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Research Article

Decentralized Utility Maximization in Heterogeneous Multicell Scenarios with Interference Limited and Orthogonal Air Interfaces

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Overlapping coverage of multiple radio access technologies provides new multiple degrees of freedom for tuning the fairness-throughput tradeoff in heterogeneous communication systems through proper resource allocation. This paper treats the problem of resource allocation in terms of optimum air interface and cell selection in cellular multi-air interface scenarios. We find a close to optimum allocation for a given set of voice users with minimum QoS requirements and a set of best-effort users which guarantees service for the voice users and maximizes the sum utility of the best-effort users. Our model applies to arbitrary heterogeneous scenarios where the air interfaces belong to the class of interference limited systems like UMTS or to a class with orthogonal resource assignment such as TDMA-based GSM or WLAN. We present a convex formulation of the problem and by using structural properties thereof deduce two algorithms for static and dynamic scenarios, respectively. Both procedures rely on simple information exchange protocols and can be operated in a completely decentralized way. The performance of the dynamic algorithm is then evaluated for a heterogeneous UMTS/GSM scenario showing high-performance gains in comparison to standard load-balancing solutions.

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1. Introduction

In today's wireless scenarios, new radio access technologies (RATs) are emerging at frequent intervals. Although operators quickly introduce new wireless systems to the market they still have a strong interest in exploiting their legacy systems. Consequently, scenarios where an operator is in charge of multiple air interfaces with overlapping coverage are a common business case. Dense urban environments in Europe, where users are often in the coverage of a cellular TDMA-based GSM and CDMA-based UMTS systems, serve as a good example. In this case, if services are offered independently of the radio access technology and terminals support multiple wireless standards, the operator has the freedom to assign users to a cell and air interface of its choice.

Over the last years there has been growing interest in academics and industry in which way these degrees of freedom should be used and how users should be assigned

in heterogeneous wireless scenarios to exploit resources more efficiently, incorporate fairness, and increase reliability. Established concepts include load-balancing, service-based, and cost-based strategies. Load-balancing strategies assign users such that overload situations are avoided in one RAT as long as there are resources left in a collocated radio system [1]. More advanced approaches are service-based strategies which select an RAT also in dependence of the requested service type [2]. These strategies exploit the fact that one wireless technology might be better suited to support a certain service-class than another one due to different granularities of distributable resources, different coding, and modulation schemes. However, both approaches neglect the fact that also the position and corresponding channel gain of a user influence the efficiency of an RAT supporting a service request. Reasons include different carrier frequencies and corresponding channel models of RATs, base station positioning, different interference situations and sensitivity

to it. A concept that considers all earlier mentioned factors, like the system load, service class, interference situation, characteristics of the RAT, and users' positions, is the cost-based approach, introduced and analyzed in [3, 4]. There, it was observed that all characteristics can be bundled together in one cost parameter per user and RAT which suffice to calculate a close to optimum assignment that maximizes the total number of supportable voice users under static conditions. Alternative approaches can be found in [5] and references therein.

In this paper, we analyze in which way users of different service classes should be assigned in a heterogeneous scenario, thereby extending ideas from [3, 4]. Users request either a fixed minimum data rate, for example, as needed for voice services, or unconstrained best-effort (BE) data services. We formulate the user assignment as a utility maximization problem which is constrained by the resources (such as power or bandwidth) of the individual base stations (BSs) as well as users' minimum data rate requirements. The utilities represent quality of service (QoS) indicators of the BE users and, by choosing appropriate utility functions, give operators the freedom to tune the operation point of the heterogeneous system. It is important to note that although our model holds for general concave utility functions we will adopt the concept of α -proportional fairness introduced in [6] which allows to variably shift the operation point between maximum sum throughput, proportional fairness up to max-min fairness by a single, parameterizable utility function. Related work on utility maximization in nonheterogeneous interference limited systems was carried out in [7–9], where the generally nonconvex utility maximization problem was turned into a convex representation (or supermodular game) using specific techniques. The major difference to the approach taken in this paper is that we consider a heterogeneous scenario where the user-wise utilities are a function of the individual link rates; this practical assumption significantly complicates the analysis and neither of the approaches in [7–9] can be applied. Based on the convex formulation and by using structural properties, we present a decentralized algorithm that solves the optimization problem for static scenarios and derive simple assignment rules using the dual representation of the utility problem. The insights gained from the static setup are then adapted to dynamic scenarios and we design a distributed protocol which requires minimal information exchange between users and BSs and still achieves considerable performance gains. Most importantly, both algorithms allow operators to arbitrarily tune the fairness-throughput tradeoff online without any system changes. Although we cannot guarantee the convergence of the simplified algorithm in the dynamic scenario we observe a close to the global optimum operation in case a sufficient number of users requests service and the variation of the channel gains due to mobility is low. This is verified by the derivation of an upper bound and comparison to simulation results. Still, also for low service request rates and stronger channel variations due to mobility and fading considerable gains in terms of throughput and sum utility are obtained in comparison to a load-balancing strategy.

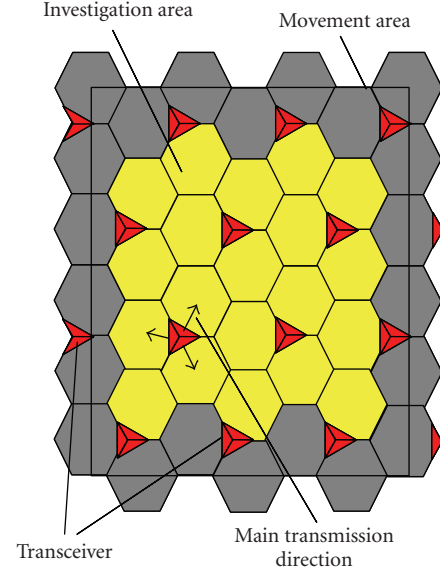


FIGURE 1: Playground with 40 GSM and 40 UMTS directional transceivers (collocated).

The paper is organized as follows: after the introduction of the system model and the utility concept in Section 2, we will formulate the optimization problem in Section 3. Algorithms that solve the problem in a decentralized way for static and dynamic scenarios are presented in Section 4. There, also the upper performance bound for the dynamic scenario is derived. In Section 5, we eventually evaluate the performance of the dynamic algorithm by comparing it to a load-balancing approach. We conclude the paper in Section 6.

Notations. In this work bold symbols denote vectors or matrices, calligraphic letters sets, and $|\cdot|$ the cardinality of a set. The transpose of a vector is $(\cdot)^T$, x_m is the m th element of \mathbf{x} , and $\mathbb{E}(\cdot)$ is the expectation. The summation over sets is defined as $\mathcal{X} = \sum_n \mathcal{X}_n = \{\mathbf{x} : \mathbf{x} = \sum_n \mathbf{x}_n, \mathbf{x}_n \in \mathcal{X}_n\}$.

2. System Model

We consider a wireless scenario in the down-link direction where multiple RATs with partly overlapping coverage are arranged in an area called playground. The set of RATs $\mathcal{A} = \mathcal{A}_{\text{orth}} \cup \mathcal{A}_{\text{inf}}$ thereby consists of two subsets: in RATs with orthogonal resources $a \in \mathcal{A}_{\text{orth}}$ time or frequency slots or subcarriers are assigned explicitly and users connected to one BS do not interfere with each other. In interference limited RATs $a \in \mathcal{A}_{\text{inf}}$ all users share the same bandwidth and the power constitutes the distributable resource. Each RAT $a \in \mathcal{A}$ consists of a set of base stations $m \in \mathcal{M}_a$ and one operator is assumed to control the set of all base stations $\mathcal{M} = \bigcup_{a \in \mathcal{A}} \mathcal{M}_a$. An exemplary scenario with one cellular UMTS system belonging to the interference limited class and one cellular GSM/EDGE air interface of the orthogonal class is depicted in Figure 1.

Since commercial wireless systems usually operate on individual frequency bands, we assume that signals of different RATs are orthogonal to each other and no intersystem interference takes place. Users can be affected by intra- and intercell interference within one radio technology, however.

The set of users \mathcal{I} can be divided into two subsets and users are equally distributed on the playground; users $i \in \mathcal{I}_v$ request a voice service with guaranteed data rate and have priority to BE users $i \in \mathcal{I}_b$ who do not have any QoS guarantees. Furthermore, it is assumed that the user equipment is able to cope with all RATs and the service requests are independent of the technology giving the operator the freedom to choose a cell and a RAT for each user that is best suited from its perspective.

Next we will describe the two classes of RATs that are covered in our scenario in more detail.

2.1. Orthogonal RATs. For the class of orthogonal systems we assume a fixed transmission power per BS and that the bandwidth, in terms of time or frequency slots, respectively, is the resource continuously distributable between users. Since commercial TDMA systems like GSM/EDGE usually have low frequency reuse factors we will assume constant intercell interference for this class of systems. The signal to interference and noise ratio (SINR) of user i and a BS m of this class

$$\beta_{i,m} = \frac{g_{i,m}\bar{P}_m}{\eta_m + I_m} \quad \forall m \in \mathcal{M}_a, a \in \mathcal{A}_{\text{orth}}, \quad (1)$$

thus depends on the channel gain $g_{i,m}$, the BS power \bar{P}_m , the constant intercell interference I_m , the thermal noise η_m , and is independent of the assigned resource. The amount of bandwidth assigned to user i by BS m is denoted by $t_{i,m}$. It is limited by the total, distributable bandwidth per BS \bar{T}_m and the constraint

$$\sum_{i \in \mathcal{I}} t_{i,m} = t_m \leq \bar{T}_m \quad \forall m \in \mathcal{M}_a, a \in \mathcal{A}_{\text{orth}}. \quad (2)$$

Due to the orthogonality of the users' signals and since the bandwidth is the distributable resource the relation between a user's data rate $R_{i,m}$ and the assigned resource is linear for this class of RATs:

$$R_{i,m} = \bar{R}_{i,m} t_{i,m}. \quad (3)$$

Here, $\bar{R}_{i,m} := f(\beta_{i,m})$ denotes the link rate per time or frequency slot between user i and base station m where $f(\beta)$ is a positive, nondecreasing SINR-rate mapping curve corresponding to the coding and transmission technology of the RAT $a \in \mathcal{A}_{\text{orth}}$. By substituting (3) into (2) the achievable rate region of each individual BS $m \in \mathcal{M}_a$ results in an I -dimensional simplex, limited by the positive orthant and a hyperplane:

$$\mathcal{R}_m = \left\{ \mathbf{R}_m : \sum_{i \in \mathcal{I}} \frac{R_{i,m}}{\bar{R}_{i,m}} \leq \bar{T}_m, R_{i,m} \geq 0 \forall i \in \mathcal{I} \right\}, \quad (4)$$

where \mathbf{R}_m is the i -dimensional vector with entries $R_{i,m}$. Since the rate assignment in one cell does not influence the feasible

rate region of neighboring cells the feasible rate region of the whole RAT results in the convex polytope

$$\mathcal{R}_a = \sum_{m \in \mathcal{M}_a} \mathcal{R}_m, \quad a \in \mathcal{A}_{\text{orth}}. \quad (5)$$

2.2. Interference Limited RATs. We assume that all users share the same bandwidth and that resources are distributed in terms of assigned power for BSs in interference limited air interfaces like UMTS $m \in \mathcal{M}_b, b \in \mathcal{A}_{\text{inf}}$. The power of each BS is limited by a sum constraint

$$\sum_{i \in \mathcal{I}} p_{i,m} = P_m \leq \bar{P}_m \quad \forall m \in \mathcal{M}_b, b \in \mathcal{A}_{\text{inf}}, \quad (6)$$

where $p_{i,m}$ is the power that BS m assigns to user $i \in \mathcal{I}$. Users are sensitive to intracell and intercell interference in interference limited systems and the SINR between BS $m \in \mathcal{M}_b, b \in \mathcal{A}_{\text{inf}}$ and user $i \in \mathcal{I}$ is given by

$$\beta_{i,m} = \frac{g_{i,m} p_{i,m}}{\rho g_{i,m} \sum_{j \neq i} p_{j,m} + \sum_{n \neq m} g_{i,n} P_n + \eta_{\text{inf}}} \quad (7)$$

$m, n \in \mathcal{M}_b, b \in \mathcal{A}_{\text{inf}}, i, j \in \mathcal{I},$

with ρ the orthogonality factor which accounts for a reduced intercell interference. In this class of systems all links of one BS share a limited power budget and are impaired by the power assigned to other users in the air interface. A well-known model for the link rate of these systems is given in [10]:

$$\begin{aligned} R_{i,m} &= C_b \log(1 + D_b \beta_{i,m}) \\ &= C_b \log \left(1 + D_b \frac{g_{i,m} p_{i,m}}{\rho g_{i,m} (\bar{P}_m - p_{i,m}) + \sum_{n \neq m} g_{i,n} \bar{P}_n + \eta_{\text{inf}}} \right). \end{aligned} \quad (8)$$

There, the positive constants C_b, D_b parameterize the system characteristics such as bandwidth, modulation, and bit-error rates. In (8), a user's data rate is in general neither convex nor concave in p (index omitted). Therefore, also the feasible rate region is not convex, which in turn will be a requirement to obtain a convex representation of the utility maximization problem in Section 3. However, assuming that all BS transmit with fixed transmission power and that the SINR of all links is not too high we can approximate the data rate by

$$\begin{aligned} R_{i,m} &= C_b \log \left(1 + D_b \frac{p_{i,m}}{I_{i,m} - \rho p_{i,m}} \right) \\ &\approx \frac{\Delta_b}{I_{i,m}} p_{i,m} \\ &=: \bar{R}_{i,m} p_{i,m}, \end{aligned} \quad (9)$$

with

$$I_{i,m} = \frac{\rho g_{i,m} \bar{P}_m + \sum_{n \neq m \in \mathcal{M}_b} g_{i,n} \bar{P}_n + \eta_{\text{inf}}}{g_{i,m}}. \quad (10)$$

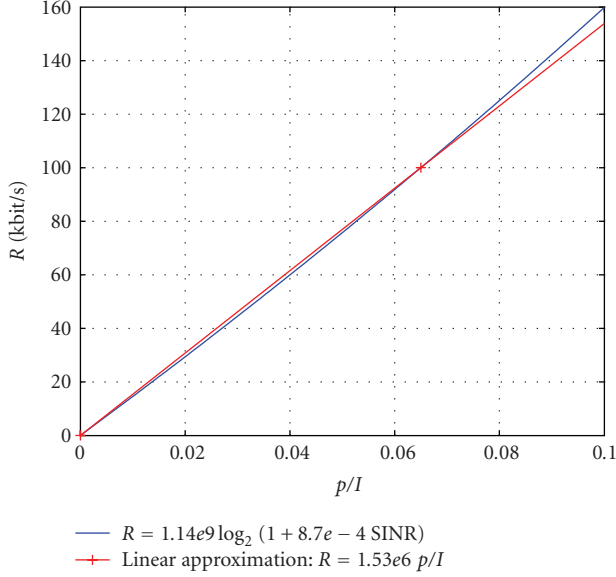


FIGURE 2: UMTS resource-rate mapping: quality of linear approximation (9).

The approximation in (9) represents the first order Taylor expansion for $p = 0$ if one chooses $\Delta_b = C_b D_b$. Clearly, this approximation holds only for low data rates and since we are interested in a good approximation for typical rates of the UMTS system, it turns out to be practical to use a higher slope $\Delta_b > C_b D_b$. Indeed we plotted the rates in (9) over p/I for UMTS in Figure 2 and chose Δ_b so that it intersects the real rate curve at the origin and 100 kbit/s which covers the range of rates that are typically assigned to users in UMTS in our scenario quite well. Obviously, this is only a model, but works fine for the problem at hand. We refer also to the discussion in Section 5.

By solving the approximation in (9) for p and substitution into (6) the achievable rate region of BS $m \in \mathcal{M}_b$ can be represented by

$$\mathcal{R}_m = \left\{ \mathbf{R}_m : \sum_{i \in \mathcal{I}} \frac{R_{i,m}}{R_{i,m}} \leq \bar{P}_m, R_{i,m} \geq 0 \forall i \in \mathcal{I} \right\}. \quad (11)$$

Since all BS are assumed to transmit with $P_m = \bar{P}_m$, the intercell interference is independent of the resource assignment and the achievable rate region of the whole RAT results in

$$\mathcal{R}_b = \sum_{m \in \mathcal{M}_b} \mathcal{R}_m, \quad b \in \mathcal{A}_{\text{inf}}, \quad (12)$$

which is a convex polytope as for the orthogonal RAT.

Our approach stands in clear contrast to [8] where a convex feasible rate region for interference limited RATs was obtained with the posynomial transform and assuming $R \approx C \log(D\beta)$. The posynomial approach has the advantage that also the BS sum transmission power P_m can be optimized. However, the corresponding rate approximation is only valid for high SINR and does not hold in our scenario. The linear structure of our approximation will further lead to simple assignment rules in Section 3.

2.3. Utility Concept and α -Proportional Fairness. Instead of maximizing a fixed metric like the system throughput, we will formulate the optimization problem in terms of utility functions, which relate assigned resources, system parameters as the SINR or the data rate to benefits such as revenues, fairness or user satisfaction. More precisely, we focus our investigations on utility functions which are concave, strictly increasing and dependent on the user's data rate in the following form:

$$U = \sum_{i \in \mathcal{I}_b} \psi_i \left(\sum_{m \in \mathcal{M}} R_{i,m} \right). \quad (13)$$

Without loss of generality ψ_i in (13) is given by

$$\psi_i^\alpha(R_i) = \begin{cases} w_i \log(R_i), & \text{if } \alpha = 1, \\ \frac{w_i}{1-\alpha} R_i^{1-\alpha}, & \text{otherwise.} \end{cases} \quad (14)$$

Utilities defined by (13) and (14) correspond to the well-established weighted α -proportional fairness [6], and are from special interest for operators since they ensure flexible tuning of the system fairness in a wide range. A rate allocation \mathbf{R}^* is said to be α -proportional fair, if for any feasible allocation \mathbf{R}

$$\sum_{i \in \mathcal{I}_b} \frac{R_i - R_i^*}{R_i^{*\alpha}} \leq 0 \quad (15)$$

holds [6]. The parameter α in (14) hereby tunes the fairness-throughput tradeoff; for $\alpha = 0$ the system throughput will be maximized, which might result in assignments where only very few users are served and which is quite unfair. A selection $\alpha = 1$ leads to proportional fairness which is equivalent to assigning equal shares of resources to all users in our scenario. For $\alpha \rightarrow \infty$ the assignment converges to the max-min fairness, where all users will be assigned equal data rates and the overall system throughput will be low [6].

Note that the definition of the utility in terms of the sum of a user's link rates in (13) is more relevant for practical application than, for example, the sum utilities of individual links $U = \sum_i \sum_m \psi(R_{i,m})$ used in [7, 9]. It turns out that it is exactly this so-called nonseparable utility formulation that leads to the desired characteristic that most users will establish only a single link, as will be shown in Section 3. By contrast, the separable utility in [7, 9] will favor multilink operation and therefore the results cannot be applied to our model. This follows from the concavity of ψ and the Jensen's inequality; assume a user is assigned a certain sum rate R_i that can be split between two links $R_{i,m}$ and $R_{i,n}$, $R_i = R_{i,m} + R_{i,n}$. Then, it is beneficial in terms of the separable sum utility to activate both links because $\psi(R_{i,m}) + \psi(R_{i,n}) \geq \psi(R_i)$.

3. Problem Formulation

Having the system model and the utility concept introduced, we now present the formal problem formulation. We want to find the user assignment in a heterogeneous multicell

scenario that maximizes the sum utility of all BE users under the constraint that all voice users are assigned at least a minimum data rate $R_{\min,i}$. Based on the earlier presented assumptions, the problem can be formulated as

$$\begin{aligned} \max_{\mathbf{R}} \quad & \sum_{i \in \mathcal{I}_b} \psi_i \left(\sum_{m \in \mathcal{M}} R_{i,m} \right), \\ \text{subject to} \quad & \sum_{i \in \mathcal{I}} \frac{R_{i,m}}{\bar{R}_{i,m}} \leq \Gamma_m \quad \forall m \in \mathcal{M}, \\ & \sum_{m \in \mathcal{M}} R_{i,m} \geq R_{\min,i} \quad \forall i \in \mathcal{I}_v, \\ & R_{i,m} \geq 0 \quad \forall i, m \in \mathcal{I}, \mathcal{M}, \end{aligned} \quad (\text{P1})$$

with Γ_m denoting available resources, $\Gamma_m = \bar{P}_m \quad \forall m \in \mathcal{M}_b$, $b \in \mathcal{A}_{\text{inf}}$ or $\Gamma_m = \bar{T}_m \quad \forall m \in \mathcal{M}_a$, $a \in \mathcal{A}_{\text{orth}}$, respectively. Problem (P1) consists of a concave objective over linear constraints and is therefore convex. Consequently, a variety of ready-to-use algorithms exists to solve it [11]. However, neither give these algorithms insights into the problem structure nor do they give a hint to a decentralized solution. We therefore develop a different approach based on duality [11, 12]; instead of solving (P1) directly we transform it into an alternative problem which is known to have the same solution as (P1) but can be solved in a decentralized way. To obtain an expression for the dual transform the Lagrangian function of (P1) is needed, which has the following form:

$$\begin{aligned} \mathcal{L}(\mathbf{R}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\sigma}) = & \sum_{i \in \mathcal{I}_b} \psi_i \left(\sum_{m \in \mathcal{M}} R_{i,m} \right) \\ & - \sum_{m \in \mathcal{M}} \lambda_m \left(\sum_{i \in \mathcal{I}_b} \frac{R_{i,m}}{\bar{R}_{i,m}} - \Gamma_m \right) \\ & + \sum_{i \in \mathcal{I}_v} \mu_i \left(\sum_{m \in \mathcal{M}} R_{i,m} - R_{\min,i} \right) \\ & + \sum_{i \in \mathcal{I}} \sum_{m \in \mathcal{M}} \sigma_{i,m} R_{i,m}. \end{aligned} \quad (16)$$

Here $\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\sigma}$ are nonnegative dual parameters. Next, we introduce the dual function of (P1) which is defined as [11]

$$g(\boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\sigma}) = \max_{\mathbf{R}} \mathcal{L}(\mathbf{R}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\sigma}). \quad (17)$$

Due to nonnegativity of the dual parameters one observes that (17) is always larger than or equal to the solution of (P1). Therefore, minimizing the unconstrained dual function over the dual parameters

$$\min_{\boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\sigma} \geq 0} g(\boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\sigma}) = \min_{\boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\sigma} \geq 0} \underbrace{\max_{\mathbf{R}} \mathcal{L}(\mathbf{R}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\sigma})}_{\text{inner problem}} \quad (18)$$

yields an upper bound on the original optimization problem (P1) and is called the dual problem of (P1). Furthermore,

by convexity of (P1) and since Slater's conditions [11] hold, the bound is tight and (18) and (P1) have the same solution. Our motivation to use the dual formulation is the possibility to decouple the optimization problem into an inner maximization problem over the primal variables \mathbf{R} and an outer minimization over the dual parameters which will be called outer loop further on. Additionally, the dual problem allows to exploit structural properties which will greatly simplify the algorithm design. The inner problem can be solved by each base station individually as we will see shortly. In addition, there exists a very limited number of degrees of freedom for the selection of meaningful dual parameters in the outer loop. To be more precise, only $\boldsymbol{\lambda}$ has to be optimized iteratively in the outer minimization. A rate allocation $\mathbf{R}(\boldsymbol{\lambda})$ that maximizes the inner problem can be calculated directly for a given $\boldsymbol{\lambda}$ independently of $\boldsymbol{\sigma}$ and $\boldsymbol{\mu}$. Before we go into the details the KKT conditions are given, which are necessary and sufficient for the optimum solution of (P1) (or equivalently (18))[11] and will be exploited later:

$$\frac{\partial \mathcal{L}(\mathbf{R}^*, \boldsymbol{\mu}^*, \boldsymbol{\lambda}^*, \boldsymbol{\sigma}^*)}{\partial R_{i,m}} = 0 \quad \forall m, i \in \mathcal{M}, \mathcal{I}, \quad (19)$$

$$\lambda_m^* \left(\sum_{i \in \mathcal{I}} \frac{R_{i,m}^*}{\bar{R}_{i,m}} - \Gamma_m \right) = 0 \quad \forall m \in \mathcal{M}, \quad (20)$$

$$\mu_i^* \left(R_{\min,i} - \sum_{m \in \mathcal{M}} R_{i,m}^* \right) = 0 \quad \forall i \in \mathcal{I}_v, \quad (21)$$

$$\sigma_{i,m}^* R_{i,m}^* = 0 \quad \forall i, m \in \mathcal{I}, \mathcal{M}. \quad (22)$$

Here $(\cdot)^*$ denotes the variables at the optimum.

3.1. Inner Problem. Rearranging terms in (16) results in the following:

$$\begin{aligned} \mathcal{L}(\mathbf{R}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\sigma}) = & \sum_{i \in \mathcal{I}_b} \psi_i \left(\sum_{m \in \mathcal{M}} R_{i,m} \right) \\ & + \sum_{i \in \mathcal{I}_v} \sum_{m \in \mathcal{M}} R_{i,m} \left(\sigma_{i,m} - \frac{\lambda_m}{\bar{R}_{i,m}} + \mu_i \right) \\ & + \sum_{i \in \mathcal{I}_b} \sum_{m \in \mathcal{M}} R_{i,m} \left(\sigma_{i,m} - \frac{\lambda_m}{\bar{R}_{i,m}} \right) \\ & + \sum_{m \in \mathcal{M}} \lambda_m \Gamma_m - \sum_{i \in \mathcal{I}_v} \mu_i R_{\min,i}. \end{aligned} \quad (23)$$

From (23), one observes that (17) is only finite if and only if

$$\sigma_{i,m} - \frac{\lambda_m}{\bar{R}_{i,m}} + \mu_i = 0 \quad \forall m, i \in \mathcal{M}, \mathcal{I}_v, \quad (24)$$

$$\frac{\lambda_m}{\bar{R}_{i,m}} > \sigma_{i,m} \quad \forall m, i \in \mathcal{M}, \mathcal{I}_b, \quad (25)$$

and hence it follows that (24) and (25) are necessary conditions to obtain a meaningful solution in (18). Furthermore, the first KKT condition (19) has to hold for any rate

assignment that solves (17) which after substituting (24) into (23) simplifies to

$$\frac{\partial \mathcal{L}}{\partial R_{i,m}} = \psi'_i \left(\sum_{m \in \mathcal{M}} R_{i,m} \right) + \sigma_{i,m} - \frac{\lambda_m}{R_{i,m}} = 0 \quad \forall m, i \in \mathcal{M}, \mathcal{I}_b. \quad (26)$$

Here, $\psi'_i(x) = \partial \psi'_i(x)/\partial x$ and (26) are necessary and sufficient conditions for the maximum of the Lagrangian function which is independent of the voice users. Although the optimization of the dual parameters is formally performed in the outer problem, one observes already here that only certain σ can lead to the optimum solution of (P1). More precisely, for a given λ only one element $\sigma_{i,m}$ can be chosen freely for each user i so that (26) is not violated. All other elements $\sigma_{i,m}, n \neq m$ result directly from $\sigma_{i,m}$ by (26). This is shown in the following example: assume one element $\sigma_{i,m}$ and λ are given for user i from the outer loop. Then, for the rate assignment that maximizes the inner problem $u_i := \psi'_i(\sum_{m \in \mathcal{M}} R_{i,m}) = (\lambda_m/\bar{R}_i, m) - \sigma_{i,m}$ has to hold (from (26)). Since (26) is a necessary condition also for all $n \neq m$ it follows that $\sigma_{i,n} = u_i(\sigma_{i,m}) + (\lambda_m/\bar{R}_i, n)$, $n \neq m$ which is therefore uniquely determined by $\sigma_{i,m}$. This observation reduces the degrees of freedom to select meaningful σ to one scalar element per user in the outer loop. From (26), it further follows that $\sigma_{i,m} = 0$ can only hold for $m \in \mathcal{M}_{\text{opt},i}(\lambda)$, with

$$\mathcal{M}_{\text{opt},i}(\lambda) = \left\{ m'_i \in \mathcal{M} : m'_i = \arg \min_m \frac{\lambda_m}{R_{i,m}} \right\}. \quad (27)$$

This is a direct consequence of the nonnegativity of the dual parameters and u_i based on (26). Having $\sigma_{i,m} = 0$, however, is a necessary condition for $R_{i,m}^* > 0$ since for any optimum rate assignment of (P1) the last KKT condition (22) has to be fulfilled. Therefore, regardless of the outer optimization we can already state here that $\sigma_{i,n} > 0 \forall n \notin \mathcal{M}_{\text{opt},i}, i \in \mathcal{I}_b$ and only rate assignments

$$R_{i,m} \begin{cases} \geq 0 & \forall m \in \mathcal{M}_{\text{opt},i}(\lambda), \\ = 0 & \text{else} \end{cases} \quad (28)$$

have to be considered as solution for (P1). Furthermore, setting $\sigma_{i,m} = 0$ $m \in \mathcal{M}_{\text{opt},i}$ if possible is required to allow for assignments with $R_{i,m} > 0$. Only if the maximum slope of the utility function $\psi'(0)$ is smaller than $\min_m (\lambda_m/\bar{R}_{i,m})$ this will result in $\sigma_{i,m} > 0 \forall m \in \mathcal{M}_{\text{opt},i}$ then so that (26) is not violated. In this case user i will not be assigned any resources. The KKT conditions lead to similar optimality conditions for the voice users; from (24) as well as the argumentation above it follows that

$$\mu_i = \min_m \frac{\lambda_m}{R_{i,m}} \quad \forall i \in \mathcal{I}_v, \quad (29)$$

and that (28) is also a necessary condition for the voice users. It is noted here that for a given λ the solution of (17) is uniquely determined (see proof of Theorem 1 in Section 4). However, the corresponding rate assignment might not be unique. Multiple optimum rate assignments can exist in the

rare case when $\exists \{m, n \in \mathcal{M}, m \neq n : \lambda_m/\bar{R}_{i,m} = \lambda_n/\bar{R}_{i,n}\}$ and therefore $|\mathcal{M}_{\text{opt},i}(\lambda)| > 1$. For all other users it follows by (26) and the discussions on σ that the rate assignment

$$R_{i,m}(\lambda) = \begin{cases} \psi_i'^{-1} \left(\frac{\lambda_m}{R_{i,m_i}} \right) & \text{if } \psi_i'(0) > \frac{\lambda_m}{R_{i,m}}, \\ & m \in \mathcal{M}_{\text{opt},i}(\lambda), \forall i \in \mathcal{I}_b, \\ R_{\text{min},i} & \text{if } m \in \mathcal{M}_{\text{opt},i}(\lambda), \forall i \in \mathcal{I}_v, \\ 0 & \text{else} \end{cases} \quad (30)$$

maximizes the inner problem and solves (17). In this case, the rate assignment is unique and only depends on λ . In (30), ψ'^{-1} is the inverse of the derivative of the utility function with $\psi'(\psi'^{-1}(x)) = x$.

Equation (30) gives some valuable insights to the optimum cell/RAT selection of users and the corresponding resource assignment. First, it can be shown that almost all users are assigned to exactly one BS since $|\mathcal{M}_{\text{opt},i}| = 1$ in general. Second, this BS can be determined independently by each user if λ is known and under the assumption that each user i can measure $\bar{R}_{i,m} \forall m \in \mathcal{M}$. Both characteristics rely on the linear connection between the data rate and the assigned resources and on the user based utilities and greatly simplify the distributed solution of (P1). In contrast, one would obtain that $R_{i,m}^* > 0 \forall i, m \in \mathcal{I}, \mathcal{M}_b, b \in \mathcal{A}_{\text{inf}}$ under the high SINR assumption in [7, 9], which implies that all users have active connections to all BSs in the interference limited air interface. Third, the maximum slope of the utility function $\psi_i(0)$ defines a threshold which can be tuned to switch off BE users with low $\bar{R}_{i,m}$, as will be described in Section 5.

3.2. Outer Problem. Since for μ (24) has to hold, λ and formally σ are the only dual parameters that have to be considered in the outer optimization. In order to minimize the dual (17), clearly all entries of σ have to be as small as possible and chosen in a way that (26) holds. Therefore, $\sigma_{i,m'_i} = 0 \forall \{i, m'_i : i \in \mathcal{I}_b, m'_i \in \mathcal{M}_{\text{opt},i}(\lambda), \lambda_{m'_i}/\bar{R}_{i,m'_i} \leq \psi(0)\}$. A subgradient approach can be applied to minimize the dual over λ [12]. Assume for a given $\hat{\lambda}$

$$\hat{\mathbf{R}} = \arg \max_{\mathbf{R}} \mathcal{L}(\mathbf{R}, \hat{\lambda}) \quad (31)$$

is the solution of inner problem, obtained by (30). Then, the following holds for the dual function [12]

$$g(\lambda) \geq \mathcal{L}(\hat{\mathbf{R}}, \lambda) = \mathcal{L}(\hat{\mathbf{R}}, \hat{\lambda}) + \sum_{m \in \mathcal{M}} (\lambda_m - \hat{\lambda}_m) \left(\Gamma_m - \sum_{i \in \mathcal{I}} \frac{\hat{R}_{i,m}}{\bar{R}_{i,m}} \right), \quad (32)$$

where the last equation is obtained by adding and subtracting the terms $\sum_{m \in \mathcal{M}} \hat{\lambda}_m (\Gamma_m - \sum_{i \in \mathcal{I}} (\hat{R}_{i,m}/\bar{R}_{i,m}))$ to $\mathcal{L}(\hat{\mathbf{R}}, \hat{\lambda})$ and the assumption that $\sigma_{i,m} R_{i,m} = 0 \forall i, m \in \mathcal{I}, \mathcal{M}$. Further,

it can be shown from (32) that the vector \mathbf{v} , with $v_m = (\Gamma_m - \sum_{i \in \mathcal{I}} (\hat{R}_{i,m}/\bar{R}_{i,m}))$ is a subgradient.

A descriptive explanation of the subgradient approach is as follows: for a given $\hat{\lambda} \neq \lambda^*$ the rate assignment $\hat{\mathbf{R}}$ might either violate the feasible rate region constraint or will not exploit all available resources. Both cannot be optimal since the first case is not feasible and in the latter case the assignment of more resources to any BE user would increase the sum utility. Then, the subgradient gives the direction how λ should be updated so that the resource constraints are less violated or more resources are assigned. At the global optimum of (P1), all entries of the subgradient will be zero and all resource constraints are met with equality. The subgradient will be used in the decentralized algorithm, which will be presented in Section 4.

4. Algorithm

We will now present two decentralized algorithms for (P1) in a static and dynamic scenario, respectively. In the static setup, all user requests and channel gains are assumed to be fixed, while in the dynamic one the requests and user mobility are subject to stochastic processes. The static algorithm hereby serves as motivation for the dynamic one which is adapted for practical applications with the advantage of requiring almost no signaling information.

4.1. Static Scenario. Based on the optimality conditions of the inner problem and the subgradient of the outer loop in Section 3, we are able to formulate the static Algorithm 1, where l denotes the index of the iteration, $\delta(l)$ is the step size, and ϵ a constant for the stopping criteria. The algorithm consists of an iterative procedure where in each cycle at first all BSs broadcast the BS weights λ_m to all users. Then, each user i evaluates $\lambda_m/\bar{R}_{i,m}$ for all BSs and sends an assignment request (and the corresponding $\bar{R}_{i,m}$ or $R_{\min,i}$) to a BS $m'_i \in \mathcal{M}_{\text{opt},i}$. Next, each BS m individually calculates the rate assignment for all users that sent an assignment request to it. The rate assignment hereby depends on λ_m and might lie either inside, on, or outside the feasible rate region of BS m and thereby either under exploit, meet with equality or violate the resource constraint. Correspondingly, BS m will update λ_m using the subgradient and the cycle starts again by broadcasting the updated BS weight. Although Algorithm 1 might not converge to the optimum rate assignment in case $\exists \{m, n \in \mathcal{M}, m \neq n : \lambda_m^*/\bar{R}_{i,m} = \lambda_n^*/\bar{R}_{i,n}\}$ and therefore results in $|\mathcal{M}_{\text{opt},i}(\lambda^*)| > 1$, we can formulate the following theorem.

Theorem 1. *Assume that for the series $\lim_{l \rightarrow \infty} \delta(l) = 0$, $\limsup_{l \rightarrow \infty} \sum_l \delta(l) = \infty$ holds and that a feasible allocation for the voice users exists, then Algorithm 1 converges to the optimum dual weights λ^* . In case $|\mathcal{M}_{\text{opt},i}(\lambda^*)| = 1 \forall i \in \mathcal{I}$ the corresponding rate assignment of Algorithm 1 is also optimal. In case $\exists i \in \mathcal{I} : |\mathcal{M}_{\text{opt},i}(\lambda^*)| > 1$ an optimum rate assignment*

that solves (P1) can be obtained by solving the set of linear equations:

$$\begin{aligned} \sum_{m \in \mathcal{M}_{\text{opt},i}} R_{i,m}^* &= \psi'^{-1} \left(\min \left\{ \min_m \frac{\lambda_m^*}{\bar{R}_{i,m}}, \psi'_i(0) \right\} \right), \quad \forall i \in \mathcal{I}_b, \\ \sum_{m \in \mathcal{M}_{\text{opt},i}} R_{i,m}^* &= R_{\min,i}, \quad \forall i \in \mathcal{I}_v, \\ \sum_{i \in \mathcal{I}} R_{i,m}^* &= \Gamma_m, \quad \forall m \in \mathcal{M}. \end{aligned} \quad (33)$$

Proof. In Section 3.1, it was shown that steps (3) and (4) of Algorithm 1 maximize the inner problem of (18) in case $|\mathcal{M}_{\text{opt},i}(\lambda)| = 1 \forall i \in \mathcal{I}$. Step (5) corresponds to an update of λ in direction of the negative subgradient which was derived in Section 3.2. Since (P1) is a convex optimization problem and Slater's condition holds, it is proven in [12] that the dual problem (18) has the same solution as (P1). Further, it is shown in [12] that dual subgradient algorithms like Algorithm 1 converge to the global optimum for the given step-width constraints. The proof can be extended to the case where $\exists i \in \mathcal{I} : |\mathcal{M}_{\text{opt},i}(\lambda)| > 1$ by observing the fact that the maximum of the inner problem is independent of the BS $m_i \in \mathcal{M}_{\text{opt},i}$ which is selected by user i in step (3) (however, it clearly matters for complying with the feasible rate region constraints); from (26) it follows that

$$R_i = \sum_m R_{i,m} = \psi'^{-1} \left(\underbrace{\frac{\lambda_m}{\bar{R}_{i,m}} - \sigma_{i,m}}_{\zeta_i} \right) \quad \forall m, i \in \mathcal{M}, \mathcal{I}_b \quad (34)$$

is necessary and sufficient for the maximization of the inner problem and that by (21) $\sum_{m \in \mathcal{M}} R_{i,m} = R_{\min,i} \forall i \in \mathcal{I}_v$ holds. Substituting this into the Lagrangian (23) together with (24) results in a dual function

$$\begin{aligned} g(\lambda) &= \sum_{i \in \mathcal{I}_b} \psi(\psi'^{-1}(\zeta_i)) - \sum_{i \in \mathcal{I}_b} \zeta_i \psi'^{-1}(\zeta_i) \\ &+ \sum_{m \in \mathcal{M}} \lambda_m \Gamma_m - \sum_{i \in \mathcal{I}_v} \mu_i R_{\min,i}, \end{aligned} \quad (35)$$

which is independent of the actual BS selection of the users. Therefore, Algorithm 1 will converge to the optimum λ^* and to the maximum utility also if $\exists i \in \mathcal{I} : |\mathcal{M}_{\text{opt},i}(\lambda)| > 1$. The optimum rate assignment of users that are in multilink operation results then from λ^* by solving the set of KKT conditions which reduce to (33) since $\lambda_m^* > 0 \forall m \in \mathcal{M}$, $\mu_i > 0 \forall i \in \mathcal{I}_v$ for any nontrivial solution. \square

4.2. Dynamic Scenario. In a dynamic scenario where users and service requests follow stochastic mobility and traffic models, respectively, applying Algorithm 1 might be a good choice from a theoretic perspective. Practically, however, the procedure is too expensive, since, having the optimum user assignment at any point in time, it would have to be executed any time a user's channel gain or interference

(1) Each BS initializes $\lambda_m, \nu_m = 1 \forall m \in \mathcal{M}, l = 0$.
while $!((\nu(\boldsymbol{\nu})^T > \epsilon) \vee (l < l_{\max}))$ **do**
 (2) Each BS broadcasts λ_m to all users.
 (3) Each user $i \in \mathcal{I}$ evaluates $\mathcal{M}_{\text{opt},i}(\boldsymbol{\lambda})$ with (27) and announces an assignment request to $m'_i(\boldsymbol{\lambda}) \in \mathcal{M}_{\text{opt},i}(\boldsymbol{\lambda})$. If $|\mathcal{M}_{\text{opt},i}(\boldsymbol{\lambda})| > 1$ it picks one BS of the set randomly.
 (4) Based on the assignment requests each BS calculates the rate assignment that maximizes its sum utility and that fulfills the voice user's rate constraints corresponding to (30).
 (5) Each BS evaluates its sub-gradient component $\nu_m = (\Gamma_m - \sum_{i \in \mathcal{I}} (R_{i,m} / \bar{R}_{i,m}))$ and updates its dual weight $\lambda_m(l+1) = \lambda_m(l) - \delta(l)\nu_m; l = l+1$.
end while
 (6) Assign users to $m'_i(\boldsymbol{\lambda}^*)$ with $R_{i,m}$ corresponding to (3), (4).

ALGORITHM 1: Decentralized utility maximization.

situation changes (and therefore \bar{R}) and in case a service request arrives or leaves the system. Each execution thereby might trigger reassignments of a whole set of users and a considerable amount of signaling information would have to be exchanged between users and BSs in each iteration. (It is noted here that higher utilities might be obtainable in the dynamic scenario by exploitation of mobility information or, e.g., under the fluid assumptions [13].) We therefore suggest the following adaptation of Algorithm 1 to a dynamic procedure which can be split into two almost independently operating parts, the cell/RAT selection of users and the resource assignment inside each BS.

A user's heterogeneous cell/RAT selection procedure is described in Algorithm 2(a). It is similar to the one in the static setup; the BSs broadcast $\boldsymbol{\lambda}$ and each user selects a BS $m \in \mathcal{M}_{\text{opt},i}$. However, unlike in Algorithm 1 where all users directly update their cell/RAT selection if $\boldsymbol{\lambda}$ is updated the selection is only triggered once at the beginning of a service request or if the user would be dropped from the air interface where it is currently assigned to. For the selection, only local information ($\bar{R}_{i,m}$ can be measured or estimated for all BSs by a user) and the BS weights $\boldsymbol{\lambda}$ are needed similar to the static procedure. After a user selected a cell/RAT or in case that the request, the channel or the interference situation changed, an update of the resource assignment will be triggered in the corresponding base station. Thereby, the triggers are independent for each BS and no information from neighboring cells is needed for the resource assignment. Also, contrary to the static Algorithm 1, the resource update will not trigger the cell/RAT selection of users and users stay assigned to their current BS in general. Only in case a user cannot be supported by a BS anymore and no intrasystem hand-over is possible the user will execute Algorithm 2(a) again leading to a possible intersystem hand-over. The resource assignment in a cell will be updated following the iterative procedure in Algorithm 2(b). Algorithm 2(b) maximizes the sum utility of the BS over all BE users that are assigned to it and assures that all voice users comply with their minimum rate requirement. Thereby, the rates will be assigned in a way that all available resources are exploited and that the resource constraint of the BS is met with equality

before $\boldsymbol{\lambda}$ is broadcasted again. This stands in clear contrast to the static algorithm where $\boldsymbol{\lambda}$ is updated based on the subgradient.

Since in Algorithm 2 each user only actively selects a RAT/cell once at its call setup and it does not trigger reassignments of other users in general almost no signaling information has to be exchanged between users and BSs. The simplicity of Algorithm 2 however, comes at the cost of its optimality. The influence of new users on $\boldsymbol{\lambda}$, mobility, and the restriction that users stay in the actual air interface if possible lead to situations where a user j might find itself assigned to a BS $m \neq \mathcal{M}_{\text{opt},j}(\boldsymbol{\lambda})$. Wrong assignments will lead to deviations of $\boldsymbol{\lambda}$ and it cannot be guaranteed that the procedure approaches to $\boldsymbol{\lambda}^*$, which would be the optimum weights for the current request and channel situation in the static scenario. Since Algorithm 1 is difficult to implement in our simulation tool, we will derive a simple upper bound. The bound allows us to evaluate the maximum degradation of an assignment obtained with the dynamic procedure from the optimum solution of (P1). Since the bound overestimates (P1), it is also an upper bound for Algorithm 1 and could be used to evaluate the quality of the static Algorithm 1, which might be nonoptimal in case $|\mathcal{M}_{\text{opt},i}(\boldsymbol{\lambda}^*)| > 1$.

4.3. Utility Bound. Assume that the dynamic algorithm approaches $\boldsymbol{\lambda}^+$ and a rate assignment \mathbf{R}^ϵ at a certain point in time. Then, there exists a corresponding dual function $g(\boldsymbol{\lambda}^+)$ which is an upper bound on (P1):

$$\begin{aligned} g(\boldsymbol{\lambda}^+) &= \max_{\mathbf{R}} \mathcal{L}(\mathbf{R}, \boldsymbol{\lambda}^+) = \mathcal{L}(\mathbf{R}^+, \boldsymbol{\lambda}^+) \geq \mathcal{L}(\mathbf{R}^*, \boldsymbol{\lambda}^*) \\ &\geq \mathcal{L}(\mathbf{R}^\epsilon, \boldsymbol{\lambda}^+) = \sum_{i \in \mathcal{I}_b} \psi_i \left(\sum_{m \in \mathcal{M}} R_{i,m}^\epsilon \right). \end{aligned} \quad (36)$$

Therefore, the deviation to the global optimum of a rate assignment \mathbf{R}^ϵ can be bounded by the difference of $\mathcal{L}(\mathbf{R}^+, \boldsymbol{\lambda}^+)$ and $\mathcal{L}(\mathbf{R}^\epsilon, \boldsymbol{\lambda}^+)$

$$\begin{aligned} \Delta \mathcal{L} &= \sum_{i \in \mathcal{I}_b \cap \mathcal{I}_\epsilon} \psi_i(R_{i,m}^+) - \psi_i(R_{i,m}^\epsilon) \\ &\quad - \sum_{m \in \mathcal{M}} \lambda_m^+ \left[\sum_{i \in \mathcal{I}_\epsilon} \left(\frac{R_{i,m}^+ - R_{i,m}^\epsilon}{\bar{R}_{i,m}} \right) \right], \end{aligned} \quad (37)$$

(a) Cell/RAT Selection of user i .

- (1) User i measures the channels and evaluates $\bar{R}_{i,m}$ for all BS/RATs in its vicinity
- (2) Based on the broadcasted λ user i evaluates $\mathcal{M}_{\text{opt},i}(\lambda)$ with (27) and sends an assignment request to $m \in \mathcal{M}_{\text{opt},i}$.

(b) Resource Assignment of BS m .

- (1) Initialize $\nu_m, l = 1$ if not initialized: $\lambda_m = 1$
- while** $|\nu_m| > \epsilon$ **do**
- (2) For all users i that are assigned to BS m set $\mathcal{M}_{\text{opt},i} = m$ and calculate $R_{i,m}$ with (30)
- (3) BS m evaluates its sub-gradient $\nu_m = (\Gamma_m - \sum_{i \in \mathcal{I}} (R_{i,m}/\bar{R}_{i,m}))$ and updates its dual weight $\lambda_m(l+1) = \lambda_m(l) - \delta(l)\nu_m; l = l+1$
- end while**
- (3) Assign users $R_{i,m}$ corresponding to (2) and broadcast updated λ_m

ALGORITHM 2

with $\mathcal{I}_\epsilon = \{i \in \mathcal{I}, m'_i \notin \mathcal{M}_{\text{opt},i}(\lambda^+)\}$. Only the rates \mathbf{R}^+ are needed for the evaluation of the bound which can be easily calculated by (30).

5. Simulation Results

In this section, the performance of Algorithm 2 will be evaluated by comparing it to a load-balancing algorithm. We therefore employ Alcatel-Lucent's C++ based MRRM-Simulator which is an event driven simulation environment for heterogeneous wireless scenarios. It supports cellular UMTS/HSDPA, GSM/EDGE air interfaces, a WiMAX hotspot, and different service classes such as VoIP, streaming, circuit-switched voice and best-effort data services. For the simulations we consider a 2-RAT scenario consisting of a cellular GSM/EDGE and UMTS air interface with 42 BSs each. The BSs of both RATs are arranged as indicated in Figure 1; on each site there are 3 BSs with directional antennas of both RATs collocated with the distance between sites being 2400 m. All RAT specific parameters are listed in Table 1. Equally distributed inside the rectangular movement area (see Figure 1), there are users that are moving corresponding to the pedestrian mobility model in [14] with 3 km/h and randomly requesting services based on a Poisson process with exponentially distributed service duration with a mean of 120 seconds. For voice services a constant data rate of 12.2 kbit/s is required while no minimum requirements for best-effort services exist.

The load-balancing strategy and Algorithm 2 differ only by the cell/RAT selection procedure which are triggered at a call setup or at an intersystem hand-over request. All other mechanisms like intrasystem hand-overs and the triggers themselves correspond to the standards and stay untouched. Both algorithms perform the resource assignment inside a BS corresponding to Algorithm 2(b) so that the sum utility of each BS is maximized. In case of load balancing a new user that requests service or an intersystem hand-over performs the cell/RAT selection as follows: at first it short-lists one BS of each air interface where the one with the strongest pilot signal that could accept the call in the users vicinity is selected. Usually, these are the closest UMTS and GSM BSs

TABLE 1: Simulation parameters.

$P_{\text{max,UMTS}} = 20$ W
$P_{\text{max,GSM}} = 15$ W
Time slots GSM $\bar{T}_m = 21$
Antenna pattern: Sector 90° [14]
Path-loss GSM [dB], r distance in m : $L = 132.8 + 38 \lg(r-3)$ [15]
Path-loss UMTS [dB]: $L = 128.1 + 37.6 \lg(r-3)$ [14]
Rate-SINR mapping UMTS: $C_b = 1.4e9$ $D_b = 1e-3$
Thermal noise GSM, UMTS: -100 dBm
Intercell interference GSM: -105 dBm
Orthogonality factor UMTS: $\rho = 0.4$

to the user. Then, the user sends the request to the BS with the lower load value. Hereby, the load values are obtained by signaling and are defined as $l_{v,m}, l_{b,m}$ in case of a voice or best-effort requests, respectively:

$$l_{v,m} = \begin{cases} \sum_{i \in \mathcal{I}_v} \frac{t_{i,m}}{\bar{T}_m} & \forall m \in \mathcal{M}_a, a \in \mathcal{A}_{\text{orth}}, \\ \sum_{i \in \mathcal{I}_v} \frac{P_{i,m}}{\bar{P}_m} & \forall m \in \mathcal{M}_b, b \in \mathcal{A}_{\text{inf}}, \end{cases} \quad (38)$$

$$l_{b,m} = \mathbb{E}_{i \in \mathcal{I}_b} \left(\frac{1}{R_{i,m}} \right) \quad \forall m \in \mathcal{M}$$

For the UMTS air interface the used normalized resource-rate mapping curve and the linear approximation corresponding to (9) are shown in Figure 2. The slope of the linear approximation is chosen so that it intersects the real rate mapping curve at the origin and at 100 kbit/s, which corresponds to $\Delta_b = 1.53e6$ bit/s. For the GSM air interface, the envelope of the coding and modulation corresponding to [15] serves as SINR-rate mapping with the additional requirement from the standard that voice users are not able to share a time slot with other users. As utility curve, a shifted

version of the α -proportional fair curve with $\alpha = 1/2$ is used, which is a more throughput oriented metric:

$$\psi(R_i) = \sqrt{\frac{R_i}{\text{bit/s}} + 1000} - \sqrt{1000}. \quad (39)$$

The shifting operation leads to a finite slope of the curve at the origin which is essential to enable switching off users. Otherwise, a user in a deep fade might be assigned almost all resources, if $\lim_{x \rightarrow 0} \psi'(x) = \infty$.

In the simulation scenario, there are in average 10 voice service call setup requests per second inside the movement area which corresponds to approximately 36 active voice users and a voice traffic load of 440 kbit/s per cell area in average. Additionally, a varying number of BE users request service. For the simulation statistics, only the investigated cells (see Figure 1) are considered. In Figure 3, the throughput of the BE users based on the real SINR-rate mapping and the approximation is shown over the average number of active BE users. As can be observed, Algorithm 2 achieves up to 30% more throughput compared to load-balancing. The real and approximated rates match pretty well in the region for low user request rates, but also at high load the deviation is small compared to the gain. The sum utility per cell area and the upper bound are shown in Figure 4. The utility gain of Algorithm 2 compared to load-balancing is also almost as large as of the throughput because of the low curvature of ψ . The distance to the bound is of special interest; at high call arrival rates the distance is almost zero, indicating that Algorithm 2 performs close to optimum and no significant gains could be achieved by using Algorithm 1 instead. At lower rates this is different. Here, the dynamic procedure pays the price for its simplicity in terms of performance loss. The main reason for the loss results from the fluctuation of λ . At low request rates a user's call setup or service termination has a great impact on the resource allocation of the other users in the cell and therefore leads to strong variations of λ over time. The fluctuation of λ directly influences the set of optimum BSs \mathcal{M}_{opt} of users and therefore often leads to the case that users find themselves assigned to a currently nonoptimal BS. In this case, the dynamic algorithm loses performance since the cell selection is only allowed once per user in general. Higher utility values could be obtained here by allowing users to perform intersystem hand-overs so that each user would be assigned to \mathcal{M}_{opt} again. This characteristic is also reflected in the looseness of the bound. Unlike to low request rates, if the average number of users in a cell is high the influence of a single-user arrival or departure from a cell on λ is diminishing and a user's optimum BS hardly changes during the service time. In this case the performance is almost optimal and the bound gets very tight. The tightness also indicates that the influence of the users pedestrian mobility and therefore the variation of \bar{R} (and on \mathcal{M}_{opt}) is negligible in this scenario.

For the heterogeneous UMTS GSM/EDGE system the following interpretation of the optimum assignment strategy can be given. One observes that \bar{R} is a monotonically increasing function of a user's SINR for both air interfaces. Therefore, for a given λ the optimum cell/RAT selection

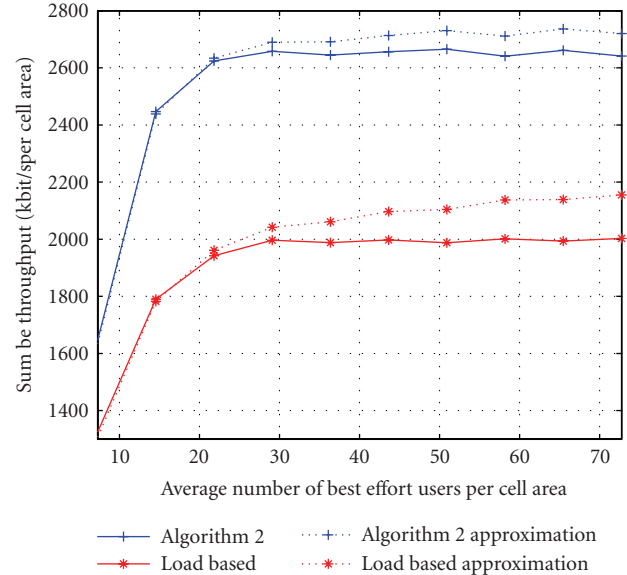


FIGURE 3: BE throughput with and without linear approximation (9) without slow fading.

$m_{\text{opt},i} = \arg \min_m \lambda_m / \bar{R}_{i,m}(\beta_{i,m})$ reduces to an SINR threshold. This threshold depends on the air interface and the service type through $\bar{R}(\beta)$ and on λ which can be interpreted as the load situation of the BS. The threshold characteristic can be observed in Figure 5, where the BE user assignment in terms of the selected RAT is shown by color shades; Algorithm 2 assigns users to UMTS that are in the red area close to the BSs and users in the blue area to GSM. The border of both areas is characterized by the threshold SINR of each RAT which has a lobe pattern because of the directional antenna characteristics. The pattern looks very regular in Figure 5 due to equal average loads in each cell of an air interface (and therefore equal λ for BSs of one RAT) and collocated sites of UMTS and GSM BSs. However, Algorithm 2 will also flexibly adapt itself to the optimum configuration in case of arbitrary, not necessary collocated, BS positioning and varying load situations without any change in configuration of the algorithm. The optimum area pattern will then of course look different. Contrary to the BE users Algorithm 2 will assign almost all voice users to UMTS in the presented scenario. This is due to the fact that time-slot sharing is not possible in GSM for voice users. Therefore, the maximum slot rate of a voice user is much lower than in UMTS. Thus, a much lower λ of the GSM BS compared to the λ of the UMTS BS would be required to make GSM attractive for an assignment. This instance might suggest that also the major part of the gain of Algorithm 2 is based on the low effectivity of voice in GSM, which is not avoided in load balancing. Simulations however show that also for pure BE traffic gains of more than 20% are obtained.

So far slow fading has not been active in the simulations to demonstrate that the utility bound can be tight and to visualize the assignment policy of Algorithm 2 qualitatively. In Figure 6, the sum utility and the bound is shown for the scenario above however this time with slow fading

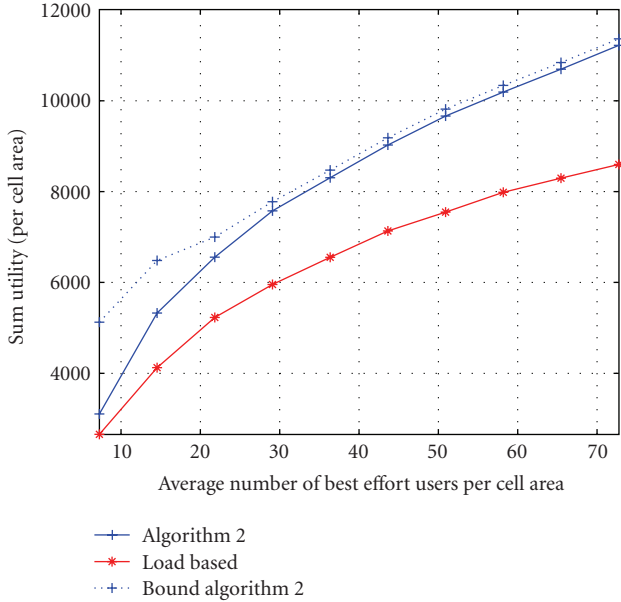


FIGURE 4: Sum utility $U = \sum_{i \in \mathcal{I}_b} \psi_i(R_i)$ and upper bound $U + \Delta \mathcal{L}$ without slow fading.

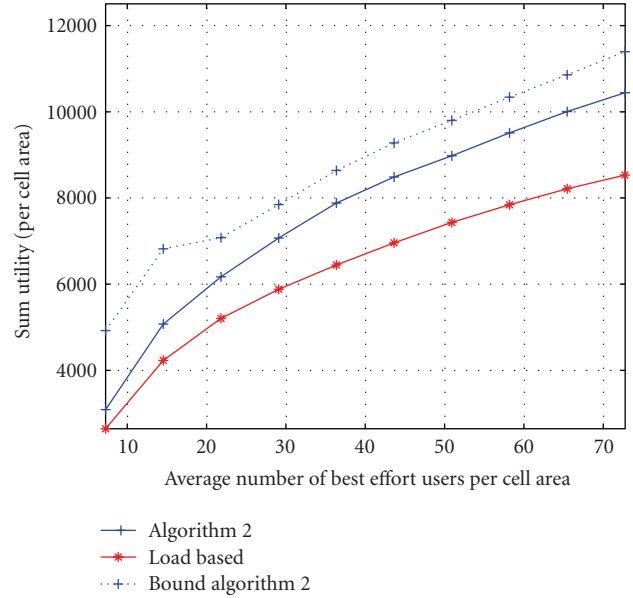


FIGURE 6: Sum utility and upper bound with slow fading 6 dB.

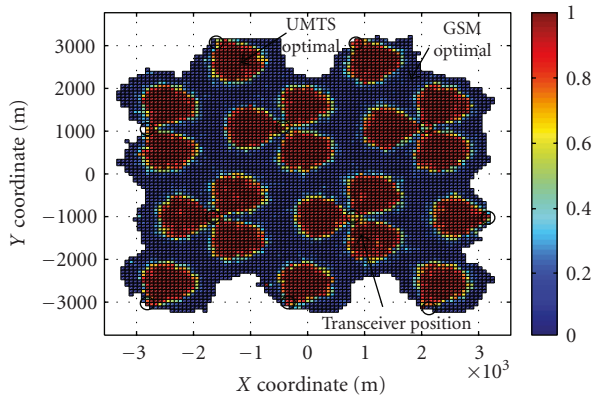


FIGURE 5: RAT assignment of BE users without slow fading: 1 \rightarrow 100% assigned to UMTS 0 \rightarrow 100% assigned to GSM.

corresponding to [14] in both air interfaces with a variance of 6 dB. Considering load balancing, the slow fading does hardly influence the performance. For Algorithm 2 however the users' mobility in connection with the slow fading has a nonnegligible impact. Now, even small changes in position can result in large channel gain and therefore \bar{R} differences which lead to more wrongly assigned users and looseness of the bound. Nevertheless, still a gain of approximately 20% is achieved. Similarly the performance of Algorithm 2 decreases and the bound gets less tight without slow fading in case the velocity is increased. For completeness, it is noted here that in case users do not change their position the tightness of the bound under slow fading is similar to Figure 4.

The observations made in Section 3 and in the simulations open up the way for even more simplified algorithms that might be interesting for practical applications. For given

scenarios fixed base station weights λ or service dependent SINR, channel or even distance thresholds could be applied for the cell/RAT selection or as triggers for intersystem handovers. Additionally, in case users are subject to strong channel variations, for example, by mobility or fading during a service request updating the cell/RAT selection and therefore executing Algorithm 2(a) at more frequent intervals is an option to improve the performance and get close to the optimum again.

6. Conclusions

In this paper, we developed an optimization framework for wireless heterogeneous multicell scenarios. Having derived the feasible rate regions for air interfaces with orthogonal resource assignment and a convex approximation for interference limited radio access technologies we introduced a convex utility maximization problem formulation for heterogeneous scenarios. We gained general insights on the problem solution and derived simple assignment rules that lead to the global optimum by exploiting the dual problem formulation. These observations were then used to develop decentralized algorithms for static scenarios and then simplified for dynamic settings. Although the simplifications came at the cost of the optimality still high gains in comparison to a simple load-balancing algorithm were obtained and close to optimum performance could be shown by simulations based on a duality bound.

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