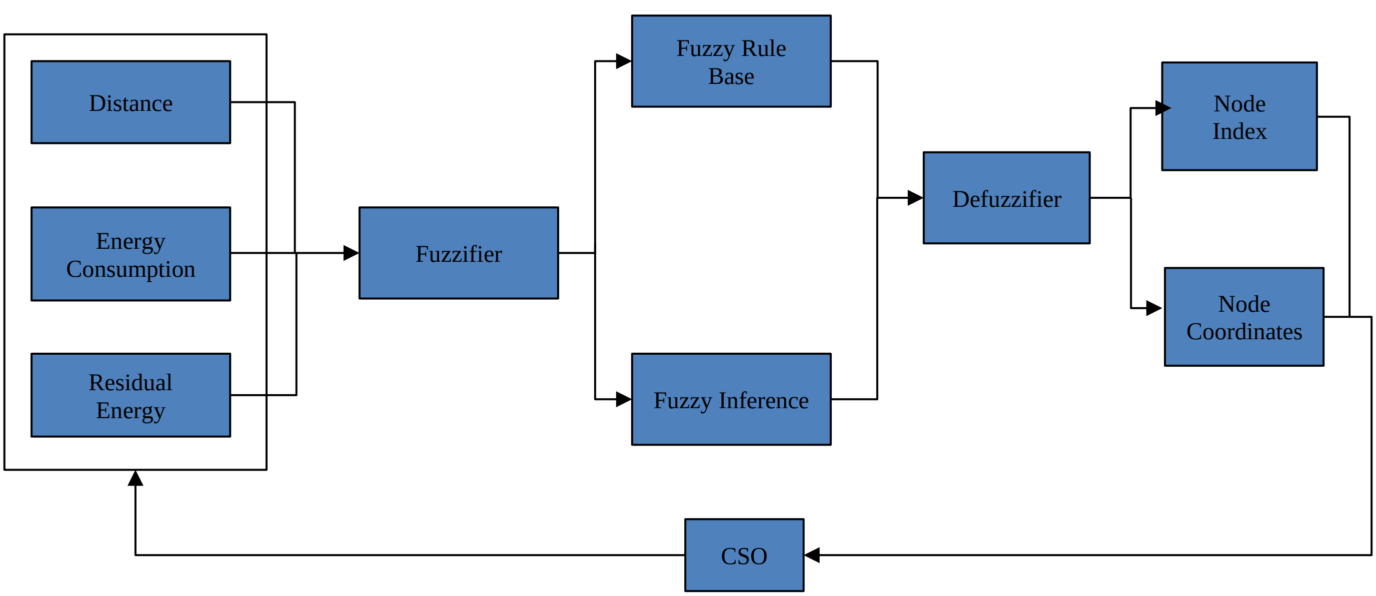


**Fig. 2 Combined Fuzzy-LSCSO for localization**

Below, algorithm 4 presents the combined model of these approaches for localization.

| **Algorithm 3**: Chicken Swarm Optimization | **Algorithm 4**: Combined CSO and Fuzzy Logic |
|---|---|
| **Input:** $N$ Number of chicken agents $D$: Dimensionality of the search space (usually 2D for x-y coordinates in localization), $L$: Max. count of loops, LB and UB: Lower and upper bounds of the search space for each dimension<br>Output: optimized solution for the given localization problem | **Input:** network, parameters, CSO parameters, fuzzy logic configuration<br>Output: optimized solution |
| Step 1: **Initialization**:<br>• Initialize $N$ chicken agents randomly within the search space defined by LB and UB.<br>• Assess the fitness of each chicken agent based on the objective function.<br>Step 2: Optimization process<br>**Iterate**:<br>• **For** $i = 1$:<br>  • **For** each chicken agent $i$ from 1 to $N$:<br>    • Determine the movement direction based on the following:<br>      • **Global Search**: Move towards the best position found by any chicken.<br>      • **Local Search:** Move towards the best position found by nearby chickens within a certain radius.<br>      • **Randomization:** Introduce randomness to explore new areas.<br>    • Update the position of the chicken agent $i$ using the following:<br>$$x_i(t+1) = x_i(t) + \Delta x_i$$<br>where$\Delta$ represents the direction of movement<br>    • Ensure the updated position $x_i(t+1)$) remains within the search space bounds LB and UB.<br>    • Evaluate the fitness of the new position $x_i(t+1)$<br>    • Update the best position found by the chicken if the new position has better fitness.<br>  • **End For**<br>• **End For**<br>**Termination:**<br>Step 3: **Stop**:<br>• When the maximum number of iterations $L$ is reached.<br>• Or if a satisfactory solution is found.<br>• Or based on other stopping criteria (e.g., convergence).<br>Step 4: **Output:**<br>**Return**:<br>• The best solution found corresponds to the positions of the chicken agents that optimize the objective function for WSN node localization. | Step 1: Initialize the chicken positions randomly<br>Step 2: Compute the fitness of each chicken, identify the global best position for the corresponding population and the local best position for every chicken<br>Step 3: Estimate the $\%G$, and if $\%G = 0$, then sort all chickens in descending order of their fitness<br>Step 4: The best fits are selected as roosters, the worst fitness individuals are selected as chicks, and others are hens.<br>Step 5: Randomly divide the population into different groups, which include roosters, hens and chicks.<br>Step 6: Update the positions of these entities based on (9), (10), and (11) and reevaluate their fitness values. //This function uses the fuzzy logic model to compute the fitness<br>Step 7: Update the global best for the entire population and local best solution for each individual<br>Step 8: Iterate until the stopping criteria are met. |

## 4. Results and Discussion

This part of the paper presents the resultant output of the suggested model and contrasts the attained results with state-of-the-art methods. This model is implemented using the MATLAB simulation tool running on the Windows platform. The system has 8GB of RAM capacity and 4 GB of NVIDIA graphics card. The obtained results are assessed in terms of localization error with respect to varied numbers of nodes, transmission range and anchor nodes. The localization error for varied node counts measures the performance in terms of error when the node count is increased. Similarly, localization error for varied transmission range represents the performance when varying the transmission range of the nodes and finding the localization error. Generally, increasing the transmission range reduces the localization error. Similarly, the localization error for the varied number of nodes shows the impact of an increased number of anchor nodes. Table 1 displays the various simulation parameters of experimental work. According to these simulation parameters, a 2D network is considered to have an area of 100 x 100 m2 where a sensor network is deployed randomly. Initially, the transmission range is fixed to 25 m, which can be extended to 40m to evaluate its impact on localization performance. First, the localization error performance is measured for varied transmission ranges and compared its performance with state-of-art optimization methods.

The figure below depicts the performance obtained for this experiment. The obtained performance is compared with traditional CSO, PeSOA, PSO, and BPSO. The comparative analysis is depicted in Figure 3. According to this experiment, the average localization error is found as 0.06440 m, 0.0805 m, 0.1170, 0.35m and 0.570 by using the proposed Fuzzy LSCSO, PeSOA, PSO and BPSO methods, respectively.

**Table 1. Simulation parameter**

| Simulation Parameter | Considered Parameter |
|---|---|
| Network Deployment Region | 100 x 100 $m^2$ |
| Anchor Node Count | 10-40 |
| Iteration Count | 150 |
| Range of Transmission | 25-40 |
| Initial energy | 0.5J |
| Radio elec energy | 50 nJ/bit |
| Radio propagation | Free space |
| $\epsilon_{fs}$ | 10 pJ/bit/m |
| $\epsilon_{mp}$ | 0.0015 pJ/bit/$m^4$ |

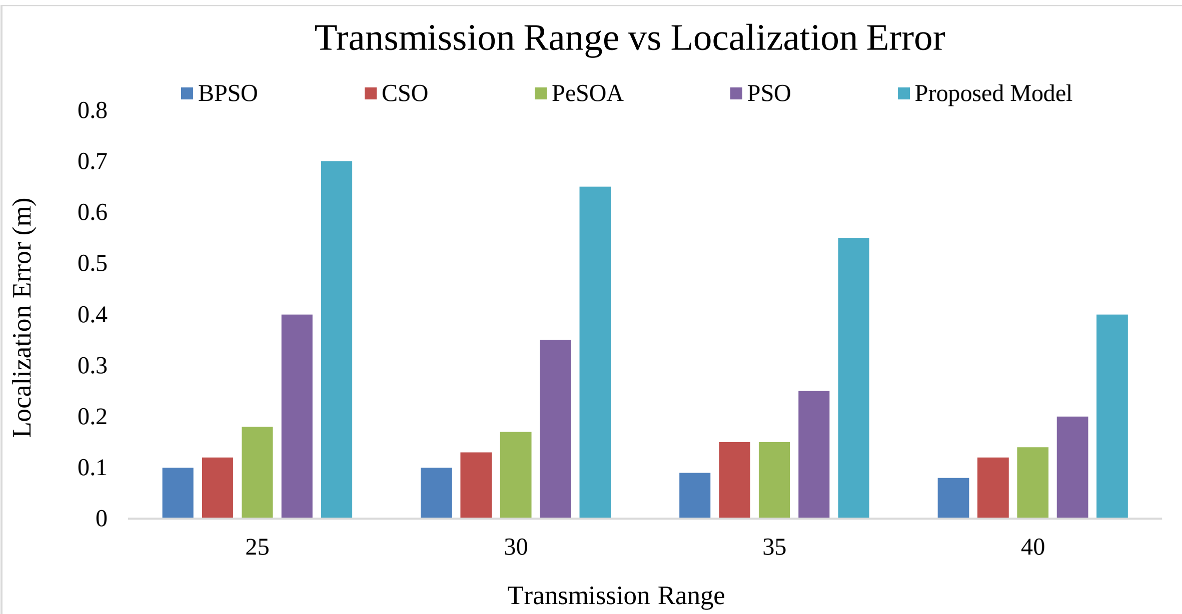


**Fig. 3 Localization error performance for varied transmission range**

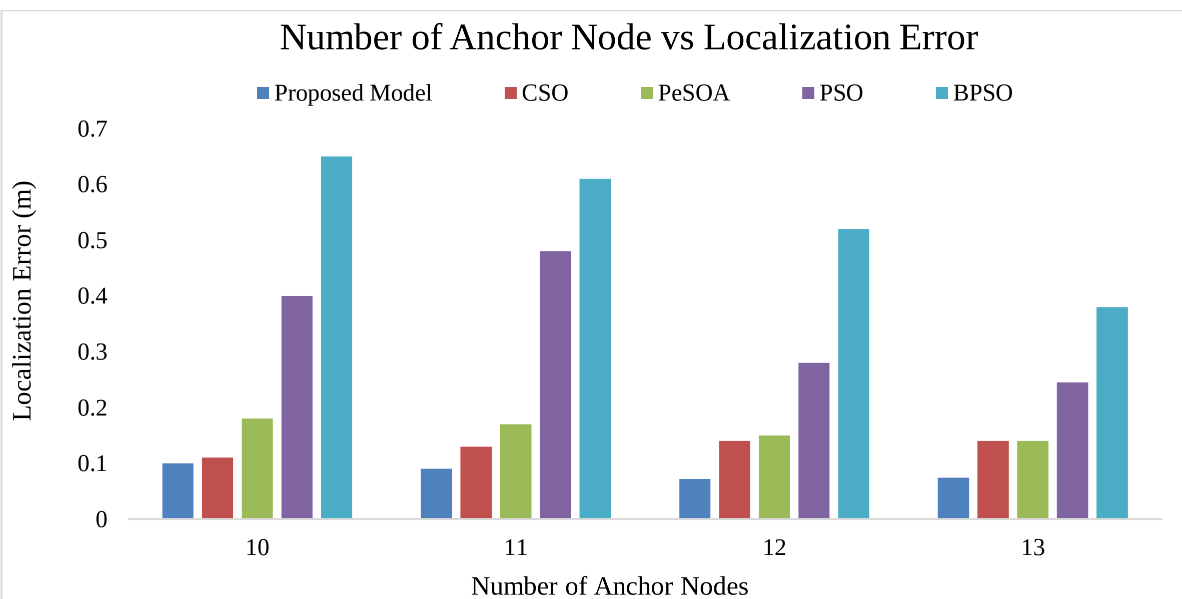


**Fig. 4 Number of anchor nodes vs localization error performance**

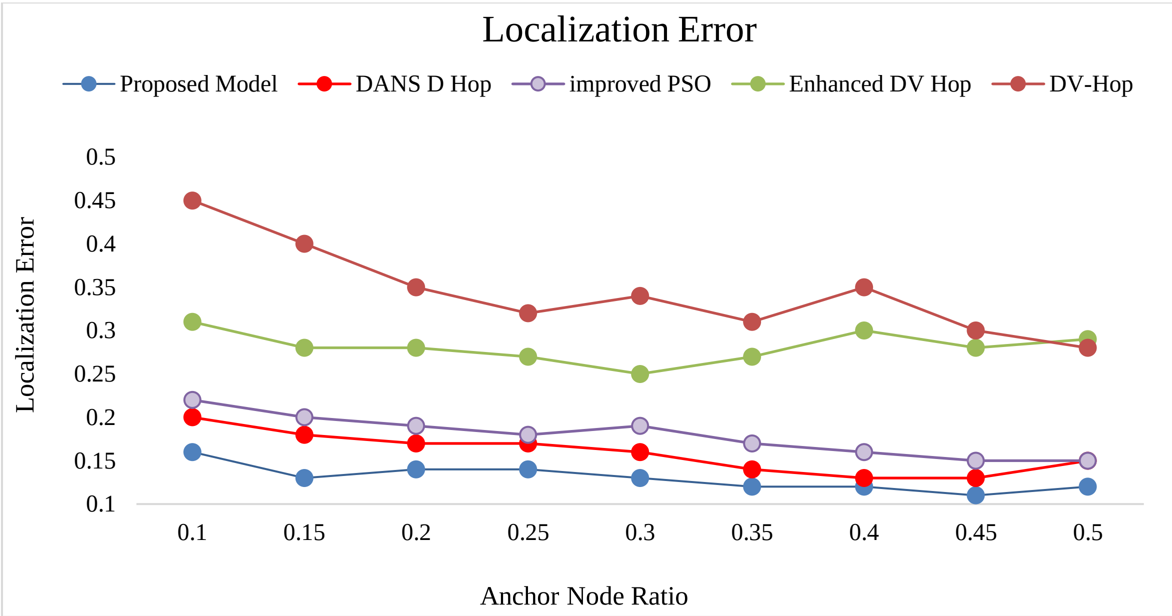


**Fig. 5 Localization Error for varied Anchor Node Ratio**

**Table 2. Iteration counts to carry out the complete localization process**

| Algorithm | Time taken (150 Iterations) |
|---|---|
| "PSO" | 875 |
| "BPSO" | 645 |
| "PeSOA" | 408 |
| "CSO" | 256 |
| Proposed Approach | 155 |

In the next experiment, the loc. error is measured for the varied number of anchors. Initially, it assumes 10 anchor nodes and measures the localization error performance. Figure 5 depicts the comparative analysis where the average localization error is obtained as 0.085, 0.115, 0.3515 and 0.549 using the proposed approach, CSO, PeSOA, PSO, and BPSO algorithms, respectively. This experimental analysis is extended further and measures the localization error performance for varied ratios of anchor nodes.

This experiment considers the communication range as 30 m, and the total number of nodes is considered as 200. The anchor node ratio varies from 0.1 to 0.5. The figure demonstrates the obtained performance. According to this experiment, the average localization error is obtained as 0.125, 0.355, 0.275, 0.150 and 0.1450 by using the proposed approach, DV-Hop, enhanced PSO, weighted DV Hop and DANS D-hop algorithms, respectively." The literature review analysis has reported that the traditional optimization and meta-heuristic approaches face computational complexity related, which can impact the network's overall lifetime performance. In the next experiment, the performance is evaluated in terms of the total time taken to perform the localization, and the performance is compared with existing models. Table 2 shows the obtained performance for this experiment. According to this experimentation, the suggested technique has reported the average time taken is 155 iterations, whereas existing models have reported the average iterations count as 875, 645, 408, and 256 by using PSO, BPSO, PeSOA, and CSO, respectively.

## 5. Conclusion and Future Work

This research work is mainly focused on the development of a robust approach for sensor node localization. Several methods have been introduced to achieve improved localization; however, it has become a challenging issue for several reasons. Therefore, in this work, a hybrid approach is introduced, which is established on the least square and DV hop-based localization. Further, the final decision-making process is improved by incorporating fuzzy logic.

Finally, chicken swarm optimization is implemented with a Fuzzy CSO approach to enhance the localization performance. The experimental analysis demonstrates that the proposed approach has overall localization errors of 00.0644, 0.085 and 0.125 for varied transmission ranges, anchor nodes and ratio of anchor nodes, respectively.

## References


[1] Dionisis Kandris et al., "Applications of Wireless Sensor Networks: An Up-to-Date Survey," *Applied System Innovation*, vol. 3, no. 1, pp. 1-24, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Qi Yu, Feng Xiong, and Yiran Wang, "Integration of Wireless Sensor Network and Iot for Smart Environment Monitoring System," *Journal of Interconnection Networks*, vol. 22, no. Supp02, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Samayveer Singh et al., "A Threshold-Based Energy Efficient Military Surveillance System Using Heterogeneous Wireless Sensor Networks," *Soft Computing*, vol. 27, no. 2, pp. 1163-1176, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Srinivas Sethi, and Ramesh K. Sahoo, *Design of WSN in Real Time Application of Health Monitoring System*, Virtual and Mobile Healthcare: Breakthroughs in Research and Practice, IGI Global, pp. 1-16, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Zhiyi Qu et al., "A Fault-Tolerant Sensor Scheduling Approach for Target Tracking in Wireless Sensor Networks," *Alexandria Engineering Journal*, vol. 61, no. 12, pp. 13001-13010, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] Ramin Yarinezhad, and Sadoon Azizi, "An Energy-Efficient Routing Protocol for the Internet of Things Networks Based on Geographical Location and Link Quality," *Computer Networks*, vol. 193, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Shivakumar Kagi, and Basavaraj S. Mathapati, "Localization in Wireless Sensor Networks: A Compact Review on State-of-the-Art Models," *2021 6th International Conference on Inventive Computation Technologies*, Coimbatore, India, pp. 5-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Iram Javed et al., "3D Localization for Mobile Node in Wireless Sensor Network," *Wireless Communications and Mobile Computing*, vol. 2022, no. 1, pp. 1-12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] S. Rabhi, F. Semchedine, and N. Mbarek, "An Improved Method for Distributed Localization in Wsns Based on Fruit Fly Optimization Algorithm," *Automatic Control and Computer Sciences*, vol. 55, no. 3, pp. 287-297, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[10] Lei Shi et al., "Distributed Localization in Wireless Sensor Networks Under Denial-of-Service Attacks," *IEEE Control Systems Letters*, vol. 5, no. 2, pp. 493-498, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] Nan Jing, Bowen Zhang, and Lin Wang, "A Novel Anchor-Free Localization Method Using Cross-Technology Communication for Wireless Sensor Network," *Electronics*, vol. 11, no. 23, pp. 1-20, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] Weiwei Hu, Junxiang Chen, and Shenying Yang, "Two-Mobile Anchor Node-Based Localization in Wireless Sensor Networks," *Journal of Ambient Intelligence and Humanized Computing*, vol. 15, no. 1, pp. 697-709, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Sumit Kumar, Neera Batra, and Shrawan Kumar, "Optimized Localization in Large-Scale Heterogeneous WSN," *The Journal of Supercomputing*, vol. 79, no. 6, pp. 6705-6729, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Rahma Mani et al., "Improved 3D Localization Algorithm for Large Scale Wireless Sensor Networks," *Wireless Networks*, vol. 30, no. 6, pp. 5503-5518, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Yuxiao Cao, and Jinbao Xu, "DV-Hop-Based Localization Algorithm Using Optimum Anchor Nodes Subsets for Wireless Sensor Network," *Ad Hoc Networks*, vol. 139, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Salim El Khediri et al., "Improved Node Localization Using K-Means Clustering for Wireless Sensor Networks," *Computer Science Review*, vol. 37, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[17] Ndubueze Chuku, and Asis Nasipuri, "RSSI-Based Localization Schemes for Wireless Sensor Networks Using Outlier Detection," *Journal of Sensor and Actuator Networks*, vol. 10, no. 1, pp. 1-22, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Xianfeng Ou et al., "Cuckoo Search Algorithm with Fuzzy Logic and Gauss-Cauchy for Minimizing Localization Error of WSN," *Applied Soft Computing*, vol. 125, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Zhenwu Wang et al., "An Adaptive Fuzzy Chicken Swarm Optimization Algorithm," *Mathematical Problems in Engineering*, vol. 2021, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Elie Tagne Fute, Doris-Khöler Nyabeye Pangop, and Emmanuel Tonye, "A New Hybrid Localization Approach in Wireless Sensor Networks Based on Particle Swarm Optimization and Tabu Search," *Applied Intelligence*, vol. 53, no. 7, pp. 7546-7561, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Yedida Venkata Lakshmi et al., "Accurate Range-Free Localization with Hybrid DV-Hop Algorithms Based on PSO for UWB Wireless Sensor Networks," *Arabian Journal for Science and Engineering*, vol. 49, no. 3, pp. 4157-4178, 2023. [CrossRef] [Google Scholar] [Publisher Link]