Multiple Objective Channel Allocation Problem in 5G Networks

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***Abstract*—5G networks, as an emerging technology, calls for novel solutions to several research problems, many of them having in focus a better usage of sparse spectrum capacity. In the attempt to leverage spectrum, additional unlicensed band, available for wireless technology, is combined with the licensed part of the spectrum, managed by traditional mobile providers, thus making a heterogeneous network environment of Primary Networks (PNs). In such an environment desirous users (i.e. Secondary Users (SU)) equipped with multiple radio access technology are able to select the appropriate network considering not just interference, but other parameters as well (e.g. QoS, data rates, prices etc.).**

We consider the architecture with central Cognitive Network Provider (CNP) and several heterogeneous PNs, in which SUs are contending for empty channels in one of the PNs that best suit their needs for bandwidth, data rate and price. Applying cognitive radio network principles leads to the well-known problem of Network Selection and Channel Allocation. CNP has to solve this NP-hard problem by considering equally the demands of the heterogeneous PNs as well as the best interest of SUs.

In this paper we propose two different bi-objective models and solve them by generating their non-dominated points. First model allocates SUs to networks with respect to costs, target interferences, and data rate capacities; while the second model splits PNs in channels, and allocates SUs to channels with respect to their additional demands for low latency. We generate the efficient sets of the instances found in the literature; and compare our results with the existing results obtained by the nature inspired meta-heuristic approaches.

***Index Terms*—channel allocation, network selection, 5G heterogeneous networks, optimization**

I. Introduction

The appearance of Internet of Things (IoT) inspired diverse forecast based on increasing the both number and variety of further applications (see [5], [6], [7]). As an answer to foreseen demand in bandwidth and speed of communication, mobile networks start to transform their main set of standards used to provide coverage, toward new ones that are able to provide enough speed and capacity for future networks. These processes are leading to work on novel solution/standard for 5G networks.

So far, the multi-tier architecture is adopted as a solution at different places in the network (see [12]). In RAN (Radio Access Network) the macro-cell stays in the top-tier and the small-cell appears in the lower tier, enabling dramatical enhancement at RAN, and trying to achieve a noticeable improvement in three directions: spectrum extension, spectrum efficiency and network densification (see [1]).

In attempt to achieve a spectrum extension, an additional spectrum for 5G networks – that is available mainly above 3GHz and is suitable for short-range wireless technology – has to be combined with the licensed part of the spectrum, managed by traditional mobile providers, thus making a heterogeneous network environment (5G HetNets). In such an environment, a lot of attention is put on dynamic spectrum access/sharing – the technology that enables it, i.e. cognitive radio; and algorithms that are required for a dynamic assignment of available resources.

As it is traditionally recognized, the cognitive radio provides the capability to use opportunistically the available portions of a licensed spectrum intended for licensed (primary) users in order to improve the application performance for unlicensed (secondary) users (see [2]). This is a widely studied subject. Taxonomy, open issues, and challenges related to channel assignment algorithms in cognitive radio networks can be found in [2]. Diverse approaches, as overlay, underlay, coordinated, non-coordinate are described in the literature (see [4], [10]), and applied under several architectures. The attempt to achieve a better performance by trying to control/combine the ISO/OSI L1/L2 parameters (as interference, data rate, transmission power) when selecting the transmission channel for/by the secondary users is common to the most of them. But, it seems that well known cognitive radio approaches should be combined both in a new way and with the other functionalities in 5G, in order to achieve a better spectrum efficiency in 5G [12].

Finally, network densification is the name for the energy-efficient dense deployments of radio access concept, achieved by a small cell.

A user equipped with multiple radio access technology are able to join one of surrounding networks. So, the problem of how to select an appropriate network for/by a user arises in a small cell as well as in a macro-cell. A huge difference is made by the number of users that appear in a small cell (between a few and 100) compared to the number of users that can appear in a macro-cell (about few thousands). There are several approaches regarding the mathematical modeling for network selection in heterogeneous wireless networks, analyzed in [13] with respect to objectives, the speed of making decision, implementation complexity, precision and whether they are decentralized, user-centric, mobility-oriented or traffic-oriented.

Cloud-based architectures or cloud-based radio accessed networks (C-RAN) for 5G split their data-plane (D-plane) from control-plane (C-plane), thus enabling the consideration of diverse requirements when making decision on which network the mobile users should join, or which transmission channel should be selected [12]. Such architectures demand an integration of the requirements coming from L1/L2 of ISO/OSI (interference, power transmission control, bandwidth allocation), and requirements related to congestion condition at L3 and above (data rate, latency/delay); with the requirements coming from beyond the ISO/OSI (price policy of different mobile/cognitive providers in 5G).

In the literature there are many examples of attempts to model cognitive behavior considering both the requirement of parameters related to L1/L2, and pricing separately. For example, the pricing issue in the cognitive small cell network is studied in [9], where the authors proposed an optimal pricing strategy for mobile/service operators. Later on, two attempts were made to model the network selection in cognitive radio HetNets considering minimization of interference with minimization of the price for users under the constraints of price that each user is willing to pay for delivered data rate. In [8] a model with a single criterion function is introduced, and solved with GA and PSO heuristic, while in [11] one more criterion is added to maximize the data rate achieved by all users who made an allocation. This model is solved by FLACSA heuristic, i.e. a fuzzy logic ant colony system algorithm.

As we see it, because of a cellular paradigm shift happened in several ways, according to [3], the new attempts should be made to reconsider the analysis of cognitive radio techniques under new conditions and in aim/direction to integrate well-known requirements with new one, having in mind the request for "zero latency" at the first place.

In this paper we describe the model for channel allocation/network selection in HetNets. We use a centralized authority, that gets advantage on D-plane/C-plane split architecture, for being able to collect information about the network condition and users requirements from both RAN and cloud. Regarding SUs requirements, we tried to include all considerations that are important for the practical deployment, having in mind HetNets impact on the changes on metric and cell association and recommendations (see [3]) to stop measuring the performance only with the bit error rate (BER) or signal-to-interference-plus-noise-ratio (SINR) distribution (due to their strong correlation with the low level rate and quality of service (QoS) achieved by the users), and instead, to start use of the rate distribution (user-perceived) as more relevant metric. The cell association is based on diverse requirements, both technical and economic, considered as equally important, because the customers are willing to pay for the provisioned service, and the user's experience/satisfaction with the service depends mainly on the application-level/related to the QoE (Quality of Experience) instead of QoS. As it is explained in [1], the "... QoE describes the subjective perception of the user as to how well an application or service is working. QoE is highly application – and user – specific and cannot be generalized. Despite the diversity of QoE requirements, providing low latency and high bandwidth generally improves QoE". Finally, the 5G technology is expected to support an ultra-low latency in order to be able to provide a range of real-time applications like tactile Internet, as shown in [12].

Our approach differs from previous work in few key aspects. First, we recognized the two categories of users/applications needs, i.e. needs for data hungry applications for more bandwidth/data rate, and needs to provide the low latency/delay for sensitive applications. Second, our aim is to solve the network selection multiple objective problem, though it is $NP-$hard.

The remainder of the paper is organized as follows: in Section 2 the channel allocation problem in 5G networks is explained in details. Section 3 describes the multiple objective model that we propose for solving the given problem. This section also outlines the technique for deriving efficient solutions to the formulated model. Experimental results are presented in Section 4. Finally, in Section 5 we offer conclusions and ideas for further work.

II. Channel Allocation Problem in 5G Networks

We considered a two-tier network architecture in Radio Access Technology layer with small cell that provides capacity, and macro-cell that provides basic connectivity and coverage. The resource allocation in a small cell is centrally coordinated by a common authority, namely the Cognitive Network Provider (CNP). The CNP is aware of the status of the heterogeneous network (HetNets) environment, that consists of N primary networks (PN), each of them providing services to its users, i.e. to primary users (PU). It is supposed that the whole portion of the spectrum of one PN is not entirely occupied all the time by its PUs. So, that portion of PN's spectrum, left empty after the fulfillment of the needs of its PUs, is temporary available for those users which do not belong to that PN, namely for the secondary users (SU). The temporarily unused spectrum of one PN is expressed in a number of temporary available channels in that PN. It is clear that the number of the temporary available channels in each of PNs (let us denote it O^{max}) depends to a great extent on the behavior of its PUs. We may suppose that this number does not exceed the maximum number of available channels for each PN (denoted by O_k^{max}, $k \in \{1, \dots, N\}$). Thus we compute $O^{max} = \max_{k \in \{1,2,\dots,N\}} O_k^{max}$. Then, the pool of maximum $N \times O^{max}$ channels is available to M secondary users (SU), for an opportunistic use according to their requirements.

Considering the huge wireless paradigm shift brought by 5G HetNets, and its impact on practical deployment (see [1], [3]), we conclude that SUs requirements can be specified in terms of data rate (d_i), latency (τ_i), and price (p_i) reasonable to be paid to the CNP for the requested service, where $i \in \{1, ..., M\}$ is an index of SU. We assume that each SU can dynamically determine/measure two performance measures (data rate, and latency) and send them to the CNP when enters the system, or whenever it attempts to improve its QoE.

We also assume that the CNP can support the following two categories of the end users according to their requirements. One category consists of users with common requirements for data rate. The users/applications from another category differs in their needs for low or near zero latency. In order to enable a low latency service in HetNet environment, they must be encompassed: the users that request such service; the PNs that may provide low latency condition on some of their channels; and the price policy for the provided service.

The latency τ_i, demanded by the $i-$th user, is equal to 12 if the $i-$th user does not need the low latency service; or otherwise it represents the maximal demanded/accepted value. The service will be provided to the user if there is a temporarily available channel, able to deliver the specified low latency or smaller, in any of the PN networks. Otherwise, a channel will not be allocated to user at all.

Each available channel j = $\{1,..., N \times O^{max}\}$, in any of the PNs, is described in terms of its maximal capacity/bandwidth (c_j), latency (t_j), and the level of interference (h_{ij}) created when i-th SU joins it. As the channels at higher frequency bands operate in short distance providing high data rate transmission with lower latency (compared to the low frequency channels/bands), we suppose that the interference of SUs that use the low latency channels can be neglected, whether they request or not low latency service. Consequentlly, when j-th channel is able to support low latency, h_{ij} is set to zero, for all i, i.e all SUs.

Finally, we assume that there are two price policies one for each of the two categories of the end users. The first one is denoted by f_{ik}, and it represents the amount that $i-$th SU have to pay for common/data rate service in $k-$th PN. The second one is denoted by g_{ik}, and it represents the amount that $i-$th SU have to pay in addition for low latency service in $k-$th PN.

We considered a few possible objectives to direct the process of available channel allocation to SUs in HetNet. Traditionally, one objective is to minimize the interference created by SUs. The second one is to minimize the cost paid by SUs for both categories of users requirements.

The set of feasible solutions is defined by a set of constrains. First, unique allocation should be established, so that a user can access only one of available channels in any PNs, and each channel can be allocated to just one user. Second, the value of the cumulative interference of all SUs using channels in the same PN should not exceeded the interference threshold ε_k , defined for the $k-$th PN. The rest of conditions ensure that a channel can be allocated to a user if and only if it satisfies the user's requirements in terms of data rate, low latency and price.

III. Solving the Channel Allocation Problem

There are different approaches in the literature for solving the Channel Allocation Problem. In this paper we propose two different bi-objective models and solve them by generating their non-dominated points. First model allocates SUs to networks with respect to costs, target interferences, and data rate capacities; while the second model splits PNs in channels, and allocates SUs to channels with respect to their additional demands for low latency.

A. Optimization models

We start from a basic model, that is applied when the CPN does not provide any low latency service because neither any SU is requesting the service nor any temporary available channel in any of the PN networks exists. In such a case the bi-objective is to minimize both the accumulative interference and cost. We compare this model to the model introduced in [8], and solve the same scenarios.

Given N primary networks, that are the components of 5G heterogeneous network, and M secondary users, that are not subscribed users but request access to enter the 5G network through CNO, we use the following notation:

- Parameters for primary network:
  - C_m^{max}, the maximum capacity in bps per channel in the primary network m, for each $m = 1, 2, \ldots, N$;
  - ε_m, interference threshold, i.e. target interference in the primary network m, for each $m = 1, 2, \ldots, N$;
- parameters for secondary users requirements and preferences:
  - d_j, the data rate (in bps), for each $j = 1, 2, \ldots, M$;
  - p_j, the price that secondary user j is willing to pay, for each $j = 1, 2, \ldots, M$;
- a parameter for SU's interference to PUs of a particular network PN
  - h_{jm}, interference of $j-$th SU on primary users in $m-$th primary network, for each $j = 1, 2, \ldots, M$, and $m = 1, 2, \ldots, N$;
- auxiliary parameter
  - f_{jm}, the amount that $j-$th SU have to pay for using the primary network m, $m = 1, 2, \ldots, N$.
- binary decision variables
  - x_{jm}, that is set to 1 if the $j-$th SU is assigned to the $m-$th network, and to 0 otherwise, for each $j = 1, 2, \ldots, M$, and $m = 1, 2, \ldots, N$.

Then, the basic proposed model in the algebraic form is:

$$\min \quad Q_1(x) = \sum_{j=1}^{M} \sum_{m=1}^{N} h_{jm} x_{jm}$$

$$\min \quad Q_2(x) = \sum_{j=1}^{M} \sum_{m=1}^{N} f_{jm} x_{jm}$$

subject to

$$\begin{aligned}
&\sum_{m=1}^{N} x_{jm} = 1, && j = 1, 2, ..M, \\
&\sum_{j=1}^{M} h_{jm} x_{jm} \le \varepsilon_m, && m = 1, 2, ..N, \\
&d_j x_{jm} \le C_m^{max}, && j = 1, 2, ..M,\ m = 1, 2, ..N, \\
&f_{jm} x_{jm} \le p_j, && j = 1, 2, ..M,\ m = 1, 2, ..N.
\end{aligned} \tag{1}$$

TABLE I
THE NUMERICAL RESULTS OBTAINED FOR SCENARIOS 1 AND 2, USING THE SINGLE-OBJECTIVE MODEL FROM [8]

Algorithm	Scenario 1		Scenario 2	
	Q_1	Q_2	Q_1	Q_2
GA [8]	15	540	16	580
PSO [8]	20	700	18	610
Optimal	13	530	15	560

TABLE II
THE NON-DOMINATED POINTS OBTAINED FOR SCENARIOS 1, 2, 3 AND 4 USING THE BI-OBJECTIVE MODEL (1)

Scenario 1	
Q_1	Q_2
12	550
13	530

Scenario 2	
Q_1	Q_2
12	580
13	570
15	560

Scenario 3	
Q_1	Q_2
13	805
14	785

Scenario 4	
Q_1	Q_2
14	710

The optimization model introduced in [8] has a single objective function that corresponds to the aggregation Q_1+Q_2, and the same constraints as in Model (1). In our opinion, Q_1+Q_2 is not a very useful aggregation, since Q_1 and Q_2 are of different order of magnitude and have different measuring units. Without a proper normalization, the result of such optimization will never assure a good compromise between interferences and costs in the system (see the numerical results presented in Section IV).

In order to improve Model (1), we consider directly the networks channels instead of the networks themselves (having in mind that two channels of the same network may differ with respect to the capacity, latency, interference etc); and we consider two categories of secondary users: those that are willing to pay for data rate, and those that are willing to pay for low/zero latency. The new parameters are:

- N, the set of networks;
- U, the set of users;
- C, an indexed set of channels, such that
- $C\left(k\right)$ is the set of channels that belong to the network k, for each $k \in N$;
- h_{ij}, the interference of $i-$th SU when joining the $j-$th channel, for each $i \in U$, $j \in C$;
- f_{ik}, the amount that i-th SU have to pay for data rate when joining the primary network k, for each $i \in U$ and $k \in N$ (in fact, $i-$th user joins the $j-$th channel, that belongs to the network $k = m\left(j\right)$, where $m\left(j\right)$ is the function that maps each channel j to its network k);
- g_{ik}, the amount that i-th SU have to pay for low latency when joining the primary network k, for each $i \in U$ and $k \in N$;
- p_i, the price that secondary user i is willing to pay, for each $i \in U$;
- τ_i, the latency demanded by the $i-$th user (it is equal to 12 if the $i-$th user does not want to pay for low latency);
- t_j, the latency on channel j, for each $j \in C$;
- d_i, the data rate (in bps) for i-th SU, for each $i \in U$;
- c_j, the maximum capacity (in bps) of the $j-$th channel, for each $j \in C$.

The new binary decision variables are x_{ij}, $i \in U$, $j \in C$, that are set to 1 if the $i-$th SU uses the $j-$th channel, and to 0 otherwise. The new mathematical model is

$$\begin{aligned} \min \quad & Q_1\left(x\right) = \sum_{i\in U}\sum_{j\in C} h_{ij}x_{ij} \\ \min \quad & Q_2\left(x\right) = \sum_{i\in U}\sum_{j\in C} \left(f_{\mathrm{im}(j)} + g_{\mathrm{im}(j)}\right) x_{ij} \end{aligned}$$

subject to

$$\begin{aligned} & \sum_{j\in C} x_{ij} = 1, && \forall i \in U, \\ & \sum_{i\in U} x_{ij} \le 1, && \forall j \in C, \\ & \sum_{i\in U}\sum_{j\in C(k)} h_{ij}x_{ij} \le \varepsilon_k, && \forall k \in N, \\ & t_i x_{ij} \le \tau_j, && \forall i \in U, \forall j \in C, \\ & d_i x_{ij} \le c_j, && \forall i \in U, \forall j \in C, \\ & \sum_{j\in C} \left(f_{\mathrm{im}(j)} + g_{\mathrm{im}(j)}\right) x_{ij} \le p_i, && \forall i \in U, \\ & x_{ij} \in \left\{0,1\right\}, && \forall i \in U, \forall j \in C. \end{aligned} \tag{2}$$

The complexity of Model (2) may be reduced significantly if, for each secondary user $i \in U$, we define the set L_i of the channels with feasible capacity and latency, i.e. $L_i = \left\{j \in C \middle| \left(d_i \le c_j\right) \wedge \left(\tau_i \ge t_j\right)\right\}$. These sets L_i, $i \in U$ are evaluated in the preprocessing step, thus simplifying the optimization process. In this case, the final model is

$$\begin{aligned} \min \quad & Q_1\left(x\right) = \sum_{i\in U}\sum_{j\in L_i} h_{ij}x_{ij} \\ \min \quad & Q_2\left(x\right) = \sum_{i\in U}\sum_{j\in L_i} \left(f_{\mathrm{im}(j)} + g_{\mathrm{im}(j)}\right) x_{ij} \end{aligned}$$

subject to

$$\begin{aligned} & \sum_{j\in L_i} x_{ij} = 1, && \forall i \in U, \\ & \sum_{i\in U} x_{ij} \le 1, && \forall j \in C, \\ & \sum_{i\in U}\sum_{j\in C(k)\cap L_i} h_{ij}x_{ij} \le \varepsilon_k, && \forall k \in N, \\ & \sum_{j\in L_i} \left(f_{\mathrm{im}(j)} + g_{\mathrm{im}(j)}\right) x_{ij} \le p_i, && \forall i \in U, \\ & x_{ij} \in \left\{0,1\right\}, && \forall i \in U, \forall j \in L_i. \end{aligned} \tag{3}$$

B. Solving approach

In multiple objective optimization problems there is no single optimal solution that simultaneously optimizes all the objective functions. The decision maker wishes to find a solution that assures a good trade-off between objectives. In a priori methods the decision maker expresses his preference information before the optimization process. As a consequence, the derived solution is the final solution. A posteriori

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TABLE III
SU'S SPECIFIED REQUIREMENTS FOR DATA RATE, LATENCY AND PRICE FOR SCENARIOS 3 AND 4

Users requirements		Indexes for SUs											
		1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***
Latency (τ_i)		12	12	12	2	12	12	12	2	12	12	2	10
Price	Scenario 3	100	100	100	150	100	100	100	150	100	100	150	100
	Scenario 4	80	75	70	120	60	150	60	110	55	95	120	170

TABLE IV
MAXIMAL CAPACITY (IN BPS) / LATENCY (IN MS) SEPARATELY PER CHANNELS FOR SCENARIO 5

k	Channels						
	1	***2***	***3***	***4***	***5***	***6***	***7***
1	80/3	20/1	80/2	80/50	80/50	40/50	80/50
2	70/10	70/10	70/2	70/2	50/10	70/1	70/10
3	70/10	70/3	70/5	70/10	70/2	70/10	70/10
4	90/30	60/4	90/5	90/1	90/1	90/30	90/30
5	100/7	100/2	70/3	100/7	100/1	100/7	100/1
6	70/10	70/50	70/10	70/7	70/50	70/50	70/5
7	60/5	60/70	60/4	60/70	60/1	60/2	60/70

TABLE V
PNS POLICIES IN TERMS OF LATENCY AND ADDITIONAL FEES FOR SCENARIOS 3 AND 4

Parameters	**Primary networks**						
	1	***2***	***3***	***4***	***5***	***6***	***7***
Latency	10	10	10	1	1	10	10
Additional fees	0	0	0	40	40	0	10

approache provides a set of non-dominated points (if not the entire Pareto front) to the decision maker that chooses one of them, the one that satisfies the best his preferences.

We use the $\varepsilon-$constraint method to solve Models (1) and (3). This method is one of the most convenient a posteriori approaches in the case of bi-objective optimization problems. The general idea of this approach is to keep optimizing one of the objectives; and restrict all the other objectives within some specified values. Thus, in the bi-objective case the problem

$$\begin{aligned} \min \quad & Q_1(x), \\ \min \quad & Q_2(x), \\ \text{s.t.} \quad & x \in X, \end{aligned}$$

TABLE VI
PNS POLICIES IN TERMS OF TARGET INTERFERENCE THRESHOLD AND SUBSCRIPTION FEES FOR SCENARIO 5

Parameters	**Primary networks**						
	1	***2***	***3***	***4***	***5***	***6***	***7***
Price for data rate	80	60	65	60	70	40	50
Price for low latency	20	30	10	40	40	50	10
Interference threshold	7	6	7	10	19	15	9

is replaced by

$$\begin{aligned} \min \quad & Q_1(x), \\ \text{s.t.} \quad & x \in X, \\ & Q_2(x) \leq \varepsilon. \end{aligned}$$

Varying the value of ε, distinct non-dominated points are obtained. The main advantage of this method is that any efficient solutions can be obtained, thus it can be successfully used for non-convex optimization problems. The solution to the multi-objective problem essentially depends on the selection of the ε values. In particular, any ε value must be chosen between the minimum and maximum value of the corresponding objective function. When the number of the objectives increases, more information from the decision maker is required, and the applicability of the approach becomes cumbersome.

IV. EXPERIMENTAL RESULTS

In order to test our approach we first recall the example given in [8] and use Model (1) to solve it. The experiments reported in [8] were performed under two scenarios using different data sets. The main difference between scenarios is the price that SUs are willing to pay to the Cognitive Network Operator (CNO). In Scenario 1, each SU can join any network because it is ready to pay more than the maximum cost of joining any primary network. On the other side, in Scenario 2, a SU may be unable to join a network due to the cost constraints. The information about the parameters of both PNs and SUs for Scenarios 1 and 2 can be found in [8].

The numerical results reported in [8] are shown in Table I together with the exact values for the optimal interference and accumulative price for Scenarios 1 and 2 obtained using the single-objective model introduced in [8]. As expected, since the problem size is quite small, the exact solution of the optimization problem can be obtained directly, and in short time (about 0.03 seconds).

Table II shows the non-dominated points obtained using Model (1). As expected, the optimal value of the objective function in the model introduced in [8] is equal to the non-dominated point with minimal price for both Scenarios 1 and 2. This is due to the lack of normalization in model [8], where the accumulative price and interference were summed with equal weights despite the different orders of magnitude and measuring units.

We also performed additional experiments using Model (3), that involves channels instead of networks.

TABLE VII
SU'S SPECIFIED REQUIREMENTS FOR DATA RATE, LATENCY AND PRICE FOR SCENARIO 5

User requirements	**Indexes for SUs**											
	1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***
Data rate (bps)	50	70	70	20	60	40	50	40	50	60	40	40
Low latency	12	12	12	12	12	12	1	2	12	12	5	10
Price	180	175	170	120	160	150	160	110	155	195	120	170

TABLE VIII
INTERFERENCES h_{ij} FOR SCENARIO 5

Channel (j)	**Indexes for SUs**											
	1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***
$j \in \overline{1,7}$	2	2	4	3	1	2	1	4	3	1	3	2
$j \in \overline{8,14}$	1	1	1	2	3	2	2	1	3	1	1	2
$j \in \overline{15,21}$	3	2	1	2	3	1	1	2	1	2	1	1
$j \in \overline{22,25}$	1	4	3	2	2	3	1	1	1	2	1	1
$j \in \{26,27\}$	0	0	0	0	0	0	0	0	0	0	0	0
$j = 28$	1	4	3	2	2	3	1	1	1	2	1	1
$j \in 29,32$	2	2	1	2	1	2	1	2	3	1	1	2
$j \in \{33,34\}$	0	0	0	0	0	0	0	0	0	0	0	0
$j = 35$	2	2	1	2	1	2	1	2	3	1	1	2
$j \in \overline{36,42}$	1	2	1	4	1	2	2	1	1	1	2	1
$j \in \overline{43,49}$	2	1	3	4	1	1	2	1	3	3	3	2

Since neither in Scenario 1 nor in 2, users did not request latency service we created Scenarios 3 and 4, where three users ($i \in \{4, 8, 11\}$) request to have access to a network that is able to provide 2 ms latency or lower. Each user is willing to pay additional price (the same, 50 in Scenario 1, and 30, 35, 20 respectively in Scenario 4) for this service. There are also two PNs out of seven providers that can guarantee 1ms latency on their channels, and requesting additional price of 40 for this service. The additional parameters for Scenarios 3 and 4 are shown in Tables V and III.

Comparing the numerical results obtained for Scenario 3 to the solution obtained for Scenario 1, we may notice that, as expected, the total price increased (due to the bigger price payed by the users that demanded low latency); and the total interference also increased (since the allocation made for Scenario 1 does not fulfill the low-latency constraints, thus it is not feasible anymore). Something similar may be concluded comparing Scenario 4 to Scenarios 1 and 2. For Scenario 4 ideal values, i.e. optimal for both criteria, were found. All non-dominated points for each scenario were obtained exactly, in less than 1 second.

We also created Scenario 5, were channels in PNs have different parameters, thus various offers are made available to SUs. The parameters are reported in Table VI (where channels are indexed from 1 to 7 for each PN separately), Table VII and Table VIII (where channels are indexed from 1 to 49). All 10 non-dominated points were found in 0.832 seconds. The non-dominated points are shown in Table IX.

The experiments were conducted on Intel® Core™ i3 at 1.80GHz and 8GB RAM. For optimization we used GLPK (GNU Linear Programming Kit) version v4.61.

V. CONCLUSION AND FUTURE WORK

In this paper, we studied network selection and channel allocation problem in 5G HetNets, where the resource allocation in a small cell was centrally coordinated by a common authority of Cognitive Network Provider (CNP). We proposed two different bi-objective models. First model allocated SUs to networks with respect to costs, target interference, and data rate capacities; while the second model split PNs in channels, and allocated SUs to channels with respect to their additional demands for low latency.

We solved both models for 5 scenarios using $\varepsilon-$constraint method thus generating their efficient solutions, that consisted of a range form 1 to 10 non-dominated points for Scenario 4 and Scenario 5, in a time frame range from 16ms to 832ms. Obtained results showed that the zero/low latency demand should be combined with a resource reservation algorithm rather than an on-demand resource allocation algorithm.

The proposed model can be extended gradually in twofold: defining one more criterion imposed by CNP leading to three-criterion model; or adding more granular control in each of the criterion function (i.e PN, SU or CNP oriented) leading to a fractional form of the problem.

This work can be a basis for further integration of the requirements of the primary networks and users, and an attempt of the provider to improve the quality of experience (QoE) generally by minimizing the overall latency/delay for users in small cell. The decision made at this level of small cells could be part of a wider multi step decision-making

TABLE IX
NON-DOMINATED POINTS (INTERFERENCE / PRICE) OBTAINED FOR SCENARIO 5

Q_1 **(accumulative interference)**	17	16	15	14	13	12	11	10	9	8
Q_2 **(accumulative cost)**	825	835	850	860	875	890	910	940	960	990

framework. It is expected that various application of future 5G technology will have different requirements, some of them being preprocessed/anticipated before users enter under the coverage of small cell.

ACKNOWLEDGMENTS

This research was partially supported by the Ministry of Education and Science, Republic of Serbia, Project numbers TR36006 and TR32013.

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