Chapter 4
Utility-Based Dynamic Resource Allocation in IEEE 802.11ax Networks: A Genetic Algorithm Approach

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4.1 Introduction

Wireless local area networks (WLANs) have grown extensively over decades as advanced services such as ultra HD and 4K video, multimedia streaming, and rapid file transfer have become widespread among the general public. As a result, the number of personal devices, including smartphones, laptops, and high-definition multimedia devices, dramatically increases. As the number of devices increases, it leads to severe congestion, and the devices can hardly be connected to the Internet. Because of the congestion, the latest WLAN standard, IEEE 802.11ax [1], is primarily aimed at improving efficiency in high-density WLANs.

One of the most promising techniques in IEEE 802.11ax to deal with the dense deployment scenario is orthogonal frequency division multiple access (OFDMA), which has been adopted in various existing standards such as IEEE 802.16e WiMAX [2], long-term evolution (LTE), and 5G new radio (NR). In the OFDMA technique adopted in IEEE 802.11ax, the entire bandwidth is divided into several resource units (RUs). By allowing multi-user channel access and multi-user data

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transmission through orthogonal RU allocation, OFDMA can significantly reduce contention and preamble overhead.

On the other hand, as the number of access points (APs) is rapidly increased, each basic service set (BSS) becomes seriously overlapped. Therefore, a network-wide optimization for OFDMA resource allocation should be considered. Only a few studies considered adjacent BSSs; however, they only investigated interference mitigation issues through directional transmissions, and OFDMA resource allocation was not taken into consideration in detail.

In this chapter, we propose a utility-based dynamic resource allocation (UDRA) scheme in which a network-wide utility maximization problem is formulated to consider AP throughput and fairness among associated stations jointly. Since the formulated problem is an NP-hard problem, we map the optimization problem onto the genetic algorithm for a realistic WLAN environment. Extensive simulation results demonstrate that the proposed genetic algorithm has much lower complexity than the exhaustive search algorithm, while its performance in terms of throughput and fairness is nearly identical to the exhaustive search algorithm.

This chapter's key contribution is twofold. The first is that the frequency resource can be dynamically optimized using an interaction without any wired connectivity among APs. The simulation shows that depending on the given parameters, the network throughput of UDRA is 38% higher than conventional algorithms, or Jain's fairness index [3] of UDRA is higher than that of other algorithms. The second is that UDRA exhibits nearly the same performance thanks to the genetic algorithm compared to an exhaustive searching algorithm while the running time of UDRA is significantly reduced.

The remainder of this chapter is organized as follows. Sections 4.2 and 4.3 summarize the related works on OFDMA resource management. Sections 4.4 and 4.5 describe OFDMA operation in 802.11ax, which is a foundation for UDRA and demonstrates the formulated problem and the genetic algorithm to solve it. Simulation results and concluding remarks are given in Sects. 4.6 and 4.7, respectively.

4.2 Related Works

A fundamental problem for OFDMA resource management is how to allocate limited resources to the stations efficiently. That is, to increase spectral efficiency, stations should be allocated to appropriate time and frequency resource. Unfortunately, the problem of finding the optimal allocation was shown to be NP-hard in [4]. Therefore, many studies have focused on reducing computational complexity for resource management. The approaches to overcome this computational complexity can be categorized mainly into (1) solving sub-optimal solutions relying on relaxation [5–8] and (2) introducing alternative frameworks [9, 10].

A mixed integer nonlinear problem (MINLP) was formulated in [5], and the authors proposed a sub-optimal solution to the MINLP problem relying on convex relaxation. In [6], an optimal problem of assigning users to RUs while maximizing their sum rate was formulated, and a relaxed scheduling and resource allocation problem utilizing the divide-and-conquer approach was introduced. One approach assumes a more realistic and practical assumption. Since OFDMA is a technique for enabling multi-user transmission, the authors of [7] developed a resource allocation algorithm in which a scheduled duration is optimally determined to minimize the padding overhead occurring in the stations that are not transmitting at that time. In [8], the authors defined resource allocation as a selecting block for services, in order to meet some requirements such as the latency or traffic demands. The authors then proposed a sub-optimal and low-complexity algorithm to perform the assignment of blocks to services.

In [9], the authors defined a welfare function that reflected the total benefit covering all players and formulated the resource allocation problem as a game-theoretical framework. In [10], an auction-theoretic approach is proposed for the resource allocation problem to reduce the computation time. In this literature, several resource allocation schemes have been proposed, but most of them attempt to optimize OFDMA resource allocation within BSS without considering resource allocation information from adjacent BSSs.

Recent works on resource management consider a more challenging environment with multiple and densely deployed APs. In [11, 12], transmit beamforming was considered to mitigate the effect of inter-cell interference. The authors also investigated an achievable rate when transmit beamforming is applied. Indeed, this approach, such as transmit beamforming, is challenging to adopt in a WLAN because it requires a directional transmission. Although these studies considered adjacent BSSs, they only investigated interference mitigation issues through directional transmissions, and OFDMA resource allocation was not taken into consideration in detail.

4.3 Background on OFDMA and RU Allocation in IEEE 802.11ax

The basic OFDM principle is to utilize orthogonal subcarriers in frequency for data transmissions. Thus, broadband wireless radio channels with frequency-selective fading are replaced by a set of narrow-band channels (subcarriers) with flat fading. Each data symbol is then transmitted in one subcarrier, which is robust for multipath propagation. Additional advantages of OFDM are its highly efficient use of frequencies, its cost-effective and flexible digital signal processing, and its low complexity of MIMO principles.

802.11ax, which is the most widely used standard for WLAN, supports bands of 20 MHz, 40 MHz, 80 MHz, 80+80 MHz (combining two 80 MHz channels), and 160 MHz (single 160 MHz channel) [1]. In OFDMA transmission, the spectral band is divided into several resource units (RUs). In the time domain, the RU spans the

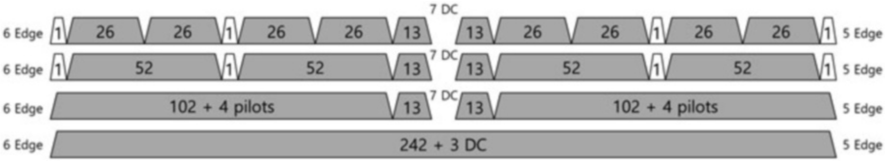

Fig. 4.1 Subdividing 20 MHz channel using OFDMA in IEEE 802.11ax

Table 4.1 Total number of RUs by channel bandwidth

RU type	20 MHz	40 MHz	80 MHz	160 and 80+80 MHz
26-subcarrier RU	9	18	37	74
52-subcarrier RU	4	8	16	32
106-subcarrier RU	2	4	8	16
242-subcarrier RU	1	2	4	8
484-subcarrier RU	N/A	1	2	4
996-subcarrier RU	N/A	N/A	1	2
2x996-subcarrier RU	N/A	N/A	N/A	1

entire data portion of the High Efficiency (HE) PLCP Protocol Data Unit (PPDU). In the frequency domain, it consists of a subset of successive subcarriers. In the frequency domain, RUs can be 26, 52, 106, 242, 484, or 996. RUs in HE multi-user (MU) PPDUs that use OFDMA transmissions can be one of these sizes. The position of the RU in the HE PPDU is fixed. Each RU, larger than 26, can be divided into two smaller RUs. The entire bandwidth can be used as a single 484-tone RU, or divided into two 242-tone RUs, each of which can be split into smaller RUs until a 26-tone RU is reached. When an RU is created, the AP assigns one RU to each user or a group of users for transmission. When bandwidth is split into RUs and is allocated to each user, the transmission is pure OFDMA, which can also be used for MU-MIMO if the RU is a 106 or higher subcarrier, then referred to as a joint transmission between MU-MIMO and OFDMA. Figure 4.1 illustrates how an 802.11ax system multiplexes a 20 MHz channel using different resource unit (RU) sizes. The smallest division of the channel can support up to 9 users simultaneously for every 20 MHz of bandwidth. The number of users that can be supportable for the RU type and various available channels are listed in Table 4.1. In this chapter, we follow the existing parameters regarding OFDMA.

4.4 System Model

In this section, UDRA, an optimization problem that jointly considers the network throughput and the fairness index in OFDMA resource allocation, is addressed. To this end, we first describe a system model on which UDRA is based and demonstrate

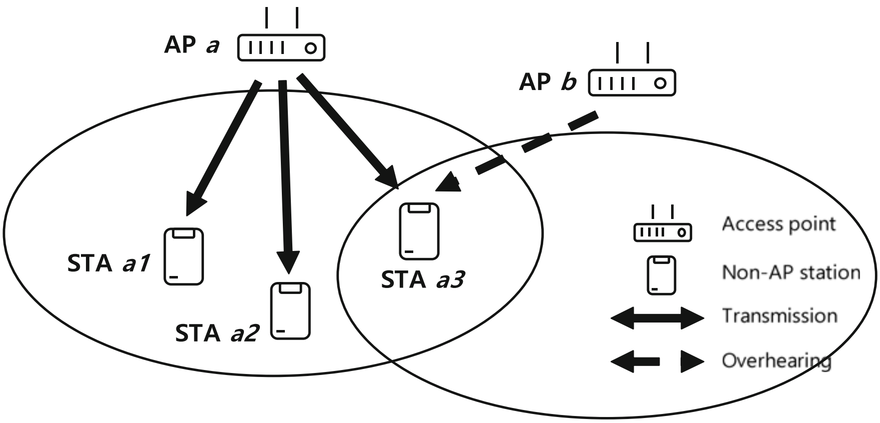

Fig. 4.2 Schematic representation of UDRA

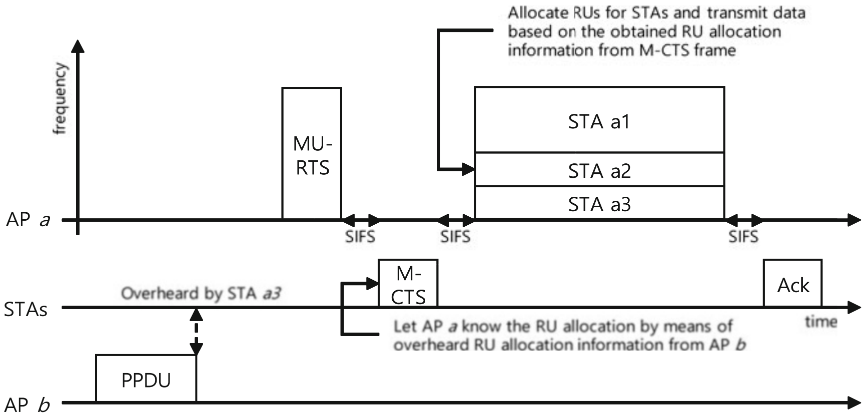

Fig. 4.3 The timing diagram of UDRA in the system model

an illustrative example of UDRA. Next, a modified CTS (M-CTS) frame structure, which is essential to operate UDRA, is followed.

In our model, each BSS consists of one AP and one or more STAs. Only downlink traffic from APs to STAs is considered since it occupies a dominant portion of traffic for WLAN applications. Furthermore, we assume that the AP's buffer to be transmitted to associated stations is in a saturated state, which means the APs always have frames to be sent.

Figures 4.2 and 4.3 show a schematic example of how UDRA works. In this example, as shown in Fig. 4.2, there are two APs, APs a and b, where STAs $a1$, $a2$, and $a3$ are connected to AP a. STA $a3$ is on the area where two transmission ranges are overlapped. The solid arrows and the dotted arrows stand for determined transmissions and overheard transmissions, respectively. Once STA $a3$ that resides in the overlapped area overhears a data frame from AP b, it will know RU

Frame Control	Duration/ID	TA	RA	Interference Strength	RU Allocation	Duration	FCS

MAC header

Fig. 4.4 A modified CTS (M-CTS) frame

information of AP b by means of the PHY preamble in the data frame. When STAs $a1$, $a2$, and $a3$ receive a multi-user request-to-send (MU-RTS) frame from AP a, all the STAs are required to respond with an M-CTS frame, which will be addressed in the next section. Besides, STA $a3$ reports the RU allocation information of AP b to AP a by including the information in the M-CTS frame, as shown in Fig. 4.3. As a result, AP a can obtain network-wide RU allocation information, which will then be used for the utility optimization problem in Sect. 4.5.

Some information, such as transmission duration and transmission signal power from adjacent BSSs, is required to formulate a network-wise utility maximization problem. Since an AP can receive the signal only from associated STAs in the existing IEEE 802.11, a new method to deliver the information collected by adjacent APs is needed. To this end, we introduce the M-CTS frame, which includes the identification (e.g., transmitter ID), overheard signal power, RU allocation information, and transmission duration of the overheard data frame. When a STA listens to a data frame whose destination is another STA, it first records the signal strength and time stamp. After that, the STA decodes the overheard data frame and detects the RU allocation information. Once AP solicits the STA via the MU-RTS frame, the STA transmits the M-CTS frame so that AP can know the above information.

Figure 4.4 shows the M-CTS frame structure. Interference Strength field describes the signal strength for letting the associated AP know the amount of interference that the STA suffers. The AP can be aware of the RU allocation status of adjacent BSS utilizing RU Allocation field. Duration field lets the AP know how long the transmission of adjacent BSS lasts. Although Interference Strength, RU Allocation, and Duration fields have not been defined in the existing CTS frame, we can modify some existing fields to describe them or define a newly designed frame format. Formatting these fields is beyond the scope of this chapter, and the formats of these fields are not restricted.

4.5 Utility-Based Dynamic Resource Allocation Scheme

In this section, an optimization problem that jointly considers the network throughput and the fairness [3] in OFDMA resource allocation is defined. Also, as a practical solution to the problem, we mapped UDRA to genetic algorithm in the following subsection.

4.5.1 Optimal Resource Allocation Problem Formulation

Let N and M be the number of STAs and the number of sub-channels, respectively. $Y = \{0, 1\}^{N \times M}$ represents the assignment matrix where an element of Y, $y_{n,m}$, is 1 if STA n occupies sub-channel m; otherwise, $y_{n,m} = 0$. Meanwhile, $I = \mathbb{R}^{N \times M}$ is the interference matrix where an element of I, $i_{n,m}$, is the value included in the Interference Strength field of the M-CTS frame. $S = \mathbb{R}^{N \times M}$ is the signal power matrix where its element, $s_{n,m}$, refers to the signal power of STA n in sub-channel m.

To jointly consider both throughput and fairness index, we need to calculate the normalized throughput and fairness. For the normalized throughput, signal-to-interference-plus-noise ratio (SINR) needs to be first defined. When STA n occupies sub-channel m and the assignment matrix is given by Y, SINR can be expressed as

$$SINR_{n,m}(Y) = \frac{t}{T} \cdot \frac{s_{n,m}[\text{mW}] \cdot y_{n,m}}{i_{n,m}[\text{mW}] \cdot N_0[\text{mW}]}, \tag{4.1}$$

where t is the length interfered by the adjacent AP, which can be obtained by overhearing data frames from adjacent AP, while T is the frame length in bytes. N_0 is the thermal noise, which is expressed as $-174 + 10\log_{10}\frac{B}{M}$ [13, 14] and $f[\text{mW}]$ represents that f is in a milli-watts scale. Then, the attainable throughput of STA n from sub-channel m is expressed as

$$c_{n,m}(Y) = \frac{B}{M} \cdot \log_2(1 + SINR_{n,m}(Y)). \tag{4.2}$$

Since there are M resource units, the total attainable throughput of STA n is given by:

$$c_n(Y) = \sum_{m=1}^{M} c_{n,m}(Y) = \sum_{m=1}^{M} \frac{B}{M} \cdot \log_2(1 + SINR_{n,m}(Y)). \tag{4.3}$$

Using Eq. (4.3), the attainable network throughput per transmission and the fairness index can be derived. First of all, the attainable network throughput per transmission can be expressed as

$$c(Y) = \sum_{n=1}^{N} c_n(Y). \tag{4.4}$$

Meanwhile, the Jain's fairness index can be computed as

$$f(Y) = \frac{\left(\sum_{n=1}^{N} c_n(Y)\right)^2}{N \cdot \sum_{n=1}^{N} c_n(Y)^2}. \tag{4.5}$$

Using Eqs. (4.4) and (4.5), the utility to balance the throughput and fairness can be defined as

$$u(Y) = \alpha \cdot c(Y) + (1 - \alpha) \cdot f(Y), \tag{4.6}$$

where α is a weighting factor to prioritize either the attainable network throughput or the fairness between STAs. For example, once α approaches to one, the attainable network throughput will be prioritized. On the contrary, when α approaches to zero, the fairness among STAs is preferred and the fairness will be emphasized.

Finally, the utility optimization problem can be expressed as

$$\begin{aligned} &\max_{Y \in \{0,1\}^{N \times M}} u(Y), \\ &s.t. \sum_{n=1}^{N} y_{n,m} \le 1, \forall m \in \{1, 2, \ldots, M\}, \end{aligned} \tag{4.7}$$

where the constraint represents that two or more STAs cannot occupy the same sub-channel.

Assuming the signal powers of sub-channels that suffer channel fading are independently and identically distributed (i.i.d.), the complexity of the utility optimization problem in (4.7) can be $O(2^{M \cdot N})$ with big-O notation, which is known as NP-hard. Thus, we will explain a practical genetic algorithm for this problem in the next subsection.

4.5.2 Genetic Algorithm

Genetic Algorithm (GA) is a meta-heuristic popular in computer science [15]. GA applies the principle of survival of the fittest to produce a better and better approximation to the solution of the problem that GA is trying to solve. For each generation, a new set of approximations is created through the process of selecting individuals according to their level of fitness in the problem domain, and propagating the individuals together using operators borrowed from genetic processes carried out in nature (e.g., crossover and mutation) is created. This process, as occurs in natural adaptation, leads to the evolution of groups of individuals who adapt better to the environment than the individuals from which they were created.

Genetic algorithm is a well-known heuristic algorithm to deal with the NP-hard problem, which emulates the evolution process in nature and the process consists of natural selection, reproduction, and mutation.

In the genetic algorithm, the following concepts are employed to find the optimal solution. First of all, a *chromosome* is a set of parameters, which defines a proposed solution to the problem that the genetic algorithm is trying to solve. For standard optimization algorithms, this can be the domain of the objective function. This set of chromosomes is called *population*. On the other hand, the *fitness function* represents a function to be optimized, i.e., objective function, and the *fitness value* is the output of the fitness function when one of chromosomes is given by an input.

For each *generation*, a predetermined number of chromosomes are arbitrarily selected and their fitness values are compared among them. After the comparison, the natural selection process starts with the selected chromosomes that have greater fitness value than others. This selected chromosomes are then *reproduced* for the next generation. Above-mentioned procedure continues for a certain number of generations.

A problem mapping the optimization algorithm on genetic algorithm is depicted in Fig. 4.5. In our RU allocation problem, we denote an assignment matrix, Y, as a *chromosome*. A *fitness value* is calculated for each chromosome. In this problem, the fitness value can be a utility, $u(Y)$, as seen in Eq. (4.7). Chromosomes are randomly generated within the universal set, which is a binary matrix with M rows and N columns that satisfy constraints.

A detailed procedure for solving the RU allocation problem can be represented as follows. This procedure is depicted in Algorithm 3. First of all, the generation number, i, is initiated (see line 1). Once an AP transmits MU-RTS to associated STAs, some respond to MU-RTS by transmitting M-CTS if they overheard any data frames from adjacent APs. In so doing, the AP can obtain the interference matrix I and the signal power matrix S (see line 2). At the first generation, the AP randomly generates j_{max}, a predefined population size, assignment matrices. After that, the AP calculates the utility for each matrix (see lines 6 to 9). Next, some “winner” matrices are survived, and the next generation will be triggered. This procedure continues until the difference between the utility of the ith generation and the $(i-1)$th is smaller than a predefined threshold, $u_{threshold}$, or the maximum running time, $T_{maxstall}$, elapsed.

Even though the exhaustive search requires exponential processing time, the genetic algorithm has a polynomial executing time because it runs up to $i_{max} \cdot j_{max}$ cycles at most and each cycle requires polynomial processing time. In the literature, several studies have been conducted to determine the optimal number of populations, j_{max}. Since the derivation of the optimal number is beyond the scope of this chapter, j_{max} is set to $10 * M \cdot N$ according to [16].

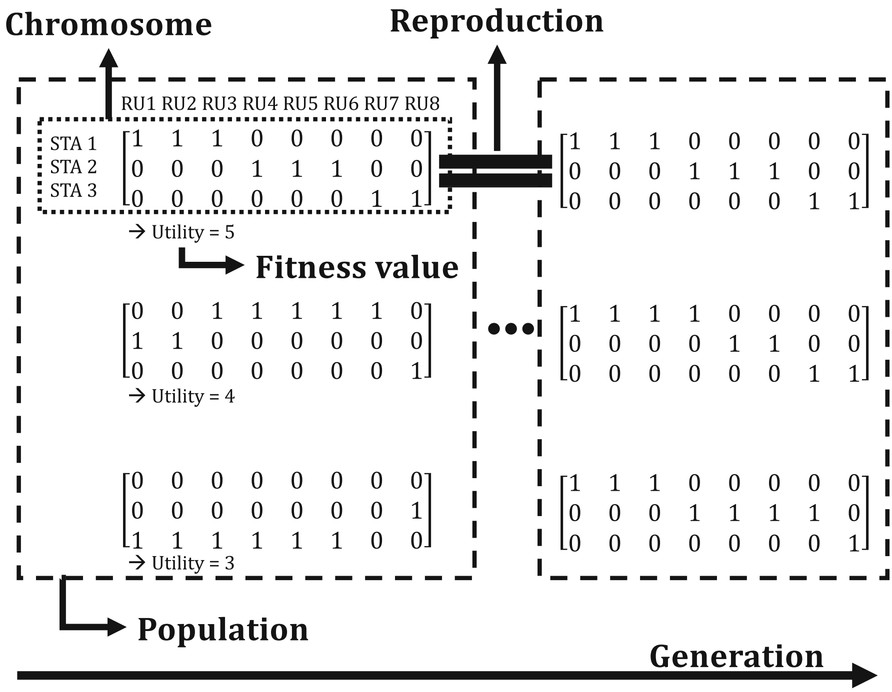

Fig. 4.5 Mapping from UDRA to genetic algorithm

4.6 Simulation Results

Extensive simulations have been conducted by a MATLAB simulator to evaluate the performance of UDRA. Simulation parameters are based on the IEEE 802.11ax standard. Defined parameters are summarized in Table 4.2. First of all, we show how UDRA performs and how fast it runs compared to an exhaustive search. After that, we analyze the throughput and fairness aspects of UDRA compared to conventional algorithms for α and examine the effect of α in detail.

4.6.1 UDRA vs. Exhaustive Search

Complexity and the resulting performance degradation between exhaustive search and UDRA are presented in Fig. 4.6. Specifically, this figure shows how much can UDRA reduce its running time compared to exhaustive search and how much does UDRA underperform exhaustive search. Since the complexity of exhaustive search grows exponentially, the simulations are conducted in a small-scale environment with 2 to 4 stations and 8 RSUs.

Algorithm 3 Genetic algorithm for UDRA

$i = 1$
Obtain the interference matrix I and the signal power matrix S
Randomly generate a set of j_{max} assignment matrices $\mathbb{Y}_i$ which meet the constraint of the optimization problem in Eq. (4.7)
while $|u_i - u_{i-1}| > u_{threshold}$ for $T_{maxstall}$ times **do**
    $j = 1$
    for each assignment matrix $Y_{i,j}$ in $\mathbb{Y}_i$ **do**
        Calculate a utility for the assignment matrix by means of Eqs. (4.1)–(4.7)
        $j = j + 1$
    end for
    Calculate the best utility, $u_i = \max_{\forall j} u(Y_{i,j})$
    Select a portion of the assignment matrices and leave them for the next population
    Randomly generate assignment matrices and make a set of assignment matrices with the survived assignment matrices for the next generation $\mathbb{Y}_{i+1}$
    $i = i + 1$
end while
Determine the assignment matrix that makes the utility maximum value
return assignment matrix Y

Table 4.2 Simulation parameters

Parameter	Value
Multiple access scheme	OFDMA
Channel bandwidth	80 MHz
RU type	106-subcarrier RU
Number of RUs	8
Noise model	Thermal noise
Optimization methodology	Genetic algorithm
Number of populations	$10 * M \cdot N$
Max stall generations	150

As shown in Fig. 4.6, UDRA exhibits the same performance when the number of STAs is 2. Meanwhile, UDRA shows degraded throughput compared with the exhaustive search by 3.56 and 3.77% when the numbers of STAs are 3 and 4, respectively. Even though the genetic algorithm has slightly reduced throughput, it significantly reduces running time compared with the exhaustive search. For example, UDRA can achieve 31.25, 2.93, and 0.24% of the exhaustive search for the running time for the cases with 2, 3, and 4 STAs, respectively.

4.6.2 Network-Wise Throughputs and Fairness Indexes

Figures 4.7 and 4.8 show the total network throughput and the Jain's fairness index for UDRA, round-robin algorithm, and randomly allocation algorithm as the number of stations varies. From Fig. 4.7, it can be seen that the throughputs of round-robin

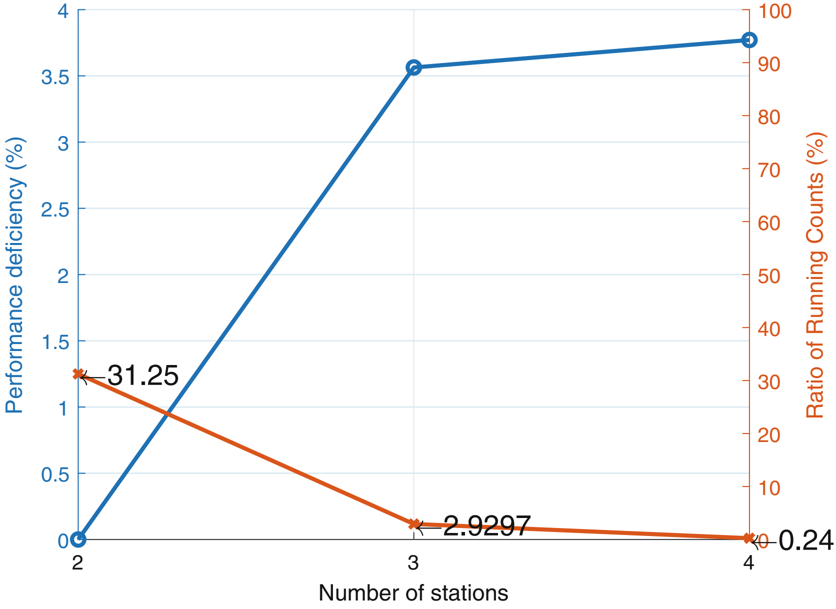

Fig. 4.6 UDRA vs. exhaustive search

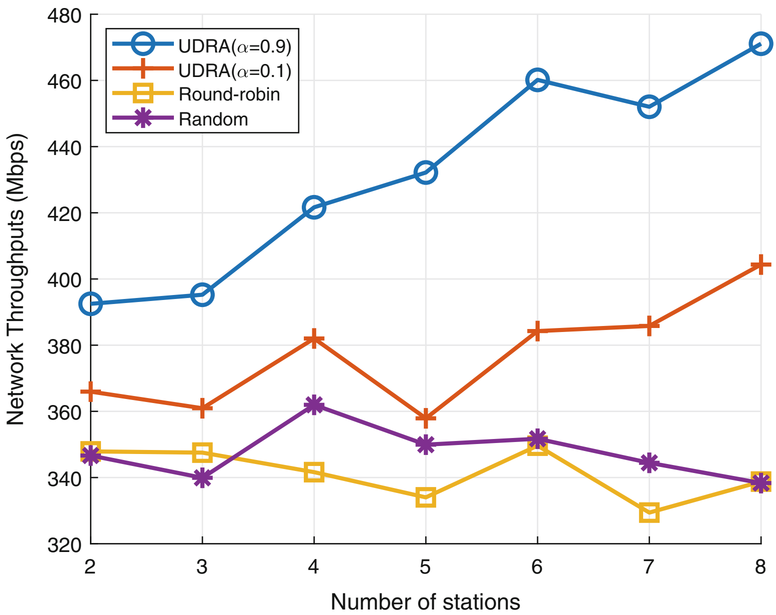

Fig. 4.7 Throughputs

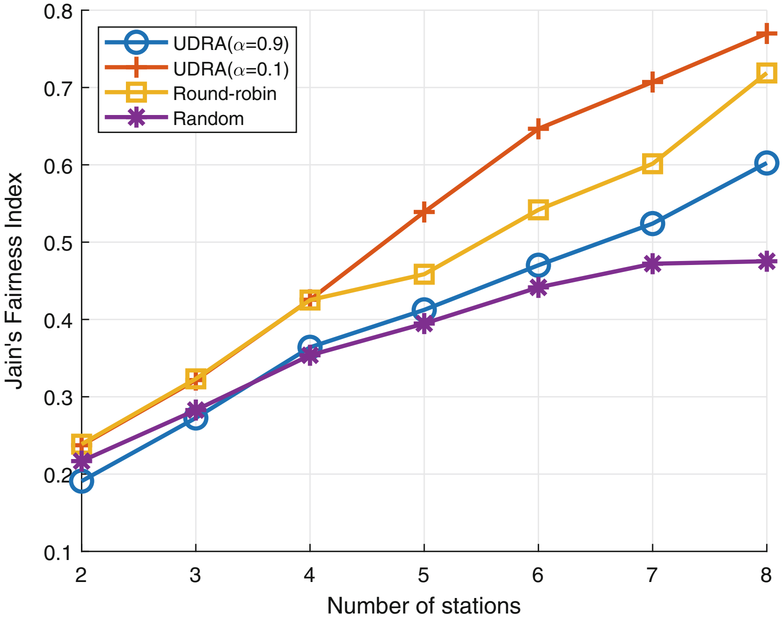

Fig. 4.8 Jain's fairness indexes

and random allocation hardly increase as the number of STAs increases. This is because the total resource, i.e., the channel bandwidth, to be allocated is identical regardless of the number of stations, and they allocate the resources evenly to the stations in the long term. On the other hand, the AP in UDRA can finely allocate RUs to STAs by solving the formulated optimization. Therefore, it can be found that the network throughput of UDRA increases with the increase in the number of STAs, although the total resource does not vary. Specifically, UDRA with $\alpha = 0.1$ and with $\alpha = 0.9$ exhibits from 5.6 to 19.5% and from 13.2 to 39.2% higher throughputs compared to conventional algorithms as the number of stations varies, respectively. Meanwhile, throughput of UDRA with $\alpha = 0.1$ is 16.9–27.0% lower than that with $\alpha = 0.9$. This is because UDRA with $\alpha = 0.1$ prioritizes the normalized fairness rather than the normalized throughput.

Figure 4.8 shows the Jain's fairness index depending on the number of STAs. It can be seen that overall fairness trends consistently increase as the number of stations increases. UDRA with $\alpha = 0.1$ outperforms other algorithms in terms of fairness. Also, it can be seen that the fairness indexes of the random algorithm are inferior to the other algorithms. This is because the random algorithm does not consider whether an associated station is affected by adjacent AP's transmission or not, and this causes severe collisions, especially when the number of APs becomes large.

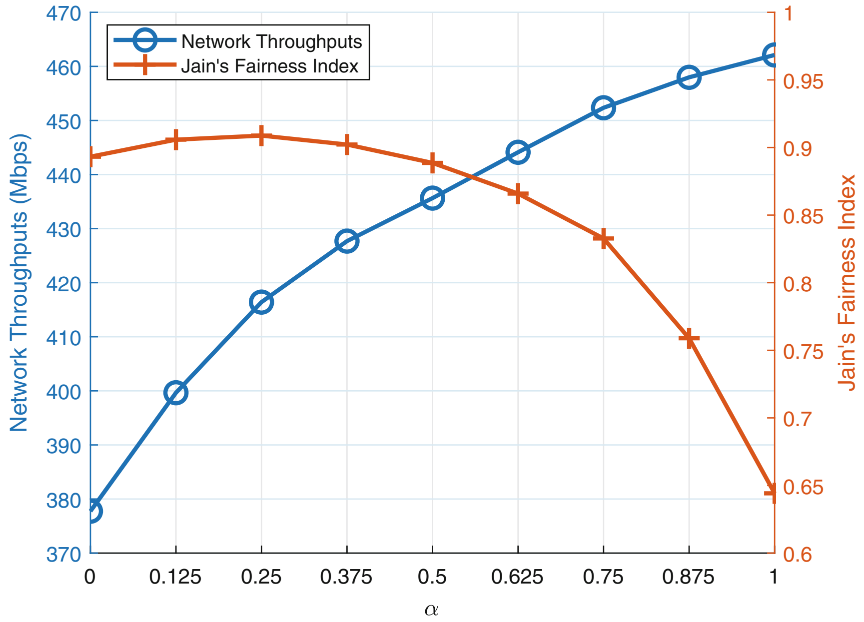

Fig. 4.9 Effect of α

Figure 4.8 also shows the Jain's fairness index depending on the number of STAs. It can be seen that overall fairness trends consistently increase as the number of stations increases for the same reason mentioned above.

As shown in Figs. 4.7 and 4.8, the performance of UDRA is highly affected by α, and thus we analyze the effect of α. From Fig. 4.9, the throughput becomes higher while the fairness index gets smaller as α increases. This can be explained as follows. When α is high, the normalized throughput is emphasized, and thus each AP tends to allocate the best sub-channel to the best STA, leading to a severe imbalance of throughput. For example, an STA whose SINR is much stronger than other STAs will occupy most of the RUs, and thus the STA can get much higher throughput for a high value of α.

On the other hand, the normalized fairness is prioritized when α is low, and therefore each AP tends to allocate sub-channels fairly to the STAs. In this case, STAs residing in the overlapped area, e.g., station $a3$ in Fig. 4.2, will have an opportunity to access the medium since it has a higher opportunity to suffer higher interference than station $b1$. Apparently, such fair resource allocation leads to degraded network throughput, and thus the optimal value of α should be carefully chosen under the service requirements.

Besides, the slope of network throughputs increases nearly linearly, whereas the slope of Jain's fairness index tends to decrease sharply as seen in Figs. 4.7 and 4.8. When $\alpha = 1$, UDRA would behave as if it allocates RUs to the stations in a greedy manner, and thus the metric of fairness becomes degraded. Also, at $\alpha = 1$, the network throughput increases linearly, while the fairness index decreases sharply, so a small amount of concern for fairness can result in a quite fair resource allocation while performing large throughputs.

4.7 Conclusion

In this chapter, a utility-based dynamic resource allocation algorithm for OFDMA-based wireless networks is proposed. By using M-CTS, stations residing in overlapped area can overhear RU allocation and interference power. Then the station can deliver information to its associated AP and thus the AP can utilize it for utilizing RUs efficiently. After that, AP operates utility maximization problem with a factor, α. By adjusting α, the throughput as well as the fairness can be achieved. We next formulate genetic algorithm that operates in polynomial running time. The simulation results demonstrated that the genetic algorithm has few or no performance drop while its running time remarkably decreases.

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