SuperBS: A Methodology for Resource Management in Heterogeneous Wireless Networks

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***Abstract*—Resource management in heterogeneous wireless networks has been approached from various angles by the research community. The complexity of the network and the heterogeneity of clients make the conclusive comparison of the various resource allocations challenging. This work introduces *superBS*, an approach defining a theoretical optimal resource allocation that adheres to the required resource management policies and can be used as a reference for the performance of considered algorithms, mitigating the heterogeneity of the system. Two applications that leverage superBS are developed, an implementation of a heuristic resource management algorithm, and the enhancement of a popular fairness metric with support for clients of different classes and traffic demands. Simulations demonstrate the performance of superBS and the proposed algorithms.**

***Keywords*—Heterogeneous Wireless Network, Network Selection, Priority Class, Resource Management, Heuristic, Fairness**

I. Introduction

Traditional cellular service providers are increasingly expanding their networks with new Radio Access Technologies (RAT), such as femtocells, LTE and WiFi hotspots, creating partially overlapping Heterogeneous Wireless Networks. Most modern client devices are also equipped with multiple wireless interfaces, enabling them to connect to any RAT operated by the Wireless Service Provider (WSP). However, they are configured to preferably attach to the faster RAT, even if this causes congestion, while leaving the slower ones underutilised. In our previous work, we described Utility-based Resource Management (URM), an approach that differentiates the offered service level between different classes of clients, and utilises all available wireless resources to achieve network-wide provision of comparable level of service to users of the same class regardless of their attachment point, while offering premium service level to users of higher classes [1].

In order to ensure that the network resources stay optimally utilised over time, URM has to be run in short intervals. However, its computational complexity deems it unfit for real-time operation and precipitates the need for heuristic algorithms that follow the same intra-class fairness, inter-class differentiation policy. URM maximises the total per-client utility, a logarithmic function of the allocated throughput, different for every class and mathematically bound to follow the defined policy and provide Max-Min fairness [2]. The heuristics however, provide sub-optimal solutions that are not guaranteed to perfectly adhere to the policy.

Deriving from our work in URM, this paper introduces a process for comparing the performance of resource management algorithms (RMA) for heterogeneous wireless networks. The idea of *superBS* is presented, a single virtual Base Station (BS) that supersedes all available BSs in the real network. The superBS theoretically serves all clients at once, considering a number of parameters affecting the performance of the multi-BS network. It provides an upper limit to the total utility, ideally differentiates the allocated throughput of clients that belong to different classes while maintaining Max-Min fairness among clients of the same class. This allocation method assures that there is a single maximum throughput in a class, achieved by all clients unless their demand is lower. The superBS resource allocation vector can be used as a benchmark, *i.e.* a normalisation factor, for comparing and grading the performance of RMAs.

This work makes two additional contributions. First, it presents Ideal-aware Resource Management (IRM), a novel heuristic RMA based on superBS theoretical allocation. IRM approaches the optimal resource allocation problem with linear complexity, in contrast to URM's analytic exponential complexity, while adhering to the intra-class fairness and inter-class differentiation requirements. Second, it discusses the complications in defining fairness in a heterogeneous wireless network. The well-known fairness metrics have difficulty dealing with different traffic demands and service differentiation. Jain Fairness considering the superBS resource allocation vector as optimal is shown to be able to cope with such client, traffic, and network heterogeneity.

II. Related Work

Utility-based resource allocation in telecommunications networks was first presented by Kelly [3], where a Network Utility Maximisation (NUM) problem is formulated to express the source rates, link capacities and design goals of the modeled network. NUM is used by many researchers to model a number of different resource allocation problems and network protocols. A survey paper [4] summarises the theories, algorithms and applications that derive from NUM, including research on resource management packet level dynamics, mainly focusing on stohastic wireless network models. Bellavista *et al.* [9], in an extensive survey paper, provide a

TABLE I. INDEX OF TERMS

Term	Symbol
Client	$i \in (1, \cdots, n)$
Base Station (BS)	$s \in (1, \cdots, S)$
Priority class of Client i	P_i
Priority class tuning parameter	α_i
Bandwidth allocated for Client i at the associated BS	B_i
Throughput of Client i	T_i
List of visible BS to Client i	L_i
Bandwidth of BS s	C_s
Maximum achievable throughput estimation of Client i associated to BS s	$\widehat{T_{i,s}}$
Spectral Efficiency of Client i associated to BS s	$R_{i,s}$
Maximum and minimum Demand of Client i (BS-independent)	D_i^{max}, D_i^{min}
Theoretical Bandwidth allocated for Client i at superBS	$B_{i,sBS}$
Theoretical Throughput of Client i at superBS	$T_{i,sBS}$

classification model for resource management and network selection algorithms. They identify three first-level classification directions, namely management scope, evaluation process, and continuity management.

Resource allocation in wireless networks is inextricably entwined with the notion of fairness, with many models defining different fairness types. The ones most commonly considered are max-min fairness, proportional fairness, utility-based fairness, the popular Jain fairness index, the Gini index, and other approaches based on the theory of majorization [3], [5]–[7]. It is common to extend these fairness metrics to better fit specific resource allocation problems. For example, Dianati *et al.* [8] demonstrate the need for an appropriate definition and a clear methodology for quantization of fairness, and propose a fairness index suitable for a single-hop, single cell wireless network. The effect that different types of objective functions in NUM-based resource management have on fairness has been questioned in recent research. Collucia *et al.* [2] identify and study a number of objective function families that can be used to achieve max-min fairness.

Corci *et al.* [10] exploit the different mobility profiles of cellular clients. They demonstrate the benefits of simplifying the mobility management support for low-mobility clients. Heterogeneity in the context of competing WSPs is also a popular research topic. Previous work, such as [11], often assumes that clients are comfortable with opportunistically switching providers in order to optimise session cost, QoS, or bandwidth. However, customers churn to different WSPs at much coarser intervals, and generally prefer to subscribe for flat-rate service plans with a single WSP [12]. On this principle Hassan *et al.* [13] describe a non-cooperative game that optimises the WSP revenue against user churning due to low Quality of Experience for wireless VoIP. Our work considers users with different flat-rate service plans, in the context of heterogeneous wireless networks operated by a single WSP, as is the common situation today.

III. SYSTEM DESCRIPTION

A. Problem Statement

We now describe the problem of optimal resource management in a heterogeneous wireless network for clients belonging to different priority classes. The operating scenario assumes a number of partially overlapping heterogeneous BSs, nomadic users requesting connections at the beginning of their sessions, and that a number of parameters are known to the optimising entity. The optimal allocation offers the same throughput to clients of the same class and differentiates between users of different classes across all BSs controlled by the Wireless Service Provider (WSP). In order to achieve this optimal allocation, the WSP uses the utility function to quantify the value of the throughput offered to the clients of each class. We defined a single optimisation problem, that combines the BS selection and the resource allocation subproblems, solved by maximising the total per-client utility. As we reported in [1], the utility function used for URM is:

$$f_{P_i}(T_i) = \alpha_i \ln\left(\frac{e-1}{\alpha_i}T_i + 1\right), \tag{1}$$

where T_i is the throughput offered to client i and α_i is a class-specific tuning parameter to change the curvature of the utility function, different for each priority class P_i. Table I lists all the optimisation parameters and notation used in the rest of this paper. The objective is to maximise the sum of user utility (eq. 2), and thus, optimise the intra-class fairness and inter-class differentiation across all BSs.

$$\underset{T_i}{\text{Maximise}}\ U = \sum_i f_{P_i}(T_i) \tag{2}$$

This work takes a closer look into the problem of bandwidth management in a heterogeneous wireless network and more specifically examines the issues of optimality and fairness. URM showed that the identification of the optimal resource allocation is computationally demanding, hindering real-time operation. This paper considers the same problem by reducing its dimensions and contributes three computationally feasible applications. It first defines *superBS*, a simplified view of the network that considers a theoretical single-BS scenario and estimates the optimal allocation of the clients, used for benchmarking. Second, it implements an efficient heuristic resource management algorithm using the superBS outcome. Third, it discusses the notion of fairness and augments Jain Index with superBS to support client and demand heterogeneity.

B. Network Model and Assumptions

A heterogeneous wireless network with partially overlapping BSs is assumed, with their bandwidth C_s considered known and constant. A number of clients are randomly placed in the network coverage area, with at least one visible BS per client.

Each BS offers a number of nominal connection data rates, corresponding to adaptive modulation and coding (AMC) techniques used in different technologies. For each client *i* the maximum achievable throughput $\widehat{T_{i,s}}$ via BS s is assumed to be known.

When a client connects to a BS, a portion of its available bandwidth is allocated to that client. It is worth noting that this allocated bandwidth, denoted as B_i, would correspond to a user throughput, denoted as T_i, according to

$$T_i = R_{i,s} B_i, \tag{3}$$

where R_i, s represents the spectral efficiency of user i at BS s. Typically, the spectral efficiency is dependent on the user-BS channel condition and the adopted AMC.

Each client has a maximum and minimum traffic demand. The maximum demand reflects the maximum throughput of the session, such as the download bitrate offered by a web server, or the bitrate of a video stream. The demand can be communicated to the WSP, or estimated with stohastic prediction methods on monitored traffic. As the WSP is considered to be context-agnostic and differentiates users solely based on their class, traffic is viewed as greedy. Clients connect to only one RAT and BS, keeping in line with current routing and power conservation practices. The network is considered as a series of independent snapshots, so as to focus on the performance and effectiveness of the proposed algorithms, rather than the effects of continuous wireless sessions.

IV. Proposed Algorithms

A. SuperBS

The complexity of resource allocation in heterogeneous wireless networks makes the comparison of various RMA extremely difficult. Different factors influence the performance of a client, some of them RMA-dependent (*e.g.* BS congestion and resource allocation), while others such as channel capacity are RMA-independent. Such complexity is further increased with the presence of multiple user classes. Deciding which RMA performs better requires the definition of the optimal resource allocation and a comparison methodology able to capture the relative ranking of competing algorithms.

The combination of the resource pools significantly reduces the dimensions of the resource management problem, allowing for a computationally simple approach. The optimal resource allocation of a multi-BS network scenario can be upper-bounded by defining and solving an equivalent problem for a single BS. The superBS algorithm presented in this section defines this single BS problem by combining a number of parameters for each client of the network, and provides an optimistic resource allocation vector, with the following steps.

1) Compute the superBS bandwidth.

$$C_{sBS} = \sum_s C_s, s \in \bigcup L_i \tag{4}$$

The superBS has bandwidth equal to the sum of the bandwidth of all BSs visible by the clients.

2) Set the Estimated Maximum Throughput ($\widehat{T_{i,sBS}}$) of clients.

$$\widehat{T_{i,sBS}} = \max(\widehat{T_{i,s}}), \forall s \in L_i \tag{5}$$

Use the maximum $\widehat{T}$ each client gets from any of the visible BSs.

3) Set the user spectral efficiency (R).

$$R_{i,sBS} = \max(R_{i,sBS}), \forall s \in L_i \tag{6}$$

Use the maximum R each client gets from any of the BSs visible.

4) Calculate the optimal bandwidth allocation vector ($B_{i,sBS}$ and $T_{i,sBS}$). For the considered policy this is achieved by solving URM on superBS.

The superBS algorithm considers a virtual BS and client properties based on the real network. Steps 2 and 3 identify the connection quality of the clients. Due to the heterogeneity of the network, for different demand and actual throughput, $\hat{T}$ and R may have a different effect on the overall resource consumption in the real network. Hence, the selection of $\hat{T}$ and R is not linked for the definition of the superBS environment.

For example, let's consider a network comprising 2 BSs, A and B, with $C_A = 100$ and $C_B = 15$ bandwidth units (Bu), and a client with $D^{max} = 20$ throughput units (Tu), $\widehat{T_A} = 50$ Tu, $R_A = 0.5$, and $\widehat{T_B} = 15$ Tu, $R_B = 1$. The client can connect to BS A, consuming $B_A = 20/0.5$ Bu for $T_A = 20$ Tu, or to BS B with $B_B = 15/1 = 15$ Bu for $T_B = 15$ Tu. The client can get 15 Tu of throughput from BS B, or 20 Tu from BS A and meet his demand, albeit this increase comes with 25 Bu of bandwidth overhead. Since superBS is only aware of the maximum demand and not the final throughput the client will have on the virtual BS, it avoids limiting the client's performance by considering the most optimistic combination of $\widehat{T_{sBS}} = 50$ Tu, and $R_{sBS} = 1$. This design decision is a cause for possible under-estimation of consumed resources, and the reason why the superBS bandwidth allocation vector may be infeasible in the real network. For clarity, bandwidth units should be considered similar to bandwidth in Hz, used for a wireless data transmission, while throughput units similar to the bit rate of the transmission in bits/sec.

While step 4 finds the policy-optimal resource allocation for the simplified single-BS network by running URM, other RMAs can be used for different policies. The solution of the resource allocation problem for a single BS is considered trivial, and various policies and algorithms exist in the bibliography. SuperBS provides a useful upper bound that can be utilised in a number of applications, as we demonstrate in the remainder of the paper.

B. Heuristics

SuperBS produces a best-case bandwidth allocation solution, but does not provide an indication for the client assignment to BSs. This section describes Ideal-aware Resource Management (IRM), a simple heuristic algorithm that uses SuperBS as an input to assign clients to BS. IRM uses $B_{i,sBS}$ as a metric for BS selection. The steps of the algorithm are:

1) Sort clients in a descending $B_{i,sBS}$ order. Initialise the theoretical available bandwidth: $availC_s = C_s$.
2) For each client calculate the expected resource consumption for all visible BSs. $\widehat{B_{i,s}} = T_{i,sBS}/R_{i,s}$.
   a) If the theoretical available bandwidth of the BS with the maximum R is enough, assign client to this BS. (if $availC_s > \widehat{B_{i,s}}$).
   b) Else assign client to the BS with maximum $(availC_s - \widehat{B_{i,s}})/C_s$.
3) Update the theoretical available bandwidth of the BS: $availC_s = availC_s - \widehat{B_{i,s}}$. Negative values are allowed.
4) With all clients assigned to BSs, perform the Class Sharing (CS) bandwidth assignment with weighted water filling. The weight for each client is α_i.

IRM first considers the clients with the highest impact on the overall network, *i.e.*, the clients with the highest expected bandwidth consumption at the superBS. It selects which BS they should be assigned to by minimising their impact on the real network. This is done by either assigning the client to the BS with the lowest R, minimising the consumed resources (step 2a), or to the BS that, relatively, would be affected less (step 2b). The relative effect a client has on the BS is measured with $(availC_s - \widehat{B_{i,s}})/C_s$. It calculates the expected available resources, or, if negative, resources clients assigned to the BS will have to share, if the client was to connect to each BS, normalised to the BS's bandwidth.

A second heuristic is proposed, Dmax-CS, that uses the same algorithm, albeit with a fundamental change. It considers the maximum estimated demand (D_i^{max}) instead of $B_{i,sBS}$. Dmax-CS does not need a prior computation of superBS as $\widehat{B_{i,s}}$ is defined as: $\widehat{B_{i,s}} = D_i^{max}/R_{i,s}$. Clients are sorted to a descending order of their respective minimum $\widehat{B_{i,s}}$. Comparison of the two RMAs will demonstrate the benefits, if any, of using superBS as a guide to resource allocation.

V. Performance analysis

The performance of the proposed heuristics is examined with MATLAB simulations as we focus on the decision-making methods and not on specific protocols and network types. Two additional RMAs, that were used in [1], are also considered for the performance analysis, the Most Available Bandwidth (MAB-CS) and the RSS-equivalent (RSS-CS). They perform network selection by considering clients in a random order and selecting the BS with the most available bandwidth or the one offering the best $\widehat{T_i}$, respectively. RSS-CS resembles the current BS selection practice where the client attaches to the BS of the best technology with the best signal strength. MAB-CS is a simplistic load-balancing improvement of RSS-CS, where clients are attached to the BS with the least traffic load.

The network consists of one *Fast*, one *Medium*, and one *Slow* BSs, all partially overlapping. The bandwidth of these generic BS types roughly corresponds to LTE, WiFi and UMTS. We consider three distinct user classes, namely Gold Class (GC), Silver Class (SC), and Bronze Class (BC), with α values of 0.6, 0.3, and 0.1 respectively. α has an effect analogous to weights in weighted water filling, and different sets of α values demonstrate similar qualitative behaviour. Results are averaged over 100 experiments, each based on a randomly generated snapshot, as explained in Section III-B. The number of clients is chosen so that the total maximum demand is 1.5 times the network capacity, and each is assigned a priority class with a discrete uniform distribution. The network is saturated to showcase the effect of the bandwidth sharing mechanism of the RMAs. The clients are randomly assigned data rates (that define $\widehat{T_i, s}$) and their respective $R_{i,s}$ from Table II, simulating a random placement on the coverage area. The client traffic is considered greedy, with D_i^{min} 0 and D_i^{max} set with a uniform distribution between 0 and 40 Tu. The maximum demand of a client can overwhelm the *Slow* BS, and consume a considerable portion of the *Medium* and *Fast* BSs, similar to clients with demands that saturate a UMTS BS.

Fig. 1 shows the average utility, throughput, fairness and denied throughput per class. Fairness is computed using Jain Index with D_i^{max} as optimal, and is discussed in more detail in the next section. Denied throughput considers $D_i^{max} - T_i$, and expresses the dissatisfaction of the demand of the clients. URM shows the utility-optimal resource allocation for the heterogeneous wireless network. SuperBS, due to the expected under-estimation of resource utilisation, noticeably but not excessively outperforms URM in terms of utility and throughput, while achieving similar levels of fairness. The analytical, utility-based approach of URM is able to closely match the policy-optimal allocation of superBS, unfortunately with significantly higher computational cost.

TABLE II. BS Data and Utilisation Rates

BS type	Min	Max	Step Size
Fast BS Data Rates (Tu)	30	300	30
Medium BS Data Rates (Tu)	10	100	10
Slow BS Data Rates (Tu)	1.5	15	1.5
R (respective to Data Rate for all BS)	1/2.8	1	1/0.2

TABLE III. Average Correlation of T_i with $T_{i,sBS}$.

URM	0.9119
IRM-CS	0.8663
Dmax-CS	0.8123
MAB-CS	0.6016
RSS-CS	0.6654

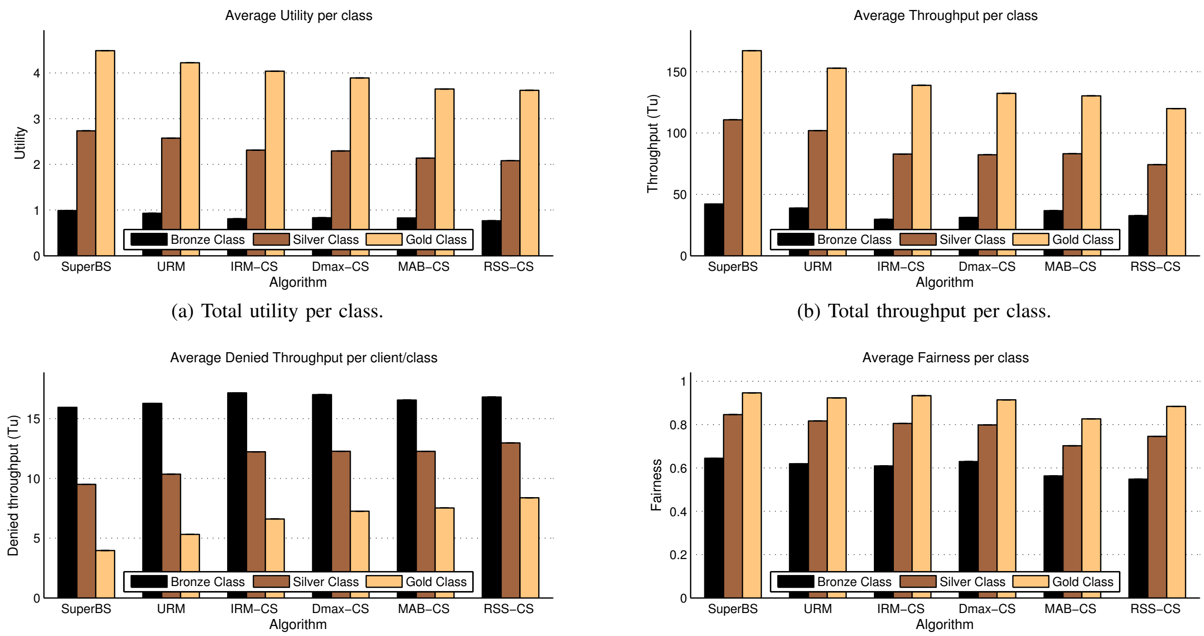
IRM-CS and Dmax-CS make well-informed selections of which BS should serve each client, and consistently achieve comparable throughput with URM and superBS, as shown in Table III. On the other hand, MAB-CS with its simplistic network selection algorithm, fails to be as consistent. This happens as clients are sub-optimally assigned to BSs without considering the actual throughput they will get, resulting in varying per-client throughputs, even between the same class. The CS bandwidth allocation algorithm is still able to differentiate between the classes, making the average throughput seem comparable to URM. However, throughput greatly varies between clients, and has a very low correlation to superBS. Jain Index is not able to capture this irregular behaviour, showing only a slight decrease in fairness, as it is masked by the co-existence of users with low demand that satisfy it and high demand that are not getting enough throughput.

RSS-CS performs the worst in terms of throughput and utility, but has a better correlation of throughput to superBS than MAB-CS. This happens as RSS-CS selects the fast BS for most clients, resulting in an assignment similar to a single-BS scenario, albeit with the bandwidth of only the fast BS.

The complexity of the various RMAs should be noted. URM, with a worst-case analytic approach, has a complexity of $O(nS^n)$. SuperBS, since it is essentially URM in a single BS is $O(n)$, as are MAB-CS and RSS-CS. IRM-CS and Dmax-CS are significantly lower than URM with $O(nS)$

VI. On the issue of fairness

Various notions have been proposed to define fairness, such as the Max-Min fairness and index, the Jain Index, and the Gini Index, each appropriate for specific problems and generally best for greedy traffic. Unfortunately, none can cope with the complexity of a heterogeneous wireless network, especially when traffic has a maximum sustainable throughput,



(a) Total utility per class.

(b) Total throughput per class.

(c) Denied throughput per client/class.

(d) Fairness per class.

Fig. 1. Average statistics over 100 snapshots.

as demonstrated with the example that follows. Things become more complicated with multiple client classes, as there is an interdependency of the available bandwidth of one class with the utilised bandwidth of the other.

Let's consider the Max-Min index, a simple metric defined as $I_{maxmin} = min\{x_i\}/max\{x_i\}$, and a throughput assignment of (1, 1, 1, 2) Tu to 4 clients of the same class. The first three clients have a maximum demand of 1 Tu and the fourth is greedy. This assignment would have $I_{maxmin} = 0.5$, even though it follows exactly the idea of Max-Min fairness, namely that the increase of the throughput of client 4 has not affected negatively any other clients by lowering their throughput. Additionally, if a RMA was able to additionally allocate 2 Tu to this class (1, 1, 1, 4), it would result to $I_{maxmin} = 0.25$, indicating even less fairness. Similarly, the Gini index would give values of 0.1 and 0.21 for the same throughput allocations (Gini index notes fairness with 0 and unfairness with 1).

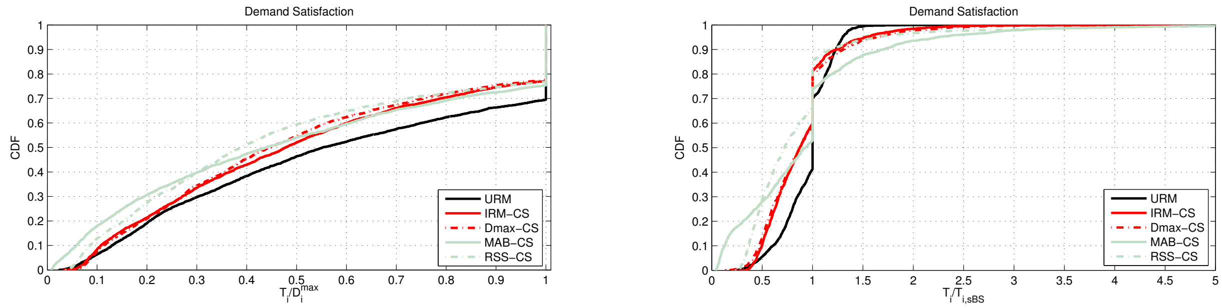
Jain Fairness Index (eq. 7) is a relative fairness measure, comparing the throughput assignment (x_i) with an optimal one (O_i). O_i is commonly set equal to the average x_i.

$$I_{Jain} = \frac{\left(\sum_i \frac{x_i}{O_i}\right)^2}{n \sum_i \left(\frac{x_i}{O_i}\right)^2} \tag{7}$$

Figure 1d considers $O_i = D_i^{max}$, and shows the inability to distinguish between clients with low demand fulfilling their need and clients with high demand receiving throughput noticeably lower than D_i^{max}. Figure 2a shows the CDF of the demand satisfaction rate for all clients. As expected from a congested network, a number of clients fulfill their demand, while others receive reduced throughput, since the traffic demand between clients is different.

A fair resource allocation could be considered to be the one that complies with the policy requirements. SuperBS provides a reference for that, namely it provides an estimation of the throughput each client should receive under a strict policy-adhering RMA. Figure 2b shows the CDF of the demand satisfaction against the throughput allocation of superBS ($T_{i,sBS}$). The closer the curve is to $x = 1$, the more policy-compliant the bandwidth allocation is. Sub-optimal BS selection causes some clients to have $T_i/T_{i,superBS} > 1$ at the expense of other clients in more saturated BSs. By visual inspection it can be seen that URM is the one closest to optimal, while IRM-CS and Dmax-CS outperform MAB-CS and RSS-CS.

As differences between two RMAs are becoming less obvious, the need for the quantification of Figure 2b becomes prominent. The Jain Index is computed again, this time with $O_i = T_{i,sBS}$. The superBS allocation acts as a normalisation factor, allowing the direct comparison of Jain fairness between clients of different classes, since the optimal allocation for a client already considers the class of the client, the existence of other clients and their demands. Table IV shows the fairness index across the 100 snapshots, while Figure 3 plots the average fairness per class and the reliability of each RMA. URM, as expected, is the best performing RMA, consistently achieving fairness higher than 0.9, with very small confidence intervals. IRM-CS follows next, with fairness 0.85 to 0.95, albeit with slightly wider confidence intervals. Dmax-CS performs slightly worse, while RSS-CS and especially MAB-CS have significantly lower fairness, with considerably wider confidence intervals, meaning that they deliver these fairness levels unreliably. The performance of IRM-CS and Dmax-CS show that computationally simple RMAs with an intricate knowledge of the network can achieve near-optimal results.



(a) Throughput against demand.

(b) Throughput against superBS.

Fig. 2. Demand Satisfaction (CDF).

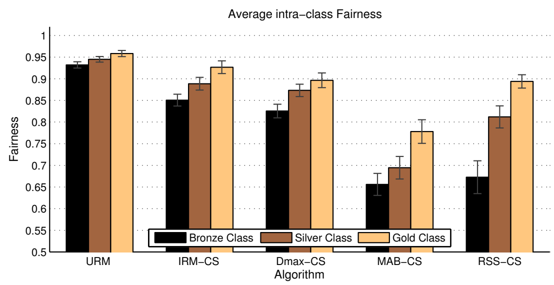


Fig. 3. Average fairness with superBS as optimal over 100 snapshots with 95% confidence intervals.

TABLE IV. FAIRNESS ACROSS ALL SNAPSHOTS WITH SUPERBS AS OPTIMAL

URM	0.9420
IRM-CS	0.8691
Dmax-CS	0.8397
MAB-CS	0.6522
RSS-CS	0.6986

Moreover, the computation of superBS allows IRM to achieve noticeably better utility, throughput and fairness than Dmax. On the other hand, MAB and RSS follow an over-simplistic approach for BS selection that leads to significant deviation from the optimal allocated throughput.

VII. Conclusion & Future Work

This work presented the process of representing a multi-BS heterogeneous wireless network as a single theoretical BS to simplify the approximation of the optimal resource allocation. It is shown that this theoretical optimal solution can be used effectively in heuristic resource management algorithms and benchmarking of the various approaches. In particular, with this theoretical optimal solution, Jain fairness is able to cope with the heterogeneity of the different user classes and demands, and conclusively determine whether the clients are allocated a fair amount of resources in respect to what the resource sharing policy commands.

The main future direction is to support client mobility and handoffs, making the network model more realistic. A major resource allocation question arises when ongoing sessions collide with a new one. Moreover, the heterogeneous nature of the network implies significant costs for vertical handovers, making the definition of the optimal resource management problem challenging. The applicability and effectiveness of the various RMAs needs to be examined with the increase of the network model complexity and realism.

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References

[1] I. Tsompanidis, A. Zahran, and C. Sreenan, “Towards utility-based resource management in heterogeneous wireless networks,” in *ACM MobiArch*, Aug. 2012.

[2] A. Coluccia, A. D’Alconzo, and F. Ricciato, “On the optimality of max–min fairness in resource allocation,” *Annals of Telecommunications*, vol. 67, no. 1-2, pp. 15–26, 2012.

[3] F. Kelly, “Charging and rate control for elastic traffic,” *European Transactions on Telecommunications*, vol. 8, pp. 33–37, 1997.

[4] Y. Yi and M. Chiang, “Stochastic network utility maximisation-a tribute to Kelly’s paper published in this journal a decade ago,” *European Transactions on Telecommunications*, vol. 19, no. 4, pp. 421–442, 2008.

[5] D. Bertsekas, R. Gallager, and P. Humblet, *Data networks*. Prentice-Hall International, 1992, vol. 2.

[6] R. Jain, D. Chiu, and W. Hawe, “A quantitative measure of fairness and discrimination for resource allocation in shared computer systems,” DEC-TR-301, Digital Equipment Corporation, Tech. Rep., Sep. 1984.

[7] A. Marshall, *Inequalities: Theory of majorization and its applications*. New York: Academic Press, 1979.

[8] M. Dianati, X. Shen, and S. Naik, “A new fairness index for radio resource allocation in wireless networks,” in *IEEE WCNC*, Mar. 2005.

[9] P. Bellavista, A. Corradi, and C. Giannelli, “A unifying perspective on context-aware evaluation and management of heterogeneous wireless connectivity,” *Communications Surveys Tutorials, IEEE*, vol. 13, no. 3, pp. 337–357, 2011.

[10] M. Corici, J. Fiedler, D. Vingarzan, and T. Magedanz, “Optimized low mobility support in massive mobile broadband evolved packet core architecture,” in *Networks (ICON), 2011 17th IEEE International Conference on*, Dec. 2011.

[11] O. Ormond, G. Muntean, and J. Murphy, “Economic model for cost effective network selection strategy in service oriented heterogeneous wireless network environment,” *Symp. Network Operations and Management*, Jan. 2006.

[12] T. J. Gerpott, “Biased choice of a mobile telephony tariff type: Exploring usage boundary perceptions as a cognitive cause in choosing between a use-based or a flat rate plan,” *Telematics and Informatics*, vol. 26, no. 2, pp. 167–179, 2009.

[13] J. Hassan and et al., “Managing Quality of Experience for Wireless VoIP Using Noncooperative Games,” *Selected Areas in Communications, IEEE Journal on*, vol. 30, no. 7, pp. 1193–1204, 2012.