PSO-Optimized DV-Hop Localization Algorithm for Wireless Sensor Networks

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Abstract— **Accurate node localization remains a fundamental challenge in Wireless Sensor Networks (WSNs), as it directly influences network performance and reliability. The Distance Vector-Hop (DV-Hop) algorithm is widely used due to its simplicity and range-independence, but its accuracy significantly depends on network parameters. To address this limitation, this paper proposes an optimized DV-Hop localization scheme based on Particle Swarm Optimization (PSO). The proposed approach optimizes the connectivity range, beacon node coordinates, and beacon node ratio to minimize the localization error. Simulation results demonstrate that the PSO-optimized DV-Hop algorithm achieves a substantial reduction in Root Mean Square Error (RMSE) compared to the conventional DV-Hop algorithm.**

Keywords—*wireless sensor networks, DV-Hop, Particle Swarm Optimization, Localization*

I. INTRODUCTION

Localization is a crucial component of WSNs since the majority of network operations, including data aggregation, event tracking, and routing, require knowledge of the physical locations of sensor nodes, Precise localization enhances network performance and permits insightful data interpretation. However, obtaining accurate position estimation is still a difficult task because of energy constraints, inexpensive hardware, and environmental uncertainties. According to recent studies, localization is still one of the most important and developing research topics in WSNs, particularly with the incorporation of intelligent computing methods and optimization algorithms [1], [2].

In WSNs, localization algorithms are typically divided into two categories: range-based methods, which use distance or angle measurements such as the Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), Time Difference of Arrival (TDoA), or Angle of Arrival (AoA) as the basis for localization, and range-free methods, which only use connectivity (e.g., hop counts) instead of precise distance measurements [3]. Due to its ease of use and low hardware requirements, DV-Hop is a popular range-free technique; however, it has serious drawbacks, including imprecise hop-size estimation and sensitivity to network topology and beacon node geometry [4], [5].

Recent research has looked into integrating Particle Swarm Optimization (PSO) into the DV-Hop framework in order to address these drawbacks. Hadir *et al.* [6] proposed a PSO-based DV-Hop optimization to minimizing errors in estimating the average hop size and refine the estimated locations of sensor nodes in IoT and WSN environments. Chen *et al.* [7] introduced an enhanced DV-Hop method based on weighted iteration and an optimal beacon set, where per-hop errors are minimized through an iterative weighted MMSE approach. In [8], a PSO-based DV-Hop localization algorithm for WSNs is proposed to overcome the sensitivity of the least squares method used in traditional DV-Hop. By optimizing node coordinate estimation with PSO, the algorithm achieves faster convergence and significantly improves localization accuracy compared to the standard approach.

In this paper, we concentrate on improving the DV-Hop algorithm and suggest a PSO-based DV-Hop scheme that optimizes several key parameters, including connectivity range, beacon node coordinates, and beacon node ratio, in order to attain a higher localization accuracy. The remainder of this paper is structured as follows: The theoretical background and relevant literature of DV-Hop localization algorithm are presented in Section II, the suggested PSO-based DV-Hop method is explained in Section III, the simulation setup and outcomes are covered in Section IV, and the paper is concluded in Section V.

II. LOCALIZATION IN WSNS

A. *WSN ARCHITECTURE*

A WSN consists of spatially distributed sensor nodes that cooperatively monitor physical or environmental parameters and transmit the collected data wirelessly to a central sink or base station [1]-[2]. Four primary components are usually integrated into each node: a transceiver, a processing unit, a sensing unit, and a power supply [2]. Despite typically having limited energy, memory, and computational resources, these nodes are able to self-organize and communicate via multiple hops [1]. While some nodes in typical deployments serve as beacon nodes (having known positions), other nodes are unknown and their locations are estimated using localization

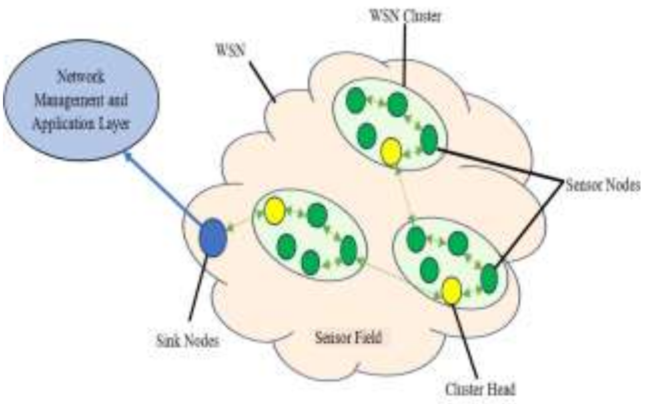

Fig. 1. General WSN architecture

algorithms. In order to reach the sink or access point, peripheral sensor nodes communicate with one another via intermediary head cluster nodes, which is a common hierarchical model used in WSN architecture. Fig. 2 illustrates the general architecture of a WSN, where the Network Management and Application Layer comprises the gateway, computer network, application requirements, and the WSN designer/manager [9].

For scalability and energy efficiency, hierarchical architectures are often adopted, particularly in large-scale WSNs. Such architectures divide the network into multiple clusters, each managed by a cluster head responsible for collecting and aggregating data from its leaf sensor nodes before transmitting it to the sink node [9]. Modern WSN implementations commonly employ IPv6-based protocols such as 6LoWPAN, which enable automated IP addressing and hierarchical parent-child communication structures between nodes and the access point [2].

B. *DV-Hop Localization Algorithm*

The technique of estimating the approximate location of network sensor nodes is known as localization. The localization process is a fundamental task which offers several advantages to WSNs. Network coverage can be maximized and data accuracy improved by carefully placing sensors or nodes and knowing their positions. Localization enables WSNs to accomplish optimal data collecting, efficient routing, and effective network management by fusing the network topology with the specific locations of WSN nodes [1]. This enhances the overall functionality and performance of the network.

Localization also facilitates adaptive power management, which allows nodes to modify their transmission power according to their proximity to the base station or nearby nodes. This dynamic modification optimizes the overall energy efficiency of the network, reduces energy waste, and strikes a balance between power consumption and connectivity [2].

Localization in WSNs usually is categorized into two groups depending on whether range is measured, i.e. range based localization and range free localization. Among range-free localization algorithms, the DV-Hop method [4]–[6] has attracted significant research attention since it was first introduced by Dragos Niculescu and Badri Nath in [10]. The main advantages of the DV-Hop algorithm are the low demand for hardware devices, convenient operation, high efficiency and low energy consumption [11]. Therefore, it can be widely applied to practical applications.

The DV-Hop algorithm's concept is that each unknown node uses the first information it receives from a beacon node to estimate its average hop distance. The average hop distance is then multiplied by the minimum hop count between beacon nodes to determine the physical distance between them. The unknown node uses trilateration or maximum likelihood estimation techniques to find its coordinates after the locations of three or more beacon nodes are known [11]. The execution of the standard DV-Hop algorithm can be divided into three principal steps, as outlined below [4],[7],[11]-[13]:

Step 1: Minimum Hop Count Estimation: Using a flooding mechanism, each beacon node broadcasts a beacon to its neighboring nodes in the first phase, including its position and an initial hop count value (usually set to zero). Every node logs the minimum number of hops to that particular beacon after receiving a beacon. The node modifies its record, increases the hop count by one, and rebroadcasts the updated beacon to its neighbors if a recently received beacon offers a lower hop count than the value that was previously stored. All nodes in the network eventually receive the minimum hop count to each beacon node as a result of this iterative flooding process.

Step 2: Average Hop Size (AHS) Estimation: Using the hop counts and known locations of other beacons acquired in Step 1, each beacon node calculates its Average Hop Size (AHS) in the second stage. The average physical distance between beacons per hop is known as the AHS, and it is computed as follows:

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

where $(x_i, y_i)$and $(x_j, y_j)$are the coordinates of beacons i and j, and $h_{ij}$is the minimum hop count between them.

After that, each beacon uses controlled flooding to broadcast its calculated AHS. If the first received AHS matches the nearest beacon, unknown nodes log it and send it on to their neighbors. Each unknown node calculates its distance to beacon i using the hop counts and stored AHS from Step 1 as follows:

$$d_{ui} = AHS_i \times h_{ui} \tag{2}$$

where d_{ui} denotes the estimated Euclidean distance between the unknown node u and beacon node i.

This step allows every unknown node to approximate its physical distance to multiple beacons, preparing for position estimation in Step 3.

Step 3: Position Estimation: In the final phase, each unknown node estimates its position using the distances to at least three beacon nodes obtained from Step 2. The method is typically based on trilateration or the maximum likelihood estimation (MLE) approach.

Let (x_u, y_u)denote the coordinates of an unknown node u, and (x_i, y_i)denote the known coordinates of the i^{th}beacon node. The estimated distances d_{ui}between the unknown node and each beacon satisfy:

$$(x_u - x_i)^2 + (y_u - y_i)^2 = d_{ui}^2, i = 1,2,\dots,n \quad (3)$$

By rearranging these equations, they can be expressed in matrix form:

$$A = -2\begin{bmatrix} x_1 - x_n & y_1 - y_n \\ x_2 - x_n & y_2 - y_n \\ \vdots & \vdots \\ x_{n-1} - x_n & y_{n-1} - y_n \end{bmatrix},$$

$$B = \begin{bmatrix} d_{u1}^2 - d_{un}^2 - x_1^2 + x_n^2 - y_1^2 + y_n^2 \\ d_{u2}^2 - d_{un}^2 - x_2^2 + x_n^2 - y_n^2 + y_n^2 \\ \vdots \\ d_{u(n-1)}^2 - d_{un}^2 - x_{n-1}^2 + x_n^2 - y_{n-1}^2 + y_n^2 \end{bmatrix} \quad (4)$$

Then, the estimated coordinates of the unknown node are obtained by the least squares method:

$$\begin{bmatrix} x_u \\ y_u \end{bmatrix} = (A^T A)^{-1} A^T B \quad (5)$$

This step provides the final estimated position of each unknown node in the network using the geometric relationships with surrounding beacons.

III. OPTIMIZATION OF WSNS PARAMETERS USING PSO

The population-based metaheuristic known as PSO was motivated by the foraging habits of fish schools and flocks of birds [14]. A point in the search space with a corresponding position and velocity is represented by each possible solution, also known as a particle. In order to converge toward an ideal solution, the PSO algorithm iteratively updates these particles based on their individual and collective experiences.

Assume a swarm of Nparticles in a D-dimensional search space. The position and velocity of the i^{th}particle are denoted as [2],[5],[8],[13]-[14]:

$$Xi = (x_{i1}, x_{i2}, \dots, x_{iD}), V_i = (v_{i1}, v_{i2}, \dots, v_{iD}) \quad (6)$$

Each particle remembers its best position found so far, $P_{best,i} = (p_{i1}, p_{i2}, \dots, p_{iD})$, and the global best position of the swarm is represented as $G_{best} = (g_1, g_2, \dots, g_D)$.

During each iteration, the particle updates its velocity and position according to:

$$\begin{aligned} v_{id}(t+1) = \omega v_{id}(t) + c_1 r_1 \left(P_{best,id} - x_{id}(t)\right) \\ + c_2 r_2 \left(G_{best,d} - x_{id}(t)\right), \\ x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \end{aligned} \quad (7)$$

where ω is the inertia weight controlling exploration versus exploitation, c_1 and c_2 are the acceleration constants, and $r_1, r_2 \in [0,1]$ are random coefficients introducing stochasticity. The inertia weight is often dynamically adjusted as:

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min}) \times t}{t_{max}} \quad (8)$$

to promote global search at the beginning and convergence at the end of iterations.

Where $\omega_{\max}$is the initial (maximum) inertia weight, providing higher exploration capability at the start of the search, $\omega_{\min}$is the final (minimum) inertia weight, promoting stronger exploitation near convergence, t is the current iteration number, $t_{\max}$ is the maximum number of iterations for the algorithm.

The optimization process follows four main stages:

- **Initialization:** Randomly initialize the positions and velocities of all particles within the feasible search space.
- **Fitness Evaluation:** Compute the fitness value for each particle according to the objective function. In localization, this is typically the mean position error between estimated and true node coordinates.
- **Update:** Each particle updates $P_{best,i}$and the swarm updates G_{best}if better solutions are found.
- **Termination:** Repeat the update process until convergence criteria, such as maximum iterations or target accuracy, are satisfied.

The velocity update equation includes three influences:

- $\omega v_{id}(t)$: particle's momentum (inertia component),
- $c_1 r_1 (P_{best,id} - x_{id})$: cognitive component (self-experience), and
- $c_2 r_2 (G_{best,d} - x_{id})$: social component (collective experience).

The choice of parameters ω, c_1, c_2 , and swarm size significantly affects the algorithm's efficiency and accuracy.

In this work three crucial DV-Hop localization algorithm parameters that have a big impact on positioning accuracy are independently optimized using PSO: the connectivity range R, the beacon nodes ratio BNR, and the spatial deployment of beacon nodes. To determine the precise impact of each parameter on the overall localization performance, each optimization is carried out independently.

In the optimization phase, a particle represents a candidate solution for a single parameter. For example, during the optimization of R, each particle encodes a value within predefined bounds:

$$R_{\min} \le R \le R_{\max} \quad (9)$$

For each parameter, the standard DV-Hop localization process is executed, and the RMSE between the true and estimated coordinates of all unknown nodes is computed as the fitness function:

$$f = \sqrt{\frac{1}{N_u} \sum_{i=1}^{N_u} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2]} \quad (10)$$

where (x_i, y_i) and $(\hat{x}_i, \hat{y}_i)$ denote the actual and estimated positions of the i^{th}unknown node, respectively.

The optimization proceeds until convergence or until $t_{\max}$ is reached. The optimal value of each parameter is determined independently as:

$$R^* = \arg\min_R f(R), BNR^* = \arg\min_{N_a} f(\text{BNR}),$$
$$\{(x_k^*, y_k^*)\} = \arg\min_{\{x_k, y_k\}} f(\{x_k, y_k\}) \quad (11)$$

These individually optimized parameters are then used to configure the final DV-Hop localization model used in performance evaluation.

IV. SIMULATION RESULTS

To evaluate localization performance, both DV-Hop and the PSO-optimized DV-Hop algorithm were simulated using MATLAB platform. Under the same network environment, the performances of the two algorithms were compared in term of RMSE. In the PSO-optimized DV-Hop, the connectivity range R, the number of beacon nodes, and their coordinates were optimized using the PSO algorithm

In our simulation, 100 sensor nodes were randomly deployed over a square area of 100 m × 100 m. Each sensor node was assigned a connectivity range of 50 m, enabling information exchange with other nodes located within this maximum distance. Eight specific nodes were designed as beacon nodes. Their positions were pre-defined and denoted as (x_i, y_i) for each beacon, where $i = 1, \ldots, 8$. These beacon nodes serve as reference points within the network of 100 deployed sensors. Fig. 2 illustrates the overall topology, highlighting the spatial distribution of all nodes and the placement of the beacon nodes.

A. *Optimization of the Connectivity Range R*

In this simulation, all network parameters were kept constant according to the values listed above. The PSO-optimized DV-Hop algorithm was then implemented to determine the optimal value of the connectivity range R, aiming to minimize the objective function. The optimal connectivity range obtained is Ropt=26.8917 m.

Fig.3 shows the variation of the RMSE as a function of the number of deployed nodes. A reduction in localization RMSE is observed after optimizing R through the application of the PSO-optimized DV-Hop algorithm. It is noted that the localization RMSE obtained with the optimized DV-Hop algorithm is more favorable compared to that of the conventional DV-Hop method. Specifically, the RMSE ranges from 30.43 m to 33.32 m for the standard DV-Hop algorithm, whereas for the optimized DV-Hop, it decreases to25.13 m to 29.24 m. Thus, the optimized DV-Hop algorithm provides higher localization accuracy compared to the original DV-Hop.

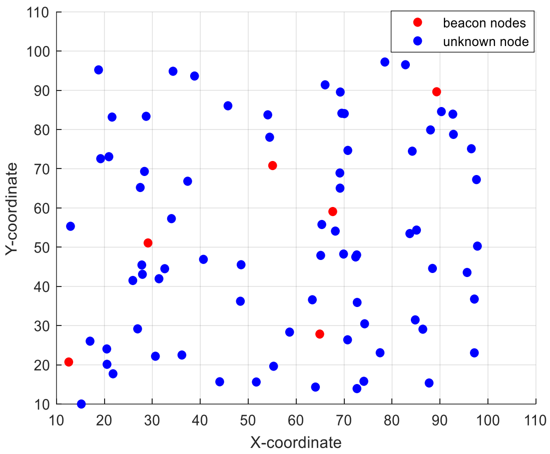

Fig. 2. Layout of the studied WSN

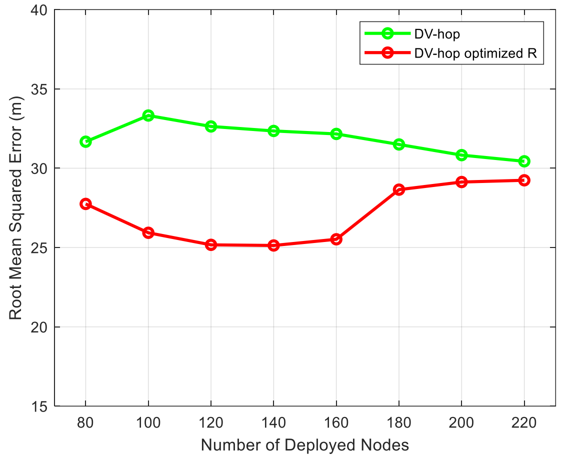

Fig. 3. RMSE c omparison between DV-Hop and DV-Hop with optimized connectivity range R.

This improvement results from the integration of the PSO optimization approach to fine-tune the connectivity range, allowing the DV-Hop algorithm to identify an optimal hop distance and thereby enhance distance estimation between nodes.

B. *Optimization of the Beacon Node Rate(BNR)*

In this Part, The PSO-optimized DV-Hop algorithm was applied to determine the optimal value of the ANR. The obtained optimal value is ANR_{opt}=10.61%. Thus, for a network of 100 nodes, the approximate number of required beacon nodes is 11.

Fig.4 illustrates the variation of the RMSE with respect to the number of deployed nodes for both algorithms. In the standard DV-Hop algorithm, where the beacon node ratio is set to BNR=0.08 (corresponding to 8 beacon nodes), the RMSE varies between 30.43 m and 33.32 m. In contrast, the optimized DV-Hop algorithm achieves a lower RMSE, ranging from 28.78 m to 29.46 m. This optimization enables the DV-Hop algorithm to better adapt to the specific characteristics of the network, resulting in a more accurate estimation of inter-node distances.

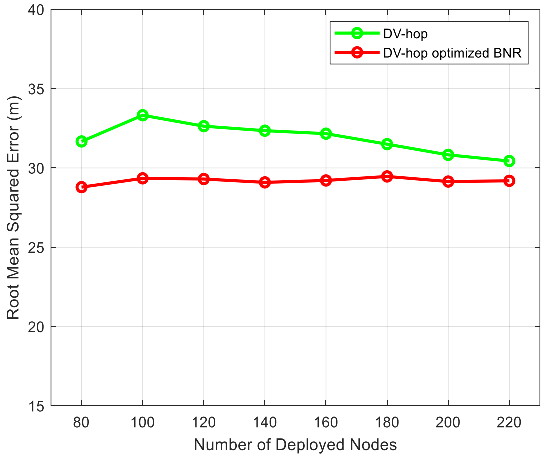

Fig. 4. RMSE comparison between DV-Hop and DV-Hop with optimized beacon node rate BNR

C. *Optimization of Beacon Node Positions*

During this simulation, the PSO-optimized DV-Hop algorithm was implemented to determine the optimal coordinates of the beacon nodes (eight coordinates to be optimized). We obtained the optimal values of these coordinates, which are presented in Table I.

TABLE I. OPTIMIZED COORDINATE OF BEACON NODES

Optimized Beacons Nodes Coordinates								
X[m]	52.43	39.75	75.42	38.33	38.40	51.56	60.88	51.62
Y[m]	42.31	42.35	02.72	35.71	43.61	35.96	31.68	41.31

Fig.5 illustrates the studied network, highlighting the positions of the unknown nodes, the original beacons node locations, and the newly optimized beacons nodes positions obtained through the PSO algorithm. With these optimized coordinates, a significant improvement in network performance is anticipated.

Fig.6 illustrates the variation of RMSE with the number of deployed nodes for both the standard DV-Hop and the PSO-optimized DV-Hop algorithms, where optimization is based on the beacon node coordinates. The optimized algorithm achieves lower RMSE values, ranging from 21.50 m to 22.61 m, compared to the traditional DV-Hop. This improvement demonstrates that optimizing the beacon node coordinates through PSO enhances the adaptability of the DV-Hop algorithm to the network's characteristics, resulting in more accurate distance estimation and better overall localization performance.

D. *Comparative Analysis of DV-Hop Optimization Results*

Fig.7 presents the RMSE obtained using the standard DV-Hop algorithm and the PSO-optimized DV-Hop algorithm under the three optimization approaches: optimization of the beacon node rate, optimization of the connectivity range, and optimization of the beacon node coordinates. By analyzing the obtained results, it is evident that optimizing the beacon node coordinates provides the most effective improvement in reducing the RMSE.

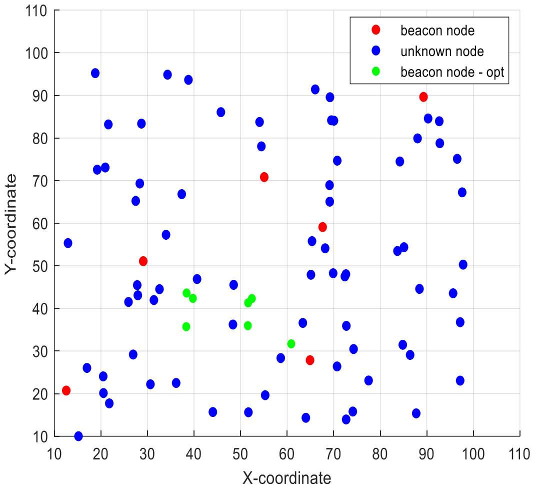

Fig. 5. WSN topology showing optimized beacon node (beacon node-opt) positions

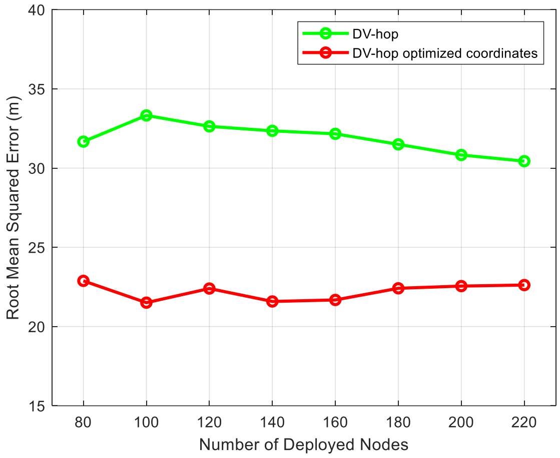

Fig. 6. RMSE comparison between DV-Hop and DV-Hop with optimized beacon node coordinate

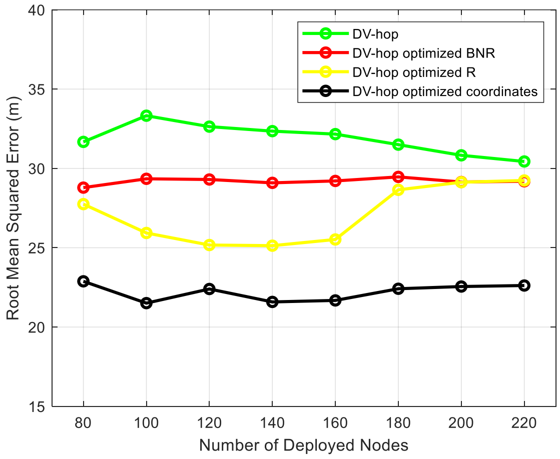

Fig. 7. RMSE comparison between standard DV-Hop and PSO-optimized DV-Hop approaches

Fine-tuning the beacon node positions leads to higher localization accuracy, resulting in notably lower RMSE values. The second-best performance is achieved through the optimization of the connectivity range, which, although slightly less effective than coordinate optimization, still yields a significant reduction in RMSE and demonstrates a positive impact on localization precision. Finally, the optimization of the beacon node rate proves to be the least effective among the three approaches, offering only minor improvements compared to the other optimization methods.

V. CONCLUSION

This paper presents a simulation study designed to evaluate and compare the localization accuracy of the traditional DV-Hop algorithm and its optimized counterpart enhanced by the PSO algorithm. The beacon node ratio, communication range, and beacon node spatial distribution were among the important parameters examined. In terms of positioning accuracy, the simulation results unequivocally showed that the PSO-optimized DV-Hop algorithm performed noticeably better than the traditional DV-Hop. This improvement results from more accurate node position estimation due to the optimal parameter selection made possible by the PSO-based optimization process. From this angle, future studies could concentrate on creating a multi-objective optimization framework that dynamically adjusts to network conditions while simultaneously minimizing localization error, energy consumption, and communication cost.

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