Enhancing Indoor Positioning Accuracy using a Hybrid Li-Fi/Wi-Fi System with Deep Learning Support

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ABSTRACT

This study proposes a new indoor positioning system that utilizes Li-Fi/Wi-Fi technology and the Received Signal Strength (RSS) triangulation method, aided by a Deep Neural Network (DNN) for better system accuracy. The proposed system uses several Light-Emitting Diodes (LEDs) as light emitters and photodetectors as receivers to determine the position of a user in an indoor environment. Photodetectors measure the RSS of a Li-Fi or Wi-Fi signal, which is then used to calculate the distance between the light sources and the user. RSS values are entered into a DL model to improve the accuracy of the positioning system by predicting the location of the user in more detail. The proposed system was experimentally tested and the results show that this method can achieve high positioning accuracy. The main objective of this work was to locate the mobile user within a room equipped with Li-Fi technology and obtain the best possible coverage of service to the user. In the first stage of data simulation, the triangulation technique achieved average errors of 2.174×10^{-14} cm, 6.450×10^{-14} cm, and 4.657×10^{-11} cm for the x, y, and z axes, respectively. This indicates the proximity of the simulation results to the actual ones. In the second stage, when RSS triangulation was applied with noise effects, the average error was 2.060×10^{-3} cm, 4.565×10^{-3} cm, and 5.110×10^{-3} cm for the x, y, and z axes, respectively. A DL technique was used to handle noise, and the greatest error for the x, y, and z axes was 2.520 cm, 2.260 cm, and 4.230 cm in a 6×4×3 m indoor environment.

Keywords-Li-Fi; RSS; UWB; triangulation; DL; Wi-Fi; LEDs; VLC

I. INTRODUCTION

Indoor positioning systems have become increasingly important in various industries, including healthcare, retail, and entertainment. These systems enable tracking and monitoring of people, assets, and equipment within an indoor environment. Traditional indoor positioning systems use technologies such as Wi-Fi, RFID, and Bluetooth, but these technologies have limitations in accuracy, coverage, and reliability. In recent years, Li-Fi technology has emerged as a promising alternative for indoor positioning due to its high-speed data transmission, low latency, and security advantages. Li-Fi technology uses Visible Light Communication (VLC) to transmit data between LED light sources and photodetectors. However, interference, reflected signals from walls, and obstructions can cause the Li-Fi channel's quality to fluctuate.

When operating a hybrid network, it is essential to distribute traffic evenly across all APs to maintain a constant and high data rate for all users. As a result of their ability to adapt to their surroundings, RSS-triangulation-based algorithms have garnered a lot of interest for use in such scenarios. This approach can be used to locate a user in an indoor environment. The RSS of Li-Fi and Wi-Fi signals can be measured, and then the triangulation technique can be applied to calculate the distance between the user and the light sources. However, the accuracy of this technique might be affected by various factors, such as noise, interference, and reflections.

The ability to locate individuals and objects within an indoor environment has attracted much interest in the last few years because it can be practically helpful in many areas such as retail, healthcare, or entertainment. However, the usual positioning systems, such as GPS, are not suitable for indoor positioning due to attenuation and multipath effects. This has prompted the advancement of different technologies for indoor positioning, such as Bluetooth, Wi-Fi, and Ultra-Wide-Band (UWB), all utilizing radio signals for determining a user's position. This study introduces a new method for indoor positioning, combining RF technology with VLC, using RSS triangulation. This method shows promise in achieving results that are more exact and faster than those of other technologies so far.

VLC is a wireless communication technology that utilizes visible light for data transfer. It has advantages such as high bandwidth, low latency, and immunity to electromagnetic interference. The proposed system utilizes various LED lights as light sources and photodetectors to receive it, to determine the distance between the user and these light sources. The calculation is based on the strength of the signal received by the detectors. This study uses a DNN to process RSS values and predict the location of the user to improve the accuracy of this hybrid positioning system. The proposed system was tested experimentally in a laboratory setting. The results show that it can achieve high accuracy for positioning, even with disturbances present.

II. ASSESSMENT OF INDOOR POSITIONING SYSTEMS BASED ON A HYBRID NETWORK

Li-Fi uses visible light as a medium for transmitting data, while RF relies on radio frequencies for the same purpose. A system combining these technologies can facilitate quick communication with minimal latency and immunity to electromagnetic interference. The probable benefits are faster positioning, better accuracy, and superior security compared to typical indoor locating systems using radio signal methods. The evaluation of indoor hybrid localization systems includes analyzing and testing how well Li-Fi-based indoor positioning systems work in different places, such as offices, shops, or hospitals. In general, the evaluation is based on the precision, accuracy, and reliability of this positioning system along with its ability to function when there is noise or interference present. Understanding how these systems work is very important to decide if they can be used in different ways, such as navigation, security, and tracking assets. Therefore, to meet the growing demand for precise and reliable indoor positioning solutions, experts and users continue to study and improve the functioning of such systems [1-8].

A. Representation Of LDPC Codes

Position estimation is the process of locating an object or a user in an indoor environment. Li-Fi, which stands for light fidelity, is a wireless system that transmits data using visible light. Wi-Fi is a wireless communication system that sends data using radio frequencies. The accuracy of position estimation through a hybrid network relies on some factors such as how many and where Wireless Access Points (WAPs) are located, the sensitivity of the receiver, and whether there are obstacles inside the indoor environment that might affect the transmission of Li-Fi signals. Therefore, careful design and fine-tuning of the system is vital to ensure accurate position estimation. In summary, hybrid technologies show promise for indoor localization systems, as they can provide high data rates, secure communication, and low latency. However, more studies are required to enhance the systems' performance in position estimation and address the difficulties linked with incorporating signals into real-life surroundings.

B. Triangulation

In indoor localization systems, triangulation refers to a method that estimates a user's or an object's position through signal strength or time-of-flight from various access points/beacons. The strength of the signal from the access points or beacons to the user/object and the time taken to travel can give an idea of how far they are apart. When measurements are made with a minimum of three access points/beacons, the system can work out exactly where the user or the object is located using the triangulation technique. Triangulation, a method often utilized in GPS systems to locate an object or a user on a map, can also find application in indoor localization systems. The accuracy of triangulation could be better than proximity-based methods. However, it requires more complex calculations and adjustments of beacons or APs. Location tracking using triangulation is typically combined with other methods to achieve the highest accuracy possible.

C. Angulation

In terms of indoor localization systems, angulation is often combined with methods such as fingerprinting or triangulation to improve the accuracy of position estimation. Combining angle measurements with distance measurements from multiple reference points aids in a more accurate estimate of where the user or object is located. Localization systems based on angulation are frequently utilized in certain applications such as the robot or vehicle tracking within an indoor environment. This is beneficial because precise position knowledge is important for proper navigation and control. However, angulation can be influenced by factors such as multiple path reflections, signal interference, and variations in the orientation of sensors or antennas, which could lower its accuracy. Systems that use angulation for localization should be calibrated meticulously and tested within the particular environment to confirm dependable functioning.

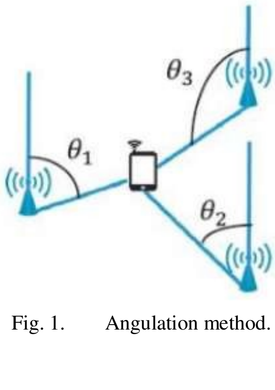

Fig. 1. Angulation method.

D. Lateration

The position of a mobile target could be determined by localization algorithms. Triangulation equations are used to measure the distance between WAPs and the mobile target, as can be seen in Figure 2. The distances obtained from such a localization algorithm are used with an RSS approach to calculate the signal strength at the target. This hybrid method uses both triangulation and RSS approaches to provide precise and reliable results for the localization of objects [9].

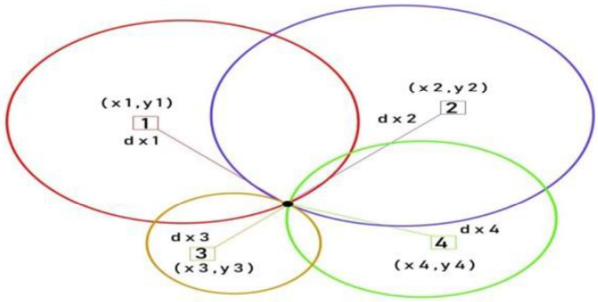

Fig. 2. Lateration method.

The calculations regarding a lateration equation are complicated because of their non-linear nature in the specification of the intersection related to multiple circular lines in a single geometric approach [10, 11]. Handling such a problem needs an estimation method, and the RSS approach is frequently used for calculating the distance between the LED and the user. This calculation depends on the coordinates of the LED, represented by x_1, y_1, and z_1, and the coordinates of other LED access points, represented by x_i and y_i (where i ranges from 1 to 4), as well as the actual coordinates of the mobile station, represented by x, y, and z. The Euclidean distance between the mobile station and each LED access point can be determined using [10]:

$$dxy_1^2 = (x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2 \quad (1)$$

$$dxy_2^2 = (x_2 - x)^2 + (y_2 - y)^2 + (z_2 - z)^2 \quad (2)$$

$$dxy_3^2 = (x_3 - x)^2 + (y_3 - y)^2 + (z_3 - z)^2 \quad (3)$$

$$dxy_4^2 = (x_4 - x)^2 + (y_4 - y)^2 + (z_4 - z)^2 \quad (4)$$

Using equation subtraction, the following equations can be derived, which can be described in a matrix form.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \frac{1}{2} \times \begin{bmatrix} (-x_1 + x_3) & (-y_1 + y_3) & (-z_1 + z_3) \\ (-x_2 + x_3) & (-y_2 + y_3) & (-z_2 + z_3) \\ (-x_1 + x_4) & (-y_1 + y_4) & (-z_1 + z_4) \end{bmatrix}^{-1} \times$$

$$(-x_1^2 + x_3^2)(-y_1^2 + y_3^2)(-z_1^2 + z_3^2) \quad (5)$$

$$((-dxy_1^2 + dxy_3^2)) \quad (6)$$

$$(-x_2^2 + x_3^2)(-y_2^2 + y_3^2)(-z_2^2 + z_3^2)(-dxy_2^2 + dxy_3^2) \quad (7)$$

$$(-x_1^2 + x_4^2)(-y_1^2 + y_4^2)(-z_1^2 + z_4^2)(-dxy_1^2 + dxy_4^2) \quad (8)$$

These equations are considered the most accurate due to minimal time delay, making it a suitable option for minimizing positioning loss caused by time delay. This can be achieved since we have four Equations and three unknown variables (x, y, and z). Subtracting equations allows us to obtain three groups of Equations: (1, 3), (2, 3), and (1, 4) [9]. Applying this technique results in three equations that can be expressed appropriately in a matrix. By deriving the triangulation equation, it is possible to determine the user's location coordinates using :

$$V = \frac{1}{2} \times A^{-1} \times B \quad (9)$$

E. *Fingerprinting*

Fingerprinting can be defined as an approach utilized in indoor localization systems to estimate the position of an object or a user based on a map of signal strength or other properties of wireless signals in the environment. The fingerprinting method involves creating a database of signal patterns or fingerprints at different locations in an indoor environment, and after that utilizing such patterns for estimating the location of an object or a user depending on the patterns detected through their device. In indoor localization systems, fingerprinting usually means collecting data by measuring the strength as well as other properties of Wi-Fi or Bluetooth signals at various locations in an indoor environment. These measurements are used to create a map or database that displays signal patterns for each location. When a user's device or an object enters this indoor environment, it acquires characteristics such as measuring signal strength and other features from surrounding signals. The measurements are then compared with fingerprints in a database to estimate the location at a current time [12].

Fingerprinting can be more accurate than proximity- or triangulation-based methods, as it considers the distinctive features of signals in the environment. These signals might differ due to factors such as interference, reflections, and obstructions. However, fingerprinting needs thorough calibration and mapping of the environment and could be affected by alterations, such as objects moving around or changes in the location of wireless APs. In general, it is a promising method for indoor localizing systems and has shown success in the past. For example, this technique has been used effectively in location-based tasks such as navigation, tracking, and indoor mapping. However, more research is required to enhance the precision and strength of fingerprinting-based localization systems in actual settings [13].

F. *Positioning Principles*

Positioning principles are the basic ideas and ways to accurately locate an object. These principles play a crucial role in many applications that require location services, such as navigation, tracking, and indoor localization. Some main positioning principles consist of measuring the distance between objects and reference points, figuring out what angle something arrived at, analyzing signal power, and using time difference when things arrive. Combined or alone, these principles can help estimate the target's location with precision. The selection of a principle relies on the particular application and resources. For example, in indoor localization using Li-Fi methods, fingerprinting, proximity, lateration, and triangulation are applied to estimate the position of a mobile device.

G. *Time Difference of Arrival (TDOA) - Time of Arrival (TOA) Methods*

The TOA and TDOA techniques focus on measuring the time it takes for a signal to travel from a transmitter to a receiver. In TOA, the exact times of both sending and receiving the signal are calculated. The distance is found by multiplying the difference in time by the speed of light. TDOA calculates the delay of signals that reach different receivers, locating the object using hyperbolas or circles from a constant TDOA intersect of each other.

For indoor localization systems, TDOA and TOA are often used with Ultra-Wideband (UWB) technology or Wi-Fi-based systems. UWB can provide very precise ranging measurements, but it needs many anchors and has complex algorithms for localization. Wi-Fi-based systems depend on the Round-Trip Time (RTT) of Wi-Fi signals between user devices and Wi-Fi APs, providing reasonably accurate results with fewer hardware needs. However, these techniques are affected by obstacles and multipath propagation, which can cause substantial errors in position estimation [14].

H. Angle of Arrival (AoA)

AoA is a location approach that determines the angle from which a signal arrives at the receiver antenna, originating at the transmitting antenna. It is often applied in wireless communication systems, such as radar and wireless localization systems, to approximate where an object might be located. The AoA method requires a group of receiving antennas located at certain positions, and each antenna measures the phase difference of the signal received. The phase difference between the antennas can determine the angle of the arriving signal. In the case where a signal comes from one angle, it will have a different phase shift than if it came from another angle to reach the receiving antenna. AOA can be found by calculating such phase differences through trigonometric functions. AoA offers several advantages. It could provide precise results, function in both indoor and outdoor settings, and track targets on the move. However, it has some disadvantages, such as the need for an array of antennas for accuracy, high processing power needs, and being susceptible to interference and multipath effects [16].

I. Received Signal Strength (RSS)

RSS is commonly used for indoor positioning. It functions by gauging the signal strength received from a transmitter to a receiver. This approach is based on when increasing the distance between the transmitter and the receiver, signal strength becomes weaker. The RSS method can be implemented using Bluetooth, Wi-Fi, and other wireless technologies. ZigBee is the most common choice for this method. In the RSS method, the receiver examines the signal's strength from several transmitters or APs. This helps to calculate how far away the receiver is located from each transmitter using trilateration. For trilateration to work, a minimum of three APs with known locations are required to determine where the receiver may be situated. The position of the receiver can be determined by finding where circles, with radii equal to estimated distances from receiver to APs, intersect with each other.

The RSS positioning approach is influenced by some factors, such as the number of APs and the way that they are spread out, signal strength, the presence or situation of obstacles, and interference or noise in the setting. In addition to that, multipath propagation can also affect this method. The issue results from a signal that diffracts or reflects, which makes it difficult to make an accurate estimation of the distance. Complex algorithms, such as fingerprinting or ML, can enhance the accuracy of the RSS approach [17], addressing the effects of multipath propagation on indoor positioning systems.

RSS is easy to put into action because it is comparatively simple to implement. All that is required is measuring the signal strength from wireless APs that are already present in the environment. It is also cost-effective, as it only requires the use of existing WAPs and does not require additional hardware [15]. WAPs are easily found in indoor environments, so RSS can be used effectively for indoor localization. The RSS technique is less affected by obstacles compared to other techniques, such as AoA and ToA, which need direct visibility between the mobile device and the WAP. This characteristic enables it to provide quite accurate location estimation, even when there is no clear line-of-sight between the device receiving signals and its source WAP. Additionally, the RSS method can be simply scaled up by including more WAPs to cover large indoor areas. This feature makes it ideal for use in large indoor areas, such as airports, shopping malls, hospitals, etc. [18].

The DC gain of the channel in LiFi systems is directly linked to radiant intensity, and the RSS measurement model for Li-Fi relies on effective light collections.

$$H = f(x) = \begin{cases} R_0(\emptyset) A_{eff}(\psi), & 0 \le \psi \le \psi_c \\ 0, & \psi \ge \psi_c \end{cases} \quad (10)$$

The definitions of the transmitter radiant intensity, represented by $R_0(\emptyset)$, and the effective signal collection area, represented by $A_{eff}(\psi)$, are given as follows:

$$R_0(\varphi) = \frac{v+1}{2\pi} \times \cos^{v}(\varphi) \quad (11)$$

$$A_{eff(\psi)} = A \times \cos(\psi) \times T_s(\psi) \times g(\psi) \quad (12)$$

The received optical power measurements are only available in the form of noisy data. Thus, considering the noise, the following equation can be used:

$$g(\psi) = \left(\frac{\eta_c}{\sin(\psi_c)}\right)^2 \quad (13)$$

The radiation angle for the transmitter's vertical axis is denoted by φ, while ψ represents the incidence angle for the receiver. The optical filter gain is represented by $T_s(\psi)$, and the concentrator gain is expressed as $g(\psi)$. ψ_c denotes the concentrator Field Of View (FOV), and η_c denotes the internal refractive index.

$$PR_i = \frac{H_i P_T}{dxy_i^2} \quad (14)$$

This Equation. incorporates zero-additive Gaussian noise with two constants. The probability function of the RSS for a VLC network involves an additional Gaussian noise distribution that is expressed in relation to an unknown received site [10], and may be described by:

$$\partial i^2 = \partial\{shot\}^2 + \partial\{thermal\}^2 \quad (15)$$

The semi-angle at half power of the transmitters is denoted by $\varphi_{1/2}$.

$$\partial\{shot\}^2 = 2 \times q \times r \times p_r + 2 \times q \times I_{bg} \times l_2 \times B \quad (16)$$

This equation includes some variables that represent the elementary charge, Boltzmann's constant, and photodiode responsivity [19].

III. MODEL FOR THE HYBRID SYSTEM

This study aimed to develop a hybrid indoor localization system that utilizes RSS and triangulation to achieve greater accuracy, faster processing times, and reduced expenses in a confined environment consisting of four ceiling-mounted LEDs with one Wi-Fi at a center and an unidentified user position (x, y, z) within the room, as illustrated in Figure 4. Matlab 2021 was used to implement the proposed two-stage approach for calculating the user location. The first stage involved the triangulation approach for simulating the data without any noise and computing the user's location error, as shown in Figures 4 and 5.

The second stage involved simulating the data under the influence of noise. This simulation was based on triangulation and RSS to determine parameters such as the user's location, the received power, the distance error, and the incidence angle, as seen in Figure 6. Table I summarizes the parameters used in the 3D indoor system, and Table II shows the parameters of the Wi-Fi simulation.

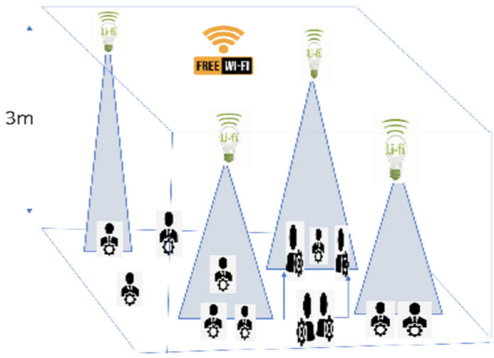

Fig. 3. Hybrid indoor system environment.

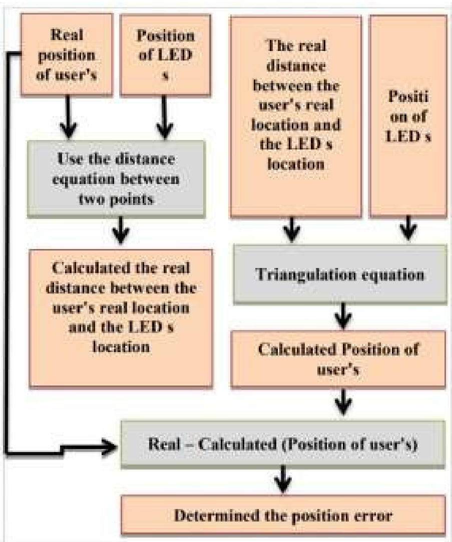

Fig. 4. The sequential steps involved in the triangulation method.

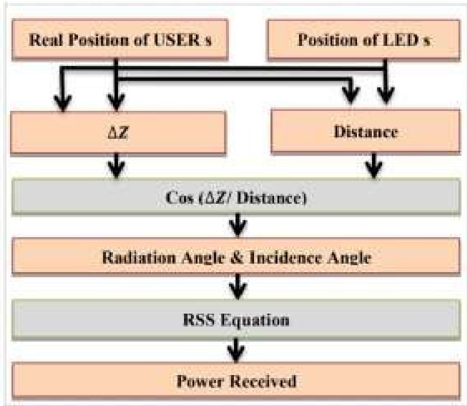

Fig. 5. Flowchart of the RSS-triangulation method.

TABLE I. LI-FI SIMULATION PARAMETERS

Parameters	Symbol	Value
Room dimensions	*(L, W, H)*	5×5×3m
Power of each LED	*PT*	2 W
Upper and lower range	*(x-y-z)*	upper = (5.0m, 5.0m, 2.80m) lower =(0m, 0m , 0m)
Field Of View receiver	*FOV*	70°
Lambertian order	*v*	1
Photodetector area	*A*	1 cm^2
Optical filter gain	T_S	1
Internal refractive index	η_c	1.7
Boltzman constant	K	1. 3806505 × 10–23
Absolute temperature	T_k	295 K
Open-loop voltage gain	G_0	10
Field-effect transistor of the channel	*L*	1.50
Noise bandwidth factor	I_2	0.5620
Fixed capacity	*O*	112 pF cm–2

TABLE II. SIMULATION PARAMETERS

cc	Symbols	Values
Transmit power	$P_{Wi\text{-}Fi}$	20 dBm
Shadowing loss	*XSF*	3dB
Bandwidth per Wi-Fi AP	$B_{Wi\text{-}Fi}$	20MHz
PSD of noise	$N_{Wi\text{-}Fi}$	-174dBm/Hz
Breakpoint distance	D_{BP}	5cm
Central carrier frequency	F_c	2.4 GHz

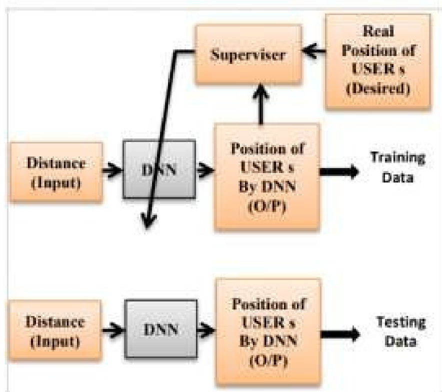

Fig. 6. Flowchart of the proposed DNN sequence based on the RSS-triangulation approach.

The flowchart in Figure 6 illustrates how the RSS approach was used for generating the data. The distance measured was used as the input to evaluate the DL algorithm's accuracy in determining the user's location. Table IV shows details of the DNN using the RSS-triangulation method. Figure 7 shows the method used to calculate the location. Figure 8 describes the DNN approach.

TABLE III. DNN SPECIFICATIONS

Deep Neural Network	Specification
Hidden layers size	(84,84,84,84,84,84,84,84,84)
Total number of neurons	756
Neurons at the output layers	3
Activation function	Bipolar sigmoid
Percentage of training samples	70%
Percentage of testing samples	30%
Training algorithm	Backpropagation
Optimizer	ADAM
Alpha parameter	0.1
Learning rate	0.001
Epochs	300,000

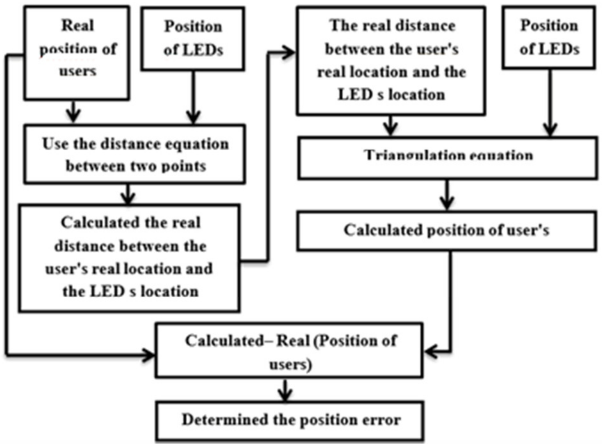

Fig. 7. Proposed triangulation method.

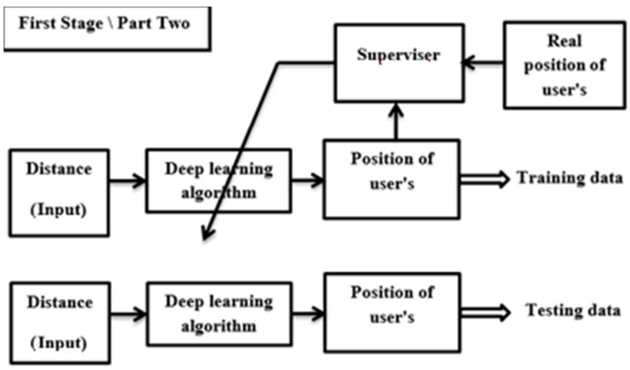

Fig. 8. Proposed DNN based on the triangulation method.

IV. SIMULATION RESULTS AND ANALYSIS

The first method employed the triangulation method without considering noise. Although it is impossible to find a completely noise-free environment, this scenario was used to provide evidence for the method's validity. The second approach uses the proposed method with noise present.

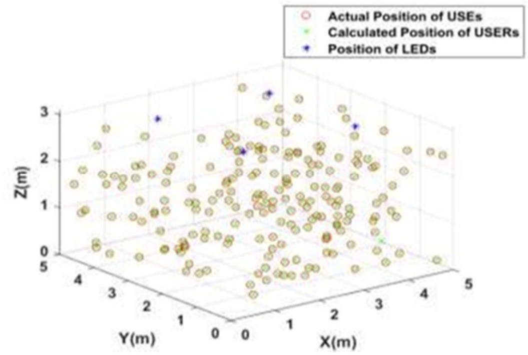

Fig. 9. User's location: actual and estimated by triangulation.

(a)

(b)

(c)

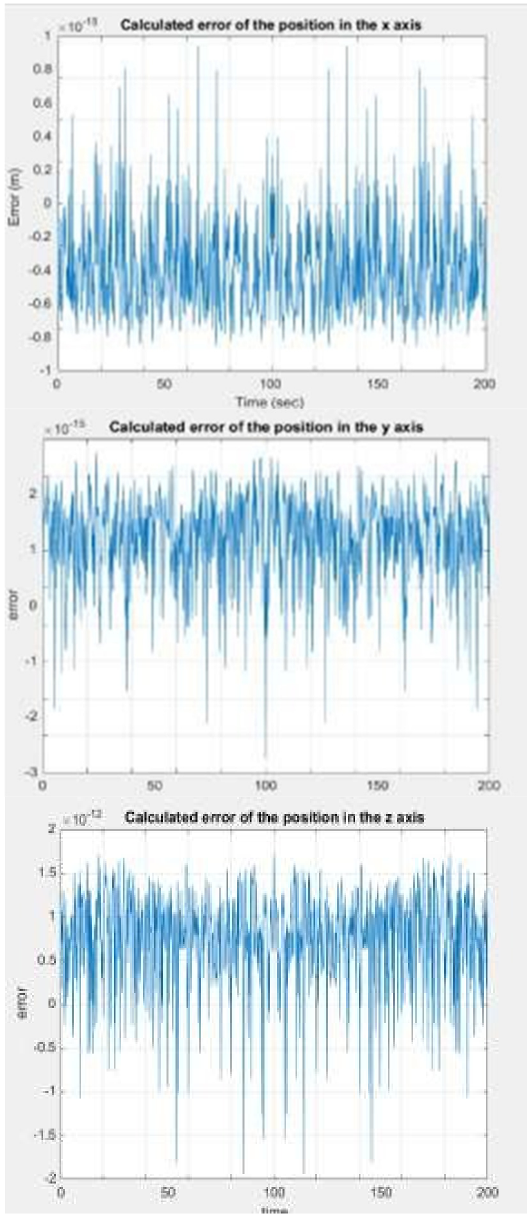

Fig. 10. Position error ratio along the (a) x, (b) y, and (c) z axes with the triangulation method.

A. Results of the Triangulation Method

This simulation did not consider noise. A selection of 100-200 of the 80,000 user sites that were used are shown in the results, as shown in Figure 9. The blue color depicts the LED location, the red color shows the user's actual location, and the green color shows the user's calculated location based on triangulation. Figure 10 shows the location error rate in the three axes, while Table V lists the average, maximum, and minimum errors. These results are regarded ideal, as triangulation was applied precisely and without noise.

TABLE IV. LOCALIZATION ERROR OF THE TRIANGULATION METHOD

Axes	Average error	Maximum error	Minimum error
X-axis	2.17344×10^{-14} cm	1.77636×10^{-13} cm	-1.33227×10^{-13} cm
Y-axis	6.44762	4.44089	-3.66374

(a)

(b)

(c)

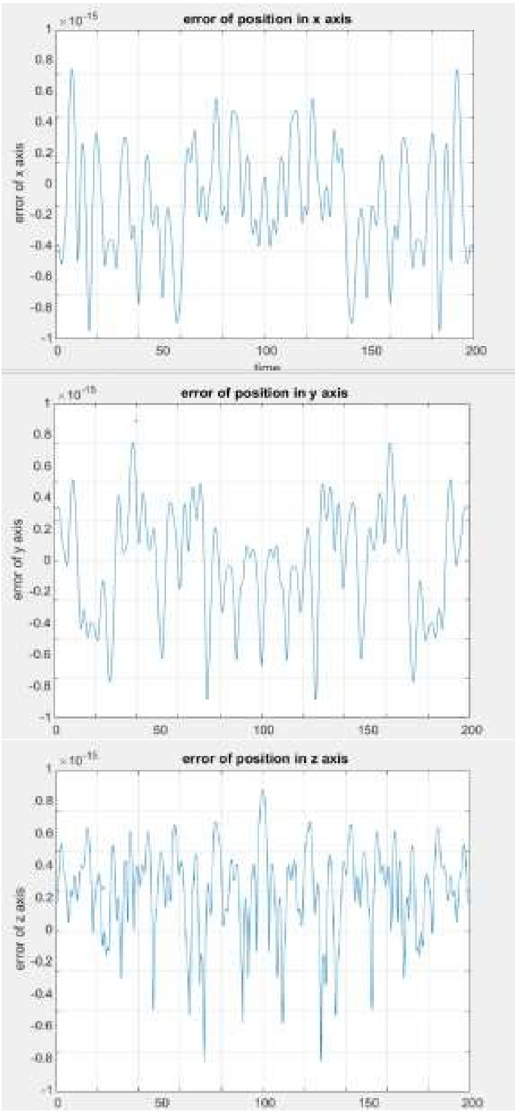

Fig. 11. Noise impact on the three axes of a user's location as determined by the proposed RSS-triangulation approach: (a) x-axis, (b) y-axis, (c) z-axis.

B. RSS-Triangulation Simulation Results

This section presents a performance evaluation of the proposed method, using RSS-triangulation with noise present. Distance data to determine the location of a user were analyzed using a DL algorithm. Figure 11 shows how noise affects the user's location in the three axes. Table V shows the highest and lowest location errors on the three axes as well as the average location error. Figure 12 shows how noise affects the distance between the LEDs and the users.

(a)

(b)

(c)

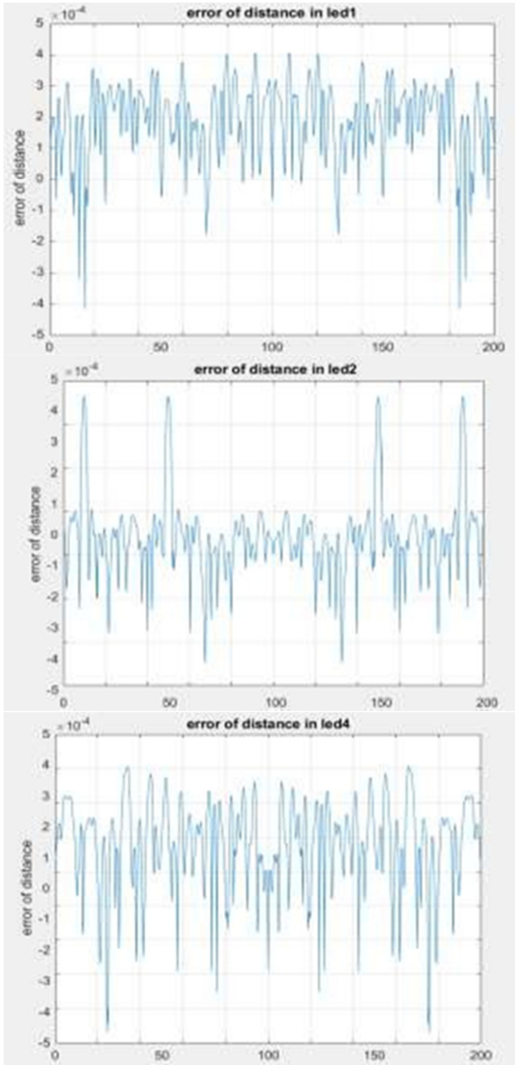

Fig. 12. Noise impact on the distance between the locations of the LEDs and the user: (a) led 1, (b) led 2, (c) led 3.

TABLE V. LOCALIZATION ERROR OF THE RSS-TRIANGULATION METHOD.

Axes	Average error (cm)	Maximum error (cm)	Minimum error (cm)
x-axis	2.05612×10^{-3}	1.11197×10^{-2}	-1.14502×10^{-2}
y-axis	4.56249×10^{-3}	2.30044×10^{-2}	-2.35818×10^{-2}
z-axis	5.10474×10^{-1}	2.57736	-2.64951

Figure 13 shows the optical power that each user in the workroom receives from the LEDs.

(a)
(b)
(c)
(d)

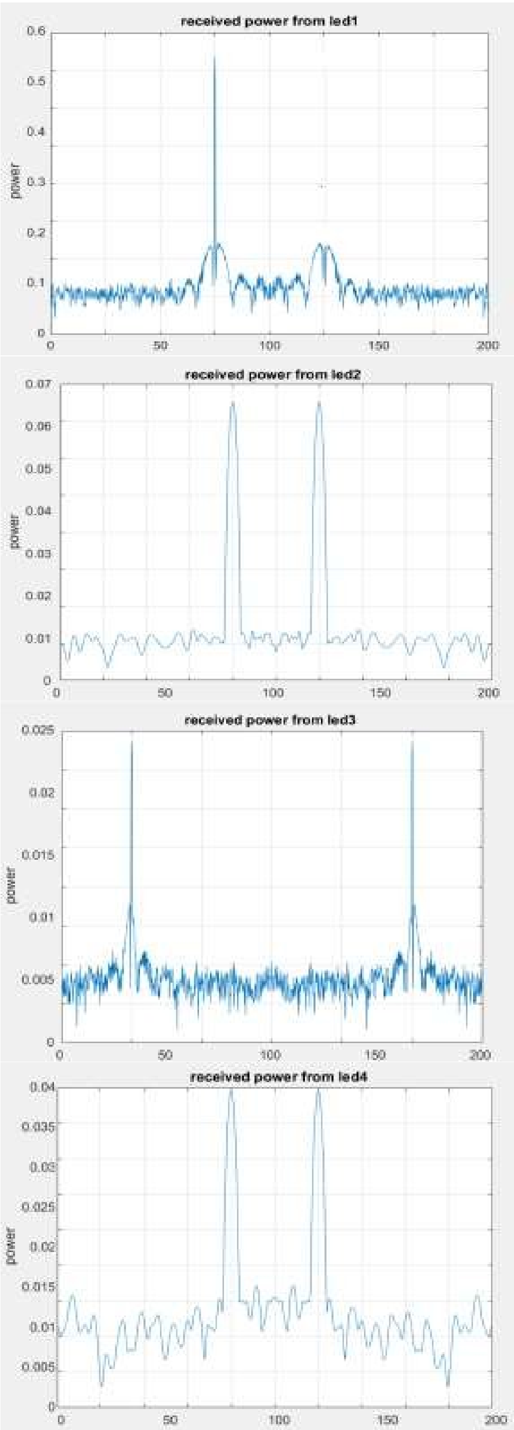

Fig. 13. Received power from: (a) LED1, (b) LED2, (c) LED3, (d) LED4.

Table VI shows the average distance error between each LED and a user. Table VII shows the minimum, average, and maximum power received from all of the LEDs. Figure 14 shows the incidence angle of LEDs at each user location to account for the incidence angle of light power. As it was already stated, the user's data was limited to the first 200 locations out of the 80,000 locations. Table VIII shows the average incidence angles.

(a)
(b)
(c)

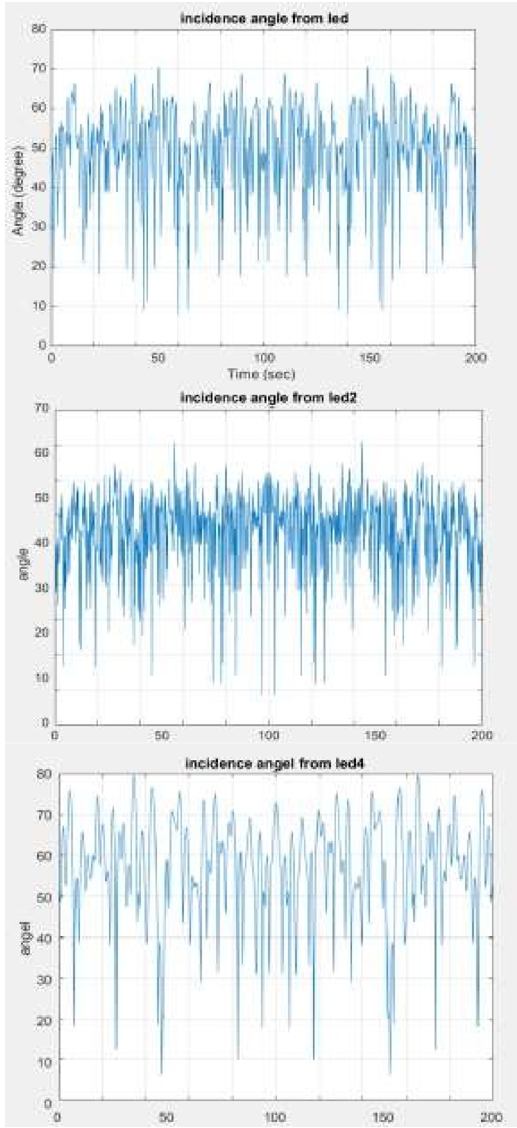

Fig. 14. Incidence angle from LEDs at each user location.

TABLE VI. DISTANCE ERROR IN LED AND USER LOCATIONS USING THE RSS-TRIANGULATION METHOD

Average distance error (cm)	Maximum Distance Error(cm)	Minimum distance error (cm)
Error in the distance between LED1 and the user		
1.02489×10^{-2}	5.25929×10^{-2}	-4.97112×10^{-2}
Error in the distance between LED2 and the user		
1.02003×10^{-2}	5.681090×10^{-2}	-6.47339×10^{-2}
Error in the distance between LED3 and the user		
1.02125×10^{-2}	5.68236×10^{-2}	-5.28430×10^{-2}
Error in the distance between LED4 and the user		
1.024080×10^{-2}	5.400860×10^{-2}	-5.667840×10^{-2}

TABLE VII. POWER RECEIVED FROM THE LEDS AT THE PHOTODETECTOR

Avg. received power (W)	Maximum received power (W)	Minimum received power (W)
Power received by the photodetector from LED 1		
1.47607×10^{-3}	1.83483	6.19386×10^{-6}
Power received by the photodetector from LED 2		
1.53278×10^{-3}	1.95597	6.00296×10^{-6}
Power received by the photodetector from LED 3		
1.38966×10^{-3}	1.69117	6.30993×10^{-6}
Power received by the photodetector from LED 4		
1.41845×10^{-3}	1.85245	6.09794×10^{-6}

TABLE VIII. AVERAGE INCIDENCE ANGLES OF THE LEDS ON USER LOCATION

	Average incidence angle (°)
LED 1	4.56143×10
LED 2	4.53390×10
LED 3	4.54908×10
LED 4	4.54754×10

C. Simulation Results of RSS-Triangulation and Discussion

A deep learning algorithm was utilized to evaluate the distance data generated through the RSS-triangulation approach with noise. Table X shows the simulation parameters.

TABLE IX. ERROR RATES IN THE THREE AXES FOR TRAINING LOCATION DATA USING DNN

Axis	Mean error	St. dev. error	Max. error	Min. error
x-axis	1.67506×10^{-3}	2.1986×10^{-3}	3.10615	0.000002
y-axis	1.4608×10^{-3}	1.95448×10^{-3}	2.84597	0.000001
z-axis	2.8687×10^{-3}	4.03088×10^{-3}	5.57300	0.000004

Figure 15 shows the evaluation of the deep learning algorithm's performance on distance data with noise obtained from the simulation using RSS-triangulation. These results were obtained after multiple attempts of training and tuning the DNN parameters in 0.6 s. Based on specific parameters shown in Table III, several experiments were used to achieve optimal results. Figure 16 presents the test results on the distance data, while Figure 17 provides a detailed view of actual and estimated locations using the DNN for the three axes.

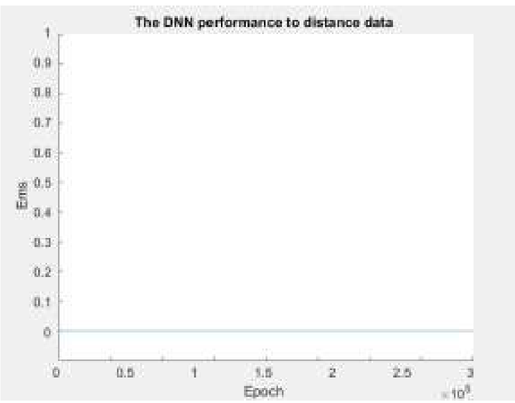

Fig. 15. DNN performance on distance data.

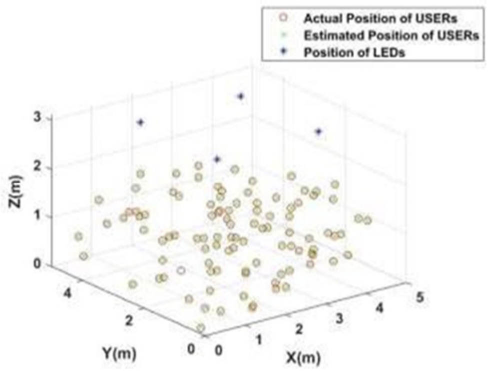

Fig. 16. The true location of the user and the location predicted through the DNN in testing.

(a)

(b)

(c)

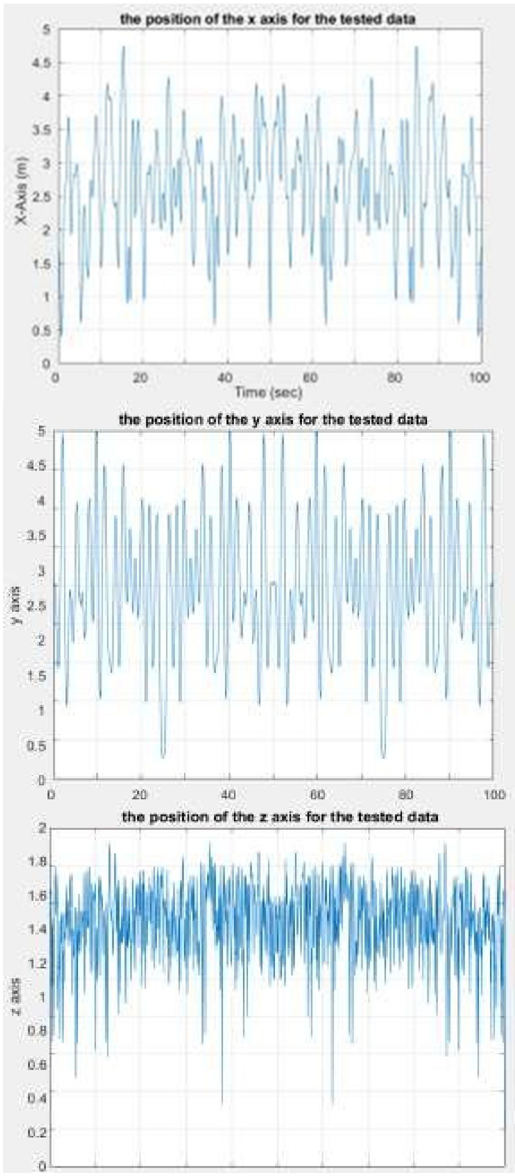

Fig. 17. The real location of the user and the location estimated by DNN in the x (a), -y (b), and z (c) axes in testing.

Figure 18 shows the error for each axis at different user locations, and Table X provides details on the error for every axe. The deep learning algorithm required 0.3 s to test the distance data with noise.

TABLE X. ERROR RATIOS ALONG THE THREE AXES WHEN UTILIZING THE DNN TO TEST DESTINATION DATA

Axis	Mean error	Std. dev. error	Max. error	Min. error
x-axis	1.68643×10^{-3}	2.23855×10^{-3}	2.51535	0.000007
y-axis	1.45876×10^{-3}	1.94815×10^{-3}	2.25903	0.0000006
z-axis	2.85546	3.99429	4.2289	0.000007

(a)

(b)

(c)

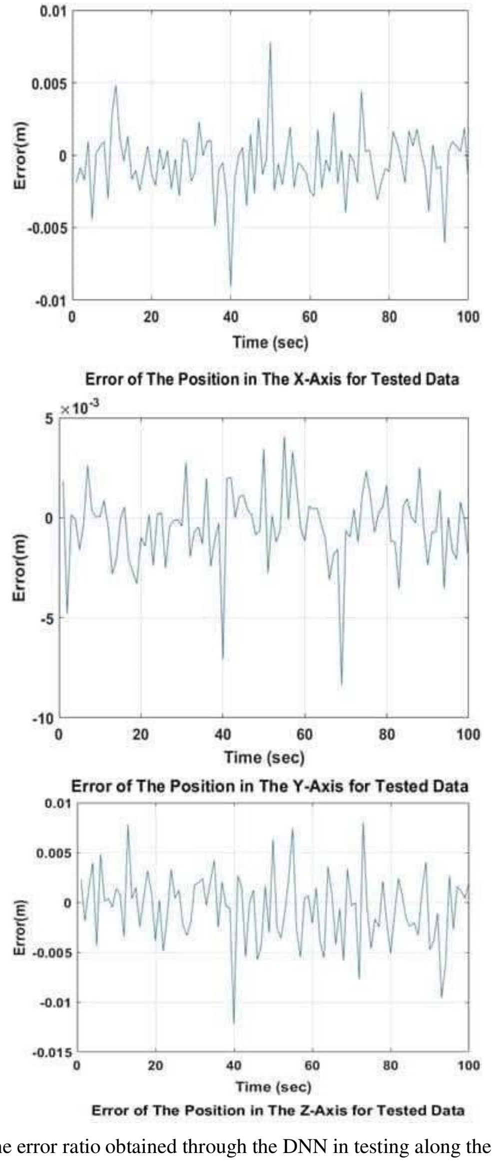

Fig. 18. The error ratio obtained through the DNN in testing along the (a) x, (b) y, and (c) z axes.

V. DISCUSSION

The proposed internal Li-Fi localization system achieved a desirable performance in locating the user when it was tested with a deep learning algorithm after data simulation using the RSS method. The main contribution of this work lies in the implementation of a data simulation model based on the RSS method and equipped with a Li-Fi channel equalizer. The deep learning algorithm was used to reduce the computation time of the system and achieve high accuracy in locating the user. The primary contribution of this study is the implementation of a data simulation model depending on the RSS approach with a Li-Fi channel equalizer. The deep learning algorithm reduced the system's processing time and achieved greater accuracy in user localization. Future research will focus on deploying optimized decoders in various communication standards and power-constrained situations to meet the evolving requirements of wireless infrastructure.

Based on these results, the suggested internal hybrid localization system exhibited desirable user localization performance when tested using a deep learning algorithm after simulating data in the RSS method. The primary contribution of this study is the implementation of a data simulation model based on the RSS approach with a Li-Fi channel equalizer. The deep learning algorithm was utilized to reduce the system processing time and achieve greater accuracy in user localization, surpassing the results of previous research.

VI. CONCLUSION

This research presented a mechanism for simulating mobile location data of users in an indoor environment using the RSS-triangulation approach in a hybrid wireless system. After that, utilizing MATLAB as the foundation and DL, the user's location was determined accurately. This technique is divided into two phases, each of which consists of a set of instructions for simulating user location. The viability of the suggested method was sufficiently confirmed by testing and analyzing 3D user positioning in a 5×5×3 m space. To show the accuracy of the approach, the triangulation approach was employed noise-free, and the error was calculated for 80,000 user locations. The results indicated errors of 2.17344×10^{-14} cm on the x-axis, 6.44762×10^{-14} cm on the y-axis, and 4.656×10^{-11} cm on the z-axis. To validate this work and enable its continuation in the subsequent stage, the triangulation approach was utilized in the first stage to replicate noiseless data and produce explicit results. The RSS-triangulation approach was also used to simulate 80,000 user locations with noise, where the average error on the x-axis was 2.05612×10^{-3} cm, on the y-axis was 4.56249×10^{-3} cm, and on the z-axis was 5.10474×10^{-1} cm. The angle and power of light received by the user were calculated using RSS. The deep learning algorithm exhibited great accuracy on the site when the simulation was run by combining the data from the RSS-triangulation approach. These results show that the proposed approach is a competitive alternative to recent research in the field, and it is worth noting that the potential of deep learning could surpass previous approaches.

This work can be further extended to include:

- Test the proposed system in real time.
- Use a DNN to test the received optical power and the angle of incidence of the light to improve the accuracy of user location.
- Study the effect of the user's mobile device orientation inside the workroom and its impact on the user's location.

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