RAT Selection Optimization in Heterogeneous Wireless Networks

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Abstract. While wireless access networks are rapidly evolving, constantly increasing both in coverage and offered bandwidth, the vision for Next Generation Wireless Networks (NGWNs) encompasses a core network incorporating various Radio Access Technologies (RATs) in a unified and seamless manner. In such an environment, providers with multi-RAT technologies will aim at the maximization of the satisfaction of their subscribers, while attempting to avoid overloading their subsystems. In this paper we deal with the network selection problem in a multi-RAT environment where users are equipped with multimode terminals. We introduce a utility-based optimization function and formulate the problem of allocating user terminals to RATs as an optimization problem under demand and capacity constraints. This problem is recognized as NP-hard and we propose an optimal Branch and Bound (BB) algorithm, as well as a greedy heuristic which exploits a metric that measures the utility gained versus the resource spent for each allocation. BB manages to significantly reduce the search procedure, while greedy produces optimal allocation results similar to BB but with very low computational cost.

Keywords: Next Generation Wireless Networks, network selection, optimization, Branch and Bound.

1 Introduction

Cellular networks have developed significantly in the past decade from voice-mainly 2G systems to voice and data 3G networks, mainly suitable for high coverage but with relatively low to higher bandwidth. On the other hand, Wireless LAN technology has emerged as an omnipresent technology, offering very high bandwidth compared to

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cellular networks but significantly lower coverage. Apart from the aforementioned technologies, other wireless systems have also emerged, such as 802.16 [1], DVB and HSPA [2] [3].

NGWNs will be characterized by even higher bandwidth, e.g. LTE [4], along with the coexistence of various RATs. 3GPP has already developed a series of documents to deal with the 3G-WLAN coexistence, while the IEEE 1900.4 standard [5] describes the architecture and protocols for distributed decision making to optimize radio resource usage in heterogeneous wireless networks. In a multi-RAT environment, various issues are about to arise mainly due to such coexistence. According to the concept of being Always Best Connected (ABC) [6], the notion of “Best” can be represented by the satisfaction a user gains by using the network. In ABC networks, user satisfaction will become an important variable to successful network operation, since technological and market advancements will make it much easier for a user to migrate from one RAT to another within a single or multiple cooperating providers even on session level basis.

In this paper we examine the network selection problem, which deals with the assignment of each terminal to the most suitable RAT and is similar to well-known NP-hard problems, such as the Knapsack and the Generalized Assignment Problems [7]. We follow the approach in [8] and formulate it as an optimization problem which attempts to maximize a utility-based objective function under requirement and capacity constraints. We develop a Branch and Bound (BB) algorithm and a Greedy heuristic which exploits the special characteristics of the problem. It turns out that the Greedy heuristic behaves quite well compared to the BB under various traffic loads with significant computational savings.

The rest of this paper is organized as follows. In the next section we illustrate some related works. In Section 3, we briefly outline the system model of our study and formulate the optimization problem of access selection in multi-RAT environments. In Sections 4 and 5 we present the BB and the Greedy algorithms, while in Section 6 we present our simulation results. The paper is concluded in Section 7.

2 Related Work

There has been numerous works that deal with the Network Selection problem in different ways. For example, in [9] users are assigned to subsystems, in order to minimize blocking probability and at the same time maximize the system capacity, while the formulation is done according to the Online Bin-Packing Problem. In a similar context, the authors in [10] study resource allocation in the context of ABC using the Knapsack Problem formulation. The overall goal is to maximize the users' utility, while taking their preferences and satisfaction into account, through a quality-to-utility mapping.

A thorough study on the utility theory to define an appropriate decision mechanism in the frame of the access network selection was made by the authors in [11] who proposed new single-criterion and multi-criteria utility forms to best capture the user satisfaction and sensitivity facing up to a bundle of access network characteristics. In [12], the authors point out the need of the existence of a Common Radio Resource

Management (CRRM) as a fundamental part of the upcoming next generation wireless systems. They formulate the problem as a Generalized Access Selection Problem (GASP) and expose the optimization criteria that define the solution. They also formulate a Strict version of the Access Selection Problem (SASP) and in order to obtain the solution they use a heuristic strategy based on a Genetic Algorithm (GA).

In [13], users' allocation is compared to a competition among group of users in different service areas to share the limited amount of bandwidth in the available wireless access networks. Eventually the problem is formulated as a dynamic evolutionary game where the evolutionary equilibrium is considered to be the solution to this game. Finally, in [14] the authors cast the problem as a non-cooperative game where users and access networks act selfishly according to their objectives while in [15] bandwidth allocation and admission control algorithms are presented based on the bankruptcy game.

3 System Model and Problem Formulation

A representation of the entities involved in the scope of this paper is depicted in Fig. 1. We assume that there is a specific server responsible for collecting all necessary measurements and reaching the required decisions, such as the CRRM entity described in [12]. Upon arrival, the users' requests are forwarded to the CRRM whose optimization module is responsible for assigning each user to an available RAT, or even allocating different portions of its requested rate to various RATs.

Although the case of multiple providers can be formulated accordingly, we assume one provider offering network services, through a set of N RATs. Users arrive dynamically and are allocated resources from some RAT for a limited period of time, and then depart, releasing the occupied resources from that RAT. We denote the currently available data rate capacity of RAT j as C_j, $j = 1,\ldots,N$. We assume that each user i declares upon arrival its data rate requirements R_{Di}, along with $S_i \subset \{1,\ldots,N\}$, the preferable set of RATs, mainly to exclude some of the available RATs. Without loss of generality we assume that $S_i = \{1,\ldots,N\}$. When admitted to some RAT j, user i may be assigned rate R_{ij} at that RAT, which may be less or equal to the requested rate R_{Di}.

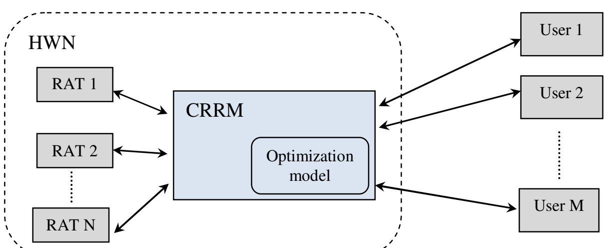


Fig. 1. Network selection model

To capture the gratification level of user i when served by some RAT j, we use *utility function* $U(R_{ij},R_{Di})$, which measures the normalized satisfaction of user i by taking into account the rate R_{ij} assigned at RAT j compared to the rate requested by the user. Thus, when a user gets exactly the rate requested, the utility should be high, while if the user is not accepted at some RAT the corresponding utility should be low. Users can then be differentiated by the way utility varies with respect to the rate assigned with normalized values ranging from zero (if zero rate is assigned) to one (if the requested rate is assigned). Below we define three different kinds of users:

- Linear-Expectation users (LEU) gain satisfaction that grows proportionally to the rate assigned. In this case, we assume that the utility function is a linear function of the rate assigned.
- High-Expectation users (HEU) are willing to spend a large amount of money but are very demanding regarding the level of service they get. In this case, the utility function should produce very low utility values, when they are assigned low rates compared to the rates requested, and should gradually increase only when the rates assigned approach the values of their requests.
- Between the two extremes we can define a class of users that are less demanding than HEU but more demanding than LEU. We will refer to these users as Mid-Expectation users (MEU).

We use the following utility functions for LEU, MEU and HEU users, respectively:

$$U_{LEU}\left(R_{ij},R_{Di}\right)=\frac{R_{ij}}{R_{Di}} \ ,$$

$$U_{MEU}\left(R_{ij},R_{Di}\right)=\left(\frac{R_{ij}}{R_{Di}}\right)^2 \ ,$$

$$U_{HEU}\left(R_{ij},R_{Di}\right)=\left(\frac{R_{ij}}{R_{Di}}\right)^4 \ .$$

The plots of these functions are also shown in Fig. 2. For example, if a HEU is requesting a rate of 256Kbps and the possible rates at some RAT are 128Kbps and 256Kbps, depending on the prevailing network conditions, the corresponding utility gain is 0.0625 and 1.00 when the lower or higher rate is assigned, respectively.

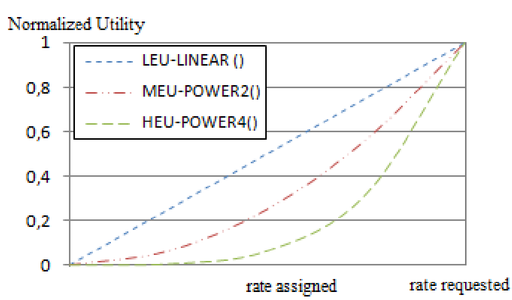


Fig. 2. Utility functions for LEU, MEU and HEU users

We can now formulate the network selection problem as follows:

$$\text{maximize} \quad \sum_{i=1}^{M}\sum_{j=1}^{N} U(R_{ij}, R_{D,i})$$

$$\sum_{i=1}^{M} x_{ij} \cdot R_{ij} \le C_j, \quad j = 1,\dots,N \tag{1}$$

$$\sum_{j=1}^{N} x_{ij} \cdot R_{ij} \le R_{D,i}, \quad i = 1,\dots,M \tag{2}$$

$$\sum_{j=1}^{N} x_{ij} \le 1, \quad i = 1,\dots,M \tag{3}$$

$$x_{ij} = \begin{cases} 1, \text{ if user } i \text{ is assigned to RAT } j \\ 0, \text{ otherwise} \end{cases} \quad i = 1,\dots,M, \; j = 1,\dots,N \tag{4}$$

Equations (1) and (3) stand for the capacity constraints and the requirement constraints, respectively, while x_{ij} is an indicator variable that prohibits users from getting rate from more than one RATs. This policy corresponds to a scenario where no more than one hardware interface can be open at each multimode terminal. Finally, we assume that, even if a RAT supports more than one possible rates for user i of some class requesting rate R_{Di}, the problem is formulated after the final decision on the offered rate $R_{ij} \le R_{Di}$ is taken based on the current traffic conditions at that RAT.

4 Branch and Bound

BB is designed to treat the above optimization problem under the last assumption of the previous section, namely when the rate and the corresponding utility gained by each RAT j for a specific user request i are known in advance and form two $M\times N$ matrices $\boldsymbol{R}=[R_{ij}]$ and $\boldsymbol{U}=[U_{ij}]$. The algorithm takes as input these two matrices and vector $\boldsymbol{C}=[C_j]$ with the available capacity of each RAT and its goal is to find, among all the possible assignments, the optimal assignment of all user requests to RATs which maximizes the utility function. Assuming that every user $i=1,\dots,M$ can, theoretically, connect to every RAT $j=1,\dots,N$, all possible assignments form a feasible state space of N^M states.

A search algorithm starts developing the feasible solutions tree by creating all possible assignments of users to RATs, examining users one by one and considering user i at step i, $i=1,\dots,M$. The algorithm keeps track of all the feasible assignments in the form of paths along the solution tree. It begins by assigning the first user to all possible RATs, thus creating the first N paths which are stored in set S_1. At the next step, it attempts to extend the N existing paths, by adding to each existing path one new assignment of the current step user to one of the N RATs, thus creating $N\times N$

paths which are stored in set S_2. This exhaustive procedure will finally create the full state space of N^M paths stored in S_M. It is obvious that an exhaustive search is intractable and thus we employ a branch-and-bound technique to limit our search and avoid the extension of some of the existing paths of set S_{k-1} at step k.

The main condition for avoiding the unnecessary extension of some paths is based on the following idea. It is not necessary to further extend a path of set S_{k-1} if the sum of the utility gained up to step k-1 for that path and the maximum possible utility that can be obtained from the next M-k+1 steps is less than the utility gained up to step k-1 by some other path in S_{k-1}. More formally, at step k of the algorithm we can define an upper bound $\bar{U}_k$ of the maximum utility which may be achieved in the remaining steps k+1, …,M of the algorithm as:

$$\overline{U}_k = \sum_{i>k} \max_j (U_{ij}) \ . \tag{5}$$

Note that this is an upper bound which may not be achievable because the corresponding solution path may not be feasible due to some other problem constraint. If we now denote by $U_k^{(p)}$ the utility gained from path p of set S_k, including the assignment during step k, then the extension of path p is excluded from the next steps of the algorithm if the following inequality holds:

$$U_k^{(p)} \leq \max_q U_k^{(q)} - \overline{U_k} \ . \tag{6}$$

Indeed if this inequality holds for path p, then the total possible achievable utility including the remaining steps of the algorithm will be less than the utility already gained by some other path q without considering the remaining steps of the algorithm.

Additional checks for reducing the number of paths to extend at step k of the algorithm are imposed by the capacity constraints of (1). According to these, at step k the extension of some path p of set S_{k-1} is performed for RAT j only if the existing RAT capacity is greater than or equal to rate R_{kj}. If we denote by $C_j^{(k,p)}$ the capacity consumed by RAT j in path p until step k-1, then the extension of path p, by assigning user k at RAT j, is excluded if the following inequality holds:

$$R_{kj} > C_j - C_j^{(k,p)} \ .$$

We will use the example below to illustrate the behavior of BB algorithm, where we assume that there are N=2 RATs and M=3 users. The data in the following matrices which are fed as input to the algorithm are used only for the sake of the example:

$$U = \begin{bmatrix} 1 & 3 \\ 1 & 2 \\ 1 & 1 \end{bmatrix}, R = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix}, C = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

We can construct the upper bound $\bar{U}_k$, k=1,…,M in advance as follows:

$$\left[\max_j U_{ij}\right] = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} \quad and \quad \left[\bar{U}_k\right] = \begin{bmatrix} 3 \\ 1 \\ 0 \end{bmatrix}$$

Each node of the solution tree is represented at step k by a triplet $[a_i],[C_j\text{-}C_j^{(k,p)}],U_k^{(p)}$. $[a_i]$ is the 1x3 allocation vector, whose values denote the RAT user i is allocated to, and corresponds to some path p. $[C_j\text{-}C_j^{(k,p)}]$ is the 1x2 vector of the remaining capacity in each RAT, while $U_k^{(p)}$ is the utility gained so far if allocations are made as shown in the allocation vector.

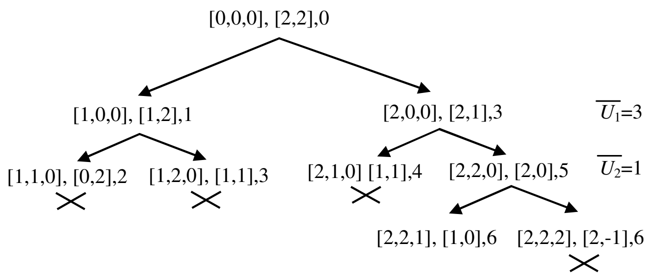


Fig. 3. Branch and Bound algorithm example

As we can see in Fig. 3, if the first user is allocated at the first RAT [1,0,0] at step 1, and the second user is allocated at the first RAT [1,1,0] as well at step 2, then the total utility gained so far at step 2 is 2. However, the best that we could achieve at step 2 is $\max_q U_k^{(q)} = 5$, in case both users are allocated to the second RAT and the maximum utility that the algorithm can achieve in the remaining third step is $\bar{U}_2 = 1$. Thus the path corresponding to allocation [1,1,0] is not further extended because (6) holds for that path. The same inequality holds also for the paths corresponding to allocations [1,2,0] and [2,1,0] and these paths are excluded from further expansion in step 3.

Finally, at the last step we illustrate how the capacity constraint is violated if the third user is allocated to the second RAT and thus this solution is excluded from the feasible set, rendering an optimum solution with allocation vector [2,2,1] and total utility value 6.

5 Greedy Heuristic

BB significantly reduces the computational cost compared to the exhaustive search procedure, and is useful for obtaining optimum solutions to compare with other non-optimal algorithms. Nevertheless, its time complexity, even for small problem instances, is prohibitive for problems which require finding a solution within reasonable time limits, as the one studied in this paper. Thus, it is necessary to devise heuristics that are computationally efficient and can produce near-optimum solutions.

Our greedy heuristic exploits the special characteristics of the problems and favors allocations of users to RATs that produce higher utility values, with relatively low RATs capacity consumption. The algorithm uses the ratio *utility gained per resource used* $\gamma_{ij} = U_{ij}/R_{ij}$ which is actually a measure of the utility that will be gained if user i is allocated to RAT j. So, instead of favoring allocations with high utility values, this heuristic favors allocations which yield higher values for this metric. Ties are resolved by favoring the allocation with the higher utility value.

The algorithm takes as input the same $M \times N$ matrices $\boldsymbol{U}$ and $\boldsymbol{R}$ and RAT capacity vector $\boldsymbol{C}$ and initially computes the $M \times N$ ratios γ_{ij}, which are then sorted in a list in decreasing order of their values. The algorithm performs the allocation of the users to RATs in M steps, each step consisting of the following two phases:

Phase 1: the first element γ_{ij} in the list of ratios is picked, and a check whether capacity constraints are violated is performed. If RAT j has greater capacity than R_{ij}, then user i is allocated to RAT j, the available capacity of RAT j is reduced by R_{ij}, and the algorithm proceeds to the second phase. Otherwise, user i cannot be allocated to RAT j, γ_{ij} is removed from the list and the algorithm repeats phase 1.

Phase 2: the remaining list of ratios is searched, and all the remaining γ_{il} ratios for user i that has been previously allocated to RAT j are removed from the list, $l \neq j$.

This procedure is repeated M times until all M users are assigned to RATs, or the available capacities of all RATs are too low to accept a user. Since there are M users to assign and the length of the initial list is $M \times N$, the time complexity of this heuristic is bounded by $O(M^2 \times N)$.

6 Simulation Results

Apart from BB and Greedy, we developed two Bin-Packing heuristics for comparing the efficiency of our algorithms. The first one is a variation of the First Fit (FF) strategy, while the second one is a variation of the Worse Fit (WF) strategy. Instead of using any utility based criterion for selecting the most appropriate RAT, both algorithms base their decisions only on rate requests and existing RAT capacities. FF assigns users to the first RAT that has enough capacity to accommodate the user requests, while WF assigns users requests to the RAT which will have the largest available capacity after the allocation.

We consider a wireless environment composed of 2 different RATs, RAT-1 and RAT-2, with capacities 256kbps and 512kbps, respectively. We assume that each incoming user requests 128kbps and may be allocated part of the rate requested depending on the prevailing network conditions and the RAT which is hosting the request. In this way, we can simulate different situations, where RATs cannot support the total requested rate, either due to RAT technology constraints or due to network traffic or inefficient channel conditions.

Table 1, summarizes the several combinations of rates assigned and utility gains under the different scenarios used in our study. Three different network conditions were considered. Depending on the probability of being fair or bad the network conditions can be distinguished as propitious, balanced or ominous. When network conditions are fair the rate allocated is 64kbps at RAT-1 and 128kbps at RAT-2. Thus, RAT-1 supports only half of the requested rate, even when conditions are good, and this assumption is mainly due to RAT technology constraints. On the contrary, when network conditions are bad the arriving user gets only 32kbps (64kbps) if allocated to RAT-1 (RAT-2). This assumption is made mainly because network traffic is high or channel conditions are bad.

Table 1. Rates assigned and utilities gained under different network conditions

Propitious Network Conditions	Fair - 70%		Bad - 30%	
Balanced Network Conditions	Fair - 50%		Bad - 50%	
Ominous Network Conditions	Fair - 30%		Bad - 70%	
RAT	RAT-1	RAT-2	RAT-1	RAT-2
Rate Assigned	64	128	32	64
LEU-Utility gained	0.5	1	0.25	0.5
MEU-Utility gained	0.25	1	0.0625	0.25
HEU-Utility gained	0.0625	1	0.003906	0.0625

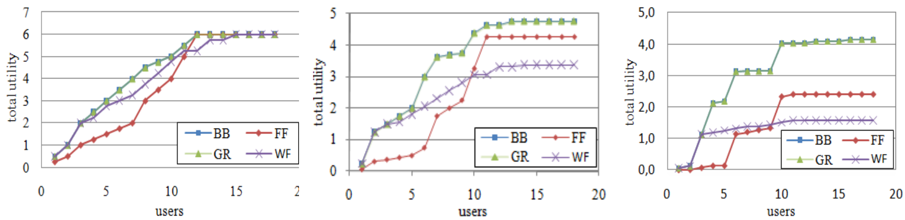
Each user request is statistically categorized as arriving when network conditions are fair or bad, and this statistical outcome is used as input to the algorithms. According to Table 1, if for example a HEU arrives when ominous network conditions prevail, there is 70% chance the network conditions to be bad and 30% chance to be fair. If the user is statistically categorized as arriving when bad networks conditions prevail, then the utility gained is 0.003906 if assigned at RAT-1 and 0.0625 if assigned at RAT-2.

We estimate the efficiency of BB in reducing the number of necessary searches until the optimum solution is found, by measuring the total number of nodes examined, compared to the total number of tree nodes examined by an exhaustive search procedure. In Table 2 we present the results on the pruning performed by BB until the optimum solution is found when we run the BB algorithm for each of the three kinds of users in every possible network condition. We do not include results for number of users below 8 because the reduction is negligible for very light traffic load. As we can see, significant reductions in the search procedure start to appear when the number of users exceeds 9. In any case, when the system is fully loaded the saving of BB climb up to 20% and more, reducing efficiently the number of the extended paths. However, when the system is overloaded, BB's reduction of the search space is extremely high but the actual number of nodes examined remains quite high as well and cannot performed in real time.

Table 2. Total number of tree nodes examined

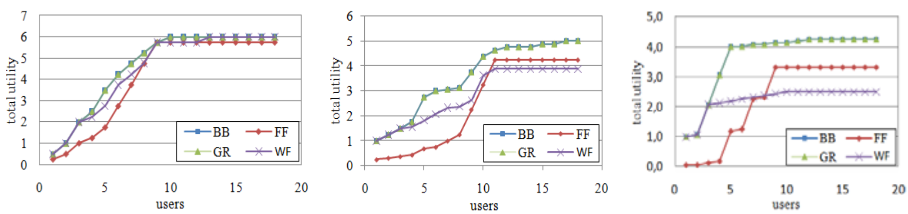
Number of Users	8	9	10	11	12	13	14	15	16	17	18
Exhaustive search	510	1022	2046	4094	8190	16382	32766	65534	131070	262142	524286
Propitious Network Conditions											
LEU-BB	469	862	1514	2680	4429	6889	10090	15029	22348	28657	30401
LEU-Reduction (%)	8	16	26	35	46	58	69	77	83	89	94
MEU-BB	470	862	1590	2755	4504	6942	9987	14656	18733	19521	19582
MEU-Reduction (%)	8	16	22	33	45	58	70	78	86	93	96
HEU-BB	495	951	1753	3081	5138	8113	12081	16716	20663	21425	21486
HEU-Reduction (%)	3	7	14	25	37	50	63	74	84	92	96
Balanced Network Conditions											
LEU-BB	498	977	1902	3673	7020	13249	23170	37371	54614	69577	73429
LEU-Reduction (%)	2.4	4.4	7	10	14	19	29	43	58	73	86
MEU-BB	486	912	1603	2844	5002	8630	12024	16453	21384	21522	21522
MEU-Reduction (%)	4.7	11	22	31	39	47	63	75	84	92	96
HEU-BB	495	951	1693	2678	4426	7455	12560	20837	24659	24707	24708
HEU-Reduction (%)	2.9	7	17	35	46	54	62	68	81	91	95
Ominous Network Conditions											
LEU-BB	504	1000	1925	3692	6583	11637	20083	33380	44806	55783	61476
LEU-Reduction (%)	1.2	2.2	5.9	9.8	20	29	39	49	66	79	88
MEU-BB	494	966	1848	3452	5380	8505	13244	19667	26811	32489	32494
MEU-Reduction (%)	3.1	5.5	9.7	16	34	48	60	70	80	88	94
HEU-BB	509	1005	1371	2060	2447	3063	4013	4071	4137	4184	4189
HEU-Reduction (%)	0,20	1.7	33	50	70	81	88	94	97	98	99

Fig. 4, 5 and 6 depict the total utility gained by each algorithm examined (BB, Greedy, FF, WF) under increasing traffic load, for every different class of users (LEU, MEU, HEU) and every network condition assumed. The results obtained by BB are optimal and are used to evaluate the performance of the other heuristics. Greedy produces very good results like BB at low, medium and high traffic loads, and this is justified by the metric used for sorting the user requests. The metric attempts to maximize the utility gained per capacity used and yields optimal results in the above example scenarios. On the other hand, FF and WF allocate user requests following the same pattern and behave relatively worse, since they do not take into consideration the corresponding utilities, but instead take into account only the rate requests and the available capacity at each RAT.



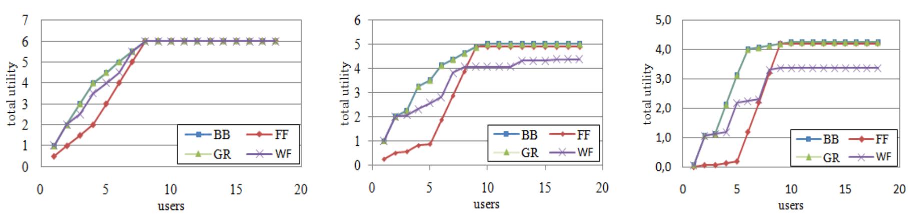
(a) LEU (b) MEU (c) HEU

Fig. 4. Total utility under ominous network conditions



(a) LEU (b) MEU (c) HEU

Fig. 5. Total utility under balanced network conditions



(a) LEU (b) MEU (c) HEU

Fig. 6. Total utility under propitious network conditions

7 Conclusions

In this paper we presented our work on the study of a multi-RAT environment. Specifically, we focused on the network selection problem where users are equipped with multimode terminals. We formulated this problem as an optimization problem and introduced a utility-based optimization function. We proposed an optimal Branch and Bound algorithm and a greedy algorithm which exploits a metric that measures the utility gained versus the resource spent for each allocation. In order to verify their efficiency, we compared them against two simplified algorithms based on the Bin-Packing problem, the First Fit and the Worse Fit algorithms. Our results showed that BB significantly reduces the search procedure and that the greedy heuristic is very efficient in achieving allocations of users to RATs that maximize utility values as BB does with much lower computational cost. However, even though the pruning of BB seems to be quite high for the settings of our simulation scenario, further investigation is necessary to reveal the dependency of the BB algorithm behavior on the parameters of the problem, namely the utility functions, RAT capacities and available RAT rates, and network conditions.

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