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Adaptive Neural Fuzzy Inference System for Accurate Localization of Wireless Sensor Network in Outdoor and Indoor Cycling Applications

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ABSTRACT When localizing wireless sensor networks, estimating the distances of sensor nodes according to the known locations of the anchor nodes remains a challenge. As nodes may transfer from one place to another, a localization technique that can measure or determine the location of a mobile node is necessary. In this paper, the distance between a bicycle when moves on the cycling track and a coordinator node (i.e., coach), which positioned on the middle of the cycling field was estimated for the indoor and outdoor velodromes. The distance was determined based on two methods. First, the raw estimate is done by using the log-normal shadowing model (LNSM) and later, the intelligence technique, based on adaptive neural fuzzy inference system (ANFIS) is applied to improve the distance estimation accuracy, especially in an indoor environment, which the signal is severely dominated by the effect of wireless multipath impairments. The received signal strength indicator from anchor nodes based on ZigBee wireless protocol are employed as inputs to the ANFIS and LNSM. In addition, the parameters of the propagation channel, such as standard deviation and path loss exponent were measured. The results shown that the distance estimation accuracy was improved by 84% and 99% for indoor and outdoor velodromes, respectively, after applying the ANFIS optimization, relative to the rough estimate by the LNSM method. Moreover, the proposed ANFIS technique outperforms the previous studies in terms of errors of estimated distance with minimal mean absolute error of 0.023 m (outdoor velodrome) and 0.283 m (indoor velodrome).

INDEX TERMS Accuracy, ANFIS, propagation channel, WSNs, ZigBee.

I. INTRODUCTION

Inaccurate estimation of node locations in a wireless sensor network (WSN) is a principal problem in WSN localization. Many range-free and range-based techniques are employed in WSN localization. Range-based techniques are used to determine the angles and distances among WSN nodes. Some examples of these techniques are time difference of arrival (TDoA), angle of arrival (AoA), time of arrival (ToA) [1], global positioning system (GPS) [2], received signal strength indicator (RSSI) [3], and acoustic energy [4]. Meanwhile, distance estimation and localization accuracy are crucial factors for WSN applications [5], because they can reduce the power consumption of the WSN nodes. When the distances among the WSN nodes are measured accurately, the transmitted radio frequencies of the transceivers of the sensors and mobile nodes can be modified to reduce their power consumption, thereby prolonging the battery lifetime [6]. Among the range-based techniques, the RSSI is the most employed for the measurement of the distances among WSN nodes [7]. In the current cycling or any sports application, the mobile node had limited energy sources and minimal equipment requirement. Thus, by using RSSI, we were able to minimize power consumption because it did not require additional hardware. In the current work, a path loss model known as Log-Normal Shadowing Model (LNSM) will be adopted to determine the distance between network nodes based on RSSI measurements. On the contrary, the range-free technique has low accuracy and is less cost-effective. It assumes that information about the angle or distance is unavailable and rely on the communication link between stationary nodes, known as anchor nodes, and mobile nodes to estimate the node locations.

WSNs have played a significant role in sports applications for monitoring the athlete's activities. One such application is in track cycling. In the track cycling, the physiological and biomechanical parameters of both cyclist and bike can be monitored to evaluate the performance and fitness of the cyclist, such as speed, cadence and torque [8]. In this work, the RSSI of a ZigBee sensor node is used to determine the bicycle position on the cycle track, because it does not require any extra hardware [9]. The RSSI can be used together with a derived LNSM for distance estimation between the coordinator node (i.e., coach) and the movable bike on the cycling track. Additionally, channel factors, such as the standard deviation and path loss exponent are measured. The reason for using LNSM is that it is a conventional wireless propagation model [10]. Moreover, much research has adopted LNSM for channel modeling, in indoor and outdoor environments to measure the distance between the sender and receiver [11]. However, the LNSM method is not highly accurate. Therefore, the mobile node localization error on the track cycling was improved by using Adaptive Neural Fuzzy Inference System (ANFIS) technique. ANFIS is used to achieve the non-linear approximation algorithms. Therefore, it is suitable for our application, where the collected RSSI are non-linear data. ANFIS is a well-known technique for evolution self-organizing neuro-fuzzy systems with several practical applications [12].

The contribution of this paper is as follows (i) modelling the wireless channel path loss based on RSSI measurements in indoor and outdoor velodromes, (ii) estimation the physical parameters of the wireless channel path loss model for indoor and outdoor velodromes based on LNSM, and (iii) to improve the distance estimation accuracy based on ANFIS intelligent technique. It is expected that the proposed distance estimation based on ANFIS outperformed other state-of-the-art systems in terms of mean absolute error (MAE).

II. MOTIVATION BEHIND DISTANCE ESTIMATION

In cycling applications, sensor nodes are placed on bikes for cyclists to monitor biomechanical and physiological parameters, but the electrical power supply of sensor nodes is limited. Therefore, sensor nodes need batteries as the power source. Reducing power consumption and prolonging battery life is essential because the battery power of sensor nodes is limited. Several techniques can be used to conserve energy in wireless sensor networks (WSNs). One of these techniques is transmission power control (TPC). TPC can be implemented via distance measurement between nodes in WSNs. When a mobile node (i.e. bicycle) approaches the anchor or coordinator node (located at the centre of the cycle track), the transmitted power of sensor nodes is minimised to conserve energy and extend battery life. Accurate distance estimation is necessary for such an application, thus, become the main motivation in this paper.

III. RELATED WORKS

Recently, several localization techniques that use artificial intelligence (AI) have been implemented. Complemented by optimization algorithms, these techniques, such as ANFIS [13], [14], artificial neural network (ANN) [15], [16], and fuzzy logic (FL) [17], [18], increase the accuracy of WSN localization. Meanwhile, the optimization algorithms often used in WSN localization are gravitational search algorithm (GSA) [19], [20], bacterial foraging algorithm (BFA) [21], particle swarm optimization (PSO) [22], [23], and genetic algorithms (GAs) [24]. Several researchers have used ANFIS for WSN node localization. In one study [13], ANFIS was able to locate people moving in a specific zone with 95% accuracy. These people wore trackable wristbands, and three Wi-Fi access points were used for the localization. In another study [14], a robot that uses ANFIS was designed. This robot was able to locate itself in a risky outdoor environment and used extended Kalman filter (EKF) to adapt the RSSI values of a ZigBee wireless protocol. Based on its position relative to the static sensor nodes, its localization accuracy was 2–10 m [14]. In [17], WSN objects were localized in an indoor environment through a multi-nearest neighbor scheme and fingerprint-based on fuzzy inference system algorithm. The algorithm improved the localization accuracy and minimized the calculation cost. The overall localization accuracy of this study was 0.43 m. Another indoor localization study [25] demonstrated that localization could be achieved by using the RSSI measurements from the Wi-Fi networks. In this study, the curve fitting, ANFIS, and interpolation are employed to develop the indoor wireless channel propagation model. The RSSI was then transformed into a physical distance, and EKF was used to improve the localization accuracy. The obtained localization accuracies of the interpolation, curve fitting, and ANFIS (based on two Gaussian membership functions) were 2.7, 2.5, and 2.1 m, respectively. Mestre *et al.* [26] enhanced the localization accuracy by using fingerprinting, which was based on fuzzy logic, thus improved the localization accuracy by 10.24%–49.43%. They were also able to obtain an average localization error of approximately 3 m. Meanwhile, Lin *et al.* [27] combined the location awareness system (LAS) with ANFIS to locate indoor patients. LAS composed of a server, location nodes, client monitor, gateway, and control unit. This system has low-power consumption and uses low-cost wireless protocols, such as ZigBee [28]. The RSSI values of the three sensor nodes were used to determine the distance between the position of each sensor node and the patient location. In [29], the RSSI or link quality indicator (LQI) of the ZigBee wireless protocol was used to recognize the location of the tag of a vision robot. The recognition process was based on

ANFIS and WSN. In this study, an ANFIS-based WSN was constructed to develop a location identification system (LIS) with tags, location nodes, and gateways. The RSSI measurements were used to identify the locations of the tags. The performance of indoor localization of robot was improved, because of the combination of ANFIS and LIS. In [30], two algorithms were used to locate a small ZigBee mobile device in a wildlife environment. The first algorithm used FL to obtain a fractional solution, while the second algorithm used a centralized technique that combined all the partial solutions. The FL was more effective than centroid algorithm (i.e., without fuzzy system) in terms of improving accuracy and minimizing localization error.

Nekooei and Manzuri-Shalmani [31] used neuro-fuzzy (NF) systems and genetic fuzzy (GF) to localize a mobile node from the RSSI measurements. To localize itself, the sensor node gathered the RSSI and position of each anchor node. They concluded that the NF system outperforms the GF and weighted centroid localization (WCL) (WCL; which was considered in [18]) in terms of average localization error. The localization errors of the NF system and GF were 0.9014 and 0.9501 m (based on eight Gaussian membership functions), respectively.

The ANN is used in localization or distance estimation techniques to determine the location of sensor nodes or distances among the nodes in a WSN. ANN exhibits high speed, fast convergence, and low computation cost [23], [32]. Payal *et al.* [15], [32], [33] used ANN to localize the sensor nodes in a WSN. They used RSSI values to train and test the ANN for the estimation of the sensor node locations. They were able to obtain the following localization errors: 0.7855 [15], 1.1862 [32], and 0.49 m [33]. Irfan *et al.* [34] adopted two different ANN algorithms, namely, Bayesian regularization and gradient descent, to estimate the location of moving sensor nodes in indoor environments. To estimate the location of the sensor nodes, they combined the RSSI and LQI of the ZigBee wireless protocol to train (the initial phase) and test (the evaluation phase) the ANN. They obtained a location accuracy of 1.65 m.

One study [35] used the feed-forward neural network to localize a moving robot in an indoor environment according to the LQIs of the three sensor nodes that used the ZigBee wireless protocol. The average localization error obtained in this study was 2.8 m. Chuang and Jiang [16] suggested a new ANN scheme for node localization. In addition, they adopted a Dijkstra algorithm and log-normal shadowing model (LNSM) to compute the shortest paths among nodes in a WSN. They also collected the RSSI values to determine the distance of hop counts. Their simulation was conducted in 3,600 m^2 and 2,500 m^2 areas with communication distances of 25 m and 20 m, respectively. They showed that the average location error and transmission distance in the 2,500 m^2 were 6–7 and 25 m, correspondingly. Rahman *et al.* [36] proposed WCL and generalized regression neural network (GRNN) for node localization. They used two GRNNs to train the neural network separately for y and x coordinates using the RSSI values of reference nodes, which were determined through the access points. By doing so, they were able to employ neural networks for the identification of the approximate position of a target node and its adjacent nodes in an indoor environment. They then estimated the position of the target node by computing the weighted centroid of the nearest neighbors. The localization accuracy of their proposed method was compared with that of some available RSSI-based methods. The results shown that the localization accuracy was reasonable, and their proposed method was simple and did not require additional hardware. In this study, the localization errors of the GRNN and combined GRNN and WCL were 1.298 and 1.127 m, respectively.

In [21], BFA and PSO were employed as optimization algorithms to improve the location accuracy of nodes in a WSN. Twelve anchor nodes were used to estimate the location of 40 nodes. The simulation results of this study indicated that the PSO was faster but less accurate than the BFA. The obtained average localization errors of the PSO and BFA were 0.05412 and 0.03976 m, respectively. Yu *et al.* [37] then proposed a PSO-based RSSI for the ZigBee wireless protocol to optimize the LQI (which was deviated by the environment) of an unknown node. The LQI of this node was received from the sink node. The LQI was then transferred to RSSI based on a propagation model to determine the distance between a sink node and unknown node. Yu *et al.* [37] were able to obtain a distance error of 0.49 m. Tewolde and Kwon [22] used the RSSI of Wi-Fi networking structure for low-cost and accurate indoor localization. They applied an efficient and simple localization algorithm and used PSO that relied on the propagation path loss model. Their method was conducted in a simulation environment and then established to achieve suitable localization accuracy in an indoor environment. They obtained an average error of 4 m in a 50 × 50 m^2 area under a noisy environment. Li *et al.* [38] proposed an optimized algorithm based on PSO to improve the accuracy of the estimated distance of an unknown node. They used RSSI values in LNSM to estimate the distance among nodes in a network. They obtained an average localization error of 0.2383 m in their simulation.

Overall, the current research differs from previous related works based on AI in the following aspects: First, the ANFIS in the current study used non-linear RSSI data as inputs and physical distance as output to accurately estimate the distance between the mobile bicycle and coordinator node. Second, eight types of membership functions with three, five, and seven numbers of input membership functions were adopted for the selection of suitable types and numbers of the membership functions. This procedure minimized the error. Third, an empirical wireless channel path loss model was derived from the RSSI measurements in indoor and outdoor velodromes. Fourth, a comparative analysis between path loss model and ANFIS, both based on distance estimation, was performed to show the feasibility of the proposed ANFIS. Fifth, our proposed distance estimation-based ANFIS was compared with previous AI techniques or algorithms to show the improvement of our proposed technique in terms of distance estimation accuracy.

IV. WIRELESS CHANNEL MODEL

Previous research works have evaluated propagation characteristics of ZigBee-based WSN in both outdoor and indoor surroundings [39]. However, the previous works are not an ideal fit for track cycling application. Most ZigBee wireless protocol support RSSI, thus the received power at the receiver is measured for every data packet. The power or energy of electromagnetic wave traveling among several nodes, i.e. the mobile bike node and coach coordinator node is a signal parameter that includes information representing the communication range or distance between these nodes. The signal parameters are employed alongside path loss and LNSM to determine the distance between nodes. Accordingly, the path loss model is known as [40] and [41],

$$P_L(d) = P_{Lo}(d_o) + 10\beta log_{10}(d/d_o) + \gamma_\sigma \tag{1}$$

where $P_L(d)$ is the reference channel path loss at different locations on the cycling track measured in dBm, $PL_o(d_o)$ is the channel path loss at d_o (i.e., reference distance equal to 1 meter [6] adopted in this study), which may be gained from the real measurements in the track cycling or calculated based on the Friis formula measured in dBm, β is the channel path loss exponents, d is the distance between the coordinator and mobile node, which changes with the bicycle's location on the cycling track, and γ is the Gaussian random variable with zero-mean and standard deviation σ.

The parameters of the LNSM can be measured practically through the track cycling field, as will be seen in the results section. The RSSI in dBm can be computed in the mobile node as in Equation (2) [42]:

$$RSSI = P_{Tr} - P_L(d) \tag{2}$$

where P_{Tr} is the coordinator node output power measured in dBm (2 dBm adopted in this work). Therefore, the received signal strength power by the mobile bicycle node is computed as follows [43], [44]:

$$RSSI = P_{Tr} - P_{Lo}(d_o) - 10\beta log_{10}(d/d_o) + \gamma_\sigma \tag{3}$$

In this work, both $P_{Lo}(d_o)$ and d_o are assumed to be constant. The path loss exponent β is related to the environment and can be varied between 2 (free space) to 6 (urban) [45]. For our application, β depends on the real measurements in the track cycling field, which were found to be 1.6308 (outdoor) and 2.0369 (indoor). For the LNSM, three parameters can be assumed constant, which are widely used in many research works [43]:

i) β remain constant in the considered areas (indoor & outdoor).
ii) Zero-mean Gaussian random variable, γ_σ remains constant.
iii) The path is symmetrical due to the shape of the velodrome track, and
iV) The RSSI from the mobile node to the coordinator node is equal to the RSSI from the coordinator node to the mobile node.

V. ADAPTIVE NEURAL FUZZY INFERENCE SYSTEM (ANFIS)

In this section, an AI technique will be considered to improve the localization accuracy relative to the LNSM method. For this purpose, ANFIS was implemented in Matlab simulation software. In this work, an ANFIS editor block is developed in Matlab to estimate the distance between the coach coordinator node and a moving bicycle on the cycle track (in the indoor and outdoor environment) by using seven *gbell* membership functions. The ANFIS editor block involves data loading, initialization and generating fuzzy inference system (FIS), FIS structure, membership function types, number of membership functions, ANFIS training and data testing against trained FIS. ANFIS has been utilized in several studies [14], [17], [25] to estimate the distance between nodes or the position of nodes in WSNs. ANFIS was proposed by Jang in 1993 [46] to solve problems in FL and neural networks (NN).

The performance of FL relies on the number of membership functions (*mfs*), forms of membership functions and the rule basis. These parameters are determined through a trial and error process, which is time-consuming. In several cases, paramount results cannot be achieved [47]. Despite the advantages of NNs, such as handling of nonlinear data, connecting layers with various weight values, generalization capabilities, adaptive structure and independent design from system variables, NNs lack definite rules for selecting the numbers of layers and neurons in each hidden layer, cannot determine the learning rate and present an instruction problem [47].

ANFIS combines techniques, knowledge and methodologies from different sources. ANFIS can serve as a basis for forming a set of fuzzy "IF–THEN" rules with membership functions to create specified input–output matching by employing a hybrid algorithm, i.e. back propagation (BP) and least squares estimation [48]. The membership functions are adjusted to the input–output information. By gathering input–output information, ANFIS tunes the initial fuzzy inference system with a BP algorithm. FIS and NN are complementary technologies in ANFIS. The reason for combining NN with FIS is to maximize the learning capability of NN. However, the learning capability of NN is an advantage from the viewpoint of FIS, whereas from the viewpoint of an NN, additional advantages can be obtained from a combined system. Prior knowledge can be integrated into the system because FIS relies on linguistic rules, and this integration can significantly reduce the learning process.

The basic construction of FIS involves three conceptual parts: (i) a database that describes membership functions employed in the fuzzy rules, (ii) a rule-based that includes selected fuzzy rules and (iii) a reasoning mechanism that achieves inference on the basis of the rules and provided facts to obtain reasonable conclusion or output. Two systems of FIS can be executed: Takagi–Sugeno and Mamdani. The Takagi–Sugeno system is computationally more efficient and compact than the Mamdani system since it allows the use of adaptive techniques to build fuzzy models [49], [50]. Adaptive learning techniques (ALTs) are utilized to optimize fuzzy membership functions for FIS to model the data well. FIS based on ALT is called ANFIS. However, ANFIS performs better than ANN and FL techniques. In addition, selecting the appropriate type and a large number of membership functions can improve the performance of ANFIS. As a result, small errors are obtained during training and data checking.

The ANFIS technique is a fuzzy Sugeno paradigm within the framework of adaptive networks utilized to simplify adaptation and learning [51]. The Sugeno fuzzy paradigm was proposed by Takagi–Sugeno to formalize a systematic methodology of creating fuzzy rules on the basis of an input-output dataset. In our adopted ANFIS technique, three inputs (i.e., RSSI values), single output (i.e., distance), two rules and the first-order Takagi–Sugeno method are considered. The rules of FIS are expressed in Equations (4) and (5).

$$\textbf{Rule 1}: \quad If\ x = A_1, \quad y = B_1\ and\ z = C_1, \quad then\ g_1 = m_1x + n_1y + p_1z + r_1. \tag{4}$$

$$\textbf{Rule 2}: \quad If\ x = A_2, \quad y = B_2\ and\ z = C_2, \quad then\ g_2 = m_2x + n_2y + p_2z + r_2. \tag{5}$$

In these rules, x, y and z are the input vectors; g is the output function; A_i, B_i and C_i represent the membership functions for the inputs; and p, m, n and r are the output variables.

Figure 1 shows ANFIS architecture that comprises five layers that accomplish various functions. The figure contains circle and square nodes; the circle form indicates a fixed node, and the square nodes point to an adaptive node. The ANFIS structure can be described as follows.

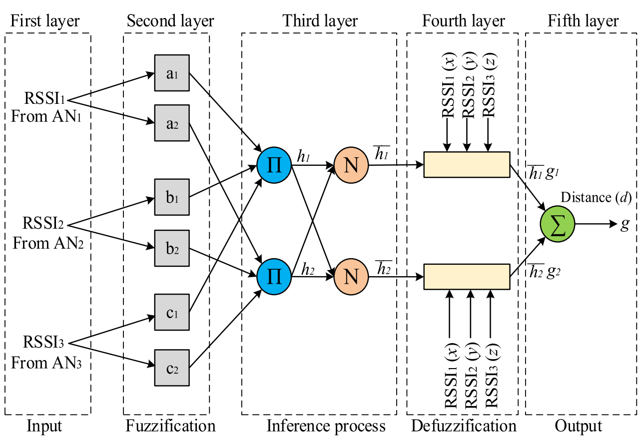

FIGURE 1. The adopted ANFIS framework.

A. FIRST LAYER (INPUT)

This layer includes input variables *mfs*. Each node in this layer is considered an adaptive node. The output values of the nodes of this layer represent the adopted generalized bell-shaped membership function (*gbellmf*), which is expressed in Equation (6). The output signal provides membership functions and membership functions with degrees of the input value. Fuzzification is achieved in this layer. Thus, bell-shaped *mfs* with the lowest value of 0 and the highest value of 1, as expressed in Equation (6) are used in this layer.

$$\mu A_i(x) = 1/[1 + |(x - c_i)/a_i|^{2b_i}] \tag{6}$$

where a_i, b_i and c_i represent the parameters that can change the shape of *gbellmf*; hence, they are employed to adjust the membership degrees of inputs. These parameters are tuned during the training phase of the network. Other types of *mfs*, such as triangular, trapezoidal, Gaussian curve, two-sided Gaussian curve, pi-shaped curve, the difference of two sigmoid functions and the product of two sigmoid functions, can also be used instead of the generalized bell-shaped curve, as will be seen in Table 2.

The output values ($O_{1,i}$) of nodes in this layer can be expressed as Equation (7). In our application, the inputs of this layer represent the RSSI values collected from AN1, AN2 and AN3 in outdoor or indoor environments.

$$O_{1,i} = \mu A_i(x) \tag{7}$$

B. SECOND LAYER

The nodes in this layer are represented by circular shapes, and the output of this layer can be explored from the input signals by using one of the t-norm operators. This layer realizes the FIS process, and the output of each node exhibits the rule firing level. The firing level of a rule can be calculated in this layer through the multiplication of the *mfs* of all inputs. The output of this layer ($O_{2,i}$) can be obtained by applying the following equation:

$$O_{2,i} = h_i = \mu A_i(x) \times \mu B_i(y) \times \mu C_i(z) \quad i = 1, 2, 3 \ldots \tag{8}$$

C. THIRD LAYER (RULES)

The nodes in this layer are represented by circular shapes and marked as N. The normalization process occurs in this layer, where each node provides the ratio of the firing vigour of the i^{th} rule to the overall firing level. Therefore, the third layer computes the normalized firing level, as shown in Equation (9).

$$O_{3,i} = \bar{h}_i = h_i/(h_1 + h_2) \quad i = 1, 2, 3, \ldots \tag{9}$$

D. FOURTH LAYER (OUTMFS)

The nodes in this layer are represented by square shapes. Inference of the rules generates the output. This layer creates an adaptive correlation between the normalized firing value (i.e. the output of the third layer) and resulting function (g). In other words, defuzzification is performed in this layer.

$$O_{4,i} = \bar{h}_i g_i = \bar{h}_i(m_i x + n_i y + p_i z + r_i) \tag{10}$$

where $\bar{h}_i$ is the output value of the third layer and m_i, n_i, p_i and r_i are the result parameters.

E. FIFTH LAYER (OUTPUT)

The nodes in this layer are represented by a single circle and labelled as $\sum$. The output signal of this layer can be obtained via the summation of the input signals incoming from the previous layer (i.e. fourth layer), as shown in Equation (11). All incoming signals to this layer from the previous layer are added, and the fuzzy grouping outcomes are converted into a crisp value.

$$O_{5,i} = \sum \bar{h}_i g_i = \sum_i h_i g_i / \sum_i h_i \tag{11}$$

In our study, the output of the fifth layer represents the estimated distance based on the ANFIS technique (d_{ANFIS}). Consequently, MAE using the ANFIS technique can be calculated by applying Equation (12).

$$MAE = (1/k) \sum_{i=1}^{k} |d_{actual} - d_{ANFIS}| \tag{12}$$

where k represents the number of samples of the actual and tested distances on the basis of ANFIS.

VI. EXPERIMENT SETUP

To investigate the propagation model for track cycling application, two experiments were implemented using ZigBee WSN. The first one is conducted in an outdoor velodrome (i.e., cycling field in Cheras, Kuala Lumpur) and the other experiment is implemented in an indoor environment (i.e., a sports hall inside a university campus).

A. OUTDOOR ENVIRONMENT

The experiment was carried out in the track cycling field in an outdoor environment. The WSN consists of one coordinator node (the coach or AN1) and one mobile node (i.e., bicycle) as shown in Figure 2a. The mobile node (which fixed on the bike) is moving on the cycling track, whereas the coordinator node is static in the middle of the cycling field, as shown in Figure 2a. The mobile bicycle node uses the collected RSSI to estimate the physical distance between the coordinator node and itself based on LNSM. The area of the track cycling field is 130 m × 65 m, and the track circumference is 333 meters. The minimum and maximum distances are 32 and 65 meters respectively, measured from the middle of the track field between the coordinator node and mobile node. It is worth mentioning that the RSSI values are collected based on actual measurements in the track cycling field (i.e., velodrome), where the adopted velodrome size is similar to the actual velodrome which is endorsed by Union Cyclist International (UCI) world track championships. The cycling track area is divided into four symmetrical sections (1, 2, 3, and 4). The RSSI measurements were done for Section 1 and the measured RSSI value is applied to the rest other sections since they are symmetrical. The RSSI is measured for ten predefined locations in Section 1, as shown in Figure 2a, which presented in black arrows.

B. INDOOR ENVIRONMENT

The indoor velodrome is represented by the sports hall of the Universiti Kebangsaan Malaysia (UKM) since there is

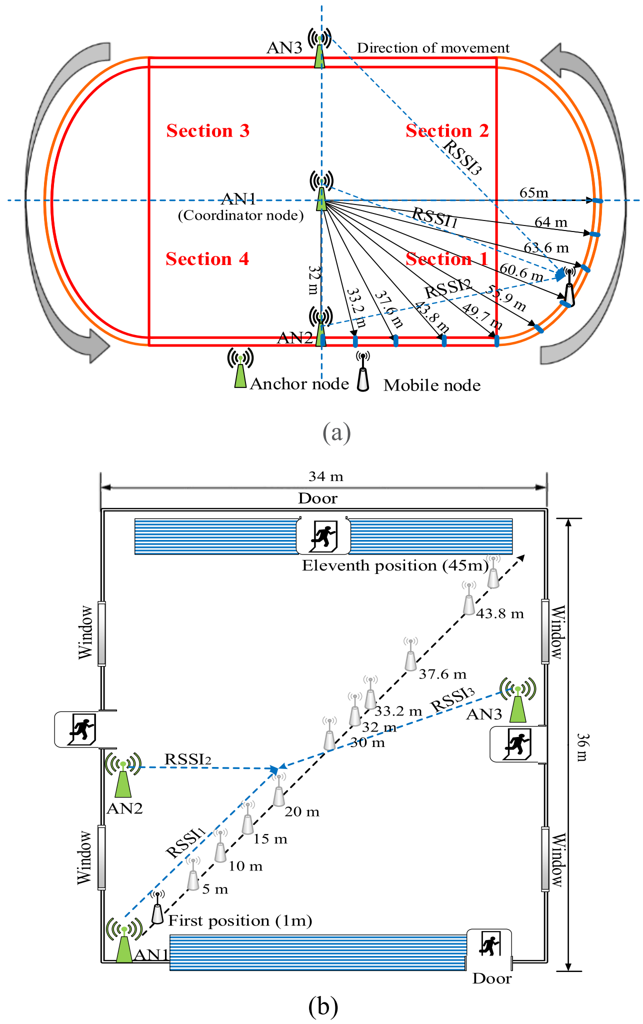

FIGURE 2. Cycle track area (a) outdoor environment and (b) sports hall indoor environment.

no indoor velodrome in Malaysia at the moment of writing. The dimension of the building is 36 m × 34 m, as illustrated in Figure 2b. Since the size of this building is not equivalent to the actual velodrome, a diametrical distance was adopted to get a farthest physical range between the bicycle mobile node and coordinator node. The coordinator node AN1 is fixed at a left corner of the sports hall, while the bike moves away from the coordinator node in predefined positions. The RSSI measurements were conducted at eleven predefined locations as shown in Figure 2b.

VII. RESULTS AND ANALYSIS

A. RSSI MEASUREMENT

In this paper, the XBees of the coordinator and mobile nodes were configured using X-CTU software. Hundred RSSI samples were registered for each location, one sample every second. Each sample includes single data packet frame; every data packet frame consists of ten bytes. The RSSI was obtained by averaging the hundred samples from the mobile bike node for each location. Figure 3 shows the path loss for

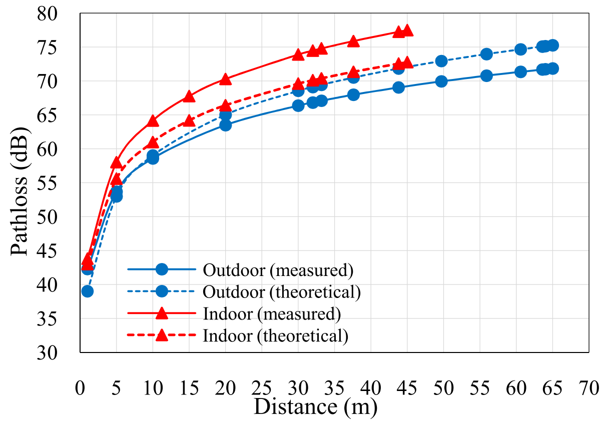

FIGURE 3. Path loss versus distance for indoor and outdoor velodromes.

both outdoor and indoor. It is clear that the indoor environment influences the path loss of the wireless link more than the outdoor environment. The measured values for outdoor and indoor attenuation were compared with the theoretical model, which is based on Equation (1). Figure 3 shows a convergence between the theoretical and measured plots for the indoor and outdoor velodromes at a small distance. However, the divergence between these plots increased when the distance increased. A convergence between the theoretical and measured plots has been observed for the outdoor velodrome. On the contrary, there is a big divergence among the theoretical and measured plots for the indoor velodrome relative to the outdoor velodrome. This is because of the multipath effect, due to the presence of reflections, scatters and diffractions from indoor objects such as furniture, doors, windows, and walls in the sports hall.

B. DERIVED LNSM

The link between the average of RSSI values and logarithmic values of the distances (which is established in advance) is plotted to obtain the LNSMs in indoor and outdoor environments (Figure 4). The standard deviation σ and path loss exponents β are determined through the use of a linear fitting line over the indoor and outdoor curves in Figure 4.

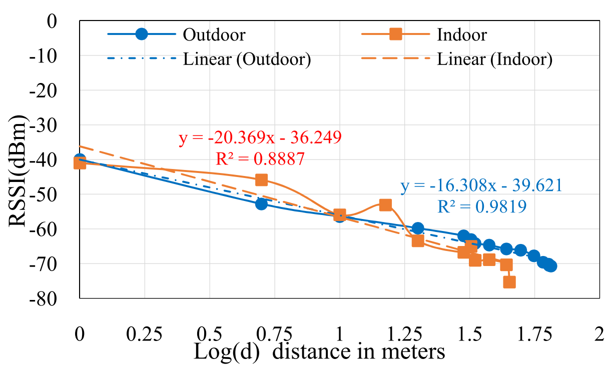

FIGURE 4. The fitting curve for indoor and outdoor velodromes.

TABLE 1. Ideal and measured parameters of LNSM for indoor and outdoor velodromes.

Parameters	Symbol & unit	Outdoor		Indoor	
		Measured	Ideal	Measured	Ideal
Reference distance	d_o (m)	1 [52]	0.1-10	1	0.1–10
Path loss at d_o	$Pl_o(d_o)$ (dBm)	40	37 [6]	41	37
Path loss exponent	β	1.6308	2 [42]	2.0369	1.6–1.8 [44]
Std. deviation	σ (dB)	2.271	2-14 [53]	2.791	2-14

The predestined regression line is generated through Equations (13) and (14).

$$RSSI_{outdoor} = -16.308Log(d/d_o) - 39.621 \quad (13)$$

$$RSSI_{indoor} = -20.369Log(d/d_o) - 36.249 \quad (14)$$

Comparing Equations (13) and (14) with Equation (3). Equations (15) and (16) can be used for outdoor and indoor, respectively to compute the standard deviation (σ) and path loss exponent (β). Consequently, the LNSM parameters are obtained and introduced in Table 1, where, the coordinator node output power, P_{Tr} is 2 dBm and the $PL_o(d_o)$ is 40 dBm (outdoor) and 41 dBm (indoor) obtained from measurements.

$$\left.\begin{aligned} 16.308 &= 10\beta \\ P_{Tr}\,(dBm) - Pl_o\,(d_o) + \gamma_\sigma &= -39.621 \end{aligned}\right\} \quad (15)$$

$$\left.\begin{aligned} 20.369 &= 10\beta \\ P_{Tr}\,(dBm) - Pl_o\,(d_o) + \gamma_\sigma &= -36.249 \end{aligned}\right\} \quad (16)$$

C. ERROR CALCULATION

Equations (13) and (14) can be re-arranged, yielding Equations (17) and (18) to estimate the distance for the outdoor and indoor velodromes, respectively.

$$d_{outdoor} = d_o 10^{-(RSSI_{outdoor}+39.621)/16.308} \quad \text{in meters;} \quad (17)$$

$$d_{indoor} = d_o 10^{-(RSSI_{indoor}+36.249)/20.369} \quad \text{in meters;} \quad (18)$$

Based on the above equations, the error between the real or actual physical distance and measured distance can be obtained as in Figure 5. The figure clarifies the estimated error for both outdoor and indoor velodromes. In addition, the MAE for outdoor (blue dash-dot line) and indoor (red dash line) environments were calculated based on Equation (19). The MAE was found 6.534 and 5.556 m for indoor and outdoor velodromes as shown in Figure 5, respectively.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |d_{actual} - d| \quad (19)$$

where d_{actual} is the actual physical distance measured between predefined locations on the cycle track and coordinator node (AN1) through the use of distance meter measurements, d is the estimated distance from Equation (17) for outdoor and Equation (18) for indoor, and N represents the number of the estimated and actual distance samples.

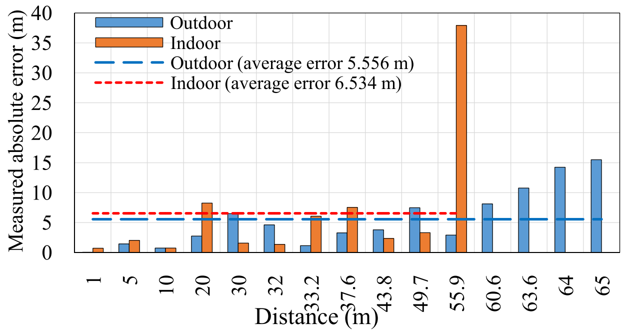

FIGURE 5. Estimated absolute error relative to distance and MAE for both indoor and outdoor velodromes.

Figure 5 shows that the error growths with distance and the MAE obtained for outdoor is better than for the indoor by 15%. Root Mean Square Error (RMSE) can be taken into account as defined in Equation (20) [54] to evaluate the measurement accuracy for both the outdoor and indoor environments. In addition, RMSE will be used in the next section to compare the performance of the distance estimation accuracy based on LNSM and ANFIS. The RMSEs are 7.256 m (outdoor) and 12.156 m (indoor) according to LNSM.

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{n}\left(d_{actual} - d\right)^2} \tag{20}$$

The correlation coefficient, R, between the estimated and actual physical distances is a good index for LNSM performance evaluation. Figure 6 presents a positive correlation for the outdoor measurement ($R = 0.9418$; blue dash line) and weak positive correlation for the indoor measurement ($R = 0.8157$; black dash-dot line). In the indoor environment, a mismatch between the actual and estimated distances is apparent. The mismatch is due to the multipath effect, which occurs when the distance increases.

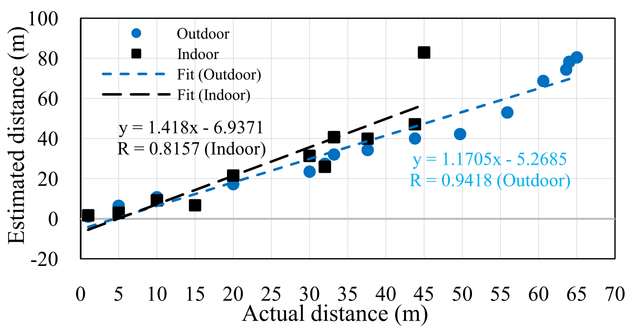

FIGURE 6. Correlation between actual and estimated distances for indoor and outdoor environments.

A transmitted signal that passes through a wireless channel experiences deviations in outdoor and indoor environments, as can be seen from the low and high fluctuations. Such effect leads to imprecise distance estimation. In indoor environments, obstacles, such as doors and walls, weaken or block the transmitted signal between the anchor and mobile nodes. Consequently, the estimated distance between these nodes is inaccurate according to the wireless channel path loss model. In this work, an AI technique, such as ANFIS, is used to improve the accuracy of the estimated distance.

D. ANFIS-BASED DISTANCE ESTIMATION

Three, five, and seven membership functions (*mfs*) were used for each input to train and test the ANFIS. Also, eight types of mfs, i.e., triangular (*tri*), trapezoidal (*trap*), bell-shaped (*gbell*), Gaussian curve (*gauss*), two-sided Gaussian curve (*gauss2*), pi-shaped curve (*pi*), difference of two sigmoid (*dsig*), and product of two sigmoid (*psig*) membership functions were considered in ANFIS. 48 simulation examples were conducted for training data, 24 simulation examples for outdoor and 24 for indoor environments. Each simulation example is performed based on 1,000 epochs.

The same procedure was repeated for testing data. The reason for using different numbers and types of the membership functions is to select the best values that give minimum localization or distance estimation error. However, for training and testing the ANFIS, an enormous number of RSSI values are needed. Therefore, a 900 and 780 samples of RSSI were collected from three anchor nodes for outdoor and indoor as shown in Figures 7 and 8, respectively. To construct a connection between the output physical distances and inputs of RSSI values, the collected RSSI values are employed to train and test the ANFIS. Consequently, the error is estimated for various types and numbers of ANFIS membership functions for indoor and outdoor, as listed in Table 2. This table clarifies the best localization error occurs when seven membership functions are chosen for each input. In addition, the bell-shaped membership (gbellmf) type is better than the other membership function types for both indoor and outdoor.

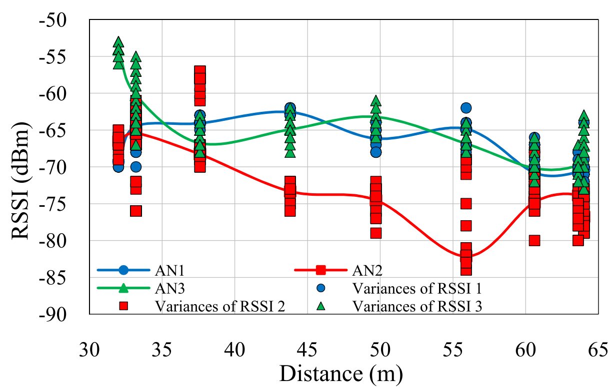

FIGURE 7. Input RSSI values and actual distance of ANFIS in the outdoor velodrome.

Figures 9 and 10 show the correlation between the actual physical distance (situated on the *x-axis*) and estimated distance (situated on the *y-axis*, which obtained from ANFIS) in the indoor and outdoor environments. Figures 9a, b, and c depict the distributions of the distance estimations for the 3, 5, and 7 gbell*mfs*, respectively, in outdoor environments.

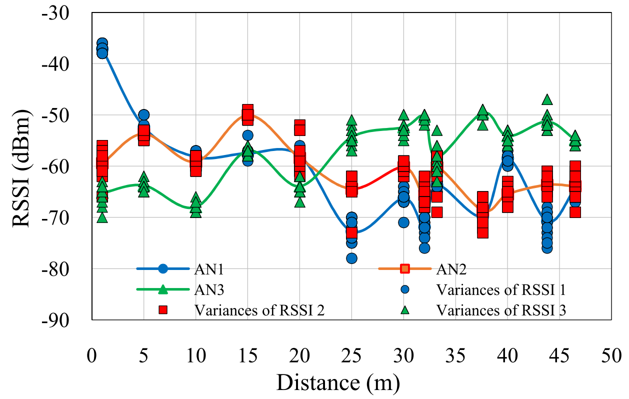

FIGURE 8. Input RSSI values and actual distance of ANFIS in the indoor velodrome.

TABLE 2. Comparison of distance estimation errors for different numbers and types of ANFIS membership functions.

ANFIS *mf* type	$RMSE_{outdoor}$ (meter)			$RMSE_{indoor}$ (meter)		
	Three *mfs*	Five *mfs*	Seven *mfs*	Three *mfs*	Five *mfs*	Seven *mfs*
tri	3.19	2.33	0.93	4.88	3.37	2.41
trap	3.48	1.78	1.79	5.18	3.73	3.75
gbell	2.82	0.75	0.05	4.80	2.69	1.10
gauss	3.11	1.60	0.27	4.79	2.85	1.52
gauss2	2.84	0.53	0.24	4.62	2.61	2.36
pi	3.21	1.37	1.02	4.87	3.47	3.61
dsig	3.01	1.15	0.19	4.77	3.40	2.12
psig	2.62	1.15	0.19	4.65	3.17	2.12

Figures 10a, b, and c depict the distributions of the distance estimation for the 3, 5, and 7 gbell*mfs*, respectively, in indoor environments. The regression coefficient *R* can be considered when evaluating the accuracy of an estimated distance. Figure 9c shown that the actual and estimated distances of 7 gbell*mfs* in the outdoor velodrome completely agreed with each other, which can be supported by the *R* value that equals to 1.

Similarly, in Figure 10c, a high correlation between the estimated and actual physical distances of 7 gbellmfs is observed in the indoor velodrome, where the R value is 0.994. The regression coefficient *R* in Figure 10c is similar to that of 5 gbellmfs in the outdoor velodrome (Figure 9b). This similarity reduces used during the training and testing of ANFIS. The mismatch between actual and estimated distances in the indoor environment is due to the multipath effect that is prominent in an indoor environment. Compared with 7 gbell*mfs*, 3 and 5 gbell*mfs* in the indoor and outdoor velodromes suggest a low correlation between the actual and estimated distances, as shown in Figures 9a and b (outdoor) and Figures 10a and b (indoor). Therefore, 7 gbell*mfs* are considered for ANFIS training and testing in both velodromes to accurately determine the distance between the coordinate node and mobile node moving on the cycling track.

Figure 11 compares the distance estimation accuracy between classical method based on LNSM and intelligent technique based on ANFIS for outdoor and indoor in terms of RMSE, which calculated from Equation (11). The figure shows the RMSE for outdoor is better than indoor environment based on LNSM. In addition, the figure disclosed that the RMSE at outdoor is better than indoor when ANFIS is applied. Whereas, it is significantly improved by 84 % and 99% based on 7 gbellmfs relative to LNSM for indoor and outdoor, respectively.

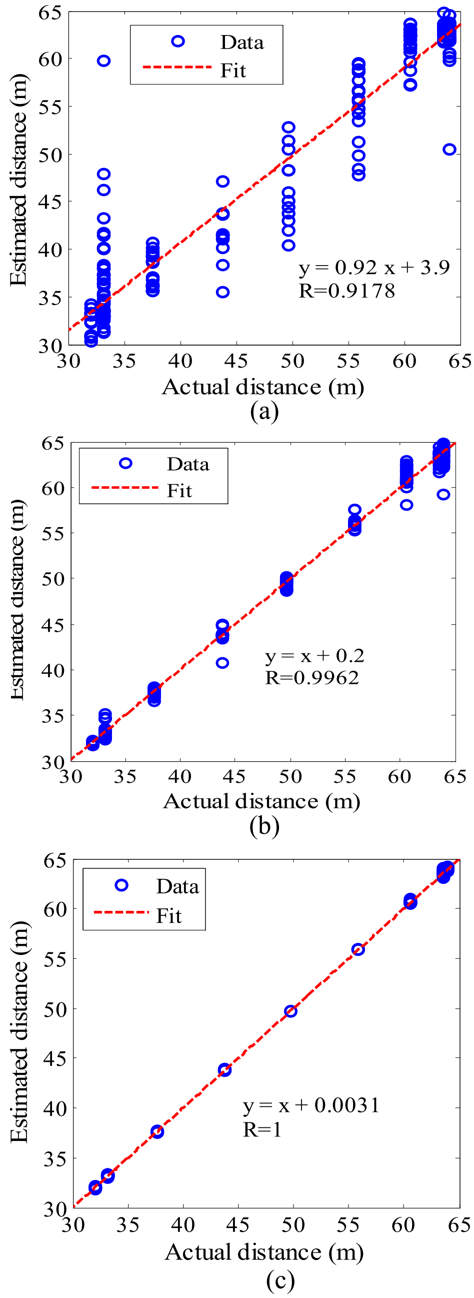

FIGURE 9. Outdoor environment: (a) 3 gbell*mf*, (b) 5 gbell*mf*, and (c) 7 gbell*mf*.

ANFIS is trained and tested offline. The RSSI measurements of the anchor nodes (i.e., AN1, AN2, AN3) are used as inputs to the ANFIS, and the real physical distance between the coordinator node (AN1) and mobile bicycle node are

TABLE 3. Comparison between the proposed ANFIS technique and the techniques or algorithms of previous related works in terms of MAE.

Ref.	Year	Localization technique/algorithm	Location technology	Environment	MAE (m)
[25]	2007	ANFIS	WiFi	Indoor	2.1
[56]	2008	ANFIS	UHF (CC1000)	Outdoor	0.9886
[14]	2012	ANFIS	ZigBee	Outdoor	2
[57]	2013	FL	WiFi	Indoor	3.133
[32]	2013	ANN	Simulation model	Simulation	0.49
[58]	2013	MFL and SFL	IEEE 802.15.4	Simulation	0.89 (MFL) and 0.94 (SFL)
[59]	2013	ANN	RFID	Indoor	1
[60]	2013	ANN	Simulation model	Simulation	0.15
[61]	2013	ANN	Hive5	Indoor	0.99
[62]	2014	FL	WiFi	Indoor	7.6
[32]	2014	ANN	Simulation model	Simulation	1.1862
[35]	2014	ANN	ZigBee	Indoor	2.8
[16]	2014	ANN	Simulation model	Outdoor	6 -7
[63]	2014	ANN	ZigBee	Indoor	0.85
[64]	2014	ANN	Simulation model	Indoor	0.3
[65]	2014	EMMWC	ZigBee	Indoor	1
[66]	2014	EMMWC	IEEE 802.15.4	Indoor/outdoor	< 2
[15]	2015	ANN	Simulation model	Simulation	0.7855
[17]	2015	ANFIS	WiFi	Indoor	0.43
[67]	2015	ANN	Simulation model	Indoor	1.98 (RMSE)
[67]	2015	ANN	Simulation model	Outdoor	1.42 (RMSE)
[68]	2015	ANN	Simulation model	Simulation	0.11958
[17]	2015	MVFL	IEEE 802.11b	Indoor	0.98
[69]	2016	PSO- ANN	Simulation model	Simulation	0.288
[70]	2016	FL	ZigBee	Indoor	0.8
[71]	2016	FL and ELM	Simulation model	Outdoor	0.15 (FL), 0.26 (ELM)
[72]	2016	ELM	Simulation model	Indoor	5.25
[55]	2016	Adaptive FL	Bluetooth	Indoor	0.15
[73]	2016	Deep Neural Network	WiFi	Indoor/outdoor	0.398
[74]	2016	Mobile and fixed nodes	Simulation model	Indoor/outdoor	< 1
[75]	2016	SVM	WiFi	Indoor	1.2
[76]	2016	RSS-based GLS	IEEE 802.15.4	Indoor	0.3
[77]	2016	SVM	Simulation model	Simulation	0.1
[50]	2017	MFL and SFL	Simulation model	Simulation	0.5 (MFL) and 0.3 (SFL)
[78]	2017	MSVM	Simulation model	Simulation	1.632
[79]	2017	Intelligent water drops	Simulation model	Simulation	1.602
[80]	2017	MDS-KNN	WiFi	Indoor	1.2 (MSE)
[81]	2017	H-Best PSO	Simulation model	Simulation	0.4139
[82]	2017	HMS	Simulation model	Simulation	4
[83]	2017	DCNN	Image-based	Indoor	1.14 (RMSE)
[84]	2017	GA	Simulation model	Simulation	0.89
[85]	2017	Bluetooth LE and MEMS	Bluetooth LE	Indoor	2.29
[86]	2017	Weighted Centroid	Simulation model	Simulation	1.009
[87]	2017	FL	Simulation model	Simulation	0.898
[88]	2017	PSO	Simulation model	Simulation	0.5
[89]	2017	Hierarchical structure poly-PSO	ZigBee (CC2530)	Outdoor	0.624
[90]	2017	BFO	Simulation model	Simulation	0.05
[91]	2017	FL based on Invasive Weed Optimization	Simulation model	Simulation	0.507
[92]	2017	CSO	Simulation model	Simulation	0.11
[93]	2017	GWO and WOA (Swarm Intelligence)	Simulation model	simulation	1.4
[94]	2018	MLP	Bluetooth LE	Indoor	1.75
[95]	2018	FL	Simulation model	Indoor	0.192
[96]	2018	Radio Map	WiFi	Indoor	3.5
[97]	2018	IPSO	Simulation model	Simulation	0.35
[98]	2018	BPANN	Simulation model	Simulation	0.057
[99]	2018	CNN	UWB	Indoor	0.65
[100]	2018	Logistic Regression Classier	IEEE 802.15.4	Indoor	1.45
[101]	2018	Twi-Adaboost Algorithm	Smartphone	Indoor	0.39 m
[102]	2018	FP-MPP-APIT Algorithm	Simulation model	Outdoor	1.3
[103]	2018	CRRV	Simulation model	Simulation	0.5
Proposed ANFIS		ANFIS	ZigBee	Outdoor	0.023
Proposed ANFIS		ANFIS	ZigBee	Indoor	0.283

BFO: butterfly optimization algorithm; BPANN: Back Propagation ANN; CNN: convolutional neural network; CRRV: connectivity and the RSS rank vector; DCNN: deep convolutional neural network; EMMWC: extended min-max and weighted centroid; FP-MPP-APIT: Fermat point-mid perpendicular plane-approximate point in triangulation test GLS: geometrical least square; GWO: Grey Wolf Optimizer; HMS: heuristic multidimensional scaling; IPSO: improved PSO; MDS-KNN: multi-dimensional scaling k-nearest neighbor; MEMS: microelectromechanical systems; MFL: Mamdani FL; MSVM: multidimensional SVM; MVFL: multivariable fuzzy localization; SFL: Sugeno FL; CSO: chicken swarm optimization; MLP: Multilayer Perceptron; WOA: Whale Optimization Algorithm

used as output. Simulation in MATLAB is performed to train and test ANFIS. However, there is no concern with respect to the time characteristic, in which the offline training time is 30, 162, and 1345 s for 3, 5, and 7 gbellmfs, respectively. After the offline training of the ANFIS, the new RSSI values received by the mobile bicycle node correspond to the

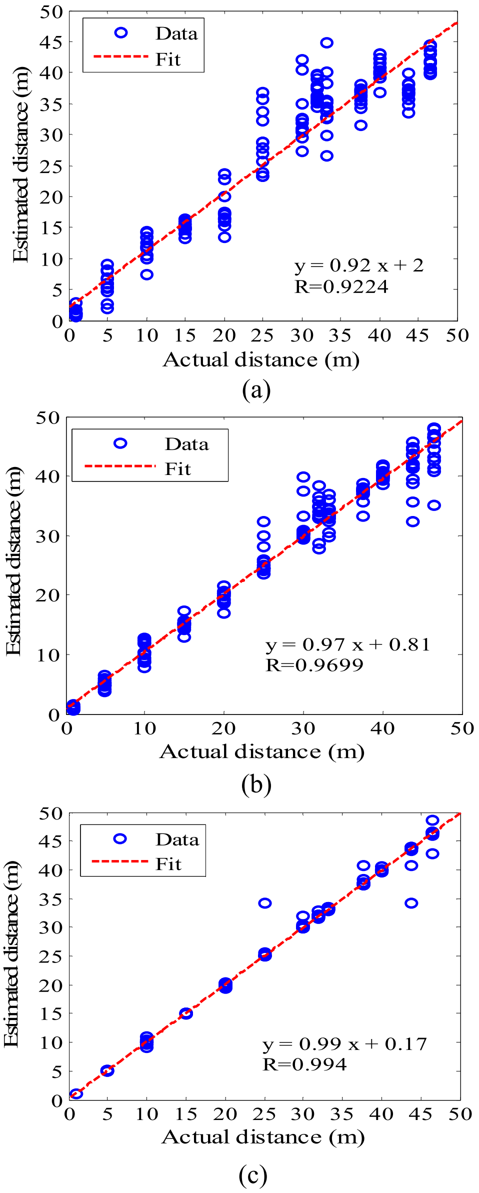

FIGURE 10. Indoor environment: (a) 3 gbell*mf*, (b) 5 gbell*mf*, and (c) 7 gbell*mf*.

estimated distance in real time. Meanwhile, the ANFIS technique in the current study is compared with the techniques used in the previous studies in terms of MAE in the localization or distance estimation (Table 3). In this comparison, similar studies that have used ANFIS, FL, PSO, GA, extreme learning machine (ELM), support vector machine (SVM), and ANN localization or distance estimation techniques are considered. Furthermore, most of the previous works have employed ZigBee, Wi-Fi or combination of both wireless technologies and used the RSSI to train and test the AI. These protocols are selected because their RSSI measurements are easy to implement and does not require additional hardware. The RSSI metric has been used by the researchers as an input to AI processes, while the positions of the x and y coordinates of the nodes or the physical distances (d)

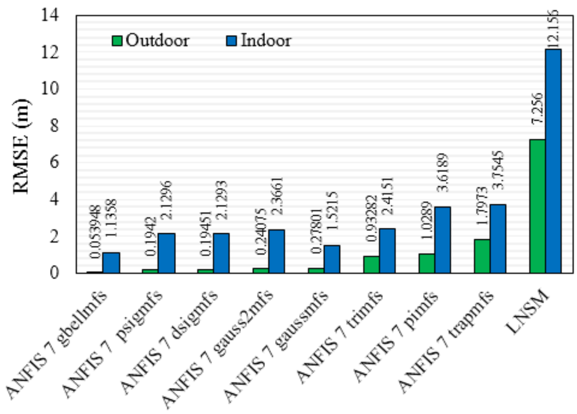

FIGURE 11. Distance estimation accuracy between LNSM and different types of ANFIS.

among the nodes are used as outputs. Our results indicate that our ANFIS technique is superior to the techniques used in previous studies in terms of MAE performance. Particularly, we have obtained an RMSE of 0.053 m and MAE of 0.023 m in our outdoor application and RMSE of 1.1 m and MAE of 0.283 m our indoor application (Table 3). However, [55] is better than our work, because its mobile node moves with a maximum distance of 18.6 m, whereas the mobile node in our work moves with a maximum diagonal distance of 45 m in indoor environments. In other words, the accuracy of our work decreases because of increased distance, which is prone towards the effect of channel imperfections, such as scattering, reflection, and diffraction.

VIII. CONCLUSIONS

Given the advantages of using RSSI information from constant nodes AN1, AN2 and AN3, the proposed ANFIS technique is much more accurate than the range-based method that employs LNSM. A path loss model is derived from the linear fit along with RSSI to determine the actual physical distance between the coordinator and mobile nodes on the cycle track. RMSE and error calculations reveal that distance estimation using LNSM is accurate for short communication distances in outdoor surroundings; however, it is inappropriate for long-distance applications for indoor and outdoor velodromes. The LNSM approach cannot satisfy the distance estimation accuracy for indoor environments, but it is suitable for short distances in outdoor velodromes. Therefore, ANFIS was used to optimize the estimated distance accuracy of the mobile node on the cycling track.

The results disclosed that the distance estimation accuracy based on ANFIS was significantly improved by 84% and 99% relative to LNSM in indoor and outdoor environments, respectively. Furthermore, the proposed ANFIS technique outperformed methods used by previous works in terms of MAE. The number and type of the ANFIS membership functions significantly affected the distance accuracy. When the numbers of membership functions increased, the estimated distance improved considerably. However, in this case, the computational and convergence time increased. Therefore, a trade-off between computational time and accuracy is necessary.

Several conclusions are obtained. First, LNSM can be applied to short distances in outdoor environments. Second, LNSM is unsuitable for use in indoor environments. Third, AI techniques, such as ANFIS, can be employed to improve distance accuracy. Fourth, the proposed ANFIS obtained better results than other algorithms because the performance of ANFIS is improved by increasing the number and type of membership functions. In this work, the accuracy of the estimated distance is improved, and the error is significantly minimized due to the selection of seven gbell membership functions. Fifth, ANFIS is trained and tested in the offline phase. However, ANFIS training and data testing consume a large amount of time, especially when the number of membership functions is large, because the amount of data and the complexity of ANFIS increase with the number of membership functions. After the offline phase, three new RSSI values are received in the online phase. Consequently, the distance between the mobile bicycle node and the coordinator node can be accurately estimated in real time.

Finally, the ANFIS technique supports multiple input-single output. Therefore, it is suitable for distance estimation, such as in the current cycling application. For x and y localization, the RSSI dataset consists of two input: one for the x coordinate and the other for the y coordinate. The RSSI dataset must be fed separately to two ANFIS systems. For future work, the distance estimation precision can be optimized further by increasing the number of anchor nodes, especially in an indoor environment.

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