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The Unscented Kalman Filter for Real-Time Target Localization and Tracking in WSN Using Hybrid NPO-ANN Method

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Abstract: Utilizing received signal strength indicators (RSSIs) is one of the most widely used cost-effective techniques for the localization and tracking of mobile targets using wireless sensor networks (WSNs). Significant estimation errors in target localization are caused by the noise variability in received signal strength indicator (RSSI) readings, particularly in indoor environments. In this paper, a new method is proposed based on a Nomadic People Optimizer (NPO) and Artificial Neural Network (ANN) to overcome the weaknesses of the traditional method, which is called NPO+ANN algorithm to improve the accuracy of target localization and tracking. This study presents a novel method for estimating the initial location of a single target moving in a 2-D space within a wireless sensor network (WSN) that combines hybrid NPO+ANN as a substitute for the common RSSI-based method. The Unscented Kalman Filter (UKF) is then used to improve and fine-tune these preliminary estimations to increase target localization accuracy, the research suggests NPO+ANN+UKF. The simulation outcome validates the NPO+ANN+UK architecture's capability for solving the real-time target tracking issue in WSN utilizing RSSI. The NPO+ANN+UKF provides a remarkable improvement of 98.2%, and 88% over the traditional RSSI, and NPO+ANN, respectively.

Keywords: RSSI, Accuracy, Log-normal shadowing model (LNSM), Indoor environments, WSN.

1. Introduction

In wireless sensor networks (WSNs) several sensors are placed over a sizable area to monitor a variety of environmental characteristics. It is essential to guarantee proper data transfer between these network nodes. The fundamental goal of L&T is to determine the positions of moving targets and trace their paths based on field measurements collected at consistent intervals. To address the tracking challenge, a series of localization challenges must be tackled periodically [1].

Current localization technologies are divided into three groups: range-free, range-based, and AI-based [2]. Calculating the distances or angles between an unknown node and the network's known nodes is crucial when trying to pinpoint where it is to other nodes. This approach called the range-based method [3], such as angle of arrival, time of arrival, phase of arrival, time difference of arrival, received signal strength indicator (RSSI), global positioning system (GPS), and acoustic energy [4, 5]. Among these methods, the RSSI approach offers several advantages (i) There is no requirement for further hardware, (ii) it is cost-effective and (iii) No requirement for time synchronization [6].

On the other hand, the range-free method offers cost-effectiveness but suffers from reduced accuracy in estimating the location of sensor nodes. The distances between nodes do not need to be estimated when using range-free localization techniques. Such methods have the benefit of not requiring additional hardware for sensors to measure distance, such as DV-hop hexagonal intersection, Approximate Point in Triangle (APIT), rectangular intersection, and centroid [2].

In localization approaches for numerous applications, such as wireless sensor networks and tracking systems, AI-based solutions have demonstrated promising results. Several AI-based localization techniques include ANNs [7], Support Vector Machines (SVM), k-nearest Neighbours (k-NN), Decision Trees, Fuzzy Logic, and Adaptive Neural Fuzzy Inference System (ANFIS) are a few examples of machine learning algorithms that can be trained using received signal strength (RSS) data to forecast the location of a target node inside a wireless sensor network [2, 8, 9].

Despite being often employed for target localization and tracking, RSSI field measurements are susceptible to high levels of noise and fluctuations, particularly in challenging indoor RF environments. Significant localization mistakes are caused by the difficulties faced by RSS-based L&T systems, which include indoor interference, multipath fading, noise, and different obstructions [1]. Due to its simplicity of use, trilateration, a straightforward method for target L&T, is extensively used. However, because of the ambiguities in RSSI measurements or the dynamic nature of interior surroundings, it frequently has low localization accuracy. The erratic nature of RSS measurements frequently has an impact on the precision of trilateration [10]. Contrarily, ANN algorithms offer advantages over trilateration in more dynamic indoor environments with reflections, interference, and obstructions. more accurate and reliable target localization. Therefore, in this research, we adopted the use of neural networks to overcome the weaknesses of the traditional method. To obtain the best performance of artificial neural, we need to adjust a set of parameters to achieve the desired goals in the accuracy of localization. The number of neurons in each concealed layer and the hyperparameter of the training process (Learning Rate) are key factors in Artificial Neural Networks. However, choosing these criteria is not simple and frequently entails trial and error, which might not always produce the best result. To solve this problem, The optimal number of neurons in each hidden layer and the most suitable learning rate for the ANN are chosen using the Nomadic People Optimizer (NPO) technique. The NPO algorithm can strike a balance between global exploration and local exploitation, ultimately leading to the discovery of the optimal solution for our problem in adjusting the number of neurons in each hidden layer and the learning rate are two important parameters in the ANN architecture. By reducing the localization error, this hybrid strategy also referred to as the "NPO+ANN algorithm" enhances the performance of the ANN. The approach improves its accuracy in determining the best parameter settings for the neural network by integrating NPO with ANN, which improves overall performance across a range of applications. After obtaining the estimated coordinates we enhance these location estimates by employing the Unscented Kalman filter (UKF) to attain enhanced results.

The following are the research's main findings:

1. A novel hybrid NPO-ANN localization and tracking model was introduced, utilizing RSSI measurements to address the challenges posed by dynamic RSSI readings in indoor environments. The proposed approach was compared with a trilateration-based scheme using six RSSI measurements for both methods and localization accuracy was rigorously evaluated through simulations.
2. The NPO-ANN-UKF framework was created by applying the Unscented Kalman filter (UKF) to the location estimations produced from the NPO-ANN scheme. In comparison to the trilateration and basic NPO-ANN-based systems, the performance of the NPO-ANN-UKF-based scheme performed better. The NPO-ANN-UKF-based system outperformed the other two approaches in terms of target location estimate, confirming its potency in enhancing localization accuracy.

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 Nomadic People Optimizer and Artificial Neural Network. Comprehensive simulation studies, which delve into the system architecture and performance evaluation of the proposed methods, are explained in Section 4. Concluding remarks are highlighted in Section 5.

2. Related works

The localization of sensor nodes in WSNs has recently attracted a lot of concern in academic research. The two primary kinds of indoor target localization and tracking (L&T) algorithms that make use of RSSI readings are machine learning (ML) -based approaches and filter-based methods. ML-based approaches frequently make use of supervised learning concepts and RF fingerprinting techniques. Radial basis function, recurrent neural network, k-nearest Neighbour, multilayer perceptron, extreme learning machine, backpropagation neural network, convolutional neural network, backpropagation neural network, and support vector machine are a few examples of popular ML-based solutions that have been studied in the literature. By learning patterns and characteristics from the RF fingerprints obtained from RSSI measurements, these machine learning

ML-based approaches seek to increase localization and tracking accuracy [10-12].

In the study [13] the researchers developed two algorithms: RSSI + Kalman filter (KF) and RSSI + Unscented Kalman filter (UKF), which were carried out in a simulated environment that covered a 100m x 100m area. To provide a smoother target trajectory, these techniques were proposed to enhance the estimations produced from the conventional RSSI-based methodology. Concerning the three scenarios, the working area contained 4, 6, and 8 anchor nodes. The simulation results for each scenario show that better tracking results are obtained by increasing the density of anchor nodes. The scenario with 8 anchor nodes shows the greatest improvement in tracking accuracy. In particular, when compared to the conventional RSSI-based method, the RMSE in the RSSI + KF and RSSI + UKF algorithms is lowered by roughly 70% and 90%, respectively. This suggests that greater tracking precision is associated with more anchor nodes. Despite the positive results, the accuracy of localization depends on increasing the number of anchor nodes and thus increasing the cost.

Using RSSI measurement and artificial neural networks, this paper [14] proposed a method for localization possibilities for wireless sensor networks. To achieve the best outcomes, three distinct learning algorithms LM, Bayesian regularized artificial neural networks (BRANN), and Back Propagation (BP) are used. Different ANN topologies with various hidden layer and node counts were tested. The 12-12-2 ANN structure was then assessed. The three learning algorithms were applied to this ANN structure to train it. The learning strategies are compared using the maximum and average distance error. The smallest maximum error was obtained using the BRANN approach, but the smallest average error was obtained using the LM method. Though tiny, method-to-method mistake exists. The drawback is the need to adjust a set of parameters in NN. With the number of neurons in each hidden layer, choosing these criteria is not simple and frequently entails trial and error, which might not always produce the best result.

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 [15] 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. Even if the findings were good, the computations became more complicated when the coordinates were found using the Centroid and Trilateration methods and then added to the RSSI as inputs to GRNN.

In this research [16], a localization system using LoRaWAN-RNN is presented. Various experiments were conducted, involving different learning rates (0.0002, 0.002, 0.02, 0.2, and 2) and different numbers of hidden neurons (8, 16, and 20) to assess the system's performance and accuracy in an indoor environment, considering both LOS and NLOS scenarios. The results indicated that in the LOS scenario, the best localization accuracy was achieved with a learning rate of 0.2 and 20 hidden neurons in the RNN network architecture, resulting in a minimum average localization error of 0.12 meters. Conversely, for the NLOS scenario, the minimum localization error was 13.4 meters. In this study, the researcher relied on the principle of trial and error to choose a parameter, learning rate, and the number of neurons, and this led to an increase in the time taken and maybe not getting optimal results.

In the context of WSNs with uncertain measurement noises, this paper [1] suggests using Generalized Regression Neural Networks (GRNN) to improve real-time target tracking efficiency in the Kalman Filtering (KF) framework. To effectively track a single moving target in 2-D in the WSN, two RSSI-based methods, GRNN+KF and GRNN+UKF, are introduced. The target's initial location estimates are initially determined using a GRNN-based method, and they are then further improved using the KF&UKF framework. The results show a about 50% reduction in RMSE when comparing the RMSE of the GRNN+UKF algorithm with the conventional RSSI+UKF, demonstrating that the GRNN+UKF approach beats the conventional RSSI-based method. In this study, the researchers relied on choosing the important factor the spread constant in GRNN based on trial and error, which is insecure and does not always yield the best result.

In [17], a target-localization technique based on Convolutional Neural Network (CNN) was proposed, utilizing RSSI data as inputs. The intricacy of the online estimating stage was successfully transferred to an offline training stage. As a result, a localization accuracy of 2 meters was achieved. For this localization, thousands of RSSI fingerprints in a size area of 12.5 meters by 10 meters were used, employing the Access Points (APs) deployed in the environment. The average localization errors obtained using the recommended fingerprint-based methods were 4.11 meters, 4.16 meters, and 3.91

meters, respectively, using SVM, KNN, and CNN-based methodologies. These results demonstrate the effectiveness of the CNN-based approach. 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.

In [18] The suggested WiFi-fingerprinting localization method offers good indoor localization performance while saving time and effort when creating a radio-map. The system employs FFBP neural networks and GRNN for location estimation, with FFBP outperforming GRNN when it comes to structural simplicity and GRNN outperforms other models, yielding more precise prediction results with an average distance error as low as 0.48 meters.

Instead of the traditional RSSI-based approach, this study [19], suggested a hybrid technique termed particle swarm optimization-generalized regression neural network (PSO-GRNN) to increase the sensor nodes' capacity to predict location and target tracking with better accuracy. The RSSI values can be used by the GRNN method as start data to determine the target node's location and trace it. The spread constant (σ) is a crucial part of the GRNN design. The ideal GRNN spread constant value is found using the PSO approach. The hybrid tracking algorithm PSO-GRNN beat the traditional LNSM approach and yielded remarkable outcomes. By comparing the suggested approach to the traditional RSSI, a significant 87.58% gain can be achieved. The GRNN provides a robust initial estimate but may not fully capture the dynamic nature of the localization process, especially in the presence of uncertainties and noise.

3. Propose system

Both the conventional approach (based on RSSI data and LNSM) and a hybrid NPO-ANN algorithm were used to estimate the localization.

3.1 LNSM based on RSSI

The Log-Normal Shadowing Model used in this work as the foundation for the simulated RSSI measurements has the following mathematical formula [20,21].

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

Where A is RSSI evaluated at the reference distance receiver node d0 1m from the transmitter, k is the Path loss exponent, Xσ 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~ (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.

Table 1. Frequently used symbols.

Symbol	Definition
Pr	RSSI value at reference distance $d0$
$RSSI$	Received Signal Strength Indicators
n	Attenuation factor
$X\sigma$	Normal random variable
d	Distance between transmitter and receiver nodes
A1& A2	The number of neurons in the first and second hidden layers respectively
LR	Learning rate
di	Discretization time step
$vx_i\,\&\,vy_i$	The speed in x and y directions respectively at i time instant
$UB\,\&\,LB$	Upper bound and lower bound respectively
$X_0\&\,Y_0$	Coordinates of the central point (origin) within the circle
$R_1\&\,R_2$	The random coordinates of a point located within the circle's boundary
σ	Leaders
σc	The positions of the leaders
θ	The angle value
$X_i^N\ \&\,X_i^O$	The current family's new and old position
Φ	The number of families in each clan
ΔPos	the normalized distance between the optimal Leader and the normal Leader
σ^E	The position of the optimal Leader
σ_C^N	the position of the normal Leaders
Ψ	Direction
D	The number of dimensions
T_i	Current iteration
T	Total number of iterations
σ_c^{new}	A new position of the normal Leaders
α_C	Distance between all of the normal families
$RMSE$	The Root-Mean-Square Error
ALE	Average Localization Error

3.2 Nomadic people optimizer

The inspiration behind Nomadic People Optimizer (NPO) is the movement and behaviour of nomadic people in their search for sources of life, such as water or grass for grazing. The algorithm simulates how nomadic people have lived for hundreds of years, continuously migrating to the most comfortable and suitable places to live. It is designed based on the multi-swarm approach, where each clan within the algorithm looks for the best solution based on the position of their leader. The

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algorithm also incorporates the Meeting Room Approach (MRA), which represents the communication between the clans and helps balance exploration and exploitation. The exploration capability of NPO is achieved through the use of several members of swarms, differentiating it from other metaheuristics that commonly use a specific mechanism between the global best solution and the whole swarm [22].

The NPO algorithm consists of five primary operations: Initial meeting, Semi-circular distribution, Family searching, Leadership transition, and lastly, Periodic meeting.

1. Initial meeting

A collection of Leaders (σ), denoted σ= (σ1, σ2, σ 3,…, Clans), The positions of the leaders(σc) in each clan are initialized randomly using an Eq.2 that takes into account the upper bound (UB) and lower bound (LB) of the search space, as well as a random value between 0 and 1.

$$\sigma c = Rand * (UB - LB) + LB \tag{2}$$

2. Semi-circular distribution

The families (represented by the set of families, x) in the NPO algorithm are distributed around their leaders (represented by σ). The arrangement of points is based on the angle value, which determines their position in the circular pattern.

$$X = cos(\theta) * \left(\sqrt{R_1} * R_d\right) + X_0 \tag{3}$$

$$Y = sin(\theta) * \left(\sqrt{R_2} * R_d\right) + Y_0 \tag{4}$$

X_0 and Y_0 denote the coordinates of the central point (origin) within the circle, whereas R_1 and R_2 indicate the random coordinates of a point located within the circle's boundary. Additionally, θ represents the angle value of this point, a random value falling within the range of [0, 2π].

3. Families searching

When the swarm does not contain a new local best solution, the exploration phase of the NPO algorithm is carried out. This means that the families in the swarm begin looking for better positions in the search space. Every family in the swarm moves in a separate direction inside the search space during the exploration phase. The Levy Flight formula generates random steps and directions that dictate their movement's direction and distance.

$$X_i^N = X_i^O + (\alpha_C * (\sigma_C - X_i^O) \oplus Levy) \tag{5}$$

Where X_i^N and X_i^O stand for the current family's new and old positions, respectively, and α_C stands for the clan's area, which is the mean distance between all of the normal families and σ_C. This formula can be used to determine σ_C: -

$$\alpha_C = \frac{\sum_i^{\Phi} \sqrt{(\sigma_C - X_I^O)^2}}{\Phi} \tag{6}$$

where Φ denotes the number of families in each clan.

The value of α_C determines the distribution of the families around the leader. If the families are distributed in a small circle around the leader, the value of α_C will be small, leading to a small step size in the exploration phase. On the other hand, if the families are distributed far from the leader, the value of α_C will be large, allowing for larger steps in the exploration phase. The families move in various directions and with arbitrary step sizes that are produced by the Levy flight (λ_C) equation as follows:

$$Levy \sim v = t^{-\lambda} \quad (1 < \lambda < 3) \tag{7}$$

The Levy flight equation is based on a Levy distribution, which has an infinite mean and variance. A random walk is generally a Markov chain, meaning that the future steps only depend on the current location and not on the past steps.

4. Leadership transition (exploitation)

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

5. The periodical meetings (exploitation–exploration)

Periodical meetings among the Leaders in the desert aim to resolve external problems and discuss relocation locations without arousing the ambitions of others. The meetings occur in two stages, with the first phase determining the most powerful Leader who proposes solutions for other Sheikhs to update their locations based on the variance between the strongest Leader and the normal Leader as shown in the equation that follows:

$$\Delta Pos = \left(\frac{\sqrt{\sum_i^{D} (\sigma^E - \sigma_C^N)^2}}{D}\right) * \Psi \tag{8}$$

where σ^E indicates the position of the optimal Leader, and σ_C^N signifies the position of the normal Leaders. Meanwhile, D represents the number of dimensions within the problem, Ψ denotes the direction, and ΔPos signifies the normalized distance between the optimal Leader and the normal Leader. The direction variable Ψ guides the normal Leaders towards more advantageous positions, contingent upon the fitness value of the optimal sheikh, as follows:

$$\Psi = \begin{cases} 1 & if\ \mathcal{F}\,(\sigma^{E}) \geq 0 \\ -1 & \text{otherwise} \end{cases} \tag{9}$$

Using Eq. (10), normal Leaders modify their positions. A part of the NPO exploring phase is represented by this equation:

$$\sigma_c^{new} = \left(\Delta Pos * (\sigma^{E} - \sigma_C^{N}) * \frac{T_i}{T}\right) + \sigma_C^{N} \tag{10}$$

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.

All normal leaders have their positions revised during the periodic meeting. The Leader remains in the new position if it is superior to the previous one, with the exception of creating a new clan based on the second step (semi-circular distribution) if not, he moves back to the previous location. It is worth noting that the periodic meeting represents a cooperative arrangement for several swarms, making it a special means of information exchange amongst swarms. Every clan is a separate swarm and contact between them is facilitated by the regular meeting. MRA is a cooperative multi-swarm approach that enables them to achieve faster convergence than other standard versions of the algorithms by balancing exploration and exploitation.

The MRA helps guide normal leaders to follow the best leader by using the direction variable Ψ, which guides them towards better places and positions for their clans. By incorporating the MRA, NPO ensures that the clans within the algorithm work together towards finding the best solution, balancing between exploration and exploitation capabilities. The NPO method uses the Root Mean Square Error [18] as its fitness function, as demonstrated in the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E)^2} \tag{11}$$

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

3.3 Learning by NPO

In this study, the Levenberg-Marquardt (LM) training algorithm and a feed-forward neural network type are chosen for MATLAB training. The LM training algorithm is chosen due to its minimal localization error, which has been demonstrated, as well as its quickness and effectiveness [23] . However, this technique necessitates a sizeable working memory resource. Six inputs, two hidden layers, and two outputs are taken into account in this study when training the neural network.

The goal is to use artificial neural networks (ANN) to represent the process of correct localization. The number of neurons in each hidden layer and the learning rate are crucial factors in the ANN. However, figuring out the ideal values for these factors can be difficult and frequently calls for a trial-and-error method, which might not always produce the greatest outcomes. The Nomadic People Optimizer (NPO) technique is used to discover the ideal number of neurons in each hidden layer and the best learning rate for the ANN to solve this problem. The "NPO-ANN algorithm" a hybrid strategy, enhances the performance of the ANN by reducing localization errors. NPO and ANN are combined in the algorithm to increase localization accuracy and produce a more trustworthy solution to the parameter selection problem in the ANN architecture. In this algorithm, each particle is made up of three parts: the learning rate (LR), the number of neurons in the first hidden layer (A1), and the number of neurons in the second hidden layer (A2). The results for A1, A2, and LR are then used to train an ANN to improve the mobile node's localization accuracy. Fig. 1 illustrates the flowchart of the suggested approach.

The elaborate flow of the suggested algorithms for one-time step t is given in the following algorithm.

I: Offline NPO+ANN Training Stage

Step 1: A dataset containing 880 pairs of RSSI measurements obtained from anchors and their associated actual positions of the moving target is used to train the NPO+ANN model. To figure out the ideal ANN learning rate and the optimal number of neurons for each hidden layer.

II. Online Position Estimation using ANN

Step 2: Every time an anchor node transmits RSSI, the moving target receives it. The base station receives these RSSI readings.

Step 3: Every time a moving target, the base station runs an ANN (using A1, A2, and LR obtained from step 1) algorithm to determine its position. The estimated x and y positions' errors are computed and recorded.

III. Online Position Estimation with UKF

Step 4: The base station utilizes Unscented Kalman Filter (UKF) algorithms to improve the position estimates produced by the artificial neural network (ANN). At particular sample instants, the errors in the estimated x and y positions are calculated and recorded.

Step 5: The process described in steps 2 to 4 is iteratively repeated for each subsequent time step until the total simulation period is completed.

IV. Computation of Performance Metrics

Step 6: All techniques (Traditional RSSI, NPO+ANN, and NPO+ANN+UKF) have their RMSE and Average Localization Error (ALE) computed.

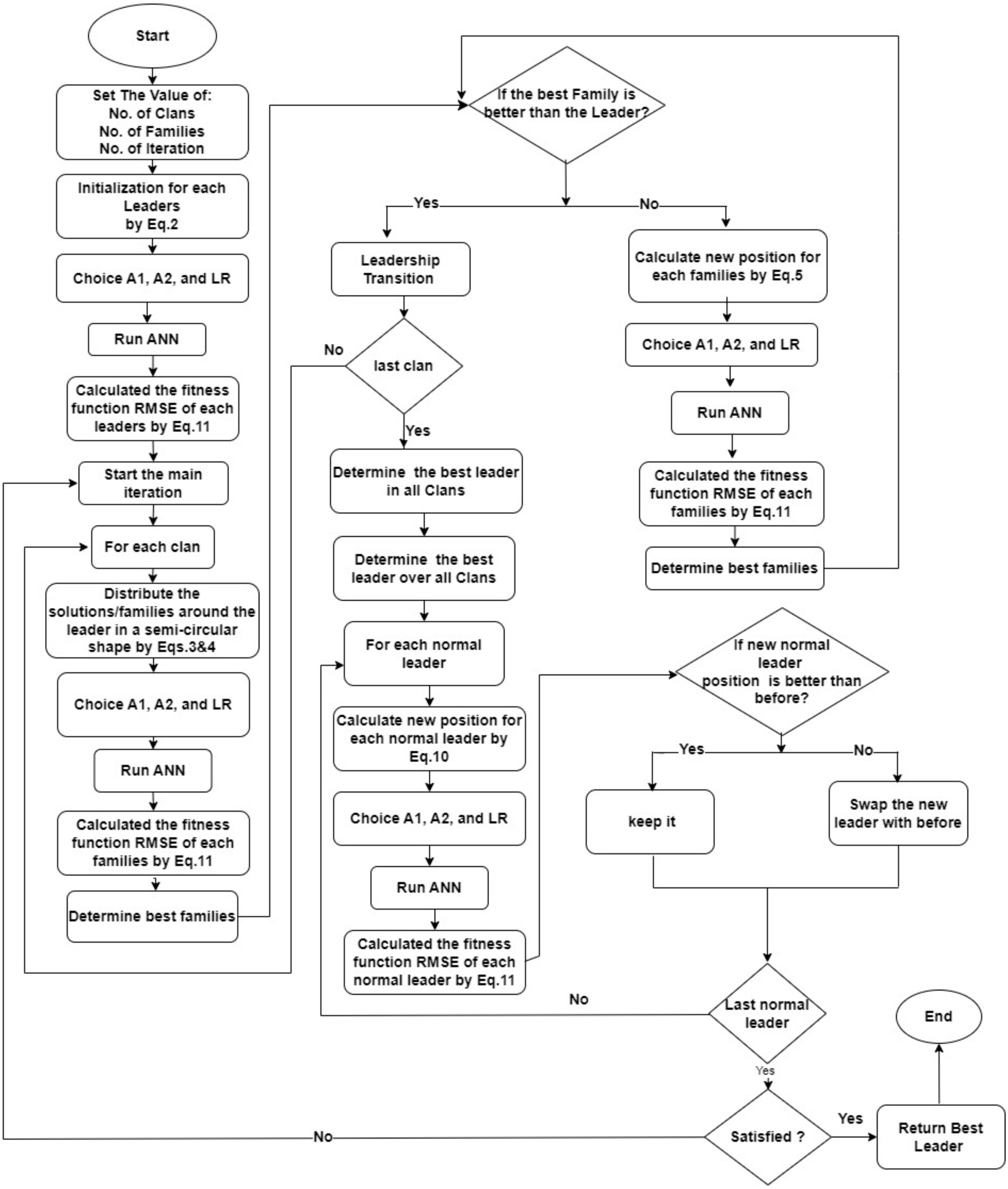

Figure. 1 Flowchart of the hybrid NPO+ANN algorithm

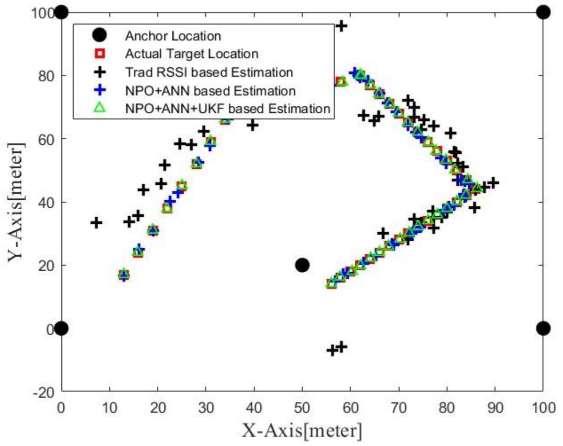

Figure. 2 Actual and target estimated by the Traditional RSSI, NPO+ANN, and NPO+ANN+UKF

4. Result and discussion

The suggested system is made up of a collection of anchor nodes that are positioned within a simulated area that is 100 M^2. In Fig. 2 a mobile target with a wireless sensor node attached is shown, and a base station outside the simulation area is not visible in Fig. 2. The mobile target, which serves as a receiver, receives the RF signals broadcast by the anchor nodes at each time step (i). The RSSI data acquired from each anchor node are transmitted to a base station outside the simulation area at the end of each time step. The laptop that complies with the following specifications is connected to the base station using 8GB RAM, Core i7, and 2.3 GHz.

A feed-forward neural network with the Levenberg-Marquardt (LM) algorithm is implemented using the MATLAB software. The estimated x and y coordinates are the neural network's outputs. The neural network's inputs are the RSSI measurements, designated as RSSI1, RSSI2, RSSI3, RSSI4, RSSI5, and RSSI6. The UKF approaches are used to further improve the findings after the neural network's initial estimation. To increase the precision of the localization estimation, the neural network's training and testing processes take into account and optimize every parameter, including inputs, A1, A2, LR, weights, and output. To get the best localization outcomes for the target, the ANN is trained and evaluated using the data that is available.

To enhance the overall performance of the ANN, the NPO algorithm optimizes the number of neurons in each hidden layer and the learning rate. In turn, the ANN seeks to reduce the localization process error. The fitness functions produced when the NPO algorithm is run with the following swarm sizes (No. of Clans x No. of Families): 20 (5 x 4), 40 (5 x 8), and 60 (5 x 12) are displayed in Fig. 1. These fitness functions show how well the NPO algorithm performs while improving the ANN's parameters, which in turn influences the system's localization accuracy. The best performance of artificial neural networks was obtained when the swarm size was 40. Where the number of neurons was 8 and 12 in the first and second hidden layers, respectively, and the learning rate was 0.2291. In this study, we have opted to utilize a target motion model with constant velocity. The following equations describe how the target moves:

$$x_i = x_{i-1} + vx_i\, di \quad (12)$$

$$y_i = y_{i-1} + vy_i\, di \quad (13)$$

where x_i and y_i pecify the position. vx_i and vy_i the speed in x and y directions respectively at i time instance, and the time elapsed between two subsequent time instants is denoted by the discretization time step (di).

Throughout the study, these equations are used to explain the target's movement pattern. The motion representation is made simpler by the constant velocity model, which also allows us to concentrate on particular elements of the localization and tracking process. Consequently, as indicated in Table 2, the parameters of a hybrid NPO+ANN and LNSM can be obtained. The offline and online localization phases are the two phases in which the study is carried out, as previously mentioned. Run a hybrid NPO+ANN to ascertain the optimal value before moving on to the analysis step of online localization to ascertain the wireless scenario.

Table 2. 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)
LR	Learning rate	0.2291
	Number of inputs	6
	Number of outputs	2
	Number of hidden layers	[8 12] for A1&A2

The effectiveness of the Localization. LNSM and the suggested approach are evaluated statistically using metrics like Root Mean Square Error (RMSE) and Average Localization Error (ALE) [24]. The findings show that, particularly in indoor settings, the LNSM approach does not satisfy the accuracy requirements. Consequently, the research offers the Hybrid NPO-ANN algorithm as a substitute strategy to improve the accuracy of localization and tracking.

$$ALE = \frac{1}{t}\sum_{i=1}^{t}\frac{(\hat{x}_i - x_i)+(\hat{y}_i - y_i)}{2} \quad (14)$$

The online localization phase is processed within the identical network parameters as the training phase, using the best value (A1, A2, and LR) ascertained from the training process. Fig. 2 portrays the target paths deduced by both traditional RSSI and NPO-ANN methodologies. Red squares identify the target position, While Black circles designate anchor nodes. The black, and blue plus signs respectively, signify the estimated positions derived from RSSI, and NPO+ANN at a given time instance t, and the green triangle the estimated positions by NPO+ANN+UKF. The simulation data demonstrate that the NPO+ANN+UKF-derived approach holds an advantage over RSSI in matters of localization and tracking efficiency.

In MATLAB, RSSI values are generated through simulation using the log-normal shadow fading model. It's worth noting that the parameter represented as the normal random variable Xσ in Eq. (1) introduces variability, leading to fluctuations in the mean localization error values for the algorithms across different runs. The mean localization errors are average values of 20 simulation trials for traditional RSSI, NPO+ANN, and NPO+ANN+UKF are 6.5748, 1.0270, and 0.1227, respectively. demonstrating that the NPO+ANN+UKF framework can solve real-time target tracking issues in WSN utilizing RSSI. In comparison, the NPO+ANN+UKF provides a remarkable improvement of 98.2%, and 88% over the traditional RSSI, and NPO+ANN, respectively. Fig. 3, Fig. 4, and Fig. 5 depict the contrast in localization errors for the x estimate, y estimate, and both x and y estimates across all the algorithms mentioned earlier, respectively.

Table 3. Error Analysis of all the Algorithms.

Algorithm	Avg. Localization Error (M)	Avg. RMSE in x-y Estimation(M)
Traditional RSSI	5.2246	8.6939
NPO+ANN	0.3694	0.7300
NPO+ANN+UKF	0.1227	0.2444

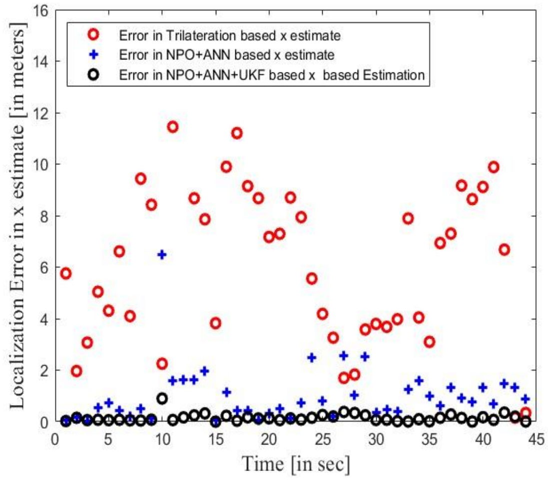

Figure. 3 Localization Errors in x estimates for Traditional RSSI, NPO+ANN, and NPO+ANN+UKF

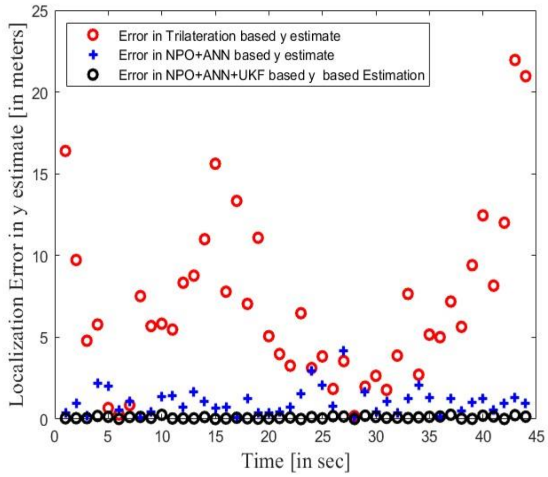

Figure. 4 Localization Errors in y estimates for Traditional RSSI, NPO+ANN, and NPO+ANN+UKF

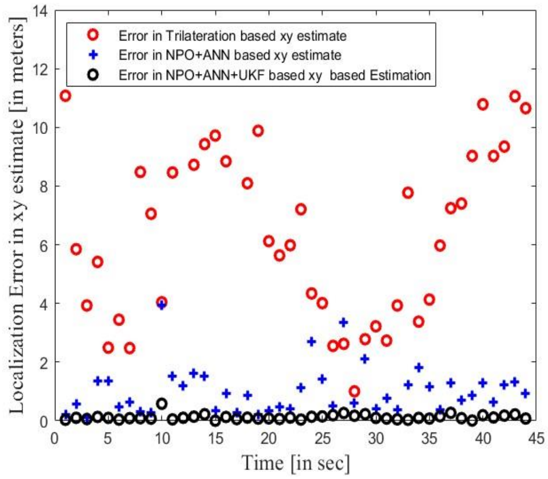

Figure. 5 Localization Errors in x-y estimates for Traditional RSSI, NPO+ANN, and NPO+ANN+UKF

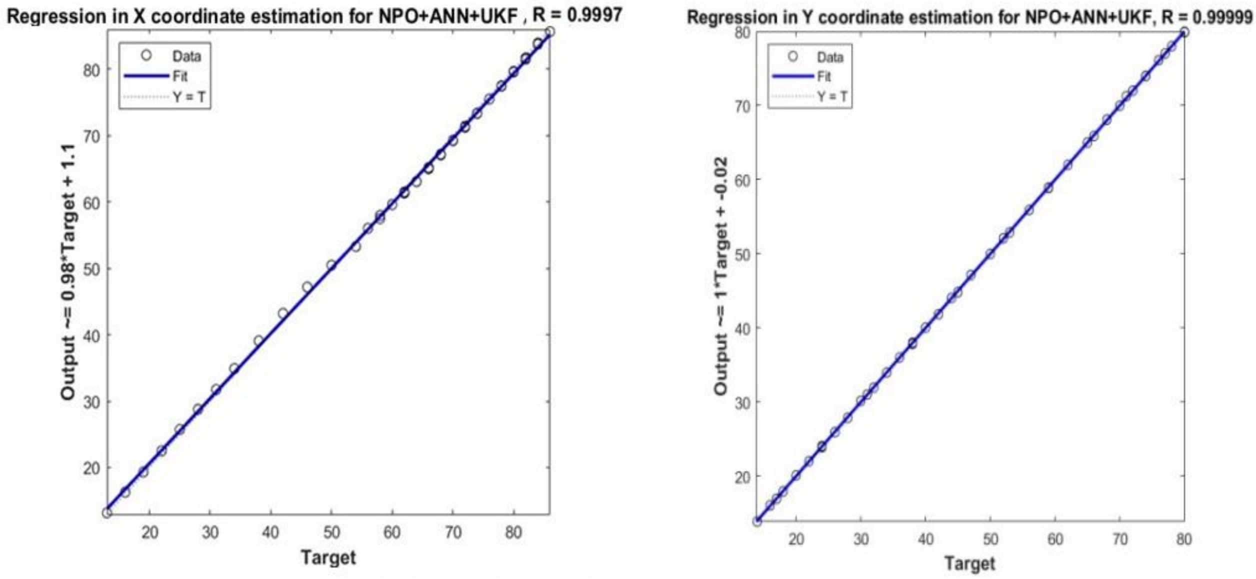

Figure. 6 The regression coefficient for x and y

Table 4. Summary error analysis of the hybrid NPO+ANN+UKF algorithms with previous works

Ref	Location technology algorithm	ANN type or learning framework	Metric	Environ ment	Tested area (m)	Average localizatio n error	RMSE
[1]	Simulation	GRNN+UKF	RSSI	Indoor	100x100	0.38	0.49
[14]	ZigBee	LM BRANN BP	RSSI	Indoor	4x6	0.22 0.35 0.33	/
[15]	Simulation	TCGRNN	RSSI	Indoor	100x100	3.39	4.91
[18]	APs	GRNN FFBP	RSSI	Indoor	37×32	0.48 0.97	/
[12]	APs	RNN	RSSI	Indoor	54x32	1	/
[11]	APs	KNN	RSSI	Indoor	69x45	< 2m	/
[19]	Simulation	PSO+GRNN	RSSI	Indoor	100x100	0.88	1.63
(Propos ed Method)	Simulation	NPO+ANN+UK F	RSSI	Indoor	100x100	0.12	0.24

The algorithms' computed equivalent RMSE values differ (See Table 3). It is clear from the simulation studies that the NPO+ANN+ UKF strategy has the lowest ALE and RMSE overall tracking accuracy when compared to the other approaches.

As shown in Fig. 6 study of regression coefficients for predicting x and y coordinates, the regression coefficient (R) of determination can be a useful indicator of how effectively the hybrid NPO+ANN+UKF algorithm predicts the real position. The estimated and actual locations have a high degree of agreement when the regression coefficient (R) value is 1. The hybrid NPO+ANN+UKF method for localization in wireless sensor networks (WSNs) performs better than the algorithms used in earlier studies, as shown in Table 4.

All these research as indicated in Table 4 trained and tested the gathered RSSI data for localization using ANN algorithms. Because RSSI is inexpensive, smooth implementation, and requires no additional hardware, it has been employed in indoor environment research in different area sizes. The neural network uses the RSSI performance metric as its input, and its target node's position within the network as its output. For comparison, the ALE or RMSE are considered. Our suggested hybrid NPO+ANN+UKF approach, with average errors of

0.1227 m and 0.2444 m for RMSE, performs better than the algorithms of these prior studies.

5. Conclusion

The NPO and ANN-based technique is described in this work as a means of enhancing real-time target tracking performance. To choose the ideal number of neurons in the two hidden layers and to attain the ideal learning rate for ANN, the NPO and ANN algorithms were combined. calculating the initial location of a single target traveling across a wireless sensor network (WSN) in a two-dimensional area. Then, these initial estimations are improved and adjusted using the Unscented Kalman Filter to improve the precision of target localization. RMSE and average localization error are used to evaluate the overall tracking performance. The outcomes of the simulation trials showed greater tracking accuracy despite rapid changes in target velocity and unpredictable measurement noise. The simulation findings demonstrate that, in terms of tracking performance, the NPO+ANN+UKF-based strategy beats all others. The simulation outcome validates the NPO+ANN+UK architecture's capability for solving the real-time target tracking issue in WSN utilizing RSSI. In comparison, the NPO+ANN+UKF provides a remarkable improvement of 98.2%, and 88% over the traditional RSSI, and NPO+ANN, respectively.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

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

References

[1] 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.

[2] R. Ali, R. Liu, Y. He, A. Nayyar, and B. Qureshi, “Systematic Review of Dynamic Multi-Object Identification and Localization: Techniques and Technologies”, *IEEE Access*, Vol. 9, pp. 122924–122950, 2021.

[3] 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.

[4] S. J. Bhat and K. V. Santhosh, “Is Localization of Wireless Sensor Networks in Irregular Fields a Challenge?”, *Wireless Personal Communications*, Vol. 114, No. 3, pp. 2017–2042, 2020.

[5] S. Kumar and D. K. Lobiyal, “An advanced DV-Hop localization algorithm for wireless sensor networks”, *Wirel Pers Commun*, Vol. 71, No. 2, pp. 1365–1385, 2013.

[6] B. A. Labinghisa and D. M. Lee, “Neural network-based indoor localization system with enhanced virtual access points”, *Journal of Supercomputing*, Vol. 77, No. 1, pp. 638–651, 2021.

[7] W. L. Chin, C. C. Hsieh, D. Shiung, and T. Jiang, “Intelligent Indoor Positioning Based on Artificial Neural Networks”, *IEEE Netw*, Vol. 34, No. 6, pp. 164–170, 2020.

[8] T. Yang, A. Cabani, and H. Chafouk, “A survey of recent indoor localization scenarios and methodologies”, *Sensors*, Vol. 21, No. 23, p. 8086, 2021.

[9] R. M. M. R. Rathnayake, M. W. P. Maduranga, V. Tilwari, and M. B. Dissanayake, “RSSI and Machine Learning-Based Indoor Localization Systems for Smart Cities”, *Eng*, Vol. 4, No. 2, pp. 1468–1494, 2023.

[10] 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.Suciu, “Energy Efficient Received Signal Strength-Based Target Localization and Tracking Using Support Vector Regression”, *Energies*, Vol. 16, No. 1, p. 555, 2023.

[11] M. Borhani Afuosi and M. R. Zoghi, “Indoor positioning based on improved weighted KNN for energy management in smart buildings”, *Energy Build*, Vol. 212, p. 109754, 2020.

[12] M. Elbes, T. Alrawashdeh, E. Almaita, S. AlZu’bi, and Y. Jararweh, “A platform for power management based on indoor localization in smart buildings using long short-term neural networks”, *Transactions on Emerging Telecommunications Technologies*, Vol. 33, No. 3, p. e3867, 2022.

[13] S. R. Jondhale and R. S. Deshpande, “Modified Kalman Filtering Framework Based Real Time Target Tracking Against Environmental Dynamicity in Wireless Sensor Networks”, *Ad Hoc & Sensor Wireless Networks.* Vol. 40, 2018.

[14] B.Krupanek and R. Bogacz, “Localization technique of IoT nodes using artificial neural networks (ANN)”, *International Journal of Electronics and Telecommunications*, Vol. 66, No.4, PP. 769-774 , 2020.

[15] S. R. Jondhale, AS Jondhale, P.S. Deshpande, J. Lloret, “Improved trilateration for indoor localization: Neural network and centroid-based approach”, *International Journal of Distributed Sensor Networks*, Vol. 17, No.11, p. 15501477211053997, 2021.

[16] W. Ingabire, H. Larijani, R. M. Gibson, and A. U. H. Qureshi, “LoRaWAN Based Indoor Localization Using Random Neural Networks”, *Information*, Vol. 13, No. 6, p 101548, 2022.

[17] 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.

[18] 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.

[19] S. M. Tariq and I. S. Al-Mejibli, “WSN Localization Method Based on Hybrid PSO-GRNN Approach”, *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 5, pp. 717–727, 2023, doi: 10.22266/ijies2023.1031.60.

[20] A. Guidara, G. Fersi, M. Ben 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.

[21] H. A. Hashim, S. L. Mohammed, and S. K. Gharghan, “Path loss model-based PSO for accurate distance estimation in indoor environments”, *Journal of Communications*, Vol. 13, No. 12, pp. 712–722, 2018.

[22] S. Q. Salih and A. R. A. Alsewari, “A new algorithm for normal and large-scale optimization problems: Nomadic People Optimizer”, *Neural Comput Appl*, Vol. 32, No. 14, pp. 10359–10386, 2020.

[23] A. Payal, C. S. Rai, and B. V. R. Reddy, “Analysis of Some Feedforward Artificial Neural Network Training Algorithms for Developing Localization Framework in Wireless Sensor Networks”, *Wirel Pers Commun*, Vol. 82, No. 4, pp. 2519–2536, 2015.

[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 (CSNC 2021) Proceedings:* Vol 2, pp. 616–627, 2021.