Intelligent Combination of DV-HOP and RSSI Based Positioning Approaches in the IoT Era

Abdelrahman Almomani[1,*] and Fadi Al-Turjman[2,3]

[1] Electrical and Electronic Engineering Department, Near East University, Nicosia, Turkey
[2] Department of Artificial Intelligence, Software, Information Systems Engineering, AI and Robotics Institute, Near East University, Mersin 10, Turkey
[3] Faculty of Engineering, University of Kyrenia, Kyrenia, Turkey
Email: momaniyj@gmail.com (A.A.); fadi.alturjman@neu.edu.tr (F.A.-T.)
*Corresponding author

***Abstract*—The Internet of Things (IoT) is increasing and encompasses various areas such as smart homes, smart cars, and e-healthcare. Identifying the source of the transmitted data is important because information without a known source is meaningless. The running applications must be able to determine their position without relying on the Global Positioning System (GPS), as the signals are attenuated indoors and in difficult environments. Wireless Sensor Networks (WSNs) play an important role in positioning IoT devices. The Distance Vector-Hop (DV-Hop) algorithm can be utilized to localize unknown sensor nodes. DV-Hop is used due to its simplicity and low cost. It is used to locate a node several hops away from anchor nodes. However, the accuracy achieved is not satisfactory. On the other hand, the Received Signal Strength Indicator (RSSI)algorithm is employed to approximate the positions of the sensor nodes, but its effectiveness is limited to a single hop from the anchor nodes. In this paper, the Kalman Filter Multilayer Perceptron-Distance Vector Received Signal Strength Indicator (KF-MLP-DVRSSI) algorithm is presented to improve the accuracy and reliability of the DV-Hop algorithm without the need for additional hardware. The proposed algorithm adjusts the RSSI values of connections between one-hop neighbors using the Kalman Filter (KF). The Kalman filter predicts the variables and estimates the states of the future system based on the prior predictions. A Multilayer Perceptron (MLP) is then used to learn from the actual data and adjust the weights to produce accurate output data. The simulation results demonstrate the performance of the proposed approach compared to three existing models.**

***Keywords*—wireless sensor networks, Distance Vector Hop (DV-HOP), sensor node localization, localization accuracy**

I. Introduction

Wireless Sensor Networks (WSNs) based on the Internet of Things (IoT) are often used for various monitoring applications. Interest in localization has increased as the positioning of sensor data is crucial in the IoT. Therefore, it is essential to localize these sensor nodes [1].

The Distance Vector-Hop (DV-Hop) algorithm works in a multi-hop process. It utilizes the network topology to estimate the position of the sensor nodes. With this technique, the sensor nodes can reach the anchor nodes several hops away from the anchor nodes. A smaller number of anchor nodes can reduce cost [2]. However, most multi-hop localization algorithms can only make accurate position predictions if the sensors are well connected. This connectivity can be achieved through a denser network structure. The DV-Hop algorithm first calculates the average hop distance using anchor nodes. Subsequently, each unknown node determines its distance from an anchor node by multiplying the number of hops from such an anchor node by the average hop distance. Then, the triangulation technique may be utilized to calculate its approximate position. The errors in calculating the average hop distance and estimating the hop count are the main issues with the DV-Hop technique, which reduces the localization accuracy [3].

The authors in [4] suggested improving the accuracy of the DV-HOP model in the distance estimation and position calculation steps by utilizing evolutionary computation.

Artificial Neural Networks (ANNs) are used to mitigate the effects of nonlinearity and multimodality in indoor environments. Several approaches based on ANNs have been presented to identify the connections between input and output vectors by training actual data in an offline phase. The Multilayer Perceptron (MLP) is one of these approaches [5].

The novelty in this work is the Kalman Filter Multilayer Perceptron-Distance Vector Received Signal Strength Indicator (KF-MLP-DVRSSI) algorithm, which decreases the DV-HOP algorithm's localization error. The proposed algorithm combines DV-HOP and the Received Signal

Manuscript received June 3, 2024; revised July 22, 2024; accepted August 6, 2024; published September 24, 2024.

Strength Indicator (RSSI)to improve the average hop distance calculation. The proposed algorithm also employs Kalman Filter (KF) and MLP to refine RSSI values and mitigate the effects of nonlinearity and indoor environment. The paper is organized as follows: Section I contains an introduction, Section II provides related work, Section III introduces the system model, Section IV provides the methodology, and Section V offers the results for various scenarios. Finally, Section VI concludes the paper. Section VII contains limitations and future work.

II. Related Works

As technology advances, there will be significant benefits for a wide range of human activities. The capabilities of sensor nodes will increase while manufacturing costs will decrease. Consequently, the range of WSN applications, as shown in Fig. 1, is expected to continue. In these applications, the data obtained via the network is of little use if it lacks location information. including of location information plays a vital role in both the networking and application of WSNs [6].

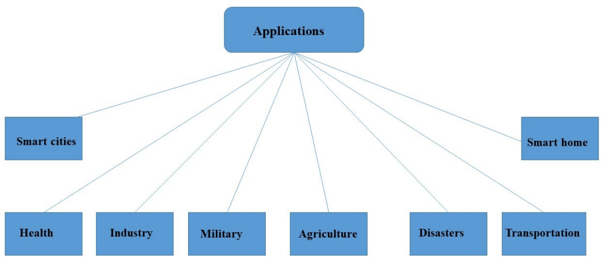

Fig. 1. WSNs application fields.

GPS is the most important method for determining position outdoors. But using the Global Positioning System (GPS) is not feasible indoors. However, the localization of any object with GPS is associated with higher power consumption and costs. Since GPS requires a direct line-of-sight (LoS) for satellites, it is impractical to use GPS indoors. In addition, the accuracy of GPS is five meters, which is efficient for outdoor use but not indoor use. In typical indoor localization systems based on WSNs, anchor nodes act as reference nodes that obtain their location from the GPS or a manual configuration. The other type of sensor node is considered the majority in the network and starts its operation without prior knowledge of its coordinates. The position of most of these sensor nodes is the main objective of localization by utilizing the information of the anchor nodes [2].

Given the characteristics of networked sensors, such as limited power, small size, and low cost, localization is a challenge in WSNs-IoT. The indoor environment influences the transmission rate, scalability of the network, and management of sensor nodes [7]. The factors that influence the management of sensor nodes are spectrum congestion, power consumption, network lifetime, and packet collisions [8].

A. *Indoor Positioning Issues*

Since radio signals propagate between nodes, the main issue of indoor positioning is random obstacles that cause signal reflection, diffraction, absorption, and scattering. Consequently, Non-Line-of-Sight (NLOS) communication occurs between the nodes. This can be characterized by the approximation of NLOS errors to various distributions, including Gaussian, uniform, and exponential distributions, depending on the prevailing conditions. Location determination becomes more challenging in real-world scenarios when nodes are affected by NLOS communication, terrain irregularities, and hardware malfunctions. Irregularities in the field can lead to network holes where signal propagation is completely obstructed in certain areas. This can be caused by significant obstructions such as rocks or buildings. Larger holes force the signals to take longer paths, resulting in substantial deviations from the distance between nodes [9].

B. *Localization Algorithms Overview*

Localization algorithms can be divided into centralized and distributed algorithms. Centralized algorithms use a central unit to perform all calculations. while distributed algorithms perform all calculations at each sensor node. Therefore, most localization studies are based on distributed algorithms. There are two main categories of distributed algorithms: ranging-based and ranging-free algorithms.

Ranging-based techniques are utilized to measure the distances between neighboring sensors. These measurements are time and power-dependent. Time-of-Arrival (TOA) and Time-Difference of Arrival (TDOA) are time-based measurements. The ToA technique calculates the distance between sensors by evaluating signal's arrival time difference from the source sensor to the target sensor. In contrast, the TDoA technique calculates the distance between sensors by evaluating the difference in arrival time of the signal between the source sensor and the target sensor. On the other hand, ToA and TDoA require time synchronization between the sensors to reduce the localization error. The Received Signal Strength Indicator (RSSI) is an example of a measurement that depends on power to compute the distance between sensors. The RSSI technique is attractive because it is inexpensive and does not require additional hardware such as clock synchronization. Nevertheless, the RSSI technique is affected by dynamic environments and interferences that reduce localization accuracy [1–4]. Range range-based approaches can achieve high precision, but require additional hardware, higher costs and higher power consumption [3].

When a large number of anchor nodes are deployed, ranging-based algorithms suffer from latency, power consumption, costs, and localization errors. The authors in [10] proposed an underwater localization algorithm to mitigate these issues. The proposed fitness function integrates hop count, delay, and ToA error. Compared to existing localization algorithms, the proposed algorithm effectively mitigates these issues. However, the optimization performance is affected by insufficient convergence of the Particle Swarm Optimization (PSO).

Ranging-free techniques work in multi-hop that utilize the network topology to estimate the position of the sensor nodes. In these techniques, the sensor nodes can reach the anchor nodes several hops away from the anchor nodes [2].

Connectivity, communication range, received signal strength (RSS), directly and indirectly received signals (through multi-hop communication), the number of anchor nodes, WSN density, noise, interference, and obstacles, all these factors influence positioning in WSNs. The DV-HOP method is an example of a range-free approach [4]. The authors in [11] have identified certain shortcomings of the original DV-HOP algorithm, including issues related to dynamic environments, accuracy, and stability. In contrast, the authors in [12] presented many advantages of the DV-HOP algorithm. First, DV-HOP is classified as a range-free algorithm, which means that it does not require any additional hardware. It also minimizes communication overhead, power consumption, and congestion. Furthermore, the uniformly distribution of sensors can be adjusted. This adaptability makes DV-HOP suitable for different network sizes and densities. Scalability in large networks is another advantage, ensuring its performance and simplicity in location estimation of sensor nodes. These features make DV-HOP a preferred choice for positioning in various applications, instilling confidence in its performance in large networks.

The authors in [11] combined DV-HOP and RSSI values to improve the estimation of hop size. This combination reduced the localization error. The improvement in [13] was done using RSSI and polynomial approximation with the DV-HOP technique to obtain more accurate distances between sensor nodes. The Improved Least Square DV-Hop algorithm (ILS-DV-HOP) in [14] integrates the DV-Hop technique with the weighted least squares method. The integration aims to adjust the hop size calculation to enhance localization accuracy. Improving connectivity in the network is essential to enhance localization accuracy. The authors in [15] proposed a distributed connectivity-based DV-Hop algorithm by considering the connectivity within two hops.

The authors in [16] suggested an approach named Optimum Anchor Nodes Subsets. The proposed approach utilizes the binary PSO algorithm to select the optimal subset of anchor nodes as reference nodes to calculate the hop size. The results of the proposed algorithm demonstrate better localization accuracy.

To solve the topology issues, the authors in [17] proposed a combination of DV-HOP and adaptive particle swarm. The proposed algorithm calculates the hop size using the DV-HOP technique, and then applies the PSO algorithm. The results show higher accuracy for network topology issues.

The effects of signal attenuation, NLOS conditions, multipath fading phenomena and RSSI measurements limit RSSI accuracy.

To minimize costs and power consumption, only the anchor nodes are equipped with GPS modules. The other nodes can identify their location utilizing localization algorithms. The procedure for determining a node's unknown location is termed node self-localization. Table I shows the gaps in related works. The proposed algorithm improves the localization accuracy with minimum costs. The proposed algorithm in this paper overcomes most of the weaknesses of the related works listed in Table I and improves the localization accuracy at minimum cost.

TABLE I. SEVERAL HYBRID ALGORITHMS WITH STRENGTHS AND WEAKNESS POINTS

Reference No.	The algorithm and strengths	Weakness
[18]	-An innovative clustering based technique for identifying outliers in distance measurements to reduce errors, since the accuracy of RSSI is limited by the effects of signal attenuation, non-line-of-sight (NLOS) conditions, multipath fading phenomena and RSSI measurements. -Spatial correlation analysis is used to determine the location where the largest proportion of beacon signals are detected. -mean shift clustering is utilized.	Computational complexity and obstructions in WSNs.
[19]	RSSI-Least Squares Support Vector Regression which saves costs and ensures reliability.	Accuracy and the noise interference.
[20]	The algorithm is based on clustering and particle swarm optimization (PSO) to mitigate the NLOS effects. If sensor nodes are located in a certain area with obstacles, it is not possible for a pair of nodes to communicate directly. Instead, the data must be sent via many intermediate nodes.	Scalability and reliability in a changing environment.
[21]	A new triangle centroid localization algorithm to improve accuracy by mitigating the fluctuations of RSSI values using the Kalman filter.	It is susceptible to errors caused by NLOS, and it is sensitive to signal fluctuations.
[22]	The algorithm uses Multi-Communication Radius Broadcasting, the weight correction factor is applied and the Sparrow search algorithm. All these steps are implemented in the DV-Hop improvement, which is called Hop Count Optimization and ranging correction (HCRDV-Hop) and is based on hop count optimization and ranging correction.	Complexity and energy consumption
[23]	The algorithm introduces an additional communication radius. The algorithm revises the minimum hop count received by the unknown node that is closer to the anchor node. This technique mitigates the problem that the actual distances vary greatly for the same number of hops.	Complexity, environmental issues, communication overhead and energy consumption
[24]	Indoor positioning system uses AI approaches with fuzzy logic to improve localization accuracy.	Cost, power consumption, and processing time.
[25]	An improved adaptive genetic algorithm (IAGA) is introduced to improve localization accuracy.	Complexity, power consumption, and convergence speed.
[26]	This approach improves the localization accuracy of the moving objects by integrating a Feed Forward Neural Network (FFNN) and RSSI. 13 anchor nodes with RSSI are used. The RSSI values are used as input for the FFNN.	Environmental changes, not comprehensive, mobility and scalability.
[27]	This approach to localize Alzheimer's patients combines artificial neural network (ANN), RSSI values via the X-CTU software. 4 anchor nodes are used.	Real time processing issues, complexity and environmental issues.

	The X-CTU software is used to collect RSSI measurements. ANN is used for training, backpropagation and location estimation.	
[28]	The combination of MLP and RSSI fingerprint data in non-isomorphic grid regions achieves precise localization. The approach is implemented by training anchor node information.	Environmental changes and complexity of non-isomorphic grid design.
[29]	In this approach, the information is combined in a fusion method by integrating a linear and adaptive Kalman filter to combine the positions obtained from multiple ultrasonic local positioning systems (ULPS).	Interference, limited range that requires LOS, complexity and synchronization requirements.
[30]	To filter RSSI values, a Fourier-transform Fuzzy c-means KF (FFK) is used in this approach.	High processing requirements, noise variation of RSSI values and complexity.
[31]	Integration of DV-HOP, RSSI and Kalman filter to improve positioning accuracy. The improvement of DV-HOP is up to 50%,	Environmental changes, nonlinearity issues and mobility.
This work	Integration of DV-HOP, RSSI Kalman filter and MLP to improve positioning accuracy without additional hardware.	Mobility.

III. System Model Discerption

Consider a random distribution of WSNs in an indoor environment covering a square area. The network environment is considered dynamic. All sensors are equipped with the same transmission power and communication range. Assumptions are made about large-scale fading and multipath fading. It is also essential to consider the dynamic nature of the network environment. Given the random distribution of the sensor nodes, the standard model for indoor positioning is not applicable in this scenario. The reason is that the distance between each pair of sensors is different, which leads to an increase in the average localization error. Each sensor has its own KF so all filters can work simultaneously and produce their respective estimates.

There are two categories of sensor nodes: Anchor nodes, which are manually configured and used during the training phase to collect RSSI measurements for building the training database; Each neuron in the hidden layer uses its sigmoid activation function to produce the final output. Through this process, each neuron compares the generated output with the desired output to calculate the error. Similar to a data scientist, the error is passed backward to the previous layers to adjust the weights of these neurons. This adjustment aims to determine the optimal value for the average hop distance between the anchor nodes and the hop count in the network. Unknown sensors are another category that needs to be localized using the DV-HOP approach and improved by the proposed algorithm. The broadcasted identifier packets reach the unknown nodes in the multi-hop. Calculating of distance between anchor nodes and unknown nodes considers the best path-based counter that computes the minimum hop count between them. The RSSI model is limited by RSS, but it is used to refine the distance between nodes. KF is used to refine the RSS values. We assume static conditions for unknown nodes and anchors in the network. The anchor nodes are randomly distributed over the network area to ensure comprehensive coverage. The communication range of anchor nodes and unknown nodes is identical. The sensors collect data and transmit it to the cloud, where AI models process it. The sensors act as data collectors.

IV. Methodology

The DV-HOP approach presented in [32] can be used to predict the location of unknown sensors in WSNs. The DV-HOP approach uses the hop size and hop count values to estimate the distance between sensor nodes. After estimating distances in the network, trilateration is utilized to obtain the sensor location. On the other hand, several factors affect DV-Hop's accuracy such as: Obstacles, interferences, errors in hop size and hop count.

The proposed approach involves the following phases: Flooding: In the flooding phase, the anchor nodes broadcast packets with an identifier (id), the coordinates of the anchor nodes (x_i, y_i), and h_i, which signifies the number of hops from anchor node i, with the value of initially starting at zero. When an adjacent node receives a smaller hi packet from a particular anchor node, it records the anchor node and increments the hi counter value by one before forwarding it to its adjacent nodes. After the procedure is completed, each unidentified node receives the lowest hop count (h_i) and discards packets with higher hi values as state data. The distance between the nodes is then calculated. The process begins by computing each anchor node's hop distance (hopsizei) using Eq. (1).

$$hopsize_i \frac{\sum\sqrt{((xi-xj)^2+(yi-yj)^2)}}{\sum hij} \tag{1}$$

The anchor nodes i and j locations are (x_i, y_i) and (x_j, y_j) respectively, while h_{ij} denotes the minimum number of hops between them. The anchor nodes utilize controlled flooding to distribute the hops in the network. Then, Eq. (2) is employed to ascertain the distance between the unidentified node and the anchor node i.

$$d_{u,i} = hopsize_i \times h_{u,i} \tag{2}$$

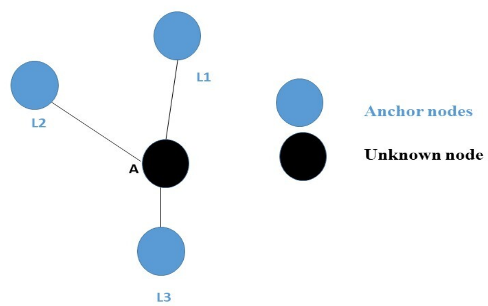

Fig. 2. DV-HOP algorithm requires three anchor nodes (ANs) for localization.

Determine the position node: (x, y) is the position of the unknown node. Therefore, Eqs. (3)–(5) represent the distance to the anchor nodes as shown in Fig. 2.

$$d_1^2 = ((x_1 - x)^2 + ((y_1 - y)^2 \tag{3}$$

$$d_2^2 = ((x_2 - x)^2 + ((y_2 - y)^2 \tag{4}$$

$$d_3^2 = ((x_3 - x)^2 + ((y_3 - y)^2 \tag{5}$$

The above Eq. (3)–(5) can be represented as AX = B, where A, X, and B are defined in Eq. (6)–(8).

$$A = \begin{vmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ .. & .. \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{vmatrix} \tag{6}$$

$$B = \begin{vmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{vmatrix} \tag{7}$$

$$X = \begin{vmatrix} x \\ y \end{vmatrix} \tag{8}$$

To solve the equation AX = B, least squares approach is utilized.

$$X = (AA^T)^{-1} A^T \, b \tag{9}$$

The received power in the free space propagation model can be articulated as:

$$\frac{Pr}{Pt} = \frac{GtGr\lambda^2}{(4\pi d)^2} \tag{10}$$

Pt: transmitted power, Pr: received power, Gt: T_x antenna gain, Gr: Rx antenna gain, d: distance in meters, and λ: wavelength per meter.

The correlation between distance and received power, simplified for a reference distance of 1 meter, is as follows:

$$RSSI = -10\,\eta \log(d) + A \tag{11}$$

The parameter A must be known in advance, as it is determined solely by the actual features of the radio, and η: path loss exponent.

RSSI estimates of distance between T_x and R_x using RSS and an appropriate signal. Many localization methods utilizing RSSI primarily depend on trilateration which requires three anchor nodes to localize unknown nodes as shown in Fig. 3.

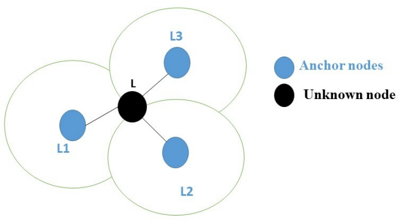

Fig. 3. RSSI algorithm by trilateration technique.

$$P_{r,dB}(d) = P_{r,dB}(d_0) - \eta 10 log_{10}\left(\frac{d}{d_0}\right) + X \tag{12}$$

$P_{r,dB}(d)$ and $P_{r,dB}(d_0)$ represent the received signal power at distances d and d_0, respectively.

$$d = d_0 10^{[\frac{P_{r,dB}(d_0) - P_{r,dB}(d)}{10\eta}]} \tag{13}$$

The RSSI value demonstrates considerable fluctuations during the measurement process, and the implementation of filtering techniques has proven helpful in removing these unwanted fluctuations. The KF is utilized to process the RSSI data. The equations used in the KF refer to two models, one representing the process and the other modelling the measurements.

$$x_k = F_k x_{k-1} + w_k \tag{14}$$

$$z_k = H_k x_k + v_k \tag{15}$$

$$P(w) \sim N(0, R_k) \tag{16}$$

$$P(v) \sim N(0, Q_k) \tag{17}$$

F_k: the state transition matrix from time k to time k−1, while W_k: the process noise with a zero-mean normal distribution and covariance R. Z_k: the observation vector at time k, where H_k is the matrix connecting the state vector to the measurements. v_k: the observation noise with a zero-mean white Gaussian distribution and covariance Q. The KF cycle contains two separate phases: a prediction step and a correction step.

In the prediction step, the estimated state at time k−1 is applied to create the expected state estimate (a priori) at time k, based on the following expression:

$$\hat{x}_k^- = F_k \hat{x}_{k-1} \tag{18}$$

The covariance matrix of the expected errors can be represented with respect to the prior covariance matrix of the estimated errors P_{k-1} and the covariance matrix of the process noise R, as shown below:

$$P_k^- = F_k P_{k-1} F_k^T + R \tag{19}$$

Update step: This step includes the computing of the KF gain, which is defined as follows:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + Q)^{-1} \tag{20}$$

The matrix that represents the covariance of the measurements is commonly referred to as Q, while the observation matrix is represented by H. Eventually, the posterior state estimate X_k and the accompanying covariance matrix P_k are revised according to the following procedure: To summarize, the posterior state estimate X_k and its corresponding covariance matrix P_k are updated using the following equations:

$$x_k = x_k^- + K_k(z_k - H_k x_k^-) \tag{21}$$

$$P_k = (I - K_k H_k) P_k^- \tag{22}$$

Machine learning approaches, such as Neural Networks (NNs), can be employed to enhance the accuracy of the

DV-Hop algorithm. For this purpose, an Artificial Neural Network (ANN) can be trained with a dataset of anchor nodes and the position estimates derived from the Distance Vector Hop (DV-Hop) method. Subsequently, the trained ANN can be utilized to predict the localization of the sensor node considering new coordinate values.

While AI can improve the accuracy of the DV-Hop algorithm itself, it is not a replacement for the algorithm. The algorithm still needs to be used to obtain initial position estimates, which can then be refined using AI. Furthermore, the effectiveness of AI-based techniques depends on the quality of the data as well as the particular problem and data set. NN model used in this article is the MLP. The KF-MLP-DVRSSI approach shown in Fig. 4 is based on the range-free approach used in isotropic WSNs. MLP, which consists of two hidden layers. As illustrated in Fig. 4, the MLP model can be divided into three separate layers: the input layer, the hidden layer, and the output layer. It efficiently maps different inputs to a predefined set of needed outputs. MLP is learned using supervised learning methods such as Bayesian regularization and backpropagation. During the feed-forward phase, each neuron in the hidden layer passes the received signal to the next layer. Each neuron applies sigmoid activation function. Then, the signal is forwarded to the next layer. MLP can undergo training to predict the optimal weights for the distance calculation, considering factors such as h_i, RSS values, and $hopsize_i$.

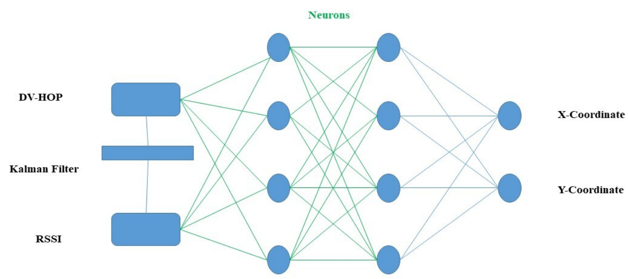

Fig. 4. KF-MLP-DVRSSI proposed model.

The KF-MLP-DVRSSI algorithm, shown in Fig. 5, uses DV-Hop and RSSI. DV-Hop is used to locate unknown nodes at a distance of many hops from the anchor nodes, while RSSI is limited to one hop distance and multipath fading.

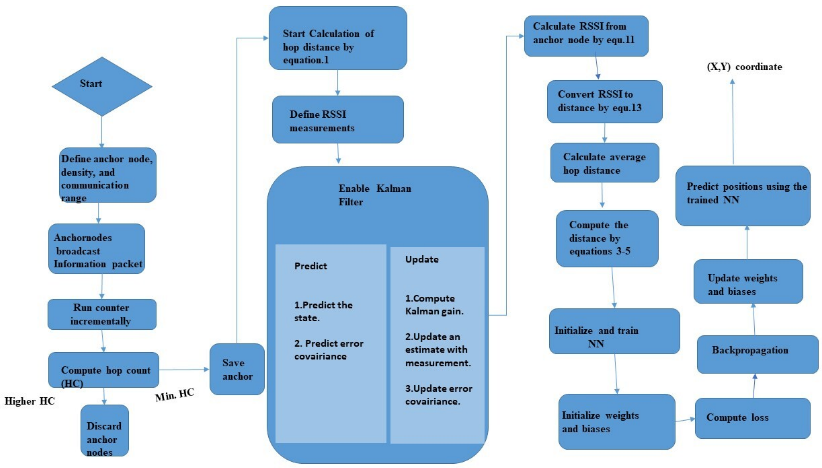

Fig. 5. Flow chart of KF-MLP-DVRSSI.

The DV-Hop algorithm incorporates RSSI values of the one-hop neighbors. The average of 20 RSSI measurements is used, which is then refined by KF. The parameters, h_i, RSS values and $hopsize_i$ are used as inputs for the MLP model. These techniques are integrated as characteristics inside MLP model, which can optimize the weights to improve accuracy. The KF-MLP-DVRSSI algorithm is specifically designed for managing sensor nodes in the IoT era.

Proposed approach evaluation: The evaluation criterion is established by computing the Average Localization Error (ALE) using the formula given:

$$ALE\,\frac{\sum_{i=1}^{N-M}\sqrt{((xi-xj)^2+(yi-yj)^2\,)}}{R(N-M)} \tag{23}$$

The variable (N-M) represents the number of nodes whose value is unknown, while R represents the communication range.

V. Simulation Results and Comparison

This section refers to an evaluation of the efficiency of the algorithm we have developed. We performed simulations for 50 randomly selected scenarios and computed the ALE values for these scenarios. The simulations which were conducted in an indoor environment with dimensions of 100 m × 100 m were carried out using MATLAB.

In the first phase of the simulation, the distance vector hop (DV-HOP) algorithm is executed. In the second phase of simulation, RSSI is applied. In the third simulation phase, MLP-RSSI is implemented. In the last phase, KF-MLP- DVRSSI is executed, which aims to enhance the precision of the DV-HOP model by employing a NN with two hidden layers and five neurons in each layer. The training process utilizes the NN Toolbox in MATLAB. Fig. 6 illustrates the configuration of anchor and unknown nodes, represented by red and black asterisks, respectively.

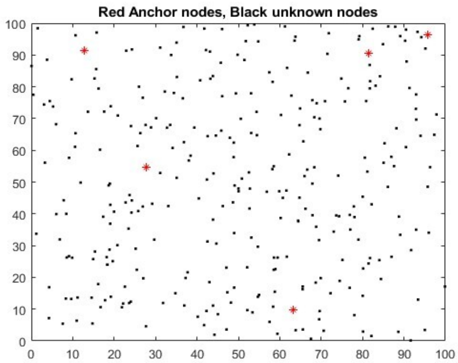

Fig. 6. The distribution of sensor nodes in area 100×100 msquared.

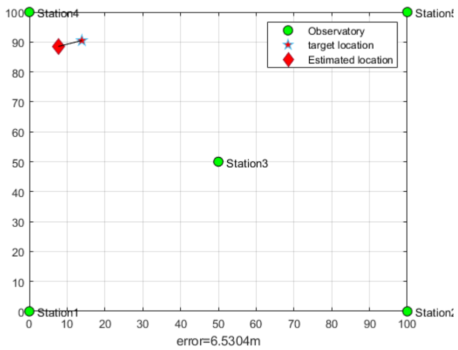

Fig. 7. RSSI Error with R = 10 m, path loss exponent = 3.

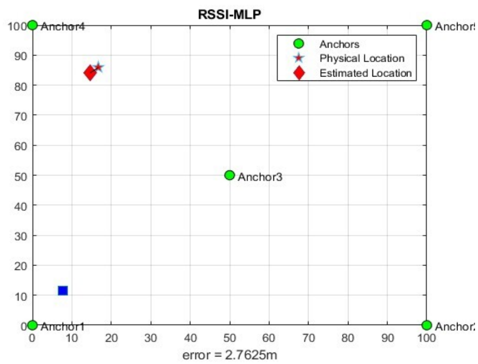

Fig. 8. RSSI-MLP localization error with R = 10 m, path loss exponent = 3.

Fig. 7 demonstrates the results of the RSSI-based localization algorithm, which has an error of 6.5304 m. This error is due to the dynamic environment and multipath fading, considered relatively high for indoor positioning systems.

Fig. 8 shows the error of the RSSI-MLP algorithm, which combines RSSI and MLP with specific parameters (R = 10 meters, path loss exponent = 3, reference received power = −45.65 dB, learning rate = 0.01, activation function is a sigmoid function). The error obtained is 2.7625 m. A comparison with the results in Fig. 6 shows an enhancement in accuracy through the implementation of RSSI-MLP.

The NN is fed with input parameters such as the resulting coordinates, hopsize$_i$, minimum h$_i$, and average RSSI values, which are features that can be extracted from the data.The NN can be employed to understand a decision boundary that distinguishes the target nodes from the non-target nodes in the DV-Hop algorithm based on RSSI within hopsize$_i$. A widely used approach to avoid overfitting and ensure generalization is to reserve 10% of the data for validation and 10% for training. The extent of improvement will vary based on the specific characteristics of the data and the neural network's design. Moreover, it is crucial to recognize that the NN serves as just one element of the DV-Hop algorithm, with additional factors like pre-processing, feature engineering, and experimental configuration significantly influencing the algorithm's overall performance. Moreover, the enhancement is anticipated to vary depending on the specific application and the current level of accuracy already achieved.

In this phase of the simulation scenario of KF-MLP-DVRSSI, we changed the ratio of anchor nodes to evaluate the ALE. Throughout the localization phase, we assume static conditions for all nodes and anchors in the network. Table II displays the values of the parameters for Scenario 1 (evaluating the varying ratio of anchor node), Scenario 2 (evaluating the varying network density), and Scenario 3 (evaluating the varying R). Fig. 9 displays the ALE results of sensor node positioning using the KF-MLP-DVRSSI approach, compared to other algorithms [4, 14], called ILS DV-HOP, and DV-HOP.

It can be observed that all algorithms perform poorly initially but improve as the ratio of anchors increases. The precision of all algorithms enhances with addition of more anchor nodes. The ALE of KF-MLP-DVRSSI is the lowest.

Fig. 10. demonstrates the results of varying the number of unknown nodes, as given in Table I, keeping the number of anchor nodes and R constant. The results show that the accuracy improves with increasing node density as the connectivity increases due to a larger number of neighboring nodes. Conversely, higher node density leads to higher energy consumption due to more active nodes and higher processing requirements. The proposed algorithm reduces the ALE of the original DV-HOP algorithm at density = 200 by up to 94% and compared to [4] and ILS DV-HOP by 81 % and 93%, respectively. On the other hand, the ALE of KF-MLP-DVRSSI with 100 unknown nodes closely resembles the ALE with 300 unknown nodes reported in [4].

TABLE II. VALUES OF PARAMETERS THROUGH ALL SCENARIOS

Algorithm	**Scenario1 (ALE versus anchor nodes ratio)**	**Scenario 2(ALE versus density)**	**Scenario 3 (ALE versus communication ranges)**
Dv-hop	300 unknown nodes, R = 20 m, anchor nodes ratio varies from 10% to 30%.	Anchor nodes ratio= 10%, R= 20 m, unknown nodes varies from 100 to 300	300 unknown nodes, anchor node ratio = 10%, and R varies from 15 m to 30 m

ILS DV-HOP	300 unknown nodes, *R* = 15 m, anchor nodes ratio varies from 5% to 30%.	Anchor nodes ratio = 10%, R = 15 m the number of unknown nodes varies from 200 to 500	300 unknown nodes, anchor node ratio = 10%, and R varies from 15 m to 40 m
[4]	100 unknown nodes, *R* = 20 m, anchor nodes ratio varies from 10% to 40%.	Anchor nodes ratio = 20%, R = 20 m the number of unknown nodes varies from 100 to 300	100 unknown nodes, anchor node ratio = 20%, and R varies from 20 m to 40 m
KF-MLP-DVRSSI	300 unknown nodes, *R* = 20 m, and the anchor nodes ratio varies from 10% to 30%.	Anchor nodes ratio = 10%, R = 20 m the number of unknown nodes varies from 100 to 300	300 unknown nodes, anchor node ratio = 10%, and R varies from 15 m to 30 m

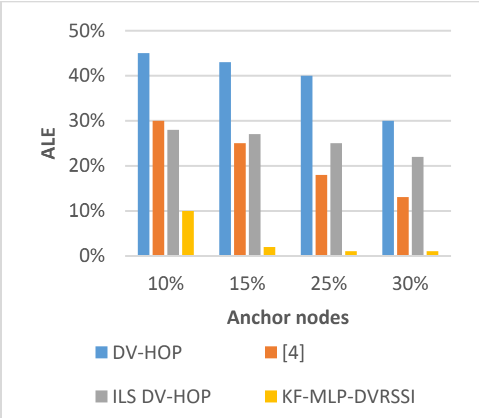

Fig. 9. ALE versus anchor nodes ratio.

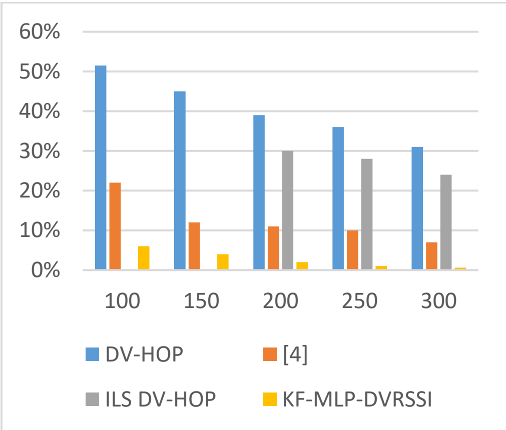

Fig. 10. ALE versus density.

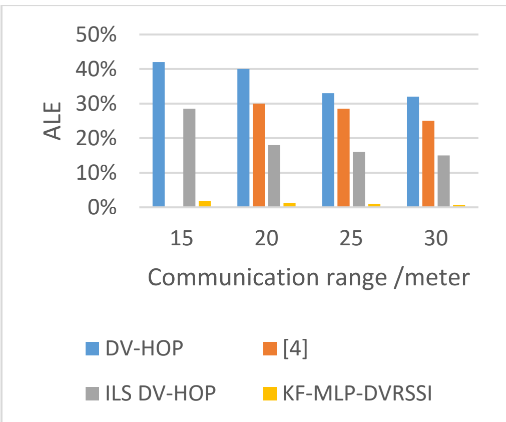

Fig. 11. ALE versus communication range.

However, the results of the DV-HOP algorithm have higher energy consumption and processing requirements due to the higher node density.

Fig. 11 shows the influence of increasing R on the ALE with a constant number of unknown and anchor nodes as shown in Table II. However, the decline in ALE is coupled with greater communication latency due to the higher communication range and propagation distance. For example, the ALE achieved by KF-MLP-DVRSSI with R = 15 is lower than the ALE of ILS DV-Hop with R = 30, KF-MLP-DVRSSI has lower latency than the original DV-HOP and other algorithms.

The comparison between the proposed algorithm and the algorithm in [31] is critical, since the proposed algorithm adds MLP to the integration of Ref. [31] to mitigate the effects of nonlinearity and multimodality in indoor environments. For example, in a density scenario with a high density of 300 nodes [31], the improvement of DV-HOP is up to 53.8%, while the improvement of the proposed algorithm is 98 %.

VI. Conclusion

The DV-Hop model, with its simplicity, scalability, and cost-effectiveness, is a valuable technique for WSNs. However, its accuracy limitations can be overcome by integrating AI techniques. These techniques can learn complex relationships between hop counts, RSSI values, average hop distance, and actual distances, thereby enhancing the DV-Hop model's accuracy.

This paper presents a novel KF-MLP- DVRSSI algorithm to address the localization in IoT-WSN. The KF-MLP- DVRSSI is an ANN-based algorithm introduced to improve localization in IoT-WSN. The KF-MLP-DVRSSI algorithm uses a combination of distance, average RSSI values and hop counts to determine the location of an object. Integrating Kalman filter, DV-HOP algorithm and RSSI with AI improves accuracy without the need to add new hardware.

The proposed algorithm is designed for precise localization, that enhanced the accuracy of the original DV-HOP algorithm by up to 94% and compared to [4] and ILS DV-HOP 87 % and 89%, respectively. This ensures both longer network lifetime and high localization accuracy which is crucial for WSN. The simulation results show a significant performance improvement of the proposed multihop based algorithm over the DV-HOP algorithm and the single hop based RSSI algorithm. In addition, the results demonstrate energy-efficient model with reduced latency.

VII. Limitations and Future Work

In future work, we will perform the necessary tests to validate the effectiveness of the proposed algorithm in real indoor environments. The mobility scenario will be investigated to determine the location.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The first author conducted the literature review, conceptualization of the study, simulation, design, implementation of the proposed algorithm, writing and approving the final version of the manuscript. The second author acted as project leader and reviewed the manuscript, providing feedback on both the technical content and the overall presentation and approving the final version of the manuscript.

References

[1] S. Sadowski and P. Spachos "Rssi-based indoor localization with the internet of things," *IEEE Access*, vol. 6, pp. 30149–30161, 2018.

[2] V. Sneha and M. Nagarajan, "Localization in wireless sensor networks: A review," *Cybernetics and Information Technologies*, vol. 20, no. 4, pp. 3–26, 2020.

[3] F. Zafari, A. Gkelias, and K. K. Leung, "A survey of indoor localization systems and technologies," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2568–2599, 2019.

[4] Q. Shi, C. Wu, Q. Xu, and J. Zhang, "Optimization for DV-Hop type of localization scheme in wireless sensor networks," *The Journal of Supercomputing*, vol. 77, no. 12, pp. 13629–13652, 2021.

[5] A. Nessa, B. Adhikari, F. Hussain, and X. N. Fernando, "A survey of machine learning for indoor positioning," *IEEE Access*, vol. 8, pp. 214945–214965, 2020.

[6] G. Wang, Y. Shi, and J. Liu, "Optimization of the DV-hop localization algorithm in wireless sensor networks," *Journal of Physics: Conference Series*, vol. 2037, no. 1, p. 012088, 2021.

[7] O. I. Khalaf and B. M. Sabbar, "An overview on wireless sensor networks and finding optimal location of nodes," *Periodicals of Engineering and Natural Sciences*, vol. 7, no. 3, pp. 1096–1101, 2019.

[8] A. Adeel, M. Gogate, S. Farooq, C. Ieracitano, K. Dashtipour, H. Larijani, and A. Hussain, "A survey on the role of wireless sensor networks and IoT in disaster management," *Geological Disaster Monitoring Based on Sensor Networks*, 57–66, 2019.

[9] M. A. Bhatti, R. Riaz, S. S. Rizvi, S. Shokat, F. Riaz, and S. J. Kwon, "Outlier detection in indoor localization and Internet of Things (IoT) using machine learning," *Journal of Communications and Networks*, vol. 22, no. 3, pp. 236–243, 2020.

[10] M. Nain, N. Goyal, L. K. Awasthi, and A. Malik, "A range based node localization scheme with hybrid optimization for underwater wireless sensor network," *International Journal of Communication Systems*, vol. 35, no. 10, e5147, 2022.

[11] H. Ghribi, F. Khelifa, A. Jemai, and M. B. B. Salah, "A review of DV-Hop localization algorithm," in *Proc.* 2021 *31st International Telecommunication Networks and Applications Conference (ITNAC)*, 2021, pp. 121–126.

[12] O. M. Cheikhrouhou, G. Bhatti, and R. Alroobaea, "A hybrid DV-hop algorithm using RSSI for localization in large-scale wireless sensor networks," *Sensors*, vol. 18, no. 5, 1469, 2018.

[13] S. Messous, H. Liouane, O. Cheikhrouhou, and H. Hamam, "Improved recursive DV-hop localization algorithm with RSSI measurement for wireless sensor networks," *Sensors*, vol. 21, no. 12, 4152, 2021.

[14] R. Mani, J. L. Sevillano, and N. Liouane, "Improved least-square DV-hop algorithm for localization in large scale wireless sensor network," in *Proc. 2022 International Conference on Control, Automation and Diagnosis (ICCAD)*, 2022, pp. 1–6.

[15] L. Gui, F. Xiao, Y. Zhou, F. Shu, and T. Val, "Connectivity based DV-hop localization for Internet of Things," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 8, pp. 8949–8958, 2020.

[16] Y. Cao and J. Xu, "DV-Hop-based localization algorithm using optimum anchor nodes subsets for wireless sensor network," *Ad Hoc Networks,* vol. 139, 103035, 2023.

[17] Q. Shi, Q. Xu, and J. Zhang, "An improved DV-Hop scheme based on path matching and particle swarm optimization algorithm," *Wireless Personal Communications*, vo. 104, pp. 1301–1320, 2019.

[18] N. O. Chuku, "Development and evaluation of RSSI-based localization schemes for wireless sensor networks to mitigate shadowing effects," Doctoral dissertation, The University of North Carolina at Charlotte, 2020.

[19] L. Zhang, H. Yang, Y. Yu, and F. Peng, "A three-dimensional node security localization method for WSN based on improved RSSI-LSSVR algorithm," in *Proc. 2018 10th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)*, 2018, pp. 182–186.

[20] S. Phoemphon, C. So-In, and N. Leelathakul, "Improved distance estimation with node selection localization and particle swarm optimization for obstacle-aware wireless sensor networks," *Expert Systems with Applications*, vol. 175, 114773, 2021.

[21] Z. Z. Yu and G. Z. Guo, "Improvement of positioning technology based on RSSI in ZigBee networks," *Wireless Personal Communications*, vol. 95, pp. 1943–1962, 2017.

[22] L. Huachao, S. Chong, C. Xin, and W. Chunjiang, "Recent advances in catalytic asymmetric 1, 3-dipolar cycloaddition reactions with kinetic resolution," *Chinese Journal of Organic Chemistry*, vol. 42, no. 10, 3322, 2022.

[23] T. Li, C. Wang, and Q. Na, "Research on DV-Hop improved algorithm based on dual communication radius," *EURASIP Journal on Wireless Communications and Networking*, pp. 1–10, 2020.

[24] A. Islam, M. T. Hossan, M. Z. Chowdhury, and Y. M. Jang, "Design of an indoor positioning scheme using artificial intelligence algorithms," in *Proc. 2018 International Conference on Information Networking (ICOIN)*, 2020, pp. 953–956.

[25] A. Ouyang, Y. Lu, Y. Liu, M. Wu, and X. Peng, "An improved adaptive genetic algorithm based on DV-Hop for locating nodes in wireless sensor networks," *Neurocomputing*, vol. 458, pp 500–510, 2021.

[26] M. W. P. Maduranga, "Improved indoor localization with machine learning techniques for IoT applications," arXiv preprint, arXiv:2402.11433, 2024.

[27] Z. Munadhil, S. K. Gharghan, A. H. Mutlag, A. Al-Naji, and J. Chahl, "Neural network-based Alzheimer's patient localization for wireless sensor network in an indoor environment," *IEEE Access*, vol. 8, pp. 150527–150538, 2020.

[28] Z. Sun, Y. Zhang, and Q. Ren, "A reliable localization algorithm based on grid coding and multi-layer perceptron," *IEEE Access*, vol. 8, pp. 60979–60989, 2020.

[29] K. Mannay, J. Ureña, Á. Hernández, J. M. Villadangos, M. Machhout, and T. Aguili, "Evaluation of multi-sensor fusion methods for ultrasonic indoor positioning," *Applied Sciences*, vol. 11, no. 15, 6805, 2021.

[30] C. H. Tseng and W. J. Tsaur, "FFK: Fourier-transform fuzzy-c-means Kalman-filter based RSSI filtering mechanism for indoor positioning, *Sensors*, vol. 23, no. 19, 8274, 2023.

[31] R. Mani, S. Messous, G. Campobello, F. Battaglia, and N. Liouane, "Improved distance vector based Kalman filter localization algorithm for wireless sensor network," in *Proc. 2023 International Conference on Control, Automation and Diagnosis (ICCAD)*, 2023, pp. 1–6).

[32] J. Wang, A. Hou, Y. Tu, and H. Yu, "An improved DV-hop localization algorithm based on selected anchors," *Comput. Mater. Contin.,* vol. 65, pp. 977–991, 2020.