Resource Allocation with Vickrey-Dutch Auctioning Game for C-RAN Fronthaul

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Doruk Sahinel
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
d.sahinel@tue.nl

Simon Rommel
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
s.rommel@tue.nl

Idelfonso Tafur Monroy
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
i.tafur.monroy@tue.nl

***Abstract*—The network slicing concept divides physical networks into logical networks and abstracts the network resources. With the help of virtualization technologies, these abstracted network resources can be allocated to service providers and resources can dynamically be added to these slices based on users' demands. The infrastructure sharing model with slicing makes it possible for services to lease the resources of the infrastructure provider. This study considers optical network resource allocation from a profit generation perspective with a game, in which service providers bid to lease C-RAN fronthaul paths via auctioning with Vickrey-Clarke-Groves outcomes. The game aims to distribute fronthaul resources with a social-welfare maximizing outcome. Service providers maximize their revenue by predicting user demand and requesting bandwidth resources from the infrastructure provider by bidding in the auction. Users have the option to change their association and switch between the service providers to maximize their utility. The results display that a balanced profit and social welfare trade-off can be achieved in converged optical and mmWave radio networks infrastructure sharing scenario with Vickrey-Dutch auctioning and distributed decision-making.**

***Index Terms*—resource allocation, auctioning game, millimeter wave, C-RAN**

I. Introduction

The increasing number and diversity of services offered by different service providers (SPs) make slicing for shared fronthaul and radio resource allocation a complex problem for infrastructure providers (InPs). To solve this problem, beyond-5G and 6G networks require a distributed network management paradigm that takes the objective functions of stakeholders into account. Creating an efficient 6G fronthaul structure is highly dependent on capturing the key technological advancements in the optical networks that provide high-capacity such as space division multiplexing (SDM) [1], [2], and managing the increasing number of remote radio heads (RRHs) with millimetre-wave (mmWave) radio transmission.

In this paper, we design a dynamic fronthaul path allocation game for SPs that lease the resources from the InPs. The game is designed as an iterative descending auction that starts with a high price at the first iteration and the price drops at each auction until the fronthaul path is leased. A Vickrey-Dutch auction is a modified version of this auction, where the player with the highest sealed-bid wins the auction; however, the player pays the amount of the second highest bid [3].

Applying Vickrey-Clarke-Groves (VCG) outcomes to auctioning for leasing provides a social-welfare maximizing results for resource allocation among self-interested services that demand optical resources for slices. The InP uses a descending Vickrey-Dutch auction to reach VCG outcomes with truthful bidding for multiple homogeneous items and non-decreasing marginal values [4]. The bid of SP k depends on its valuation of a elements of the item set, denoted with $v_k(a)$, and this SP has non-increasing marginal values if the requirement

$$v_k(a) - v_k(a-1) \geq v_k(a+1) - v_k(a) \tag{1}$$

is satisfied. A similar VCG-based profit maximization problem with infrastructure sharing for FiWi nodes [5] and a resource allocation scheme based on Vickrey-Dutch auctioning [6] have been proposed. This work extends these approaches by distributing decision-making algorithms among stakeholders, as visualized in Fig. 1. In addition to auctioning, the resource allocation problem among SPs and users is defined as a Stackelberg game [7].

II. System Model

In this study, users are scattered inside an $400\,\mathrm{m}^2$ open square area using a Poisson point process [8]. Ten mmWave RRHs with center frequency $f_c = 28\,\mathrm{GHz}$ are distributed inside this area. The coverage zones of RRHs are separated with Voronoi tessellation [9], and the users are connected to the closest RRH. The 5GCM open square omnidirectional line-of-sight (LOS) urban microcell model in Eq. (2) is used to calculate the path loss, in which d_{3D} represents the 3D distance between the user and the RRH [10].

$$PL_{\mathrm{LOS}} = 32.4 + 18.5 \cdot \log_{10}(d_{3D}) + 20 \cdot \log_{10}(f_c) \tag{2}$$

The data rate DR_n of each user is calculated by using a simple user bandwidth to rate conversion model with overhead and loss factors OF and LF in Eq. (3) [11]. Both OF and LF take values between 0 and 1. The bandwidth is assumed to be distributed equally among all users connected to the RRH before the SP game.

$$DR_n = (1 - OF) \cdot b_n \cdot \log_2(1 + (1 - LF) \cdot SNR) \tag{3}$$

Users try to optimize their utility by comparing their utility to the average utility of all users, and switch their SP based

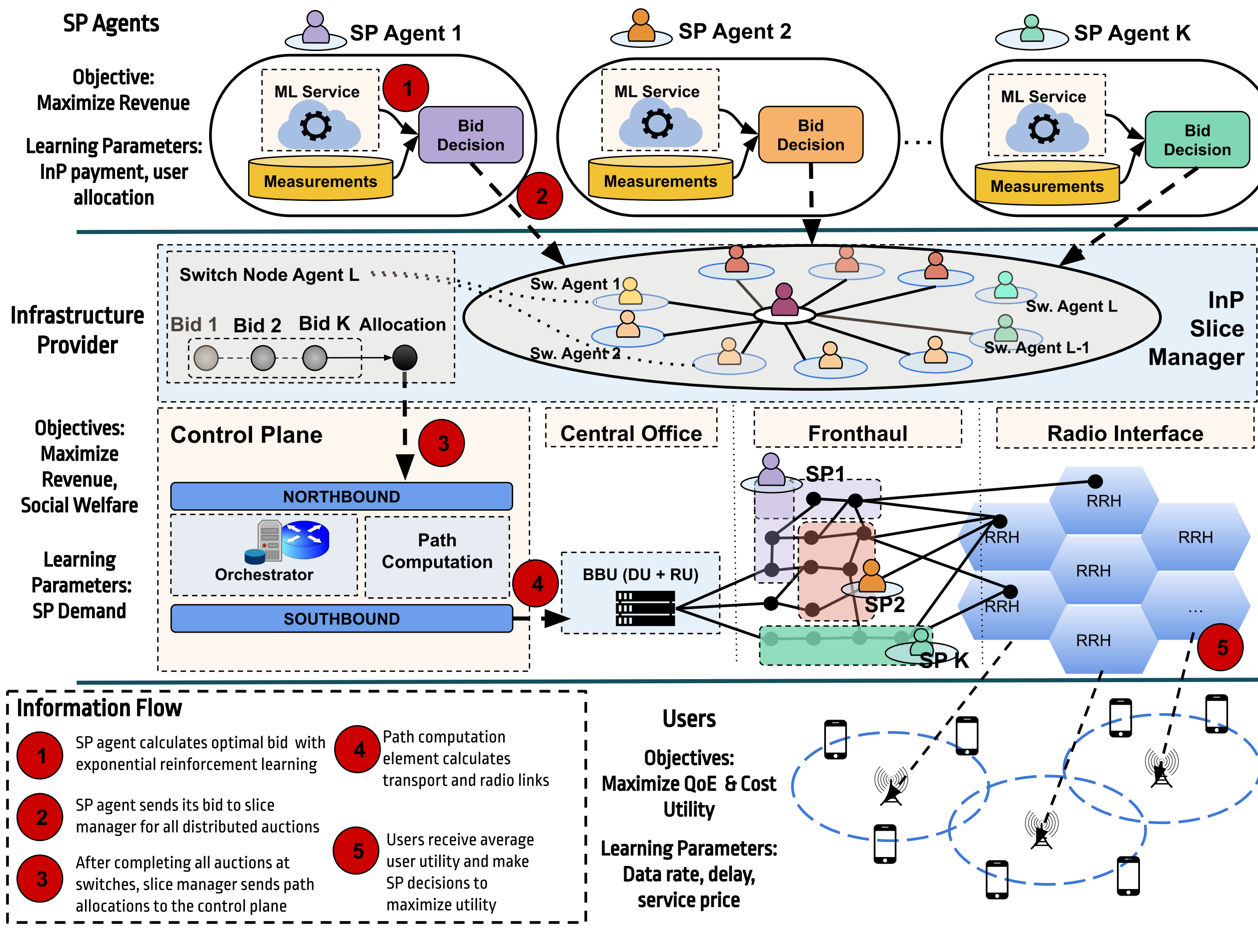

Fig. 1: High level resource allocation architecture representing the stakeholders of the game and the information flow between them.

on a probabilistic function if they are below the average. The probability to switch increases with the difference between user utility and average utility. The utility of user n is given in Eq. (4) [12], where DR_n represents user data rate, d_n is the transmission delay, and p_n is the price set by the SP for the users to connect to the service.

$$U_{\text{user},n} = \ln(\alpha_1 \cdot DR_n) - \alpha_2 \cdot d_n - \alpha_3 \cdot p_n \quad (4)$$

As given in Eq. (3), data rate DR_n is a function of the user bandwidth b_n, calculated as $b_n = \frac{b_k}{n_k}$; b_k represents the fronthaul bandwidth allocated by SP k, and n_k is the number of users connected to this SP. α_1, α_2, α_3 are the weights of the utility function that can be adjusted depending on the data rate and delay requirements of the service, and the cost requirements of the user.

The study is based on an SDM-enabled C-RAN network architecture where many RRHs are connected with a centralized BBU pool [13]. The transport network provides a number of optical paths per RRH in a square area. The increased fronthaul capacity requirement is covered with a mixed stage spatial-spectral tree connection topology, in which the inner SDM tree provides the required capacity expansion in the paths from central office (CO) to the switch nodes and wavelength division multiplexing (WDM) paths reach from the switch nodes to the RRHs [14]. The bidding takes place only for the WDM paths that reach the RRHs, the rest of the slice paths is provided automatically. The losses of the network elements in optical paths and the splitting losses are neglected so that each path in the auction is the same.

The InP network slice manager is responsible for creating slices for SPs [15]. The logically centralized BBU pool possesses data forwarding functionalities with the transport SDN controller and orchestration framework having a complete view of the fronthaul topology and the optical resources. The network slice manager on top of the orchestrator creates end-to-end network slices and assigns the optical resources by running distributed auctions for each fronthaul path reaching the RRHs.

The fronthaul topology is divided into sub-graphs for these slices and the paths are leased with an iterative descending auction. As demonstrated in Figure 1, the auction runs over distributed agents that represent each RRH, and when the auctions for all paths are finalized the resulting SP path allocation is forwarded to the control plane. The control plane keeps the virtual topology information and divides the network into sub-graphs to isolate SPs as tenants. To reach a socially optimal solution in this auctioning game, InP payments of an SP increase when it gains more paths than other SPs. The payment C_k for SP_k is given in Eq. (5) [6], where i represents the auction round, ω is the expected bid of SP in round i, and R_{-k} is the residual demand of all SPs other than SP k.

$$C_k = C_k(i) + \omega(i) \cdot (R(\omega(i))_{-k} - R(\omega(i-1))_{-k}) \quad (5)$$

$$R(\omega(i))_{-k} = \min(N^k_{\text{path}}, \sum_{j \neq k} D_j(\omega(i) - N^j_{\text{path}}) \quad (6)$$

As seen in Eq. (6), $R(\omega(i))_{-k}$ calculation includes number of allocated paths N^k_{path} by SP k, and maximum demand D of SPs other than SP k. The utility function of SP k is:

$$U_{SP,k} = \beta_1 \cdot p_n \cdot n_k - \beta_2 \cdot C_k \quad (7)$$

where $p_n \cdot n_k$ is the revenue of provider k, calculated by multiplying the SP price p_n for users with the number of users n_k connected to SP k; C_k is the SP's total VCG payment to InP for the allocated paths at the end of auction; β_1 and β_2 are the weights of revenue and cost, respectively.

Exponential reinforcement learning is used by the SP agents to predict future utilities calculated by using $U_{SP,k}$, N^k_{path}, b_k, p_k and total available paths in auction [16]. SPs do not need to know the topology of the system; hence the algorithm is regarded as stateless [12]. SPs make a bid by calculating their maximum path request for the next auction round. The following constitutes SP learning algorithm:

$$Z_k(m+1) = Z_k(m) + \gamma_m \cdot l_k(b_k(m)) \quad (8)$$

$$b_k(m+1) = B_k \frac{e^{Z_k(m+1)}}{1 + e^{Z_k(m+1)}} \quad (9)$$

Equation (8) predicts the optimal bids at the next auction, where k represents the k-th SP and m is the iteration of the association game between users and SPs; $Z_k(m)$ represents the recursive score calculated by adding the SP marginal utility $l_k(b_k(m))$ to the score at iteration m, where $b_k(m)$ is fronthaul bandiwidth allocated to SP_k fronthaul bandwidth; γ_m is the step size equal to $\gamma_m = \frac{1}{m}$. The calculated score $Z_k(m+1)$ for $m+1$ is then used in a sigmoid function given in Eq. (9) to determine the optimal bandwidth request for the next game iteration $b_k(m+1)$, which is a proportion of the total available bandwidth in all fronthaul paths, represented with B_k.

The score calculation in Eq. (8) aims to calculate the Stackelberg equilibrium of the user association game. Stackelberg equilibrium can be solved with backward induction method [7], meaning that first solving the optimal outcome for the users and then computing the optimal choice of SPs provides the desired solution. Applying this method and starting with the follower game, it can be stated that user side equilibrium is reached when the utility of all users are equal, i.e. $U_{\text{user},n} = U_{\text{user},n'}$, for all $n, n' \in S$ [12]. This user side equilibrium distribution is indicated with $n*$. Given $n*$, a profile is the Stackelberg equilibrium for service providers when $U_{\text{SP},k}(b*, n*) \geq U_{\text{SP},k}(b, n*)$ for all SP_k, where $b \in \Psi$ is any bandwidth vector that contains bandwidth requests of each service provider, Ψ is the set of all bandwidth vectors, and $b* \in \Psi$ indicates the bandwidth vector that satisfies the equilibrium condition $b* = \arg\max U_{\text{SP},k}(b_k, b*_{-k}, n*)$. Finally, the sequence diagram of the game that includes both InP auction and user association is given in Fig. 2.

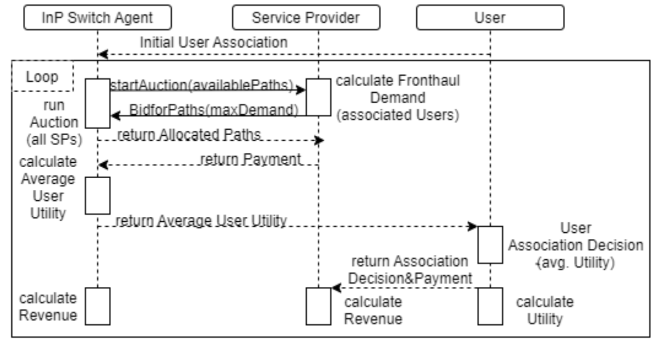

Fig. 2: Game sequence diagram between InP, SP and users.

TABLE I: Simulation parameters.

User	$\alpha_1 = 2$, $\alpha_2 = 1$, $\alpha_3 = 1$
SP	$\beta_1 = 1$, $\beta_2 = 2$, $p_{\text{user}} = 1$
Path	$b_{\max} = 100\,\text{MHz}$, $d_{\text{user}} = 5\,\text{ms}$
Rate	$LF = 0.5$, $OF = 0.2$

III. Results

To evaluate the proposed resource allocation and auction mechanisms, the game is played with one InP and three SPs. The total number of iterations i and auction rounds t are equal to ten, with the price descending one unit price from ten to one. Each fronthaul path to RRH has a maximum bandwidth of 100 MHz. The transmitter power P_{tx} is set to 30 dBm [17], and overhead and loss factors OF and LF are used in the SINR to rate conversion [11]; Table I lists the simulation parameters.

In order to observe the convergence behavior of the game in a path distribution that cannot be allocated equally by all SPs, the game is played with 100 users and 7 fronthaul paths. We assume that the users do not disconnect or hand over to other RRHs during the game. The price and delay values for the users are kept constant. As for the weighting parameters, in α_1 in Eq. (4) is given a higher value to be able to observe the impact of the data rate on the switching behavior of users. Similarly, β_2 in Eq. (7) is higher than β_1 for SPs to avoid high payments from SPs to the InP. Figure 3 displays the distribution of the paths allocated by each SP, users connected (n_k) to each SP, and the recursive score ($Z_k(m)$) values of SPs at each game iteration. Fig. 4 shows the data rate distribution of all users and the total number of users changing their SP association at each game iteration.

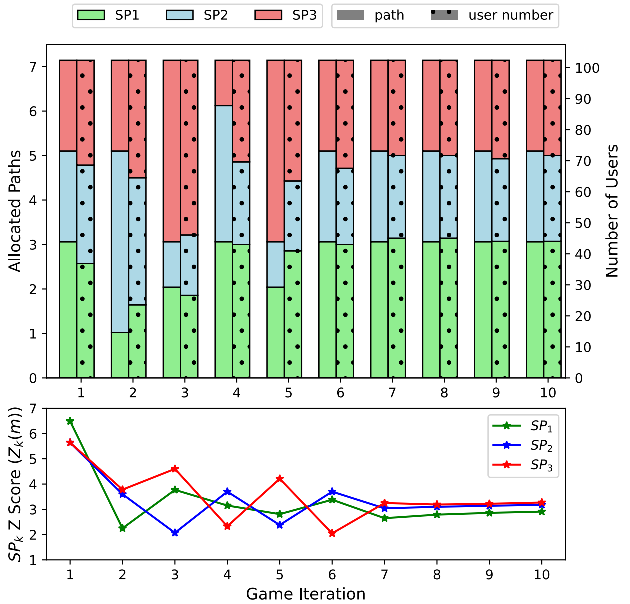

Fig. 3: SP path allocation, user number, and marginal utility values.

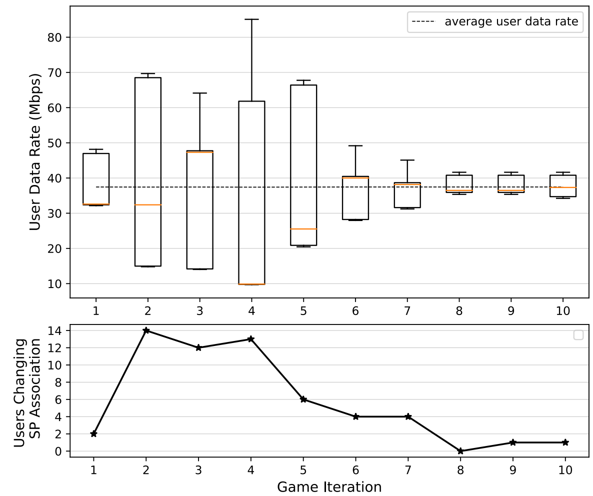

Fig. 4: User data rate distribution and total number of users changing their SP association at each iteration.

The SPs have an initial user association distribution of $[34, 33, 33]$. One extra user increases the recursive score of SP_1 when compared to SP_2 and SP_3, as shown in Fig. 3. As an expected outcome, SP_1 bids more for the paths and gets 3 paths at the end of the first iteration, with overall path allocation distributed as $[3, 2, 2]$. The user distribution at the end of the first iteration is recorded as $[36, 31, 33]$. As seen from the first iteration in Fig. 3, there is a negative difference between the proportion of allocated paths and the number of users of SP_1, resulting in a higher negative difference in the recursive score of SP_1, as score is calculated for the $n*$ profile of the Stackelberg game. The difference between the $n*$ profile and the actual user distribution is due to the fact that switching the association is a probabilistic function; therefore a user might remain connected to the same SP despite having a lower utility than the average utility. The difference between the average user utility and the user's current utility determines the probability to switch, and this probability is low in the first round as the game starts with a nearly uniform user-SP distribution.

The bids for the auction in iteration $i = 2$ is based on the SP recursive score values in Fig. 3. The scores indicate that SP_2 and SP_3 start demanding fronthaul paths at higher prices than SP_1. As a result, overall path allocation in iteration $i = 2$ ends as $[1, 4, 2]$, and the user distribution. If there is a tie in the bids of the SPs in the auction, the additional paths are distributed at random such that the maximum demand of any SPs is not exceeded [6]. In the given example, the ties are randomly broken in favor of SP_2. The user distribution at the end of $i = 2$ is $[23, 40, 37]$. SP_2 has a lower number of users than the $n*$ profile of this iteration, which is theoretically close to [14, 57, 29]. whereas SP_1 and SP_3 have higher recursive scores. Consequently, iteration $i = 3$ ends with [2,1,4] path allocation. The SP that has more allocated paths also cannot reach the expected utility by reaching the $n*$ profile in the user distribution in $i = 4$ and $i = 5$. As seen from Fig. 4, the data rate provided to users after the first round expands to a large interval due to the changes in SP path allocation. For instance, the data rate difference between the user that obtains the best data rate and the worst data rate is higher than 70 Mbps at game iteration $i = 4$. It can also be observed that the number of users that change their association is high, as more than 12 users change their association in each round between $i = 2$ and $i = 4$. While not reaching their expected utility values, SPs demand paths by increasing the price of their bids, which can be observed in the increase in the InP revenue for 7 paths in Fig. 6. InP revenue at each round is a direct result of the increase in SPs payments.

The auction ends with a $[3, 2, 2]$ distribution for seven paths after game iteration $i = 6$, and the SP path demands converge to this distribution in the following rounds, as seen in Fig. 3. The user distribution at the end of the last iteration is [43, 27, 30], which is close to the $n*$ profile for the identical users. The total number of users switching decays after $i = 6$, and the data rate difference between least well-off and the best performing user is minimized, with all users concentrated around the mean data rate value of 37.5 Mbps, as the game converges to an equilibrium. Fig. 4 demonstrates that the convergence behavior of users differs from the classical idea of convergence at the equilibrium due to the probabilistic switching function of users. However, a distance minimization to a particular $n*$ profile is achieved in the user distribution, as the number of users switching after the SP path allocation

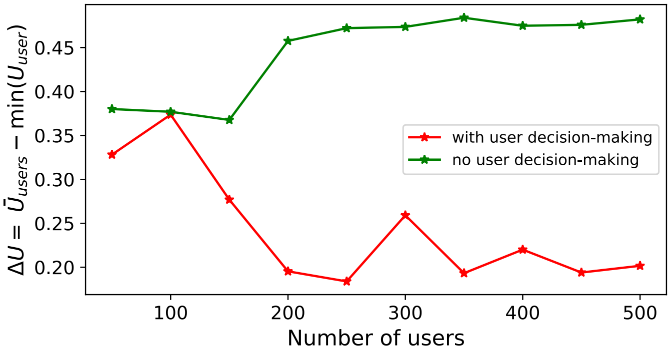

Fig. 5: The difference between average user utility and least well-off user utility for switching and no switching scenarios.

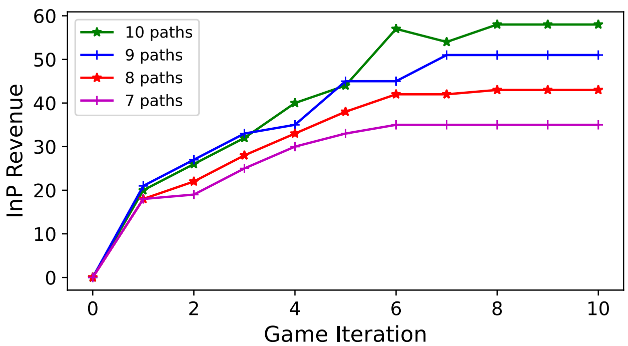

Fig. 6: InP revenue evolution for 3 SPs and 100 users and different numbers of paths.

convergence is sufficiently small. Hence, it can be concluded that Vickrey-Dutch auction with VCG outcomes and Stackelberg game solved with exponential reinforcement learning provide a profit—social welfare trade-off for non-cooperative SPs in sharing fronthaul resources.

Finally, we discuss the user utility of the least well-off user with increasing number of users and InP revenue with different numbers of paths in auction. Fig. 5 shows the difference ΔU between the average utility of all users and the least well-off user utility for a range of users between 50 and 500. The utility values with user decision-making and no decision-making are compared, and it is shown that the utility of the least well-off user improves with simple decision-making with increasing number of users. Thus, the InP also increases social welfare by sharing average user utility value with the users. InP revenue in Fig. 6 is evaluated for cases from seven to ten paths with 100 users. The markers indicate the revenue obtained in that iteration. InP revenue increases with the increasing number of paths, with SP provider bids reaching an equilibrium point after eight iterations in all cases.

IV. Conclusions

This study focuses on a distributed network management paradigm, in which InP and SP profits are optimized with an iterative descending Vickrey-Dutch auction. Besides, the interaction among users and SPs is modeled as a Stackelberg game. SP side learning is handled with reinforcement learning, and users change their SP association based on utility comparison. The results show that a balanced profit—social welfare trade-off can be achieved with distributed decision making. Different game outcomes can be achieved by adjusting the system parameters, and these results can be exploited especially during a pre-deployment phase in which different fronthaul topology options can be simulated to reach a desired market solution by choosing the optimal profit-making topology.

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