

Optimizing Wi-Fi RSSI and Channel Assignments Using a Genetic Algorithm for Wi-Fi Tuning

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ABSTRACT

In this work, we propose a genetic algorithm-based Wi-Fi-tuning platform to facilitate network administrators in coping with the co-channel interference triggered by other wireless sources. Generally, with a well-designed WLAN, signal interference from adjacent areas is usually minimal. Unfortunately, when other wireless sources are introduced into the WLAN system, co-channel interference is inevitable. Interference usually causes degradation and/or disruption in network services. Resolving this issue becomes even more complicated when the interfering signals come from access points owned by other ISPs and are not accessible by the network administrators. This paper proposes a Wi-Fi tuning platform that allows the automatic reconfiguration of WLAN settings by finding the best settings for channel assignment and power transmission. When signal interference is detected, the platform attempts to find heuristic solutions for wireless settings based on a genetic algorithm. Our experiments show that the proposed algorithm can regenerate the WLAN settings, providing stronger signal levels and higher coverage ranges while reducing interference levels in the deployment area. With the proposed platform, troubleshooting becomes less complicated, requiring less cost and time. With the help of the Wi-Fi tuning platform, network administrators can react promptly to incidents, enhancing the availability, reliability, and consistency of the WLAN system.

Keywords: Wi-Fi Tuning, Wireless Local Area Network, WLAN, Received Signal Strength Indicator, RSSI

1. INTRODUCTION

Implementing a wireless local area network (WLAN) that provides timeliness, robust, consistent,

and reliable wireless fidelity (Wi-Fi) requires several phases, including wireless planning, design, tuning, and a site survey. The Wi-Fi planning phase focuses on defining the quality of services (QoS) required by wireless users. The design phase focuses on finding the best system settings to meet the predefined QoS requirements. Wi-Fi tuning occurs during wireless deployment. The objective of Wi-Fi tuning is to enhance the wireless network by updating the system parameters to cope with any design flaws or system interruption. Finally, a wireless site survey may be introduced to investigate coverage or interference levels within buildings and ensure that the QoS requirements have been satisfied. Generally, Wi-Fi planning and design are performed during the pre-deployment phase whereas Wi-Fi tuning and a survey are performed post-deployment to revalidate the WLAN settings.

In populated areas, wireless access point deployment is usually dense. Avoiding inter-channel interference in these areas is crucial, especially over the 2.4 GHz frequency band where only three limited independent bandwidths are available. Most previous research work in this field has focused on the wireless planning and design phase, e.g., finding the best placement for the access points, and optimizing transmission power. In this work, we focus on campus networks. Once implemented, we have witnessed that even with a well-designed WLAN, unpredictable signal interference can be found in the WLAN system, extensively introduced by third-party access points owned by other internet service providers (ISPs). This problem is challenging since network administrators have no access to these rogue access points. The only way of mitigating this problem is to perform Wi-Fi tuning by reconfiguring existing access points within the domain to adopt other frequency bands.

Currently, wireless access point manufacturers allow two types of configurations: static and dynamic. Static configurations require network administrators to manually reconfigure the settings. Hence, this method cannot promptly handle incidence detection. On the other hand, dynamic configurations can immediately avoid or cope with the incidence and are effective in small networks since they provide a timely response. However, in large-scale networks where access point deployment is dense, the modification

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of settings in one access point generally affects the performance of others in the surrounding areas. Thus, dynamic configurations usually trigger the successive modification of numerous access point settings in the surrounding area. Such modifications are sometimes stuck in an infinite loop. Thus, the motivation of this paper is to try to overcome the drawbacks associated with existing solutions.

In contrast to other research work in this domain which focuses on the Wi-Fi planning and design phases, Wi-Fi tuning also plays a vital role in providing a satisfactory network performance service. Wi-Fi tuning is essential especially for a WLAN with a dynamic change in network size and topology. This paper is formulated as follows. Firstly, preliminary studies are investigated and the framework is then defined. We later propose a genetic algorithm for use in Wi-Fi tuning and then discuss the results in the final section.

2. PRELIMINARY STUDY

The demand for wireless network deployment has drastically grown in the past decade. Although wire networks are more stable and provide higher bandwidths, wireless networks are more beneficial in terms of mobility management, installation cost, and convenience of use. In populated areas where the demand for wireless connectivity is high, spectrum scarcity and signal interference become problematic.

With a well-designed WLAN, interference can be mitigated. Many research works focused on the planning and design phases to avoid co-channel interference in the WLAN systems [1–5]. However, even with a well-designed WLAN, some issues are exacerbated such as interference and growth in network size from new nodes being introduced into the system exacerbated. Interference issues can be resolved in the physical layer by applying the appropriate channel selection strategies proposed in [6–10]. It can also be mitigated at the medium access level by applying a well-designed carrier sensing technique [11]. In this paper, we focus on the physical layer protocol. According to the literature review, most research work in this field focuses extensively on dynamic channel assignment. Nevertheless, other factors exist that may impact WLAN performance. In this paper, we jointly investigate various factors. Under a multi-objective problem where constraints are not limited to one parameter, a genetic algorithm (GA) is known to be an effective tool in finding heuristic solutions. During the WLAN design process, many research works have adopted GA for Wi-Fi planning and design to provide optimal wireless access point placement under certain conditions and constraints. In [1, 6], node placement was jointly investigated with path-loss from indoor obstacles. In [2], GA was adopted to provide a cost-effective WLAN in terms of coverage and capacity under

budget constraints. In [5], both channel selection and the QoS of WLAN requirements were jointly optimized, while the authors in [4] suggested using GA to consider additional metrics such as capacity, cost, coverage, and interference. Apart from node placement optimization, GA in WLAN design can also be included in the design of patch antennas [12, 13] as well as the handover process between Wi-Fi and LTE in the unlicensed spectrum, as described in [14]. So far, we have not seen any work that mentions the use of GA during the Wi-Fi tuning phase. Instead of finding optimal node placement, in this paper we focus on resolving interference and tuning the WLAN parameter settings when an interference issue is detected. Accordingly, the access points in our context are at a priori fixed time.

This research focuses mainly on a wireless campus network. One problem encountered by network administrators is that many third-party access points randomly appear in the WLAN system and cause unpredictable signal interference, and ultimately affect service availability. The issues may become more intense when node deployment is dense. Addressing this issue is challenging since the network administrators do not have access to these rogue access points. Wi-Fi tuning could be performed by reassigning new frequency channels and transmission power to the access points in the domain to avoid interfering signals. During Wi-Fi tuning, since more than one parameter needs to be considered, we propose adopting a genetic algorithm to search for a heuristic solution to the problem.

3. THEORY

Wi-Fi tuning is useful for improving wireless performance during network deployment. Once an interference incident is detected, Wi-Fi tuning allows the re-finding of the best configuration for the system. In this paper, we mutually investigate two parameters: channel assignment and transmission power. It is widely acknowledged that using the same frequency band in an adjacent area can trigger inter-channel interference, while use of the adjacent frequency band can also trigger adjacent-channel interference. Higher transmission power may increase the coverage range, but it also introduces interference into the surrounding area.

3.1 Power Level Adjustment

The geographical coverage of an access point is represented by a geographical area where communication is available between an access point and a communication device. This value is relatively proportional to the detection and communication range. Generally, the coverage area directly depends on the effective radiation of the transmitter and radio sensitivity of the receiving antenna. Higher transmission power generates larger signal coverage.

The received power P_r in dBm at distance d is subject to attenuation loss P_L as shown in Eq. (1).

$$P_{r_{dBm}} = P_{t_{dBm}} - P_L(d). \quad (1)$$

For free-space propagation, the value $P_L(d)$ is the reduction in the power level that decays with distance d meters from the transmitter. However, for the indoor environment, path-loss is not only affected by the distance, but also by other disturbances such as multipath propagation and attenuation loss from building structures such as walls and floor partitions. The authors in [15] proposed an ITU indoor propagation model that imitates signal propagation indoors. This model is described as

$$P_L(d) = P_L(d_0) + 10n \log \frac{d}{d_0} - K - \sum_{i=1}^{N_f} FAF_i - \sum_{i=1}^{N_p} PAF_i \quad (2)$$

where d_0 represents the reference distance, usually taken 1 meter from the transmitter. K is a constant value. $\sum_{i=1}^{N_f} FAF_i$ and $\sum_{i=1}^{N_p} PAF_i$ represent attenuation loss caused by floor and wall partitions, respectively.

In this paper, the ITU model is adopted as described above. We reformulated it using two constant values n and c to characterize the propagation. The relevant equation can be re-written as

$$P_L(d) = P_L(d_0) + 10 \cdot n \log \frac{d}{d_0} - c. \quad (3)$$

Here, the value of n represents the path-loss exponent while c represents the total accumulated attenuation loss. By fitting Eq. (3) with the attenuation loss observed from real experiments using Marquardt-Levenberg linear regression, we obtained the value of $n = 2.6$ and $c = -7.36$. Further details can be found in [16].

3.2 Interference Avoidance

Signal interference usually occurs when neighboring access points transmit signals over the same frequency channels. In a WLAN, interference is extensively found on a 2.4 GHz frequency band rather than a 5 GHz. This is because transmitting at a lower frequency is less attenuated and produces a larger coverage range. Since there are only three independent frequency channels to choose from on the 2.4 GHz band, when a third-party wireless access point is introduced into the system, interference is extensively found on this band. Signal interference could cause an interruption in network services. Thus, in this research, once interference is detected, we propose reconfiguring the access point settings by adjusting the power levels and reassigning the frequency channels to mitigate this issue.

3.3 Access Point Reconfiguration

Nowadays, the setting of access points allows both static and dynamic configuration. Static configuration requires the network administrator to manually configure the settings and the values then remain permanent. Dynamic configurations, on the other hand, promptly react and resolve the issues by automatically reconfiguring the settings according to channel conditions. Unfortunately, as previously mentioned in the introduction to this paper, using dynamic configuration in a dense network causes it to endlessly search for optimal settings. Moreover, modifying one parameter may create a chain reaction in the settings of other access points.

3.4 Genetic Algorithm

To design a reliable, secure, and readily available wireless network, several factors need to be investigated. For example, an increase in transmission power may improve the coverage, but also cause mutual interference in neighboring access points, degrading signal quality. A genetic algorithm is a heuristic search that reflects the process of natural selection based on Charles Darwin's theory. In natural selection, parents produce offspring who inherit some of their characteristics. If their offspring are fitter, they have a better chance of survival. If we want to find the fittest individual, we can keep tracking the offspring reproduced from generation to generation until the fittest individuals are identified. This notion can be applied to a search problem. We consider a set of solutions for the problem and select the best ones. Several steps occur in genetic algorithms for problem-solving: (1) defining the population, (2) finding a fitness function, (3) selection, (4) crossover, (5) mutation, (6) evaluation, and (7) replacement. Generally, a genetic algorithm consists of the following steps.

1. In the first phase, defining the population involves initializing a set of individuals or solutions to address the problem. This set of individuals is called the population. Each individual is characterized by their genes. A gene is a variable. A set of genes forms a chromosome.

2. Next, a fitness function is defined. The fitness function will determine the fitness level of an individual. A fitness score will be given to each individual. The selection rate of each individual taking part in the evolution will be based on their fitness score.

3. During selection, two pairs of individuals (parents) are selected based on their fitness scores. The higher the fitness scores, the greater their chances of being selected for reproduction and passing their genes on to the next generation.

4. The crossover process occurs in each set of parents mated. Crossover means that the chromosomes of the parents will be crossed with the crossover

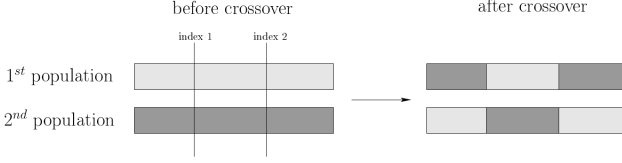


Fig. 1: Crossover process.



Fig. 2: Mutation process.

point chosen at random. The offspring is created by exchanging genes from the parents as shown in Fig. 1. New offspring are then added to the population.

5. In some cases, mutation can occur to prevent premature convergence. Mutation allows some genes to be modified in a specific way to create diversity among the population as illustrated in Fig. 2.

6. Once the offspring have been created, they need to be evaluated for a fitness value to be assigned. This fitness value is used to sort the populations. The fittest individuals have a better chance of being selected.

7. In some cases, a replacement is performed to merge new populations with the parents. This is done by replacing old populations with new child populations.

These steps are repeated in a cycle as illustrated in Fig. 3.

4. METHOD

Our proposed algorithm and framework will be presented in this section.

4.1 Proposed Algorithm

As mentioned in the previous section, a genetic algorithm can be adopted as a tool to find heuristic settings for the access points to obtain optimal network performance in terms of coverage and overall interference level. We propose implementing the following algorithm.

- **Defining Population:** Since the values to be adjusted during Wi-Fi tuning include transmission power and the frequency channel, each gene represents a set of random values between the power level and channel number. Based on the setting of Wi-Fi access points deployed at the 2.4 GHz frequency band, power values ranging from 1 and 6 were chosen, represented by $P_t \in [1, 6]$ while a channel number C_h was picked from 1, 6, and 11, represented by $C_h \in \{1, 6, 11\}$.

- **Defining Fitness Function:** The performance metrics we expect to obtain consist of the highest

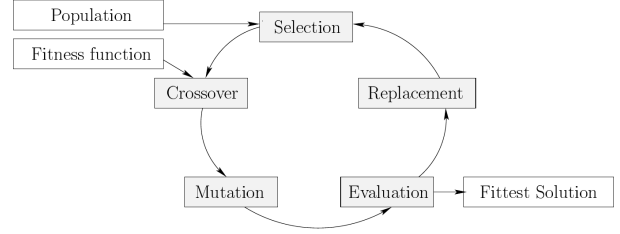


Fig. 3: Evolutionary cycle of genetic algorithm.

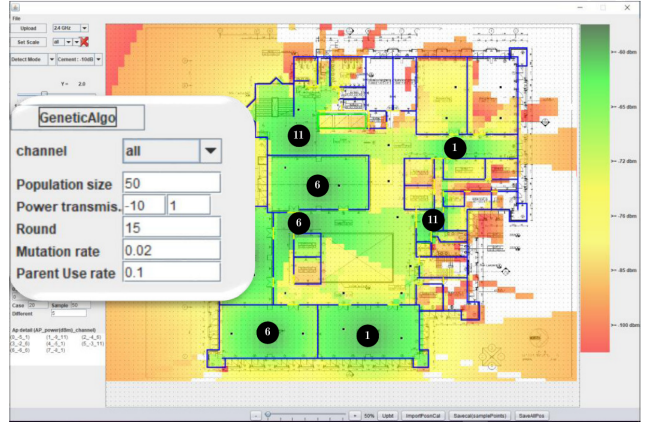


Fig. 4: User interface of the Wi-Fi tuning platform. Several parameters can be configured during the optimization process.

signal coverage and lowest level of interference. We picked N locations within the floor plan for performance evaluation. These selected N positions are represented as black circles in Fig. 4. The overall fitness function F is defined as the sum of fitness functions evaluated among N positions. The fitness function at each position i^{th} of interest is defined as f_i . The overall fitness function can be expressed as the sum of fitness function at each i^{th} position as follows:

$$F = \sum_{i=1}^N f_i \quad (4)$$

where f_i is the strongest signal detected at location i subtracted by a penalty value, defined by counting the inter-channel interference detected from adjacent wireless sources. The fitness function f_i can be written as

$$f_i = s_i - p_i \quad (5)$$

where s_i is the maximum RSSI detected at position i on the floor plan. Given $R = \{r_1, r_2, r_3, \dots, r_P\}$ the received signal is detected at position i :

$$s_i = \max(R). \quad (6)$$

p_i is the penalty cost that occurs when signal interference is found on the same channel as s_i . Given $V = \{v_1, v_2, \dots, v_M\}$ a set of signals detected on the


```

find fitness population 1
find geneFitness
gene(power_channel) -2_11,-8_1,1_6,-4_11,-10_6,-7_6,-9_1,-5_11,

Detect: 0
MostValIndex (AP_db): 0_-51.842968
penalty channel 11(AP_db_penaltyVal)
(0_-51.842968 -51.842968)(3_-79.23875_-24.44719)
tmpVal-penalty = -51.842968 - -76.29016
current total penalty = 24.447193

Detect: 1
...
Detect: 19
MostValIndex (AP_db): 1_-67.61533
penalty channel 1(AP_db_penaltyVal)
(1_-67.61533_-67.61533)
tmpVal-penalty = -67.61533 - -67.61533
current total penalty = 788.46625

Fitness = fs - fp = -1194.0405 - 788.46625 = -1982.5068

```

Fig. 5: Screenshot of the evolution process.

same channel as s_i , the cost of the penalty p_i can be expressed as

$$p_i = \max(V) - \sum_{j=1}^M (\max(V) + |\max(V) - v_j|). \quad (7)$$

Finally, the proposed fitness function defines the QoS of a WLAN. The higher the value of F , the better QoS the WLAN can offer.

4.2 Framework

Since JAVA GUI is cross-platform, we developed our Wi-Fi tuning application based on the JAVA programming language. Our program allows the network administrators to customize the testing environment by uploading a floor plan of the building as well as placing walls and building partitions. This framework was initially represented in [17]. The platform can retrieve the WLAN settings from the network controller and create a heatmap to represent the received signal strength indicators (RSSI) of Wi-Fi signals in a 3D heatmap, as shown in Fig. 4. During Wi-Fi deployment, an interruption in network services would trigger a reconfiguration of Wi-Fi parameters. A genetic algorithm is therefore introduced to find the optimal settings. All steps of the evolution process for the genetic algorithm are summarized in Fig. 5. Once the computation is complete, the fittest individual is obtained as a solution to the problem. The new setting values are sent to the access points and updated via the network controller. Since signal interference is unpredictable, Wi-Fi tuning must be performed regularly.

5. RESULTS AND DISCUSSIONS

In this section, we discuss the improvement in network performance after optimizing the proposed genetic algorithm. We also propose the following optimal parameters for the platform.

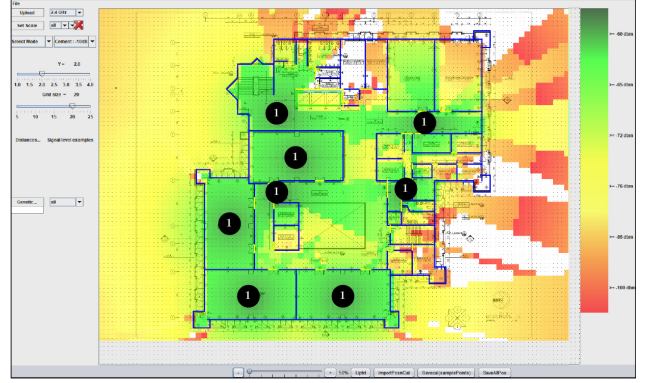


Fig. 6: User interface displaying Wi-Fi heatmap before applying the proposed genetic algorithm.

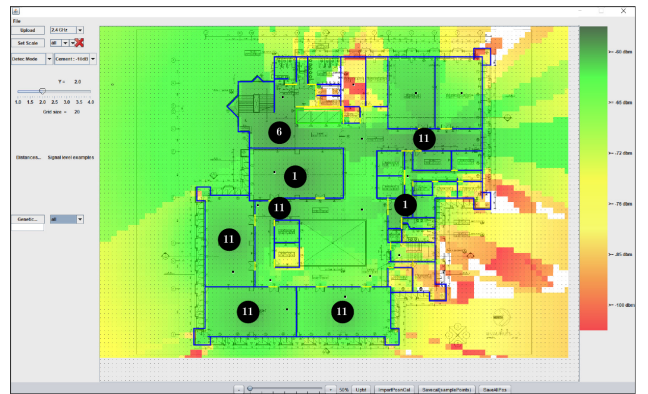
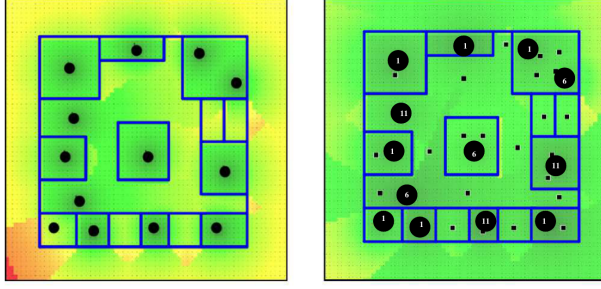


Fig. 7: User interface displaying Wi-Fi heatmap after applying the proposed genetic algorithm.

5.1 User Interface Display

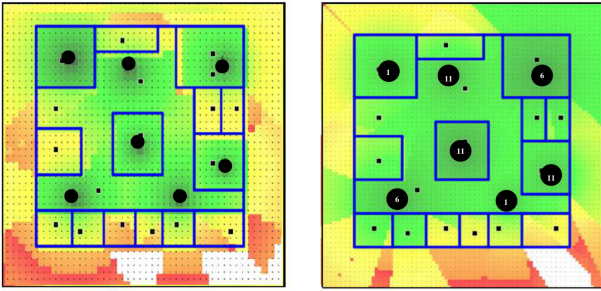
Our proposed platform visualizes a Wi-Fi heatmap, representing the wireless signal strength of each position on the floor plan. Wi-Fi tuning is triggered upon detection of interference. New settings are consequently updated for all access points in the WLAN system. Wi-Fi tuning could resolve any incidents potentially occurring in the WLAN in a real-time manner. From the network management perspective, this could save both time and investigation costs.

Figs. 6 and 7 represent the user interfaces before and after genetic computation. The black circles indicate the positions of the access points enumerated with their channel assignment. The black squares represent the position at which the performance metrics are evaluated. The platform could be observed to reconfigure the current setting and propose an optimal solution where the power level is stronger and covers a larger area of the floor plan for both dense and sparse networks as shown in Figs. 8 and 9, respectively. In terms of interference, Figs. 10 and 11 visualize the heatmap for all channels and per channel assignment. It can be observed that for channels 1, 6, and 11, signals from different access



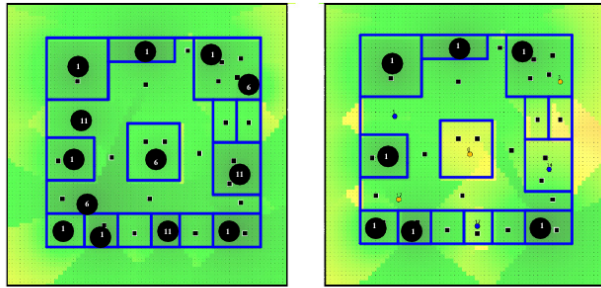
(a) before applying genetic algorithm (b) after applying genetic algorithm

Fig. 8: Wi-Fi heatmap (a) before and (b) after applying a genetic algorithm to a dense network configuration.



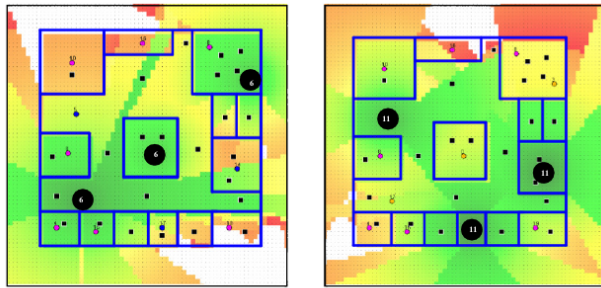
(a) before applying genetic algorithm (b) after applying genetic algorithm

Fig. 9: Wi-Fi heatmap (a) before and (b) after applying a genetic algorithm to a sparse network configuration.



(a) all channels

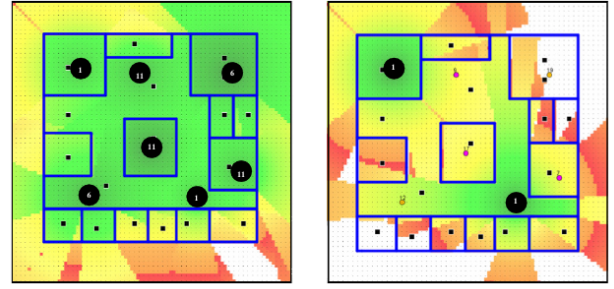
(b) channel 1



(c) channel 6

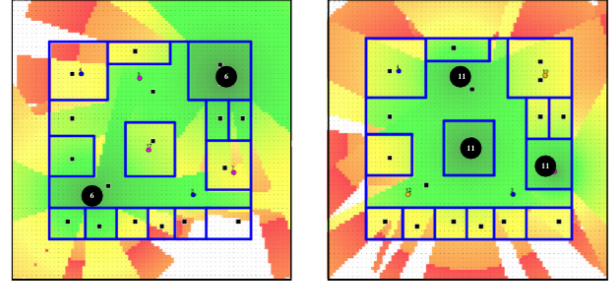
(d) channel 11

Fig. 10: Wi-Fi heatmap after applying a genetic algorithm to a dense network configuration for (a) all channels and specific channels: (b) 1, (c) 6, and (d) 11, respectively.



(a) all channels

(b) channel 1



(c) channel 6

(d) channel 11

Fig. 11: Wi-Fi heatmap after applying a genetic algorithm to a sparse network configuration for (a) all channels and specific channels: (b) 1, (c) 6, and (d) 11, respectively.

points hardly overlap. The platform could maintain interference levels in a satisfactory manner.

Thus, our proposed algorithm not only increases the Wi-Fi coverage area but also eliminates potential inter-channel interference issues. Interference could be prevented significantly by assigning different frequency channels to adjacent access points.

5.2 Parameter Settings

In this section, we discuss the optimal parameter settings for our proposed platform. The settings investigated include population size, mutual rate, replacement rate, and number of runs. The performance metrics under study rely upon the wireless coverage ratio, interference level, and computational time. The Wi-Fi coverage ratio is defined as the number of positions where detected Wi-Fi signal strength is above the -72 dBm threshold. The interference level found at the evaluated position is considered a penalty and its value must be deducted from the fitness value.

5.2.1 Population Size

Each population is defined as a pair of values between RSSI and the channel number. Population size is defined by the total number in the population. Fig. 12 illustrates the relationship between population size and the WLAN performance metrics. The results from running the experiment 100 times with the mutation ratio set to 0.0 indicate that a larger

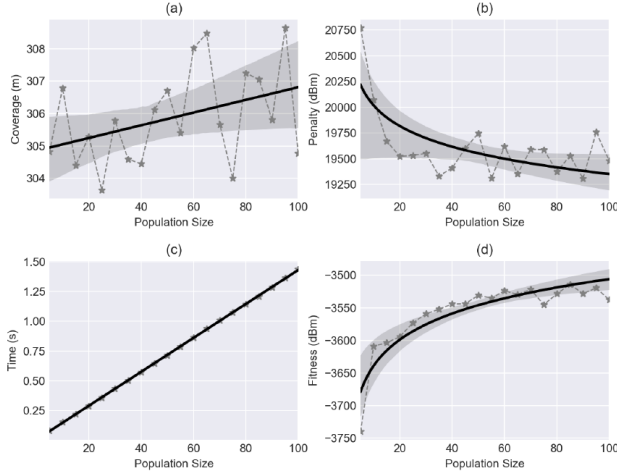


Fig. 12: Effects of population size on (a) Wi-Fi coverage, (b) penalty cost from signal interference, (c) computational time, and (d) fitness value

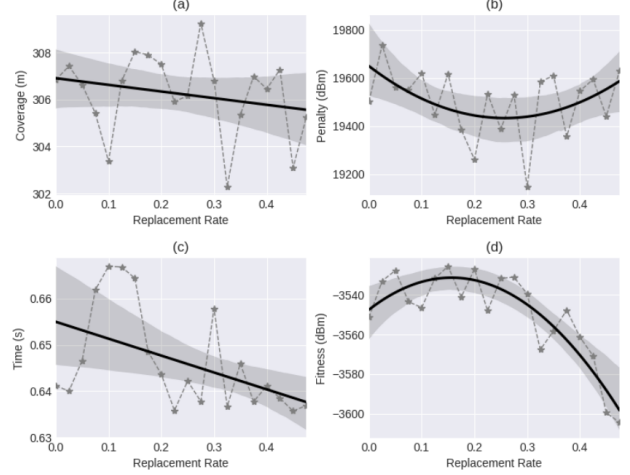


Fig. 14: Effects of replacement rate on (a) Wi-Fi coverage, (b) penalty cost from signal interference, (c) computational time, and (d) fitness value

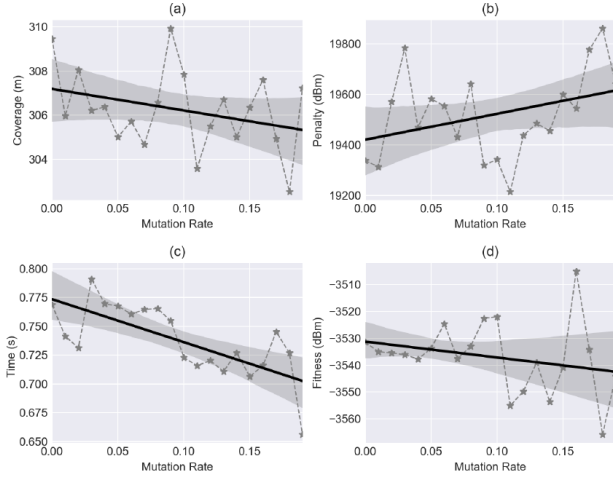


Fig. 13: Effects of mutation rate on (a) Wi-Fi coverage, (b) penalty cost from signal interference, (c) computational time, and (d) fitness value

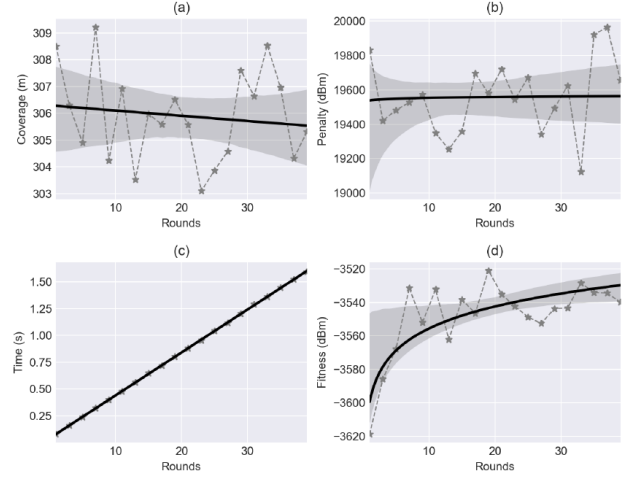


Fig. 15: Effects of number of experiments on (a) Wi-Fi coverage, (b) penalty cost from signal interference, (c) computational time, and (d) fitness value

population size yielded a higher coverage area and lower interference level. However, a higher population size provoked an increase in computational time. The fitness function started to converge into a constant value when the population size grew. Varying the population size between 60–100 resulted in a small difference to the fitness value.

5.2.2 Mutation Rate

In terms of mutation rate, the results in Fig. 13 show that a rise in the mutation rate tends to reduce Wi-Fi coverage and increase the interference level. Thus, increasing the mutation rate reduces the fitness value. Although the mutation rate enhances exploration during genetic evolution, a high mutation rate might prevent the optimization process from converging.

5.2.3 Replacement Rate

Generally, replacement strategies are introduced to maintain population diversity and avoid premature convergence. Increasing the replacement rate to a specific value, in this case up to around 0.2, caused a rise in the fitness value (Fig. 14). The main aim of adjusting the replacement rate is to find a trade-off between the exploration and intensification of the evolution algorithm. On the other hand, a replacement rate which is too high reduces the performance of the evaluation.

5.2.4 Number of Experiments

Fig. 15 illustrates the evolution of fitness value in terms of the number of times the experiments are run. The fitness value appears to converge with more than

20 experiments. On the other hand, a higher number of experiments increases the total computational time. Based on the previous experiments, we propose running the platform with a population size larger than 60, a mutation rate equal to 0.0, a replacement rate approximately equal to 0.2, and more than 20 experimental runs.

6. CONCLUSION

In this work, we propose a genetic algorithm-based Wi-Fi tuning platform capable of automatically re-configuring the WLAN settings to avoid inter-channel interference from third-party wireless sources when introduced into the WLAN system. The Wi-Fi tuning process adopts a genetic algorithm to mutually search for optimal settings in frequency channel selection and power transmission. In our experiment, the proposed algorithm leads to the enhancement of signal strength and coverage range while mitigating interference. Our proposed platform could assist network administrators in resolving instability and unavailability issues in network services. This work could be extended in the near future to include more configurable parameters of the WLAN settings.

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