Received: June 27, 2022. Revised: September 5, 2022.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Load Balancing Performance Optimization for LI-Fi/Wi-Fi HLR Access Points Using Particle Swarm Optimization and DL Algorithms

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Abstract: The increasing number of mobile devices challenges the current radio frequency (RF) networks. A hybrid RF/VLC network (HLRN) is proposed to mitigate the spatial fluctuation of data rate, offering a system throughput greaterthan that of standalone visible light communications (VLC) or radio frequency (RF) networks. In hybrid networks, themain problem is load balancing, which reduces network performance. Therefore, to solve this problem, the load balancing(LB) schemes in HLRNs are studied and focus on the AP assignment for the users. In that, efficient spectrum sensing is found essential to prevent the wrong holes detection in the band using five technologies divided into three stages, namely: Received signal strength (RSS), particle swarm optimization (PSO) and deep learning methods: Feed forward neural network (FFNN), convolutional neural network (CNN) and cascade back propagation neural network (CBPNN). An event such as high energy noise availability or primary user fluctuation (mobility) impact on the throughput is studied, which was carried out in three stages depending on MATLAB. In the first stage, the received signal strength (RSS) algorithm is proposed, which is used the SNR to calculate throughputfor fixed and mobility user and user satisfaction. In stage two, the particle swarm optimization (PSO) algorithm is proposed to achieve a better performance than the RSS algorithm. At last, in stage three, the DL algorithms (FFNN, CNN,CBPNN) are used to enhance the performance's accuracy and compare them. The results in stage one show that throughput using RSS technique is decreasing when the number of users increases by achieving 390 Mbps approx. is detected with single user existence while 180 Mbps approx. is detected with 10 users' existence. And it can be noted that most of the users are connected to wireless fidelity (Wi-Fi) AP. Hence the Wi-Fi is overloaded. Further, only 34 % of the users in RSS based scheme will achieve the desired performance if a user satisfactionthreshold of 0.5 is considered for the system. The results in stage two shown that throughput using the PSO technique is outperformed over the others by achieving high average throughput of 960 Mbps approx. Also, it has offered acceptable load balancing for the access points with good user satisfaction reach to 80 % of the users will achieve the desired performance when the user satisfaction threshold is considered to be 0.9 for the system. In stage three, deep learning methods for system performance enhancement are used (as compared with the standard RSS method). throughput is improved, and this improvement is lesser than that in the case of the PSO algorithm. 800 Mbps approx. is achieved using the CNN method, and it is realized that 70 % of the users will achieve full user satisfaction when the user satisfaction threshold is considered 1.2 for the system.

Keywords: Li-Fi, Wi-Fi, HLR, PSO, RSS, CNN, VLC, FFNN, CBPNN.

1. Introduction

Visible light communications (VLC) is a data transfer technology that modifies data using visible light. Due to the propagation distance of light emitting diodes (LED), VLC is a short-range communication technology [1]. In the visible spectrum of the electromagnetic spectrum, wavelengths span from 350 nm to 800 nm, and frequencies range from 4.3 x 1014 Hz to 7.5 x 1014 Hz. Light emitting diodes (LEDs) are used in visible light communications (VLC) technology because their current intensity can be easily regulated, unlike incandescent and fluorescent light bulbs. Compare to incandescent and fluorescent light bulbs, light emitted diodes (LEDs) are based on a doping process, enhancing their efficiency, durability, and longevity

[2]. Traditional lightbulbs are expected to be replaced by LEDs in all lighting applications (general illumination, signs, displays, and vehicle lights, to name a few). They'll be used for lighting and communication purposes [3]. Like any other communication approach, VLC transmission is represented by a transmission matrix, which is a mathematical description of the channel impulse response [4]. The number of LED groups and the number of LEDs per group define the size of this matrix. By mixing many blocks of various LEDs, extremely high data rates may be attained [5] when the transmission is polluted by noise and interference from undesired sources, equalization methods for channel pre-compensation, together with knowledge of channel behaviour, help in the recovery of symbols [6]. VLC technology adoption is beset with challenges: Some people are interested in the design of communication systems, while others are interested in how they are implemented [7]. In order to construct a successful visible light communication (VLC) system, lighting limits based on average optical power and communication goals based on throughput must be met. Under dimming conditions, light emitted diodes (LED) flickering must be avoided during transmission, and the data rate must be reduced greatly [8].

Due to the development in communication systems, i.e., internet expansion; and thedevelopment of handset technology, data exchanged over the networks has dramatically expanded in the amount [9]. With this data expansion, the performance local/short coverage network is no longer consistent with overcoming the user's demand. It is essential for the existing networks, e.g.,Wi-Fi, to preserve good data rate/speed irrespective of the amount of data that being exchanged over the network. However, wireless fidelity (Wi-Fi) suffers from coverage problem and signal scattering due to interference with other Wi-Fi access points [10]. Theuse of visible light communication to overcome such challenges is proven acceptable performance in terms of network speed and coverage preserved because ofthe physical nature of light. On the other hand, blind spots are major challenges in this technology as the surrounding objects impact light coverage. More recently, radio and light are integrated to enhance the data rate and the coverage under the so-called hybrid light and radio (HLR) communications [11]. Under this technology, wireless fidelity (Wi-Fi) and light fidelity (Li-Fi) are used together to provide good coverage and data rate for network users. To this end, the network capacity problem may still be faced as most users are linked to one of the access points, which causes excessive data load on the said access point. In contrast, the other access points are free or facing lesser demand [12]. That triggers the need for essential features called resource allocation for load balancing, which are to be adopted by the network users [13].The other parts in the presented work are: section 2 is presented the hybrid light radio system (HLR), while section 3 shows user assignment, section 4 describes the system modelling, while section 5 shows the proposed load balancing methods, section 6 shows this study's simulation results and analysis, and section 7 presents a comparison and discussion. Finally, conclusions in section 8.

The above aspects and challenges are discussed, and effective solutions are provided. The access point assignment (APA) problem in the hybrid RF/VLC network was addressed by a variety of the approaches that may be categorized in general to three classes, which are, fuzzy logic (FL), optimization algorithms, and machine learning (ML). Several recent works on indoor hybrid systemshave modernized a large study area. Several related studies in the same field as this work were conducted,as follows in Table 1.

2. Hybrid light radio system (HLR)

The number of mobile devices has grown at an exponential rate. According to the CISCO visual network index (CVNI) [24], by 2023, almost 70 % of the world's population will have access to a mobile phone. As the number of mobile phones increases, so does interest in new mobile/cellular network applications, such as the internet of things (IoT), to enable smart homes and cities, including vehicular communication [25]. Data consumption is expected to rise due to the exponential development in the size and breadth of mobile networks. Indoors will account for around 48 percent of IoT traffic and around 80 serious competitors [28]. Data transfer speeds of up to 1 Gbps are achievable with the VLC's wider frequency range [29]. Because visible light cannot percent of other mobile traffic, according to the CVNI [26] data use patterns on mobile networks are projected to be comparable in the open air. To support many devices and meet growing traffic demands, the wireless research community has been looking for extra spectrum in the higher frequencies range, such as millimetre waves (for 5G) in the 30 to 300 GHz region. Higher radio spectrum use, on the other side, may result in increased interference, which can lower throughput [27]. In the hunt for a more high-frequency spectrum, visible light communications (VLC), which employs the visible light spectrum in the 430 THz to 730 THz regions, is a pass through walls, it may be kept within a room to prevent eavesdroppers from listening in [30]. VLC's rapid

Table 1. Summary comparison of the pertinent studies

Ref.	Year	Algorithm	Access technology	System Model	Throughput of (10) users	User Satisfaction
[14]	2017	Optimization-based scheme, the (EGT) based scheme and (FL) based scheme	TDMA	A multi-user indoor hybrid Li-Fi /RF network	-------------	50%
[15]	2017	JOA and SOA	TDMA	A multi-user indoor hybrid Li-Fi/RF network	38.6 Mbps	90%
[16]	2017	A novel APA	TDMA	One Wi-Fi AP with 4 Li-Fi AP	850 Mbps	-----------
[17]	2017	Fuzzy logic	TDMA	Multi user with 4 VLC AP and one RF AP	10 Mbps	91.9%
[18]	2018	QoE-driven optimized LB scheme	TDMA	4×4 Li-Fi AP matrix and a single Wi-Fi AP	0.6 Gbps	--------
[19]	2019	optimization algorithm	TDMA	HLR network with single Wi-Fi AP and four Li-Fi APs	72 Mbps	80%
[20]	2019	Fuzzy logic	TDMA	one Wi-Fi AP and a four Li-Fi APs.	400 Mbps	------
[21]	2020	Reinforcement Learning (RL)	TDMA	4 Li-Fi APs and 1 WiFi AP	175 Mbps	100%
[22]	2020	RL Method	FDMA	hybrid Li-Fi Wi-Fi network with four Li-Fi APs and one Wi-Fi AP	110.69 Mbps	100%
[23]	2021	(CFPSO) technique	FDMA	MUEs are connected to their serving MeNBs, and HUEs to serve HeNBs	48 Mbps	-------

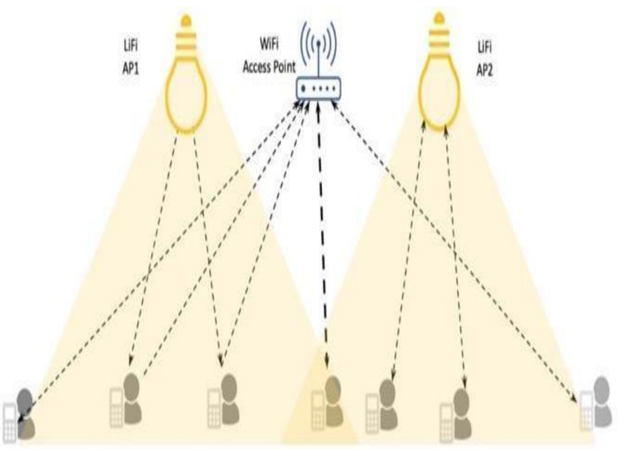

Figure. 1 System topology of the HLR communication

acceptance has been aided by the extensive use of LED-based lighting infrastructure as shown in Fig. 1. Furthermore, Li-Fi/VLC can live alongside Wi-Fi and cellular technologies like LTE and 5G without interfering. Li-Fi is a competitive competitor for new wireless communication technologies both indoors and out because of these advantages. Li-Fi will be combined on the interior with Wi-Fi to increase capacity, reduce latency, and increase throughput [31]. On the other hand, Li-Fi might be used in conjunction with 5G outside to enable smart cities, notably vehicle communication, where low-latency safety-critical data can be conveyed by visible light [32].

3. User assignment

In this section, three technologies are being used for this purpose namely: Received signal strength (RSS), a heuristic method using particle swarm optimization (PSO) and deep learning method using (feed forward neural network, convolutional neural

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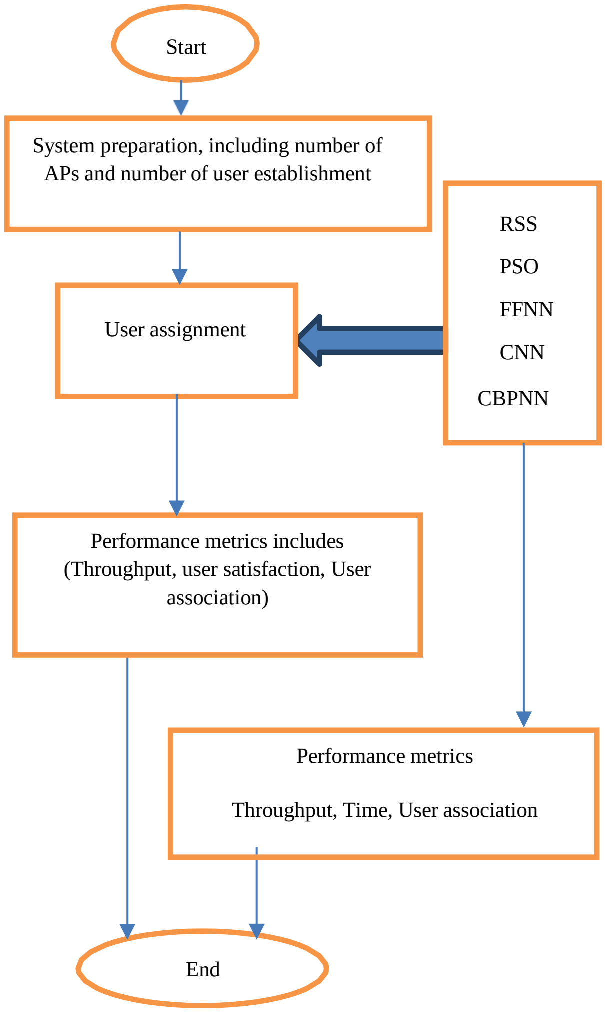

Figure. 2 Overall flow diagram for the proposed work

network and cascade back propagation neural network. In hereinafter, primary or licensed users is termed to those users who exist on channel band at the time other users are willing to participateon the channel. The secondary users are those users who are waiting to get access to the channel. The user assignment methods proposed in this paper is demonstrated in Fig. 2.

4. System modelling

To implement the objective of an indoor hybrid system represented by higher capacity, lower latency and higher throughput, a multi-user hybrid RF/VLC network with two Li-Fi AP and one Wi-Fi AP is considered, The Wi-Fi AP is located in the room's centre in order to provide coverage to the whole room in a typical room of 6 *4* 3 m3. as shown in Fig. 4. Each Li-Fi AP coverage is limited to a smaller area. A central unit (CU) is connected to the Wi-Fi as well as the Li-Fi access points in this system, and it is responsible for the decisions of load balancing. Through an error-free feedback link, it has been considered that the central unit is capable of accessing the required information.

The 2019 version of MATLAB is used to implement the methodology to achieve efficient load balancing in the hybrid system, which is divided into three main stages. The first stage is a presentation of the system by using conventional method (RSS) to calculate throughput, user association and user satisfaction, furthermore, used frequency-division multiple access (FDMA) for supporting multiple users connecting to one access point as well as a round-robin based approach for the resource allocation for the sake of simplicity. while in the second stage, which is under the influence of additive white Gaussian noise (AWGN), present the system use heuristic algorithm (PSO) to optimize the performance by calculate throughput, user association and user satisfaction, furthermore, also used frequency-division multiple access (FDMA) for supporting multiple users connecting to one access point as well as a round-robin based approachfor the resource allocation for the sake of simplicity. In the third stage the data is trained and tested on a deep learning algorithm (FFNN, CNN, CBPNN) to assign the access point in less time and with higher throughput and user satisfaction. The basic steps for each stage in this methodology are described in the following sections and the overall proposed methodology is shown in Fig. 3.

In this work, each station is randomly moving within the room. where the ceiling mount access points are placed, throughput, in this case, is a game of line-of-sight (LOS) maintenance between the mobile station and access points. Hence, LOS occurrence may not be maintained all the time (within simulation time) and hence throughput in case of mobility can be dropped from time to time. As the radio spectrum is established and allotted for all primary users, the challenge raised at the time of sharing the spectrum between primary users (those who are existing the spectrum) and secondary users (who are willing to join the spectrum and looking for the spectrum hole). Our model involves ten primary and secondary users, all to be transmitted over 100-1000 KHz band at the presence of AWGN.

In general, most of the studies consider the random way point (RWP) model for mobility. It is a simple model in which a user selects a random destination and moves towards that destination at a constant speed. After reaching the destination, the user picks up a new destination and starts moving in that direction, and this process continues. However, it is also interesting to consider that inside a room. There are hotspots where the users would gather with

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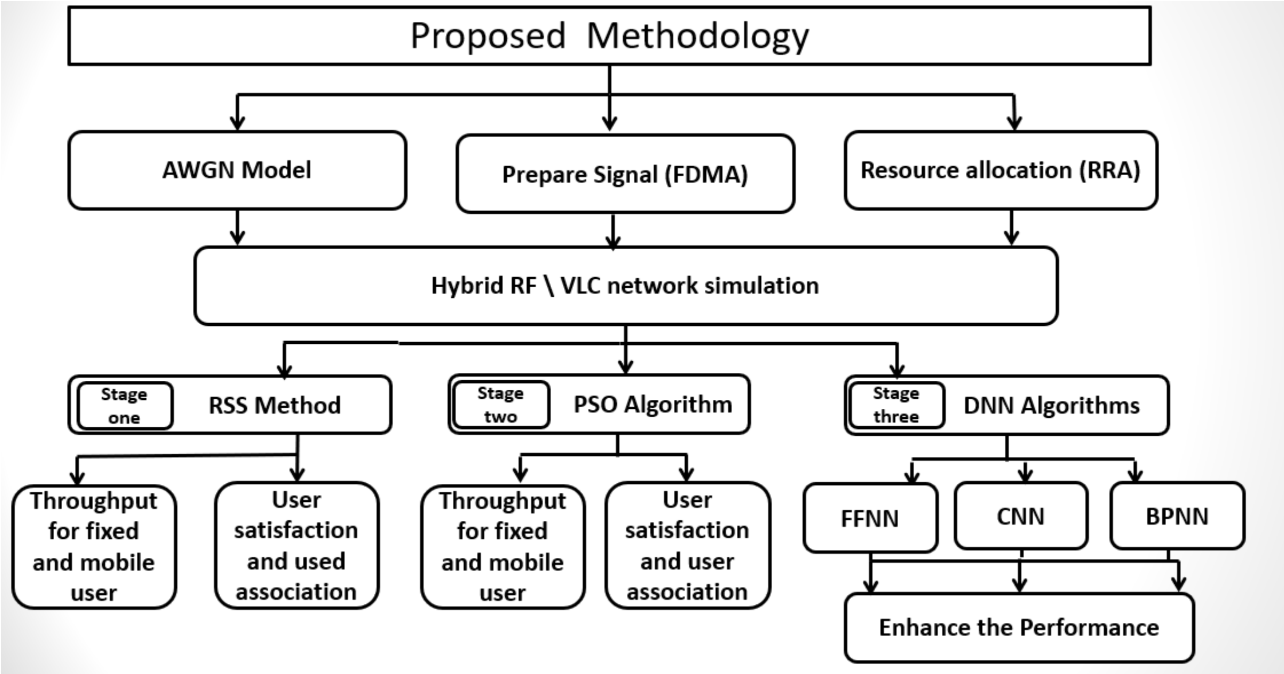

Figure. 3 Overall proposed methodology

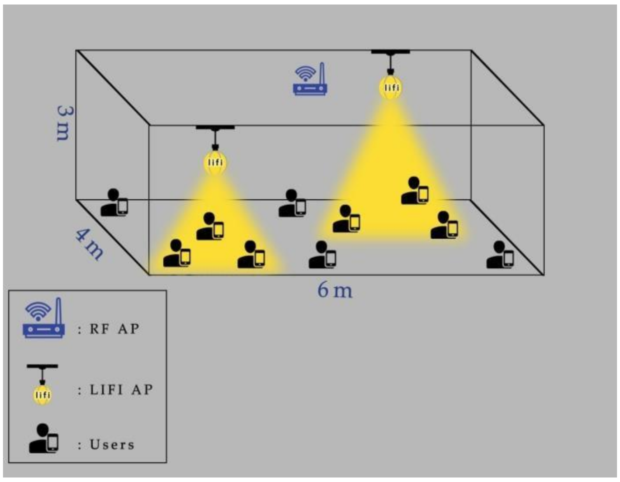

Figure. 4 Indoor hybrid simulation model

high probability. For example, users may collect under the LEDs for better illumination [33].

5. Proposed load balancing methods

5.1 RSS method

Most techniques used to perform spectrum sensing were majorly dependent on the energy detection method, which conducts spectrum analysis with received signal strength (RSS). This technology is more sensitive to channel disturbanceslike noise and fading at such incidents more likely when noise takes over an empty band, the decision ofthe energy detector may be corrupted by noise inference and return wrong information about the spectrum availability [34]. Known that spectrum congestion and scarcity problems become a serious threat to communication's future, a strong spectrum sensing is required to avoid any non-précis decision.However, a proactive approach is proposed in this study for establishing a noise-independent spectrum sensing model underlying time estimator information. Table. 2 details the throughput of the RSS in the Li-Fi technique. Received signal strength(RSS) is used to detect the signal at the receiving endby sensing the received power from the particular transmitter. The transmitting and receiving antennas need to be adequate with the threshold power level to be received/sensed. Signal transmitted from the transmission end is susceptible to path losses where the power of the mentioned signal is scaled down by the amount of power loosed in the path. Assuming the distance-related losses in the path to be PL_{ref}. Conversely, additive white Gaussian noise (AWGN) is also considered a potential member in the loss's formula. P_n is AWGN noise power. If the transmitted signal with power P_x. The received signal power can be written as in below:

$$P_r = P_x - P_{path} \quad (1)$$

$$P_r = P_x - [P_{distance} + P_{AWGN}] \quad (2)$$

$$P_r = P_x - [P_{distance} + 10 \log P_{AWGN}] \quad (3)$$

Where p_r was represent received power and p_n is formulate noise power and p_x is referred the power of transmitted signal. Throughput in case of mobility of user station can be expressed in Eq. (4).

$$TH_{total} = \sum_{T\leftarrow 1}^{T} Th_{ST(1)} + \sum_{T\leftarrow 1}^{T} Th_{ST(2)} + \cdots + \sum_{T=1}^{T} Th_{ST(N)} \quad (4)$$

Where TH is the throughput of each user station and ST is referred to user station and N was represented to maximum number of users. A list of A symbols isdescribed below in Table 3.

Thus, RSS value is equivalent to P_r value; to optimizeLOS connectivity in an mm Wave network adaptively, we consider infrastructure mobility as a promising candidate solution, as infrastructure mobility allows for changing the location of the AP adaptively. Furthermore, PSO, FFNN, CNN and CBPNN are used for user assignment. Fig. 5 is demonstrated proposed RSS method based on user assignment of the channel. The default parameters of the proposed system are given bellow in Table 2.

5.2 Heuristic method

Particle swarm optimization (PSO) algorithm has a noteworthy performance in tackling multi-dimensional problems in engineering and sciences. Birds' social and biological actions inspire the heuristic approach of the PSO algorithm while they search for food [40]. The standard PSO or SPSO works for evaluating the best particle in the swarm of particles by updating the position and velocity of the particle in multiple iterations [35]. Let the swarm be located at $the\ y\text{-}axis$ and composed by the large number of particles (N particles). m_i denotes the i^{th} particle in the swarm; hence, p_i denotes particle m_i's position in the swarm. So, particle position in the swarm moving on y-dimensional can be expressed as:

$$p_i = (p_{i1}, p_{i2}, p_{i3}, \cdots, p_{iy}) \quad (5)$$

The particle m_i is varying its position by moving on the swarm domain by velocity s_i, which is given as the following vector:

$$s_i = (s_{i1}, s_{i2}, s_{i3}, \cdots, s_{iy}) \quad (6)$$

Table 2. The default parameters of proposed system

Particle	Value
Size of room (m)	(6, 4, 3)
Wi-Fi AP location	Centre of the ceiling
Number of (AP)	3
User distribution	Randomly
Mobility model	RWP
Simulation time (T)	10,000
Number of users	60

Table 3. The description of the symbols

Symbol	Description
pr	Received power
PX	Transmitted power
pn	Noise power
TH	Throughput of user station
ST	User station
N	Maximum number of users
$\boldsymbol{pi}$	particle m_i's position in the swarm
$\boldsymbol{mi}$	the i^{th} particle in the swarm
Si	Velocity of particle
ui	Position of particle
p_i^0	Best position
C1, C2	cognitive coefficients
p^g	Global position
r1, r2	Random distribution number

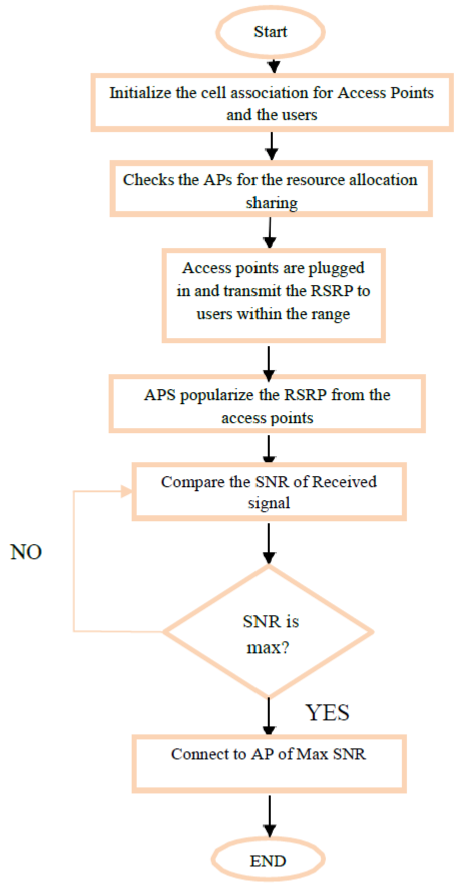

Figure. 5 Proposed RSS method based on access point assignment

Hence, SPSO may attempt to evaluate the best positions of particle mi in a swarm and yield that in a

Received: June 27, 2022. Revised: September 5, 2022.

vector as in Eq. (7)[36]:

$$u_i = (u_{i1}, u_{i2}, u_{i3}, \cdots, u_{iy}) \quad (7)$$

Some other terminologies are used in PSO, more likely, the social and cognitive acceleration constants (c_2 *and* c_1) as well as the weight of inertia (W) [37]. In order to express the other PSO parameters mathematically, firstly weight of inertia is expressed as [37]:

$$W = W_{min} + \left[\frac{k}{K} \times r_3 \times (-W_{min} + W_{max})\right] \quad (8)$$

$$s_{ix}^{k+1} = r_1^k c_1 (u_{iy} - p_{iy}^k) + r_2^k c_2 (u_{gy}^k - p_{iy}^k) + s_{iy}^k W \quad (9)$$

$$p_{iy}^{k+1} = p_{iy}^k + v_{iy}^{k+1} \quad (10)$$

Where K is maximum iterations and r_1, r_2, r_3 are random number having values in the range of [0, 1] [37]. PSO optimization may begin with swarm generation or population generation. In order to execute the PSO algorithm; parameters such as a number of populations (swarm) (N), social and cognitive coefficients (c1, c2), random distributed numbers (r1, r2), inertia weight coefficient (W) as well as the global best (GP) are required to be set. PSO works to search the weight (particle) to ensure the best approximation of fitness function [36]. In this work, PSO is used for optimizing the user assignment performance by optimizing the parameters participated in channel configurations. The velocity of *the* i^{th} particle is to be updated in order to reach the best position. Let s_i is the velocity of the i^{th} particle at $t = t_0$; hence the velocity at $t = t_1$ can be expressed in Eq. (10)[35]. The simulation parameters are shown in Table. 4.

Fig. 6 shows the PSO operations, which optimize the channel parameters and insert the user information sequence X into the channel.

$$s_i^{t1} = W \times s_i^{t0} + c_1 \times R \times p_i^{diff} + c_2 \times R \times p_i^{diff} \quad (11)$$

$$p_{diff} = p_i - p_i^b \quad (12)$$

Where, R is a random variable and p_i^b is the best position of *the* i^{th} particle.

5.3 Deep learning method

An artificial neural network (ANN) is known for its ability to learn complex problems and provide solutions by simply learning the infrastructure (hidden) relationships of the input strings [36]. For simple single hidden layer ANN(net) shown in Fig. 7 [37], supervised learning is to be initiated by

Table 4. Simulation parameters are based on PSO algorithm

Parameters	Value
Max iteration number	200
Dimension	6
C1	2
C2	2
Max velocity	100
Size of swarm	30
Weight inertia	0.4, 0.9

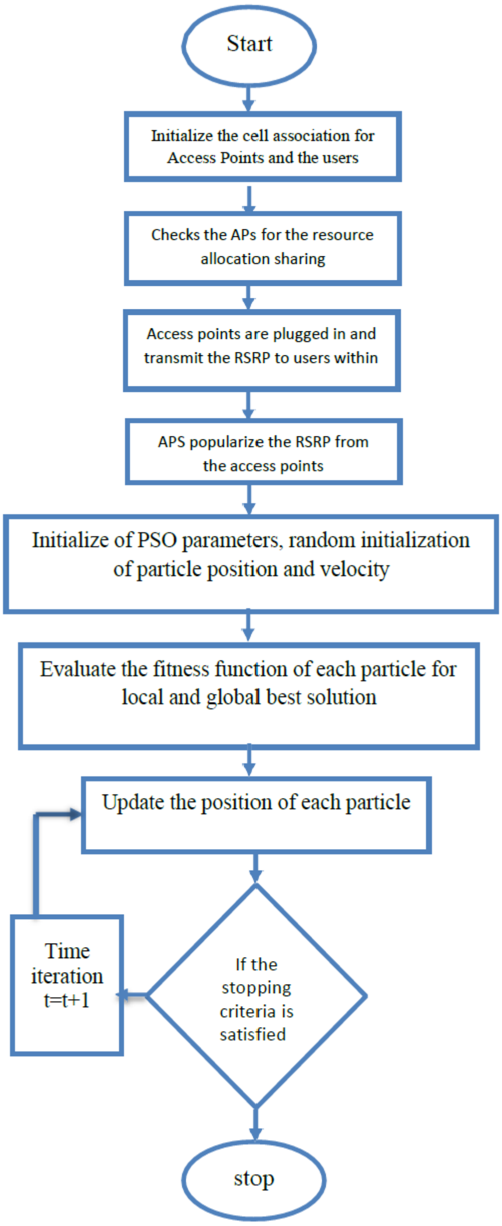

Figure. 6 Proposed PSO method, which optimizes the channel parameters

Received: June 27, 2022. Revised: September 5, 2022.

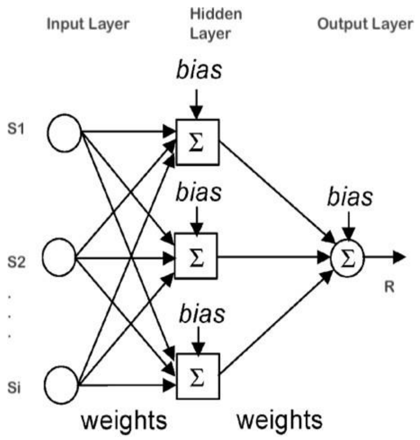

Figure. 7 ANN layer structure demonstrating the input, weights/biases and output

providing both input vector $r = [r_1, r_2, r_3, \ldots, r_i]$ and target vector $T = [T_1, T_2, T_3, \ldots, T_i]$. Weight coefficients that intermediate the layers can be adjusted to meet the output at minimum error [37]. Error to be identified by obtaining the correlation between the resultant vector and target vector as expressed in Eqs. (12), (13), respectively. Where r stands for a random variable at S^{t0}

$$R = net(r) \tag{13}$$

$$R = W \times r + b \tag{14}$$

Where, R is the output vector and b is model bias. Hence, the net may adjust W coefficients in order to achieve the best correlation between R and T [38]. In other words, the learning process is about finding the minimal value expressed in Eqs. (14), (15) as:

$$e = R - T \tag{15}$$

$$MSE = \frac{\sum_{n=1}^{i} e(n)^2}{i} \tag{16}$$

Where, e is the error vector, and MSE is the mean square error, MSE is considered a metric for training/learning performance [39].

net is trained on guessing the velocity value that yields the best fitness for channel configuration.

Three ANN models are used for this system:

- Feed forward neural network (FFNN)
- Convolutional neural network (CNN)
- Cascade backpropagation neural network (CBPNN)

All models are being trained using the users'

Table 5. Artificial neural network configurations

Particle	Details
Number of hidden layers	9
Training algorithm	Backpropagation
Number of epochs	100
Gradient Decent	1 e (-30)
Performance metric (training)	Mean square error (MSE)
Target training performance (MSE)	1 e (-20)
ANN types (respectively)	FFNN, CNN, CBPNN
Learning rate	0.01
Epoch rate	300,000
Percentage of samples for training	70 %
Percentage of samples for testing	30 %
The percentage of data used in our work	20000

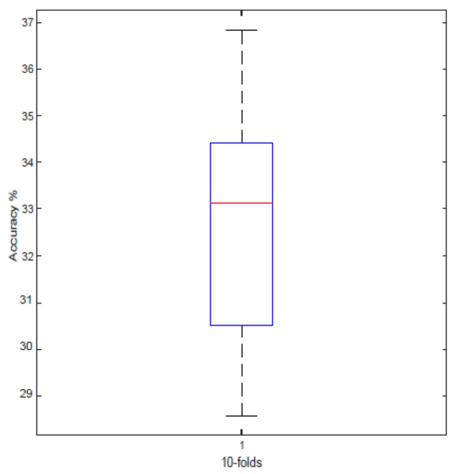

Figure. 8 FFNN performance metrics based on accuracy

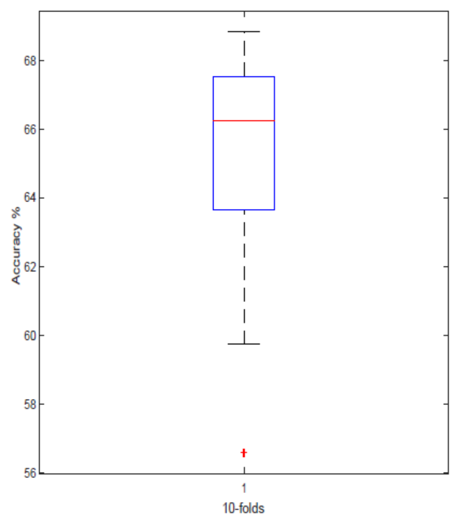

Figure. 9 CBPNN performance metrics based on accuracy

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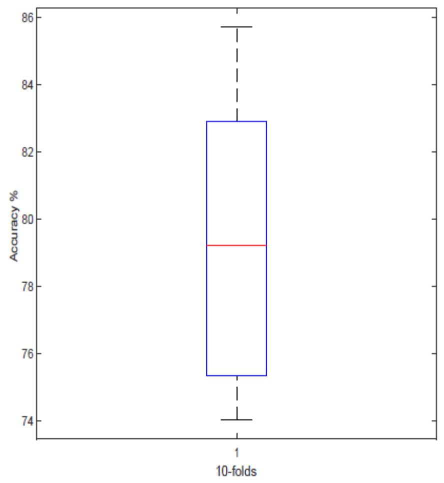

Figure. 10 CNN performance metrics based on accuracy

behaviours dataset so that they can forecast channel holes so that users can be assigned into the channel. The configurations of the neural network models are given in Table 5:

The best model is showing high accuracy performance is the CNN model, which achieved 86 percent of forecasting accuracy. Respectively, the error is the lowest in the case of CNN over the other FFNN and CBPNN. The same is depicted in Figs. 8, 9, and 10.

6. Simulation results and analysis

In this section, we present a performance analysis of the proposed methodology described in section 4. for stage one and stage two, under the influence of RSS and PSO methods that throughput, queuing time (s) and user association and user satisfaction are determined. Hereinafter, in stage three, deep learning approaches are applied where the same performance metrics are obtained. For the FFNN, CNN, and CBPNN methods, respectively, and since it is a forecasting technique, statistical results are obtained, reflecting the method's performance that retrieves how precisely dose method work.

6.1 Simulation results of stage one based on RSS method

This section presents the results of simulating the RSS method in user assignment within the workroom by applying the equations explained in section (5.1). were used 60 users and displayed (1- 10) of these users within the view results.

Throughput is calculated for the proposed model in two stages: in the stationary model and in the mobility model. The throughput is calculated if there is one user (one station) at the time, and the same calculation is repeated in the case of two, three, four,

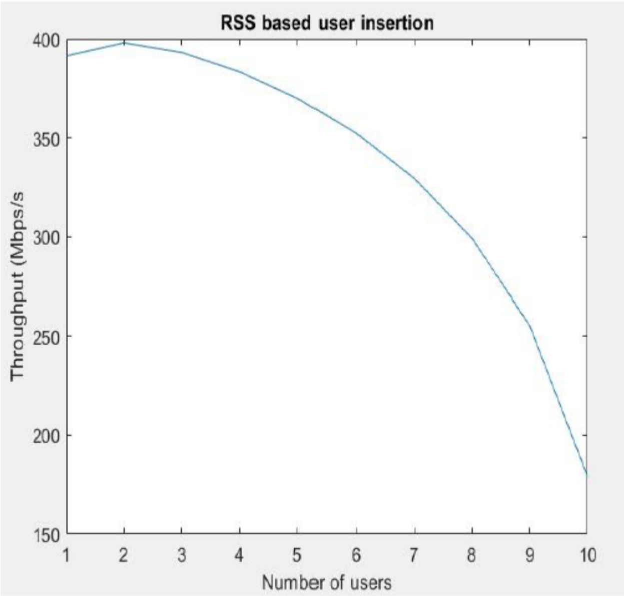

Figure. 11 Throughput of ten users based on RSS method

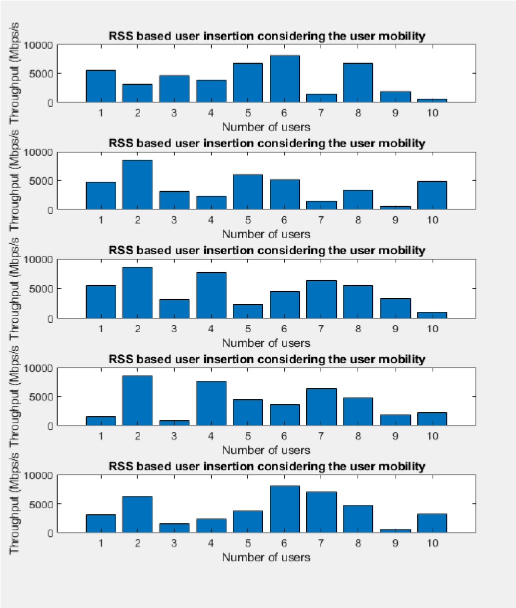

Figure. 12 Throughput for mobility user at 2m/s speed based on RSS method

five through ten users in the room, respectively. Fig. 11 shows the throughput values of the mentioned scenarios. It is realized that throughput drops when the number of users increases.

On the other hand, with ten users in mobility conditions (random mobility within the room), throughput is measured. The results are demonstrated in Fig. 12. It is realized that mobility impacts the throughput since line-of-sight communication is not maintained all the time due to the user's mobility throughput for ten users is calculated when the motion of users is random. To better understand the mobility impact on the throughput, the same scenario

Received: June 27, 2022. Revised: September 5, 2022.

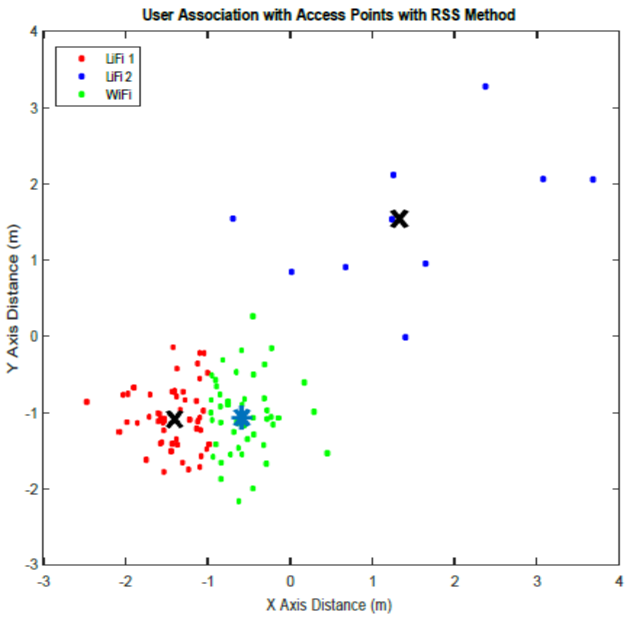

Figure. 13 User association based on RSS method

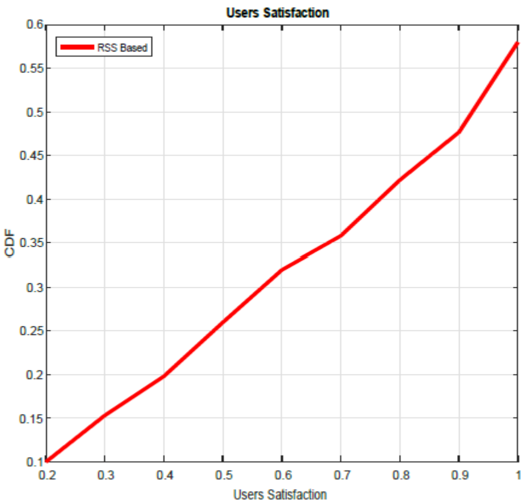

Figure. 14 User satisfaction based on RSS method

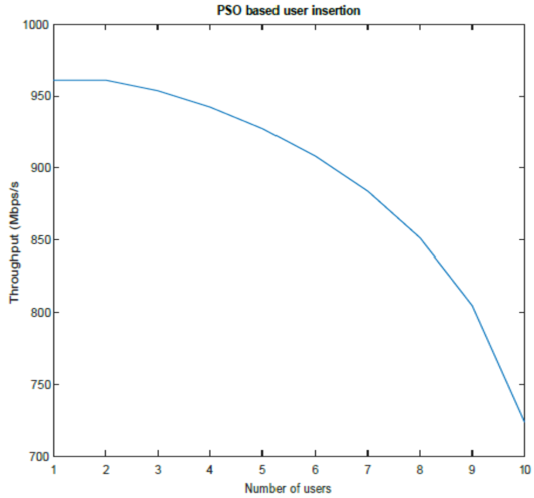

Figure. 15 Throughput for ten users based on PSO method

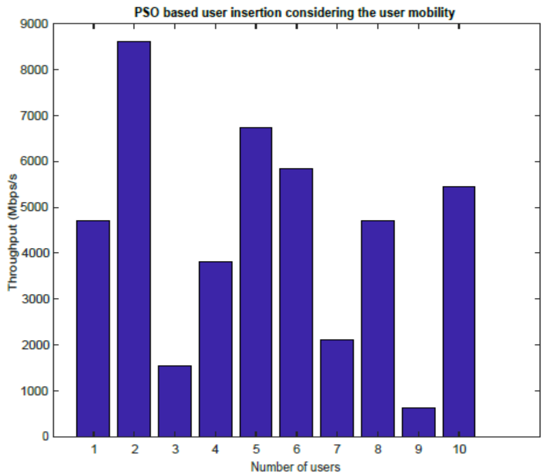

Figure. 16 Throughput for users in mobility at 2m/s speed based on PSO method

is repeated for five iterations. The throughputchanges randomly if the user station is in mobile mode.

User association is then calculated, which shows the distribution of those users among the three access points. Wi-Fi, Li-Fi 1 and Li-Fi 2. Fig. 13 indicates that most users are linked to the access point in the middle of the room (Wi-Fi). The user satisfaction for the RSS method is shown at Fig. 14 it shows only 34 % approx. of the users will achieve the desired performance if a user satisfaction threshold of 0.5 is considered for the system.

6.2 PSO simulation results based on stage two

Using the PSO method, throughput is calculated for the proposed model in two stages, namely: in stationary fashion as well as in mobility fashion. The throughput is calculated if there is one user at the time, and the same calculation is repeated in the caseof two, three, four, five through ten users in the room, respectively. Fig. 15 show the throughput values of the stationary scenario. It is realized that throughput drops when the number of users increases. From the other hand, with ten users, in the mobility model (random mobility within the room), throughput is measured, and the results are demonstrated in Fig. 16.

User association is then calculated, which shows the distribution of those users among the three access points, Wi-Fi, Li-Fi 1 and Li-Fi 2. Fig. 17 illustrates load of the network has been balanced accurately between Wi-Fi and Li-Fi access points. More users have been related to Li-Fi access points, which is why the resources of the Wi-Fi access point are freed up and may be used for mobile users. The user satisfaction for the PSO method is shown in Fig. 18.

Received: June 27, 2022. Revised: September 5, 2022.

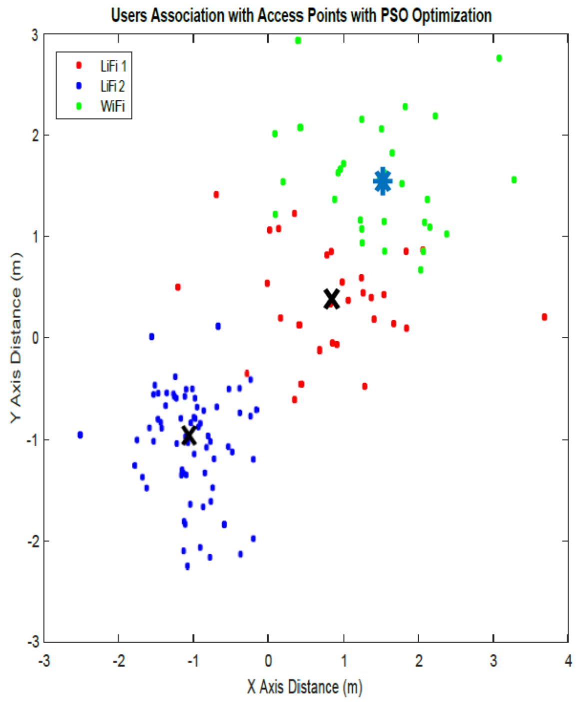

Figure. 17 User association based on PSO method

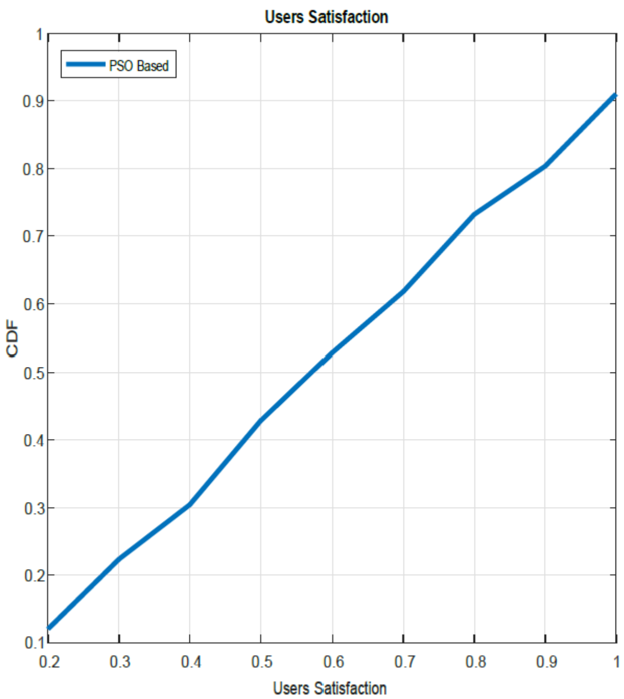

Figure. 18 User satisfaction based on PSO method

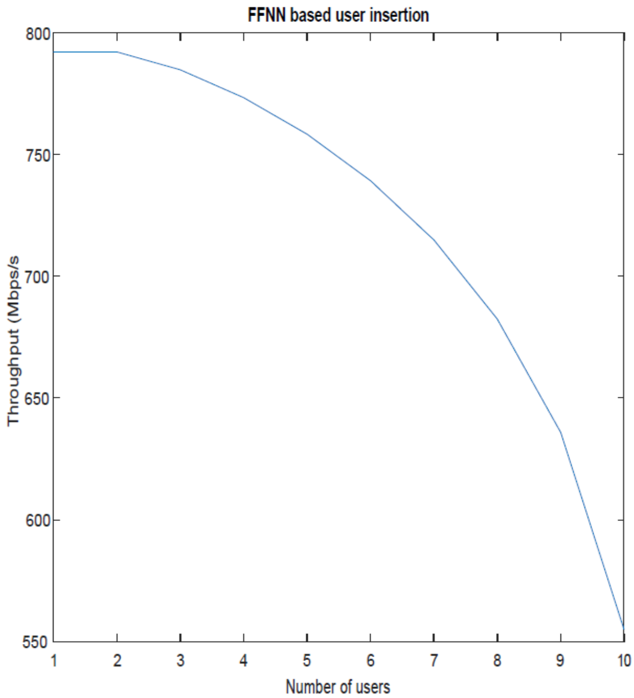

Figure. 19 Throughput of ten users for FFNN method

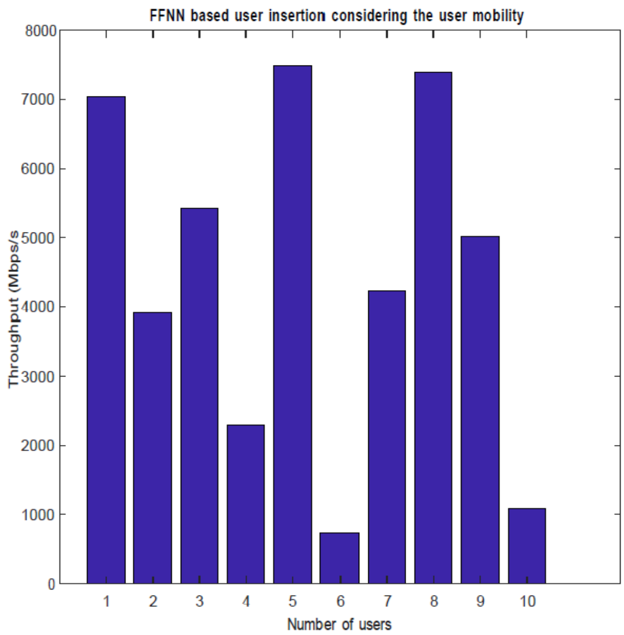

Figure. 20 Throughput for user in mobility at 2m/s speed based on FFNN method

It shows approx. 80 % of the users will achieve the desired performance when the user satisfaction threshold is considered to be 0.9 for the system.

6.3 DNN simulation results based on stage three

After simulating the data by the RSS method and PSO method, this data was used in a deep learning algorithm to train and test to evaluate the same performance metric under three DNN algorithms (FFNN, CNN, CBPNN), where (1- 10) of these users were displayed within the results view.

6.3.1. FFNN simulation results

In this section, throughput is calculated for the proposed model in two stages: in the stationary model and in the mobility model. The throughput is

Received: June 27, 2022. Revised: September 5, 2022.

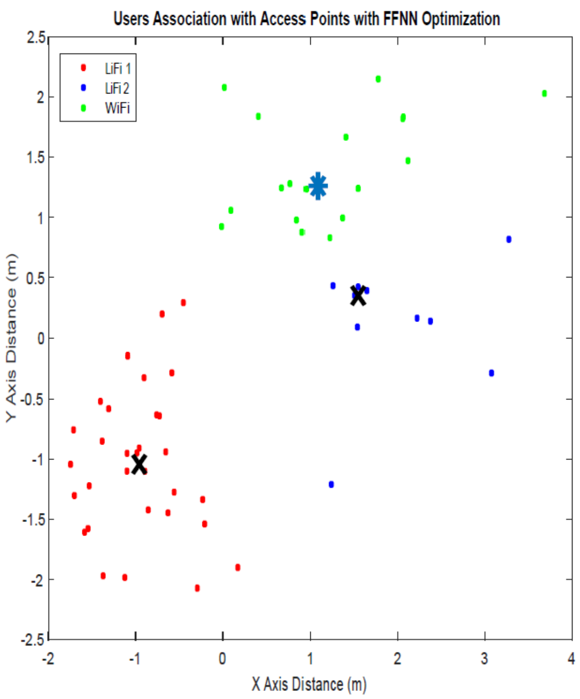

Figure. 21 User association based on FFNN method

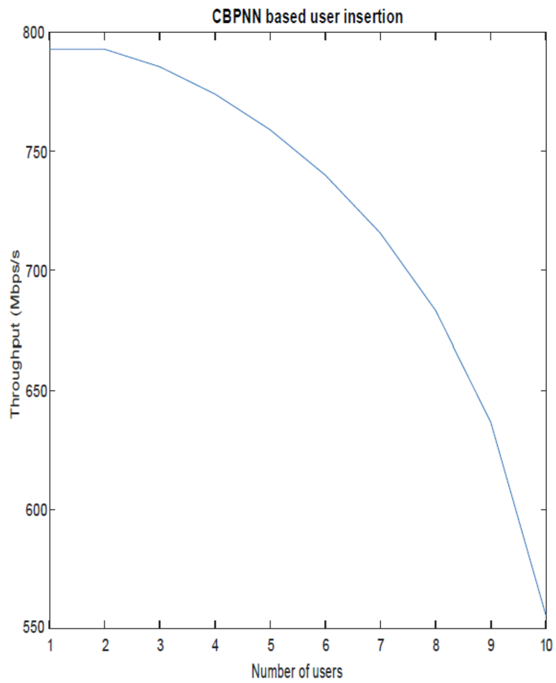

Figure. 23 Throughput of proposed system based on CBPNN method

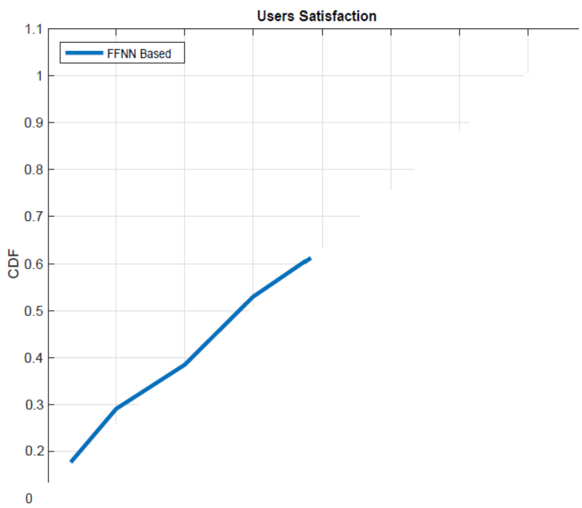

Figure. 22 User satisfaction based on the FFNN method

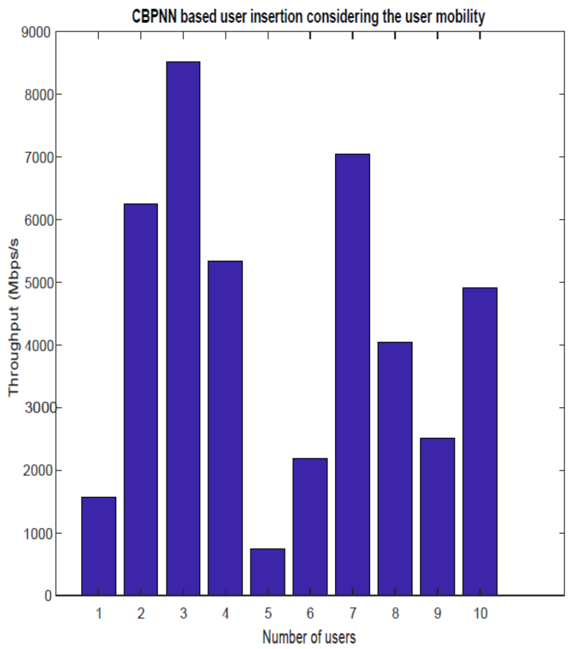

Figure. 24 Throughput for mobility users based on CBPNN method

calculated if there is one user (one station) at the time, and the same calculation is repeated in the case of two, three, four, five through ten users in the room, respectively. Fig. 19 shows the effect of the number of users on system throughput. It can be observed that the system throughput decreases with an increase in the number of users. Further, it can be noted that the optimized scheme can provide significantly high throughput compared to the conventional RSS-based scheme. However, as the number of users increases.

On the other hand, with ten users in mobility conditions (random mobility within the room) throughput is measured, and the results are demonstrated in Fig. 20. It is realized that throughput changes randomly if the user station is in mobile mode.

User association is then calculated, which shows the distribution of those users among the access points. Fig. 21 shows that most users are linked to the access point (Li-Fi 1). The user satisfaction for the FFNN method is shown in Fig. 22 it shows 65 % approx. of the users will achieve the desired performance when the user satisfaction threshold is considered to 1 for the system.

6.3.2. CBPNN simulation results

Using the CBPNN method, throughput is also calculated for the proposed model in two stages, namely: in stationary fashion as well as in mobility fashion. Fig. 23 show the throughput values of the stationary scenario. It is realized that throughput drops when the number of users increases. On the other hand, with ten users, in mobility model (random mobility within the room) throughput is measured, and the results are demonstrated in Fig. 24.

The user association for CBPNN based scheme is shown in Fig. 25. It can be noted that most of the users are connected to Li-Fi 2 AP and hence is overloaded. Thus, Wi-Fi AP resources are freed up and can be utilized for mobile users.

To provide more information about the performance of those schemes, complementary cumulative distribution function (CCDF) of the user satisfaction and the likelihood of the capacity outage for certain throughput have been provided. Fig. 26. illustrates CCDF of the user satisfaction for various numbers of the users under the CBPNN scheme of load balancing.

6.3.3. CNN simulation results

This section shows the average network throughput for the different number of users under the CNN method in Fig. 27.

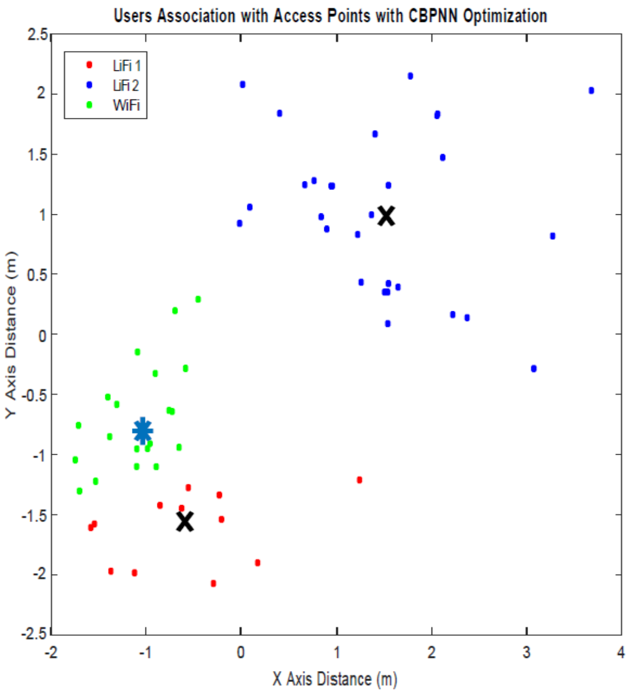

Figure. 25 User association for proposed system based on CBPNN method

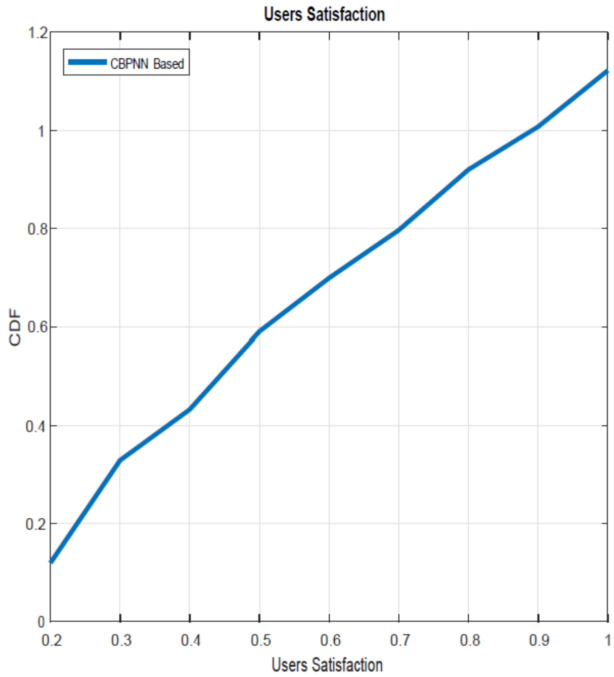

Figure. 26 User satisfaction for CBPNN method

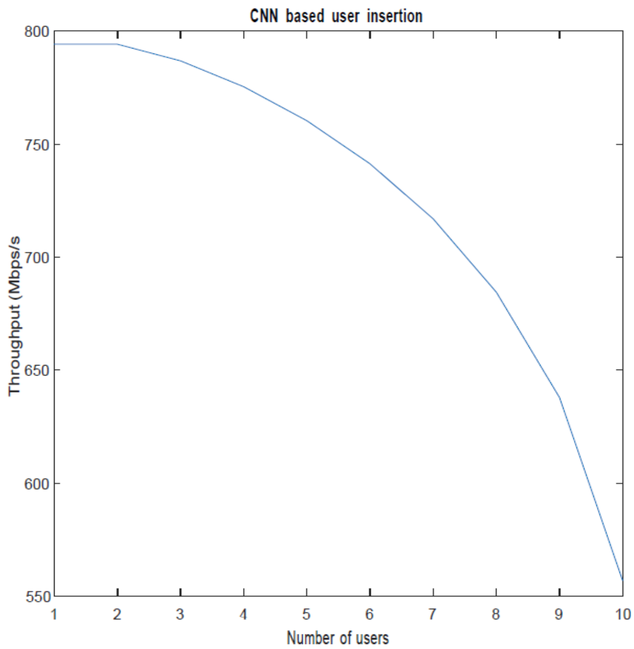

Figure. 27 Throughout the proposed system basedon CNN method

On the other hand, with ten users in mobility conditions (random mobility within the room), throughput is measured, and the results are demonstrated in Fig. 28. It is realized that mobility impacts the throughput since Line-of-sight communication is not maintained all the time due to the user's mobility. throughput for ten users is calculated when the motion of users is random, and to get better idea of the mobility impact on the throughput, the same scenario is repeated for five

Received: June 27, 2022. Revised: September 5, 2022.

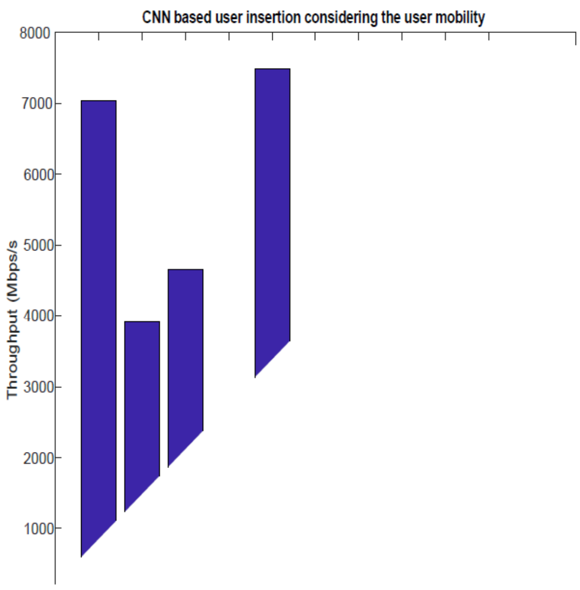

Figure. 28 Throughput for mobility users based on CNN method

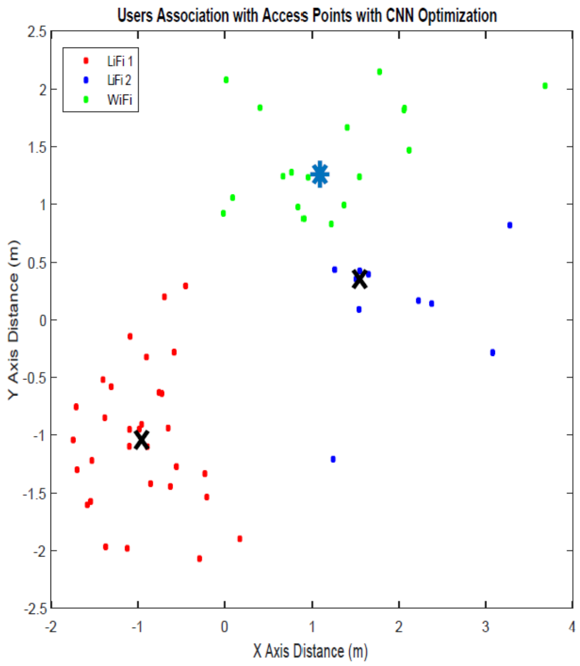

Figure. 29 User association graph based on CNN method

iterations. It is realized that throughput changes randomly if the user station is in mobile mode.

User association is then calculated, which shows the distribution of those users among the three access points. The load of the network is properly balanced between the Li-Fi and Wi-Fi APs. More users are associated with Li-Fi APs. Thus, Wi-Fi AP resources are freed up and can be utilized for mobile users, as shown in Fig. 29. The user satisfaction based on the CNN method is shown in Fig. 30. It is realized that 70 % of the users will achieve full user satisfaction

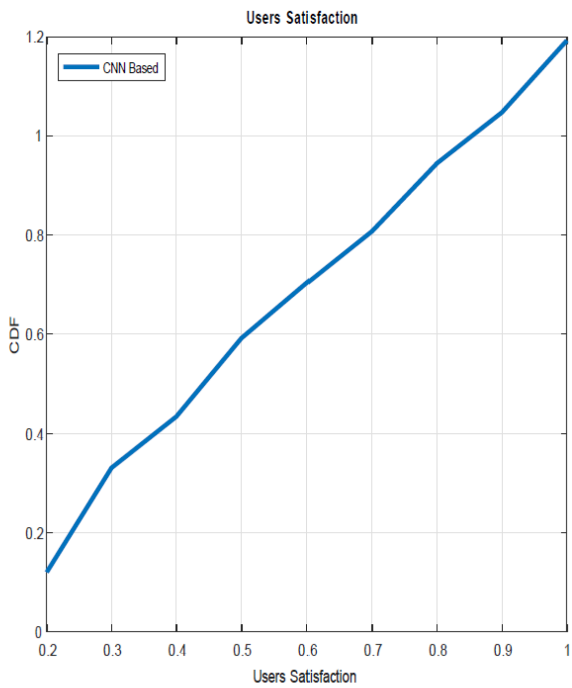

Figure. 30 User satisfaction based on CNN method

Table 6. Average network throughput (Mbps)

Number of Users	RSS Algorithm	PSO Algorithm
1	390 Mbps	960 Mbps
5	360 Mbps	920 Mbps
10	180 Mbps	725 Mbps

Table 7. Average throughput of DL techniques

Number of Users	FFNN Algorithm	CBPNN Algorithm	CNN Algorithm
1	790 Mbps	795 Mbps	800 Mbps
5	760 Mbps	765 Mbps	770 Mbps
10	560 Mbps	565 Mbps	570 Mbps

when user satisfaction threshold is considered to 1.2 for the system.

7. Comparison and discussion

With 60 users in the proposed workstation, the results are obtained as depicted in the previous sections, and the following are the observations and noteworthy points.

1) throughput of the system is increased after using the PSO technique as compared to the RSS method. 960 Mbps is achieved using PSO method. The average throughput for severalnumbers of users is stated in Table. 6.
2) throughput is further increased when deep learning techniques are applied, and the top throughput is realized when the CNN method is applied as compared with FFNN and CBPNN, 800 MBPS is

Received: June 27, 2022. Revised: September 5, 2022.

achieved using the CNN method as the state in Table. 7.

3) However, proposed systems are maintained similar performance when users are mobilized. The mobilityimpact on system throughput is examined by conducting 10 iterations when users randomly move inside/within the workstation. Throughput is realizedafter the above experiments as randomly fluctuating.
4) using deep learning methods for system performance enhancement (compared with the standard RSS method), throughput is improved, which is less than that in the case of the PSO algorithm, as stated in Table. 8.
5) using PSO methods, load balancing (LB) is achieved, which can be seen from the user association graphs. The best user association is achieved by usingthe PSO method as shown in Fig. 17.
6) it is realized that better user satisfaction is achieved when the method of CNN is applied as shown in Fig. 31.

Table 8. Average network throughput (Mbps)

No. users	RSS technique	PSO Technique	FFNN Technique	CBPNN Technique	CNN Techni que
1	390 Mbps	960 Mbps	790 Mbps	795 Mbps	800 Mbps
5	360 Mbps	920 Mbps	760 Mbps	765 Mbps	770 Mbps
10	180 Mbps	725 Mbps	560 Mbps	565 Mbps	570 MBPS

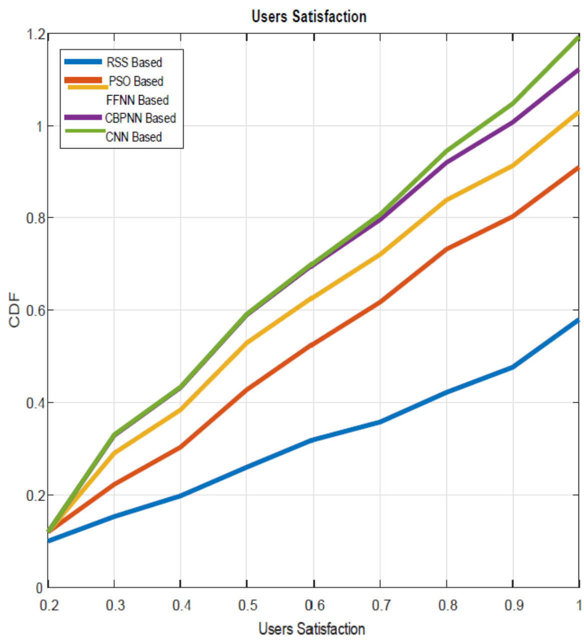

Figure. 31 User satisfaction depict for all proposed algorithms

The main contribution of this work lies in implementing a data simulation model based on the RSS method and heuristic algorithm, and DL algorithms with a hybrid system. The heuristic and deep learning algorithms were used to reduce the latency and maximize system throughput and user satisfaction. the system compared to previous researches. Table 9. shows a comparison between the proposed method and the latest relevant researches in the hybrid network (HLR).

Table 9. Comparison between the performance of the proposed hybrid system and the performance of the hybrid system in previous works

Ref.	year	Algorithm	Access technology	System model	Throughput of 10 users	User satisfaction
[19]	2019	Optimization Algorithm	TDMA	HLR network with single Wi-Fi AP and four Li-Fi APs	72 Mbps	80%
[20]	2019	Fuzzy Logic	TDMA	one Wi-Fi AP and a four Li-Fi APs.	400 Mbps	------
[21]	2020	Reinforcement Learning (RL)	TDMA	4 Li-Fi APs and 1 Wi-Fi AP	175 Mbps	100%
[22]	2020	RL Method	FDMA	hybrid Li-Fi/Wi-Fi network with four Li-Fi APs and one Wi-Fi AP	110.69 Mbps	
Proposed System	2022	PSO Algorithm and DL Methods	FDMA	hybrid RF/VLC Network with two Li-Fi APs and one Wi-Fi AP	725 Mbps by PSO algorithm and 570 Mbps by CNN deep learning algorithm	98%

8. Conclusion

Radio communication is suffering from congestion due to a dramatic hike in subscribers' amount, which forces thinking of other alternatives for communication channels. Optimization communication, including visible light communication, is one of the substantial solutions that offers unlimited bandwidth and improves user satisfaction. Visible light communication comes with several challenges manifested by light disability to propagate inside the particles even behind the objects, which triggers blind areas for the communication.

In this study, the hybrid system using radio and the visible light access point is implemented to enhance the system performance by letting users share the available access points fairly.

PSO algorithm is improved method for fulfilling the objectives of this study. It has successfully achieved a higher data rate for fixed and mobility users. It also achieved the best load balancing when all users were in moving.

Form the other hand, results are compared with deep learning-based approaches for user assignment, which was performed by letting those algorithms learn about user behaviours dataset. The deep learning methods have also improved the conventional RSS method's results.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review, and editing, visualization, have been done by 1st author. The supervision and project administration has been done by 2nd author.

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