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Spectrum-Efficient Wireless Backhaul with Renewable Energy Powered Base Stations

Liu Yang[a], Xiangyuan Bu*[b]
[a]Beijing Institute of Technology, Beijing, China, yangliupersonal@126.com;
[b]Beijing Institute of Technology, Beijing, China, bxy@bit.edu.cn
[*] Corresponding author: bxy@bit.edu.cn

ABSTRACT

Wireless backhauling with renewable powered base stations (BSs) provides an attractive and cost-effective solution to enabling ultra dense cellular networks to meet the ever-increasing traffic demands of massive Internet of Things applications. To address the spectrum shortage in wireless backhaul networks, we propose to offload the delay-tolerant data traffic to the shared spectrum bands and jointly consider BSs' energy consumption, spectrum allocation, and data routing to maximize the amount of delivered data. Numerical results demonstrate that the adopted sequential fixing algorithm implements a near-optimal solution and our scheduling strategy significantly outperforms the conventional strategies which only considers spectrum allocation. Moreover, the impacts of resources availability on the performance of obtained strategies are analyzed.

Keywords: Wireless backhaul, renewable energy, spectrum sharing, routing and link scheduling

1. INTRODUCTION

Wireless backhauling is widely recognized as a promising solution to facilitate cost-effective and flexible deployment of ultra dense cellular networks, which attracts research interests from both academia and industries[1]. Unfortunately, given the limited spectrum resources over the backhaul links, the usage of base station (BS) with wireless backhaul connections faces significant challenges to handle the soaring traffic generated from the rapidly growing Internet of Things (IoT) applications[2]. Therefore, an effective approach to address spectrum shortage in the wireless backhaul link and support the tremendous traffic demands from IoT devices, is in dire need.

Licensed spectrum sharing, which allows BSs to opportunistically exploit under-utilized spectrum bands in the environments for backhaul transmissions, is a useful way to meet this challenge. However, the application of shared spectrum for backhaul transmissions confronts a few challenges. On the one hand, transmissions on the shared spectrum is less reliable since the availability of shared spectrum is subject to the activities of the incumbent users. On the other hand, the licensed spectrum bands available for data transmission is spatially varying, which could lead to inefficient spectrum utilization without appropriate coordination.

The utilization of shared spectrum bands for backhaul transmissions is even more complex, since that a significant number of BSs are expected to be powered by renewable energy. Notice that renewable energy powered BSs have already attracted interests from vendors and operators, such as Ericsson and China Mobile, due to low cost and easy deployment[3],[4]. These BSs harvest energy from ambient environments, such as solar power, wind energy, and thermal energy. Therefore, the achievable data rate of each BS cannot be accurately predicated because of the uncertainty of the amount of the harvested energy. To efficiently utilize the shared spectrum bands for data delivery, the scheduling of BSs' transmissions should jointly consider the spatial variations in spectrum availability and the uncertain energy supply.

1.1 Related Work

As one of the key technologies to meet the targets in fifth-generation (5G) networks[4], wireless backhaul networks with renewable energy powered BSs have demonstrated strength by routing strategies joint with energy allocation in the past few years[5],[6],[7],[8]. In addition, the huge wireless backhaul traffic over congested spectrum is also a harsh problem, which is addressed via spectrum sharing by radio spectrum policy group (RSPG) in [9]. To enable efficient spectrum sharing in wireless backhaul network, the design of routing strategies is jointly addressed with spectrum resource allocation in [10][11][12]. However, these schemes either ignore the impact of spectrum allocation or the effect of

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energy utilization on system performance. Thus, they may result in inefficient resource utilization during the backhaul transmissions when applied to wireless backhaul networks with renewable energy powered BSs.

1.2 Contribution

To address the aforementioned challenges, we propose to carry delay-tolerant data traffic over the less reliable shared spectrum bands so that operators could save more precious licensed band to support the backhaul transmissions of the increasing delay-sensitive services. Then, we design the scheduling strategies for BSs by formulating an optimization problem where spectrum allocation, data routing, and BSs' energy consumption are jointly considered. In our formulation, the uncertain supply of renewable energy is characterized via a probabilistic constraint, which is reformulated with a confidence level to facilitate solution finding. Finally, we demonstrate the effectiveness of the obtained scheduling strategies through extensive performance evaluation.

2. SYSTEM MODEL

2.1 Spectrum Availability Model

We consider wireless backhaul network with BSs $\mathcal{N} = \{1, \dots, \mathrm{N}\}$. Among these BSs, a set of BSs are powered by renewable energy. As shown in Figure.1, wireless backhaul network is responsible for the connections of end users to the core network. To save operator's own bands for time-sensitive data transmissions, BSs opportunistically access the shared licensed bands for delay tolerant data transmissions. There are totally $\mathcal{M}$ shared licensed bands, denoted as $\mathcal{M} = \{1, \dots, \mathrm{M}\}$, and the available bands at BS i is a subset of $\mathcal{M}$, represented by $\mathcal{M}_i \subset \mathcal{M}$, which is determined by activities of primary users around the BS i. Here, $\mathcal{M}_i$ and $\mathcal{M}_j$ are possibly the same when BS i and j become close enough.

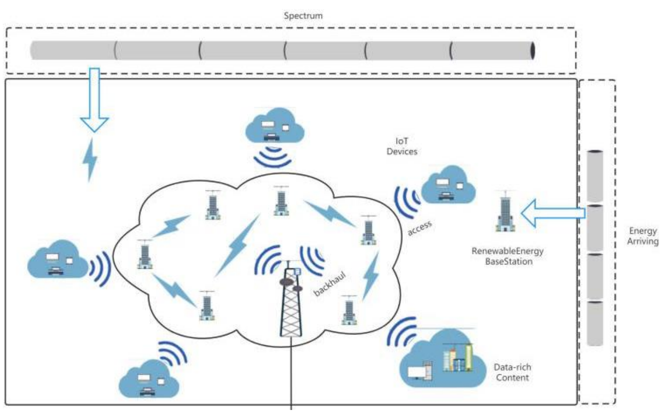

Figure 1. Illustration of wireless backhaul network.

2.2 Uncertain Energy Supply Model

In this paper, BSs harvest certain amount of energy to meet the communication demand in wireless backhaul network. The available energy $\mathrm{E_i}$ on BS i consists of initial storage in battery $\mathrm{E_0}$ and harvested energy $\mathrm{Eh_i}$, i.e., $\mathrm{E_i} = \mathrm{E_0} + \mathrm{Eh_i}$, where $\mathrm{E_0}$ is a constant and $\mathrm{Eh_i}$ might be converted from any form of energy in the unstable environment (e.g. solar power, wind power, and even hydro power, etc.). In addition, the maximum amount of energy available on BS i is $\overline{\mathrm{E}}_\mathrm{i}$, which represents the storage capacity of the battery.

Notice that the harvested energy $\mathrm{Eh_i}$ is intermittent and uncertain over time, e.g., with energy fluctuation caused by unstable solar, wind or even hydraulic patterns, which is different from conventional time-invariant energy sources. Therefore, to describe this key feature of renewable energy, $\mathrm{Eh_i}$ on BS i $(\mathrm{i} \in \mathcal{N})$ is modeled as a random variable considering the unpredictable arrivals of energy within a control period of T.

The coarser $\mathrm{Eh_i}$ is modeled, the more significant details w.r.t. arrivals of energy are ignored, which could possibly confound the scheduling decision and lead to the failure of communication. In this paper, we assume the time between two arrivals to be an exponential random variable, which means that the harvested energy packets of $\mathrm{e_0}$ (Joule) arrives following a Poisson process[13].

2.3 Propagation Model

Let P be the transmit power of BSs. Considering the receiver sensitivity, the prerequisite for the successful transmission from BS i to j is that the received power $P_j = g_{ij}P$ at BS j exceeds a fixed threshold P_T, where g_{ij} is the power propagation gain.

Let n, d_{ij} be the path loss exponent and the distance between BSs i and j, respectively. Then g_{ij} can be expressed as

$$g\_\{ij\} = \gamma d\_\{ij\}\hat{}\{-n\} \tag{1}$$

where γ is an antenna related constant.

To facilitate problem formulation, we define R_T as the transmission range of BSs. From (1) and the expression of P_j, R_T can be obtained as

$$R_T = \left(\frac{\gamma P}{P_T}\right)^{\frac{1}{n}}. \tag{2}$$

Thus, BS j needs to be within the transmission range of i to enable the communication.

Similarly, another prerequisite for correct reception at BS j is that the interference received power at BS j due to the transmission of BS $x (x \neq i, j)$ is smaller than a threshold P_I. Let R_I be the interference range of BSs. Based on (1) and the expression of P_j, R_I is determined by

$$R_I = \left(\frac{\gamma P}{P_I}\right)^{\frac{1}{n}}. \tag{3}$$

The definition of R_I implies that BS j needs to be out of the interference range R_I of BS x to enable the communication with BS i.

The transmission rate on link (i, j), i.e., the link between BS i to BS j, over band m is

$$C_{ij}^m = W^m \log_2\left(1 + \frac{Pg_{ij}}{\eta}\right), \tag{4}$$

where W^m is the bandwidth of band m and η is the noise power.

3. THE DESIGN OF SCHEDULING STRATEGIES

In this section, we will provide detailed discussion on the design of BS scheduling strategy within a control period of T by jointly considering spectrum allocation, data routing and BSs' energy consumption.

3.1 Linking Schedule and Routing Under Uncertain Energy Supply

3.1.1 Routing constraints

To ensure the data is finally delivered to the data networks, the amount of data carried over different links should satisfy the following routing constraints. First, the amount of data outgoing from the source BS s should equal to the amount of data to be transmitted, r, i.e.,

$$\sum_{j \in T_s} f_{sj} = r, \tag{5}$$

and there is no incoming flow to BS s, i.e.,

$$\sum_{i \in T_s} f_{is} = 0, \tag{6}$$

where T_s represents $\cup_{m \in \mathcal{M}_s} T_s^m$. Here T_s^m is the set of BSs within the transmission range of BS i over band m. Second, the amount of flow coming into the destination BS d should equal to the amount of flow coming out from the source BS, i.e.,

$$\sum_{i\in T_d} f_{id} = r, \tag{7}$$

and there is no outgoing flow from d, i.e.,

$$\sum_{j\in T_d} f_{dj} = 0, \tag{8}$$

where T_d represents the set of BSs within the transmission range of BS d over all bands.

Third, the flow coming into BS i and the flow coming out from BS i should be the same for any intermediate BS i, i.e.,

$$\sum_{j\in T_i}^{j\neq s} f_{ij} = \sum_{p\in T_i}^{p\neq d} f_{pi}. \tag{9}$$

3.1.2 Uncertain energy constraints

Generally, the overall energy consumption of BS i should not exceed the available energy $E_i = E_0 + Eh_i$. However, Eh_i is a random variable determined by $Eh_i = n_i e_0$, where n_i is the number of harvested energy packs in control period T and follows a Poisson process with λ_i. Therefore, E_i is also a random variable, where $i \in \{1, \dots, N\}$.

Under the unpredictable energy supply, as a tradeoff between the efficiency of energy utilization and the quality of scheduling strategies, we require the energy consumption on each BS to not exceed the amount of available energy with high probability, i.e.,

$$\Pr\left\{\sum_{m\in\mathcal{M}_i}\sum_{j,p\in T_i^m}\left(E_{ij}^m + E_{pi}^m\right) \le E_i\right\} \ge \alpha, \tag{10}$$

where α represents the confidence level and E_{ij}^m is the energy allocated used to support transmission from BS i to BS j over band m. According to the definition of E_i, (10) can be reformulated as

$$\sum_{m\in\mathcal{M}_i}\sum_{j,p\in T_i^m}\left(E_{ij}^m + E_{pi}^m\right) \le \mathcal{X}_\alpha(E_i), \tag{11}$$

where the value of E_i exceeds that of $\mathcal{X}_\alpha(E_i)$ with probability of α. E_{ij}^m determines the amount of data transmitted over link (i, j) within the control period T. Specifically, we have

$$c_{ij}^m = \frac{E_{ij}^m C_{ij}^m}{PT}, \tag{12}$$

where c_{ij}^m is the amount of data which can be transmitted within the control period T.

Then, c_{ij} can be rewritten as

$$c_{ij} = \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} \frac{s_{ij}^m E_{ij}^m C_{ij}^m}{PT} = \sum_{m\in\mathcal{M}_i\cap\mathcal{M}_j} \frac{W_2^{m\log}\left(1 + Pg_{ij}/\eta\right)}{PT} E_{ij}^m s_{ij}^m \tag{13}$$

3.1.3 Link scheduling constraints

To facilitate the formulation of link scheduling constraints, we define a binary variable s_{ij}^m as

$$s_{ij}^m = \begin{cases} 1, & \text{band m is allocated to link (i, j),} \\ 0, & \text{band m is not allocated to link (i, j).} \end{cases} \tag{14}$$

Then, the link scheduling constraints can be formulated as

$$\sum_{j\in T_i^m} s_{ij}^m \le 1, \tag{15}$$

$$s_{ij}^m + \sum_{p\in T_j^m} s_{jp}^m \le 1, \tag{16}$$

$$s_{ij}^m + \sum_{q\in T_p^m} s_{pq}^m \le 1, p \in P_j^m, p \ne i, \tag{17}$$

where (14) indicates that one BS cannot transmit to multiple BSs over the same band, (15) represents self-interference which means BSs cannot transmit and receive simultaneously on the same band, and (16) represents inter-interference which means the receiving BS cannot be in the interference range of any other transmitting BS over the same band.

Although (14)-(16) restrict the routing strategies from the view of interference, it is still necessary to guarantee that the overall flow rate f_{ij} over link (i, j) is below the channel capacity c_{ij}, i.e.,

$$f_{ij} \le c_{ij}. \tag{18}$$

3.2 Scheduling Strategy

In this paper, we aim to design a scheduling strategy for BSs to maximize the amount of data delivered through the wireless backhaul network by jointly considering spectrum allocation, data routing, and BSs' energy consumption. Notice that if (7), (8) and (9) are satisfied, it can be easily verified that (5) and (6) can be satisfied without further constraints. Based on aforementioned discussions, the design of the BSs' scheduling strategy can be formulated as the following mixed integer linear programming (MILP).

MILP:

$$\max \sum_{i\in T_d^m} f_{id}$$

$$\text{s.t.} \sum_{j\in T_i^m} s_{ij}^m \le 1$$

$$s_{ij}^m + \sum_{p\in T_j^m} s_{jp}^m \le 1$$

$$s_{ij}^m + \sum_{q\in T_p^m} s_{pq}^m \le 1, p \in P_j^m, p \ne i$$

$$\sum_{m\in M_i} \sum_{j,p\in T_i^m} \left(E_{ij}^m + E_{pi}^m\right) \le \mathcal{X}_\alpha(E_i)$$

$$f_{ij} \le \sum_{m\in M_i\cap M_j} \frac{W^m \log_2\left(1 + Pg_{ij}/\eta\right)}{PT} E_{ij}^m s_{ij}^m$$

$$\sum_{j\in T_i}^{j\ne s} f_{ij} = \sum_{p\in T_i}^{p\ne d} f_{pi}$$

$$\sum_{i\in T_s} f_{is} = 0$$

$$\sum_{j\in T_d} f_{dj} = 0$$

$$s_{ij}^m = \{0,1\}, \quad f_{ij} \geq 0,$$

where s_{ij}^m are binary optimization variables and f_{ij}, E_{ij}^m are linear optimization variables.

By solving this MILP, the optimal BSs' scheduling strategy can be obtained. As reported in [14], even though MILPs are generally NP-hard, good sub-optimal solutions can be efficiently obtained via the sequential fixing (SF) algorithm, which is an iteration of relaxed problem solving and binary variables fixing. In the following, we will verify the effectiveness of the obtained scheduling strategy and and investigate how the performance of the wireless backhaul network varies with the availability of spectrum resources and harvested energy.

4. PERFORMANCE EVALUATION

In this section, we first demonstrate the scheduling strategy obtained through the SF algorithm by comparing its performance with that of the optimal solution. Then, we will investigate how the performance of the obtained scheduling strategy varies with the availability of spectrum resources and harvested energy. In our evaluation, the SF algorithm is implemented with lp solve 5.5 and the optimal solution is obtained with MOSEK embedded in CVX. All our evaluations are performed on a computer with 4.8 GHz CPU and 32 GB RAM.

4.1 Network

We consider a network consisting of $N = 16$ BSs in a $50 \times 50\ m^2$ area. Each shared licensed band with a bandwidth of 200MHz can be opportunistically accessed by 4 close BSs in a restricted area, leveraging which the network provides abundant available links as different licensed bands support different areas. We set the path loss exponent n and the antenna related constant γ in (1) to be 4 and 1, respectively. The transmission range, interference range and confidence level are set to be 20 m, 30 m and $\alpha = 0.9$. The number of energy packets arrives at BSs $\{1,2,\dots,N\}$ during the control period are Poisson random variables with parameters $\{\lambda_1, \lambda_2, \dots, \lambda_N\}$. The positions of the BSs are randomly sampled from the area of interest by following a uniform distribution.

4.2 Results and Analysis

In Figure. 2, the achievable rate of the scheduling strategy obtained from the SF algorithm and that of the optimal solution are compared in 50 randomly generated topologies with the same number of available bands $M = 7$ and Poisson parameter $\lambda_i = 32,\ i = 1,\dots,N$. It is observed from Figure. 2 that the scheduling strategy obtained via the SF performs closely to that of the optimal solution. This indicates SF algorithm can give the near optimal solution with much lower complexity. Thus, we will compare the performance of different strategies and study the impacts of different resources on network performance using the solution obtained from the SF algorithm.

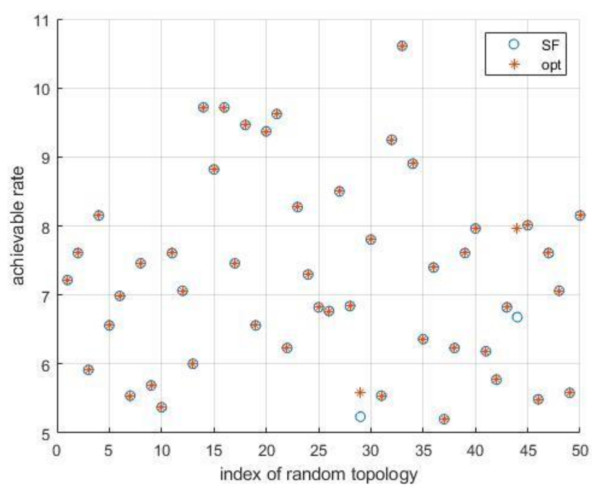

Figure 2. The comparison between the performance of the SF algorithm~ and that of the optimal solution.

In Figure. 3, we compare the proposed scheduling strategy, which jointly considers spectrum allocation and BSs' energy consumption, with the conventional strategy that only considers spectrum allocation. The conventional strategy is obtained as the optimal routing strategy without energy constraints. We consider 50 randomly generated topologies with 13 available bands and inhomogeneous Poisson parameters, where $\lambda_i = 2$ on the BS i which is closet to the source and $\lambda_j = 25$ on other BSs. Figure. 3 shows that our approach significantly outperforms the conventional strategy, which demonstrates the effectiveness of our approach.

Figure. 4 shows the impact of Poisson parameters λ. and the number of available bands M on the achievable rate in the wireless backhaul network, which indicates how the variations in resource availability affect the performance of the wireless backhaul network.

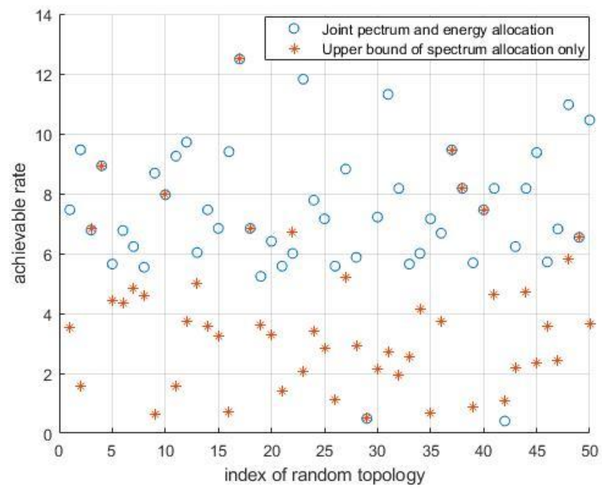

Figure 3. The comparison between the performance of the our strategy and the upper bound of conventional strategy.

From Figure. 4, the achievable rate increases with the Poisson parameters λ. This observation matches well with our intuition since higher λ. implies more harvested energy at each BS and thus more data to be transmitted. Another observation from Figure. 4 is that the increase of available bands also leads to an increase in achievable rate, since more bands provide more communication resources to support data transmissions in the wireless backhaul network. Moreover, Figure. 4 indicates that energy and spectrum resources need to be designed together to facilitate efficient resource utilization. For example, when $\lambda = 18$ fits $M = 12$, operators cannot benefit by increasing λ. beyond 18 or M beyond 12.

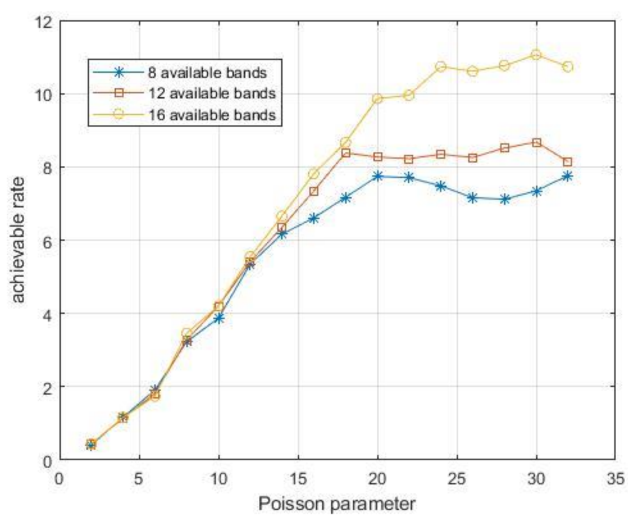

Figure 4. The achievable rate v.s. network resources.

5. CONCLUSION

To meet the soaring traffic demands of IoTs devices in wireless backhaul networks with BSs powered by renewable energy, we proposed to offload delay-tolerant data traffic to the shared spectrum bands so that more reliable spectrum resources can be saved for backhaul transmissions of the delay-sensitive services. To efficiently utilize the shared spectrum bands for data delivery, we design a scheduling strategy for BSs by formulating an optimization problem where spectrum allocation, data routing, and BSs' energy consumption were jointly considered. Then, we adopted an efficient SF algorithm for solution finding. Through extensive numerical results, we demonstrated that our strategies achieve higher rate than the existed strategies which only considers spectrum allocation. We also evaluated the impacts of the available resources on the amount of data which can be delivered in the wireless backhaul networks.

REFERENCES

[1] S. Lee, G. Narlikar, M. Pal, G. Wilfong, and L. Zhang. Admission control for multihop wireless backhaul networks with QoS support[C]. Proceedings of IEEE Wireless Communications & Networking Conference, USA: IEEE, 2006. 92-97.

[2] X. Liu and N. Ansari. Toward green IoT: Energy solutions and key challenges[J]. IEEE Communications Magazine, 2019, 57(3):104-110.

[3] J. Gozalvez. Green radio technologies[J]. IEEE VEH TECHNOL MAG, 2010, 5(1): 9-14.

[4] M. Belfqih et al. Joint study on renewable energy application in base transceiver stations[C]. Proceedings of International Communications Energy Conference, 2009. 1-4.

[5] B. U. Kazi and G. A. Wainer. Next generation wireless cellular networks: ultra-dense multi-tier and multi-cell cooperation perspective[J]. Wireless Network, 2019, 25:2041-2064.

[6] S. Rostami, K. Heiska, O. Puchko, G. P. Koudouridis, K. Leppanen and M. Valkama. Wireless backhauling for energy harvesting ultra-dense networks[C]. Proceedings of IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, Italy: IEEE, 2018. 1807-1812.

[7] D. Li, G. Zhang, Y. Xu, H. Zhao and F. Tian. Integrating distributed grids with green cellular backhaul: Ffrom competition to cooperation[J]. IEEE Access, 2018, 6:75798-75812.

[8] A. Alqasir, K. Aldubaikh and A. E. Kamal. Integrated access and backhauling with energy harvesting and dynamic sleeping in HetNets[C]. Proceedings of IEEE International Conference on Communications, virtual platform: IEEE, 2021. 92-97.

[9] V. Anis and S. Weiss. Multi-radio access network assignment using dynamic programming[C]. Proceedings of SoftCOM, USA: 2006. 1-6.

[10] Radio Spectrum Policy Group (RSPG). RSPG report on spectrum issues on wireless backhaul[R]. EUROPEAN COMMISSION, Brussels, Belgium, 2015, 15-607.

[11] R. I. Rony, E. Lopez-Aguilera and E. Garcia-Villegas. Cooperative spectrum sharing in 5G access and backhaul networks[C]. Proceedings of International Conference on Wireless and Mobile Computing, Networking and Communications, Cyprus: 2018. 239-246.

[12] M. Jaber and A. S. Alam. A reinforcement learning approach for wireless backhaul spectrum sharing in IoE HetNets[C]. Proceedings of IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, UK: IEEE, 2020. 1-6.

[13] C. Zhang, H. Wu, H. Lu and J. Liu. Throughput analysis in cache-enabled millimeter wave HetNets with access and backhaul integration[C]. Proceedings of IEEE Wireless Communications & Networking Conference, Korea: IEEE, 2020. 1-6.

[14] L. Pang, H. Zhao, Y. Zhang, et al. Energy-efficient resource optimization for hybrid energy harvesting massive MIMO systems[J]. IEEE System Journal, 2021.