On Matching Users to Specialised MNOs in Service Tailored Networks of the Future

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Abstract*—In this paper, we investigate a network model in which entities called *subscription brokers* group service level agreements with multiple specialised mobile network operators (SMNOs) into a single subscription bundle, with a fixed data allowance that can be used by the subscriber as needed across any of the SMNOs included in the bundle. Each SMNO operates a network that is designed to meet the demands of a particular service area or vertical industry. We demonstrate the performance benefits of such a model, allowing users to choose SMNOs according to the needs of the service that they are using. In particular, we focus on how to perform the matching between users and SMNOs in a bundle, adopting the Gale-Shapley matching algorithm. We argue that a stable matching is needed to ensure that both SMNOs and users are incentivised to adopt the broker-based model. We outline a framework based on the concept of utility for devising the preference lists of users, while the approach we propose for building the preference lists of SMNOs can differentiate between different classes of users based on the price they pay for their subscription. We evaluate the performance cost in terms of utility of achieving stability compared to a sum utility maximisation matching approach, showing that this cost is largely borne by the lower priority users. Overall, the proposed broker-based model performs at least as well as any one SMNO for lower priority users, and outperforms any one SMNO for higher priority users.

I. Introduction

Unlike previous generations of telecommunication networks, 5G is tasked with providing service to a large number of diverse scenarios and vertical industries. These services present a wide array of requirements ranging from high data rates, low latency, ultra-reliability, large capacity, and many more. Clearly, some of these requirements are in conflict with one another, and it is difficult to envision a single one-size-fits-all network capable of satisfying all of them.

This will lead to the emergence of multiple, specialised mobile network operators (SMNOs), likely in the form of mobile virtual network operators. The advent of service-tailored networks opens the door for new business models, enabling a marketplace of specialized network operators who create and manage bespoke tailored networks. [1] examines such a marketplace from a value chain perspective, suggesting a value chain in which the value is derived from the services rather than spectrum. This opens up the possibility for new entities such as service bundling providers, virtual network operators, and resource aggregators.

A user may benefit by subscribing to a bundle comprising services from more than one of these SMNOs. This offers two advantages; first, users do not have to manage multiple separate subscriptions to SMNOs that they may require, and secondly, users can pay a fixed price for a specified data allowance that can be used as needed across a selection of different SMNOs.

Hence we consider a business model centred on an entity called a subscription broker, which acts as a broker between service-tailored SMNOs and users, selling access to bundles of SMNOs for a fixed price. Each bundle is sold with a fixed data allowance. A similar idea of dynamically switching between multiple MNOs to improve performance is used in Google's Project Fi [2]. In our case, however, each MNO has tailored its network to meet the demands of a particular service type, which requires a completely different approach for matching users to MNOs.

When matching users to an SMNO belonging to their subscription bundle, both users and SMNOs must be satisfied that they could not have done better than the match provided to them, otherwise they would not be incentivised to agree to adhere to the broker-based model. To ensure this, we use the Gale-Shapley *college admission* algorithm [3] to match users to SMNOs. The Gale-Shapley algorithm guarantees a stable matching between two sets of entities based on the preferences of individual entities; a stable matching is one where there is no pair that would prefer to be matched to each other instead of their current partners.

Matching theory has been applied to solve resource allocation problems in many areas of wireless communications. In one of the first works to apply matching theory to wireless networks [4], the authors demonstrate that popular schedulers such as maximum throughput or proportional fair do not necessarily result in a stable matching. A comprehensive tutorial on the use of matching theory in wireless networks is provided in [5]. The authors in [6] adopt matching theory to develop a novel user-cell association approach for small cell networks using context information obtained from user devices. User association is also examined in [7], which applies matching theory to pair base stations and users in a virtualized cellular network.

In this paper, we consider SMNOs which operate service-tailored networks and demonstrate the performance advantages of adopting a broker-based model in which users can switch between multiple SMNOs in a subscription bundle compared to a one-size-fits-all type network. Achieving stable matchings is important if the broker-based model is to be viable. Hence we apply the Gale-Shapley algorithm to match users to service-tailored SMNOs, outlining how to build the preference lists of both users and SMNOs. Finally, we evaluate the cost of achieving stability compared to a maximum-utility optimisation approach.

II. System Model

We formally define the terms user, SMNO, service level agreement (SLA) and subscription broker:

Definition 1. A *user* is any entity involved in a process of data transfer that may avail of the services of an SMNO. This may be a smart phone, a connected vehicle, or a sensor.

Definition 2. An *SMNO* manages a service-tailored network (which may be a virtual network) that is designed to meet the demands of a particular vertical, service, or class of users.

Definition 3. An *SLA* is a commitment between an SMNO and a user that the SMNO will provide the user with an agreed minimum quality of service (QoS), as specified by a set of guarantees advertised by that SMNO.

Definition 4. A *subscription broker* sells SLAs on behalf of SMNOs to users. The broker groups multiple SLAs into a package, called a bundle, which it sells for a fixed price with a fixed data allowance. This data allowance may be consumed by the user across any of the SMNOs in the bundle as needed. After taking its fee, the remaining revenue from the package is distributed among the included SMNOs according to the percentage of the user's data allowance served by each SMNO.

We represent the set of SMNOs as $S = \{s_1, ...s_i, ...s_{N_S}\}, 1 \leq i \leq N_S$ and the set of users as $U = \{u_1, ...u_j, ...u_{N_U}\}, 1 \leq j \leq N_U$. Each SMNO s_i operates a network consisting of N_R^i contiguous resource blocks (RBs). The price that a user u_j pays for their bundle with a fixed data allowance D is given by p_j.

Each device estimates its received SINR using reference signals placed throughout the resource grid and then maps this SINR value to a 4-bit index known as the channel quality indicator (CQI). The CQI index specifies the maximum data rate that a device can support with a block error ratio of 10% or below, and each CQI index corresponds to a specific modulation scheme and coding rate as specified in Table 7.2.3-1 in [8].

We adopt higher layer configured sub-band reporting, as per LTE, whereby the band is divided into sub-bands and the UE reports a single wideband CQI and a CQI for each sub-band. For the purpose of CQI reporting, RBs are grouped into sub-bands consisting of h RBs. Each SMNO's s_i network is therefore divided into $N_B^i = N_R^i/h$ sub-bands. Assuming that each user is granted a single sub-band, the number of matches that an SMNO s_i is able to make, known as its quota q^i, is also N_B^i.

Each CQI value corresponds to a particular modulation order and coding rate and hence can be mapped to a measure of efficiency, which can be interpreted as the number of information bits per symbol (see Table 7.2.3-1 in [8]). The spectral efficiency for a user u_j reporting on sub-band b of SMNO s_i is denoted by $\psi_j^{i,b}$. The spectral efficiencies for all users across all SMNOs form the matrix Ψ, which has dimensions $N_U \times N_S \times N_B^i$ (assuming that each SMNO has control over an equal number of sub-bands). Ψ_j^i indexes the vector corresponding to the spectral efficiencies of user u_j for each sub-band b in SMNO s_i.

Resource allocation in a broker-based model is a two step process. First, users must be matched to SMNOs. This is the primary focus in this paper and we will use matching theory algorithms to accomplish this. However, it should be noted that users are matched to SMNOs and not specific sub-bands. Hence, after this matching has been performed, each SMNO must perform the second step of allocating specific sub-bands to its matched users. SMNOs can use custom schedulers based on well-known approaches such as proportional-fair or maximum throughput to accomplish this.

III. Preference Lists

In this section, we outline how to build the preference lists of both users and SMNOs, which are used by the Gale-Shapley algorithm.

A. User Preference List

We will adopt the concept of utility from the field of economics as a measure of preference that can be used to generate a preference list for users. Utility represents the value (often confined to a real number between 0 and 1) assigned by a user to a service according to the service's performance. A utility function therefore maps a QoS metric such as achievable rate to an abstract unit that captures the utility or value of the service. In this sense, the concept of utility is related to the idea of quality of experience, which examines users' perceptions of a service. Utility-based resource optimisation for wireless networks has received quite a lot of attention for networks with multiple classes of traffic (e.g. [9]).

The user has the following information available to it:

1) QoS guarantees: We assume that an SMNO advertises its QoS guarantees to users.
2) SINR: The user uses reference signals to determine its SINR, and uses this to make an estimate of the rate that it can achieve using a particular SMNO.

Hence, the user has four QoS metrics available to it: average latency, strict latency, packet loss ratio, and achievable rate.

Utility is a service-dependent concept and hence each service that may be employed by a user has an associated utility function. Each utility function takes the four QoS metrics outlined in the previous paragraph as inputs. However, we will first examine how to represent the individual relationships between the QoS metrics and utility. To do this, we will utilise two functions: the normalised logarithmic function and the normalised sigmoid function.

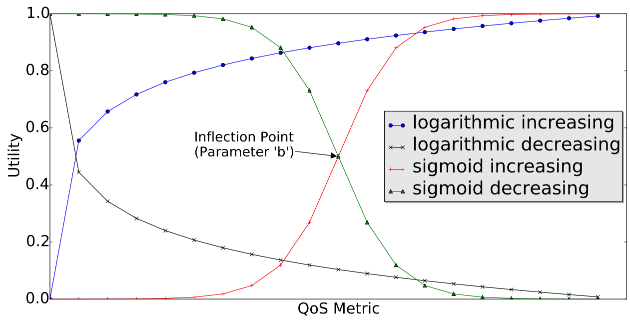


Fig. 1. The shapes of the four functions $\Omega_{\text{log}}(x)$, $1-\Omega_{\text{log}}(x)$, $\Omega_{\text{sig}}(x)$ and $1-\Omega_{\text{sig}}(x)$ can be used to capture different types of relationships between a QoS metric and utility. For the sigmoid functions, the parameter a determines the steepness of the curve and b determines the inflection point.

The normalised logarithmic function is expressed as:

$$\Omega_{\text{log}}(x) = \frac{\log(1+kx)}{\log(1+kx_{\text{max}})}, \quad (1)$$

where x is the QoS metric that we are mapping to a utility measure between 0 and 1. x_{max} is the maximum achievable value of the QoS metric (such as maximum rate). k is the rate of increase of the utility measure in relation to the QoS metric. The normalised logarithmic utility function, assuming it is parametrised correctly, can be used to capture any relationship between a QoS metric and service utility measure that is monotonically increasing, given that the performance of the service is relatively elastic in relation to that QoS metric (i.e. not critically reliant on the QoS metric). Monotonically decreasing relationships can be captured using $1-\Omega_{\text{log}}(x)$. An example of a QoS metric with a monotonically increasing logarithmic relationship with utility would be data rate for best effort communication applications.

The normalised sigmoid function is given by:

$$\Omega_{\text{sig}}(x) = \frac{1}{1+e^{-a(x-b)}}, \quad (2)$$

where a captures the steepness or slope of the curve, while b represents the inflection point of the curve. The normalised sigmoid function can be used to represent monotonically increasing relationships whereby utility has a strict reliance on a particular QoS metric; for example, the utility can be modelled as a sigmoid function of the data rate when a minimum throughput is essential to the performance of the service (such as a video streaming service).

Hence, for each service we will define the relationships between the four available QoS metrics and utility using one of four functions discussed above: $\Omega_{\text{log}}(x)$, $1-\Omega_{\text{log}}(x)$, $\Omega_{\text{sig}}(x)$ and $1-\Omega_{\text{sig}}(x)$. Fig. 1 shows an example of the shapes of these relationships. The relationship between a QoS metric and utility may be different for different services. For example, the rate relationship may be modelled as $\Omega_{\text{log}}(x)$ for a file sharing service, or $\Omega_{\text{sig}}(x)$ for a video streaming service. The parameters for each relationship are also service-dependent and must be empirically determined.

For each service, having characterised the individual relationships between the QoS metrics and utility, we must combine these into a single utility measure. The choice of method (e.g. multiplicative or additive) again depends on the particular details of a given service [10]. In this paper, we will adopt a simple multiplicative model in which the four individual utility values are multiplied together to obtain a single overall utility value for the service. Ω_j^i denotes the overall utility, and therefore preference, of user u_j for SMNO s_i.

We comment that users generate a preference measure for an SMNO, although SINR is estimated on a sub-band granularity. Hence, when estimating the achievable rate for an SMNO, the user adopts an optimistic outlook and chooses the sub-band corresponding to the maximum SINR in an attempt to achieve the maximum performance possible.

B. *SMNO Preference List*

For SMNOs, the information available locally which can be used to build a preference list includes:

1) Channel state information (CSI) for each user.
2) The package that each user is subscribed to.

SMNOs wish to maximise the share of the revenue that they receive from the subscription broker for serving users subscribed to bundles. This can be achieved in two ways: by prioritising users subscribed to more expensive bundles, and by maximising the number of useful information bits that can be transferred using a single resource (i.e. maximizing its spectral efficiency). SMNOs will therefore prefer users with good channel conditions subscribed to more expensive bundles. Hence, in order to maximise its revenue in a given time slot, an SMNO s_i wishes to solve the following maximisation problem:

$$\text{P1}: \max_{\omega_{jr}} \sum_{j=1}^{N_U} \sum_{r=1}^{N_R^i} \omega_{jr} z_i \frac{p_j}{D} \psi_j^{i,o(r)} \quad (3)$$

subject to

$$\omega_{jr} \in \{0,1\}, \forall j, r \in \mathbb{N}, j \leq N_U, r \leq N_R^i, \quad (3a)$$

$$\sum_{j=1}^{N_U} \omega_{jr} \leq 1, \forall r \in \mathbb{N}, r \leq N_R^i, \quad (3b)$$

where ω_{jr} is a binary indicator variable which is equal to 1 if user u_j is scheduled on resource block r, and 0 otherwise. $o(r)$ maps a resource block r to the sub-band containing it, and z_i specifies the number of information carrying symbols (i.e. excluding pilots and symbols belonging to control channels) in a resource block for SMNO s_i. The aim of the maximisation problem is to increase the revenue per resource block through a combination of increasing the price paid per bit and fitting more information bits into a resource block. Constraint (3a) ensures that the variable ω_{jr} only takes on binary values, while constraint (3b) ensures that a resource block is only allocated to a single user.

Algorithm 1 Generate preference list for SMNO i

DECLARE RevenuePerUser: ARRAY[1,N_U] of (FLOAT, USER) TUPLES
DECLARE PreferenceList: ARRAY[1,N_U] of USERS
for all u in U **do**
  $\psi_{\max} \leftarrow \text{MAX}(\Psi_u^i)$
  RevenuePerUser[u] $\leftarrow (z_i \frac{p_u}{D} \psi_{\max}, u)$
end for
SORT RevenuePerUser: descending, sort on first element in tuple
COMMENT: below we extract user IDs using the second element of the tuple in the sorted RevenuePerUser list
$n \leftarrow 1$
for all j in RevenuePerUser **do**
  PreferenceList[n] $\leftarrow j[1]$
  $n \leftarrow n + 1$
end for

Although the solution of P1 would yield the optimal matching of users and resource blocks for a single SMNO, it is not practical as each SMNO is competing for users and cannot simply choose its users. It also does not rank users in terms of their optimality; it just provides the optimal set. Hence, each SMNO applies Algorithm 1, which is based on optimisation problem P1, to generate its preference list. Note that estimating the revenue that can be obtained from serving a particular user is difficult, as the SMNO will not allocate its resource blocks to users until after the user-SMNO matching has been performed (i.e. it cannot allocate its resource blocks until it knows which users have been matched with it). Hence, each SMNO estimates the potential revenue to be earned from serving a particular user by summing the revenue earned from granting the user each of the available sub-bands.

IV. Stable Matching using the Gale-Shapley Algorithm

We will model our matching problem between SMNOs and users as a college admission problem, as named by Gale and Shapley [3] when referring to two-sided, many-to-one matching problems. Our problem is two-sided because it consists of two disjoint sets, and a matching must involve one entity from each set. Our problem is described as many-to-one because each SMNO can form as many matchings with users as its quota permits. The Gale-Shapley college admission algorithm can be used to obtain a stable matching in these kind of problems. Each entity must rank the entities of the other set in order of preference. We assume individual rationality, meaning that each user would prefer to be matched to any SMNO than not matched at all. Hence, each SMNO is dimensioned so that it could provide adequate QoS to any user, although some SMNOs are better suited to some users (depending on the service in use). Individual rationality also implies complete preference lists, i.e. all entities of the opposite set are included in each preference list.

The college admission algorithm works based on a series of proposals from one set to the other. For example, if the users do the proposing, then each user will first propose to its preferred SMNO. The user will then pause if the SMNO provisionally accepts the proposal, and will propose to the next SMNO in its preference list if rejected. SMNOs will provisionally accept a proposal if they have not filled their quota or if the current proposal gives them a better matching than one of its provisionally accepted matchings, and reject the proposal otherwise. The process ends when either all users are provisionally engaged, or no more possible feasible matchings exist.

We now formally define the preference relation for users and SMNOs in Definitions 5 and 6, respectively. We use the notation $a \succ_x b$ to define preference, meaning that entity x prefers a to b.

Definition 5. u_j prefers s_i to $s_{i'}$, if $\Omega_j^i > \Omega_j^{i'}$, denoted by $s_i \succ_{u_j} s_{i'}$, for $u_j \in U$, $s_i, s_{i'} \in S$, $s_i \neq s_{i'}$.

Definition 6. s_i prefers u_j to $u_{j'}$, if $z_i \times \frac{p_j}{D} \times \text{MAX}(\Psi_j^i) > z_i \times \frac{p_{j'}}{D} \times \text{MAX}(\Psi_{j'}^i)$, denoted by $u_j \succ_{s_i} u_{j'}$, for $s_i \in S$, $u_j, u_{j'} \in U$, $u_j \neq u_{j'}$.

We also define the notion of stability in relation to the matching problem outlined in this paper in Definition 7.

Definition 7. A matching M is stable if there exists no user-SMNO pair (u_j, s_i) such that u_j would prefer to be matched to s_i than to its current partner, and s_i would prefer to be matched to u_j than its current partner. That is, there exists no user-SMNO pair (u_j, s_i) such that $s_i \succ_{u_j} M(u_j)$ and $u_j \succ_{s_i} M(s_i)$.

V. Cost of Achieving Stability

The Gale-Shapley college admissions algorithm guarantees stability, which is important if both users and SMNOs are to commit to the subscription broker business model. However, we wish to compare the performance of the algorithm with conventional scheduling approaches in order to determine the cost, or performance loss, if any, in achieving stability.

It should be noted, however, that there is no such thing as a conventional scheduler for a multi-SMNO, multi-service system model, as this is still an open research problem. Although we are free to choose any number of metrics, as system designers, we will state our goal as one of maximising user utility. In order to simplify the task, we will flatten the problem from a one-to-many mapping between SMNOs and users, to a one-to-one mapping between sub-bands and users. This allows us to express the optimisation problem as one of finding the maximum weight matching in a weighted bipartite graph, which can be solved using the well-known Kuhn-Munkres algorithm.

To simplify the optimization problem, we assume that allocations are performed at sub-band granularity, and that each user is granted a maximum of one sub-band. Hence, while Ω_j^i provides a user's u_j utility estimate for a SMNO s_i, we instead consider $\Omega_j^{b,i}$, which provides a utility estimate on a sub-band granularity. This allows us to model the problem as a one-to-one matching between users and sub-bands.

The resource allocation problem involving users and sub-bands is outlined in the following optimisation problem:

$$\mathrm{P2}: \max_{\omega_{jib}} \sum_{j=1}^{N_U} \sum_{i=1}^{N_S} \sum_{b=1}^{N_B^i} \omega_{jib} \Omega_j^{b,i}, \tag{4}$$

subject to

$$\omega_{jib} \in \{0,1\}, \forall j,i,b \in \mathbb{N}, j \leq N_U, i \leq N_S, b \leq N_B^i, \tag{4a}$$

$$\sum_{j=1}^{N_U} \omega_{jib} \leq 1, \forall i,b \in \mathbb{N}, i \leq N_S, b \leq N_B^i, \tag{4b}$$

$$\sum_{i=1}^{N_S} \sum_{b=1}^{N_B^i} \omega_{jib} \leq 1, \forall j \in \mathbb{N}, j \leq N_U, \tag{4c}$$

where ω_{jib} is a binary indicator variable which is 1 when user j uses sub-band b of SMNO i, and 0 otherwise. Constraint (4a) ensures that the variable ω_{jib} only takes on binary values. Constraint (4b) ensures that each user is matched with only one sub-band, and constraint (4c) ensures that each sub-band is only allocated to a single user.

VI. Performance Evaluation

A. Evaluation Parameters

We use Monte Carlo simulations to evaluate the performance of the broker-based model. We consider four SMNOs targeting enhanced mobile broadband (eMBB) traffic, with each SMNO occupying four sub-bands and 24 resource blocks (six resource blocks per sub-band). The SMNOs advertise their packet-loss ratio, average latency, and strict latency as specified in Table I. SMNOs also advertise a rate multiplier, which is used to scale the rate to account for differences in spatial streams, coding rates, and other rate-affecting factors. A multiplier of one corresponds to the standard LTE values given by Table 7.2.3-1; [8], with only a single spatial stream.

SMNO 1 offers the best data rate, using multiple spatial streams, but has the highest strict and average latencies due to the additional processing and training needed. SMNO 2 offers the lowest average and strict latency by reducing control signalling procedures, resulting in the highest packet loss ratio. SMNO 3 offers the best reliability by employing additional redundancy which results in the lowest data rate advertised. SMNO 4 is an *all-rounder* network, offering decent values for all metrics without excelling in any particular area.

To ensure fair comparison between the stable matching and maximum-utility approaches, we assume that each user gets allocated a single sub-band. To ensure this is possible, we assume that each user has enough bits in its buffer Q_u to fill a sub-band at the maximum permissible modulation order and lowest permissible coding rate according to Table 7.2.3-1 in [8], i.e $Q_u \geq 5.5547(\text{bits/symbol}) \times z(\text{symbols/RB}) \times 6(\text{RBs/sub-band}) \forall u \in U$. The number of users will be varied

TABLE I
ADVERTISED SMNO GUARANTEES

SMNO ID	Average Latency (ms)	Strict Latency (ms)	Packet Error Rate (per 10^6 packets)	Rate Multiplier
1	10	14	7	2
2	4	8	10	1
3	9	12	2	0.6
4	8	12	8	1

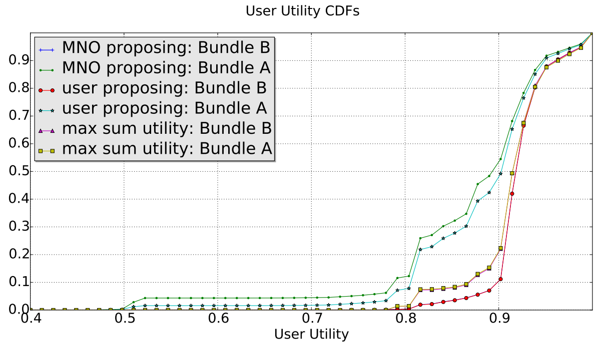


Fig. 2. Comparison of user-proposing algorithm, SMNO-proposing algorithm, and maximum utility approach for subscribers of both bundles.

so that the network is fully loaded (16 users[1], 100% capacity) and overloaded (20 users, 125% capacity).

Each user may employ one of three services, with the relationship between utility and each of the individual QoS metrics specified in Table II. As mentioned in Section III-A, these relationships are service-dependent and should be empirically determined on a service-by-service basis using real-world data. As this is not available to us, we have attempted to choose sensible values for these services. We note, however, that the actual values chosen here are not of great importance. 5G should be able to cope with any service, including those yet unforeseen.

Service S1 presents the most stringent reliability requirements, moderate data rates, and is relatively latency-tolerant. Service S2 has the lowest latency requirements of all services, but only requires fairly low data rates. Finally, Service S3 has the highest data rate requirements, as well as moderate latency and reliability requirements. As stated in the previous paragraph, we are interested in the system's ability to accommodate any service, rather than specifically the three examples presented.

The subscription bundler sells two subscription packages, A and B, with B costing twice as much as A. Both packages include service level agreements with all four SMNOs, and consist of a fixed data allowance D. After users have been matched to SMNOs, each SMNO allocates sub-bands to its matched users using a maximum throughput scheduler.

[1]There are 4 SMNOs with 4 sub-bands each, and we assume that each user gets granted a single sub-band.

TABLE II
UTILITY-QOS RELATIONSHIPS FOR SERVICES

Service	Average Latency (ms)	Strict Latency (ms)	Packet Error Rate (per 10^6 packets)	Data Rate (Mbps)
S1	1-sigmoid; a=0.5, b=18	1-sigmoid; a=1, b=20	1-sigmoid; a=1, b=10	logarithmic; k=100, $x_{\max}$=2.5
S2	1-sigmoid; a=0.5, b=12	1-sigmoid; a=1, b=15	1-sigmoid; a=0.5, b=15	logarithmic; k=100, $x_{\max}$=1.5
S3	1-sigmoid; a=0.5, b=16	1-sigmoid; a=1, b=18	1-sigmoid; a=0.5, b=15	logarithmic; k=100, $x_{\max}$=5

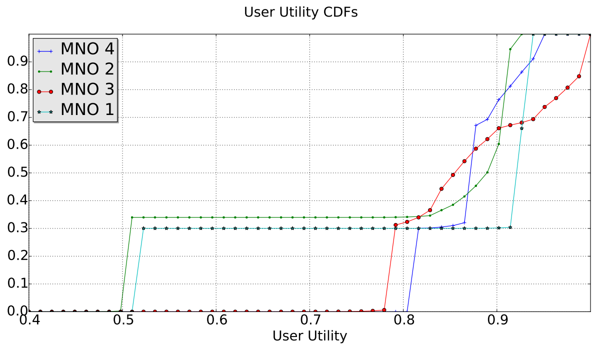
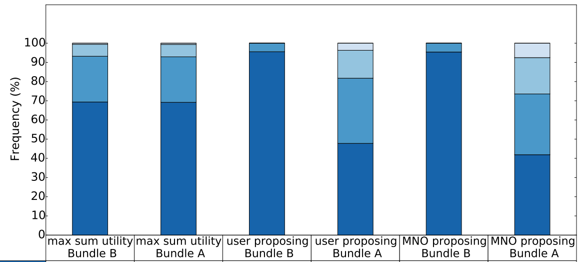


Fig. 3. User performance without a broker-based network model; no SMNO can provide high performance to all users.



	max sum utility Bundle B	max sum utility Bundle A	user proposing Bundle B	user proposing Bundle A	MNO proposing Bundle B	MNO proposing Bundle A
1st Choice	69.35 %	69.19 %	95.55 %	47.79 %	95.39 %	41.88 %
2nd Choice	23.85 %	23.71 %	4.43 %	33.96 %	4.58 %	31.67 %
3rd Choice	6.19 %	6.46 %	0.02 %	14.55 %	0.03 %	18.93 %
4th Choice	0.61 %	0.64 %	0.0 %	3.71 %	0.0 %	7.52 %
No Match	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %

Fig. 4. Matching statistics for a fully loaded network; higher priority Bundle B users achieve a higher percentage of first choice matches.

B. Results

We divide the results presented in Figs. 2-5 into five key sets of comparisons.

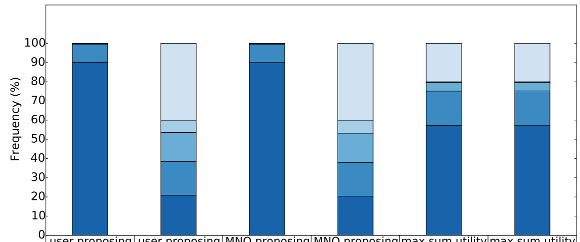
Bundle A vs Bundle B: As expected, Fig. 2 shows that Bundle B users will achieve greater performance in terms of utility compared to Bundle A users, since Bundle B subscribers are more likely to be at the top of each SMNO's preference list due to the higher revenue that can be earned from them. Note that this only applies when a matching theory algorithm is used, as the utility maximisation approach does not distinguish between Bundle A and Bundle B subscribers. For the most part, the difference in performance between subscribers of the two bundles is relatively small (less than 0.1 of a utility measure); however, while no Bundle B subscriber experiences a utility of less than 0.8, 10% of Bundle A users experience a utility between 0.5 and 0.8. Hence, subscribing to Bundle B in this case ensures a respectable minimum performance. The matching statistics provided in Fig. 4 show that Bundle B users are slightly more than twice as likely to be matched to their first choice than Bundle A users, with no Bundle B subscribers matched with their least preferred choice.

Optimal Sum-Utility vs Gale-Shapley Algorithm: As mentioned in the previous paragraph, Bundle A and Bundle B users achieve the same performance in the sum utility maximisation approach. As seen in Fig. 2, when the Gale-Shapley algorithm is adopted, Bundle B subscribers achieve marginally better performance compared to the utility maximisation approach at the expense of Bundle A users. Hence, the cost of achieving stability is primarily borne by Bundle A subscribers. The combined performance of all users, both A and B subscribers, will be slightly less when the college admissions algorithm is used instead of the sum utility maximisation approach. However, the advantage of using the college admissions algorithm is that stability is achieved. This is important if the broker-based model of packaging service level agreements into bundles is to be adopted. As per definition 7, stability ensures that there is no user-SMNO pair that would prefer to be matched to each other than to their appointed matches. Without this condition, neither SMNOs nor users would be incentivised to use a broker-based model, as some users would feel that they could gain an advantage by engaging in direct service level agreements with the SMNOs.

Broker-based Approach v One-size-fits-all Network: Fig. 3 shows the performance that would be achieved if users only had an SLA with a single SMNO. None of the SMNOs on their own can provide really high performance to all users, with SMNOs 1 and 2 in particular providing barely adequate performance to about 30% of users. The advantage of the broker-based model is that bundle subscribers can use their data allowance on any SMNO as needed. For example, Fig. 2 shows that when using the broker-based model and the Gale-Shapley algorithm, over 90% of Bundle B subscribers achieve a utility of 0.9 or higher, with no subscriber achieving less then 0.8 utility. This is an improvement over any single SMNO in Fig. 3. In the broker-based model, using the user-proposing college admission algorithm, Bundle A users also achieve performance that is either better than or comparable to any individual SMNO, with over 90% of users achieving a utility of 0.8 or more, and over 50% of users achieving a utility of 0.9 or more (see Fig. 2). SMNO 4, the catch-all network, comes closest to matching this on its own, offering a slight advantage in that no user achieves a utility less than 0.8. Hence, the broker-based model using the college admissions algorithm allows users to select the SMNO best suited to the service in use, resulting in improved performance to Bundle B subscribers, and at least as good performance to Bundle A subscribers when compared to a single one-size-fits-all network approach.

User-Proposing vs SMNO-Proposing: As described in Section V, the Gale-Shapley college admissions algorithm can be performed in user-proposing form, or SMNO-proposing form. Since Bundle B subscribers are more profitable to SMNOs, they are generally preferred by SMNOs over Bundle A users. Hence, under the SMNO-proposing variant, Bundle B users are generally proposed to first while under the user-proposing variant, Bundle B users generally have their proposals accepted by SMNOs. Hence, in both cases, Bundle B users achieve a very high percentage of first choice matches and there is no difference in performance. The case is different for Bundle A subscribers. Under the SMNO-proposing variant, a SMNO can propose to as many Bundle B subscribers as it wants before considering Bundle A subscribers. However, under the user-proposing variant, SMNOs will only receive proposals from some of the Bundle B subscribers. As a result, a Bundle A user will compete with fewer Bundle B users under the user-proposing variant than under the SMNO-proposing variant. Hence, Fig. 4 shows that a higher percentage of Bundle A subscribers are matched with their first choice under the user-proposing version than under the SMNO-proposing version. This translates to a small performance improvement in achieved utility, as can be observed in Fig. 2.

Fully-Loaded vs Over-Loaded: Fig. 5 shows the matching statistics when the network is at 125% capacity. Due to the mismatch in cardinality between the set of sub-bands and the set of users, some users will be unmatched after the algorithm is performed. We observe that when the sum utility maximisation algorithm is used, the unmatched users are distributed equally between Bundle A and Bundle B. In the case a matching theory algorithm is used instead, all unmatched users are Bundle A subscribers, with Bundle B users largely unaffected. Hence, while Bundle B subscribers only have a small advantage over Bundle A subscribers in the fully-loaded case (Fig. 2), they obtain a much greater advantage when the network is over-loaded, as they are never left unmatched.



	user proposing Bundle B	user proposing Bundle A	MNO proposing Bundle B	MNO proposing Bundle A	max sum utility Bundle B	max sum utility Bundle A
1st Choice	90.2 %	20.88 %	90.0 %	20.39 %	57.32 %	57.37 %
2nd Choice	9.44 %	17.59 %	9.63 %	17.47 %	17.84 %	17.87 %
3rd Choice	0.35 %	15.06 %	0.36 %	15.36 %	4.51 %	4.45 %
4th Choice	0.01 %	6.47 %	0.01 %	6.78 %	0.32 %	0.31 %
No Match	0.0 %	40.0 %	0.0 %	40.0 %	20.02 %	19.98 %

Fig. 5. Matching statistics when network is 125% loaded; low priority Bundle A users suffer more than Bundle B users.

VII. Conclusion

Our results demonstrate the improvement in performance that can be obtained if the proposed broker-based network model is adopted compared to a one-size-fits-all network. The benefits of the broker-based model, which is based on bundles of service level agreements with multiple SMNOs, lie in its ability to match users to suitable SMNOs according to the requirements of the service that the users are employing at that moment in time. However, in order to be successfully adopted, both users and SMNOs must be satisfied that they could not have achieved a better match. We adopt the Gale-Shapley college admissions algorithm, which provides a stable matching, to guarantee that this condition is met. We investigated a system comprising two classes of users, and proposed an approach for building the preference lists of SMNOs that relies on the self-interest of operators to maximise their own revenue, and is able to inherently differentiate between different classes of users. We show that compared to a utility maximisation approach the performance cost of achieving stability is carried by the lower priority users. Overall, the broker-based model outperforms any one SMNO for the higher priority users, while maintaining a level of performance that is at least as good as any one SMNO for lower priority users.

References

[1] L. Doyle, J. Kibilda, T. K. Forde, and L. DaSilva, "Spectrum Without Bounds, Networks Without Borders," *Proceedings of the IEEE*, vol. 102, no. 3, pp. 351–365, Mar. 2014.

[2] Project Fi. [Online]. Available: https://fi.google.com/about/

[3] D. Gale and L. Shapley, "College admissions and the stability of marriage," *The American Mathematical Monthly*, vol. 69, no. 1, pp. 9–15, 1962.

[4] E. A. Jorswieck, "Stable matchings for resource allocation in wireless networks," in *International Conference on Digital Signal Processing (DSP)*, Jul. 2011, pp. 1–8.

[5] Y. Gu, W. Saad, M. Bennis, M. Debbah, and Z. Han, "Matching theory for future wireless networks: fundamentals and applications," *IEEE Communications Magazine*, vol. 53, no. 5, pp. 52–59, May 2015.

[6] F. Pantisano, M. Bennis, W. Saad, S. Valentin, and M. Debbah, "Matching with externalities for context-aware user-cell association in small cell networks," in *IEEE Global Communications Conference (GLOBECOM)*, Dec. 2013, pp. 4483–4488.

[7] T. H. T. Le, N. H. Tran, T. LeAnh, and C. S. Hong, "User matching game in virtualized 5G cellular networks," in *18th Asia-Pacific Network Operations and Management Symposium (APNOMS)*, Oct 2016, pp. 1–4.

[8] "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer procedures ," 3GPP, Tech. Rep. TR 36.213 V14.5.0, Jan. 2018.

[9] L. Chen, B. Wang, X. Chen, X. Zhang, and D. Yang, "Utility-based resource allocation for mixed traffic in wireless networks," in *2011 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, Apr. 2011, pp. 91–96.

[10] T. Hossfelt, L. Skorin-Kapov, P. E. Heegaard, M. Varela, and K.-T. Chen, "On additive and multiplicative QOS-QOE models for multiple qos parameters," in *Proceedings of the 5th ISCA/DEGA Workshop on Perceptual Quality of Systems*, 2016.