2022 IEEE International Conferences on Internet of Things (iThings) and IEEE Green Computing & Communications (GreenCom) and IEEE Cyber, Physical & Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress

2022 IEEE International Conferences on Internet of Things (iThings) and IEEE Green Computing & Communications (GreenCom) and IEEE Cyber, Physical & Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics) | 978-1-6654-5417-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics55523.2022.00057

Demand-Oriented Allocation with Fairness in Multi-Operator Dynamic Spectrum Sharing Systems

Mengying Wang*, Wei Wang*, Wenjing Xu*, Jiameng Bi*, Qiang Ye†
*College of Electronic and Information Engineering, Nanjing University of Aeronautics and Astronautics, China,
†Department of Computer Science, Memorial University of Newfoundland, Canada
Email: mengying_w@nuaa.edu.cn, wei_wang@nuaa.edu.cn, wenjing_xu@nuaa.edu.cn, 657551649@qq.com, qiangy@mun.ca

***Abstract*—Inter-operator spectrum sharing with guaranteed operator fairness is a challenging issue due to the differentiated service requirements and operator priorities. In this paper, we introduce an incentive mechanism to promote spectrum sharing and propose a fair spectrum allocation algorithm by considering the demand and response from different operators. Specifically, we design a new fairness factor based on operator spectrum demand and utility which can affect the spectrum pricing to change spectrum allocation schemes. The spectrum allocation problem is formulated as a two-stage Stackelberg game and the proposed algorithm solves the problem by finding the Nash equilibrium of each sub-game according to convex optimization theory. Simulation results show that under maximum fairness coefficient, the proposed algorithm can improve operator satisfaction by 30% on average.**

I. Introduction

With the development of fifth-generation (5G) and the proliferation of Internet of Things (IoT), emerging wireless applications such as virtual reality (VR), augmented reality (AR), and autonomous driving have been growing dramatically. To support such new applications, the demand for spectrum resources have been increased explosively [1]. However, available spectrum resources for wireless networks are limited. Although higher frequency spectrum can be exploited to support enhanced mobile broadband (eMBB) services, the transmitted signals suffer severe path loss and blockage problems. As a promising counterpart, low frequency communication at sub-6GHz bands can achieve larger coverage with better channel propagation property. Even though the sub-6GHz frequency bands are mostly occupied, spectrum resource utilization can be greatly improved (with only 15%-85% of spectrum bands being in use) [2]. Dynamic spectrum sharing is an effective way to facilitate better spectrum utilization.

As a typical way of dynamic spectrum access, cognitive radio has been widely adopted [4]-[10], where unlicensed users can explore the utilization of licensed spectrum when it is not occupied, for improving the spectrum efficiency [3]. The allocation of discrete channels on frequency and time between mobile operators and subscribes is discussed in [4]. The authors in [5] discuss collaborative sensing, dynamic and radio-aware resource allocation, and advanced cooperative communication techniques as well as their advantages. Dynamic spectrum management from the perspective of regulation and 6G scenarios is studied in [6] and [7]. In [8], a non-cooperative game model is proposed for the subsidy-based spectrum sharing (SBSS), in which government provides subsidies to motivate spectrum providers to share spectrum resources, and implements corresponding rewards and penalties through 'sharing certificate' records. The spectrum allocation problem under spectrum uncertainty is considered in [9], where the authors set different discount indicators for unlicensed users for reducing communication collision probability. In [10], a double auction mechanism is proposed in which a pre-set winner determination algorithm is executed to prevent the dishonest behavior of licensed providers to ensure the fairness of bidding.

Some research works consider maintaining the fairness in terms of achievable data throughput [11]-[13]. A dual bargaining game model is proposed in [11] to allocate spectrum resources of TV white space (TVWS) for IoT devices. Considering the fairness problem among application services, compensation factors for different data service types are set based on the ex-ante condition and a spectrum allocation scheme is proposed where two rounds of games are successively played among different service types. In [12], the authors propose a proportional fair allocation algorithm that dynamically calculates user data rate according to priorities. Those with higher priorities are allocated more spectrum, which achieves long-term fairness among data services. In [13], a demand-oriented dynamic spectrum allocation algorithm is developed to ultimately improve user satisfaction.

However, the interaction and relation between licensed and unlicensed users needs to be further considered in designing spectrum allocation schemes, where the incentive to motivate the spectrum sharing from licensed users can be properly modeled. Recently, the application of blockchain in spectrum allocation has been under dicussion. Blockchain technology ensures the security and privacy of spectrum allocation transactions. For example, in [14] and [15], the application of blockchain technology in dynamic spectrum sharing are investigated. A spectrum blockchain system is presented in [15], where licensed and unlicensed users record spectrum transactions through the chain for spectrum allocation. In [16], the authors propose a trust-based spectrum allocation scheme Block6Tel, which did not require central authorization and anonymous features. There are few researches that study both authorized user enthusiasm and unauthorized user fairness in spectrum allocation schemes. Thus, we combine the incentive

978-1-6654-5417-9/22/$31.00 ©2022 IEEE

DOI 10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics55523.2022.00057

mechanism with appropriate fairness factor to achieve fair spectrum allocation.

In this paper, we propose a spectrum trading strategy based on price incentives and introduce a novel fairness factor to adjust the allocation of spectrum resources for promoting spectrum sharing and improving the satisfaction of users. We focus on the fairness of spectrum allocation among users where the proposed fairness factor is demand-oriented and is dynamically adjusted by changing the fairness coefficient. We formulate the spectrum allocation problem as a two-stage Stackelberg game, and the optimal solution is obtained by searching for the Nash equilibrium of each sub-game. The contributions of the paper are summarized as follows:

- We propose a new spectrum allocation model with operator fairness, where incumbent shares its vacant spectrum with multiple micro-operators which further rent spectrum to gain additional benefits, and multiple micro-operators rent spectrum to realize their own business. A new fairness factor is designed based on the product sum of spectrum demand and utility to achieve operator fairness.
- We establish a game formulation for obtaining the optimal spectrum allocation outcome, and use backward induction and Karush-Kuhn-Tucher (KKT) conditions to derive the optimal spectrum pricing and allocation strategy.
- Compared with existing algorithms, it is observed that the proposed algorithm can achieve high operator satisfaction and improve the fairness by 30% on average.

The remainder of this paper is organized as follows. Section II presents the system model and Stackelberg game formulation. Section III analyzes the designed game framework under consideration and gives the allocation algorithm. Section IV provides the simulation results and Section V concludes this paper.

II. System Model and Problem Formulation

We consider a dynamic spectrum sharing scenario with some existing incumbents and multiple micro-operators in a certain geographical area[1], where the incumbents such as Radar and fixed satellites systems may not be active and thus can temporarily rent their licensed spectrum to the operators. The dynamic spectrum sharing not only supports more smart applications with such unused spectrum by increasing the spectrum usage ratio, but also can provide more revenues to spectrum owners. Without loss of generality, we use spectrum owner to denote the incumbents with extra spectrum resources and use spectrum requestor to denote the micro-operators. In addition, we assume that the vacant spectrum allocation between the spectrum owner and the requestors are conducted periodically with a fixed period T. Similar to the assumptions in CBRS, the period T is much larger than the channel coherent time, and we only consider a certain period in the subsequent analysis for the ease of notation.

During each allocation period, the spectrum owner O will first broadcast the available spectrum bands and corresponding unit price for renting, and each spectrum requestor responds to the owner by providing its intended spectrum demand according to their own service requirements and lease costs. Denote the set of spectrum requestor R as $\mathcal{N} = \{1, 2, ..., N\}$, and p_i and b_i represent the unit spectrum price and the amount of requesting bandwidth the ith requestor. Considering the selfishness of the owner and requestors, both of them want to maximize their own revenue by adaptively adjusting the spectrum price and demanding amount. Thus, game theory model is adopted to solve the optimal pricing and resource allocation problem. Moreover, to improve the satisfaction of the requestors, a fairness factor is considered in the utility function of the spectrum owner.

A. Utility Function of Spectrum Requestors

In general, the utility of the ith spectrum requestors R_i consists of the income by providing wireless services and the cost of renting spectrum resource from the provider. The utility R_i is proportional to the data transmission capacity that is affected by the purchased bandwidth. The relationship between the revenue and the purchased bandwidth can be modeled in a logarithmic form, which is given as follows:

$$U_i(b_i, p_i) = g_i \log_2(1 + \frac{b_i}{d_i}) - b_i p_i, \tag{1}$$

where d_i is the expected spectrum demand and g_i is a positive coefficient.

B. Utility Function of the Spectrum Owner

We assume that the total available spectrum bandwidth of the spectrum owner is Q. As a rational individual, the spectrum owner will unconsciously formulate a pricing strategy to maximize its own revenue. This strategy may lead to unbalanced resource allocation. To balance the request and response among different operators, we introduce a fairness factor F in the utility function of the spectrum owner, which is given by:

$$U_p(\mathbf{p}, \mathbf{b}) = (1 - \alpha)\mathbf{p}^T \mathbf{b} + \alpha F, \tag{2}$$

where $\mathbf{p} = [p_1, p_2, \cdots, p_N]^T$, $\mathbf{b} = [b_1, b_2, \cdots, b_N]^T$ are the price and resource allocation vector, and α is a constant fairness weight. The fairness factor F should be related to the supply-demand ratio of the requestors. We define the fairness factor as:

$$F(\boldsymbol{b}) = \sum_{i=1}^{N} d_i \log_2(1 + \frac{b_i}{d_i}). \tag{3}$$

The spectrum sharing between the owner and requesters can be briefly described as two stages. In the first stage, the spectrum owner with total bandwidth Q formulates the spectrum pricing strategy by predicting requestors' reaction to the price, so as to maximize its own revenue. In the second stage, each requestor determines their own spectrum demand

[1]This scenario is similar to the Citizen Broadband Radio System (CBRS) in US, but we do not strictly restrict the number of micro-operators, i.e., Priority Access Licenses in CBRS.

considering the price announced by the spectrum owner to obtain maximum profit.

Game theory is applicable to the analysis of such decision-making process, in which the owner and requestors selfishly pursue their own maximum interests under the constraints. We formulate the interaction as a Stackelberg game, where the spectrum owner and requestors are regarded as the leader and followers, respectively. The two problems can be modeled as follows:

Problem 1. *Leader's pricing subproblem*

$$\begin{aligned} \max_{\mathbf{p}} \; & U_O(\mathbf{p}, \mathbf{b}) \\ s.t. \; & \sum_{i=1}^{N} b_i \le Q, \\ & p_i \ge 0, \forall j \in \mathcal{N}. \end{aligned} \tag{4}$$

Problem 2. *Follower's purchasing subproblem*

$$\begin{aligned} \max_{b_i} \; & U_i(b_i, p_i) \\ s.t. \; & b_i \ge 0. \end{aligned} \tag{5}$$

Moreover, we need to find a Stackelberg equilibrium (SE) point in the spectrum trading strategy, where any participant cannot obtain a higher benefit by unilaterally changing its own strategy. The SE point is defined in the follow definition.

Definition 1. *For all the spectrum requestors and spectrum owner in proposed Stackelberg game, the optimal pricing and bandwidth allocation is the Nash equilibrium point, if it satisifes the following conditions* [8]:

$$\begin{aligned} & U_O(\mathbf{p}^*, \mathbf{b}^*) \ge U_O(\mathbf{p}, \mathbf{b}^*), \\ & U_i(b_i^*, p_i^*) \ge U_i(b_i, p_i^*), \quad \forall i \in \mathcal{N}. \end{aligned} \tag{6}$$

III. Optimal Spectrum Allocation Strategy

A. Profit maximization problem of spectrum requestors

In the second stage, each requestor determines its leased bandwidth b_i with given unit bandwidth price p_i to maximize its profit. Thus, we first prove the uniqueness and existence of the equilibrium point for solving the subproblem, and the optimal purchased bandwidth is given by:

$$b_i = \begin{cases} \frac{g_i}{p_i \ln 2} - d_i, & p_i \le \frac{g_i}{d_i \ln 2}, \\ 0, & \text{else.} \end{cases} \tag{7}$$

Theorem 1. *A Nash equilibrium exsits in the requestors' purchasing subproblem.*

Proof. The first and second derivatives of the objective function in (5) can be obtained in the following form:

$$\frac{\partial U_i}{\partial b_i} = \frac{g_i}{(d_i + b_i)\ln 2} - p_i, \tag{8}$$

$$\frac{\partial^2 U_i}{\partial b_i^2} = -\frac{g_i}{(d_i + b_i)^2 \ln 2}. \tag{9}$$

Since $\partial^2 U_i / \partial b_i^2 \le 0$, U_i is concave. For a concave optimization problem, the optimal solution must exsit and satisfy the KKT conditions. Through solving the KKT conditions $\partial U_i / \partial b_i = 0$, the Nash equilibrium for SU_i can be written as

$$b_i^* = \frac{g_i}{p_i \ln 2} - d_i. \tag{10}$$

Since b_i is nonnegative, the optimal solution for problem 2 can be obtained in (7). This completes the proof. ■

From (8), it can be seen that requestors with larger g_i is easier to accept high prices for the same leased bandwidth. When the given price exceeds a certain value, the requestor will not participate in the spectrum transaction.

B. Profit maximization problem of spectrum owner

In the first stage, the spetrum owner maximizes its profit according to the reaction of requestors. We can rewrite the objective function of the spectrum owner in (4) as

$$\begin{aligned} \max_{\mathbf{p}} \; & (1-\alpha)\mathbf{p}^T \mathbf{b}^* + \alpha \sum_{i=1}^{N} d_i \log_2 \left(1 + \frac{b_i^*}{d_i}\right) \\ s.t. \; & \sum_{i=1}^{N} b_i^* \le Q, \\ & p_i \ge 0, \forall i \in \mathcal{N}. \end{aligned} \tag{11}$$

Because the number of idle spectrum band are limited, not all requirements of requestors can be satisfied. The spectrum owner needs to set diffferent price for different requesters to dynamically balance the demand and allocation. Some leased bandwidth b_i^* are zero if the given pricing do not meet the condition in (10).

To distinguish the requestors with nonzero and zero leased bandwidth, we divide them into two complementary subsets, namely $\mathcal{M} = \{1, 2, ..., M\}$ and $\mathcal{M}^+$. Thus, the objective function of the spectrum owner can be simplified as follows:

$$\begin{aligned} \max_{\mathbf{p}} \; & \sum_{j=1}^{M} \left[(1-\alpha)\left(\frac{g_j}{\ln 2} - p_j d_j\right) + \alpha d_j \log_2 \left(\frac{g_j}{p_j d_j \ln 2}\right) \right] \\ s.t. & \sum_{j=1}^{M} \frac{g_j}{p_j \ln 2} \le Q + \sum_{j=1}^{M} d_j, \\ & p_j \ge 0, \; \forall j \in \mathcal{M}. \end{aligned} \tag{12}$$

Theorem 2. *For proposed Stackelberg game, there exsits a Nash equilibrium* $\mathbf{p}^*$ *in the pricing subproblem.*

The proof of the existence of Nash equilibrium of the spectrum owner's problem is similar to that in Theorem 1. To solve this maximization problem, we introduce the dual variables associated with the bandwidth price and amount of total available spectrum constraints to form the lagrangian form of (11):

$$\begin{aligned} \mathcal{L}(\mathbf{p}, \beta, \eta) = & \sum_{j=1}^{M} \left[(1-\alpha) p_j d_j + \alpha d_j \log_2 p_j \right] \\ & - \sum_{j=1}^{M} \beta_j p_j - \eta \left(Q - \sum_{j=1}^{M} \frac{g_j}{p_j \ln 2} + \sum_{j=1}^{M} d_j \right), \end{aligned} \tag{13}$$

where β_j and η are nonnegative constants. By solving the first order conditions $\partial L(\boldsymbol{p}, \beta, \eta)/\partial p_j = 0$ for any j $\in \mathcal{M}$, the optimal solution can be obtained.

Proposition 1. *The optimal solution to the spectrum owner's profit maximization problem is given by*

$$p_j = -\frac{\alpha}{2(1-\alpha)\ln 2} + \sqrt{\left(\frac{\alpha}{2(1-\alpha)\ln 2}\right)^2 + \frac{g_j \eta}{(1-\alpha) d_j \ln 2}} \tag{14}$$

Proof: The optimal solution needs to satisfy the following KKT conditions:

$$\frac{\partial \mathcal{L}}{\partial p_j} = (1-\alpha) d_j + \alpha \frac{d_j}{p_i \ln 2} - \beta_j - \frac{\eta g_j}{p_j^2 \ln 2} = 0,\ \forall j \in \mathcal{M}, \tag{15}$$

$$\eta \left(Q - \sum_{j=1}^{M} \frac{g_j}{p_j \ln 2} + \sum_{j=1}^{M} d_j \right) = 0, \tag{16}$$

$$\beta_j p_j = 0, \tag{17}$$

$$\beta \geq 0,\ \eta \geq 0, p_j \geq 0, \tag{18}$$

$$Q - \sum_{j=1}^{M} \frac{g_j}{p_j \ln 2} + \sum_{j=1}^{M} d_j \geq 0. \tag{19}$$

From (17) and (18), it can be deduced that $\beta_j = 0$. This is because if $\beta_j \neq 0$, then $p_j = 0$, and the inequanlity in (19) does not hold any more. Accroding to (16), it has $Q - \sum_{j=1}^{M} \frac{g_j}{p_j \ln 2} - \sum_{j=1}^{M} d_j = 0$. Otherwise, the η is zero, which result in $p_j = 0$. For sloving the expresion of η, by substituting (14) into the equation, we can obtain

$$Q = \sum_{j=1}^{M} \left(\frac{g_j}{(-A_\alpha + \sqrt{A_\alpha^2 + \frac{g_j \eta}{(1-\alpha) d_j \ln 2}}) \ln 2} + d_j \right), \tag{20}$$
$$\triangleq R(\mathbf{b}, \mathbf{g}, \eta, M),$$

where $A_\alpha = \alpha/(2(1-\alpha))$. It is difficult to find the direct expression of η. Analyzing its characteristics, it can be seen that R is a monotonic decrement function of η. Therefore, given the subset $\mathcal{M}$, we can solve it numerically.

Before finding the optimal solution for problem 2, we need to select requestors who can be allocated spectrum from the owner as $\mathcal{M}$. Firstly, assuming that the total free bandwidth is large enough, i.e., all requestors can obtain the expected spectrum bandwidth at a given unit price. In this case, $\mathcal{M} = \mathcal{N}$, and P2 becomes the solution to the spectrum optimal pricing problem for each known R. However, the total idle bandwidth Q is limited. Due to competition among requestors and self-interest of the owner, some requestors cannot accept the spectrum pricing from the owner, giving up to lease spectrum and being removed the queue to be allocated. Under the circumstances, the optimal pricing strategy $\mathbf{p}$ and η will also change, all requestors allocated spectrum meet the following relationship,

$$(\frac{g_j}{d_j})_{\min} > \frac{\eta^{(N-M)} \ln 2 - \alpha}{1-\alpha}. \tag{21}$$

Here, $\eta^{(N-M)}$ is the final auxiliary variable for problem 2 to reach the optimal solution. Until the optimal solution is obtained, η has undergone N-M iterations, leaving M Rs participating in the spectrum transaction.

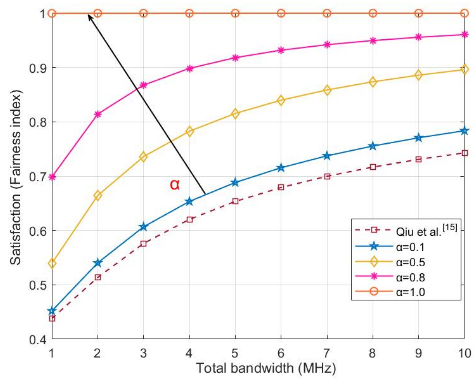
Algorithm 1 Spectrum allocation algorithm with fairness

Input: N, $\boldsymbol{b}$, $\boldsymbol{g}$, Q, α;
Output: $\mathbf{p}^*$, $\mathbf{b}^*$;
Initializatio, let $M = N$, $\mathbf{e_N} = \{1, ..., 1\}^T$
Sort all requestors in descending order of $\frac{g_i}{d_i}$
i=0
while $M > 0$ **do**
  Compute $\eta^{(i)}$ with (20)
  if $\frac{g_M}{d_M} > \frac{\eta^{(i)} \ln 2 - \alpha}{1-\alpha}$ **then**
    Break;
  end if
  $e_M = 0$; $M = M - 1$; $i = i + 1$
end while
for $j = 1; j \leq N; j++$ **do**
  if $j > M$ **then**
    $p_j = 0$;$b_j = 0$;
  else
    Compute p_j with (14);
    Compute b_j with (9)
  end if
end for
return $\mathbf{p}^*$, $\mathbf{b}^*$

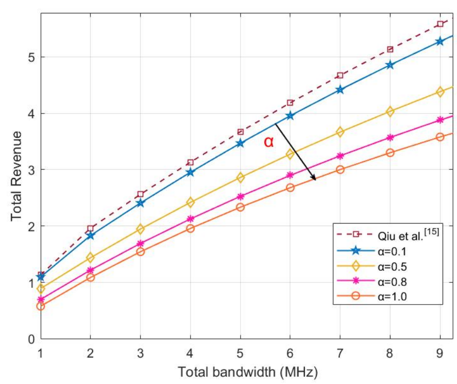
In the proposed Stackelberg game, the spectrum owner predicts the amount of bandwidth spectrum requestors will purchase at the given corresponding price accroding to spectrum requestors' revenue coefficient and bandwidth demand under the condition of asymmetric information to select the trading users, and formulates a pricing strategy for its maximum revenue. Then spectrum requestors consider the benefit maximization to make purchases, which is predicted by the spectrum owner. The convergence of optimal problem (12) is related to the number of iterations to solve the auxiliary variable η. We use a simple dichotomy to find $\eta^{(N-M)}$ that satisfies equation (20), where it is necessary to determine the solution interval before solving. Q is a monotonically decreasing function of η. If $\eta = 0$, the value on the right side of equation (20) approaches infinity. And if only one R_k successfully trades, $\eta = \alpha d_k/(Q - d_k) + g_k d_k (1-\alpha)/(\ln 2 (Q - d_k)^2)$. So it is obvious that the auxiliary variable must have a solution within the interval $[0, \max_{k \in M}\{\alpha d_k/(Q - d_k) + g_k d_k (1 - \alpha)/(\ln 2 (Q - d_k)^2)\}]$ and converge at $\eta^{(N-M)}$.

IV. Simulation ResultsAND Discussions

In this section, we evaluate the performance of the proposed algorithm in improving the allocation fairness and total utility through simulations. The simulation scenario involves a spectrum owner and three spectrum requestors i.e., N=3. We compare the evaluation results of the proposed allocation algorithm and exsiting algorithm in [15]. We first assume that the positive coefficients of all spectrum requestors are unit and identical, and the spectrum demand are $(d_1, d_2, d_3) = (1, 2, 4)$, respectively.

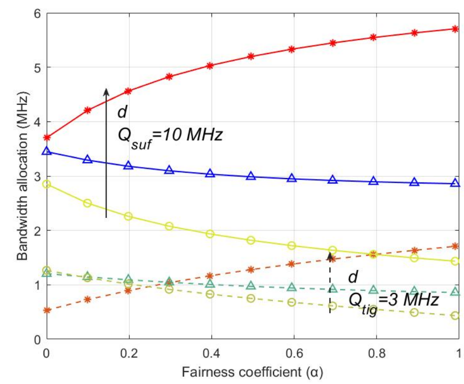


(a) The average satisfaction v.s. the total bandwidth

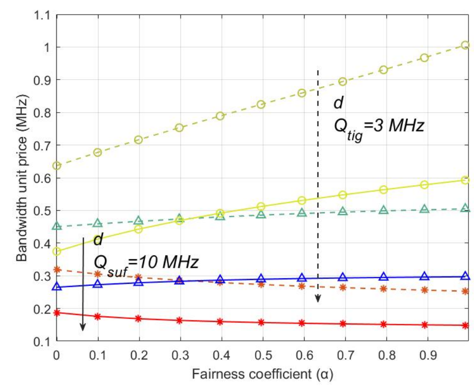


(b) The total system revenue v.s. the total bandwidth

Fig. 1. Comparisons of the average satisfaction and total system revenue between different fairness coefficient and exsiting method.



(a) The amount of bandwidth allocation for Rs v.s.fairness coefficient



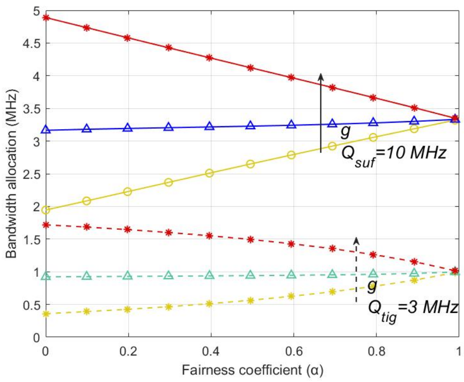
(b) The bandwidth unit prive for Rs v.s.fairness coefficient

Fig. 2. Plots of variation with α for the different spectrum demand with same revenue coefficient

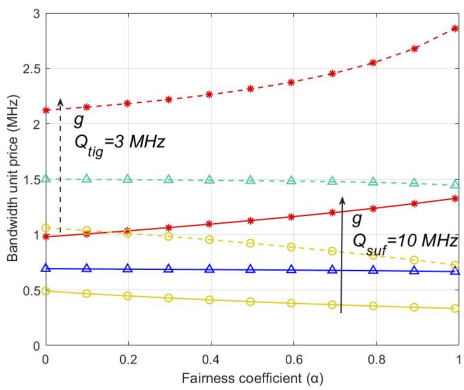
Figure 1 shows the average satisfaction and total system revenue versus the amount of total bandwidth. In Fig. 1(a), it can be seen that the average satisfaction of spectrum requestors under the proposed scheme is higher than that with the existing algorithm. The average satisfaction increases with fairness coefficient. When the fairness coefficient is equal to 1, it reaches the maximum satisfaction level which is on average 30% higher than that of the existing algorithm. But from Fig. 1(b), we find that increasing the fairness coefficient results in a decrease in the total revenue. Therefore, it is important to select an appropriate fairness coefficient considering the impact of both fairness allocation and income.

Figure 2 shows the spectrum allocation scheme of the requestors and the spectrum pricing strategy of the owner, where the dotted and solid curves represent sufficient and insufficient spectrum resources i.e., $Q_{suf} = 10$MHz, and $Q_{tig} = 3$MHz, respectively. From Fig. 2(a), we can observe that when the fairness coefficient is small and the spectrum resources are tight, spectrum requestors with less spectrum demand are allocated with more bandwidth, and if spectrum resources is sufficient, the spectrum requestors with larger spectrum demand will get more bandwidth. When the fairness coefficient is one, we can see that the allocation ratio approaches to the demand ratio of the requestors regardless of the amount of avaliable spectrum resources.

In order to evaluate the impacts of revenue coefficients on the spectrum allocation scheme, we assume that spectrum demands of all requestors are equal with a unit value of 1, and the revenue coefficients are $(g_1, g_2, g_3) = (4, 2, 1)$, and the ratio of g_i/d_i remains the same as that in Fig. 2. From Fig. 3, it is shown that the spectrum requestors with larger revenue coefficient is allocated with more bandwidth. This is because the requestors with higher revenue coefficient can accept higher expenditure cost to purchase more spectrum. As the fairness coefficient increases, the amount of spectrum allocated to each spectrum requestor tends to be the same. From the utility function of spectrum requestors, it can be seen that the amount of bandwidth to purchase is affected by the unit price. When the fairness coefficient is one, spectrum requestors divide the total bandwidth equally. The spectrum owner will allocate more spectrum resources due to higher bids from requestors with large revenue coefficients. With reference to Fig. 3(b), the changes in Fig. 3(a) can be reasonably



(a) The amount of bandwidth allocation for Rs v.s.fairness coefficient



(b) The bandwidth unit prive for Rs v.s.fairness coefficient

Fig. 3. Plots of variation with α for the same different spectrum with different revenue coefficient

explained: the increase of α weakens the influence of g_i and focus on spectrum demand. Therefore, to make the spectrum allocation scheme more compliant with the spectrum demand, the allocation algorithm will dynamically adjust the unit price of each spectrum requestor, such as the third requestor in Fig. 3, whose unit price increases resluting in a decrease in the amout of bandwidth.

Conclusion

In this paper, we have studied the spectrum allocation problem with fairness guarantee based on a pricing incentive mechanism. To improve fair spectrum allocation among operators, we define a novel fairness factor based on their spectrum demand and utility which can affect spectrum pricing to achieve fair allocation. By formulating the spectrum allocation as a two-stage Stackelberg game, our proposed demand-oriented spectrum allocation algorithm can divide the problem into two sub-game problems and find the Nash equilibrium of each sub-problem by using convex function properties, to gain the optimal allocation scheme. In addition, the algorithm can meet different fairness requirements by adjusting the fairness factor coefficient. The simulation results show that under maximum fairness coefficient, the proposed algorithm can improve the spectrum requestors satisfaction by 30% on average.

Acknowledgment

This work was supported in part by the National Natural Science Foundation of China No. 62001220, the Natural Science Foundation of Jiangsu Province BK20200440, and the Future Network Scientific Research Fund Project FNSRFP-2021-YB-03.

References

[1] A. Moubayed, T. Ahmed, A. Haque and A. Shami, "Machine Learning Towards Enabling Spectrum-as-a-Service Dynamic Sharing," in *2020 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2020, pp. 1-6.

[2] Z. Li, W. Wang, J. Guo, Y. Zhu, L. Han and Q. Wu, "Blockchain-Assisted Dynamic Spectrum Sharing in the CBRS Band," in *2021 IEEE/CIC International Conference on Communications in China (ICCC)*, 2021, pp. 864-869.

[3] R. Kaur, A. S. Buttar and J. Anand, "Spectrum Sharing Schemes in Cognitive Radio Network: A Survey," in *2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2018, pp. 1279-1284.

[4] A. Ikami, T. Hayashi and Y. Amano, "Dynamic Channel Allocation Algorithm for Spectrum Sharing between Different Radio Systems," in *2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*, 2020, pp. 1-6.

[5] G. K. Papageorgiou et al., "Advanced Dynamic Spectrum 5G Mobile Networks Employing Licensed Shared Access," *IEEE Communications Magazine*, Jul. 2020, vol. 58, no. 7, pp. 21-27, .

[6] G. Dludla and F. Mekuria, "Dynamic Spectrum Sharing for Future Wireless Networks: Regulators Perspective," in *2021 IST-Africa Conference (IST-Africa)*, 2021, pp. 1-7.

[7] L. Liu, W. Liang, G. Mang and Z. Dong, "Blockchain Based Spectrum Sharing over 6G Hybrid Cloud," in *2021 International Wireless Communications and Mobile Computing (IWCMC)*, 2021, pp. 492-497.

[8] M. Rahman, M. Yuksel and T. Quint, "A Game-Theoretic Framework to Regulate Freeriding in Inter-Provider Spectrum Sharing," in *IEEE Transactions on Wireless Communications*, Jun. 2021, vol. 20, no. 6, pp. 3941-3957.

[9] X. Dong, Z. You, L. Wang, S. Gao, Y. Shen and J. Ma, "A Truthful Online Incentive Mechanism for Nondeterministic Spectrum Allocation," in *IEEE Transactions on Wireless Communications*, Jul. 2020, vol. 19, no. 7, pp. 4632-4642.

[10] M. Devi, N. Sarma and S. K. Deka, "A Double Auction Framework for Multi-Channel Multi-Winner Heterogeneous Spectrum Allocation in Cognitive Radio Networks," in *IEEE Access*, 2021, vol. 9, pp. 72239-72258.

[11] S. Kim, "A New Bargaining Game-Based Unlicensed Spectrum Sharing Scheme for TVWS Platform," in *IEEE Access*, 2021, vol. 9, pp. 95528-95537.

[12] M. Li, "A Spectrum Allocation Algorithm Based on Proportional Fairness," in *2020 6th Global Electromagnetic Compatibility Conference (GEMCCON)*, 2020, pp. 1-4.

[13] A. Ikami, T. Hayashi and Y. Amano, "Fair Spectrum Allocation for Dynamic Spectrum Sharing between Different Radio Systems," in *2020 23rd International Symposium on Wireless Personal Multimedia Communications (WPMC)*, 2020, pp. 1-6.

[14] Z. Li, W. Wang, Q. Wu, "Blockchain-Based Dynamic Spectrum Sharing for 5G and Beyond Wireless Communications," in *Blockchain and Trustworthy Systems*, 2020, vol 1267, pp 575–587.

[15] J. Qiu, D. Grace, G. Ding, J. Yao and Q. Wu, "Blockchain-Based Secure Spectrum Trading for Unmanned-Aerial-Vehicle-Assisted Cellular Networks: An Operator's Perspective," in *IEEE Internet of Things Journal*, Jan. 2020, vol. 7, no. 1, pp. 451-466.

[16] F. Patel, P. Bhattacharya, S. Tanwar, R. Gupta, N. Kumar and M. Guizani, "Block6Tel: Blockchain-based Spectrum Allocation Scheme in 6G-envisioned Communications," in *2021 International Wireless Communications and Mobile Computing (IWCMC)*, 2021, pp. 1823-18284.