



WSN Localization Method Based on Hybrid PSO-GRNN Approach

Suphian Mohammed Tariq^{1*}

Intisar Shadeed Al-Mejibli²

¹*Informatics Institute for Postgraduate Studies,*

Iraqi Commission for Computers & Informatics College of Engineering, Al-Iraqia University, Baghdad, Iraq

²*Biomedical Informatics College, University of Information Technology and Communications, Baghdad, Iraq*

* Corresponding author's Email: phd202130676@iips.icci.edu.iq

Abstract: Determining the localization and tracking of sensor nodes in indoor environments is the goal of this study. The difficulty of significant estimation errors in target localization brought on by unpredictable noise in received signal strength indicator (RSSI) readings, particularly in indoor environments, is a major area of research right now. This study proposed a hybrid technique called particle swarm optimization- generalized regression neural network (PSO-GRNN) to improve the sensor nodes' ability to estimate location and target tracking with more precision, as an alternative to conventional RSSI-based strategy. The GRNN algorithm can use the RSSI values as initiation data of the algorithm of GRNN to locate the location and tracing of the target node. An essential component of the GRNN architecture is the spread constant(σ), The method of trial-and-error to select a value of spread constant(σ), which is insecure and does not always yield the best result, is used to choose the parameter. The PSO method is used to determine the optimal GRNN spread constant value. The hybrid PSO-GRNN method was used to overcome these drawbacks and enhance localization and target tracking accuracy without the need for further apparatuses. The tracking algorithm PSO-GRNN the hybrid outperformed the conventional LNSM technique and produced impressive results. Comparing the proposed method to the conventional RSSI, a considerable gain of 87.58% is possible.

Keywords: Received signal strength indicators (RSSIs), General regression neural network (GRNN), Target tracking, Indoor localization, Particle swarm optimization (PSO), Trilateration.

1. Introduction

In many wireless sensor networks (WSN) applications, including target tracking, person tracking, monitoring, healthcare, military purpose, and Factories and Industrial Areas [1]. Accurate localization in WSNs is still difficult to achieve, though. The two main techniques for WSN localization are range-based methods and range-free methods [2]. Calculating the distance or angle among sensory nodes is a component of the range-based approach [3]. The angle-of-arrival (AoA), global positioning system (GPS), acoustic energy, time of arrival (ToA), time difference of arrival (TDoA), and received signal strength indicator (RSSI). are some of the techniques used in this approach [4], which delivers great accuracy. GPS is a well-known technique that relies on a direct line of sight between

the satellites and the receiver and is typically used for outdoor locations. But it has flaws like high power usage and cost [5].

The range-free method in WSN localization, on the other hand, is economical but often provides lesser accuracy [3]. It depends on the connectivity between stationary or mobile sensor nodes and stationary nodes, also known as anchor nodes. The range-free strategy, in contrast to the range-based method, establishes the location of the sensor node without guessing the distance [6].

From a technical viewpoint, the determination and tracking of target location can be achieved through a wide array of technologies in wireless sensor networks (WSNs), including but not limited to radio frequency (RF), Infrared (IR), video, acoustic, and Ultra-Wideband (UWB) [7]. Among these, RF stands out because of its dominant use of RSSI measurements and its ability to traverse through non-

metallic barriers, walls, and smoke, making it a favorite choice for localization tasks. Wi-Fi access points can also be utilized to provide RF signals for indoor localization [8]. Furthermore, Bluetooth low energy (BLE) technology is increasingly receiving attention, with the growing use of BLE beacons for indoor localization applications [9].

Common techniques such as lateration and angulation are frequently employed in localization based on RSSI. The angulation-based technique calculates the position based on the angles of arrival between the nodes, while the lateration-based technique uses the distance between two sensor nodes for localization [10]. To estimate the angle of arrival of RF signals, WSN nodes need to be equipped with at least two directional antennas as per the angulation technique. Despite their frequent use, both lateration and angulation techniques face difficulties in accurately determining distances and angles in practical scenarios [11]. Such challenges often stem from sudden changes in target velocity and uncertainties in RSSI measurements due to factors like signal weakening, multipath fading, the orientation of the antenna, its height above the ground, and effects of shadowing.

The exact nonlinear correlation between RSSI and distance presents challenges for lateration-based systems. Both the lateration and the angulation methods have inherent flaws in their calculations of distance and angle. It is preferable to use localization techniques that are capable to overcome this issue resulting from environmental dynamics. Artificial neural networks (ANNs) have displayed promising capabilities in tasks related to localization and target tracking. They exhibit proficiency in handling noise-laden measurements and have a swift learning and generalization capacity [12]. Drawing inspiration from the biological neural networks of the human brain, ANNs are computational models constituted of interconnected nodes or neurons organized in layers. These are trained to understand and identify complex patterns and correlations within the provided input data. No prior knowledge of the noise distribution is required. ANNs can be used for localization to estimate the position of sensor nodes or targets grounded on collected signal strength indicators (RSSI). An ANN may be trained with a dataset of known locations and matching input qualities (such as RSSI values) to discover the underlying patterns and offer a mapping between the input data and the target location. In this study, GRNN is used in place of the conventional RSSI-based position estimation technique, so as to get PSO-GRNN algorithms. The GRNN may immediately provide position estimations for moving targets after being trained

using the pair of RSSI data and corresponding actual target position. The suggested algorithms are tested using MATLAB simulations and account for these real-time issues (uncertainty in measurement noises and abrupt changes in target velocity).

The suggested techniques successfully exclude calculations for path loss exponent, environmental calibration, and RSSI-based distances. Because of this, ANN-based localization methods show great promise. The additions of this paper are:

1. Establishing a comprehensive RSSI dataset in MATLAB utilizing the log-normal shadow fading model for localization.
2. Employing RSSI values with distance to construct a propagation channel model for indoor environments.
3. Design a hybrid PSO-GRNN algorithm with LNSM for Location and Target Tracking.
4. Utilizing a novel hybrid PSO-GRNN localization method to increase the accuracy of estimated Location and Target Tracking.

This study's main objective is to address the problem of high nonlinearity in the relationship between target location and RSSI values. A proper neural network is used to do this. The particle swarm optimization (PSO) algorithm improves the performance of the generalized regression neural network (GRNN). The smoothing factor (σ) the important parameter in GRNN's. The conventional method of choosing this parameter involves trial and error, a process that poses risks and doesn't necessarily yield the best outcome. The PSO method mitigates this issue by finding the optimal value for the GRNN spread constant, thereby potentially enhancing GRNN's performance. Six anchor nodes' RSSI values are used as the GRNN's input data, while the output is the target node's real coordinates. These data are used to train and test the GRNN. Three of the six nearest anchor nodes in the Log-Normal Shadowing Model (LNSM) are used in the conventional method. six anchor nodes are used in the hybrid PSO-GRNN method to increase the precision of localization and target tracking estimation.

This paper is structured as follows. In section 2, a brief review of significant studies related to target localization and tracking methodologies within target-tracking WSNs is presented. Section 3 lays out the approach for localizing a mobile target using a general regression neural network and PSO. Comprehensive simulation studies, which delve into the system architecture and performance evaluation of the proposed methods, are explained in section 4. Concluding remarks and potential areas for future work are highlighted in section 5.

2. Related work

Recent scientific research has shown various degrees of interest in localizing sensor nodes in WSNs. One study [13] the linear least squares method and RSSI to locate the source node. The LNSM path loss model produced the RSSI. They discovered that the predicted inaccuracy was 2.72 meters after doing the study within a simulated setting for a 50 m × 50 m area. [14] used two-stage techniques to increase localization accuracy. When using range-based location techniques, the received signal strength indicator serves as the main determining criterion. standard weighted centroid approaches, and then it was refined by reducing the reference nodes utilizing propagation model-based computational techniques. By using the Cooja simulator to test the methods, one can accurately pinpoint a position up to 97 percent of the time. In [15] the MLE-PSO indoor localization algorithm, which is based on RSSI and PSO, is introduced in this study. This algorithm's primary goal is to improve dynamic performance and localization accuracy. The MATLAB platform is used to implement and test the suggested methodology. The findings show that the MLE-PSO technique takes use of maximum likelihood estimation's (MLE) high accuracy when the ranging error is small and particle swarm optimization's (PSO) stability when the ranging error is significant. As a result, compared to both the conventional MLE algorithm and the PSO algorithm, the MLE-PSO approach achieves greater accuracy. Jondhale [16] generalized regression neural network (GRNN) technology in this study to provide a method for improving real-time target tracking performance. The study illustrates the viability of using GRNN to approximate a nonlinear function to locate RSSI-2D data. The Kalman filter (KF) and unscented Kalman filter (UKF) are used to further improve the results. The study in a simulation environment for a 100m × 100 m area. used to effectively monitor a single moving target using a GRNN-based algorithm. Trial and error are used to choose the smoothing parameter (σ) for the GRNN. The best result was obtained with equal to 3.5, yielding an RMSE of 5.3517 after analyzing various values from spread constant ranging from 0.5 to 6. This method of trial and error is time-consuming and may not produce the best results.

So, we propose in our study a hybrid technique termed PSO-GRNN to overcome this limitation. By using the particle swarm optimization (PSO) technique, the Smoothing Parameter (σ) in GRNN is optimized, leading to greater accuracy. The best

value can be determined more effectively by merging PSO with GRNN, which improves tracking precision.

As cited in references[17], the trilateration measurement strategy is widely used to pinpoint the positions of sensor nodes in WSNs. This approach is contingent on knowing the distance between the target sensor node and three anchor nodes [7]. However, given the mobility of the node in our use case, the distances between the mobile node and anchor nodes are often indeterminable upfront. This necessitates the mobile node to constantly revise its location, thereby complicating the application of the trilateration method for our research. Lately, techniques rooted in artificial intelligence, like the bat optimization algorithm [18] and ANN algorithms, have come into use to address the issue of localization in wireless networks. In [19] suggests a machine learning-based indoor positioning system (IPS) method. Using a feed-forward neural network with a single hidden layer and utilizing two different ANN Architectures with 3 and 4 neurons in this layer to estimate the coordinates target node from the RSSI dataset obtained from 4 anchor nodes. For the error estimation, 1.74 is the maximum value. The average value demonstrates how effective neuron network technologies are in solving this type of problem when compared to alternative approaches. Two different types of artificial neural networks (ANNs) are used in this study's Wi-Fi-fingerprinting localization system to estimate location[20]. These ANNs include generalized regression neural networks (GRNN) and feedforward backpropagation neural networks (FFBP). The working area of approximately 37 × 32 m² with 17 Aps. Both varieties of neural networks accomplish modelling tasks satisfactorily. The findings show that FFBP neural networks perform better than GRNN in terms of structural simplicity, nonetheless. However, GRNN produces more accurate predictions, with an average distance inaccuracy of up to 0.48 meters. Despite obtaining good accuracy in this study, it has a high cost due to the use of many access points in the workspace.

In this study [21], deep learning was utilized to increase the accuracy of location prediction for ANN-based indoor localization systems as well as to estimate the distance between wireless nodes. The ANN-based one uses noise, temperature, and humidity in addition to RSSI measurements to determine the distance and location. Since WSN have limited capabilities, this method is considered expensive in terms of the time complexity.

In [22], a CNN-based target-localization method using RSSI data as inputs was suggested. The intricacy of the online estimating stage was

Table 1. Frequently used symbols

Symbol	Definition
Pr	RSSI value at reference distance d_0
$RSSI$	Received Signal Strength Indicators
n	Attenuation factor
$X\sigma$	A normal distribution with zero-mean and σ^2 variance for random shadowing effects.
σ	Spread constant
W_{ij}	The weights between the input and pattern layers
P_i	The i th hidden neuron's output
D_i	The Euclidean distance between the input vector and training (learning) samples
X	Input (RSSI vector)
Y	Output estimation coordinates
n	Number of RSS samples
$V_i(t)$	The velocity of particle
$X_i(t)$	Particle's position
ω	The inertia factor
C_1 and C_2	Acceleration coefficients
r_1 and r_2	Random numbers that are uniformly distributed between [0, 1]
t	The current number of iterations
\dot{x} and \dot{y}	The speed in x and y directions respectively at t time instance
dt	Discretization time step
x	The actual target coordinate value
\hat{x}	The estimation coordinate value for unknown nodes
$RMSE$	The root-mean-square error
ALE	Average Localization Error

successfully transferred to an offline training stage. The proposed method produced localization accuracy of 2 m. For localization using the deployed APs, thousands of RSSI fingerprints with entries for a 12.5 m 10 m region were used. By applying SVM, KNN, and CNN-based techniques, respectively, the average localization errors produced with the suggested fingerprint-based methodology were 4.1145 m, 4.1681 m, and 3.9118 m.

The main disadvantage of target L&T methods that use CNN is the time-consuming process of fine-tuning the CNN hyper-parameters, including the activation function, threshold, and learning rate.

The received signal strength indicator (RSSI) of Wi-Fi signals is used in this study [23] work to assess the localization of indoor environments. To precisely determine indoor placements, the paper offers a closest neighbor-based method that makes use of RSS measurements. The suggested method produced an average localization error of 2.2 meters by combining mobile fingerprinting and semi-supervised learning techniques. 193 access points (APs) were used throughout the studies, which took

place in a 47 m by 36 m space, and 283 test data points were used to analyse their results.

Utilizing an LSTM-based model is an alternative and often used technique for indoor position assessment. The researchers used received signal strength (RSS) variations between nearby reference in the study [24], with a step size of 3 meters. This was carried out to lessen the volatility of RSS over time within a 113 by 43-meter indoor space. A positioning inaccuracy of 3.57 meters was achieved by using LSTM networks with a lag size of 4.

3. Log-normal shadowing model and a hybrid PSO-GRNN

3.1 Log-normal shadowing model

The signal is influenced by the channel environment after it has passed via a wireless channel. Therefore, a specific model must be used to describe the channel to estimate the variables that influence the received signal strength. The two-ray, free-space, and LNSM models are three well-known propagation models for calculating such parameters. For WSN applications, LNSM is the best model due to its universality and environment-based configuration. RSSI amounts are measurements as per the log-normal shadow fading model [21].

$$RSSI = Pr(d_0) - 10n \log\left(\frac{d}{d_0}\right) + X\sigma \quad (1)$$

Where Pr is RSSI evaluated at the reference distance receiver node d_0 1m from the transmitter, n is the attenuation factor, $X\sigma$ is a typical random variable (a measurement of the shadowing effect that often falls between 3 and 20 dBm). In this study, the parameters are selected so that $X \sim (3,1)$ with a difference of 3 dBm and 1 dBm as a standard deviation value. The mathematical symbols used frequently in this paper are summarized in Table 1.

3.2 Generalized regression neural network

A probabilistic model roughly linked to RBNN is GRNN, which was introduced by Specht in 1991 [25]. Although GRNN typically needs more neurons, design time is drastically reduced. The spread constant (σ), a single parameter used in GRNN optimization, must be determined. GRNN provides a quick and reliable method in contrast to iterative procedures [2]. When building the GRNN model, choosing the spread constant (σ) is an important step. A suitable value must be selected to get the desired

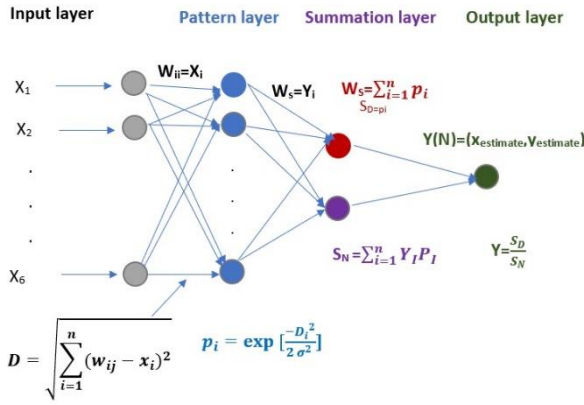


Figure. 1 GRNN structure

training results. In this study, the RSSI values of signals obtained from the anchor nodes at a specific point in time are utilized as inputs for the GRNN, and the expected x and y coordinates of the mobile node at that time are the GRNN architecture's output, as shown in Fig. 1, the GRNN architecture consists of four parts.

1. The input layer is where the initial data that will be transmitted to the following layer is received.
2. Pattern layer, or hidden layer: In this layer, there are exactly as many hidden neurons as there are learning samples. One learning sample is represented by each hidden neuron. The input values from the input layer are subjected to a radial basis function, such as a Gaussian transformation function denoted by Eqs. (2) and (3). The input parameters are represented by the weights (W_{ij}) between the input and pattern layers. The distance between the input data and the patterns that have been saved is represented by the output of the pattern layer, which is entirely connected to the third layer.

$$p_i = \exp \left[\frac{-D_i^2}{2\sigma^2} \right], i=1, 2, \dots, n \quad (2)$$

$$D_i^2 = (X - X_i)^T (X - X_i) \quad (3)$$

Where P_i denotes the i th hidden neuron's output, σ denotes the spread-constant, X for the network's input (RSSI vector), x_i for the i th neuron's learning sample, and D_i stands for the Euclidean distance between the training (learning) samples and the input vector.

3. Each hidden neuron is completely connected to the layer known as the summation layer. There are two distinct summation types in it:

- The S-summation neuron, which calculates the total of the pattern layer's weighted outputs.
- The D-summation neuron, which controls the pattern neurons' unweighted outputs.

The connection weight (W_s) between the i th hidden neuron and the S-summation neuron is the value of the target output Y_i , which equates to the i th input value.

4. Output layer: In this layer, the projected result is obtained by dividing the output of the S-summation neuron (S_N) by the output of the D-summation neuron (S_D), as shown in Eqs. (4) and (5).

$$S_N = \sum_{i=1}^n y_i p_i \quad (4)$$

$$S_D = \sum_{i=1}^n p_i \quad (5)$$

The fixed anchor node's locations, AN1, AN2, AN3, AN4, AN5 and AN6 were placed in the working area. A mobile node (target) is moving. The target node collected the RSSI values from each of the six anchor nodes. The RSSI values gathered at the target node were subsequently used for both training and testing the GRNN algorithm, to identify the location and track the target node.

Eq. (6) can be used to express the GRNN's input and output for an indoor environment. In the given equations, $RSSI_{ij}$ refers to the RSSI value of the j th anchor for the i th sample, (x_i, y_i) indicates the precise position of the target node, and n denotes the aggregate number of samples.

$$Input = \begin{bmatrix} RSSI_{11} & RSSI_{12} & RSSI_{13} & RSSI_{14} & RSSI_{15} & RSSI_{16} \\ RSSI_{21} & RSSI_{22} & RSSI_{23} & RSSI_{24} & RSSI_{25} & RSSI_{26} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ RSSI_{n1} & RSSI_{n2} & RSSI_{n3} & RSSI_{n4} & RSSI_{n5} & RSSI_{n6} \end{bmatrix}, \quad Output = \begin{bmatrix} (x_1, y_1) \\ (x_2, y_2) \\ \vdots \\ (x_n, y_n) \end{bmatrix} \quad (6)$$

3.3 PSO Algorithm

James Kennedy and Russell Eberhart introduced the evolutionary computation technique particle swarm optimization (PSO) in 1995 [26]. It is a population-based stochastic technique that works well for resolving issues with nonlinear global optimization [27]. The algorithm begins by initializing a collection of random particles and then iteratively seeks the best solution. Each particle records its best position in each iteration, known as the personal best (pbest), while the entire swarm records the best position for the entire group, known

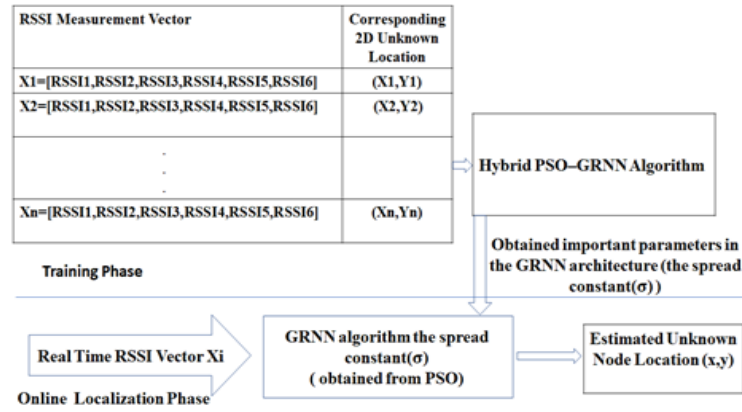


Figure. 2 Block Diagram of the hybrid PSO-GRNN algorithm.

as the global best (gbest). Each particle updates its position in the search space according to its current velocity, the distances to pbest and gbest, and its current position. The swarm is directed toward the ideal solution by this iterative process.

$$V_i(t + 1) = \omega V_i(t) + C_1 r_1 [pbest_i(t) - x_i(t)] + C_2 r_2 [gbest(t) - X_i(t)] \quad (7)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (8)$$

The velocity of particle *i* in the *i*th iteration is indicated as $V_i(t)$, and its position in the same iteration is denoted as $X_i(t)$. The algorithm updates each particle's position and velocity using several factors. These variables consist of:

- ω : The inertia factor, or omega, controls how much a particle's former velocity affects its present velocity.
- C_1 and C_2 : Acceleration coefficients that control the influence of the particle's personal best (pbest) and the global best (gbest) on its velocity.
- r_1 and r_2 : Two random constriction coefficients in the range (0,1), used to introduce randomness into the algorithm.
- t : The current number of iterations.

The velocity and position updates are performed based on mathematical equations that consider these parameters and the particle's previous velocity and position as in Eqs. (7) and (8). According to [28] the values of $c_1 = c_2 = 1.494$ and $\omega = 0.7$ were chosen after conducting experimental testing to obtain faster convergence. The PSO method keeps updating until the predetermined maximum number of iterations, t_{max} is achieved or an acceptable global best (gbest) solution is obtained. The number of iterations is specified as 100. The PSO method uses the root-

mean-square error (RMSE) [29] as a fitness function, as indicated in the following equation:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x - \hat{x})^2} \quad (9)$$

Where x is the actual target coordinate value and \hat{x} is the estimation coordinate value for unknown nodes and n is the number of RSSI samples.

3.4 Proposed Hybrid PSO-GRNN algorithm

The GRNN algorithm can be applied within a WSN to ascertain the position of a mobile node. The RSSI values are leveraged as inputs for the GRNN algorithm, aiding in the determination and tracking of the target node's location. A key component of the GRNN setup is the spread constant (σ). The conventional method of choosing this parameter involves trial and error, a process that poses risks and doesn't necessarily yield the best outcome. The PSO method mitigates this issue by finding the optimal value for the GRNN spread constant, thereby potentially enhancing GRNN's performance. In this context, the integration of PSO and GRNN forms a "hybrid PSO-GRNN algorithm," enabling the GRNN to achieve the lowest possible location error. Fig. 2 shows the mechanism of the hybrid method.

Because the PSO's operating time generally rises with the swarm size (particles' number), the swarm size is specified at 20. The MATLAB program implements the PSO method. In this technique, each particle consists of a single element called a spread constant. The spread constant value was acquired from the training phase. Employed in the online localization phase to reduce the mobile node's localization error. The suggested hybrid PSO-GRNN algorithm's flow chart is shown in Fig. 3, and it may be utilized to increase the precision of mobile node location estimates.

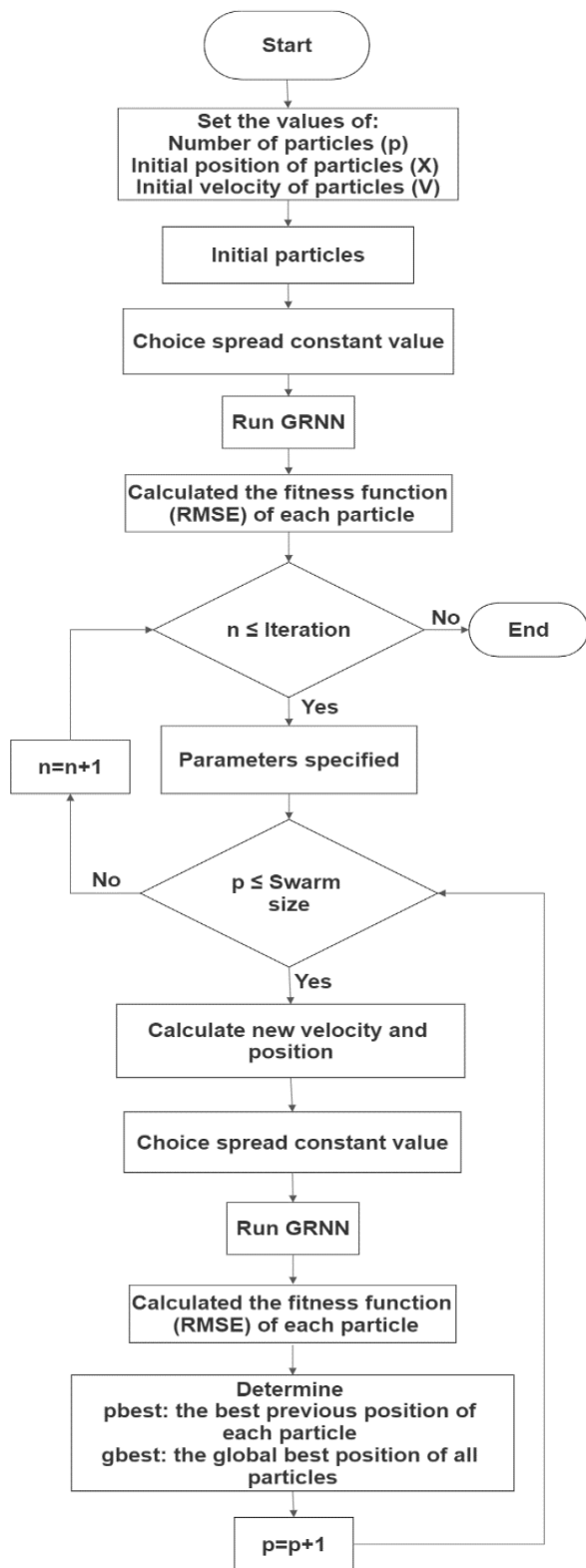


Figure. 3 Flowchart of the hybrid PSO-GRNN algorithm

A statistical study is carried out utilizing root mean square error (RMSE) and average localization error (ALE) to evaluate the LNSMs and proposed method accuracy. The Hybrid PSO-GRNN technique, which is covered in this section, is compared to the

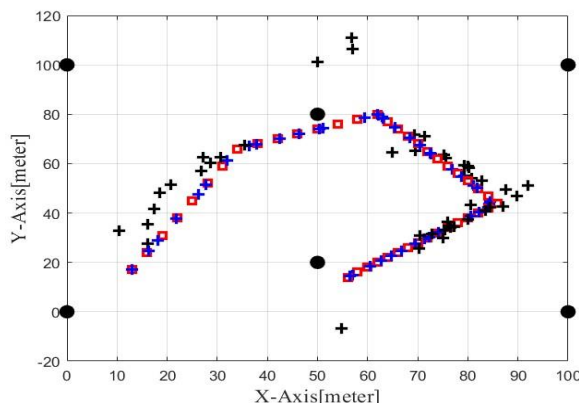


Figure. 4 Actual and target estimated by the Traditional RSSI, PSO+GRNN

classic LNSM method's error metrics. The LNSM technique does not fulfil the accuracy requirements, particularly in an interior environment. As a result, the Hybrid PSO-GRNN algorithm is presented to improve the precision of localization and tracking, as described in more depth in the following section.

$$ALE = \frac{1}{t} \sum_{i=1}^t \frac{(\hat{x}_i - x_i) + (\hat{y}_i - y_i)}{2} \tag{10}$$

4. Results and discussion

The proposed system comprises a group of anchor nodes that are placed within a simulated region that is 100 meters by 100 meters making up the proposed system. Fig. 4 shows a movable target with a wireless sensor node attached, while an external base station (not visible in the image) is situated outside the simulation region. At each time step (t), the anchor nodes broadcast RF signals, which are picked up by the mobile target, which acts as a transceiver. In each time step, the RSSI readings gathered from each anchor node are sent to a base station outside the simulation area. The base station is linked to a laptop that meets the following requirements: Using a Core i7, 2.3 GHz, 8GB RAM, a variety of analytic algorithms, such as the conventional RSSI and a hybrid PSO-GRNN, are executed. This scenario is similar to a scenario in [2] to compare the results and verify the accuracy of the proposed algorithm.

The literature has already described a range of state mobility models. In this study, we opt for a model with constant velocity. The following equations are used in this study to define the motion of the mobile target.

$$x_t = x_{t-1} + \dot{x}_t dt \tag{10}$$

$$y_t = y_{t-1} + \dot{y}_t dt \tag{11}$$

Table 2. The parameters of a hybrid PSO-GRNN and the LNSM

Symbol	Parameter	Value
X_0	Initial Target State at t-0	[10 10]
dt	Discretization time step	1s
F	Frequency of operation	2.4 GHz
$X \sigma$	Normal Random Variable	$\sim N(3, 1)$
η	Path Loss Exponent	3.4
σ	Spread Factor	2.1001

(obtained from PSO)

Table 3. Selection of best Smoothing Parameter (σ) determined by PSO+GRNN

Localization and Tracking Algorithm	Swarms numbers			
	20	40	50	60
σ	2.1001	0.3578	2.3131	1.9711
RMSR of Trad.RSSI	13.08	13.95	11.63	13.27
RMSR of PSO+GRNN	1.624	2.452	1.715	2.158

where x_t and y_t specify the position. \dot{x} and \dot{y} the speed in x and y directions respectively at t time instance, and the time elapsed between two subsequent time instants is denoted by the discretization time step (dt).

Therefore, the parameters of a hybrid PSO-GRNN and the LNSM can be gained as shown in Table 2.

The research is conducted in two phases (the training phase and the online localization phase), as was previously described. Run a hybrid PSO-GRNN to determine the ideal value before the online localization analysis phase to determine the wireless scenario.

To gain fitness function for 20, 40, 50, and 60 swarms, the PSO-GRNN algorithm will be run as shown in Table 3 via the parameter settings for PSO that are covered in Part 3.3 of the log-normal shadowing model and a hybrid PSO-GRNN. To enable the algorithm PSO to choose the swarms that can accomplish the least errors and elapsed time, several swarms are implemented. Table 3 demonstrates that 20 swarms offer the PSO-GRNN algorithm's optimum answer since they obtain a fitness function of approximately 1.624 m when σ equal to 2.1001.

The online localization phase is processed within the identical network parameters as the training phase, using the best value (σ) ascertained from the training process. Fig. 4 portrays the target paths deduced by both traditional RSSI and PSO-GRNN methodologies. Anchor nodes are designated by black circles, while the true target position is marked

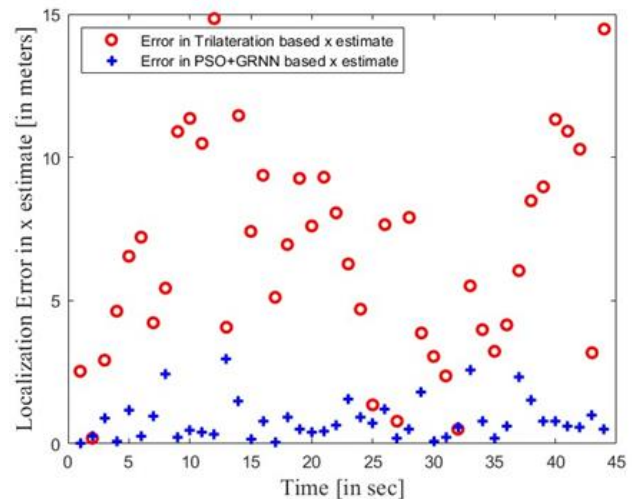


Figure. 5 Localization Errors in x estimates in Traditional RSSI, and PSO+GRNN

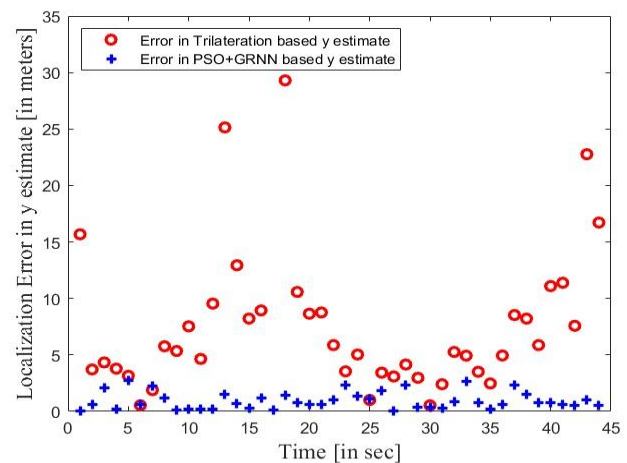


Figure. 6 Localization Errors in y estimates in Traditional RSSI, and PSO+GRNN.

by red squares. The black and blue plus signs, respectively, signify the estimated positions derived from RSSI and PSO-GRNN at a given time instance t . The simulation data demonstrate that the PSO+GRNN-derived approach holds an advantage over RSSI in matters of localization and tracking efficiency. The mean localization errors for traditional RSSI and PSO-GRNN are 7.4513 and 0.8854, respectively, providing evidence for the PSO-GRNN framework's capability to address real-time target tracking problems in WSN using RSSI. In comparison, the suggested approach provides a remarkable improvement of 87.58% over the typical RSSI method. Given the RMSE values for the algorithms change for each run due to the parameter normal random variable $X\sigma$ in Eq. (1), RSSI values are simulated in MATLAB using the log-normal shadow fading model.

Table. 4 Comparison error analysis of the hybrid PSO-GRNN algorithms with previous works

No.	Ref	Location technology algorithm	ANN type or learning framework	Metric	Environment	Tested area	Average localization error	RMSE
1	[5]	MATLAB simulation	SVR	RSSI	Indoor	100mx100m	3.92	5.75
2	[1]	APs	LSTM	RSSI	Indoor	20mx29m	/	1.73
3	[2]	MATLAB simulation	GRNN	RSSI	Indoor	100mx100m	4.74	5.35
4	[21]	MATLAB simulation	deep learning	RSSI	Indoor	9 m x 9 m	< 1.74	/
5	[22]	APs	CNN	RSSI	Indoor	12. m x10m	3.91	/
6	[23]	APs	semi-supervised learning	RSSI	Indoor	113. m x43m	2.2	/
7	[24]	APs	LSTM	RSSI	Indoor	113mx43m	/	3.57
8	PSO-GRNN (Proposed Method)	MATLAB simulation	PSO+GRNN	RSSI	Indoor	100mx100m	0.88	1.62

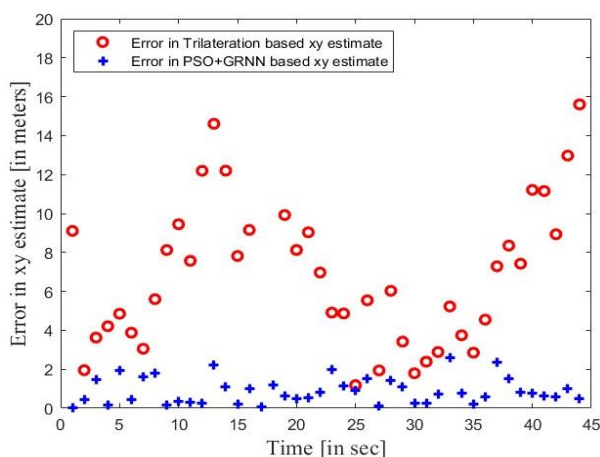


Figure.7 Localization errors in x-y estimates in Traditional RSSI, and PSO+GRNN

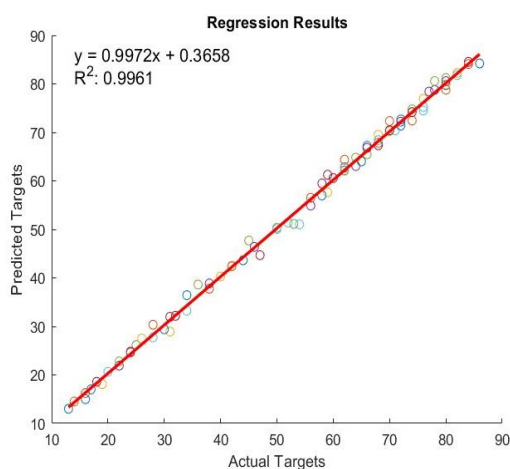


Figure. 8 Performance of the hybrid PSO-GRNN

Through the simulation results, it was found that the proposed method is superior to the search results

in [2], as the root mean square error is equal to 5.3517 and average localization error equal to 4.7437, while in our research root mean square error and average localization error equal to 1.624 and 0.885 respectively. The comparison of localization errors for the x and y estimates, using each of the above-mentioned methods, is displayed in Fig. 5 and 6, respectively. The average performance for both the x and y estimates is ascertained through Eq. (10), and this is depicted in Fig. 7, which considers the average of the errors in the x and y estimates.

The regression coefficient (R) of determination between the real and predictable position is a useful metric to examine the hybrid PSO-GRNN algorithm's prediction capabilities as shown in Fig. 8. The R values of 0.9961 indicate a good agreement between the estimated and real location.

Comparison of the proposed hybrid PSO-GRNN algorithm's performance in terms of WSN localization with that of earlier studies' algorithms, as shown in Table 4.

5. Conclusion

This study proposed two approaches for indoor localization and tracking estimation in WSNs. The first method uses a traditional LNSM approach, while the second uses a hybrid PSO-GRNN algorithm. The GRNN algorithm was improved by combining the PSO and GRNN algorithms to select the optimum value of the spread constant (σ), so it improves localization accuracy. The performance of the traditional LNSM-based method is compared with the hybrid PSO-GRNN algorithm as well as the

algorithm used in earlier studies. Comparing the results shows that the hybrid PSO-GRNN algorithm achieves significantly better MAE and RMSE scores than the traditional LNSM method, which exhibits significant localization errors. The mean localization errors and the root mean square error for PSO-GRNN are 0.8854 and 1.624 respectively, the suggested approach provides a remarkable improvement of 87.58% over the traditional RSSI method. Furthermore, the hybrid PSO-GRNN algorithm outperforms analogous systems when considering the average error in localization. Therefore, the hybrid PSO-GRNNs, especially indoors, provide a practical and effective solution for locating and tracking both mobile and stationary nodes in WSNs.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, S.M.T and I.S. Al-Mejibli; methodology, S.M.T and I.S. Al-Mejibli; software, S.M.T; validation, S.M.T and I.S. Al-Mejibli; formal analysis, S.M.T; investigation, S.M.T and I.S. Al-Mejibli; resources, S.M.T; data curation, S.M.T; writing—original draft preparation, S.M.T; writing—review and editing, I.S. Al-Mejibli; visualization, S.M.T; supervision, I.S. Al-Mejibli; project administration, S.M.T and I.S. Al-Mejibli; funding acquisition, S.M.T

References

- [1] M. Z. Karakusak, H. Kivrak, H. F. Ates, and M. K. Ozdemir, "RSS-Based Wireless LAN Indoor Localization and Tracking Using Deep Architectures", *Big Data and Cognitive Computing*, Vol. 6, No. 3, p. 84, 2022.
- [2] S. R. Jondhale and R. S. Deshpande, "Kalman Filtering Framework-Based Real Time Target Tracking in Wireless Sensor Networks Using Generalized Regression Neural Networks", *IEEE Sensors Journal*, Vol. 19, No. 1, pp. 224–233, 2019.
- [3] V. Garg and M. Jhamb, "A Review of Wireless Sensor Network on Localization Techniques", *International Journal of Engineering Trends and Technology*, Vol. 4, No. 4, pp. 1049-1053, 2013.
- [4] N. A. Alrajeh, M. Bashir, and B. Shams, "Localization techniques in wireless sensor networks", *International Journal of Distributed Sensor Networks*, Vol. 9, No. 6, p. 304628, 2013.
- [5] J. P. Molla, D. Dhabliya, S. R. Jondhale, S. S. Arumugam, A. S. Rajawat, S. B. Goyal, M. S. Raboaca, T. C. Mihaltan, C. Verma, and G. Suci, "Energy Efficient Received Signal Strength-Based Target Localization and Tracking Using Support Vector Regression", *Energies*, Vol. 16, No. 1, p. 555, 2023.
- [6] S. Kumar and D. K. Lobiya, "An advanced DV-Hop localization algorithm for wireless sensor networks", *Wirel Pers Commun*, Vol. 71, No. 2, pp. 1365–1385, 2013.
- [7] H. Obeidat, W. Shuaieb, O. Obeidat, and R. A. Alhameed, "A Review of Indoor Localization Techniques and Wireless Technologies", *Wireless Personal Communications*, Vol. 119, No. 1, pp. 289–327, 2021.
- [8] V. İlçi, E. Güllal, and R. M. Alkan, "An investigation of different Wi-Fi signal behaviours and their effects on indoor positioning accuracy", *Survey Review*, Vol. 50, No. 362, pp. 404–411, 2018.
- [9] Y. Zhuang, J. Yang, Y. Li, L. Qi, and N. E. Sheimy, "Smartphone-based indoor localization with bluetooth low energy beacons", *Sensors*, Vol. 16, No. 5, p. 596, 2016.
- [10] Y. Shi, W. Shi, X. Liu, and X. Xiao, "An RSSI classification and tracing algorithm to improve trilateration-based positioning", *Sensors*, Vol. 20, No. 15, p. 4244, 2020.
- [11] Q. Luo, K. Yang, X. Yan, J. Li, C. Wang, and Z. Zhou, "An Improved Trilateration Positioning Algorithm with Anchor Node Combination and K-Means Clustering", *Sensors*, Vol. 22, No. 16, p. 6085, 2022.
- [12] S. Kumar, R. Sharma and E. R. Vans "Localization for Wireless Sensor Networks: A Neural Network Approach", *International Journal of Computer Networks & Communications*, Vol. 8, No. 1, pp. 61–71, 2016.
- [13] Y. Xu, J. Zhou, and P. Zhang, "RSS-based source localization when path-loss model parameters are unknown", *IEEE Communications Letters*, Vol. 18, No. 6, pp. 1055–1058, 2014.
- [14] S. Sinha and S. Ashwini, "RSSI based improved weighted centroid localization algorithm in WSN", In: *Proc. of International Conference for Emerging Technology*, Belagavi, India, pp. 1-4, 2021.
- [15] C. Zhao and B. Wang, "A MLE-PSO indoor localization algorithm based on RSSI", In: *Proc. of Chinese Control Conference*, Dalian, China, pp. 6011–6015, 2017.
- [16] S. R. Jondhale and R. S. Deshpande, "GRNN and KF framework based real time target

- tracking using PSOC BLE and smartphone”, *Ad Hoc Networks*, Vol. 84, pp. 19–28, 2019.
- [17] J. Luomala and I. Hakala, “Adaptive range-based localization algorithm based on trilateration and reference node selection for outdoor wireless sensor networks”, *Computer Networks*, Vol. 210, p. 108865, 2022.
- [18] S. S. Mohar, S. Goyal, and R. Kaur, “Localization of sensor nodes in wireless sensor networks using bat optimization algorithm with enhanced exploration and exploitation characteristics”, *Journal of Supercomputing*, Vol. 78, No. 9, pp. 11975–12023, 2022.
- [19] A. Gadhgadhi, Y. Hachaichi, and H. Zairi, “A Machine Learning based Indoor Localization”, In: *Proc. of International Conference on Advanced Systems and Emergent Technologies*, Hammamet, Tunisia, pp. 33-38, 2020.
- [20] B. Sulaiman, E. Natsheh, and S. Tarapiah, “Towards a better indoor positioning system: A location estimation process using artificial neural networks based on a semi-interpolated database”, *Pervasive Mobile Computing*, Vol. 81, p. 101548, 2022.
- [21] A. Guidara, G. Fersi, M. B. Jemaa, and F. Derbel, “A new deep learning-based distance and position estimation model for range-based indoor localization systems”, *Ad Hoc Networks*, Vol. 114, p. 102445, 2021.
- [22] Z. Liu, B. Dai, X. Wan, and X. Li, “Hybrid wireless fingerprint indoor localization method based on a convolutional neural network”, *Sensors*, Vol. 19, No. 20, p. 4597, 2019.
- [23] J. Yoo and J. Park, “Indoor localization based on wi-fi received signal strength indicators: Feature extraction, mobile fingerprinting, and trajectory learning”, *Applied Sciences*, Vol. 9, No. 18, p. 3930, 2019.
- [24] X. Yang, D. Chen, J. Huai, X. Cao, and Y. Zhuang, “An improved wireless positioning algorithm based on the LSTM network”, In: *China Satellite Navigation Conference Proceedings*, Volume 2, pp. 616–627, 2021.
- [25] S. Chen, C. F. N. Cowan, and P. M. Grant, “Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks”, *IEEE Transactions ON Neural Networks*, Vol. 2, No. 2 pp. 302-309. 1991.
- [26] A. O. D. Sá, N. Nedjah, and L. D. M. Mourelle, “Distributed efficient localization in swarm robotics using Min-Max and Particle Swarm Optimization”, *Expert Systems with Applications*, Vol. 50, pp. 55-65, 2016.
- [27] S. K. Gharghan, R. Nordin, and M. Ismail, “A wireless sensor network with soft computing localization techniques for track cycling applications”, *Sensors*, Vol. 16, No. 8, p. 1043, 2016.
- [28] M. A. E. Shorbagy and A. E. Hassanien, “Particle Swarm Optimization from Theory to Applications”, *International Journal of Rough Sets and Data Analysis*, Vol. 5, No. 2, pp. 1–24, 2018.
- [29] B. Sulaiman, E. Natsheh, and S. Tarapiah, “Towards a better indoor positioning system: A location estimation process using artificial neural networks based on a semi-interpolated database”, *Pervasive and Mobile Computing*, Vol. 81, p. 101548, 2022.