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Intelligent optimisation induced 5G spectrum dynamic allocation

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Abstract: The 5G communication network system provides services with large capacity, high speed and low latency, which may make the shortage of spectrum resources become more and more serious. However, most of the existing spectrum allocation algorithms are based on continuous spectrum allocation and do not consider the needs of users. The continuous spectrum allocation will generate many spectrum fragments that cannot satisfy user's requirements. These spectrum fragments cannot be fully utilised, which results in a waste of spectrum. In order to tackle this issue, this paper adopts a spectrum allocation algorithm that can jointly consider both the needs of users and discontinuous spectrum aggregation. In this algorithm, non-contiguous spectrum fragments can be aggregated to meet the user demand of spectrum, which can make full use of small spectrum fragments to avoid waste and improve spectrum utilisation.

Keywords: 5G spectrum; spectrum allocation; spectrum segment; deep learning; distributed spectrum allocation.

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1 Introduction

From the perspective of the development history of mobile networks, it is difficult to achieve full coverage for 5G network merely using one technology or architecture. Multiple radio access technologies (M-RAT) (Ong and Khan, 2010; Shihab et al., 2023) will coexist for a long time in the future, while the integration of multiple technologies and multiple architectures is an inevitable trend. The 5G heterogeneous access network (Peng et al., 2015; Kaur et al., 2023) will be a heterogeneous hybrid network composed of multiple access networks such as GSM, WLAN, Bluetooth, 3G, 4G and 5G, Internet of Things. Owing to differences in business service, coverage and technical details of various wireless access networks, none of the wireless access networks can fully meet the requirements for coverage, delay, transmission rate, cost, etc. What 5G network adopts is not independent, brand-new wireless access technology (Mohanta, 2023). The 5G network accommodates the existing wireless access technologies, including 2G, 3G, 4G and Wi-Fi, and some latest complementary wireless access technologies. It is an integrated solution. To a certain extent, 5G network will be a truly converged network (Sufyan et al., 2023). It will provide high-speed, safe and free communication between persons, person and thing, thing and thing based on integration and unified standards.

1.1 Background

The 5G network can provide environment-conscious, user-centric personalised content and services (Kumar et al., 2024), which is widely used in Internet of Things (Zhu et al., 2021), smart home (Li et al., 2024a), consumer electronics (Li et al., 2024b). Obviously, it is completely different from the goals of 3G/4G networks, which mainly consider improving the peak rate and spectrum efficiency. The 5G network no longer emphasises the peak rate blindly, but puts the user experience first. The 5G network is a pan-technology era. Multi-service systems, multi-access technologies and multi-level coverage integration have become important features of 5G network. In the future 5G era, people have higher and higher requirements for communication

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experience in various application scenarios, such as consistent high-quality business experience in any place or any environment (the borderless high speed data business services). However, the requirements of user service are infinite, while the spectrum resources are limited. In the 5G network era, the wireless spectrum resources (Hu et al., 2018; Xu et al., 2024) become scarce due to the development trend of broadband communication networks and various services. It becomes an emergent topic to improve the utilisation of spectrum resources in continuous development of wireless communication services (Bi et al., 2009, 2010) and signal processing and transmission (Zhou et al., 2023, 2018; Zheng et al., 2023). Dynamic spectrum allocation (Wang et al., 2019, 2023; Perera et al., 2024) is one of the effective ways to solve the problem of scarcity of spectrum resources.

1.2 Motivation

In recent years, the problem of dynamic spectrum allocation in a heterogeneous network environment has attracted widespread attention from academic researchers and industrial practitioners (Belikaidis et al., 2017; He et al., 2024). The proposed schemes include spectrum allocation scheme based on graph theory (Tan et al., 2011; Wang et al., 2024), spectrum allocation scheme based on game theory (Xu et al. 2013; Debbabi et al. 2023), spectrum allocation scheme based on auction bidding (Dong et al., 2015; Hui et al., 2023) and spectrum allocation scheme based on reinforcement learning theory (Wang et al., 2019; Ju et al., 2023). These solutions only consider the problem of dynamic spectrum allocation in the homogeneous network environment of a single operator, and do not involve the problem of dynamic spectrum allocation in the heterogeneous network convergence scenario of multiple operators. Some of the solutions in the literature adopt dynamic spectrum allocation solutions for certain hotspots, which are the perspective of a single wireless access network and neglect the spectrum allocation of other wireless access networks. The utilisation rate of spectrum resources is not high. In addition, the existing dynamic spectrum scheme is based on manual calculation or the experience and knowledge of engineers to provide a feasible spectrum allocation scheme. The associated cost is relatively high and the response speed is slow. It is difficult to adapt large-scale dynamic spectrum allocation problems.

This paper adopts a self-learning-based dynamic spectrum allocation scheme by using deep learning. The proposed scheme can be suitable for the 5G heterogeneous access network. It optimises the spectrum allocation between networks and spectrum allocation within the network to improve the spectrum resource utilisation efficiency of entire 5G heterogeneous access network system and reduce spectrum allocation cost.

1.3 Contributions

The main contributions of this paper are summarised as follows:

First, a deep learning-based self-learning dynamic spectrum allocation scheme is proposed for 5G heterogeneous access network.

Second, the self-learning dynamic spectrum allocation method improves spectrum resource utilisation efficiency and reduces spectrum allocation cost.

Third, the self-learning dynamic spectrum allocation method is evaluated in simulation environment.

The rest of this paper is organised as follows: Section 2 proposes the deep learning-based dynamic spectrum allocation scheme for 5G heterogeneous access networks; Section 3 provides experiments and simulation to evaluate the proposed dynamic spectrum allocation scheme; Section 4 summarises the conclusions and future work.

2 Unified representation for 5G heterogeneous access networks and dynamic spectrum allocation scheme

2.1 Problem description

The description and expression methods of wireless resource in different wireless access networks differ from each other. The unified description and representation method for wireless resources is a prerequisite for comprehensive management of 5G heterogeneous access network resources. This paper establishes a unified features description and expression method for 5G heterogeneous access network resource. The wireless spectrum resources and user requirements are represented as the vector in a generalised vector resource space. It establishes spectrum resource constraints to divide vector resources into available vector resources, used vector resources and forbidden vector resources by using the distribution of spectrum resources. Deciding the usage of spectrum resources is converted as matching the available resource vector and demand resource vector. For incomplete, inconsistent and uncertain resource information, the generalised vector resource spatial grid is used to implement the identification, aggregation, organisation and description of resource characteristic information, and to establish a unified heterogeneous network spectrum resource representation library. The spectrum resources of each wireless communication network are collected into a library by using the unified heterogeneous network spectrum resource feature description.

Let R^j represent the spectrum resource of the wireless access network j. The spectrum resource R^j consists of n continuous channels which are denoted as $r_1^j, \ldots, r_i^j, \ldots, r_n^j$. During a cycle T, the state of each channel in the spectrum resource is invariable. For the next cycle, the state of each channel in the spectrum resource may change. Therefore, for current cycle T, the state of channel r_i has two possibility: idle state and occupied state, which is represented as follows:

$$x_{r_i}^t = \begin{cases} 0, & \text{channel is under idle state at time t} \\ 1, & \text{channel is occupied at time t} \end{cases} \quad (1)$$

The features of spectrum resource R^j can be abstracted as following triple.

$$R^j = \left\langle ID\left(R^j\right), SA\left(R^j\right), DA\left(R^j\right)\right\rangle \tag{2}$$

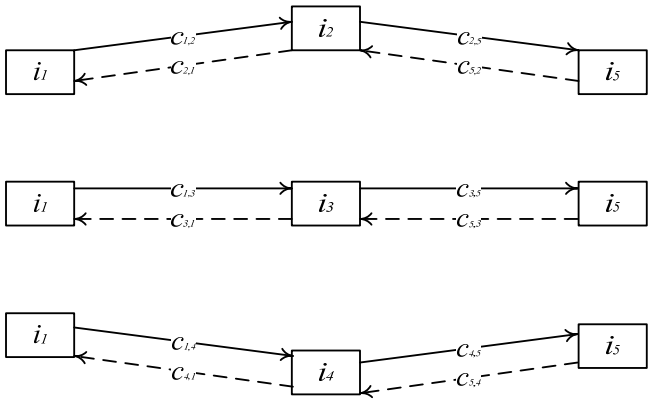
In the equation (2), $ID\left(R^j\right)$ is the unique identifier of a spectrum resource. In the whole heterogeneous network system, the spectrum resource has a global unique identifier. The $SA\left(R^j\right)$={primary user information, primary user's resource reallocation preference, channel number} is the static information description set of spectrum resource, in which the primary user information represents the primary information of spectrum resource and the primary user's resource reallocation preference is that the spectrum resource owner reallocates the spectrum resource when the secondary user applies for the free channel of the spectrum resource. The $DA\left(R^j\right)$ represents the dynamic description set of spectrum resource R^j, which is represented as $DA\left(R^j\right)$={idle state description, maximum idle block}. The idle state description represents the idle condition of each channel of spectrum resource in the period t, which is denoted as $X^t_{R^j} = \{x^t_{r_1^j}, \ldots, x^t_{r_n^j}\}$. The maximum idle block represents maximum continuous free channel blocks of spectrum. For instance, the channel state description of spectrum resource R^1 in wireless access network is represented as $X^t_{R^1} = 01011000110$, then the maximum idle block of spectrum resource R^1 during period t is the continuous idle blocks 6, 7 and 8.

By using the unified description for 5G heterogeneous access network spectrum resource, the spectrum resources of each wireless access network can be gathered into a spectrum resource vector library. The spectrum resources vector library perceives the usage state of each access network in time by using cognitive radio technology.

2.2 Deep learning-based dynamic spectrum allocation scheme

In this section, we will adopt cognitive deep learning (Wang et al., 2016; Bega et al., 2019) to solve the dynamic spectrum sharing and allocation problem for 5G heterogeneous access network. The node in cognitive deep learning is termed as cognitive node. Each source cognitive node is expected to communicate with the associated destination cognitive node to get the spectrum in spectrum resource library. The source cognitive node can connect to destination cognitive node directly or through some intermediate cognitive nodes which are determined by spectrum allocation strategy or bandwidth efficiency. The information exchange between cognitive nodes is determined by dynamic spectrum long memory and dynamic spectrum short memory. The spectrum of cognitive node and the total spectrum of wireless network are denoted as R_i^j and R_{total}, respectively. The spectrum allocation is written as $R^T = R_{i,t} + R_{j,t}$ in which $R_{i,t}$ and $R_{t,i}$ represent spectrum sharing between cognitive nodes. The R^T is initialised as the smallest total spectrum to make sure the total spectrum allocation for each channel. Then, the threshold spectrum is obtained by participation node spectrum sharing ratio. When the allocated spectrum is less than the threshold spectrum, the participation node spectrum sharing ratio is smaller than the required minimum spectrum. The neural network achieves the requirement of end-to-end spectrum allocation R^T. An illustration of spectrum allocation between cognitive nodes is shown in Figure 1.

Figure 1 The illustration of cognitive node for spectrum sharing (see online version for colours)



In Figure 1, cognitive node i_1 and cognitive node i_2 share the spectrum for $0 \le p \le p_{i_1}$, cognitive node i_1 and cognitive node i_3 share the spectrum for $p_{i_1} \le p \le p_{i_2}$, cognitive node i_1 and cognitive node i_4 share the spectrum for $p_{i_2} \le p \le 1$ by using orthogonal compress forwarding. When the spectrum allocation between cognitive nodes is stable, the information in cognitive nodes is encoded or decoded by using original codebook. The information is transmitted to the destination cognitive node in the link. The spectrum allocation should satisfy the following inequalities.

$$\begin{aligned}
R_{i_1,i_2} &\le \sum_0^{p_1} p_{i_1} \log\left(1 + \frac{c_{i_1,i_2} Q_{i_1,i_2}}{M_0}\right) \\
R_{i_1,i_3} &\le \sum_{p_{i_1}}^{p_{i_2}} \left(p_{i_2} - p_{i_1}\right) \log\left(1 + \frac{c_{i_1,i_3} Q_{i_1,i_3}}{M_0}\right) \\
R_{i_1,i_4} &\le \sum_{p_{i_2}}^{1} \left(1 - p_{i_2}\right) \log\left(1 + \frac{c_{i_1,i_4} Q_{i_1,i_4}}{M_0}\right) \\
R_{i_2,i_1} &\le \sum_0^{p_1} p_{i_1} \log\left(1 + \frac{c_{i_2,i_1} Q_{i_2,i_1}}{M_0}\right) \\
R_{i_3,i_1} &\le \sum_{p_{i_1}}^{p_{i_2}} \left(p_{i_2} - p_{i_1}\right) \log\left(1 + \frac{c_{i_3,i_1} Q_{i_3,i_1}}{M_0}\right) \\
R_{i_4,i_1} &\le \sum_{p_{i_2}}^{1} \left(1 - p_{i_2}\right) \log\left(1 + \frac{c_{i_4,i_1} Q_{i_4,i_1}}{M_0}\right)
\end{aligned} \tag{3}$$

The p_{i_1} is the spectrum allocation for the transmission from cognitive node i_1 to i_2, the $p_{i_2} - p_{i_1}$ is the spectrum

allocation for the transmission from cognitive node i_1 to i_3 and the $1-p_{i_2}$ is the spectrum allocation for the transmission from cognitive node i_1 to i_4. Minimising total spectrum allocation R^T requires to optimise the parameters p_{i_1}, p_{i_2}, Q_{i_1,i_2}, Q_{i_1,i_3}, Q_{i_1,i_4}, Q_{i_2,i_1}, Q_{i_3,i_1} and Q_{i_4,i_1}. The optimisation is written as follows:

$$O_{total}^{i_1} = \min_{p_{i_1},p_{i_2},Q_{i_1,i_2},Q_{i_1,i_3},Q_{i_1,i_4},Q_{i_2,i_1},Q_{i_3,i_1},Q_{i_4,i_1}} \left(p_{i_1}Q_{i_1,i_2} + \left(p_{i_2}-p_{i_1}\right)Q_{i_1,i_3} + \left(1-p_{i_2}\right)Q_{i_1,i_4} + p_{i_1}Q_{i_2,i_1} + \left(p_{i_2}-p_{i_1}\right)Q_{i_3,i_1} + \left(1-p_{i_2}\right)Q_{i_4,i_1}\right) \quad (4)$$

Let $R_{i_1} = \min\left(R_{i_1,i_2}, R_{i_1,i_3}, R_{i_1,i_4}\right)$ and $R'_{i_1} = \min\left(R_{i_2,i_1}, R_{i_3,i_1}, R_{i_4,i_1}\right)$, then R^T u

$$R^T \le R_{i_1} + R'_{i_1} \quad (5)$$

The spectrum needs to be allocated in the stage of pre-allocated channels. The information is transmitted from source cognitive node by using spectrum allocation scheme for the first channel in the first link. Then, the information continues to be transmitted for the second channel in the second link. Let CN_i denote the *i*-th sending cognitive node that has unit variance and zero mean, p represent the associated frequency slot by using dynamic spectrum short memory, $C_{i,j}$ represent route magnitude gain between cognitive node i and j, and $n_{i,j}$ be the noise with zero mean and variance $\sigma^2 > 0$. The signal of *j*-th receiving cognitive node is from the *i*-th sending cognitive node in the frequency slot p. The dynamic spectrum short memory is written as follows:

$$r_{i,j}[p] = c_{i,j}CN_i[p] + n_{i,j}[p] \quad (6)$$

The cognitive node for source cognitive node i is written as $P_i\left[p_{i_1}\right] = u_i\left[p_{i_1}\right]CN_i$ for frequency slot p, and is written as $P_i\left[p_{i_2}-p_{i_1}\right] = u_i\left[p_{i_2}-p_{i_1}\right]r_{i,j}\left[p_{i_2}-p_{i_1}\right]$ for frequency slot $p_{i_2}-p_{i_1}$. The cognitive node for source cognitive node j is written as $P_j\left[p_{j_1}\right] = u_j\left[p_{j_1}\right]CN_j$ for frequency slot p, and is written as $P_j\left[p_{j_2}-p_{j_1}\right] = u_j\left[p_{j_2}-p_{j_1}\right]r_{j,i}\left[p_{j_2}-p_{j_1}\right]$ for frequency slot $p_{j_2}-p_{j_1}$. The cognitive node for source cognitive node i is written as $P_i\left[1-p_{i_2}\right] = u_i\left[1-p_{i_1}\right]r_{j,i}\left[1-p_{i_2}\right]c_{i,j}$ for frequency slot $\left(1-f_{i_2}\right)$. The cognitive node for source cognitive node j is written as $P_j\left[1-p_{j_2}\right] = u_j\left[1-p_{j_1}\right]r_{j,i}\left[1-p_{j_2}\right]c_{j,i}$ for frequency slot $\left(1-f_{j_2}\right)$. The signal that the cognitive node receives by using dynamic spectrum long memory in the perpendicular medium of $c_{i,j}$ in frequency slot p is written as follows:

$$\tilde{r}_{i,j}[p] = \int c_{i,j}CN_i[p] + w_{i,j}[p] \quad (7)$$

In equation (7), the $w_{i,j}$ is the noise with zero mean and variance $\sigma^2 > 0$. Different from $n_{i,j}$, the noise $w_{i,j}$ is computed by using dynamic spectrum long memory. Let $\Gamma_i[p]$ and $\Gamma_j[p]$ be the linear fusion parameters selected by receiving cognitive node. The receiving cognitive nodes for the *i*-th subscriber are represented as the integration of two measurements as follows:

$$r_{i,j} = \int_{p_{i_1}}^{p_{i_2}} \tilde{r}_{i,j}\Gamma_j\left[p_{i_1}\right]\tilde{r}_{i,j}\left[p_{i_1}\right] + \Gamma_i\left[p_{i_2}-p_{i_1}\right]r_{i,j}\left[p_{i_2}-p_{i_1}\right] \quad (8)$$

$$r_{i,j} = \int_{p_{i_1}}^{1} \Gamma_j\left[1-p_{i_1}\right]r_{i,j}\left[1\text{-}p_{i_1}\right] + \Gamma_i\left[1-p_{i_2}\right]r_{i,j}\left[1-p_{i_2}\right] \quad (9)$$

The participation node spectrum sharing ratio for the cognitive nodes is denoted as $PNSSR_i$ and $PNNSR_j$ for transmitter and receiver, respectively. The participation node spectrum sharing ratio must satisfy the conditions in following inequalities.

$$O_i \ge \frac{\sigma_w^2}{C_{i,j}^2} PNSSR_i \quad (10)$$

$$O_j \ge \frac{\sigma_n^2}{C_{i,j}^2} PNSSR_j \quad (11)$$

In Inequality (10) and (11), the O_i and O_j indicate transmission power of source cognitive node i and j, respectively.

By assuming that the receiver can effectively connect the measurements $\left\{r_{i,j}, \tilde{r}_{i,j}\right\}$ to participation node spectrum sharing ratio and the noise can be manually excluded, the maximal ratio merging coefficients are represented as follows:

$$\frac{\Gamma_i\left[p_{i_2}-p_{i_1}\right]}{\Gamma_i\left[p_{i_1}\right]} = \frac{c_{i,j}u_j\left[p_{i_2}-p_{i_1}\right]\sigma_w^2}{c_{i,j}^2u_j^2\left[p_{i_2}-p_{i_1}\right]\sigma_n^2 + \sigma_w^2} \quad (12)$$

$$\frac{\Gamma_i\left[1-p_{i_1}\right]}{\Gamma_i\left[1\text{-}p_{i_1}\right]} = \frac{c_{i,j}u_j\left[1-p_{i_2}\right]\sigma_w^2}{c_{i,j}^2u_j^2\left[1-p_{i_2}\right]\sigma_n^2 + \sigma_w^2} \quad (13)$$

The participation node spectrum sharing ratio with maximum ratio for receiving cognitive node is represented as follows:

$$PNNSR_i = \bigcup_{p_{i_2}}^{p_{i_2}} \frac{c_{i,j}u_i\left[p_{i_2}-p_{i_1}\right]}{\sigma_w^2} + \frac{c_{i,j}^2u_j^2\left[p_{i_1}\right]u_i^2\left[p_{i_2}-p_{i_1}\right]}{c_{i,j}^2u_i^2\left[p_{i_1}\right]\sigma_n^2 + \sigma_w^2} \quad (14)$$

$$PNNSR_j = \bigcup_{p_{i_1}}^{1} \frac{c_{i,j}u_j\left[1-p_{i_1}\right]}{\sigma_w^2} + \frac{c_{i,j}^2u_j^2\left[1-p_{i_1}\right]u_j^2\left[1-p_{i_1}\right]}{c_{i,j}^2u_i^2\left[1-p_{i_2}\right]\sigma_w^2 + \sigma_n^2} \quad (15)$$

3 Experiments and simulations

During the process of dynamic spectrum allocation, the algorithm allocates the idle spectrum between and within networks when the spectrum is free. According to cognitive radio technology, the user is classified as authorised user and cognitive user. The cognitive user monitors idle spectrum by using sensing technology. In this section, the spectrum resource is represented as unified form. Then, the spectrum resource allocation is converted as channel allocation problem solved by the self-learning-based dynamic spectrum allocation scheme which is implemented by cognitive deep learning.

The main measurements for dynamic spectrum allocation include system throughput (Li et al., 2013), allocation fairness (Kumar and Kleinberg, 2000) and system utilisation (Hoang and Liang, 2006).

The system throughput is an important index to evaluate the performance of dynamic spectrum allocation algorithm. It refers to the average maximum transmission rate per MHz. In 5G communication network, the system throughput is usually used to measure utilisation of spectrum. System throughput refers to the number of units that are successfully transmitted to the network, equipment, port, virtual circuit or other facilities. In this paper, the system throughput is used as a criterion to evaluate the performance of spectrum allocation algorithm. The system throughput is defined as the sum of all cognitive users as follows:

$$Throughput = \sum_{j=1}^{N}\sum_{i=1}^{M}\left[B_i \cdot lb\left(1+SINR_i\right)\cdot w_i\right]\cdot p_{i,j} \tag{16}$$

In equation (16), the $SINR_i$ represent the signal-noise ratio of channel i, w_i $\left(0 < w_i < 1\right)$ represents the available weight. The throughput of each cognitive user is the sum of channel bandwidth, noise ratio and channel availability by access probability.

The allocation fairness refers to the difference that cognitive users obtains spectrum resource. The allocation fairness is measured by the variance of system throughput. The more evenly the spectrum sources are distributed, the lower the deviation of throughput from the mean of cognitive users is and the better the fairness of the algorithm is. The allocation fairness is rewritten as follows:

$$AF^2 = \frac{1}{N}\sum_{j=1}^{N}\left(T_j - \overline{T}\right)^2 \tag{17}$$

In the equation (17), the T_j and $\overline{T}_j$ represent system throughput of channel j and average system throughput.

The experiment simulates a 20 km × 20 km area 5G heterogeneous network environment which consists of 2G, 3G, 4G and 5G networks. The cognitive households in the area is represented as N. All N households share M spectrum channels. For each spectrum channel, it is assumed that the bandwidth is the same as 10 MHz, the weight is 0.5, the associated signal noise ratio is 10 dB, the access probability is among [0, 1] and the detection time is 0.1 second. The deep leaning-based spectrum allocation scheme is compared with graph theory scheme and game theory scheme.

First, the number of spectrum channels is fixed as 20 and the number of households range from 20 to 100 stepped by 20. The curve between the throughput and the number of households is reported in Figure 2. The curve between the allocation fairness and the number of households is reported in Figure 3.

Figure 2 The curve between the throughput and the number of households when the number of spectrum channels is fixed (see online version for colours)

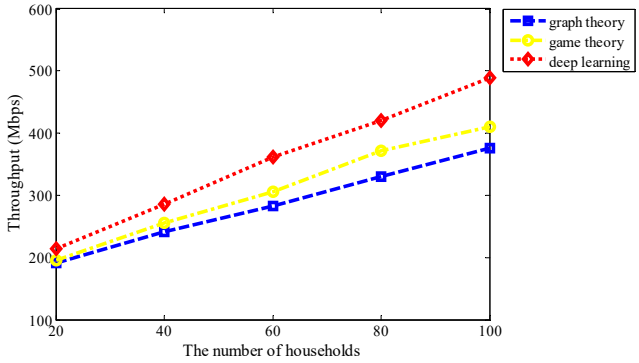
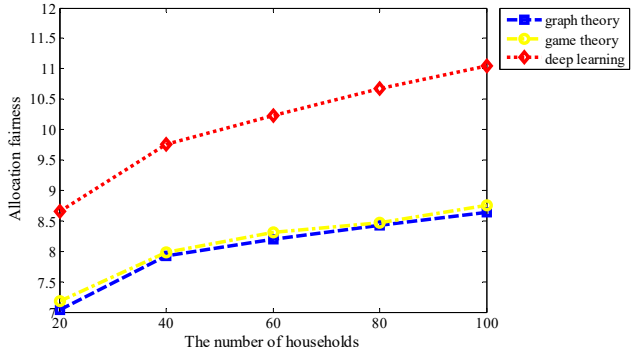


Figure 3 The curve between the allocation fairness and the number of households when the number of spectrum channels is fixed (see online version for colours)



From Figure 2, it can be found that the throughput increases with the number of households for all spectrum allocation schemes and the proposed scheme can obtain higher throughput than graph theory scheme and game theory scheme for different number of households when the number of spectrum channels is fixed. From Figure 3, it can be found that the allocation fairness increases with the number of spectrum channels for all spectrum allocation schemes and the proposed scheme can obtain higher allocation fairness than both graph theory scheme and game theory scheme for different number of spectrum channels as well when the number of households is fixed.

Then, the number of households is fixed as 20. The number of spectrum channels ranges 20 to 100 stepped by 20. Figure 4 reports the curve between the throughput and the number of spectrum channels. Figure 5 reports the curve between the allocation fairness and the number of spectrum channels.

Figure 4 The curve between the throughput and the number of spectrum channels when the number of households is fixed (see online version for colours)

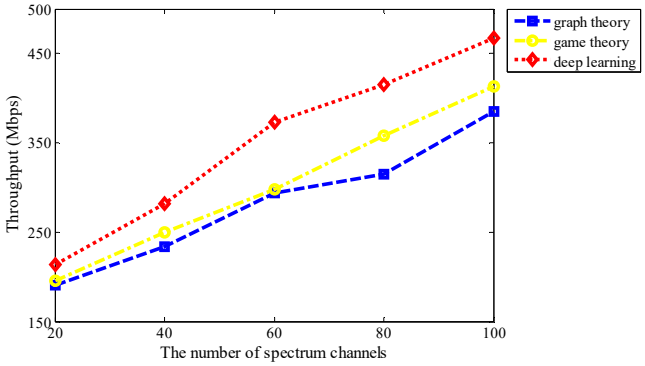
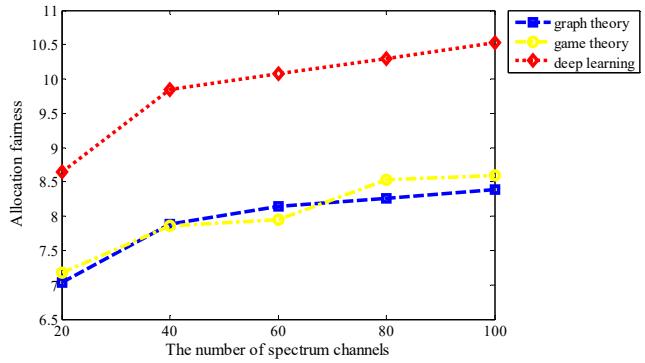


Figure 5 The curve between the allocation fairness and the number of households when the number of households is fixed (see online version for colours)



From Figure 4, it can be found that the allocation fairness increases with the number of households for all spectrum allocation schemes and the proposed scheme can obtain higher allocation fairness than graph theory scheme and game theory scheme for different number of households when the number of spectrum channels is fixed. From Figure 5, it can be found that the throughput increases with the number of spectrum channels for all spectrum allocation schemes and the propose scheme can obtain higher throughput than graph theory scheme and game theory scheme for different number of spectrum channels when the number of households is fixed.

Furthermore, the proposed self-learning-based dynamic spectrum allocation scheme is deployed in a campus network which consists of various heterogeneous access networks which are supported by 5G technology. The results show that the proposed self-learning-based dynamic spectrum allocation scheme can meet the requirements of spectrum allocation to increase the throughput and reduce the latency of the network.

4 Conclusion

In the 5G heterogeneous wireless network, there are great differences in the technical advantages and business capabilities of the access networks. Network resource management is an effective mechanism to improve the resource utilisation of heterogeneous wireless network. The spectrum dynamic allocation is one of the main tasks, which plays an important role in 5G heterogeneous wireless network. This paper proposes a deep learning-based scheme for dynamic spectrum allocation in 5G heterogeneous wireless network. First, the spectrum resources of heterogeneous network are gathered into a vector resource library by using unified representation. Then, the represented vectors are used as the input of a cognitive deep learning to learn a spectrum allocation model. The learnt deep learning spectrum allocation model can find the optimal spectrum resource allocation scheme to get high throughput and allocation fairness. The experimental results demonstrate the deep learning-based spectrum allocation scheme is superior to both graph theory-based scheme and game theory-based scheme. Furthermore, the smart applications under 5G environment needs to enhance in the future.

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