Neural Network-Based Alzheimer's Patient Localization for Wireless Sensor Network in an Indoor Environment

**ZAINAB MUNADHIL[1], SADIK KAMEL GHARGHAN[2], (Member, IEEE),
AMMAR HUSSEIN MUTLAG[1], (Member, IEEE), ALI AL-NAJI[2,3], (Member, IEEE),
AND JAVAAN CHAHL[3,4], (Member, IEEE)**

[1]Department of Computer Engineering Techniques, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq
[2]Department of Medical Instrumentation Techniques Engineering, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq
[3]UniSA STEM, University of South Australia, Mawson Lakes, SA 5095, Australia
[4]Joint and Operations Analysis Division, Defence Science and Technology Group, Melbourne, VIC 3207, Australia

Corresponding author: Sadik Kamel Gharghan (sadik.gharghan@mtu.edu.iq)

ABSTRACT The number of older adults with Alzheimer's disease is increasing every year. The associated memory problems cause many difficulties for Alzheimer's patients and their caretakers; patients may even become lost in familiar surroundings. In this article, a proposed localization system based on a wireless sensor network (WSN) and backpropagation based artificial neural network (BP-ANN) was practically implemented to detect and determine the position of an Alzheimer's patient in an indoor environment. The proposed system consisted of four ZigBee-based XBee S2C anchor nodes and one mobile node carried by the Alzheimer's patient. The received signal strength indicator (RSSI) of the anchor nodes was collected by the mobile node using a laptop supported by X-CTU software. The obtained RSSI values were used as input for training, testing, and validation processes of the BP-ANN, while two-dimension (2D) locations (x and y) were used as the output of the ANN. The results showed that the obtained mean localization errors were 0.964 and 0.921m for validation and testing phases, respectively, after applying the ANN. Based on a comparison with state-of-the-art technology, we deduced that the proposed ANN method outperformed other techniques in previous studies in terms of mean localization error.

INDEX TERMS Alzheimer's patient, indoor localization, mean localization error, neural network, RSSI, WSN, ZigBee.

I. INTRODUCTION

Today, the number of people living with Alzheimer's disease worldwide is estimated at 44 million; the number of individuals with the disease is predicted to double by 2030 and more than triple by 2050 [1]. Alzheimer's disease reduces brain function and memory, leading to forgetting recent events [2]. The number of patients is increasing with the aging of the population. In the Americas and Europe, the greatest number of patients occurs among people aged 80 to 89; in Africa, among those who are 70 to 79 years old and in Asia, from age 75 to 84 [3]. Deterioration of cognitive functions and the brain may be caused by Alzheimer's disease.

The associate editor coordinating the review of this manuscript and approving it for publication was Yang Tang.

Accordingly, patients diagnosed with these diseases face problems in daily living activities; for example, they lose their sense of location, which may lead to death in some environments. Consequently, these patients need constant assistance and special care [4]. In support of these patients, a wearable wireless sensor network (WSN) can locate their position by way of indoor localization by a system that can be used to track or determine the location of devices or objects in indoor environments. A WSN for localization, in particular, can use different range-free and range-based localization systems.

Range-free localization methods rely on a communication link between beacon nodes and mobile nodes in a network to estimate node locations but do not provide information about angle and distance. Moreover, this method offers lower accuracy than a range-based method because it depends on

the received signal strength indicator (RSSI) quality, which fluctuates with time according to environmental factors such as channel fading, reflection, scattering, refraction, multipath, etc. Conversely, range-based systems are highly accurate and more effective than range-free localization methods. The range-based methods determine the angles and distances between nodes in WSN. The most common techniques adopted in these localization methods include the following: time difference of arrival (TDoA) [5], angle of arrival (AoA), time of arrival (ToA) [6], acoustic energy [7], RSSI [8] and global positioning system (GPS) [9]. The TDoA and ToA methods require synchronization for all receiving nodes that are detecting the location of the target signal. Though TDoA offers minimal localization error, it consumes high amounts of power and requires extra hardware [10].

The AoA method relies on the accuracy of the antenna direction; needing to use an additional antenna array leads to greater cost and more hardware. Meanwhile, although GPS is the simplest method and is often used in outdoor localization, reliable positioning based on GPS is not possible in an indoor environment due to the barrier between the GPS device and the satellite. Moreover, GPS consumes more power than other methods [11]. Acoustic energy presents some challenges (e.g. bandwidth that restricts the transmitted data in the network and limited processing capability of the nodes) that prevent it from performing complex and sophisticated processes; furthermore, the audio in the network is not synchronized because each node works separately [12]. The RSSI method is cost-effective and reduces power consumption as it requires neither additional hardware, time synchronization nor antenna array [13] and involves less system complexity. That said, while RSSI can be used to determine a patient's location in the indoor environment, this technology has poor localization errors due to the aforementioned reasons. Therefore, adopting a specific error optimization algorithm in conjunction with RSSI can minimize the localization error.

The most intensely researched areas in indoor localization have involved the application of indoor localization such as the detection of people indoors, detection of patients in a hospital setting, and tracking blind individuals inside a building [14]. Several technologies such as ZigBee, Bluetooth, LoRa [15], and Wi-Fi [16] have proved useful in indoor localization. Among them, ZigBee appears to be the best way of implementing a localization system to monitor patients compared with other technologies [17] due to low power consumption [18], ease of use, cost-effectiveness, no requirement for external hardware and suitable communication distance.

This article aimed to design and implement a small wearable device to determine the 2D location of an Alzheimer's patient while improving localization error based on a backpropagation-based artificial neural network (BP-ANN).

The contributions of this article can be highlighted as follows:

1) A wearable prototype device was designed and implemented for the localization of Alzheimer's patients based on the RSSI of the ZigBee wireless protocol.
2) The localization error for Alzheimer's patients was improved by using BP-ANN in an indoor environment.
3) The localization error for Alzheimer's patients was compared to that reported in related works to verify the performance of the prototype.

II. RELATED WORKS

Several traditional approaches and artificial intelligence-based approaches to indoor localization systems have been presented in the literature. One study [19] combined particle swarm optimization (PSO) and ANN to minimize localization error in indoor conditions based on Wi-Fi technology. The PSO was able to reduce the time involved and provided closer convergence. The authors compared the proposed method to common approaches such as a backpropagation neural network (BPNN) and k-nearest neighbor (KNN). The results disclosed that combining PSO and ANN overcame the localization error of BPNN and KNN by 8% and 24%, respectively, achieving an error of 1.89m. In comparison, in [20] the authors proposed a fall-detection system for older adults in indoor environments based on ZigBee technology. The targets of this study included providing an accurate location of the happening and to detect falling in an elderly individual. The researchers adopted the ANN algorithm to detect the location of an older adult. The system consisted of ZigBee, a microcontroller, an accelerometer sensor, and a battery. The results demonstrated that this system minimized elderly indoor localization error to 0.0454 m of mean absolute error.

The investigation in [21] described an approach for indoor localization using Bluetooth beacons and a modern smartphone. The authors developed a localization algorithm based on particle swarm optimization and fuzzy path loss models implemented in the MATLAB environment. The results obtained showed that 95% of the position estimated errors were less than 1m. In [22], the authors suggested a novel indoor localization approach based on the fingerprints of RSSI measurements. They used Wi-Fi and machine learning techniques based on long short-term memory neural networks to estimate location. In their results, mean absolute error decreased when the number of hidden neurons increased. In comparison, a convolutional neural network was implemented in [23] to determine the target location using Wi-Fi technology in indoor circumstances. The Wi-Fi information was collected from the access point to train the neural network in the first phase, while the target information was gathered and applied to the neural network in the second phase, allowing the target location to be determined. The proposed method yielded a localization error of 1.365m.

In [24], a neural network-based multilayer perceptron was proposed, employing an extended Kalman filter for indoor positioning using the collected RSSI of Bluetooth Low Energy (BLE) technology. This research achieved an error

of 2.21 m. A genetic algorithm (GA) and ANN were used in [25] to improve localization error in indoor environments. The authors concluded that the GA algorithm performed less well than ANN in terms of error accuracy. Moreover, the ANN provided higher accuracy, less run-time, and more stability than the GA, achieving a localization error of 1.05 m. The researchers in [26] adopted a fuzzy logic (FL) algorithm and the weighted centroid localization method to locate a node with an unknown location. Fuzzy logic based on the Sugeno inference system and fuzzy Mamdani were used to measure the distance between the sensor and anchor nodes. Then, the authors employed a centroid algorithm to estimate the unknown position of the node. The results disclosed a localization error in the range of 1.2–0.15 and 0.8–0.05 based on the Mamdani-type and Sugeno-type FL, respectively.

In [27], a type-2 FL system was employed to determine the location of visually impaired persons based on the RSSI of the BLE wireless protocol in indoor circumstances. The mean localization error obtained using type-2 FL was about 0.43 m, with a navigation accuracy of 98.2%. The Random Forest (RF)-based fingerprinting localization technique using Wi-Fi channel information for indoor positioning was proposed in [28] and compared with other localization techniques such as KNN and weighted KNN (WKNN). The RF algorithm outperformed the KNN and WKNN in terms of localization accuracy, achieving 0.4033 m compared to KNN's results of 1.7782 m and WKNN's of 1.0517 m in a non-line-of-sight circumstance.

In [29], the fingerprint localization method was proposed to localize and track a patient with Alzheimer's disease in indoor surroundings. The experiment took place in an area comprising three rooms having different environmental characteristics. The patient was equipped with a Raspberry Pi microcontroller while BLE was used as a beacon node located in several positions in the hospital. The unknown node (carried by the Alzheimer's patient) was used to collect the RSSI of the beacon nodes. The experimental results yielded an average error of 1.6 m from all tracking locations.

This article seeks to overcome the limitations (i.e. localization accuracy) in prior studies by introducing a localization assistance system for Alzheimer's patients in indoor locations with credible localization accuracy supported by a cost-effective, low-complexity, easy-to-use system.

III. EXPERIMENTAL CONFIGURATION

The experiment involving proposed localization of an Alzheimer's patient in indoor surroundings was performed in an area sized 28 × 28 m2 on the second floor of the lab building of the Electrical Engineering Technical College (EETC) as shown in Figure 1. The Alzheimer's patient localization system was based on ZigBee (XBee S2C) WSN. The WSN consisted of five nodes: four anchor nodes (AN1, AN2, AN3, and AN4) and one mobile node (MN) carried by the Alzheimer's patient. The anchor nodes were fixed in each corner of the ceiling of the building and powered by an electrical main source from the laboratory adjacent to
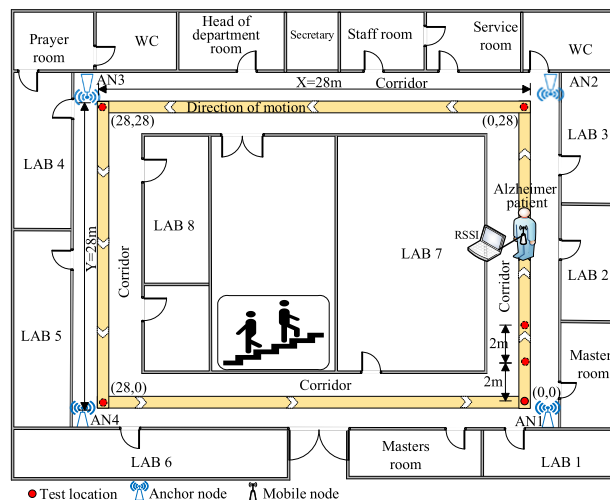

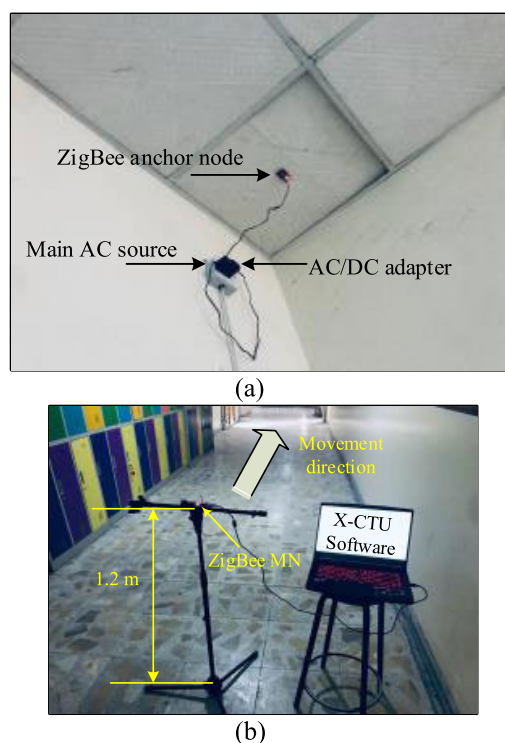**FIGURE 1.** Experimental layout for indoor localization of Alzheimer's patient.

FIGURE 2. The hardware for the Alzheimer's patient indoor localization system: (a) anchor node and (b) MN with the laptop.

the location of each node as shown in Figure 2a. The MN (configured as a coordinator node) was designed to collect the RSSI of the anchor nodes. In practice, the MN should be mounted in or on the belt of the Alzheimer's patient, but in this study, it was fixed on a stand at a height of about 1.2 m from the ground (approximating the height of an Alzheimer's patient's waist) as shown in Figure 2b.

The MN was connected to a laptop via USB cable and powered from the laptop. However, an MN carried by a patient in a real-life application should be powered by a battery.

The laptop used X-CTU software to record the RSSI samples of the anchor nodes collected by the MN. In addition, this software was used to configure the wireless connection between the anchor nodes and the MN. In the experiment, 57 locations were pre-defined on the second floor for RSSI measurements with 2 meters of distance between points. Forty samples were collected from four anchor nodes in each location (i.e. 10 samples per anchor node). A total of 2,280 samples (570 samples per anchor node) were collected from the 57 locations. The RSSI samples were employed to train, test, and validate the ANN to improve the localization accuracy of the Alzheimer's patient in an indoor environment.

In this article, the proposed indoor localization method was tested in the line-of-sight (LOS) and non-line-of-sight (NLOS) conditions. Barriers or obstacles such as walls, doors, or windows were situated in the path of the transmitted signal from the anchor nodes to the MN. The results presented in reference [20] show that the path loss of the signals in NLOS is greater than those in LOS surroundings, and the received power in NLOS is attenuated more than in LOS. Therefore, the localization accuracy in NLOS is reduced compared to LOS environments. Localization inside the LABs was not highlighted in this study because we conducted the experiments in an environment similar to the NLOS condition (i.e. inside the LABs) where the barriers (i.e. walls, doors, and windows) are available in the tested area. When the Alzheimer's patient moves in the paths from (AN1 to AN2), (AN2 to AN3), (AN3 to AN4), and (AN4 to AN1), the (AN3 and AN4), (AN1 and AN4), (AN1 and AN2), and (AN2 and AN3) will be in the NLOS condition with the patient, as shown in Figure 1. In addition, the localization in NLOS conditions was extensively addressed in our published article, which can be found in reference [20].

IV. ADOPTED ANN STRUCTURE

Neural networks are efficient computational methods that are used for knowledge representation, machine learning, and applying developed knowledge to forecast the output response of composite systems [30]. Artificial neural networks have recently been applied effectively, realizing significant achievements [31]. A biological neural network simulates the activity in the biological brain. The neurons are organized by synapses that can be improved by the training process and carry information. Various training processes have been used to train an artificial neural network, among them, the BP training method. BP involves calculation, back-propagation of error, and a feed-forward input training pattern [32]. BP-ANN consists of an input layer, output layer, and one or more hidden layers. The layers are connected serially, initiating from the input layer through the hidden layer and output layer. Each layer includes one or more neurons; the connections between layers are called weights. Two stages in the BP procedure were used: forward and backward [33]. In the design of the neural network, two important parameters that affected the final prototypical performance in unforeseen

ways were the learning rate and the number of neurons in the hidden layer of the network [34].

In this work, the BP-ANN architecture consisted of four inputs (called RSSI1, RSSI2, RSSI3, and RSSI4), two hidden layers each having 20 neurons and two output layers *x*-location and *y-location* that considered the positional coordinates for the Alzheimer's patient as illustrated in Figure 3.
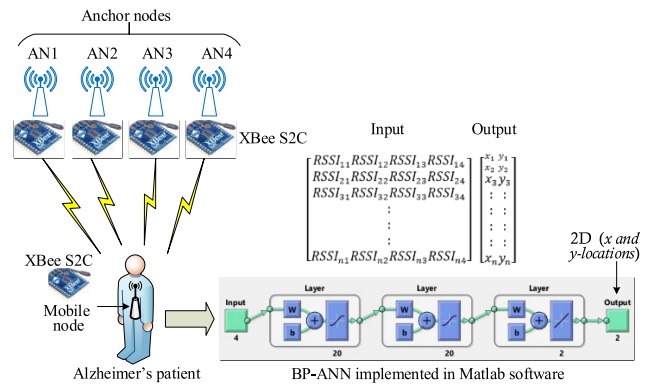

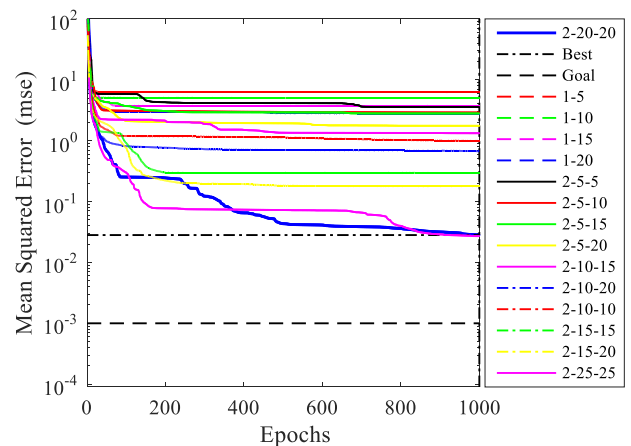**FIGURE 3.** RSSI collected by the MN.

FIGURE 4. Training performance for different ANN architectures.

To perform a low localization error, the chosen number of hidden layers and neurons was achieved by training 15 different ANN architectures, as shown in Figure 4. Hence, the number of hidden layers and neurons was increased to obtain the best ANN performance, since the Alzheimer's patient localization requires a lower error and higher correlation coefficient (R) between estimated and actual locations. First, one hidden layer was executed by changing the number of neurons from 5 to 20 in increments of 5 (1-5, 1-10, 1-15, and 1-20), as shown in Figure 4. Based on the ANN performance presented in Figure 4, we noticed that the mean square error (MSE) value of ANN training was unsatisfactory. Therefore, the number of hidden layers was increased to two and the number of neurons was changed from 5 to 25 (2-5-5, 2-5-10, 2-5-15, 2-5-20, 2-10-10, 2-10-15, 2-10-20, 2-15-20, 2-15-15, 2-20-20, and 2-25-25). As a result, two hidden layers and

20 neurons (2-20-20) and two hidden layers and 25 neurons (2-25-25) constitute the minimum MSE relative to the other ANN architectures. However, the 2-25-25 architecture produces a relatively similar performance to that of the 2-20-20, as shown in Figure 4. Therefore, the 2-25-25 architecture was excluded from the current work, and the 2-20-20 was considered to reduce the architecture complexity with a suitable convergence time relative to the 2-25-25 architecture.
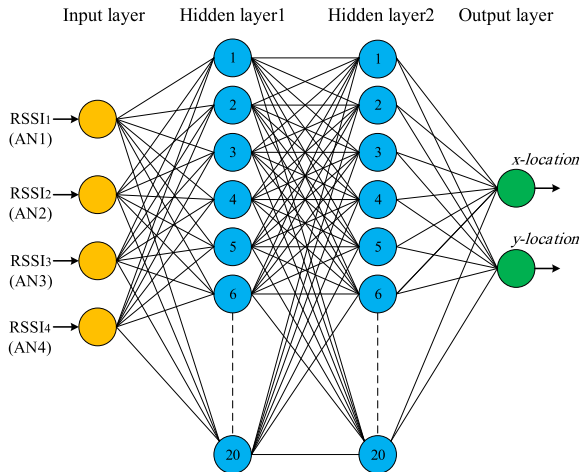

FIGURE 5. The architecture of adopted ANN.

Figure 5 shows the architecture of the ANN that was adopted. The BP-ANN was selected to improve the localization accuracy of the Alzheimer's patient while moving about in an indoor environment. From each anchor node, 570 samples were collected to train, test, and validate the data. The samples were divided into 70%, 15%, and 15% for training, testing, and validating data [20], [35], [36] corresponding to 398, 86, and 86 RSSI samples.

The flow chart of the ANN is depicted in Figure 6. It was important to identify the hidden layers, the neurons in each hidden layer and the learning rate before the ANN started the training, testing, and validation phases. Accordingly, the two hidden layers and 20 neurons in each hidden layer were selected as recommended in [13], while the learning rate was chosen based on the ANN algorithm. One hundred loops (0.01–1 with a step of 0.01) were fused with the ANN algorithm to select the value for the learning rate that could give a minimum MSE of ANN. Then, the ANN was run to find the objective function (i.e. MSE). The ANN iteration was configured to 1,000 to allow the ANN to obtain optimal MSE. However, the ANN stopped running either when reaching the best MSE or the goal was achieved (i.e. 10^{-3}).

V. RESULTS AND DISCUSSION
A. BP-ANN RESULTS
This section introduces the feed-forward BP-ANN results. The BP-ANN was adopted in the current work because it produces a superior performance than other types of neural networks, such as the cascade forward-artificial neural network (CF-ANN), Elman-artificial neural network (ELM-ANN),
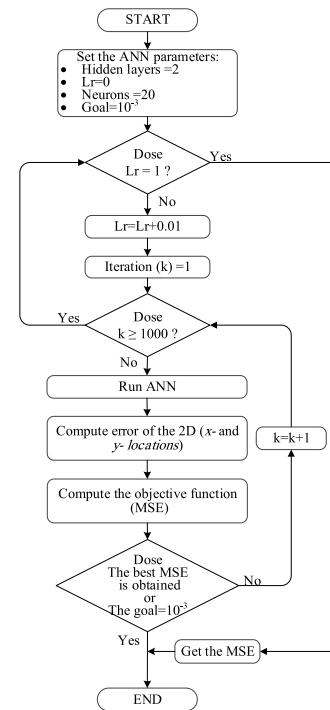

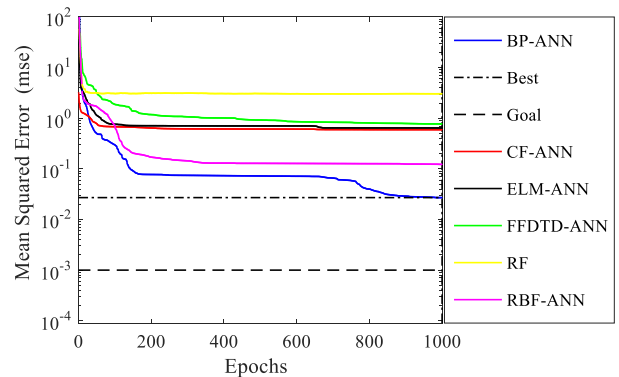**FIGURE 6.** Flowchart of the adopted ANN.

FIGURE 7. Comparison of training performance for different ANN types and learning methods.

feed-forward distributed time delay- artificial neural network (FFDTD-ANN), radial basis function (RBF-ANN), and other learning methods such as random forest (RF) in terms of MSE and convergence, as shown in Figure 7. Accordingly, the MSE for the BP-ANN was 0.027, which is significantly lower than other varieties of neural networks. In addition, the fundamental reason for using the BP-ANN algorithm in this study was to minimize inclusive output errors during the learning process such that the error could be backpropagated to modify the weights and to decrease the error between the estimated and actual values [37].

The MN collected 570 RSSI values for each anchor node as shown in Figure 8. All of the 2,280 RSSI data collected by the MN were used to train, test, and validate the ANN performance and to locate the Alzheimer's patient in the
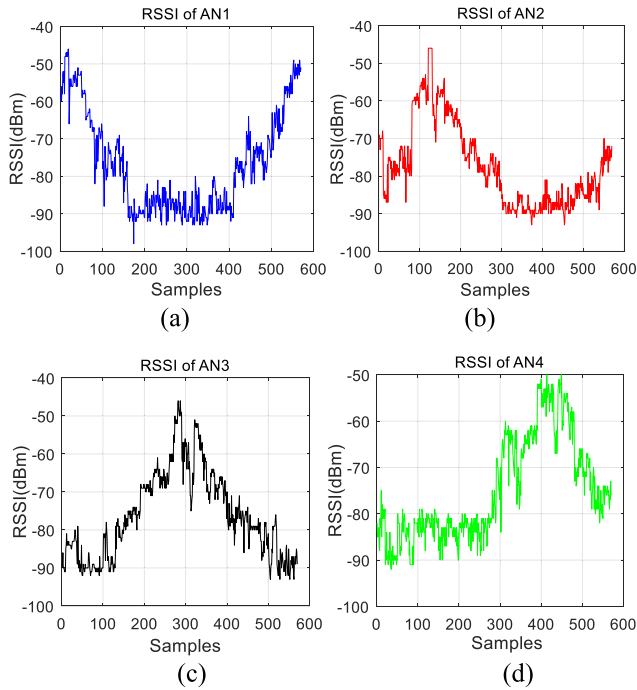
FIGURE 8. Collected RSSI by the MN of the anchor nodes: (a) AN1, (b) AN2, (c) AN3, and (d) AN4.

indoor environment. In the beginning, 70% (398 samples) of the collected RSSI data were used to train the ANN. Next, 15% (86 samples) were used to test the ANN performance. Then, 15% (86 samples) were used for validation. The performance of the BP-ANN was extracted in terms of MSE and correlation coefficient as shown in Figures 9 and 10, respectively, for the training, testing, and validation processes.

Figure 9 demonstrates the development of the objective function of the BP-ANN in terms of MSE during training, validating, and testing performance. The number of epochs to evaluate the performance for BP-ANN was set to 1,000. Figure 9 reveals that the training, testing, and validation performance did not reach the target set (i.e. 0.001 m). However, the best performances in terms of MSE were 0.027, 0.069, and 0.081 m for training, testing, and validation, respectively, at 1,000 epochs. Figure 9a confirms that the MSE of the training performance was better than the testing and validation at 1,000 epochs. Figure 9b illustrates that the testing performance was better than that for validation. However, Figure 9c provides convincing results in terms of localization accuracy, especially when used in indoor environments.

Figure 10 depicts the correlation coefficient of the training, testing, and validation of the ANN. The correlation coefficient is a good indicator for assessing the degree of agreement between actual measurements and an estimate. Therefore, it can be considered in this article to evaluate the agreement between the actual (Target) 2D locations (i.e. x and y-axis's) of the Alzheimer's patient while moving and the indoor estimated (output) locations obtained from the ANN. Figures 10a, 10b and 10c demonstrate R values
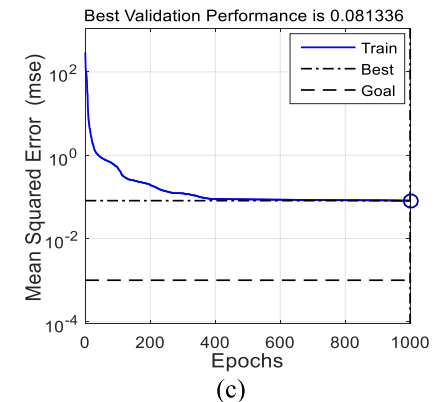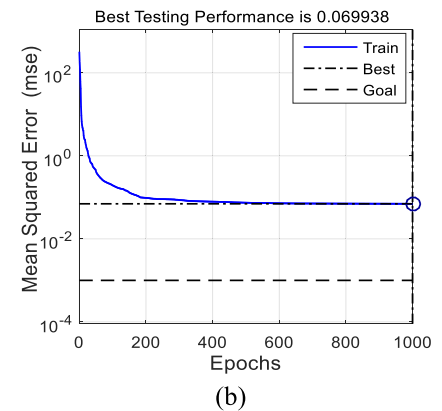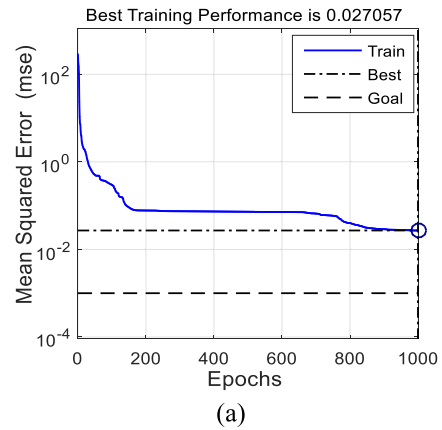
FIGURE 9. MSE of ANN for (a) training, (b) testing, and (c) validation.

of 0.9999 (training), 0.9997 (testing) and 0.9996 (validation), respectively. As a result, the correlation coefficients of ANN provide strong evidence that the proposed BP-ANN can be used to obtain high localization accuracy and improve localization error between actual and estimated locations. Consequently, the proposed localization method can produce accurate Alzheimer's patient localization.

B. LOCALIZATION ERROR RESULTS
After the training phase, the BP-ANN was used for validation and testing to localize 57 unknown pre-defined locations in the area of interest, having dimensions of 28 × 28 m^2 as

FIGURE 10. Correlation coefficient for (a) training, (b) testing and (c) validation.

FIGURE 11. Estimated and actual locations of Alzheimer's patient in an indoor environment for (a) training, (b) testing and (c) validation.

shown in Figure 11. The figure illustrates the actual locations represented by blue squares, while the estimated locations are denoted by red circles. A slight difference between estimated and r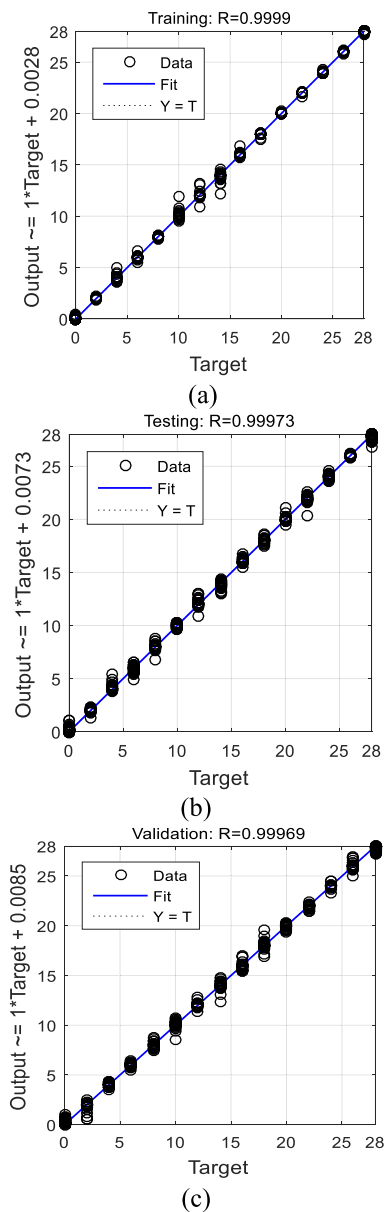eal Alzheimer's patient locations was noted for training as shown in Figure 11a. In this context, the mean error was found to be around 0.055 m, whereas a small difference was observed for testing and validation as shown in Figures 11b and 11c, respectively. The mean errors were found to be 0.964 and 0.921 m for validation and testing, respectively.

Figure 12 presents a 3D graph that clarifies the relationship between actual x-location (x-axis), y-location (y-axis), and obtained error from ANN (z-axis). Figure 10a represents the Alzheimer's patient localization error for the training

phase, which varies between 0.000145 (min) and 0.96 (max). Based on the gradual alteration of the color in Figure 11a, we can deduce that most of the error lies beyond the dark blue and blue colors where the error is less than 0.2 m. Figures 11b and 11c introduce the localization error for the testing and validation phases, respectively. The error changes between 0.0241 (min) and 5.646 (max) for the testing phase, while it varies between 0.0036 (min) and 5.075 (max) for the validation phase. Based on the piecemeal change of the colors in Figure 11b and 11c, we can observe that most of the localization errors venture beyond the dark blue and blue colors where the error is less than 1.5 m.

In examining the overall cumulative localization error of an Alzheimer's patient in an indoor environment produced

FIGURE 12. 3D graph of error concerning *x-* and *y-locations* for (a) training, (b) testing and (c) validation.

by ANN, the cumulative distribution function (CDF) shown in Figure 12 can be considered. The figure depicts the cumulative errors for 57 different locations for the training, testing, and validation phases. The CDF plot discloses that 73%, 70%, and 65% of the error for training, testing, and validation is les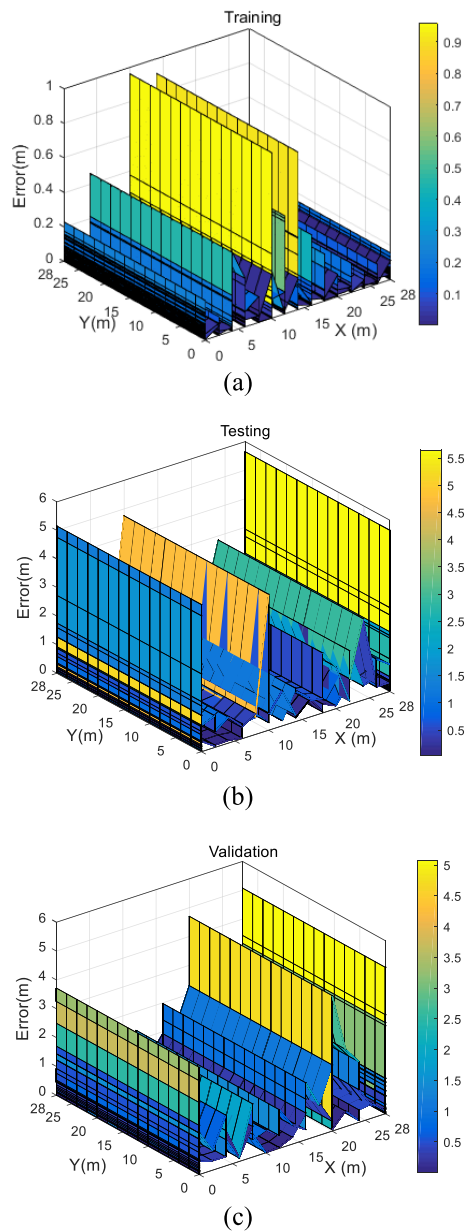s than 0.055, 0.921, and 0.964 m, respectively. However, the error is less than 0.1346, 2.106, and 2.498 m for training, testing, and validation, respectively, when the CDF plot reaches 90%.

The x-y plot (Figure 10), 3D graph (Figure 11), and CDF plot (Figure 12) provide clear evidence that using ANN can improve localization error for Alzheimer's patients who are moving about in an indoor environment. Consequently, the

proposed Alzheimer's patient localization based on the BP-ANN technique can produce accurate localization.

VI. COMPARISON RESULTS

In this section, the mean localization error produced from applying the BP-ANN is compared with other scholars' findings to confirm the proposed method for Alzheimer's patient localization as presented in Table 1. The table also introduces the adopted wireless technology for each research paper. Traditional and artificial intelligence-based localization techniques have been considered for this purpose. The traditional methods include coupled RSSI and inertial navigation system localization (CRIL), Bayesian graphical model (BGM), hierarchical voting based mixed filter (HVMF), inertial measurement unit (IMU), weighted k-nearest neighbor (WKNN), and minimum mean square error (MMSE). In comparison, the intelligent localization techniques or algorithms include ANN, PSO, FL, neural-fuzzy inference system (ANFIS), radial basis function network (RBFN), Random Forest (RF), Feedforward ANN (FFANN), non-linear regression neural network (NL-NN), support vector regression (SVR), extreme learning machine (ELM), Wi-Fi deep learning (WiDeep), generalized regression neural network (GRNN), intelligent water drops-continuous optimization (IWD-CO), deep neural network (DNN), multilayer perceptron neural network (MLPNN), recurrent neural networks (RNN), and discrete Hopfield-type neural network (DHNN).

The majority of previous articles resemble our work in that they use the RSSI metric to estimate the location of a target or MN in indoor surroundings and that they adopt soft computing techniques or intelligent algorithms. In addition, for comparative purposes, we used the mean localization error obtained directly from the calculations in previous studies and presented in their results. However, some parameters of our study differ from previous studies, such as the ANN architectures, which include hidden layers and neurons within each hidden layer, the numbers of iterations, the RSSI samples, the anchor nodes, and the size of the tested area. Most of these parameters presented in previous works (shown in Table 1) had higher values than our work. Nevertheless, our current work has surpassed the aforementioned studies in terms of our localization error. The training, testing, and validation of the dataset in the current work uses an approach that is similar to previous work but is not identical because it is difficult to find a matching dataset in earlier studies.

The mean absolute error of the localization estimation was employed to assess the average 2D localization error between estimated and actual location, in contrast to those obtained from previous papers. Based on the comparison introduced in Table 1, it is obvious that the adopted BP-ANN method – with a mean localization error of the predictable locations of 0.921 m (testing phase) and 0.964 m (validation phase) for indoor environments – outperforms other algorithms and techniques introduced in recent works.

The superiority of our proposed method, i.e. BP-ANN, over traditional methods stems from the fact that ANN

TABLE 1. Comparison of mean localization error of the current method with localization techniques of previous works.

Ref./year	Wireless protocol	Method	Structure		No. of iteration	Tested area	No. of samples	Anchor node/ reference point	Mean localization error (m)
			HL	Neurons					
[37]/2014	ZigBee	RBFN	2	5	6,000	100 m	N/M	3	3.35
[38]/2014	WSN	RF	----	---	-----	49.4 m × 14.1 m	400	27	2
[39]/2015	WSN	FFANN	1	20	5,000	100 m × 100 m	2,000	3	1.5053
[40]/2015	WIFI	NL-NN	N/M	N/M	N/M	4 m × 4 m	N/M	N/M	1–3
[14]/2016	WIFI	SVR	---	----	2,000	12 m × 4 m	105	21	1.8
[41]/2016	WIFI	CRIL	---	----	-----	40 m × 6 m	----	3	< 1
[19]/2016	WIFI	PSO-ANN	2	15	50,000	45 m × 25 m	9,400	9	1.893
[42]/2016	WSN	ANN, ELM	1	N/M	N/M	100 m × 100 m	N/M	100	5.25
[25]/2016	WIFI	ANN	2	15, 18	10^7	10 m × 28 m	96	6	1.05
[35]/2016	ZigBee	ANFIS	1	7 mf	1,000	36 m × 34 m	780	3	1.4269
[43]/2017	WIFI	BGM	---	----	10,000	51m × 22 m	30	15	2.9
[44]/2017	BLE	ANN	1	40	N/M	6.66 m × 5.36 m	85,000	6	1.908
[45]/2017	WIFI	RF	---	300 trees	-----	43.5 m × 22.5 m	19,937	520	6.46
[46]/2018	N/M	HVMF	---	----	-----	100 m × 100 m	------	8	1.568
[47]/2018	WIFI	IMU	---	----	-----	288 m²	------	5	1.15
[48]/2018	RFID	PSO	---	20 particles	200	5m × 4m × 3m	6	4	1
[24]/2018	BLE	ANN	N/M	N/M	N/M	4 m × 4 m	320	4	2.21
[49]/2019	WSN	PSO	---	50 particles	100	100 m × 100 m	------	4–20	2.101
[50]/2019	Bluetooth	PSO	---	500 particles	100	50 m × 50 m	1000	3	0.91
[51]/2019	WIFI	WiDeep	2	300, 400	20,000	14.5 m × 4.5 m	2000	59	1.21
[52]/2019	RFID	GRNN	N/M	N/M	N/M	12 m × 10 m	156	42	1.32
[53]/2019	WIFI	WKNN	---	K=4	-----	100 m²	48	1	1.91
		MMSE	---	----	-----	100 m²	53	1	2.17
[54]/2019	WIFI	IWD-CO	P=2	N=100	2,000	20 m × 20 m	-----	4	1.602
[55]/2019	N/M	FL without PSO	---	9 fuzzy rules	----	100 m²	-----	4–10	1.88
		FL with PSO	---	40 particles	20	100 m²	-----	4–10	0.95
[56]/2019	WSN	FL	---	------	1,000	100 m × 100 m	------	10	0.9–1
[57]/2019	WIFI	DNN	2	256, 128	210	20 m × 20 m	N/M	210	1.95
[58]/2020	WSN	GRNN	1	N/M	N/M	100 m × 100 m	30	12	5.932
[59]/2020	WIFI	DNN	3	400, 300, 200	N/M	19,800 m ×195 m	21,048	520	1.72
[60]/2020	BLE	MLPNN	1	8	N/M	100 m²	223	3	2.64
[61]/2020	WIFI	RNN	1	400	250	54 m × 32 m	N/M	6–7	1
[62]/2020	WIFI	MLPNN	8	22	N/M	36 m × 26.8 m	5,400	4	1.53
[63]/2020	WIFI	DHNN	1	Variable	N/M	10.01m × 6.90m	1,400	1	1.6
[64]/2020	WIFI	KNN	----	------	-----	69 m × 45m	343,458	5	< 2
[65]/2020	WIFI	DNN	N/M	N/M	N/M	92 m × 36 m	55,350	N/M	2.23
This work	**ZigBee**	**BP-ANN**	**1**	**20**	**1,000**	**28 m × 28 m**	**2,280**	**4**	**0.964 (validation) 0.921 (testing)**
NM: not mentioned; HL: hidden layer; mf: membership function; P: precision; N: number of components									

includes fast implementation, ease of use, learning capabilities, flexible modeling, and lower predicted errors, and it does not require knowledge of the propagation channel surroundings or the channel features. As a key advantage, ANN is not affected by the fluctuation of the RSSI measurement caused by the multipath effect, environmental noise, and node mobility. On the other hand, our proposed method did have to cope with the other soft computing localization techniques presented in Table 1, which we attributed to the fact that we adopted two hidden layers with 20 neurons in each hidden layer. In this case, when the number of hidden

layers and neurons increases the localization error decreases and the overall performance will be improved. In addition, we adopted 4 anchor nodes, positioned on each corner of the ceiling of the tested area, to reduce the fluctuation and degradation of RSSI produced from the multipath effect and noise during the RSSI collection.

VII. LIMITATION OF STUDY
In the current work, the Alzheimer's patient localization method largely relied on ANN to improve localization accuracy. Fifteen architecture combinations were trained to select
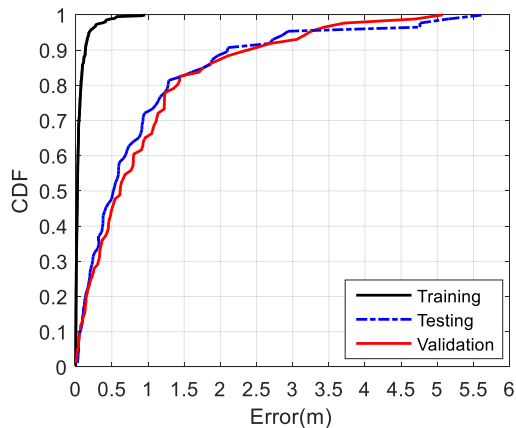
FIGURE 13. CDF plot for training, testing, and validation.

the best ANN performance in terms of the MSE. However, this strategy consumes a significant amount of time. Therefore, in future work, an optimization technique such as PSO, IWD-CO, Gravitational Search Algorithm (GSA), Backtracking Search Algorithm (BSA), or Slime Mould Algorithm (SMA), could be used to select the number of hidden layers and neurons directly without testing several ANN architectures. As a result, efficiency will be enhanced. In addition, other intelligent techniques, algorithms, or a combination of multiple soft computing techniques could be used to minimize the localization error. Another disadvantage of this study is that participants' movement during experimentation was limited inside the tested area. However, localization accuracy decreases when the number of people inside the tested area increases since these additional people act as obstacles between the Alzheimer's patient and the anchor nodes.

VIII. CONCLUSION

In this article, ANN-based Alzheimer's patient localization for a WSN in an indoor environment was presented. The backpropagation algorithm was used for training, testing, and validation of ANN. Five-ZigBee wireless technology was considered for the proposed localization technique using four anchor nodes as beacons and one MN carried by an Alzheimer's patient. The anchor nodes were fixed on the ceiling of the second floor of the EETC lab building to ensure line-of-sight between the anchor nodes and MN. The MN collected RSSI data for the anchor nodes to train, test, and validate the ANN. The number of hidden layers, neurons in each hidden layer, learning rate, and iteration of ANN were selected to confirm an optimal localization error with low system complexity and less run-time consumption. As a result, the Alzheimer's patient localization error was 0.055, 0.921, and 0.964 m for the training, testing, and validation phases, respectively. However, the localization error can be further improved to some centimeters by increasing the number of hidden layers or neurons at the expense of increasing the ANN run-time. The results show that the proposed system yields a satisfactory localization error and can be utilized

for localization and tracking an Alzheimer's patient moving about in an indoor environment.

For the outdoor environment, some possible solutions can be implemented in future work. The Geolocations of the Alzheimer's patient can be determined by GPS. The GPS is effective in outdoor settings but cannot be used indoors due to the absence of a line-of-sight between the GPS and satellite. Real-time GPS Geolocations can be provided by a smartphone over specific navigation software or by using a GPS receiving module interface with a low-power microcontroller supported by specific code and functions compatible with GPS readings. To send GPS messages containing each Alzheimer's patient's location to the caregivers or family members, GPS modules should be physically connected with wireless technologies such as a GSM module. The outdoor Alzheimer's patient positioning system can also be incorporated with an accelerometer and tilt sensors to detect the daily activity and, in case of a fall, the location of each Alzheimer's patient. However, the performance of the GPS is influenced by various factors, including multipath delays, atmospheric delays, and receiver thermal noise. Consequently, positioning errors will result from time delays. These positioning errors can be resolved by utilizing an advanced GPS such as the NEO-M8N module. The NEO-M8N preserves helpful information, such as an almanac, ephemeris, and approximate last position and time, which improve acquisition sensitivity. The NEO-M8N has high positioning accuracy, sensitivity, and a short acquisition time while operating under a low-power system with a maximum current of 70 mA.

REFERENCES

[1] G. Hernandez-Penaloza, A. Belmonte-Hernandez, M. Quintana, and F. Alvarez, "A multi-sensor fusion scheme to increase life autonomy of elderly people with cognitive problems," *IEEE Access*, vol. 6, pp. 12775–12789, 2018.

[2] M. B. Mendoza, C. A. Bergado, J. L. B. De Castro, and R. G. T. Siasat, "Tracking system for patients with Alzheimer's disease in a nursing home," in *Proc. TENCON IEEE Region Conf.*, Nov. 2017, pp. 2566–2570.

[3] A. L. Sosa-Ortiz, I. Acosta-Castillo, and M. J. Prince, "Epidemiology of dementias and Alzheimer's disease," *Arch. Med. Res.*, vol. 43, pp. 600–608, Nov. 2012.

[4] D. Jimenez, P. Cordova, and C. Gordon, "Location system and monitoring of vital signs in older adults and people with alzheimer," in *Proc. Int. Conf. eDemocracy eGovernment (ICEDEG)*, Apr. 2018, pp. 206–211.

[5] B. Jin, X. Xu, and T. Zhang, "Robust time-difference-of-arrival (TDOA) localization using weighted least squares with cone tangent plane constraint," *Sensors*, vol. 18, no. 3, p. 778, Mar. 2018.

[6] Y.-Y. Li, G.-Q. Qi, and A.-D. Sheng, "Performance metric on the best achievable accuracy for hybrid TOA/AOA target localization," *IEEE Commun. Lett.*, vol. 22, no. 7, pp. 1474–1477, Jul. 2018.

[7] Y. Yan, X. Shen, F. Hua, and X. Zhong, "On the semidefinite programming algorithm for energy-based acoustic source localization in sensor networks," *IEEE Sensors J.*, vol. 18, no. 21, pp. 8835–8846, Nov. 2018.

[8] H. A. Hashim, S. L. Mohammed, and S. K. Gharghan, "Accurate localization of elderly people based on neural and wireless sensor networks," *J. Eng. Appl. Sci.*, vol. 14, no. 11, pp. 3777–3789, Nov. 2019.

[9] S. S. Fakhrulddin, S. K. Gharghan, A. Al-Naji, and J. Chahl, "An advanced first aid system based on an unmanned aerial vehicles and a wireless body area sensor network for elderly persons in outdoor environments," *Sensors*, vol. 19, no. 13, p. 2955, Jul. 2019.

[10] L. Cheng, C. Wu, Y. Zhang, H. Wu, M. Li, and C. Maple, "A survey of localization in wireless sensor network," *Int. J. Distrib. Sensor Netw.*, vol. 8, Dec. 2012, Art. no. 962523.

[11] S. Sadowski and P. Spachos, "RSSI-based indoor localization with the Internet of Things," *IEEE Access*, vol. 6, pp. 30149–30161, 2018.

[12] M. Cobos, F. Antonacci, A. Alexandridis, A. Mouchtaris, and B. Lee, "A survey of sound source localization methods in wireless acoustic sensor networks," *Wireless Commun. Mobile Comput.*, vol. 2017, p. 24, Aug. 2017.

[13] S. K. Gharghan, R. Nordin, M. Ismail, and J. A. Ali, "Accurate wireless sensor localization technique based on hybrid PSO-ANN algorithm for indoor and outdoor track cycling," *IEEE Sensors J.*, vol. 16, no. 2, pp. 529–541, Jan. 2016.

[14] A. S. Abdou, M. A. Aziem, and A. Aboshosha, "An efficient indoor localization system based on affinity propagation and support vector regression," in *Proc. 6th Int. Conf. Digit. Inf. Process. Commun. (ICDIPC)*, Apr. 2016, pp. 1–7.

[15] E. Goldoni, L. Prando, A. Vizziello, P. Savazzi, and P. Gamba, "Experimental data set analysis of RSSI-based indoor and outdoor localization in LoRa networks," *Internet Technol. Lett.*, vol. 2, no. 1, p. e75, Jan. 2019.

[16] M. Phunthawornwong, E. Pengwang, and R. Silapunt, "Indoor location estimation of wireless devices using the log-distance path loss model," in *Proc. TENCON IEEE Region Conf.*, Oct. 2018, pp. 499–502.

[17] H. A. Alobaidy, J. Mandeep, R. Nordin, and N. F. Abdullah, "A review on ZigBee based WSNs: Concepts, infrastructure, applications, and challenges," *Int. J. Electr. Electron. Eng. Telecommun.*, vol. 9, no. 3, pp. 189–198, May 2020, doi: 10.18178/ijeetc.9.3.189-198.

[18] Y. Kwon and K. Kwon, "RSS ranging based indoor localization in ultra low power wireless network," *AEU Int. J. Electron. Commun.*, vol. 104, pp. 108–118, May 2019.

[19] N. Li, J. Chen, Y. Yuan, X. Tian, Y. Han, and M. Xia, "A Wi-Fi indoor localization strategy using particle swarm optimization based artificial neural networks," *Int. J. Distrib. Sensor Netw.*, vol. 12, no. 3, Mar. 2016, Art. no. 4583147.

[20] S. Gharghan, S. Mohammed, A. Al-Naji, M. Abu-AlShaeer, H. Jawad, A. Jawad, and J. Chahl, "Accurate fall detection and localization for elderly people based on neural network and energy-efficient wireless sensor network," *Energies*, vol. 11, no. 11, p. 2866, Oct. 2018.

[21] S. Tomazic and I. Skrjanc, "Bluetooth localization based on fuzzy models and particle swarm optimization," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Sep. 2017, pp. 1–8.

[22] M. Elbes, E. Almaita, T. Alrawashdeh, T. Kanan, S. AlZu'bi, and B. Hawashin, "An indoor localization approach based on deep learning for indoor location-based services," in *Proc. IEEE Jordan Int. Joint Conf. Electr. Eng. Inf. Technol. (JEEIT)*, Apr. 2019, pp. 437–441.

[23] H. Chen, Y. Zhang, W. Li, X. Tao, and P. Zhang, "ConFi: Convolutional neural networks based indoor Wi-Fi localization using channel state information," *IEEE Access*, vol. 5, pp. 18066–18074, 2017.

[24] T. Kawai, K. Matsui, Y. Honda, G. Villarubia, and J. M. C. Rodriguez, "Preliminary study for improving accuracy on Indoor positioning method using compass and walking detect," in *Proc. Int. Symp. Distrib. Comput. Artif. Intell.*, Cham, Switzerland, 2018, pp. 318–325.

[25] Z. Farid, R. Nordin, M. Ismail, and N. F. Abdullah, "Hybrid indoor-based WLAN-WSN localization scheme for improving accuracy based on artificial neural network," *Mobile Inf. Syst.*, vol. 2016, p. 11, Jan. 2016.

[26] S. Amri, F. Khelifi, A. Bradai, A. Rachedi, M. L. Kaddachi, and M. Atri, "A new fuzzy logic based node localization mechanism for wireless sensor networks," *Future Gener. Comput. Syst.*, vol. 93, pp. 799–813, Apr. 2019.

[27] B. AL-Madani, F. Orujov, R. Maskeliūnas, R. Damaševičius, and A. Venčkauskas, "Fuzzy logic type-2 based wireless indoor localization system for navigation of visually impaired people in buildings," *Sensors*, vol. 19, no. 9, p. 2114, May 2019.

[28] Y. Wang, C. Xiu, X. Zhang, and D. Yang, "WiFi indoor localization with CSI fingerprinting-based random forest," *Sensors*, vol. 18, no. 9, p. 2869, Aug. 2018.

[29] A. Pratiarso, A. H. Amirudin, M. Yuliana, P. Kristalina, I. G. P. Astawa, and Arifin, "Analysis of fingerprint-based indoor localization system on Alzheimer's patient position tracking system," in *Proc. 3rd Int. Conf. Inf. Technol., Inf. Syst. Electr. Eng. (ICITISEE)*, Nov. 2018, pp. 114–119.

[30] S. Amirsadri, S. J. Mousavirad, and H. Ebrahimpour-Komleh, "A levy flight-based grey wolf optimizer combined with back-propagation algorithm for neural network training," *Neural Comput. Appl.*, vol. 30, no. 12, pp. 3707–3720, Dec. 2018.

[31] C. Yang, H. Kim, S. Adhikari, and L. Chua, "A circuit-based neural network with hybrid learning of backpropagation and random weight change algorithms," *Sensors*, vol. 17, no. 12, p. 16, Dec. 2016.

[32] J. Tarigan, Nadia, R. Diedan, and Y. Suryana, "Plate recognition using backpropagation neural network and genetic algorithm," *Procedia Comput. Sci.*, vol. 116, pp. 365–372, Jan. 2017.

[33] A. A. Hameed, B. Karlik, and M. S. Salman, "Back-propagation algorithm with variable adaptive momentum," *Knowl.-Based Syst.*, vol. 114, pp. 79–87, Dec. 2016.

[34] R. Jiao, X. Huang, X. Ma, L. Han, and W. Tian, "A model combining stacked auto encoder and back propagation algorithm for short-term wind power forecasting," *IEEE Access*, vol. 6, pp. 17851–17858, 2018.

[35] S. 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, Aug. 2016.

[36] S. Kumar, S. M. Jeon, and S. R. Lee, "Localization estimation using artificial intelligence technique in wireless sensor networks," *J. Korea Inf. Commun. Soc.*, vol. 39C, no. 9, pp. 820–827, Sep. 2014.

[37] 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," *Wireless Pers. Commun.*, vol. 82, no. 4, pp. 2519–2536, Jun. 2015.

[38] L. Luoh, "ZigBee-based intelligent indoor positioning system soft computing," *Soft Comput.*, vol. 18, no. 3, pp. 443–456, Mar. 2014.

[39] Y. Mo, Z. Zhang, Y. Lu, W. Meng, and G. Agha, "Random forest based coarse locating and KPCA feature extraction for indoor positioning system," *Math. Problems Eng.*, vol. 2014, pp. 1–8, Oct. 2014.

[40] S. Pasricha, V. Ugave, C. W. Anderson, and Q. Han, "LearnLoc: A framework for smart indoor localization with embedded mobile devices," in *Proc. Int. Conf. Hardw./Softw. Codesign Syst. Synth. (CODES+ISSS)*, Oct. 2015, pp. 37–44.

[41] S. Cai, W. Liao, C. Luo, M. Li, X. Huang, and P. Li, "CRIL: An efficient online adaptive indoor localization system," *IEEE Trans. Veh. Technol.*, vol. 66, no. 5, pp. 4148–4160, May 2017.

[42] C. So-In, S. Permpol, and K. Rujirakul, "Soft computing-based localizations in wireless sensor networks," *Pervas. Mobile Comput.*, vol. 29, pp. 17–37, Jul. 2016.

[43] A. Alhammadi, F. Hashim, M. F. A. Rasid, and S. Alraih, "A new indoor localization system based on Bayesian graphical model," in *Proc. Int. Conf. Wireless Commun., Signal Process. Netw. (WiSPNET)*, Mar. 2017, pp. 1960–1964.

[44] F. Daniş and A. Cemgil, "Model-based localization and tracking using Bluetooth low-energy beacons," *Sensors*, vol. 17, no. 11, p. 2484, Oct. 2017.

[45] B. A. Akram, A. H. Akbar, and O. Shafiq, "HybLoc: Hybrid indoor Wi-Fi localization using soft clustering-based random decision forest ensembles," *IEEE Access*, vol. 6, pp. 38251–38272, 2018.

[46] Y. Wang, J. Hang, L. Cheng, C. Li, and X. Song, "A hierarchical voting based mixed filter localization method for wireless sensor network in mixed LOS/NLOS environments," *Sensors*, vol. 18, no. 7, p. 2348, Jul. 2018.

[47] J. L. Carrera V., Z. Zhao, T. Braun, Z. Li, and A. Neto, "A real-time robust indoor tracking system in smartphones," *Comput. Commun.*, vol. 117, pp. 104–115, Feb. 2018.

[48] J. Li, G. Feng, W. Wei, C. Luo, L. Cheng, H. Wang, H. Song, and Z. Ming, "PSOTrack: A RFID-based system for random moving objects tracking in unconstrained indoor environment," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 4632–4641, Dec. 2018.

[49] B. F. Gumaida and J. Luo, "A hybrid particle swarm optimization with a variable neighborhood search for the localization enhancement in wireless sensor networks," *Int. J. Speech Technol.*, vol. 49, no. 10, pp. 3539–3557, Oct. 2019.

[50] C. Zhao and B. Wang, "A UWB/Bluetooth fusion algorithm for indoor localization," in *Proc. Chin. Control Conf. (CCC)*, Jul. 2019, pp. 4142–4146.

[51] M. Abbas, M. Elhamshary, H. Rizk, M. Torki, and M. Youssef, "WiDeep: WiFi-based accurate and robust indoor localization system using deep learning," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. (PerCom*, Mar. 2019, pp. 1–10.

[52] Q. Qiua and Z. Daib, "Research on RFID indoor positioning algorithm based on GRNN neural network," in *Proc. 2nd Int. Conf. Mech., Electron. Eng. Technol. (MEET)*, Xi'an, China, Feb. 2019, pp. 19–20.

[53] A. Kokkinis, L. Kanaris, A. Liotta, and S. Stavrou, "RSS indoor localization based on a single access point," *Sensors*, vol. 19, no. 17, p. 3711, Aug. 2019.

[54] B. F. Gumaida and J. Luo, "Novel localization algorithm for wireless sensor network based on intelligent water drops," *Wireless Netw.*, vol. 25, no. 2, pp. 597–609, Feb. 2019.

[55] G. Pau, M. Collotta, V. Maniscalco, and K.-K.-R. Choo, "A fuzzy-PSO system for indoor localization based on visible light communications," *Soft Comput.*, vol. 23, no. 14, pp. 5547–5557, Jul. 2019.

[56] T. Ahmad, X. J. Li, and B.-C. Seet, "Fuzzy-logic based localization for mobile sensor Networks*," in *Proc. 2nd Int. Conf. Commun., Comput. Digit. Syst. (C-CODE)*, Mar. 2019, pp. 43–47.

[57] P. Dai, Y. Yang, M. Wang, and R. Yan, "Combination of DNN and improved KNN for indoor location fingerprinting," *Wireless Commun. Mobile Comput.*, vol. 2019, pp. 1–9, Mar. 2019.

[58] S. R. Jondhale, R. Shubair, R. P. Labade, J. Lloret, and P. R. Gunjal, "Application of supervised learning approach for target localization in wireless sensor network," in *Handbook Wireless Sensor Networks: Issues Challenges Current Scenario's*, P. K. Singh, B. K. Bhargava, M. Paprzycki, N. C. Kaushal, W.-C. Hong, Eds. Cham, Switzerland: Springer, 2020, pp. 493–519.

[59] Y. Wang, J. Gao, Z. Li, and L. Zhao, "Robust and accurate Wi-Fi fingerprint location recognition method based on deep neural network," *Appl. Sci.*, vol. 10, no. 1, p. 321, Jan. 2020.

[60] D. Cannizzaro, M. Zafiri, D. Jahier Pagliari, E. Patti, E. Macii, M. Poncino, and A. Acquaviva, "A comparison analysis of BLE-based algorithms for localization in industrial environments," *Electronics*, vol. 9, no. 1, p. 44, Dec. 2019.

[61] 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," *Trans. Emerg. Telecommun. Technol.*, Jan. 2020, Art. no. e3867, doi: 10.1002/ett.3867.

[62] C. Zhang, N. Qin, Y. Xue, and L. Yang, "Received signal strength-based indoor localization using hierarchical classification," *Sensors*, vol. 20, no. 4, p. 1067, Feb. 2020.

[63] X. Dang, X. Tang, Z. Hao, and J. Ren, "Discrete hopfield neural network based indoor Wi-Fi localization using CSI," *EURASIP J. Wireless Commun. Netw.*, vol. 2020, no. 1, p. 76, Dec. 2020.

[64] M. Borhani Afuosi and M. R. Zoghi, "Indoor positioning based on improved weighted KNN for energy management in smart buildings," *Energy Buildings*, vol. 212, Apr. 2020, Art. no. 109754.

[65] I. Ashraf, S. Hur, S. Park, and Y. Park, "DeepLocate: Smartphone based indoor localization with a deep neural network ensemble classifier," *Sensors*, vol. 20, no. 1, p. 133, Dec. 2019.

ZAINAB MUNADHIL received the B.Sc. degree in computer engineering techniques from Middle Technical University, Baghdad, Iraq, in 2007, where she is currently pursuing the M.Tech. degree in computer engineering techniques with the Electrical Engineering Technical College. She is also with the Department of Computer Engineering Techniques, Electrical Engineering Technical College, Middle Technical University. Her research interests include indoor localization based on WSN and neural networks and Alzheimer's patient monitoring systems.

SADIK KAMEL GHARGHAN (Member, IEEE) received the B.Sc. degree in electrical and electronics engineering and the M.Sc. degree in communication engineering from the University of Technology, Iraq, in 1990 and 2005, respectively, and the Ph.D. degree in communication engineering from Universiti Kebangsaan Malaysia (UKM), Malaysia, in 2016. He is currently with the Department of Medical Instrumentation Techniques Engineering, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq, as a Professor. His research interests include energy-efficient wireless sensor networks, biomedical sensors, microcontroller applications, WSN localization based on artificial intelligence techniques and optimization algorithms, indoor and outdoor path loss modeling, harvesting technique, wireless power transfer, jamming on direct sequence spread spectrums, and drone in medical applications.

AMMAR HUSSEIN MUTLAG (Member, IEEE) received the B.Sc. degree in control and computer engineering and the M.Sc. degree in control engineering from the University of Technology, Iraq, in 2000 and 2005, respectively, and the Ph.D. degree in control engineering from Universiti Kebangsaan Malaysia (UKM), Malaysia, in 2016. He is currently with the Department of Computer Engineering Techniques, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq, as an Assistant Professor. His research interests include intelligent controllers for renewable energy, microcontroller applications, developed optimization algorithms, intelligent controllers-based authentication, and intelligent decision-support systems.

ALI AL-NAJI (Member, IEEE) received the B.E. degree in medical instrumentation techniques from the Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq, in 2005, the M.Sc. degree in electrical and electronic engineering from the University of Technology, Baghdad, in 2008, and the Ph.D. degree in electrical and information engineering, University of South Australia (UniSA), Mawson Lakes, SA, Australia, in 2018. He is currently the Vice Dean of scientific and students affairs with the Electrical Engineering Technical College, Middle Technical University. He has been with the School of Engineering, UniSA, as an Adjunct Senior Lecturer, since 2018. His research interests include biomedical instrumentation and sensors, computer vision systems, and microcontroller applications. He is a member of the Engineers Australia (EA), in 2018, and the International Association of Engineers (IAENG), in 2018.

JAVAAN CHAHL (Member, IEEE) received the Ph.D. degree from The Australian National University. He joined the Defence Science and Technology Group (DST Group) as a Research Scientist, in 1999. In 2011, he joined RMIT University as a Founding Professor of unmanned aerial vehicles. In 2012, he became the Chair of sensor systems a joint appointment between the DST Group and the University of South Australia. He is a member of the Institute of Engineers Australia. He was an elected Fellow of the Royal Aeronautical Society, in 2014.

• • •