
ARTICLE

MLPDV-RSSI: Multi-Layer Perceptron-Based DV-Hop with Received Signal Strength Indicator for Localization in Wireless Sensor Networks

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ABSTRACT: In recent years, localization has emerged as a significant aspect of Wireless Sensor Networks (WSNs). The Distance Vector-Hop (DV-HOP) algorithm is a widely used localization approach for WSN due to its cost-effectiveness and simplicity. However, it suffers from accuracy issues due to the random deployment of sensor nodes, and thus, the calculation errors in hop distance and the minimum number of hops. To address these challenges, this paper proposes Multi-Layer Perceptron-based DV-HOP with Received Signal Strength Indicator (MLPDV-RSSI), a novel intelligent algorithm that enhances localization by integrating DV-Hop with Multilayer Perceptron (MLP) and Received Signal Strength Indicator (RSSI). The proposed algorithm employs the RSSI to determine the location of sensors within a defined hop from the anchor nodes (ANs). Meanwhile, the DV-HOP method effectively localizes sensor nodes over multiple hops from ANs. Combining DV-HOP with the RSSI in the proposed model enhances the accuracy, particularly in dynamic indoor environments where measurements fluctuate. Feeding the RSSI measurements, hop count, and average hop distance values into the MLP for training while adjusting the weights reduces the error in the average hop distance and further improves accuracy. The simulation results show that the proposed method applied in a static environment achieves a significant accuracy improvement by up to 42% compared to the benchmarks. In a dynamic environment under 40% mobile nodes with non-Gaussian interference, a significant performance improvement by up to 48.9% is achieved compared to DV-HOP.

KEYWORDS: DV-HOP; Localization; MLP; RSSI

1 Introduction

Recently, node localization has emerged as a major research challenge in Wireless Sensor Network (WSN) due to its crucial role in various Internet of Things (IoT) applications [1, 2]. The localization reliability is influenced by several hardware constraints, including device performance, power consumption, and network lifetime [3–6].

Localization can be achieved using either Anchor Nodes (ANs)—which are the reference nodes in a localization system, or IoT end devices. In WSN, most sensor nodes are unaware of their precise position. ANs are a subset of the WSN nodes that acquire their exact location coordinates through manual pre-deployment configuration or Global Positioning System (GPS) [7].

Localization techniques in WSN are generally categorized into two main groups: range-based and range-free localization approaches. The first category determines proximity by estimating distances through signal measurements obtained from neighboring nodes. Techniques, including Received Signal Strength Indicator (RSSI) and Time of Arrival (ToA) are the most popular in this category. In ToA, the calculation of distance between nodes is based on measuring the time it takes the signal to propagate from source to destination [8]. The main issue of ToA method is the requirement of synchronization between the source and destination. On the other hand, the RSSI method is a cost-effective alternative, which does not require

additional hardware. However, the accuracy of the RSSI method is sensitively affected by environmental noise and nonlinearities [9].

Range-free category utilizes the network structure and connectivity between nodes to estimate the distance between the sensor node and ANs. The main advantage of this category is the ability of multi-hop-to-ANs-based localization. This technique reduces the number of ANs and the cost. Among range-free localization techniques, a widely used multi-hop method is the Distance Vector-Hop (DV-Hop) algorithm. It functions as a routing protocol that calculates the minimum hop count to select the best path between the ANs and the sensor node. The DV-HOP approach estimates the distance to the ANs based on Average Hop Distance (AHD) and minimum hop count. At least three ANs are required to localize a sensor node in DV-HOP using triangulation. However, DV-HOP suffers from high localization error due to AHD and minimum hop count estimation errors [10].

A Multi-Layer Perceptron (MLP) is a type of Artificial Neural Network (ANN) used to enhance localization accuracy. One key feature of MLP is its ability to handle nonlinearity, enabling the creation of a robust localization model [11].

This paper proposes Multi-Layer Perceptron-based DV-HOP with Received Signal Strength Indicator (MLPDV-RSSI), which is a novel intelligent localization algorithm for indoor WSN that incorporates MLP and RSSI to improve the DV-HOP algorithm. The MLPDV-RSSI bridges the gap in the literature and significantly improves the accuracy of the DV-HOP. The main contributions of the paper can be summarized as follows:

1. The proposed algorithm uses DV-HOP as a routing protocol to calculate the number of hops and to select the path with the lowest number of hops to the AN.
2. In the second phase, the average hop distance AHD from the AN is calculated using the integration of RSSI and DV-HOP.
3. The obtained data in the second phase is fed into the MLP. In the training phase of the MLP, the weights and biases are adjusted to predict the coordinates of the unknown nodes (UNs).
4. The paper studies the impact of learning rate variation on the proposed algorithm.
5. The mobility of sensor nodes, the stability, and the dynamic environment are addressed to ensure the reliability and robustness of the proposed algorithm.
6. The results show that the proposed algorithm achieves significantly higher accuracy than benchmarks.

In the remainder of this paper, Section 2 discusses related research, Section 3 describes the proposed methodology, Section 4 presents the results, and Section 5 draws conclusions.

2 Related Work

WSNs serve as the core infrastructure for IoT because they are cost-effective, energy-efficient, and capable of self-organization. In this context, accurate localization of sensor nodes is crucial for effective data monitoring, as sensed readings become insignificant without precise location information [12].

Various localization techniques have been investigated, among which RSSI- and TOA-based methods are prominent. While TOA provides high accuracy, it requires extra hardware that increases energy consumption and cost. In contrast, RSSI methods do not need additional hardware but suffer from limited accuracy. Another widely utilized method is the DV-Hop algorithm, valued for its simplicity and low cost; however, it lacks accuracy [13,14].

Several prior works have focused on improving DV-HOP algorithm. For example, the authors of [15] combined DV-Hop with the weighted least squares (WLS) approach to achieve better localization accuracy by refining AHD. In [16], a Tikhonov regularization method was proposed to refine DV-HOP algorithm in WSNs. The authors of [17] proposed an adaptive particle swarm algorithm to enhance DV-HOP by calculating the AHD of DV-HOP then applying Particle Swarm Optimization (PSO). The authors of [18] proposed localizing the nodes using subsets of ANs that selected by binary PSO technique. This method enables UNs to compute the AHD using most effective subgroups of ANs. In [16], DV-HOP algorithm is improved by employing the mean square method to calculate the distance between ANs. However, the

achieved accuracy improvements of aforementioned prior works are moderate, the computational cost in [15] is high, the algorithm of [16] has a high computational overhead, the algorithm used in [18] suffers from the high latency in dense networks, and the cost in [17] is high due to the increase of number of AN.

Few works have used AI to improve the localization accuracy in DV-HOP. In [19], the authors proposed a kernel extreme learning machine algorithm to obtain the node location in WSN. In the proposed algorithm, the kernel function is defined using hop counts, while ANNs are used to train the data. In [20], the MLP model parameters were studied, including the number of hidden layers, weights, and activation function. To address the impact of the number of layers in the Neural Network (NN) on localization accuracy of DV-HOP algorithm, the authors proposed two approaches—a single and double hidden-layer extreme learning machine. The simulation results indicated that the model with two hidden layers achieved higher accuracy. The impact of weight on the convergence speed of the ANN was addressed in [21], where gradient descent technique was utilized to select the weights. The authors found that the optimal weight balance is achieved by ensuring the values are neither too large nor too small.

In [22], the authors employed RSS-based fingerprint and MLP in indoor localization. However, the storage requirements are a major concern for RSS-based fingerprinting. The authors used MLP to train non-isomorphic grid regions, leading to accurate positioning. The algorithm reduced the RSS fingerprint database by more than 80% compared to a baseline localization algorithm. The authors of [23] proposed a method for indoor localization using WiFi-RSSI fingerprinting with a Recurrent Neural Network (RNN), where a weighted average filter is implemented to mitigate the fluctuation in RSSI measurements. RSSI and four different supervised models were used by [21] to mitigate the influence of NLOS in indoor localization environments. The utilized supervised models are Generalized Regression Neural Network (GRNN), Feed-Forward Neural Network (FFNN), MLP, and Radial Basis Function Network (RBFN). A summary of the related work is provided in Table 1.

To the best of the authors' knowledge, the integration of RSSI and DV-HOP combined with MLP to improve localization accuracy in an indoor WSN environment has not been addressed in the literature. This paper bridges the gap in the literature by proposing an intelligent MLPDV-RSSI, which is a localization method that integrates DV-HOP, RSSI, and MLP with two hidden layers.

Table 1: Summary of related work.

Reference	Technique	Innovation	Limitation
[15]	DV-HOP and Squirrel Search Algorithm (SSA)	Improve the localization accuracy and stability compared with DV-HOP, PSODV-Hop, GADV-Hop, and DEIDV-Hop	Computational overhead, AN dependency, simulation-only validation
[16]	Tikhonov regularization	The algorithm obtains numerical a-posteriori error estimates with Generalized Discrepancy Principle (GDP)	High computational cost, linearity assumption, and sensitivity
[17]	Hybrid PSO-SA Algorithm and DV-HOP	Enhances the localization accuracy compared with DV-HOP and other two algorithms	Increased computational complexity, simulation only validation, communication overhead, and require parameters tuning
[18]	DV-HOP with PSO technique	This method enables UNs to compute the AHD using most effective subgroups of ANs	Computational overhead, high latency in dense networks, and simulation-only validation
[19]	DV-HOP with learning capabilities of Kernel Extreme Learning Machines (KELM)	High accuracy with non-linear mapping capabilities by bypassing the phases of distance estimation and trilateration of DV-HOP and implementing KELM	Computational overhead, simulation only validation, and the accuracy is depending on AN density

[20]	DV-HOP with Extreme Learning Machines (ELM)	Reduce average localization error (ALE) in irregular networks	Increase in computational overhead, simulation-only validation
[21]	RSSI fingerprint with MLP	Reduces fingerprint database size. Enhances accuracy over quantized based methods	Information loss, energy consumption, simulation only validation, isomorphic deployment structures are required to increase the efficiency
[23]	Integrated of Wi Fi fingerprint RSSI and Recurrent Neural Networks (RNNs)	Addresses RSSI instability and achieves high localization accuracy	Computational complexity, high sensitivity to environmental changes, and requirements of large amount of training data
[24]	weighted least-square approach with DV-HOP	Improve the accuracy of hop size to be suitable with large scale networks with no additional hardware	Simulation only validation, No comparison with other schemes
[25]	DV-HOP, Kalman Filter and MLP in stationary scenario	Reduces ALE compared to DV-HOP and benchmarks	Simulation-only validation, latency, stability, and dynamic environment are not addressed
Proposed algorithm	DV-HOP, RSSI and MLP	Reduces ALE compared to DV-HOP and benchmarks, addresses stability, mobile nodes, and dynamic environment.	Simulation-only validation, latency is not addressed

3 Proposed Algorithm

3.1 MLPDV-RSSI

In the proposed MLPDV-RSSI algorithm, MLP is used to enhance the DV-HOP method, which consists of three main parts: the input layer, the hidden layer, and the output layer.

RSSI measurements fluctuate due to the interference from other electronic devices. These unreliable RSSI readings lead to high localization errors. However, MLP mitigates this issue by filtering out some of these impacts during training to discard signal variations, thus improving the robustness of the proposed algorithm. Moreover, the proposed algorithm utilizes MLP-based retraining to dynamically respond to environmental variations without redesigning the WSN. This approach handles the change of network configuration to ensure scalability.

The MLP consists of several layers, which map diverse inputs to predetermined outputs. It is trained by back-propagation. The signal received by each input neuron is passed to the hidden layer, where neurons apply an activation function to process the incoming signal, the resulting signal is subsequently passed to the output layer. In the training phase, output layer neurons utilize an activation function to generate the predicted output, which is then compared to the target value. The error is back-propagated to adjust the weights in the neurons of the preceding layers.

Fig. 1 shows the MLPDV-RSSI model, in which the DV-HOP and RSSI serve as input features to the MLP. For practical implementation, the MLPDV-RSSI can be hosted on an edge server or cloud.

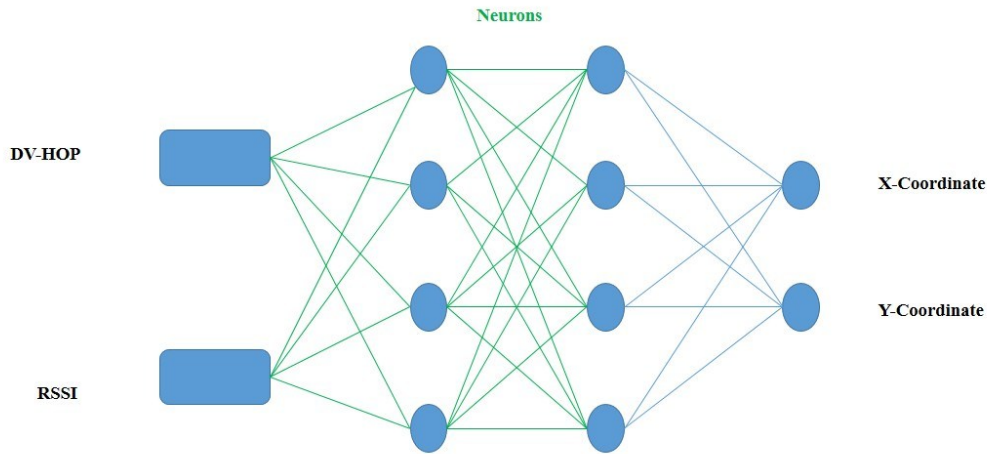


Figure 1: MLPDV-RSSI model.

The output of the input layer is calculated as follows:

$$y_j^{(1)} = \sum_{i=1}^{N_h} w_{ji}^{(1)} x_i + b_j^{(1)} \quad (1)$$

where N_h is number of hidden neurons, w_{ji} is the weight from input layer i to the hidden neuron j , b_j is the bias of hidden neuron, x_i is input features that represent $h_{u,x}$ and RSSI values ($P_{r,dB}(d)$ in Eq. (7)). The activation of hidden layer is calculated as follows:

$$z_k = \phi(\sum_{i=1}^{N_f} w_{ji}^{(1)} x_i + b_j^{(1)}) \quad (2)$$

$$N_f = [P_{r,dB}(d_1), h_{u,1}, \dots, P_{r,dB}(d_x), h_{u,x}] \quad (3)$$

where N_f is the number of features, ϕ is the activation function (sigmoid). For MLP training, the mean squared loss function (L) is as the following equation:

$$L = \frac{1}{N_t} \sum_{m=1}^{N_t} [(\hat{x}_m - x_m)^2 + (\hat{y}_m - y_m)^2] \quad (4)$$

where N_t is the number of ANs (training samples), $(\hat{x}_m, \hat{y}_m)$ is the predicted coordinates by MLP for training sample m , (x_m, y_m) is the actual coordinates.

The location with proposed algorithm is as follows:

$$x_u^{hybrid} = \delta \cdot \hat{x}_u^{MLP} + (1 - \delta) \cdot \hat{x}_u^{tril} \quad (5)$$

$$y_u^{hybrid} = \delta \cdot \hat{y}_u^{MLP} + (1 - \delta) \cdot \hat{y}_u^{tril} \quad (6)$$

where δ is 0.7 (weighting factor for MLP), the output of the Eqs. (5) and (6) is the estimated location of proposed algorithm, $(\hat{x}_u^{MLP}, \hat{y}_u^{MLP})$ are predicted coordinates by MLP, $(\hat{x}_u^{tril}, \hat{y}_u^{tril})$ are predicted coordinates by integration of DV-HOP and RSSI with weighting factor $1 - \delta$.

Fig. 2 illustrates the proposed model through a flow chart that breaks down the MLPDV-RSSI. First, the hop count is calculated using the DV-HOP algorithm as presented in Section 3.3. Then, the proposed algorithm utilizes RSSI to determine the AHD and the distance to the ANs as presented in Section 3.2. Subsequently, MLP is utilized by initializing weights and biases. The MLP computes the loss function and

then uses back-propagation to adjust the network parameters. Through iterative training cycles, the model updates weights and biases to predict the location.

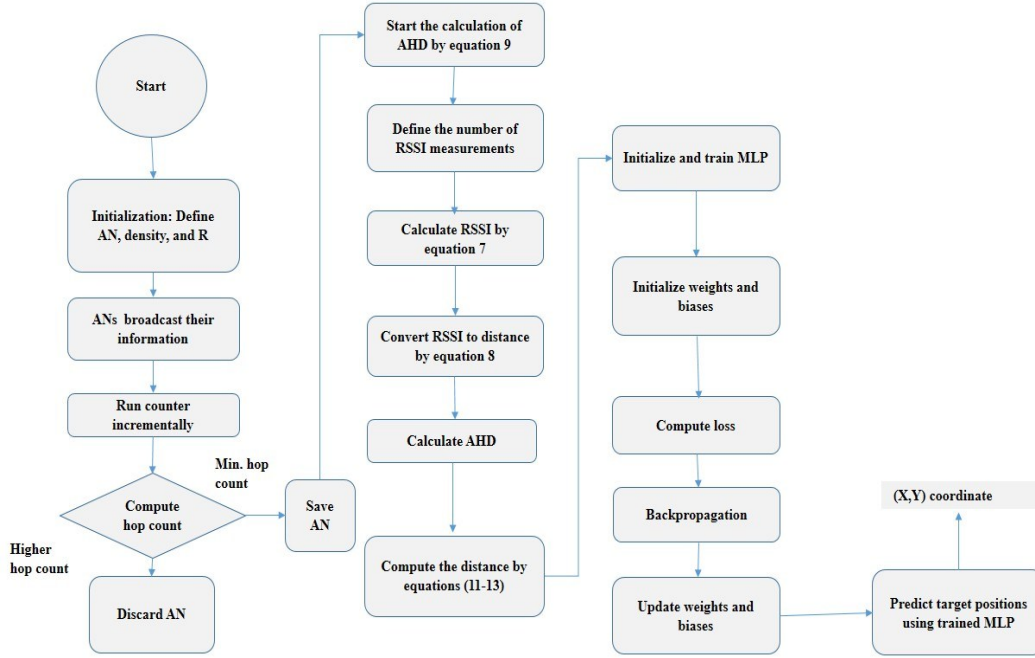


Figure 2: Flow chart of the proposed algorithm.

In the proposed MLPDV-RSSI algorithm, a learning rate of 0.01 is used to maintain the MLP scalability and stability, as a very low learning rate fails to train, and a very high value of the learning rate leads to instability and convergence issues. Moreover, the sigmoid activation function, which maps the inputs between 0 and 1, is used due to its performance in nonlinear systems [24].

The major environmental challenge of DV-HOP is obstructions in the deployment area that may increase the hop count. MLP can mitigate this issue by learning from ANs' information. Furthermore, MLP adapts to the dynamic changes indoors by learning from the variation of RSSI measurements over time [26].

The proposed MLPDV-RSSI may have limited performance in processing data in large-scale environments due to the use of MLP, as its complexity increases with the number of layers. Therefore, an MLP with 2 hidden layers is used in the proposed model, which limits the complexity to be in order of $O(m^2)$ where m is the number of WSN nodes [27,28]. Moreover, the use of 2 hidden layers mitigates the computational overhead and achieves a balance between computational efficiency and accuracy [29–31].

3.2 RSSI Calculations

RSSI-based localization converts RSSI measurements to distances. Fig. 3 illustrates that the unknown node is located at the intersection of the Received Signal Strength (RSS) regions generated by three ANs.

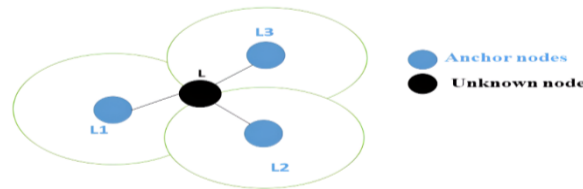


Figure 3: RSSI localization approach in WSNs.

The RSSI model is straightforward to implement, as it estimates the Tx-Rx distance using RSS values. The RSS, which represents the received signal strength, P_r can be obtained according to the following equation [13].

$$P_{r,dB}(d) = P_{r,dB}(d_0) - \eta 10 \log_{10} \left(\frac{d}{d_0} \right) + Y \quad (7)$$

where $P_{r,dB}(d)$ and $P_{r,dB}(d_0)$ define the power received in dB at distance d and reference distance d_0 , respectively. η stands for the path loss exponent. The variable Y is a zero-mean Gaussian random variable representing the noise. Accordingly, the distance between the UN and the AN can be calculated as follows:

$$d = d_0 10^{\left[\frac{P_{r,dB}(d_0) - P_{r,dB}(d)}{10\eta} \right]} \quad (8)$$

Finally, the estimated position of the unknown node is determined by the triangulation method. The major sources of error in this method are due to nonlinear systems, dynamic systems, and variations in RSSI [23].

3.3 DV-HOP Algorithm

The DV-Hop method estimates the location of the UNs using the following three steps [22]:

1. Flooding: Each AN broadcasts a packet containing its location information, including its coordinates (p_x, q_x) , identifier, and the minimum hop count, where p_x represents the x -coordinate of AN x and q_x stands for its y -coordinate. To determine the minimum hop count between a node and an AN, the node records the smaller hop count value and discards the higher value.
2. Distance estimation between nodes: In this step, the AHD for AN x is calculated using Eq. (1).

$$AHD_x = \frac{\sum \sqrt{(p_x - p_y)^2 + (q_x - q_y)^2}}{\sum h_{x,y}} \quad (9)$$

where the coordinates of ANs x and y are represented by (p_x, q_x) , (p_y, q_y) , and $h_{x,y}$, denoting the minimum hop count value between ANs x and y . Throughout the controlled flooding, each AN broadcasts its AHD. Eq. (10) is then applied to estimate the distance $d_{u,x}$ between the unknown node u and AN x .

$$d_{u,x} = AHD_x \times h_{u,x} \quad (10)$$

where $h_{u,x}$ is the minimum hop count between UN u , and AN x . If $d_{u,x}$ is less than or equal to the communication range (R), $h_{x,y}$ equals 1.

3. Determine node location: Assume (p, q) are the unknown node's coordinates and (p_n, q_n) are the coordinates of the n -th AN. Hence, the following equations are used to determine the distance from the node to the three ANs:

$$d_1^2 = ((p_1 - p)^2 + (q_1 - q)^2) \quad (11)$$

$$d_2^2 = ((p_2 - p)^2 + (q_2 - q)^2) \quad (12)$$

$$d_3^2 = ((p_3 - p)^2 + (q_3 - q)^2) \quad (13)$$

Then, the equation $AX = C$ is utilized to convert from a nonlinear system into a linear system, where

$$X = \begin{bmatrix} 2(p_1 - p) & 2(q_1 - q) \\ \vdots & \vdots \\ 2(p_{n-1} - p) & 2(q_{n-1} - q) \end{bmatrix} \quad (14)$$

$$C = \begin{bmatrix} p_1^2 - p^2 + q_1^2 - q^2 + d_n^2 - d_1^2 \\ \vdots \\ p_{n-1}^2 - p^2 + q_{n-1}^2 - q^2 + d_n^2 - d_{n-1}^2 \end{bmatrix} \quad (15)$$

$$A = \begin{bmatrix} p \\ q \end{bmatrix} \quad (16)$$

here, matrix A represents the design matrix, X is the unknown vector matrix, and C is the measurement vector matrix, n is the number of ANs.

The Least Square method is utilized to compute the initial coordinates of the unknown node u by:

$$A_u = (XX^T)^{-1}X^T C \quad (17)$$

where A_u is estimated position of UN u .

The ALE is calculated as follows:

$$ALE = \frac{\sum_{i=1}^{N-M} \sqrt{((p_x - p_y)^2 + (q_x - q_y)^2)}}{R(N-M)} \quad (18)$$

where R is the communication range of the sensors and $(N - M)$ is the number of UNs, as N is the total number of sensor nodes, M is the number of ANs.

3.4 Dynamic Environment with Non-Gaussian Interference

The RSSI measurements fluctuate in dynamic environment due to the impact of environmental variations. The interference models ($Y_{non-Gaussian}$) vary with various sources of interference that are addressed, such as, Gaussian noise, impulse noise, multipath interference, intermittent interference, and non-uniform environmental effects (skewed noise). The received power is calculated as follows:

$$P_{r,dB}(d) = P_{r,dB}(d_0) - \eta 10 \log_{10} \left(\frac{d}{d_0} \right) + Y_{non-Gaussian} \quad (19)$$

The data flow between DV-HOP, RSSI, and MLP is shown in Fig. 4. The environmental change detection (score change S) is calculated as follows:

$$S = 0.7 \cdot \frac{|\hat{e}_{rec} - \hat{e}_{old}|}{\hat{e}_{old} + 1} + 0.3 \cdot \frac{\sigma_{rec} - \sigma_{old}}{\sigma_{old} + 1} \quad (20)$$

where the first term represents the mean error with weighting factor = 0.7, the average error of last 10 iteration is $\hat{e}_{rec}$, the average error of previous iterations is $\hat{e}_{old}$. The second term measures the spread change with weighting factor equal 0.3 where the standard deviation of recent and old errors is σ_{rec} and σ_{old} respectively. The environmental change factor (S) is used to define the environmental stability update (E_{new}) as follows:

$$E_{new} = \begin{cases} \max(0.2, 1 - S), & S > 0.15 \\ \min(0.1, E_{old} + 0.02), & \text{otherwise} \end{cases} \quad (21)$$

If E_{new} equal one, the environment is stable. If it equals ≤ 0.5 , the environment is unstable due to the unreliable RSSI or network topology. Moreover the values between 0.5 and one refer to moderately stable. If the environment is stable, RSSI is more accurate than DV-HOP, while DV-HOP is more stable during environmental changes.

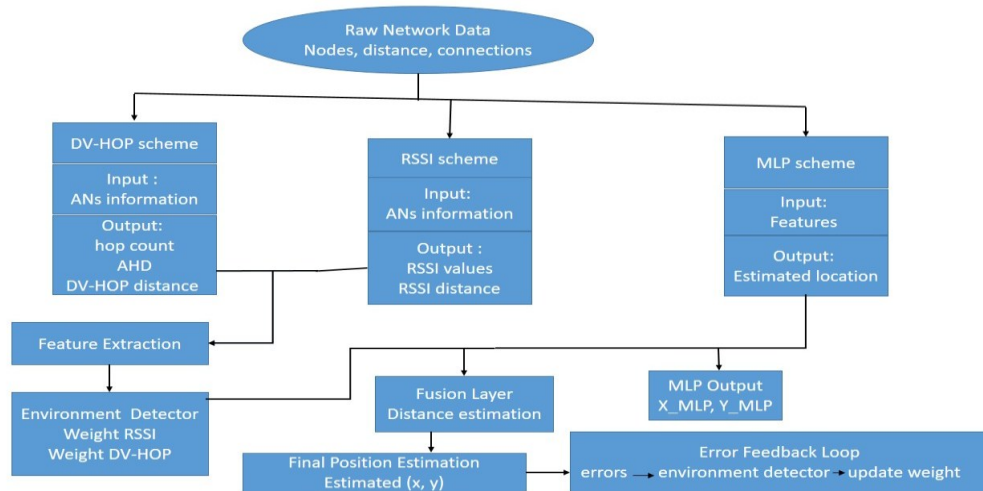


Figure 4: Data flow between DV-Hop, RSSI, and MLP.

4 Results

In this section, we assess the effectiveness of the MLPDV-RSSI algorithm through MATLAB-based simulations, where each scenario was tested 50 times at random, and average values were determined. The MLP includes 2 layers and 15 neurons. After that, the variation of learning rate was simulated. The next phase involves the evaluation of ALE of MLPDV-RSSI algorithm by considering three scenarios. Each scenario involved adjusting a single parameter while keeping the remaining two fixed. The parameters examined were the number of UNs, R, and AN ratio. Network nodes are regarded as stationary regardless of dynamic changes in environmental conditions in this phase. The performance of the proposed algorithm is compared with three benchmarks namely: the original DV-HOP algorithm, the optimized DV-HOP algorithm presented in [17], and Improved Least Square DV-Hop algorithm (ILS DV-HOP) proposed in [24]. After that, the proposed algorithm is expanded to study the change in ALE in dynamic environment. In the last phase, non-Gaussian interference is simulated.

The source of training data of the proposed algorithm is the information of anchor nodes. In static environment scenario, the training process begins in third phase with extracting the features (RSSI and number of hops to the other ANs). The dimension of training data is as follows: number of samples is five (sample for each anchor node), number of features is 10 (two features per sample), and 2 targets per sample that are the coordinates (x and y). The training process is divided into three steps, the first step is forwarding the features through the network with calculation of activation functions in each layer, the second step is calculating the error, and the third step is back-propagation to update the weight and bias and check the validation error.

In dynamic environment, the training process is divided into two steps, the first step is the initial training, which starts with first iteration, the second step is online update, which occurs every 10 iterations to maintain the stability through the environmental changes. The number of epochs is 300 to maintain the stability, reduce the computational cost, and fast adaptation. If MSE reaches 0.01, the training stops. Moreover, the five training samples are categorized into three samples for training, one sample for validation, and one sample for testing. The online update includes forward propagation, calculating the error, updating weights and biases, validation, and repeating the process until reaching the goal.

This paper considers a random deployment of the nodes, including ANs and UNs. Fig. 5 shows a sample of random distribution of the ANs and unknown node locations.

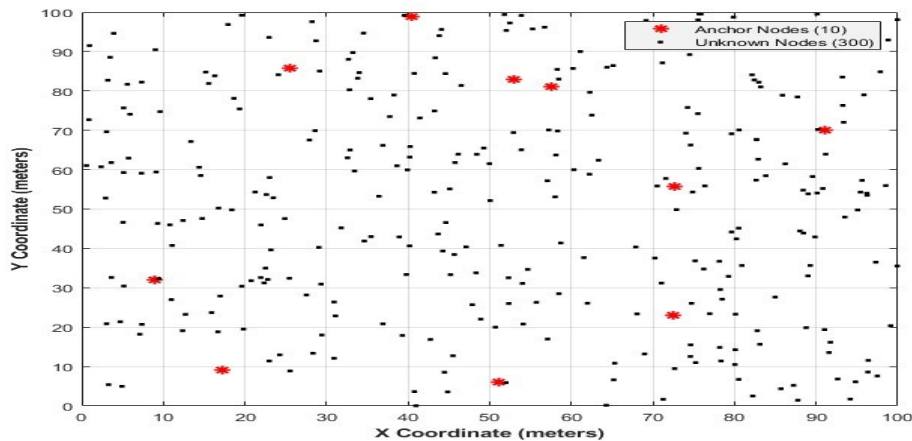


Figure 5: Distribution of ANs and UNs.

Fig. 6 shows the results of RSSI-based algorithm. The figure reveals that the achieved localization error of RSSI-based algorithm is 5.1012 m, which is considered very high in an indoor environment. Fig. 7 presents the localization error of the RSSI-MLP approach under the parameters specified in Table 2, where

the ANs data is employed to fine-tune the weights of the MLP. Fig. 7 depicts that the localization error is reduced to 2.47 m, which proves that integration of the DV-HOP algorithm with MLP enhances the accuracy.

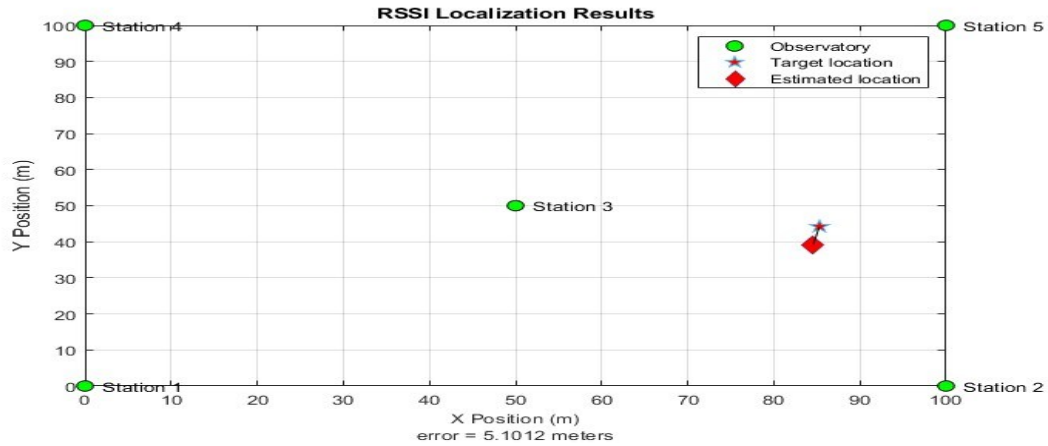


Figure 6: RSSI localization error.

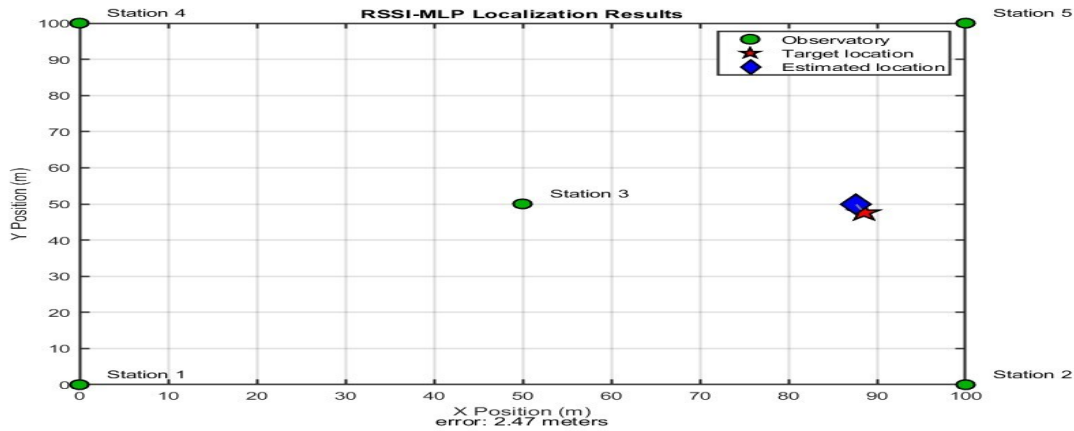


Figure 7: RSSI-MLP localization error.

Table 2: Simulation parameters of the static scenarios.

Parameter	Value
Area	100 m × 100 m
RSSI standard deviation	5 dB
ANs locations	(0, 0), (100, 0), (50, 50), (0, 100), (100, 100)
UNs locations	Randomly distributed within area
Activation function	Sigmoid
MLP weighting factor	0.7
Size of MLP hidden layer	[10, 5]
Reference RSSI	-45 dBm
Number of RSSI readings	20
Number of epochs	300
Training/testing/validation	70%, 15%, 15%
Maximum fails	50
Learning rate	0.01
RSSI and DV-HOP (trilateration) integration weighting factor	0.3

In MLPDV-RSSI, the MLP's input parameters comprise RSSI measurements, hop count, and AHD. The weighting factor through the proposed algorithm are 0.7 for MLP and 0.3 for RSSI and DV-HOP integration. The nature of the data and the MLP's structure play a key role in determining performance gains.

Fig. 8 illustrates the impact of the learning rate on the performance of the proposed algorithm, while the utilized parameters are shown in Table 2, while utilizing 5 ANs, and 50 UNs. The figure shows that the optimal localization error is achieved at 0.01 learning rate. A learning rate of 0.0001 introduces slow convergence, while a learning rate of 1.0 introduces an unstable training, resulting in poor validation performance. For these reasons, the value of 0.01 is adopted as learning rate in MLP in the rest of the study.

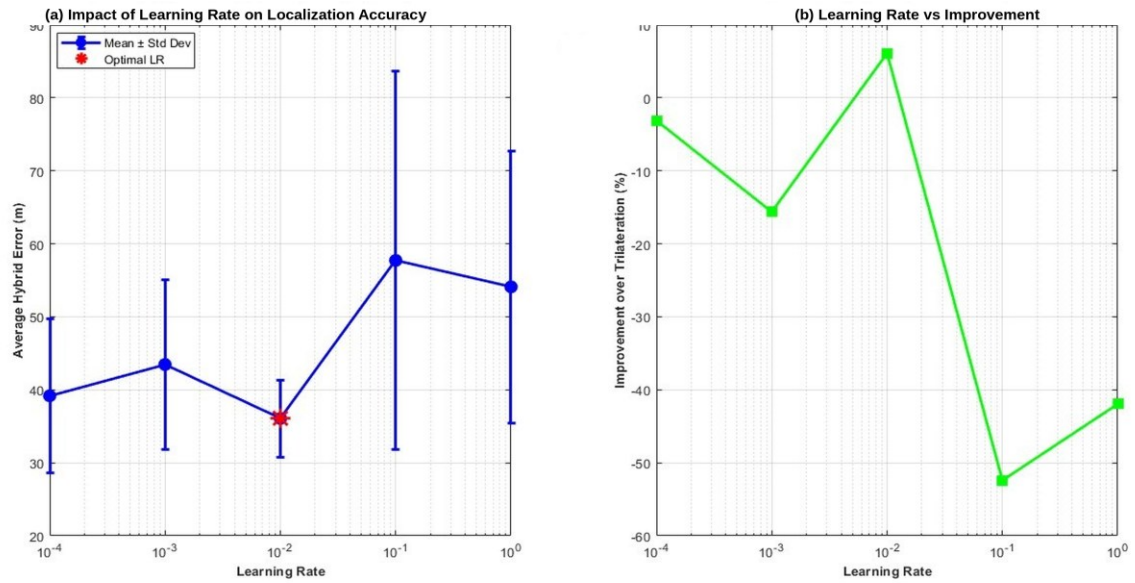


Figure 8: Impact of learning rate on average localization error of MLPDV-RSSI.

Fig. 9 studies the impact of increasing the ratio of ANs while keeping the number of UNs fixed at 100 and R at 20 m. The figure illustrates that the performance improves for all algorithms as the AN ratio increases. It also shows that the proposed algorithm significantly outperforms the benchmarks and achieves very low ALEs, where 20% ALE is achieved by increasing the ratio of ANs to 25%.

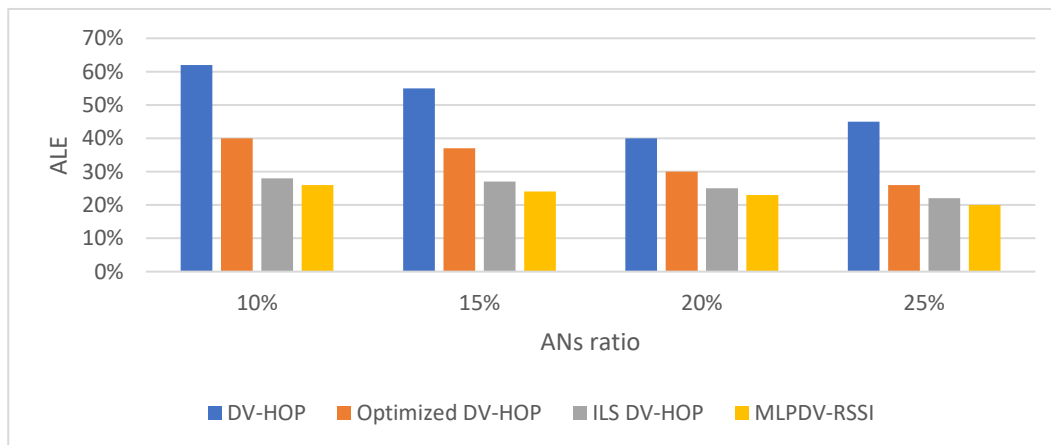


Figure 9: Localization error versus AN ratio.

Fig. 10 studies the influence of increasing the number of UNs with fixing both R to 20 m the ratio of ANs to 20%. The figure illustrates that as the number of UNs increases, the performance improves for all algorithms. The observed decrease in the ALE is due to the increase in the number of neighbors that improve the connectivity through the network. The figure also shows that the proposed algorithm always achieves lower ALEs than the benchmarks due to the optimization.

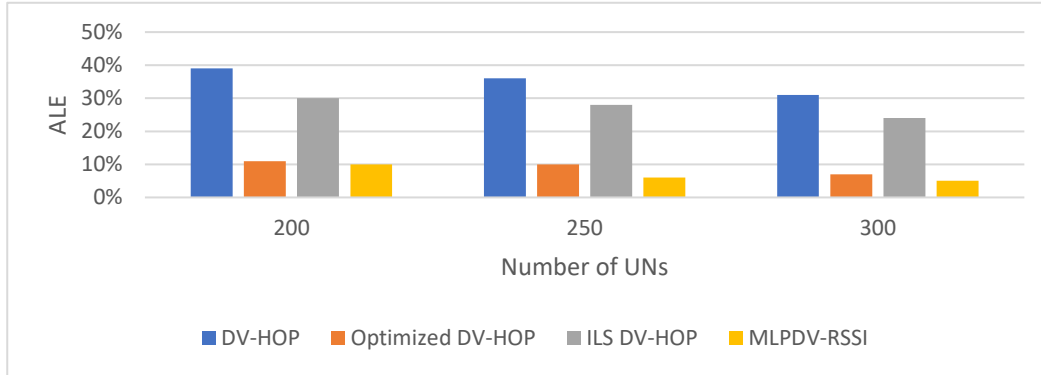


Figure 10: Localization error versus number of UNs.

Fig. 11 illustrates the ALE with increasing R while fixing the number of UNs to 300 and maintaining ANs at 10%. It is observed that the accuracy of all algorithms increases with communication range due to a decrease in the number of hops and thus an increase in network connectivity.

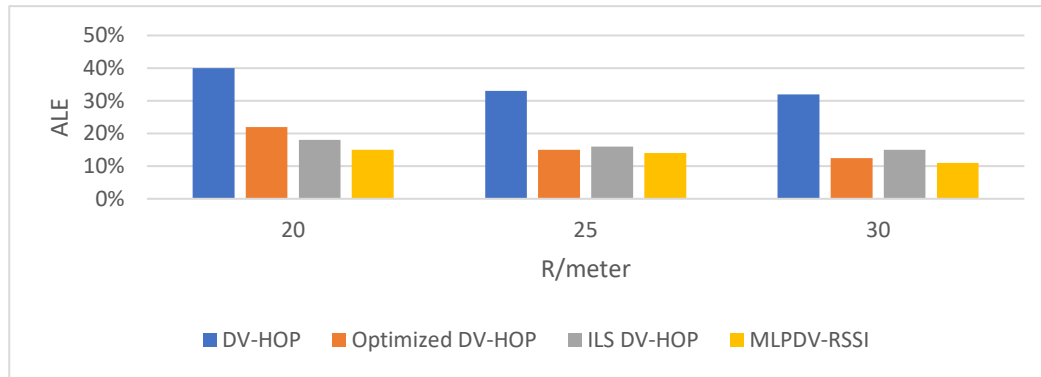


Figure 11: Localization errors versus R .

Taking the average performance of the algorithms over the previous three considered scenarios, it can be observed that the MLPDV-RSSI achieves higher accuracy than the original DV-HOP, ILS DV-HOP, and optimized DV-HOP algorithms by up to 42%, 20%, and 17%, respectively.

Table 3 provides statistical performance comparison of the proposed algorithm versus MLP and DV-HOP. The statistical results reveal that the proposed algorithm achieves lower mean error and standard deviation than DV-HOP and MLP, this enhancement is about 42% lower mean error compared to DV-HOP.

Table 3: Statistical comparison of the proposed algorithm.

Algorithm	Mean Error (m)	Standard Deviation	Confidence Interval (95%)	p -Value Versus DV-HOP	Improvement Versus DV-HOP
DV-HOP	40	10	[38, 42] m	-	0%
MLP	30	8	[28, 32] m	<0.001	25%
Proposed algorithm	20	6	[18, 22] m	<0.001	42%

The accuracy of the MLPDV-RSSI is influenced by the complexity of its implementation and the quality of the data used for training and validation. Furthermore, the gained improvement varies with the application.

Finally, MLPDV-RSSI can be utilized in various WSN applications, such as navigation, monitoring, and tracking, due to its superior localization performance. Additionally, MLPDV-RSSI may find a paved way in many healthcare applications due to its ability to enhance the indoor localization accuracy and thus the response time. For example, patients with Alzheimer's or dementia diseases suffering from cognitive impairments have issues with wandering; the proposed algorithm can be implemented in indoor environments of hospitals and healthcare centers to trigger alarms when they leave safety zones, allowing staff to respond immediately to expedite life-saving interventions.

Dynamic environment with non-Gaussian interference

The simulation parameters defined for the static environment in Table 2 are also applicable to the dynamic environment with non-Gaussian interference, while Table 4 specifies only the additional parameters associated with dynamic conditions.

The assumption of mobile nodes is necessary to assess the localization reliability in real-world IoT applications. The noise of the path loss is assumed to be Gaussian, with the parameter η increases with environmental changes.

Table 4: Simulation parameters of dynamic environment with non-Gaussian noise.

Parameter	Value
Maximum velocity	0.3 m/iteration
Probability of turning	0.1
Number of online update epochs	30
Number of ANs	5
Number of UNs	20
Number of mobile nodes	8
Noise floor (upper bound)	-95
Clipping (lower bound)	-30
Impulse probability	0.08
Dropout probability	0.1
Environment change time	50 when disturbance occurs
Environment change type	Obstacles, node failure, and noise
Initial η	2
Change in η	0.5
Environment change threshold	0.15

The environment is changing due to obstacles, noise, node failure, and a combination of these factors as shown in Fig. 12. Fig. 12 illustrates the network topology for indoor environment with non-Gaussian interference. It shows all network possible components: green triangles, white circles, red dots, and gray dots represent the anchor nodes, UNs, humans, and obstacles, respectively.

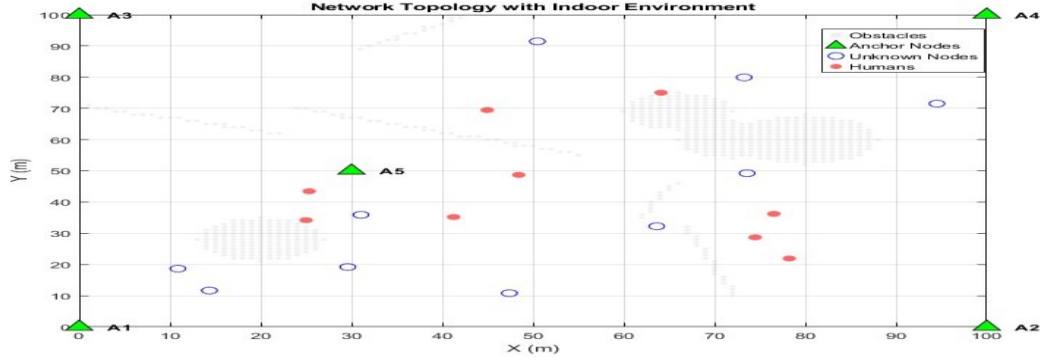


Figure 12: Network Topology with indoor dynamic environment.

It is worthy to note that both DV-HOP and RSSI are adaptive to estimate the distance based on connectivity and signal strength, respectively. Using the features (RSSI and hop count values), MLP is trained online based on the anchor nodes' data. When an error is detected, the weights are adjusted, and MLP will be updated to adapt to the new environmental pattern. The system continuously evaluates the stability of the dynamic environment during localization process. It monitors the variance of RSSI readings from anchor nodes, and the variations of hop counts that updates periodically over a sliding time window. The subplots b and c in Fig. 13 illustrate the adaptive weighting factor in the integration of DV-HOP and RSSI.

The proposed algorithm maintains the accuracy over the time as illustrated in Fig. 13a. Coefficient Variation (CV) determines the stability, the higher value indicates to higher stability. Moreover, the hop count fluctuations affect the reliability of DV-HOP algorithm. This fluctuation is a result of dynamic environment and mobile nodes that change the network topology. CV is computed from the detection of environmental changes. To reach the minimum value of ALE, the input features from RSSI and DV-HOP algorithms have to be fixed with weighting factors for both. CV identifies a stable environment when the value is more than 0.80. Accordingly, for $CV > 0.8$, the weighting factor is assigned as 0.7/0.3, i.e., 0.7 for trust RSSI for stable conditions, and 0.3 for DV-HOP (in the first and third iterations of Fig. 13c). For moderate stability when $0.50 < CV < 0.80$ as shown in Fig. 13b,c (in the second and fourth iterations of Fig. 13c), the weighting factor is 0.6/0.4. Finally, when the CV is less than 0.50 ($\sigma = 0.5 \mu$), it indicates instability with weighting factor 0.4/0.6 as in Fig. 13c (after the fifth iterations of Fig. 13c), giving priority to the DV-HOP due to the sensitivity of RSSI and robustness of DV-HOP in unstable conditions. These values of CV threshold and weights of RSSI and DV-HOP are optimized parameters.

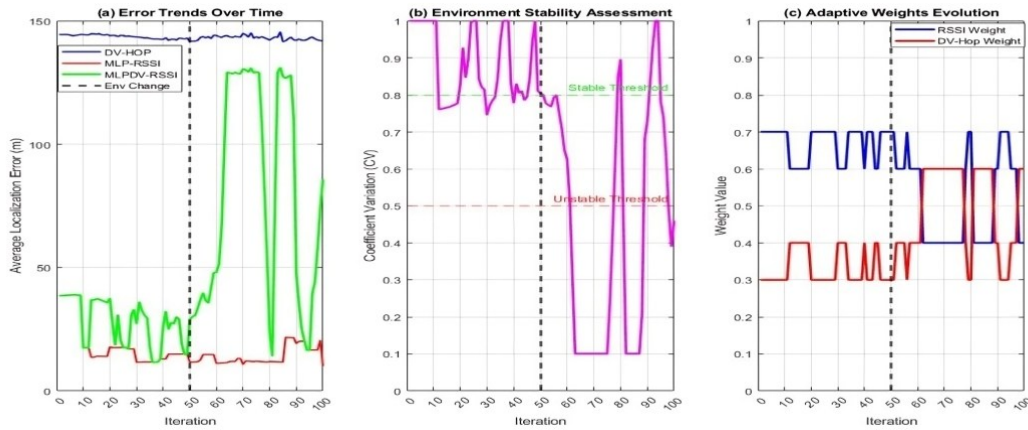


Figure 13: Comprehensive performance analysis of MLPDV-RSSI versus environmental changes.

Fig. 14a Provides a complete performance overview of DV-HOP, RSSI and MLPDV-RSSI in dynamic environment. The figure shows that the proposed method outperforms the benchmarks and achieves 48.9% lower average localization error than the original DV-HOP. Fig. 14b Shows 6.1% degradation in average localization error of proposed due to the environmental change. Moreover, this behavior shows the robustness of the proposed algorithm. Due to the utilization of adaptive weighting factor in the proposed algorithm, the effect of dynamic environment can quickly be recovered. Table 5 provides statistical performance comparison of the proposed algorithm versus MLP-RSSI and DV-HOP in dynamic environment.

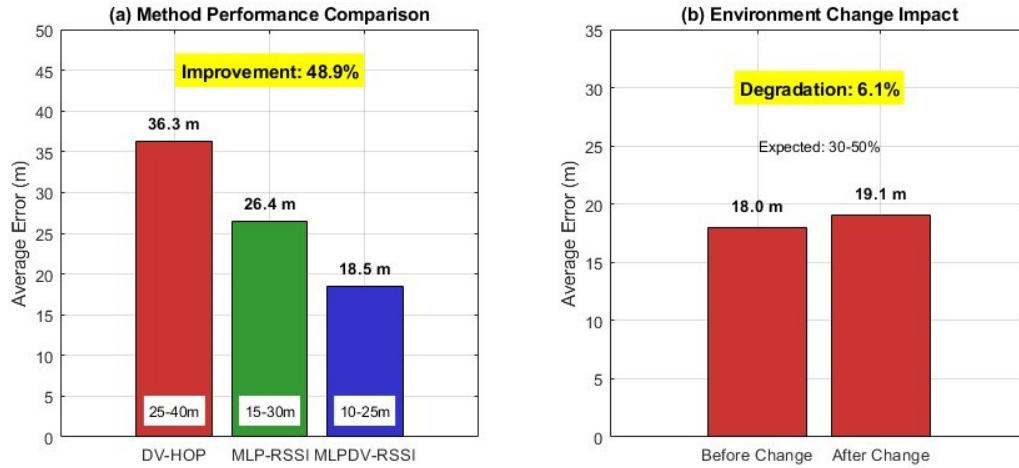


Figure 14: Performance comparison for dynamic environment.

Table 5: Statistical comparison of the proposed algorithm in dynamic environment with online update.

Algorithm	Mean Error (m)	Standard Deviation	Confidence Interval (95%)	<i>p</i> -Value Versus DV-HOP	Improvement Versus DV-HOP
DV-HOP	32	6.5	[29.2, 35.8] m	-	0%
MLP-RSSI	21.5	5	[19.5, 23.5] m	<0.001	30.2%
Proposed algorithm	16.5	4	[15, 18] m	<0.001	48.9%

Fig. 15 demonstrates the actual RSSI distribution affected by obstacles, multipath, and shadowing to represent non-Gaussian distribution in blue bars. Whereas, the red line is the ideal noise condition represented by Gaussian distribution.

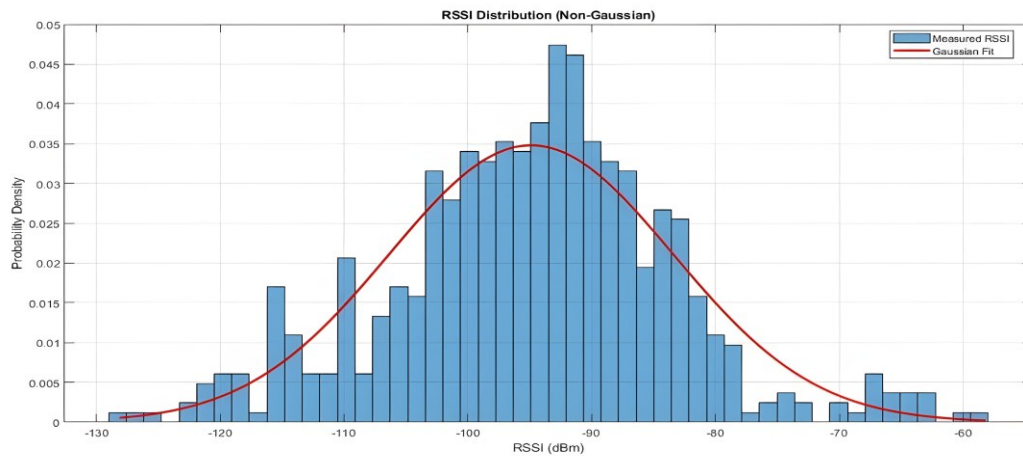
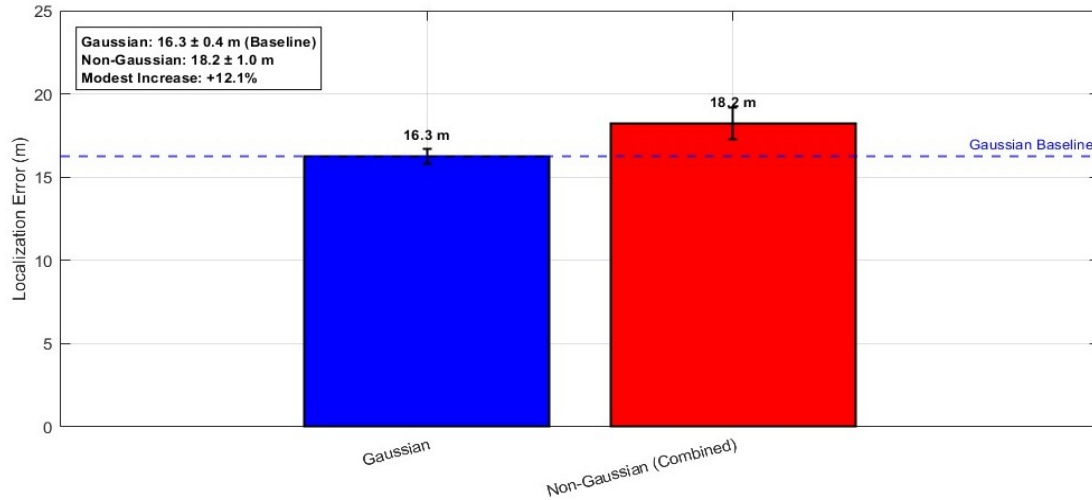


Figure 15: Non-Gaussian versus Gaussian noise.

Fig. 16 illustrates the impact of the different types of interference on the performance of the proposed method. The figure shows that the non-Gaussian interference has higher localization error than the Gaussian interference by up to 12.1%.

**Figure 16:** Gaussian versus non-Gaussian interference.

5 Conclusions

This paper proposes MLPDV-RSSI, a novel indoor localization model for WSN that boosts the localization accuracy by integrating DV-HOP with RSSI and MLP. To predict the location of an unknown node, the proposed algorithm utilizes DV-HOP to estimate the minimum hop count and AHD. The RSSI measurements are used to refine the AHD calculations. Subsequently, MLP adjusts weights and biases based on the values of RSSI, minimum hop count, and AHD. The simulation results demonstrate that the accuracy of the proposed algorithm in static environment is higher than DV-HOP, ILS DV-HOP, and optimized DV-HOP by up to 42%, 20%, and 17%, respectively. In dynamic environments with 40% mobile nodes and non-Gaussian interference, the proposed MLPDV-RSSI achieves 48.9% lower localization than the original DV-HOP. Future work will focus on real-time localization, implementing it on real WSN hardware to assess practical feasibility, and evaluating the latency across diverse scenarios to further validate and optimize its performance.

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References

1. Sivasakthiselvan S, Nagarajan V. Localization techniques of wireless sensor networks: a review. In: Proceedings of the 2020 International Conference on Communication and Signal Processing (ICCSP); 2020 Jul 28–30; Chennai, India. p. 1643–8. doi:10.1109/iccsp48568.2020.9182290.
2. Tao M, Ota K, Dong M. Locating compromised data sources in IoT-enabled smart cities: a great-alternative-region-based approach. *IEEE Trans Ind Inform.* 2018;14(6):2579–87. doi:10.1109/TII.2018.2791941.
3. Tao M, Wei W, Huang S. Location-based trustworthy services recommendation in cooperative-communication-enabled Internet of Vehicles. *J Netw Comput Appl.* 2019;126:1–11. doi:10.1016/j.jnca.2018.10.023.
4. Rehman A, Mahmood T, Alahmadi TJ, Almasoud AS, Saba T. Energy efficient and robust node localization in WSNs using LSTM optimized DV hop framework to mitigate multihop localization errors. *Sci Rep.* 2025;15:14827. doi:10.1038/s41598-025-93937-y.
5. Ghorpade S, Zennaro M, Chaudhari B. Survey of localization for Internet of Things nodes: approaches, challenges and open issues. *Future Internet.* 2021;13(8):1–26.
6. Cai R. Unmanned target vehicle navigation and path planning using improved ant colony optimization algorithm combined with GPS/BDS. *Int Arab J Inf Technol.* 2024;21(4):601–13. doi:10.34028/iajit/21/4/5.
7. Chowdhury TJS, Elkin C, Devabhaktuni V, Rawat DB, Oluoch J. Advances on localization techniques for wireless sensor networks: a survey. *Comput Netw.* 2016;110:284–305. doi:10.1016/j.comnet.2016.10.006.
8. He S, Dong X. High-accuracy localization platform using asynchronous time difference of arrival technology. *IEEE Trans Instrum Meas.* 2017;66(7):1728–42. doi:10.1109/tim.2017.2666278.
9. Sadowski S, Spachos P. RSSI-based indoor localization with the Internet of Things. *IEEE Access.* 2018;6:30149–61. doi:10.1109/access.2018.2843325.
10. Liouane H, Messous S, Cheikhrouhou O. Regularized least square multi-hops localization algorithm based on DV-Hop for wireless sensor networks. *Telecommun Syst.* 2022;80(3):349–58. doi:10.1007/s11235-022-00897-z.
11. Naskath J, Sivakamasundari G, Begum AAS. A study on different deep learning algorithms used in deep neural nets: MLP SOM and DBN. *Wireless Pers Commun.* 2023;128(4):2913–36. doi:10.1007/s11277-022-10079-4.
12. Paul A, Sato T. Localization in wireless sensor networks: a survey on algorithms, measurement techniques, applications and challenges. *J Sens Actuator Netw.* 2017;6(4):24. doi:10.3390/jsan6040024.
13. Zekavat S, Buehrer RM, Durgin GD, Lovisolo L, Wang Z, Goh ST, et al. An overview on position location: past, present, future. *Int J Wireless Inf Networks.* 2021;28(1):45–76. doi:10.1007/s10776-021-00504-z.
14. Islam A, Hossain MT, Chowdhury MZ, Jang YM. Design of an indoor positioning scheme using artificial intelligence algorithms. In: Proceedings of the 2018 International Conference on Information Networking (ICOIN); 2018 Jan 10–12; Chiang Mai, Thailand. p. 953–6. doi:10.1109/ICOIN.2018.8343265.
15. Abd El Ghafour MG, Kamel SH, Abouelseoud Y. Improved DV-Hop based on Squirrel search algorithm for localization in wireless sensor networks. *Wirel Netw.* 2021;27(4):2743–59. doi:10.1007/s11276-021-02618-x.
16. Wang Y, Leonov A, Lukyanenko D, Yagola A. General Tikhonov regularization with applications in geoscience. *CSIAM Trans Appl Math.* 2020;1(1):53–85.
17. Shi Q, Wu C, Xu Q, Zhang J. Optimization for DV-Hop type of localization scheme in wireless sensor networks. *J Supercomput.* 2021;77(12):13629–52. doi:10.1007/s11227-021-03818-0.
18. Cao Y, Xu J. DV-Hop-based localization algorithm using optimum anchor nodes subsets for wireless sensor network. *Ad Hoc Netw.* 2023;139:103035. doi:10.1016/j.adhoc.2022.103035.
19. Wang L, Er MJ, Zhang S. A kernel extreme learning machines algorithm for node localization in wireless sensor networks. *IEEE Commun Lett.* 2020;24(7):1433–6. doi:10.1109/LCOMM.2020.2986676.
20. Liouane O, Femmam S, Bakir T, Ben Abdelali A. Improved two hidden layers extreme learning machines for node localization in range free wireless sensor networks. *Jcm.* 2021:528–34. doi:10.12720/jcm.16.12.528-534.
21. Jondhale SR, Maheswar R, Lloret J. Received signal strength based target localization and tracking using wireless sensor networks. Cham, Switzerland: Springer International Publishing; 2022. doi:10.1007/978-3-030-74061-0.
22. Sun Z, Zhang Y, Ren Q. A reliable localization algorithm based on grid coding and multi-layer perceptron. *IEEE Access.* 2020;8:60979–89. doi:10.1109/ACCESS.2020.2983739.
23. Hoang MT, Yuen B, Dong X, Lu T, Westendorp R, Reddy K. Recurrent neural networks for accurate RSSI indoor localization. *IEEE Internet Things J.* 2019;6(6):10639–51. doi:10.1109/JIOT.2019.2940368.

24. Mani R, Sevillano JL, Liouane N. Improved Least-Square DV-Hop Algorithm for Localization in large scale wireless sensor network. In: Proceedings of the 2022 International Conference on Control, Automation and Diagnosis (ICCAD); 2022 Jul 13–15; Lisbon, Portugal. p. 1–6. doi:10.1109/ICCAD55197.2022.9853952.
25. Almomani A, Al-Turjman F. Wireless sensor networks DV-Hop positioning based on artificial intelligence in the IoT era. In: Artificial Intelligence of Things (AIoT). Amsterdam, The Netherlands: Elsevier; 2025. p. 55–63. doi:10.1016/b978-0-443-26482-5.00007-9.
26. Jaspreet K. Exploiting the location information for adaptive beamforming in transport systems [dissertation]. Glasgow, Scotland: University of Glasgow; 2024. <https://doi.org/10.5525/gla.thesis.84223>.
27. Tao M, Su J, Huang Y, Wang L. Mitigation of radio frequency interference in synthetic aperture radar data: current status and future trends. *Remote Sens.* 2019;11(20):2438. doi:10.3390/rs11202438.
28. Brownlee J. Understanding the Dynamics of Learning Rate on Deep Learning Neural Networks. *Machine Learning Mastery* [Internet]. 2019 [cited 2026 Jan 1]. Available from: <https://www.machinelearningmastery.com/understand-the-dynamics-of-learning-rate-on-deep-learning-neural-networks/>.
29. Barceló P, Monet M, Pérez J, Subercaseaux B. Model interpretability through the lens of computational complexity. In: *Advances in Neural Information Processing Systems* 33. p. 15487–98.
30. Wu H, Junginger S, Roddelkopf T, Liu H, Thurow K. BLE beacons for sample position estimation in a life science automation laboratory. *Transp Saf Environ.* 2024;6(3):tdad033. doi:10.1093/tse/tdad033.
31. Li T, Sun W. MLP-SLAM: multilayer perceptron-based simultaneous localization and mapping. arXiv:2410.10669. 2024. <https://arxiv.org/abs/2410.10669>