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Multi Resource Allocation for Network Slices with Multi-Level fairness

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Abstract—Network slicing is becoming the platform of choice for several applications and services. Nowadays most applications are virtualized to gain flexibility and portability. With network slicing, operators can create multiple network slices or tenants, which can be used for certain applications with specific requirements. Behind the network slicing, a slice expresses the need to access a precise service type, under a fully qualified set of computing and network requirements. Resource allocation decision encompasses a combination of different resource types (e.g., radio resource, CPU, memory, bandwidth). In this paper, we explore a differential pricing scheme that maximizes social welfare among slices as well as among end-users. To do so, we propose a pricing mechanism that makes fairness at multiple levels: fairness among slices and fairness among slice locations supported by each slice. Therefore, the proposed scheme is beneficial for both the slices and the end-users independent of their location. Additionally, we study the case where slices can manipulate their preferences to improve their utility. We show that the Fisher market game always has a pure Nash equilibrium and we prove Price of Anarchy is $\frac{1}{N}$, where N is the number of slices. Finally, we conduct simulations using Amazon EC2 instances to numerically analyze and compare the performance of the mechanisms and confirm the theoretical properties of the market model.

Index Terms—resource allocation, networking slicing, Fisher market, multi-level fairness

I. INTRODUCTION

5G networks enable new edge and fog computing paradigms by deploying virtualized resources in a multi-tenant and multi-service scenario. 5G network slicing permits Infrastructure Providers (InPs) to offer 5G differentiated services using shared resource pools to fulfill the dynamic and demanding requirements of mobile applications. A network slice or *slice* is a logical network overlay on top of a physical infrastructure which can be assigned to slice tenants, namely the Service Providers (SPs), and their end-users [1], [2]. By using technologies such as Software-Defined Networking (SDN) and Network Function Virtualization (NFV) a slice can encompass different resource types, such as, e.g., radio access capacity, edge storage memory, and computing power. InPs in turn can create multiple slices to serve specific applications or services with particular requirements, providing an ideal framework to capitalize on the inherent scaling flexibility of modern virtualized microservice architectures [1].

To satisfy demanding quality of service (QoS) requirements for slice tenants and their end-users, InPs need to perform efficient resource allocation. In the context of network slicing, the key challenge is the presence of multiple resource types and competing SPs with heterogeneous characteristics and preferences. The main goal in this context is devising efficient mechanisms to create slices while ensuring fairness both among slice tenants as well as across their end-users.

To address the aforementioned challenges, we formulate the multi-resource allocation for network slicing in the form of a Fisher Market model, where SPs act as buyers and a set of resources (divisible goods) is made available by the InP at different locations. Within the Fisher market framework, a generalized α -fairness resource allocation for SPs able to adapt the degree of fairness as a function of a parameter $\alpha \in [0, \infty)$, striking the trade-off between fairness and efficiency. Given the resource prices, each SP with a certain budget – namely the market power of the SP – buys the optimal set of multi-resources to maximize its utility under the budget constraints. The Market Equilibrium (ME) is computed as a price vector for each resource type that ensures market clearance, i.e., the demand of a resource equals its supply. In this paper, we show that it is possible to let such market equilibrium correspond to the allocations maximizing α -fair utility, which is obtained under non-linear pricing. Furthermore, we obtain a closed-form of the pricing as a function of α and resources purchased by SP.

Related work: Many existing network resource allocation schemes focus on a single resource. However, since 5G network slicing centralizes multiple types of resources under one shared platform, multi-resource allocation has recently come into the spotlight. Different multi-resource allocation techniques exist, such as Dominant Resource Fairness (DRF) [3]. In [4], authors studied the multiple resource allocation for network slicing using different fairness criteria such as DRF, Ordered weighted averaging (OWA), weighted proportional fairness (WPF) and mood value rule. Some recent works, applied the Fisher Market model to study the multi-resource allocation problem for edge computing [5], [6], [7], [8]. In these works, the resource allocation is determined by solving Eisenberg-Gale [9] convex program to obtain the related market equilibrium. This produces linear prices that do not fit well in the real world scenarios since, in general, prices are non-linear. This aspect is addressed in [10], under some

assumptions on the agent preferences in order to define price curves.

Another important aspect that seizes most of the attention in the literature is the fairness-efficiency trade-off [11], [12]: most auction-based models [13] prefer to allocate a higher share of resources to SPs with better marginal utilities – similar to the utilitarian approach – whereas the Max-min [14] allocates more resources to the SPs with weaker marginal utilities to make the resource allocation as fair as possible. Both such extreme fairness schemes can be generalized under the so-called α -fair allocations [15], [16], which provides good flexibility to the InP in the trade-off between fairness and efficiency. A key issue not addressed in such works is location dependent services: each SP has a user base that varies across locations. This motivates us to propose a new model based on the Fisher market to address these aspects of multi-resource allocation.

Main contributions: We propose a framework to consider both intra-slice and inter-slice fairness at once, combining fairness at the slice level and location level as well. Non-linear differential price curves are defined to support such general fairness scheme. Furthermore, we investigate the strategic aspect of the SPs and its impact on the overall social welfare. Finally, we provide numerical results to support our theoretical claims and demonstrate that our model is consistent and effective in the allocation of resources. This novel approach permits to incorporate intra-slice and inter-slice fairness via non-linear pricing and under the same framework and extends the literature of resource allocation for wireless networks.

This paper is organized as follows. Section II introduces the system model, section III formulates the allocation problem, characterizes the market equilibrium and introduces our new multi-level fairness mechanism. Section IV describes the strategic version of the Fisher market model. Section V presents the numerical results supporting our theoretical findings. A concluding section ends the paper.

II. SYSTEM MODEL

We begin by presenting the system of interest and introduce some basic terminology. Infrastructure resources, namely CPU, memory, radio access capacity, etc. are owned by an InP. The InP leases these resources to a set of SPs, who run different services, e.g., IoT, URLLC, eMMB, etc. SPs support subscribed customers over a set of different locations. SPs negotiate and scale resources at their need, the slice support being provided by the InP across heterogeneous access technologies (5G, LTE, 3G, and WI-FI) and different site types (macro, micro, and pico base stations).

A. Model' features outline

Development in technologies has boosted the possibility of accommodating various services under 5G, introducing several new features both at the infrastructure and the business level. Hereafter, we cover the key aspects captured by our model. *Services, SPs and InPs.* Business models related to smart cities, smart factories, autonomous driving, etc., are pushing

SPs to offer new services and seek for a sustainable business environment. Because such services are so diverse, SPs need multiple resource types to deliver them with agreed QoS. Based on the location and service type, an SP has a specific budget to procure different resource types from the InPs via network slicing. In this emerging telecom business, the InP is in charge of performing the crucial and complex task of Multi Resource Allocation (MRA) to SPs. Our model covers the case of a single InP in this paper; the case of multiple InPs owning physical resources across different locations is left as part of future works.

Resource scaling with Network Slicing. A key to a successful and sustainable business is to better serve the customers with limited resources. The flexibility of network slicing facilitates both InPs and SPs in controlling their costs. Multiple SPs with limited budgets compete for a bundle of resources; such resources may be either distributed (edge cloud) or centralized (core cloud) to run their respective services, based on the budgets and resource preferences, InP allocate resource bundle to SPs through the network slicing, each SP is assigned with a dedicated network slice that contains tailored resources.

Given the heterogeneous nature of offered SP services, a slice must contain both network and computational resources. However, the service offered to the subscribed users can be limited by any of the resources that belong to the slice: exhausting a particular resource creates a bottleneck for the whole slice and prevents the SP in offering the service to additional users. Indeed, the QoS is determined by the bottleneck resource: this concept will be encoded later on in the definition of the SP utility function.

B. Service utility

We confine the discussion to a single InP that provides a set of resource types, namely $\mathcal{R} = \{1, 2, \dots, R\}$, over a set of locations. Given that each SP is assigned with a dedicated slice by InP, the total number of slices supported by InP is $\mathcal{N} = \{1, 2, \dots, N\}$ ¹. The set of locations \mathcal{L}_i concerns SP i . The capacity of resource type r at a given location l is $C_{l,r}$. The resource requirement across locations varies based on the service type. For example, to process a single IoT request, SP may need 4 units of bandwidth, 2 units of RAM, and 2 units of storage and processing resources, respectively. Let a base resource preference vector $a_{i,r}$ represent the need for each resource type r for SP i , it is the minimum quantity to run the service with certain QoS. Under budget B_i , SP i procures resources from the InP. She obtains a resource bundle $x_i = (x_{i11} \dots x_{i1R})$, where x_{ilr} is the amount of resource type r at location l allocated to SP i . The utility function for the service level of SP i writes

$$u_i(\mathbf{x}_i) = \sum_{l \in \mathcal{L}_i} u_{il} \quad (1)$$

where, the utility of the SP i at location l u_{il} is defined as,

$$u_{i,l} = \min \left\{ \frac{x_{i11}}{d_{i1}a_{i11}}, \frac{x_{i12}}{d_{i1}a_{i12}}, \dots, \frac{x_{i1r}}{d_{i1}a_{i1r}}, \dots, \frac{x_{i1R}}{d_{i1}a_{i1R}} \right\}, \quad (2)$$

¹Since each SP is assigned with a dedicated slice the term 'slice' or 'SP' or 'tenant' is equivalent.

Where d_{il} represents the overall user demand of SP i at location l . We used *leontief function* since the resource types are perfect compliments [17], i.e, obtaining a resource type r in excess does not yield higher utility.

Here, service utility u_i depends linearly on location-based utility u_{il} , which can lead to unfair resource allocation between locations, this aspect is discussed in detail in III-C.

C. Objective of the service providers

The goal of each SP $i \in \mathcal{N}$ is to meet the variable user demand across multiple locations. Hence, it requires multiple resources in sufficient proportions at different locations to meet the SLA. For this reason, SP i with a predefined budget B_i tries to obtain the resource bundle that suffice her service. Thus the utility of each SP i , named F_i writes

$$F_i = \underset{x_i \in \mathbb{R}_+^m: C(x_i) \leq B_i}{\operatorname{argmax}} u_i(x_i) \quad (3)$$

where $C(x_i)$ is the total cost of the resource bundle that should not exceed budget B_i of SP i .

III. RESOURCE ALLOCATION PROBLEM

In this section, we present resource allocation problem and a suitable market equilibrium along with the pricing scheme for the setting described in Sec.II.

A. Fisher Market under generalized α -fair resources allocation

The classical optimization framework for the InP is to provide an efficient and fair allocation to all SPs accounting for their budgets. Since SPs may have different priorities, a weighted version of the social welfare objective is considered. The main aim of the InP is to maximize the total social welfare: this leads to the following 5G resource allocation problem (RAP)

$$\underset{r}{\operatorname{maximize}} : \sum_{i \in \mathcal{N}} B_i U(u_i) \quad (\text{RAP})$$

$$\text{subject to: } u_i = \sum_{l \in \mathcal{L}} u_{il} \quad \forall i \in \mathcal{N} \quad (4)$$

$$u_{i,l} \leq \frac{x_{ilr}}{d_{il} a_{ir}} \quad \forall i \in \mathcal{N}, l \in \mathcal{L}_i, r \in \mathcal{R} \quad (5)$$

$$\sum_{i \in \mathcal{N}} x_{ilr} \leq C_{lr}, \quad \forall l \in \mathcal{L}_i, r \in \mathcal{R} \quad (6)$$

Given that SPs generally have their services across multiple locations, their utility indeed depends upon the utility obtained from each location as mentioned previously, this location dependency is captured by the constraint (4). Under the chosen service utility, resources are perfect compliments: the utility depends on the bottleneck resource, which is the point of leontief function, (5) warrants this functionality. Constraint (6) bounds the amount of resource that can be allocated for each resource type at all the locations where SPs are active: this guarantees that the capacity is not exceeded.

Utility U belongs to the well-known class of fairness [15] that measures α -fairness. Specifically, we have

$$U(y) = \begin{cases} \frac{(y)^{1-\alpha}}{(1-\alpha)} & \text{if } \alpha \neq 1 \\ \log(y) & \text{if } \alpha = 1 \end{cases} \quad (7)$$

The values of enclosed $\alpha \in [0, \infty)$ give the trade-off between individual fairness and efficiency, the smaller α corresponds to utilitarian welfare where a social planner cares more about societal good (efficiency). In contrast, larger α corresponds to the egalitarian resources allocation, where the planner cares more about individual equality (fairness). For $\alpha = 1$, for instance, the customary log-based proportional-fair utility severely penalize serving high utility in a lightly loaded location while starving slice users elsewhere.

B. Market Equilibrium

We assume that the InP acts as a social planner or mechanism designer, whose goal is to maximize the total social welfare regardless of the budget difference among the SPs. Under the α -fair setting, the market is said to be at equilibrium if the supply provided by InP exactly matches the SPs' demand, and each SP gets its favorite resource bundle. Out of all markets mentioned in the literature, probably the simplest one is the Fisher market, where each SP owns the finite budget and the SPs purchase the resources based on the linear pricing. For $\alpha = 1$, Eisenberg and Gale [9] showed that if the SPs utilities in the fisher market are with $\alpha = 1$, then the market equilibria solution problem is equivalent to the Nash welfare optimization problem. An immediate question arises what if the social planner (InP) wishes to maximize a different welfare function? Motivated by this question, we focus on developing a pricing scheme for the market such that the market equilibrium induced through the proposed pricing scheme achieves various α fairness criteria. Without loss of generality, we consider that the total budgets of the SPs (B_i) are normalized to one, i.e.,

$$\sum_i^N B_i = 1$$

As discussed above, a Fisher market adopts a linear pricing scheme under Proportional Fairness(PF); in this work, we consider a more general pricing scheme under α -fairness, where $\alpha \in [0, +\infty)$.

Definition 1. Price curves: Let $\gamma_{ilr}(x_i) : \mathbb{R}_+^{L \times R} \times \mathbb{R}_+ \rightarrow \mathbb{R}_+$ [10], is an increasing function denoting cost for purchasing x_{ilr} amount of resource of type r at location l given bundle of resources x_i purchased by SP i , thus the total cost for purchasing bundle x_i of resources

$$C_{\gamma_i(x_i)} = \sum_{l=1}^{L_i} \sum_{r=1}^R \gamma_{ilr}(x_i) \quad (8)$$

we define the market

$\mathcal{M} := \left\langle \mathcal{N}, (B_i)_{i \in \mathcal{N}}, \bigcup_{l=1}^{L_i} \mathcal{R}_l, (u_i)_{i \in \mathcal{N}}, \gamma \right\rangle$ as follows:

- *Player set:* the set of service providers \mathcal{N}
- *Budgets:* B_i

- Resources set: $\bigcup_{l=1}^{L_i} \mathcal{R}_l$
- Utility: The utility of each SP i is equal to the u_i
- Price curve: $\gamma_{ilr}(x_i)$

Definition 2. Allocation and price curve vector $(x^*, \gamma(x^*))$ is called as market equilibrium of market \mathcal{M} if the following conditions are satisfied.

C1 Each $i \in \mathcal{N}$ SP gets her preferred bundle x_i^* , where

$$x_i^* : \underset{x_i \geq 0; C_{\gamma}(x_i) \leq B_i}{\operatorname{argmax}} u_i(x_i) \quad (\text{C1})$$

C2 Demand x^* meets supply (“the market is cleared”), i.e.,

$$\sum_{i \in \mathcal{N}} x_{ilr}^* \leq C_{lr} \quad \forall l \in \mathcal{L}_i, \forall r \in \mathcal{R} \quad (\text{C2})$$

and inequality (C2) is saturated if $\gamma_{ilr} > 0$.

C. Resource allocation with two level fairness

The aim of RAP is to obtain optimal resource allocation with various fairness settings. However, the considered utility u_i is additive over the locations’ utility and lay result in unbalanced resource allocation across locations supported by each SP. To overcome this limitation, we modify RAP to account for fairness among slices and locations supported per slice. Linear utility function (4) is replaced by a slightly tweaked CES utility function (9) to incorporate fairness between different locations of the SP as well,

$$u_i = \left(\sum_{l \in \mathcal{L}_i} (u_{il})^{1-\beta} \right)^{\frac{1}{1-\beta}} \quad \forall l \in \mathcal{L}_i \quad (9)$$

where $\beta \in [0, \infty)$ determines the fairness level among locations served by the slice i . Similar to α , here $\beta = 1$ implements proportional fairness, max-min fairness is obtained as β approaches ∞ , on the contrary $\beta = 0$ leads to the worst fairness.

As reported in the numerical section, a market equilibrium of RAP under the new utility (9) ensures a fair allocation both among SPs and across locations covered by each SP. The price curves that satisfy the ME conditions defined earlier are characterized by the following.

Theorem 1. There exist a price curve vector γ and associated market equilibrium $(x^*, \gamma(x^*))$ for the market \mathcal{M} such that the allocation x^* maximizes the social welfare (RAP) and the price curve for each resource type r at location l for SP i is characterized as

$$\gamma_{ilr}(x) = p_{lr}^* x_{ilr} \left(\left(\sum_{l \in \mathcal{L}_i} \left(\frac{x_{ilr}}{d_{il} a_{ir}} \right)^{1-\beta} \right)^{\frac{1}{1-\beta}} \right)^{\alpha-1},$$

if $d_{il} a_{ir} > 0$, (10)

where p_{lr}^* is the Lagrangian multiplier associated with the capacity constraints in (RAP).

We observe that the structure of the price function reflects the goal of α -fairness between SPs. Indeed, when α is higher, i.e., $\alpha > 1$, the price of a resource increases faster, proportional

to the total utility of SP. Therefore, the higher the α is, the more we care about SP with low utility. When $\alpha = 1$, which corresponds to PF the price function becomes linear and the resource allocation corresponds to a mix of fairness and efficiency. Indeed, under PF, if compared to any other feasible allocation of utilities, the aggregate proportional change is less than or equal to zero. When $\alpha < 1$, we have the opposite behavior since the smaller α , the more SPs with higher utility are favored. The new version of the problem is in fact an extension of RAP:

Corollary 1. If $\beta = 0$ in (10) the price curves are those for the original version of RAP.

It is worth observing that the price functions appearing in Thm. 1 account systematically for the traffic heterogeneity in different locations.

IV. INEFFICIENCY WITH STRATEGIC SPs

In a strategic setting, SPs are players, and may report a strategy profile s_{ir} instead of reporting the true preferences a_{ir} , in an attempt to gain larger utility. The use of a plain Fisher market mechanism in this situation for resource allocation induces game \mathcal{G} . There are N SPs and R resource types; for the sake of simplicity we drop the dependency on location. Now the utility of SP writes

$$u'_i = \min_{r \in [M]} \left\{ \frac{1 - s_{2r} \left(\frac{B_2}{s_2^{\max}} \right)^{\frac{1}{\alpha}}}{a_{1r}} \right\} \quad (11)$$

By inversion, it is possible to compute the expression for the best response strategy of a SP to other players actions [5]. An explicit formula for a two player market with strategies s_1 and s_2 is the following

$$s_{1r} = 1 - s_{2r} \left(\frac{B_2}{s_2^{\max}} \right)^{\frac{1}{\alpha}} \quad (12)$$

where $s_i^{\max} = \max_{r \in R} \{s_{ir}\}$.

Let $s^* = (s_1^*, \dots, s_N^*)$ be the strategy profile for the market under strategic players and \mathcal{S}_i be the strategy space for player i . The standard definition of equilibrium is as follows,

Definition 3. Strategy profile s^* is a Nash Equilibrium (NE) of the game \mathcal{G} if

$$\forall i \in \mathcal{N}, U_i(s_i^*, s_{-i}^*) \geq U_i(s_i, s_{-i}^*), s_i \in \mathcal{S}_i \quad (13)$$

Here, (s_i, s_{-i}^*) denotes the strategy profile with i^{th} element equals s_i and all other elements equal $s_{i'}^*$ (for any $i' \neq i$).

Theorem 2. A uniform strategy $(s_{ij} = \frac{1}{M} \forall j \in [M])$ is a Nash Equilibrium for the given Fisher market game with leontief utilities where the player utilities are $u_i = \frac{B_i^{\frac{1}{\alpha}}}{\sum_{k=1}^N B_k^{\frac{1}{\alpha}} d_k^{\max}}$

To, see the effect of player’s strategic nature, we use price of anarchy (POA), which is defined as the ratio between the worst NE social welfare and the optimum social welfare.

API Name	Bandwidth (Gbps)	vCPU	Memory (GB)	Instance Type
r4.16xlarge	25.00	64.00	488.00	Memory optimized
m4.10xlarge	10.00	40.00	160.00	General purpose
m4.16xlarge	25.00	64.00	256.00	General purpose
c5.9xlarge	10.00	36.00	72.00	Compute optimized
c5.18xlarge	25.00	72.00	144.00	Compute optimized

TABLE I
API INSTANCES FROM AMAZON EC2

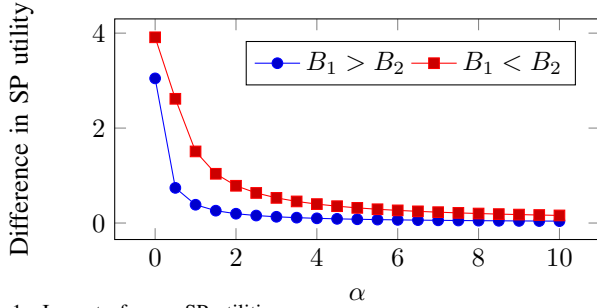


Fig. 1. Impact of α on SP utilities

Proposition 1. *The PoA of the Fisher Market under α -fair utilities is $\frac{1}{N}$*

This proposition extends the result in [5], which is covering just the case $\alpha = 1$. Here, we observe that the PoA does not depend on α . Hence, no value of α improves the efficiency when SPs behave strategically.

V. NUMERICAL RESULTS

In this section, we provide numerical results to support the mechanisms that we have described so far. We consider Amazon EC2 instances [18] to compute numerical results, some of these instances are described in table I.

First, we consider a simple set up with two slices, both slices cover demands at two locations and each SP needs three resource types to run their services. Assume that each SP provides two application services with the APIs mentioned in the table, SP1 supports API m4.10xlarge and m4.16xlarge, SP2 supports API c5.9xlarge and c5.18xlarge. In order to generate Monte Carlo simulations, we let each SP support services at each location with given probability p_{kl} per generated instance, where, p_{kl} is the probability to support API k at location l . SP i has fixed budget B_i (normalized to 1). Capacity C_{lr} is available at each location l for resource r , and resource preferences are aggregated for both SPs as they support only one service at the time:

$$a'_{lr} = p_{1l}a_{lr}^1 + p_{2l}a_{lr}^2, \quad l \in \mathcal{L} \quad (14)$$

Budget B_i , α , and demand d_{il} per location l has a great impact on the resource allocation for the slice and in turn, impact the utility of the SP. Hence, we focus on the impact that these factors have on resource allocation. For the remainder of this section, we consider the same preferences evaluated using (14) based on the Amazon instances mentioned earlier. First we provide the impact of α in tuning the degree of fairness, then

the impact of budget and parameter α . Finally we show the impact of demands by imposing higher fairness at both levels.

A. Impact of factor α

As described throughout the article, the factor α tunes fairness in the proposed mechanism, imposing different degrees of fairness across the slices. Instead of comparing the utilities U_1 and U_2 side by side, we prefer to observe the change in $|U_1 - U_2|$, which provides a better illustration for observing the fairness variation. Figure 1 displays this by varying α over the range 0-10 with an interval of 0.5. Figure 1 shows that at the increase of α , the difference between the utility of SP decreases. I.e., the allocation of resources is more and more fairly distributed, thus vanishing the difference between U_1 and U_2 . We compare two scenarios to show the consistent behavior of the fairness: first, we let $B_1 > B_2$, uniform demand across locations, and the resource preferences are as mentioned earlier (aggregated for the two APIs). In the second scenario SP 2 has higher budget. In both cases, higher α leads to higher fairness. Though the behaviour appears similar for both scenarios, the curve in the first scenario decreases sharply than the other curve. In fact, the utility depends on resource preferences as well, and not only on the budget. The preference for resources are higher for slice 1 than for slice 2. Based on the numerical results, we observe that the value of β does not play a role because corresponding fairness is at the location level not at the slice level; the objective of the comparison is at slice level.

B. Insights of user demand d_{il}

Figure 2a displays the results for different demands of SP1 at location 1. Here, $B_1 > B_2$, same resource preferences as before and the user demands $d_{12} = 1$, $d_{21} = 1.5$, and $d_{22} = 1$; $\alpha = 10$, $\beta = 5$. It can be observed that as d_{11} increases the allocation for location 1 served by SP1 increases as well, at the same time resources for location 1 of SP 2 is decreasing to satisfy the capacity constraint 6. But the increment in allocation is rather low due to fairness imposed by α and β .

C. Impact of SP budget B_i

To show the impact of purely the budget under higher fairness criteria, we consider uniform demands ($d_{il} = 1$), $\alpha = 10$, $\beta = 5$. When α and β are zero, allocations depend for the major part on budget. A trivial solution is for the SP with the higher budget to get all the resources, starving all other SPs' users due to lack of resources, as known in the literature for the utilitarian approach. The proposed scheme, as reported in figure 2b, avoids starvation at both the slice level and at the location level, whereas the SP with higher budget gets relatively higher resources. In the same figure, it can be observed that slice 2 is not allotted with higher resources compared to slice 1 even when the SP2 budget is higher than SP1, the reason being that the allocation depends not only on the budget but also on their resource preferences as described earlier.

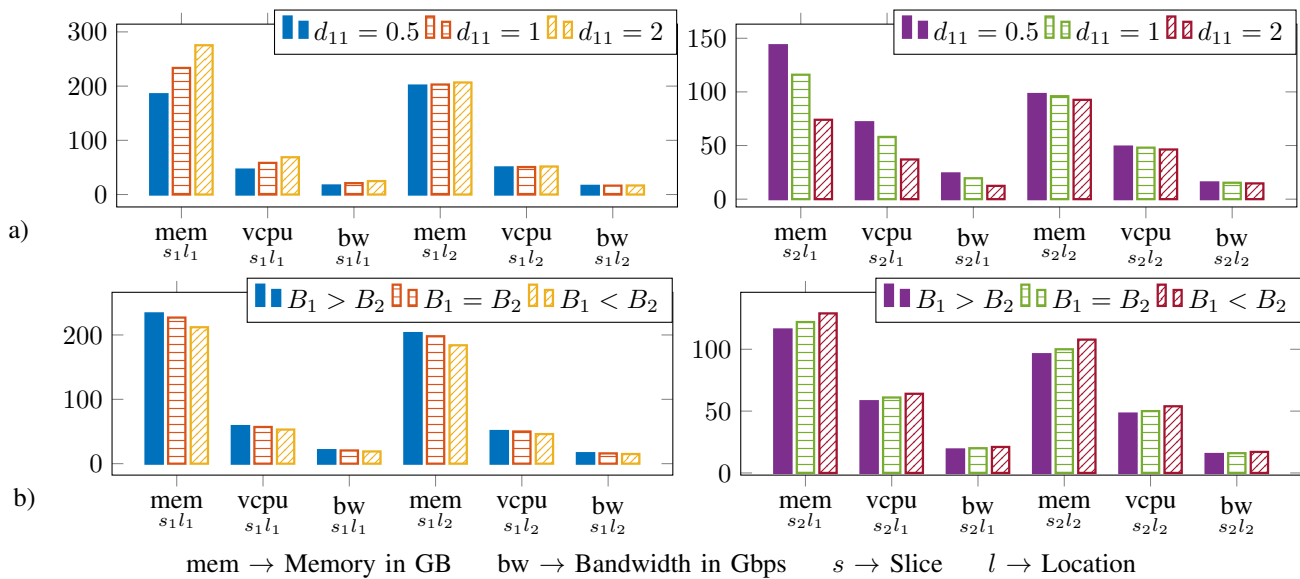


Fig. 2. Resource allocation for slice 1 and slice 2 respectively, with a) change in the demand at location 1 b) change in SP budgets

VI. CONCLUSION

Resource allocation has always been a very challenging aspect for mobile communications due to the scarcity of resources and ever increasing users demands. This is even more so in the context of 5G slicing, since virtualized mobile applications require multiple resources types at once across a slice and over multiple locations. In this work, we have investigated a method to cope up with those challenges with a scheme focused in granting a fair allocation of resources to competing SPs. We have provided a unified framework relying on a non-linear pricing scheme to allocate resources ensuring multi-level fairness and applicable to various possible scenarios of 5G networks. Our slicing model can be used to allocate multiple resource types and yet being fair both among slices and among the locations covered by a slice. The scheme is controlled by tuning 2 fairness factors α and β , respectively. They act as control parameters to balance the trade-off between fairness and efficiency. Furthermore, by defining POA, we have shown that the social welfare may deteriorate significantly when players act strategically and may report false preferences, which indicates the need for further investigation of mechanism design in this context.

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