The Hybrid NPO-GRNN Method for Real-Time Multi-Target Localization and Tracking in WSN Utilizing the Kalman Filter

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Abstract

This study aims to determine the location and track of sensor nodes in indoor spaces. The challenge of significant estimation errors in target position brought on by erratic noise in received signal strength indicator (RSSI) readings is a major area of current research focus, especially in interior conditions. In place of the traditional RSSI-based approach, this study suggested a hybrid technology called Nomadic People Optimizer-Generalized Regression Neural Network (NPO-GRNN) to increase the sensor nodes' capacity to estimate location and target tracking with more accuracy. The RSSI values can be used by the GRNN method as start data to determine and trace the target node's location. The spread constant (σ) is a crucial part of the GRNN architecture. To choose the spread constant (σ), an insecure and sometimes unreliable method by trial and error is employed. The ideal GRNN spread constant is found using the NPO approach. To get around these problems and improve L & T tracking precision without the need for additional equipment, the hybrid NPO-GRNN method was employed, and these coordinates were refined using a Kalman filter to increase accuracy. Impressive results were obtained by the tracking algorithm NPO-GRNN-UKF hybrid, which performed better than the traditional LNSM approach. By comparing the suggested approach to the traditional RSSI, a significant 98.4% and 98.1% for targets 1 & 2, respectively, gain can be achieved.

Keywords- RSSI, GRNN, NPO, Target Tracking, Indoor localization, Trilateration.

I. INTRODUCTION

Wireless networks can be broadly categorized into infrastructure networks and infrastructureless networks. Infrastructure networks comprise wireless nodes connected to a network backbone, whereas infrastructure-less networks consist of distributed, independent, dynamic topology, low-power wireless nodes designed for specific tasks. Cellular wireless networks fall into the infrastructure network category, while ad-hoc networks and wireless sensor networks (WSNs) fall into the infrastructure-less network category[1].
In ad hoc mode, wireless devices seamlessly integrate and communicate with each other by establishing dynamic wireless links. These networks often combine features from both infrastructure and infrastructure-less networks, forming a hybrid wireless network (HWN). WSNs are comprised of hundreds or thousands of wireless nodes scattered across a geographic area in an ad hoc manner[2]. These nodes collaborate to sense various physical phenomena, and the collected data is processed to yield meaningful results. A crucial role of sensor networks is to gather and transmit data to a destination, making it imperative to accurately determine the location of this data[3]. This vital information can be acquired through localization techniques in wireless sensor networks (WSNs), which involve methods to pinpoint the precise location of sensor nodes.
In a target tracking system based on WSNs, two categories of sensor nodes are employed: anchor nodes, also known as Reference nodes and non-anchor nodes. Typically, anchor nodes are strategically placed at known locations, while the positions of non-anchor nodes remain unknown. It is assumed that the moving target carries a non-anchor node. The positions of the target, as it moves, are determined by utilizing anchor nodes and facilitating internode communications.
Knowing the location of sensor data is crucial. Sensor nodes may need to locate a target or source, even when unaware of their positions. Localization involves determining the target's location using interactions between the target and other sensor nodes with known positions. Indoor localization presents distinct challenges compared to outdoor GPS-based methods. Classic GPS technique is

extremely useful for an outdoor environment; however, it is not useful for an indoor environment because buildings/obstacles block radio signals, high cost, and energy consumption [4], [5].

The Received Signal Strength Indicator (RSSI) is a cost-effective and energy-efficient method compared to other range-based techniques; it suffers from inaccuracies. This is primarily due to signal amplitude fluctuations caused by various factors like shadowing, path loss, and multipath effects.

Due to the presence of interference and the unpredictable nature of signal propagation in wireless channels, the accuracy of position estimates generated by localization algorithms is influenced. These phenomena introduce signal fluctuations that have an impact on the calculation of the location. It became imperative to develop a model that could deliver both high accuracy and rapid real-time responses without causing a surge in power consumption. The objective of this study is to develop localization and tracking for single and multi-target models that are robust against node mobility, multipath effects, signal attenuation, and environmental changes. So, this paper presents a new algorithm for localization and tracking based on NPO-GRNN to get coordinates of unknown node locations and refine these coordinates using the Kalman filter to enhance accuracy.

II. RELATED WORKS

According to Abdou et al. [6], To improve indoor localization accuracy, the author developed a Support Vector Regression (SVR) and Affinity propagation indoor localization system that takes into account the direction of mobile devices. Affinity propagation was used to decrease the computational cost. To prevent selecting the incorrect cluster during the online matching stage, various matching strategies were employed. Additionally, the strong APs approach was utilized to lessen weak APs and their effects and to lower the size of the training input space. The experimental results have demonstrated that SVR improves indoor localization accuracy due to its capacity to generalize, particularly with a limited number of training data. The disadvantage of Affinity Propagation is that you are not required to predetermine the number of clusters, even if this can occasionally be useful. This may also be a drawback because the method may generate an unanticipated or unsatisfactory number of clusters.

In [7], Using RSSI, this work suggests a range-free localization technique based on the fuzzy centroid methodology. When mobile anchor nodes exchange beacons and gather distance versus RSSI data during the training phase, we can estimate distance by comparing it to the received signal strength. The location of the unknown sensor nodes, or anchor nodes, will be the center of a circle that shows the maximum RSSI for the unknown nodes, and the radius will represent the estimated distance mapped for that RSSI.

The Centroid approach is used to approximate the location of unknown nodes, with the change in fuzzy logic-based goal functions being used to weigh the reference anchor nodes' location. Signal power and RSSI are the fuzzy system's inputs. The center point of the perpendicular bisector drawn from the previously drawn circle to the roughly estimated position is the final location of the unknown nodes.

Jondhale et al.[8] To tackle the complexities posed by dynamic RF channels and the nonlinear system dynamics inherent in indoor Localization and Tracking (L&T) of mobile targets, this study introduces an improved architecture referred to as the Trilateration Centroid Generalized Regression Neural Network (TCGRNN). Solving the challenge of indoor L&T for mobile targets necessitates addressing the issues arising from dynamic RF channels and nonlinear system dynamics. During simulations, the parameter representing the normal random variable in the LNSM path loss model is systematically varied from 3 to 9 dB in 3 dB increments to simulate the uncertainty associated with RSSI measurement noise. Despite the good results, the calculations were complicated by finding the coordinates using the Trilateration and Centroid methods and adding them to the RSSI as inputs to GRNN

This study[9] proposed a hybrid strategy called Particle Swarm Optimization- Generalized Regression Neural Network (PSO+GRNN) to boost the sensor nodes' capacity to forecast location and target tracking with better accuracy, as a substitute to the classic RSSI-based approach. The GRNN technique can locate and trace the target node using the RSSI values as start data. The spread constant (σ) is an important part of the GRNN architecture. The PSO method finds the best value (σ) of the GRNN. PSO-GRNN, a hybrid tracking algorithm, produced impressive results by outperforming the conventional LNSM method. An 87.58% gain is noteworthy when comparing the proposed method to the classic RSSI. Although the GRNN offers a reliable initial estimate, it might not adequately represent the dynamic nature of the localization process, particularly when noise and uncertainty are present.

In another study [10], This paper presents a unique localization technique that integrates 5G signals with natural geomagnetic signals using a multi input convolutional neural network (Multi-CNN). To create location fingerprint data, preprocessing is first conducted separately to the channel state information (CSI) and geomagnetic three-component data. After that, to successfully extract pertinent data features, the reconstructed CSI amplitude and geomagnetic intensity go through independent offline training. In the end, the user's location is estimated in real time using the Multi-CNN model. We find that the Multi-CNN method achieves average localization precision of 1.4 meters and 2.6 meters, respectively, when localizing users within a conference room and a hall. These accuracies are higher than those of weighted K-nearest neighbor algorithms by 34% and 28%, single input CNN methods by 21% and 15%, and Back Propagation Neural Network (BPNN) techniques by 24% and 17%. The suggested Multi-CNN-based localization method successfully combines several data sources, which may make it appropriate for a range of indoor localization uses.

In [11], This work integrates numerous machine learning techniques with the triangulation approach. techniques (naïve Bayes, logistic regression, K-nearest neighbors (K-nn), artificial neural networks, and support vector machines) to suggest a hybrid indoor localization approach based on Bluetooth low energy. Three distinct scenarios are used to test the improved model. The suggested model shows far lower error rates in hard environments when compared to either individual triangulation or standalone machine learning models, but it performs similarly to the standalone triangulation approach in easy and medium cases, according to the results. Based on accuracy measures, K-nearest neighbor (k-nn) and logistic regression (LR) show out as the best models for easy instances, whereas k-nn consistently performs best in medium and hard cases. Nevertheless, k-nn is considered inappropriate for real-time streaming data because it depends on a training set for every prediction. Because LR works well with streaming data, it has been chosen for real-time prediction, even though it is the second-best algorithm in all environments.

III. Proposed System

A. LNSM based on RSSI

The RSSI measurements are primarily a result of specific propagation models. Presently, the most widely used propagation models include the free space model, the two-ray ground reflection model, and the log-normal shadowing model (LNSM) [12]. The free space and two-ray models offer deterministic predictions of received power based on distance, assuming an ideal circular relationship between the transmitter and receiver.
However, in practice, received power at a given distance is subject to random variability due to multipath fading effects. Given its consideration of fading effects, the LNSM has gained broader acceptance within the research community[13]. This Dissertation adopts the LNSM for its analysis.

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

Where n is the attenuation factor, Xσ is a random variable, and Pr is the RSSI evaluated at the reference distance receiver node d0 1m from the transmitter. The path-loss exponent n values usually range from 1 to 3 in outdoor settings and from 3 to 5 indoors [14], [15], [16].

Trilateration localization involves the process of distance measurement and position estimation based on geometric relationships. Distance can be determined from RSSI data using a propagation model between anchor points and the receptor. The measured distance is then expressed in terms of the horizontal and vertical differences in the x and y coordinates between the anchor points

B. Generalized regression neural network

GRNN, a probabilistic model first presented by Specht in 1991 [17], is generally associated with RBNN. GRNNs normally require a larger number of neurons, but their design time is much shorter. It is necessary to ascertain the spread constant (σ), a single parameter employed in GRNN optimization. GRNN, as opposed to iterative processes, offers a fast and dependable alternative [18]. Selecting the spread constant (σ) is a crucial stage in the construction of the GRNN model. Selecting an appropriate value is necessary to achieve the intended training outcomes. The target node's predicted coordinates (x,y) at that moment are the GRNN architecture's output in this study, which uses the RSSI values received from the anchor nodes at that moment as inputs. as shown in Figure 1.

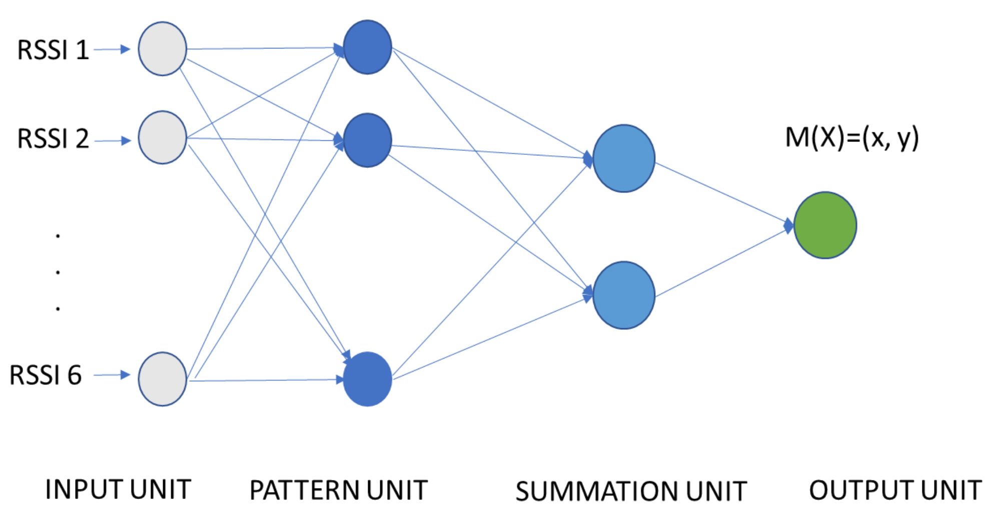

Figure 1: GRNN structure.

In summary, the propagation time through the multilayer network determines how quickly the GRNN can estimate values of M (dependent variables) for any new value of X (independent variables). The GRNN architecture is used in this study to address the target tracking issue. In this work, Mi is the estimated 2-D location of the moving target, and X, as seen in Fig. 1, represents six RSSI values from six anchor nodes. The sample values of M and X are denoted by the variables Mi and Xi. The estimate $M\ (X)$ is, as can be seen, the weighted average of all sample observations Mi, ith each observation's weight being the squared Euclidian distance between the sample X and sample Xi. Utilizing the suggested GRNN design, the 2-D Target Location, or $M\ (X)$, is estimated as follows [18]:

$$M(X) = \frac{\sum_{i=1}^{x} m_i . \exp\frac{-D_i^2}{2\,\sigma^2}}{\sum_{i=1}^{x} \exp\frac{-D_i^2}{2\,\sigma^2}} \quad (2)$$

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

The smoothing factor, denoted by σ, and the number of sample observations, or input vector dimension, is represented by x. Since six RSSI data are required as input for the created GRNN architecture, x=6 in this work. It is thought that choosing the appropriate smoothing factor has a significant impact on GRNN accuracy. As a result, choosing the right smoothing parameter value requires thought. Note that the estimate $M(X)$ is equal to the weighted average of all sample observations Mi, where the squared Euclidian distance between sample X and Xi is the weight for each observation. By scaling the input parameters, such as the standard deviation of all the input variables being equal, and selecting the appropriate sigma value, the compressive strength may be computed from GRNN. The ‖newgrnn' function in the MATLAB environment can be used to establish a GRNN network.

C. Nomadic People Optimizer

The movement and behavior of nomadic people in their pursuit of life-giving resources, including water or grass for grazing, served as the model for the Nomadic People Optimizer (NPO). The algorithm replicates how individuals on the move for hundreds of years have moved to the most hospitable and appropriate locations for their needs. Its design is predicated on the multi-swarm approach, in which every clan searches the algorithm for the optimal answer according to the standing of their leader. The Meeting Room Approach (MRA), which symbolizes clan contact and aids in striking a balance between exploration and exploitation, is another algorithmic component. Using several group members to attain its exploration capabilities sets NPO apart from other metaheuristics, which typically rely on a single mechanism connecting the global best solution and the entire swarm [19].

The NPO algorithm consists of these five primary processes:

1- Initial meeting

Groups of Leaders (σ), represented as σ= (σ1, σ2, σ 3,..., Clans), Using an Eq. 2 that considers the upper bound (UB) and lower bound (LB) of the search space in addition to a random value between 0 and 1, the positions of the leaders (σc) in each clan are initialized at random.

$$\sigma c = Rand * (UB - LB) + LB \quad (4)$$

2- Semi-circular distribution

The NPO algorithm distributes the families (represented by the set of families, x) around their leaders (represented by σ). The angle value establishes the points' placement within the circular pattern and provides the basis for their arrangement.

$$X = cos(\theta) * \left(\sqrt{R_1} * R_d\right) + X_0 \quad (5)$$

$$Y = sin(\theta) * \left(\sqrt{R_2} * R_d\right) + Y_0 \quad (6)$$

$R_1$and R_2 represent the random coordinates of a point inside the circle's boundary, whereas $X_0$and Y_0 represent the coordinates of the center point (origin) within the circle. Furthermore, the angle value of this point is represented by θ, a random value that falls between 0 and 2π.

3- Families searching

The NPO algorithm's exploration phase is executed when the swarm is devoid of a new local best solution. As a result, the families inside the swarm start to explore for better locations within the search area. During the exploration phase, each family in the swarm travels independently inside the search space. Their movement's direction and length are determined by the random steps and directions generated by the Levy Flight formula.

$$X_i^N = X_i^O + (\alpha_C * (\sigma_C - X_i^O) \oplus Levy) \quad (7)$$

The current family's new and old places are represented by X_i^N and X_i^O, respectively, and the clan's area is denoted by α_C, which is the average distance between all normal families and α_C. To calculate α_C, use this formula [19]: -

$$\alpha_C = \frac{\sum_i^{\Phi} \sqrt{(\sigma_C - X_I^O)^2}}{\Phi} \quad (8)$$

Where Φ denotes the number of families in each clan.
The distribution of the families surrounding the leader is determined by the value of α_C. The α_C value will be tiny if the families are arranged in a small circle around the leader, which will result in a small step size during the exploration phase. Conversely, in the event that the families are dispersed far from the leader, a high value of $\alpha_C$will enable larger steps to be taken during the exploration phase. The families follow the following equation, which is generated by the Levy flight (λ_C) moving in different directions and with arbitrary step sizes:

$$Levy \sim \upsilon = t^{-\lambda} \quad (1 < \lambda < 3) \quad (9)$$

A Levy distribution with an infinite mean and variance is the foundation of the Levy flight Eq. Generally speaking, a random walk is a Markov chain, which means that subsequent steps alone rely on the current location and not on previous ones. Leadership transition (exploitation)

Look for any new families in each clan that are a better fit than the leader of that clan. If so, that family becomes the leader and vice versa.

4- The periodical meetings (exploitation–exploration)

Leaders in the desert gather regularly to explore relocation sites and find solutions to outside issues without inciting others' aspirations. There are two stages to the meetings. In the first, the strongest Leader is identified, and they suggest ways for other Sheikhs to update their positions. This is based on the difference between the strongest Leader and the normal Leader, as indicated by the following equation [19]:

$$\Delta Pos = \left(\frac{\sqrt{\sum_i^D (\sigma^E - \sigma_C^N)^2}}{D} \right) * \Psi \quad (10)$$

where the optimal leader's position is denoted by σ^E and the conventional leaders' position by σ_C^N. In the meantime, ΔPos indicates the normalized distance between the optimal Leader and the normal Leader, Ψ indicates the direction, and D indicates the number of dimensions in the problem. Depending on the ideal sheikh's fitness value, the direction variable Ψ directs the normal Leaders to more favorable locations.

$$\Psi = \begin{cases} 1 & if \ \mathcal{F}(\sigma^E) \geq 0 \\ -1 & \text{otherwise} \end{cases} \quad (11)$$

Using Eq. (12), normal Leaders modify their location. A part of the NPO exploring phase is represented by the following Eq:

$$\sigma_c^{new} = \left(\Delta Pos * (\sigma^E - \sigma_C^N) * \frac{T_i}{T} \right) + \sigma_C^N \quad (12)$$

where T_i and T stand for the current iteration and the total number of iterations, respectively, and σ_c^{new} and σ_C^N for the new and old positions of the normal leader, respectively.

During the regular meetings, the positions of all normal leaders are updated. If the new position is better than the old one, the Leader stays there, except for starting a new clan based on the second step (semi-circular distribution); if not, he returns to the old location. It is important to remember that the periodic meeting serves as a cooperative arrangement for multiple swarms, which makes it a unique platform for swarms to exchange information. Each clan is its own swarm, and the regular gathering serves as a means of communication between them. By balancing exploration and exploitation, MRA, a cooperative multi-swarm technique, allows them to reach faster convergence than other standard versions of the algorithms [19].
By guiding them toward better locations and positions for their clans, the direction variable Ψ is used by the MRA to assist normal leaders in following the best leader. Through the integration of the MRA, NPO guarantees that the clans in the algorithm collaborate to discover the optimal solution, striking a balance between their capacities for exploration and exploitation. The NPO method's fitness function is the Root Mean Square Error [9], as shown by the following equation:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (E)^2} \quad (13)$$

Where E=$x - \hat{x}$, x and $\hat{x}$ are the actual and estimation positions for target nodes, respectively, and n represents the quantity of RSSI samples.

D. The Algorithm for Hybrid NPO-GRNN Proposed

In a WSN, the GRNN algorithm can be used to determine a mobile node's location. The GRNN algorithm uses the RSSI values as inputs to help determine and track the location of the target node. The spread constant (σ) is an essential part of the GRNN configuration. The traditional approach to selecting this value is trial and error, which is risky and might not always yield the greatest outcomes. By determining the ideal value for the GRNN spread constant, the NPO technique addresses this problem and may even improve GRNN's performance. Here, the combination of NPO and GRNN results in a "hybrid NPO-GRNN algorithm," which allows the GRNN to attain the minimum location error. The hybrid method's mechanism is depicted in Figure 2.
The swarm size is set at 20, as the NPO's working duration typically increases with the swarm size (particle count). The NPO method is implemented by the MATLAB software. Each particle in this method is made up of a single component known as a spread constant. The value of σ was obtained during the training phase. used to lower the localization error of the mobile device during the online localization stage. The block diagram of the proposed hybrid NPO-GRNN method is displayed in Figure 2, and it may be applied to improve the accuracy of mobile node position estimates.
The LNSMs and accuracy of the suggested approach are assessed statistically using RMSE and Average Localization Error (ALE). This section compares the error metrics of the classic LNSM method with the Hybrid NPO-GRNN methodology. The accuracy requirements are not met by the LNSM approach, especially when used inside. The Hybrid NPO-GRNN algorithm is provided To increase localization and tracking precision; this is covered in greater detail in the part that follows.

$$\text{ALE } = 1/\text{t} * \sum_{i=1}^{t} (\hat{x_i} - x_i) + (\hat{y_i} - y_i)/2 \quad (14)$$

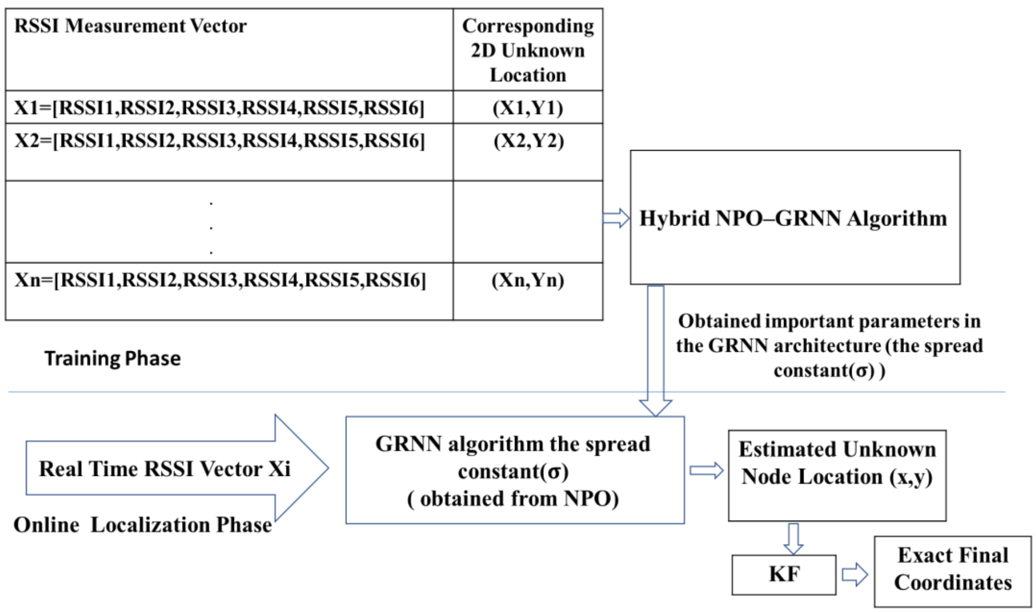

Figure 2: The hybrid NPO-GRNN-KF algorithm's block diagram

IV. FINDINGS AND DISCUSSION

The suggested system is made up of multiple anchor nodes that are dispersed over a 100-square-meter simulated region. Figure 3 shows two mobile targets with a wireless sensor node connected; however, the base station outside the simulation region is not displayed. At each time step i, the mobile target serves as a receiver and picks up the RF signals that the anchor nodes produce. The RSSI information gathered from every anchor node is transmitted to the base station outside the simulation region at the end of each time step. This base station is linked to a laptop with a Core i7 processor, 8GB RAM, and a 2.3 GHz processor.

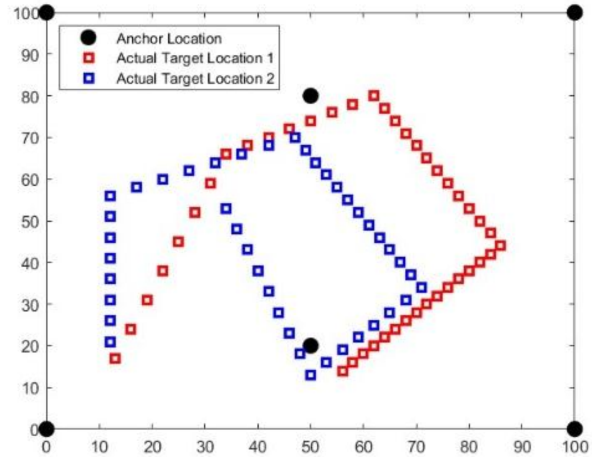

Figure 3: Actual two target Locations and 6 anchor nodes

The GRNN outputs are the estimated x and y coordinates to implement a GRNN; MATLAB software was used. The RSSI measurements, RSSI1, RSSI2,..., and RSSI6, are the GRNN inputs. After the neural network has made its initial estimation, the results are further improved by applying the KF techniques. The spread constant (σ) is considered during the GRNN training and testing procedures to improve the localization estimation's accuracy. The NPO method maximizes The GRNN aims to minimize the error in the localization process by using the ideal value of spread constant (σ). This process leads to improving the GRNN's overall performance. The following swarm sizes (No. of Clans x No. of Families) yield fitness functions when the NPO algorithm is run: 20 (5 x 4), 40 (5 x 8), and 60 (5 x 12). These fitness functions demonstrate how well the NPO algorithm enhances the GRNN, affecting the system's localization accuracy. When the swarm size was 20, GRNN performed at its best when spread constant equal to 1.327

We opted to use a target motion model moving at a constant velocity for simplicity and focus on abrupt changes in target velocity during Constant Velocity (CV) motions, along with variation in RSSI measurement in the dynamics environment. The following equations represent the target's motion:

$$x_i = x_{i-1} + vx_i\, di \tag{15}$$
$$y_i = y_{i-1} + vy_i\, di \tag{16}$$

where the position is defined by $x_i$and y_i. $vx_i$and vy_i represent the speed in the x and y directions at a given time instance. The discretization time step (di) represents the amount of time that has passed between two successive time instants.

These formulas are used to explain the target's movement pattern throughout the investigation. The constant velocity model simplifies the motion representation and lets us focus on certain aspects of the localization and tracking procedure. As a result, the parameters of a hybrid NPO+GRNN and LNSM may be derived, as shown in Table I. As was previously indicated, the investigation is conducted in two phases: offline and online localization. Before proceeding to the analytical step of online localization to determine the wireless scenario, run a hybrid NPO+ANN to determine the ideal value(σ).

Using the best value (σ) found during training, the online localization phase is done within the same network parameters as the training phase. The target pathways inferred by the NPO-GRNN and conventional RSSI approaches are shown in Figures 4&5. Black circles indicate anchor nodes, whereas red squares indicate the target's position. The estimated positions obtained from RSSI, NPO+GRNN, and NPO+GRNN+KF at a certain time instance i are indicated by the black, blue, and yellow plus signs, respectively, while the estimated positions by NPO+GRNN+UKF are represented by the green triangle. The simulation results show that in terms of tracking efficiency and localization, the NPO+GRNN+UKF-derived method performs better than RSSI.

TABLE I. THE PARAMETERS OF A HYBRID NPO+ANN AND THE LNSM

Symbol	Parameter	Value
X0	Initial Target State at t-0	[10 10]
dt	Discretization time step	1s
F	Frequency of operation	2.4 GHz
η	Path Loss Exponent	3.4
X σ	Normal Random Variable	~N (3, 1)
σ	spread constant	1.327

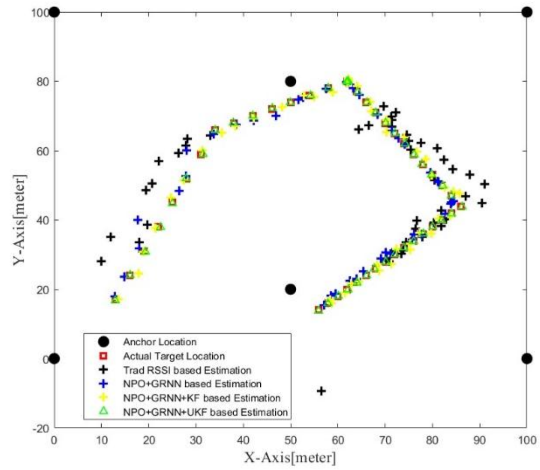

Figure 4: Actual and target estimated for target 1 by Trad RSSI and proposed methods

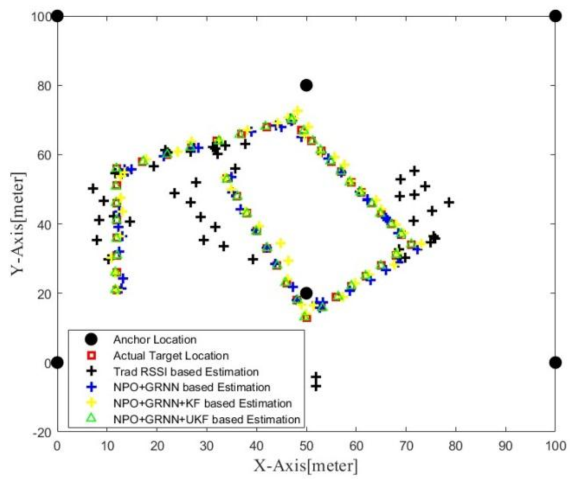

Figure 5: Actual and target estimated for target 2 by Trad RSSI and proposed methods

Figures 6 and 7 show the average performance for the x and y estimates, respectively, and take into account the average of the errors in the x and y estimates for two objectives.

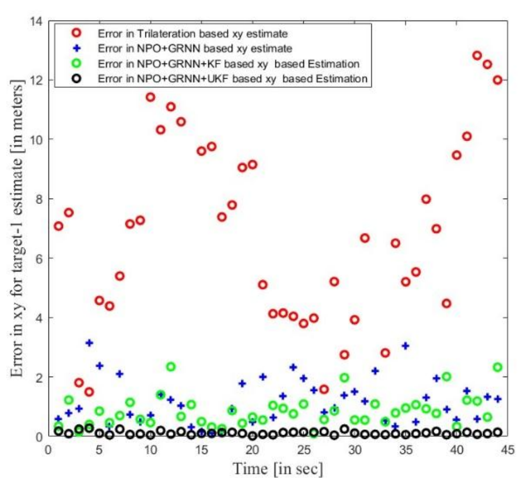

Figure 6: Localization errors in x-y estimates for target 1 in Trad RSSI and proposed methods

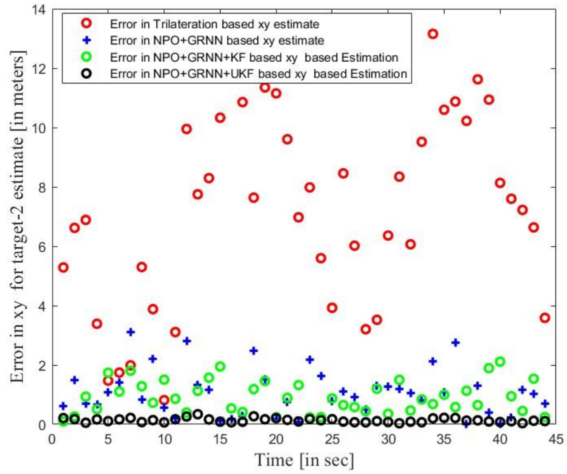

Figure 7: Localization errors in x-y estimates for target 2 in Trad RSSI and proposed methods

The following two figures show the average error and performance comparison for each RSSI+KF, RSSI+UKF, NPO+GRNN+KF, and NPO+GRNN+UKF

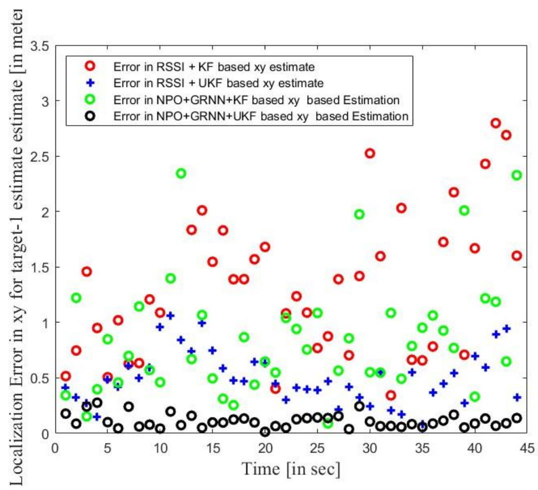

Figure 8: Localization errors in x-y estimates for target 1 in RSSI+KF, RSSI+UKF, and proposed methods

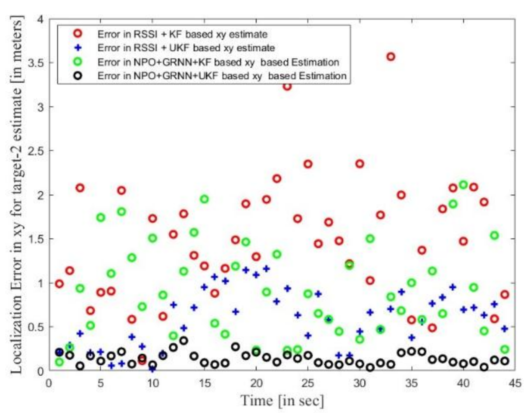

Figure 9: Localization errors in x-y estimates for target 2 in RSSI+KF, RSSI+UKF, and proposed methods

However, as the CDF plot Figures 10 & 11 illustrate, 90% of the errors in the suggested approach NPO+GRNN+UKF are less than or equal to 0.19 M and 0.21 M in targets 1 & 2, respectively.

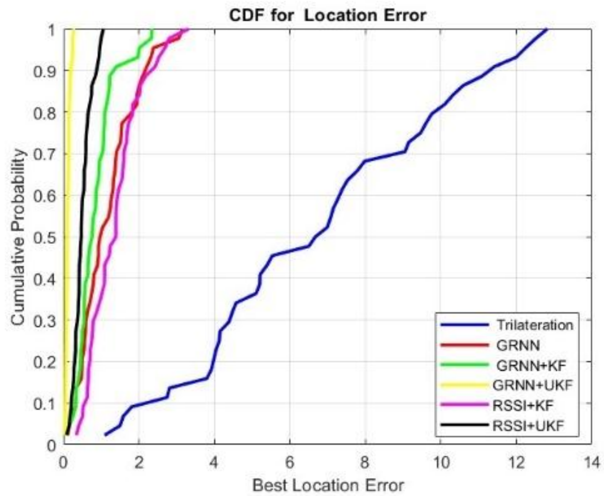

Figure 10: CDF of the location errors based on the Trilateration, GRNN, GRNN +KF, GRNN +UKF, RSSI+KF, and RSSI+UKF for target 1

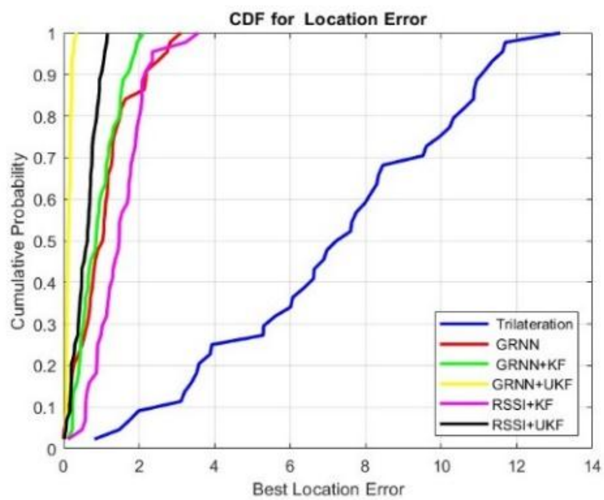

Figure 11: CDF of the location errors based on the Trilateration, GRNN, GRNN +KF, GRNN +UKF, RSSI+KF, and RSSI+UKF for target 2

The following Table II shows the comparison between the traditional method and the proposed method before and after applying the KF framework.

Impressive results were obtained from the proposed method, and it can be applied in indoor and outdoor environments because the GRNN, a one-pass learning technique, is renowned for its capacity to train rapidly on sparse data set types chosen for the proposed models and with the help of NPO in identifying the best spread constant to GRNN, the locations can be determined accurately and refinement these coordinate by KF framework.

TABLE II. COMPARISON OF ALE AND RMSE TRILATERATION, TRILATERATION+K, TRILATERATION+UK, NPO+GRNN, NPO+GRNN+KF, AND NPO+GRNN+UKF

Target NO	Algorithm	Minimum Localization Error in Average Estimation(M)	Maximum Localization Error in Average Estimation (M)	Avg. Localization Error (M)	Avg. RMSE in x-y Estimation(M)
Target 1	Trilateration	6.6373	8.07881	7.31698	11.1905
	Trilateration+KF	1.2603	1.6354	1.3655	2.3610
	Trilateration+UKF	0.4610	0.5546	0.5043	0.9329
	NPO+GRNN	0.9333	1.3668	1.1717	2.1163
	NPO+GRNN+KF	0.7941	1.0491	0.8534	1.5675
	NPO+GRNN+UKF	0.1085	0.1312	0.1114	0.2030
Target2	Trilateration	6.8912	7.5573	7.1741	12.3830
	Trilateration+KF	1.3589	1.5201	1.4901	2.5253
	Trilateration+UKF	0.5066	0.6171	0.5885	1.1685
	NPO+GRNN	0.8539	1.1441	1.0751	1.9859
	NPO+GRNN+KF	0.7748	1.0001	0.9217	1.6434
	NPO+GRNN+UKF	0.1002	0.13765	0.1377	0.2481

TABLE III. ERROR COMPARISON BETWEEN THE HYBRID NPO-GRNN-UKF MODELS AND EARLIER RESEARCH

No.	Ref	Location technology algorithm	ANN type or learning framework	Metric	Environment	Tested region	Average localization error	RMSE
1	[6]	WIFI	SVR	RSSI	Indoor	12 M X4 M	1.8	/
2	[7]	simulation	FL	RSSI	Indoor	100 M^2	0.9-1	
3	[8]	simulation	TCGRNN	RSSI	Indoor	100 M^2	3.3949	4.91
4	[9]	simulation	PSO+GRNN	RSSI	Indoor	100 M^2	0.88	1.62
5	[10]	simulation	Multi- CNN	5G	Indoor	8.4M x 13.2M	1.4	/
6	[11]	simulation	Triangulation+ logistic regression	RSSI	Indoor	80 M x 80 M	14.3	/
7	**Proposed Method**	**Simulation**	**NPO+GRNN+UKF**	**RSSI**	**Indoor**	**100 M^2**	0.11 0.13	0.20 0.24

V. CONCLUSION

This study presented two methods for tracking estimate and indoor localization in WSNs. Traditional LNSM methodology is used in the first method, and a hybrid NPO-GRNN algorithm fusion with KF is used in the second. By merging the NPO and GRNN algorithms, the GRNN method was enhanced to choose the ideal value for the spread constant (σ), hence increasing the accuracy of localization. The performance of the hybrid NPO-GRNN-UKF algorithm and the algorithm employed in previous studies is compared with that of the conventional LNSM-based technique. By comparing the outcomes, it can be seen that the hybrid NPO-GRNN-UKF algorithm outperforms the conventional LNSM approach, which has notable localization errors in terms of ALE and RMSE scores.
For NPO-GRNN-UKF, the mean localization errors for targets 1&2 are 0.20 and 0.24, respectively. The hybrid NPO-GRNN-UKF method performs better than comparable systems. As a result, hybrid NPO-GRNN-UKF offers a useful and efficient way to locate and track mobile nodes in WSNs, particularly indoors. For future work, investigation of various other target mobility models and Shifting in the direction of using TinyML for future endeavours.

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