Bio-inspired algorithm for decisioning wireless access point installation

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ABSTRACT

This paper presents the bio-inspired algorithms for decisioning wireless access point (AP) installation. In order to achieve the desired coverage capability of APs, the bio-inspired algorithms are applied for robust competition and optimization. The main objective is to determine the optimal number of APs with the high coverage capability in the concerning area using the genetic and ant colony optimization algorithms. Received signal strength indicator (RSSI) and line-of-sight (LoS) gradient approach are the most important parameters for AP installation depending on the AP signal strength. Practical experiments are tested on the embedded system using Xilinx Kria KR260 and Raspberry Pi Zero 2W boards at the tested room size about 16 m wide and 40 m long inside the building. Xilinx Kria KR260 board is used to calculate the number of AP installation and localization compared to Xcode. Then, Raspberry Pi Zero 2W board is the representation of wireless AP for measuring the signal in the testing area. Experiment results show that maximum received signals strength is equal to -35 dBm at 6 m and there are six APs installation with high coverage area and maximum received signal strength at the area of 16×40 m^2.

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1. INTRODUCTION

Bio-inspired approach is an optimization approach based on the biological evolution as genetic algorithm (GA) and ant colony optimization (ACO) [1]. A GA [2] is a metaheuristic method that optimizes problems using a process inspired by starting with a random population of solution, evaluates each solution using a fitness function, then uses the crossover and mutation method to create a new generation. The process will repeat until reach at satisfactory. An ACO [3] algorithm is a metaheuristic method using swarm intelligence based on the ant behavior with the virtual ants searching a path determined by probability rule and leaving a pheromone trail as memory. The concentration of pheromone on trail also influences other ants' decisions.

There are many algorithms for wireless networks such as coverage planning [4] and indoor optimization [5]. Several methods to optimize wireless coverage planning including deep learning assisted [6], graph-theoretical [7], and access points (AP) optimization [8]. The various wireless approaches based indoor localization consists of the fusion framework for multiple sensors [9], and a 2D surface correlation for location accuracy improvement [10].

Other research focuses on improving the accuracy of smartphone-based indoor tracking and localization by integrating Wi-Fi fingerprinting and pedestrian dead reckoning (PDR) techniques [11]. Some studies aim to maximize the line-of-sight (LoS) coverage for multiple access point (multi-AP) millimeter-wave wireless local area network (WLAN) [12], AP placement method [13], and the sensor/access-point coverage area [14]. The optimization AP placement in wireless communication networks is also explored including with the methods for maximizing the average throughput [15], minimizing inter-cell interference [16], enhancing indoor localization reliability [17], and optimizing WLAN systems in the indoor environments [18]. Optimization algorithms are applied to APs in places such as the indoor room [19], [20]. There are studies on AP management algorithms in [21], [22]. Other research also covers AP enhancement including [23]–[25]. Artificial intelligence (AI) service deployment is presented in a multi-access edge intelligent system aiming to minimize computing time and energy consumption while maximizing inference accuracy [26]. Another study deals with defeating jamming attacks in an uplink pairwise non-orthogonal multiple access (NOMA) scenario using a mobile AP by jointly optimizing power allocation and AP placement [27]. The small-cell uplink AP placement problem is studied in terms of optimal throughput and inter-cell interference [16].

The contribution of this paper is to deploy two bio-inspired algorithms as a GA and an ACO and to compute these bio-inspired algorithms on the Xilinx Kria KR260 board compared with Xcode in C/C++ programming for decisioning AP installation. Raspberry Pi Zero 2W board represents as an AP to measure the received signal strength. The organization of this paper is as: section 2 describes the received signal strength indicator (RSSI) and localization algorithm. In section 3, the bio-inspired algorithms are explained, and practical results are presented in sections 4 and 5 summaries this work.

2. RECEIVED SIGNAL STRENGTH AND LOCALIZATION ALGORITHM

Positioning refers to the process determining the object location in the physical space, which is used in a wide range of applications. The AP localization algorithm utilizes the information from surrounding APs to estimate the device's location. Additionally, the LoS gradient calculation determines the slope of the terrain between two points that is crucial in the communication systems, navigation, and terrain analysis.

The received visible light power is proportional to the distance called the received signal strength (RSS). Visible light signal form the reference node and transmitter are attenuated by increasing distance. Other works about RSS-based localization and positioning approaches are presented by using an optimal propagation model to compute the distance [18], [19]. These advantages of RSS-based methods are to perform high accuracy in LoS short-range environments without the hardware installation requirement at the target nodes and synchronization time between nodes [20].

RSSI is defined from power of received signal in unit of dBm. The AP-received signal strength P_{AP} at a given distance d_{AP} is another critical parameter that affects the quality and reliability of the wireless link, and its expression is derived using propagation models that consider various factors such as path loss, antenna gain, and environmental factors. Precise measurement and analysis of RSSI and P_{AP} values are essential for optimizing the performance of wireless networks, as they can be used to estimate the range of the AP. It can be expressed as [4].

$$P_{AP} = P_{UE} - 10\,\xi \log\left(\frac{d_{AP}}{d_{UE}} + \eta_{\sigma_m}\right) \tag{1}$$

where P_{UE} is defined from the *UE*-measured signal strength of user equipment *(UE)* at a reference distance d_{UE}. Random variables $\xi_{\sigma m}$ is added with the zero-mean Gaussian distribution. The path loss exponent ξ is set at 2 and d_{UE}=1 m in the indoor environment [4]. The distance d_{AP} is given by (2), (3):

$$log(d_{AP}) = \frac{P_{UE} - P_{AP} - \eta_{\sigma_m}}{20} \tag{2}$$

$$d_{AP} = 10^{\frac{P_{UE} - P_{AP} - \eta_{\sigma_m}}{20}} \tag{3}$$

The overlapping area between two APs is a constraint that can be minimized by (4):

$$AP_{overlapped\ area} < 20\% \tag{4}$$

where $AP_{overlapped\ area}$ denotes the percentage of AP overlapped coverage between AP cells [4]. As noted that, the AP overlapped coverage between AP cells is an important condition for designing the AP layout network. The overlapping area is computed as (5)

$$\text{Area} = 2\left(\pi R^2 P_{ratio} - \frac{1}{2}R^2 \sin(360^o \cdot P_{ratio})\right) \tag{5}$$

where R is the radius of AP coverage, and P_{ratio} is the percentage of the overlapped ratio.

3. PROPOSED BIO-INSPIRED ALGORITHMS

The proposed bio-inspired algorithm includes GA and ACO designed to identify the optimal location for the AP. Output must cover at least 80% of the specified area size and randomly generated AP locations. These algorithms will be tested on a 16-inch MacBookPro and a Xilinx Kria KR260 board to evaluate the computational speed shown in Figure 1.

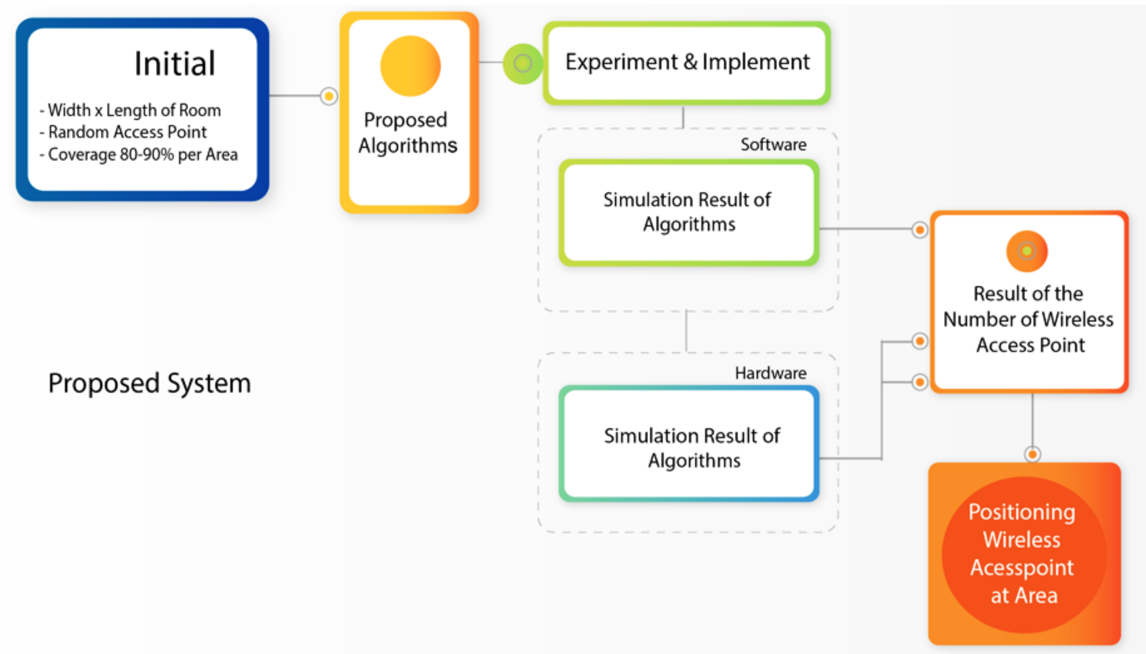


Figure 1. Proposed system

3.1. Design of decisioning system using genetic algorithm

GA is applied to an automatic AP decision indoor localization method to the different selection method as shown in Table 1, where the roulette wheel and tournament selection method are compared with the random sampling. We start at the given number of iterations and population size and then build the random width, length, and number of AP distributed in the center of random area. These conditions are used in the proposed decisioning system as: i) to consider the ratio of AP coverage and the actual area in square meters and ii) to compute the suitable difference between the AP coverage and actual area. Later, we apply the result for searching fitness value to pick up the appropriate chromosomes, select the crossover and mutation, respectively.

The pseudocode of bio-inspired decision system using GA is detailed in Table 1 above. Line 1-4 shows initialize variables for width, length, population, number of iterations and loop counters. Line 5 declares several functions that will be used in the program. The evpop function initializes the population. The cost function calculates the cost of a given chromosome. Line 6 shows the loop for number of iterations. Line 7 presents the copy current population to next population. Line 8 initializes the popcurrent array using the evpop function. Line 9 depicts the pickchroms function selects the best chromosomes for reproduction. Line 10 shows the crossover function combines the chromosomes to create new ones. Line 11 presents the mutation function introduces random changes (mutations) to the chromosomes with a low probability.

Line 12-13 shows updates the popcurrent array with the new population stored in popnext. Line 14 indicates that the result of the program will be the number of APs placed, their fitness, and their coordinates in the room.

Table 1. The pseudocode of proposed AP-decisioning system using GA

Decisioning System of AP Algorithm Using GA
1. Initial: Width, Length, Population
2. Input: number of iterations,
3. popcurrent=array of Pop_size "chrom" structures
4. popnext=array of Pop_size "chrom" structures
5. evpop(popcurrent)
6. for i=0 to num:
7. for j=0 to Pop_size:
8. popnext[j]=popcurrent[j]
9. pickchroms(popnext)
10. crossover(popnext)
11. mutation(popnext)
12. for j=0 to Pop_size:
13. popcurrent[j]=popnext[j]
14. Result: Number of AP, fitness, Coordinate AP in room

3.2. Design of decisioning system using ant colony optimization

ACO is modified for finding an automatic AP-distributed indoor localization with the different selection method as described in Table 2. The cost function of ACO is set similarly to the conditions of GA. Then, the results from iterations are applied for updating the population and pheromone used.

Table 2. The pseudocode of proposed AP-decisioning system using ACO

Decisioning System of AP Algorithm Using ACO
1. Define the cost function
2. Set the number of decision variable
3. Set the ACOSM parameters: number of iterations, population size, sample size, intensification factor, and deviation-distance ratio
4. Get the selection method (roulette wheel, tournament, random)
5. Initialize the population matrix
6. Start the ACOSM loop for the specified number of iterations
a. Select a sample of solutions using the specified selection method
b. Construct a new solution using the selected sample
c. Update the population matrix and pheromone matrix
7. Return the best solution
8. Result: Number of AP, fitness, Coordinate AP in room

The pseudocode of bio-inspired decision system using ACO algorithm is shown in Table 2 as follows. Line 1 sets the cost function, which is the function that measures the fitness of a given solution. Line 2 specifies the number of decision variables, which in this case would correspond to the number of APs in the indoor space. Line 3 defines the ACO with selection methods (ACOSM) parameters including the number of iterations, the population size, and sample size. Line 4 gets the selection methods (roulette wheel, tournament, random sampling). This line specifies the method used to select candidate solutions for the optimization process. Line 5 creates the initial population of candidate solutions which are used to start the process. Line 6 begins the optimization process using the ACOSM algorithm, which will iterate over the specified number of iterations to identify the best solution. Line 7 returns the best solution found during the optimization process, typically the solution with the highest fitness score. Line 8 specifies the result of the optimization process, which typically includes the number and location of APs, the fitness score of the solution, and the coordinates of each AP in the indoor space.

4. EXPERIMENTS

This section presents the simulation and experimental results of the proposed algorithm. The GA and ACO algorithms can manipulate the location of APs to provide wireless signal coverage to the target area. This section is divided into 3 subsections consisting of i) system implementation, ii) experiment setting, and iii) experimental results. The details are as follows.

4.1. System implementation

In the tested area, the 16×40 m^2 room at the 3rd floor library building with multipurpose space room is investigated. Experiments are measured the signal from the wireless emitter, starting with only one AP installation in the room for the worst installation possibilities. Next, it will be tested by using the results from GA and ACO installing them and testing the signals.

Implementation of proposed AP-based capacity planning algorithm is detailed in Table 3. Line 1 shows the initial inputs as the width and length of the room, and radius is an AP coverage, respectively. Line 2-4 increase the coordinates of width and length. Line 5 shows to terminate the unused AP coordinates. Line 6 is used to increase the index.

Table 3. The pseudocode of proposed AP decisioning system

```
Decisioning System of AP Algorithm
1.  Data: Input room dimensions and AP radius
2.  Initialize CoordinateAP matrix and index
3.  |       for (int x=0; x<=width; x++)
4.  |           for (int y=0; y<=length; y++)
5.  |               if (y+radius !=0 && x+radius !=0 && y
                      +radius !=length && x+radius !=width)
6.  |                   CoordinateAP[index][0]=x+radius,
                        CoordinateAP[index++][1]=y+radius;
7.  |               else
8.  |                   printf("Error: AP on room boundary\n");
9.  |                   index=index+1;
10. |           End
11. |       End
12. Result: Output CoordinateAP matrix
```

4.2. Experiment setting

Defines the Raspberry Pi Zero 2W board as a wireless transmitting device. Set the AP mode and set the frequency at 2.4 GHz. The GA and ACO algorithms are used to manipulate the location of the device.

4.2.1. Simulation of indoor localization using genetic and ant colony optimization algorithm

For simulation of the proposed indoor localization system using GA and ACO, we set the initial parameters as: 100 populations, 5% of mutation rate, and 100 iterations. The actual area following [4] is of 40 and 16 m shown in Figure 2, where the maximum random number of AP of random sampling is at 100. The radius of AP coverage is about 6 m.

The cost function is computed using two parameters, the ratio of the area covered by the access points APs to the total area being considered, and the optimal area which is determined by the difference between the area covered by the Aps. And the total area is being considered. The optimal area parameter is then used to calculate the fitness of each generation of the population, which is essential for determining the optimal solution. The cost function of proposed algorithm can be evaluated by (7), (8):

$$\text{ratio}_{AP_{area}} = \frac{\text{AP}_{cover}}{\text{Area}}, \tag{7}$$

$$optimal_{area} = \text{AP}_{cover} - \text{Area}, \tag{8}$$

where the $optimal_{area}$ is used to find the fitness of each generation of the population.

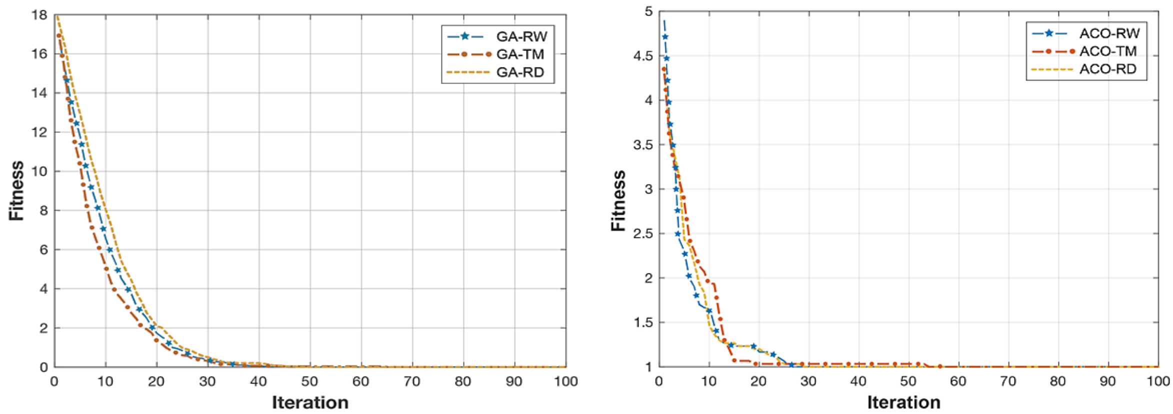
Figure 2(a) shows the fitness from GA versus the number of iterations at 100 populations that the experimental result is shown the best answer about 30 iterations with all methods. Figure 2(b) shows the comparison of the computational results a decision-making system using ACO with the random sampling, roulette wheel method, tournament methods to sample the population. Figure 2(b) yields the results of the answers chosen for the tournament method in 15, 24 and 25 iterations with the random and the roulette wheel methods, respectively.

4.2.2. Simulation of indoor localization using GA and ACO via Xilinx Kria KR260

In this section, we describe the evaluation of the proposed GA and ACO through tests conducted on two different hardware platforms. The first platform used the Xilinx Kria KR260 board in running Ubuntu 20.04 LTS with the GCC compiler, and the second platform was a MacBookPro-16inch running MacOS Monterey 12.6.1 with the Xcode compiler. These platforms were chosen to represent common computing environments in which the GA and ACO might be employed.

The performance evaluation of the algorithm uses standard C/C++ language functions for execution timing. We recorded the time it took to execute this starting from 100 iterations, increments of 100, up to 1,000 on each platform. Several experimental results were collected to calculate the average.

The purpose of testing is to identify differences or limitations in algorithm performance in different computing environments. By testing GA and ACO on two different platforms, we aim to provide information to developers and users of these algorithms who may consider implementing them in a variety of contexts. The 2019 MacBookPro features a 2.3 GHz 8-core Intel Core i9 and 16 GB of 2,666 MHz DDR4 memory.



(a) (b)

Figure 2. Entry tracking of the calculation of the number of AP installed in the building with (a) genetic algorithm and (b) ant colony optimization

The Xilinx Kria KR260 board is an affordable and compact robotic development platform that incorporates a Xilinx Zynq system-on-chip (SoC) as illustrated in Figure 3(a). This SoC integrates two ARM Cortex processors with a field programmable gate array (FPGA) fabric. ARM Cortex processors consist of the 1.5 GHz of Cortex-A53 quad-core processor and 600 MHz of Cortex-R5 dual-core processor. The platform features are 4 GB of DDR4 RAM, 16 GB of eMMC flash storage, and supports C/C++ and Python programming languages. Additionally, Figure 3(b) shows the Raspberry Pi Zero 2W board as AP [4], with dimension sizes of 65×30 mm. The Raspberry Pi Zero 2W board is powered by a 1 GHz of quad-core ARM Cortex-A53 processor and 512 MB of LPDDR4 SDRAM.

(a) (b)

Figure 3. The simulation on two hardwares (a) Xilinx Kria KR260 board and (b) Raspberry Pi Zero 2W board

Figure 4 illustrates the indoor localization using GA and ACO via MacBookPro and Xilinx Kria KR260 board. It is measured in execution time (seconds) of two algorithms. Overall, it can be seen that four increased as an execution time of two algorithms, but ACO via MacBookPro is the lowest. The GA running on embedded platforms takes 2.2 times less execution time than the ACO for 1,000 iterations. Because the

ACO algorithm does not use parallel processing application programming interfaces (APIs) to divide the work among multi-cores in the processor.

4.3. Experimental results

The best results obtained from calculations with GA and ACO algorithms are used in the multi-AP installation point decision-making process. Proposed algorithms and measure signal strength at different designated points are shown in Figure 5. When AP is Raspberry Pi Zero 2W board and *UE* as user equipment.

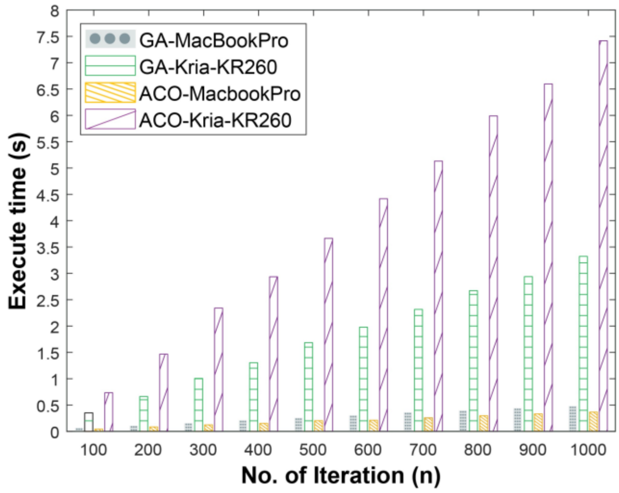


Figure 4. Indoor localization using GA and ACO via MacBookPro and Xilinx Kria KR260

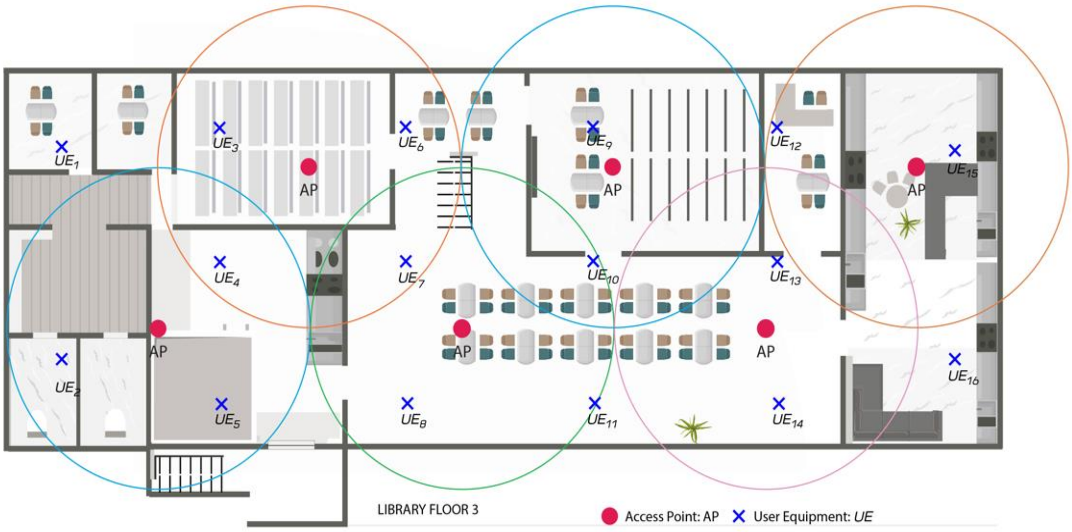


Figure 5. Design of AP position by proposed algorithms for 3rd floor the library size 16×40 m^2

The experimental results demonstrate the system's ability to an investigation on the quality of the wireless signal distribution in an indoor environment using GA and ACO algorithms. The results showed that the measured signals had high overall quality, as demonstrated in Figure 6, and that the signal strength was excellent at 11 measurement points, with values below -40 dBm. This level of signal strength was deemed sufficient for knowledge discovery. However, the study also found that some areas had weaker signal strength, such as UE_1 and UE_2, from Figure 5 and compare with result in Figure 6 due to the presence of obstacles such as concrete walls and signal-blocking materials in the construction. These results provide valuable insights into the challenges of indoor wireless communication and can be used to optimize the placement of APs for better signal distribution in similar environments.

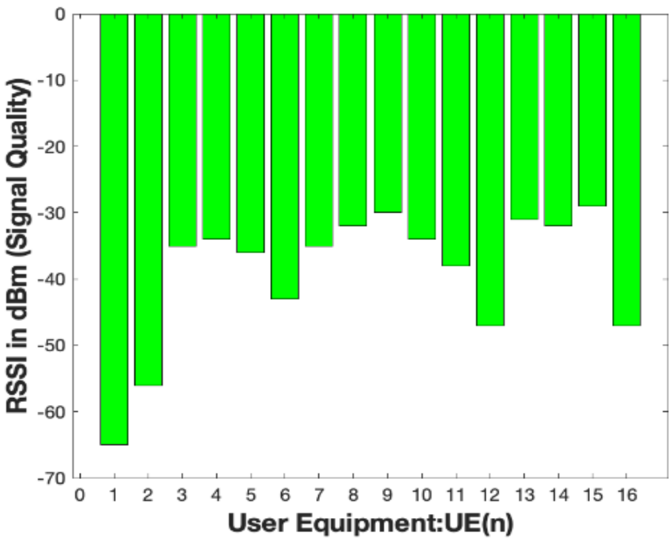


Figure 6. RSSI of UE_n measured by Raspberry Pi Zero 2W as a wireless AP, where n=1, 2, …, 16

5. CONCLUSION

In this study, we proposed bio-inspired algorithms for WLAN indoor decision-making systems, which included GA and ACO. The results showed that the proposed algorithms were effective in determining the optimal number and position of APs installation for effective signal distribution through the designated area. Notably, the GA processed 2.2 times faster on the Xilinx Kria KR260 board than the ACO for 1,000-iteration. The experimental results demonstrated that the system provided excellent signal strength in the investigated scenarios with a maximum capacity of 10 to 20 users per AP. This research has significant implications for indoor wireless communication and can be applied in a range of settings, such as educational institutions, office buildings, and public spaces. Overall, the proposed system represents a promising solution for optimizing WLAN indoor communication and signal distribution. Further research could investigate the scalability of the proposed system for larger areas and higher user capacities.

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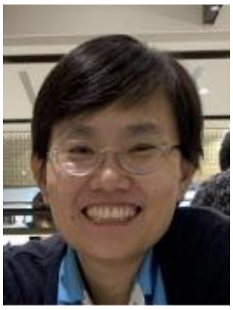

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