Proportionally Fair Resource Allocation Considering Geometric Blockage Modeling for Improved Mobility Management in 5G

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ABSTRACT

Line of Sight (LoS) blockages are a common occurrence in densely deployed cellular networks, as is the case with 5G. This leads to a significant deterioration in the signal quality on the user side. Modeling LoS blockages is crucial for simulations to obtain reliable results, but also challenging since LoS might appear and disappear occasionally because how often an LoS happens depends on the environment and the user speed. To capture LoS blockages in a realistic manner for a particular scenario in a given environment, we propose to model blockages geometrically by considering all static and mobile objects in the environment such as buildings, cars, busses and humans, including self-blockages from the user. This enables a better evaluation of the metrics of interest, such as handover rate. In dense network deployments, users make frequent handovers, which deteriorates their experience and reduces the network capacity. Also, operators should strive to provide fairness in resource allocation to all users as well as to guarantee a minimum Quality of Service (QoS). Thus, handover decisions should be considered jointly with resource allocation. To that end, in this paper, we formulate an optimization problem that provides proportional fair resource allocation, while simultaneously reducing the handover rate, and providing a minimum data rate for all users at all times. It is an integer non-linear program, which is NP-hard. We relax it to a linear problem, which allows us to find a near-optimal user-to-BS assignment and resource proportion for every user quickly. We compare the result from our optimal and relaxed approaches with other two benchmarks showing that it outperforms them considerably in terms of fairness, handover rate reduction and users' rate satisfaction. Moreover, our relaxed approach performs within above 90% of the optimum and reduces the handover rate up to 40%.

CCS CONCEPTS

• **Networks** → *Network simulations.*

KEYWORDS

Proportionally fair resource allocation, handovers, mobility management.

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1 INTRODUCTION

5G networks aim at providing high data rates and enhanced user experience [10]. Many users are mobile and enjoy network services while traveling. Thus, the impact of mobility should be studied to ensure that these users are satisfied. To evaluate the performance of the existing and new approaches, system-level simulations that represent reliably different scenarios and sites are required.

3GPP proposes channel models for macro and micro Base Station (BS) that consider path loss, shadowing and the existence of Line of Sight (LoS) among others [1]. The availability of LoS is usually modelled using a probabilistic distance-based model (proposed in 3GPP), which states that the closer the user is to the BS, the more likely the user is to have an LoS connection. This is a realistic assumption, however, it is not clear how often LoS availability might change. Moreover, due to the probabilistic nature of this blockage model, the LoS can be constantly switching from being available to not (e.g., the distance at which LoS probability is 50%). This, in turn, results in frequent handovers that are caused by poor modeling and not by a challenging simulation scenario. Furthermore, the update periodicity of LoS flag depends on the site environment itself, how crowded the area is currently and the user speed.

Therefore, we propose to model every object and users in the environment as 3D bodies and consider them as possible blockages. Then, we determine if there is an LoS connection between a user and a BS by checking if any of the objects blocks the LoS. This allows us to model transient blockages such as a human or a car passing by as well as long-term blockages that are caused by buildings or static humans in a crowded area. Geometric blockage modeling generates close-to-reality LoS availability information for system-level simulations as opposed to probabilistic distance-based model from 3GPP. The handover algorithm and its parameters can also be selected based on the environment and site crowding to keep handover rates within reasonable limits.

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Mobile users experience frequent handovers that are often unnecessary because initially the handover algorithm was developed by 3GPP for macro cells with large coverage [17]. In dense deployments, a user might be located in the coverage of multiple cells with high (and most importantly similar) Reference Signal Received Power (RSRP) values. In this case, the traditional handover algorithm forces the user to switch from one BS to another reacting to channel fluctuations. Every handover introduces a delay called Handover Interruption Time (HIT) during which a user cannot receive or transmit data. Moreover, a handover increases signaling between the user, the serving and target BS, as well as in the core network (when a downlink path switch in the core is required during a handover). Furthermore, a handover increases energy consumption and wastes signaling resources. However, handovers cannot totally be avoided. They provide smooth connectivity for mobile users and also in case a user experiences an LoS blockage. Hence, the goal is to perform only the necessary handovers that contribute to user's satisfaction.

Also, the cellular operator has to satisfy users' minimum required rate for a particular service and be fair in allocating its resources, so that certain users are not penalized by receiving very little resources. Resource allocation and handover management are challenging, mainly due to the limited network resources and the dynamic nature of channel characteristics [15]. The resources at every BS are limited, and, for example, connecting most users in the network to the BS with the best RSRP (most likely the macro BS) will not lead to satisfying results. This can happen with the 3GPP handover algorithm in an crowded outdoor area such as a city center. Therefore, it is of paramount importance to allocate resources fairly in data rates and make handover decisions while at the same time guaranteeing a minimum data rate for every user. As a result, the following questions related to 5G mobility management arise:

- How to assign users to BSs and when to perform a handover, and how to allocate resources in a proportional fair way?
- How does this approach perform compared to the 3GPP standard in terms of different metrics of interest?
- How to model LoS blockages in a realistic manner?

To answer these questions, we propose to jointly solve the problem of user assignment and resource allocation that provides proportional fairness in data rates by solving an optimization problem. Moreover, the handover rate should be limited to perform only the necessary handovers that improve user experience. So, we restrict the number of handovers per slot and consider the handover overhead in the objective to penalize handovers since they decrease the user rate and introduce latency. Furthermore, we provide a guarantee that user rates are satisfied since it is one of the most important metrics for the user.

Specifically, our main contributions are:

- We formulate an optimization problem that jointly optimizes the mobility management and provides proportional fairness while guaranteeing a minimum data rate to all users. We show that the problem is NP-hard and relaxing it we obtain a solution that is near-optimal.
- We propose a realistic way to model LoS blockages for a particular environment by modeling all users and objects in the network in 3D, and then we determine geometrically if LoS is available for every user and BS.
- We evaluate our algorithm for various user types (pedestrians, cars and busses) and show that it is capable of making resource allocation and handover decisions for users with different speeds and channel conditions, while satisfying their required data rates.

The remainder of this paper is organized as follows. In Section 2, we introduce our geometric blockage model. The optimization problem is presented in Section 3. Section 4 introduces our proposed resource allocation and handover management algorithm, while Section 5 explains two algorithms that we use as benchmarks. Some performance evaluation results are provided in Section 6. In Section 7, we discuss some related work. Finally, Section 8 concludes the paper.

2 BLOCKAGE MODELING

In this section, we first describe the 3GPP blockage model. This is followed by the proposed geometric blockage model.

2.1 3GPP Blockage Model

In 3GPP [1], for an urban micro BS, the LoS probability depends on the distance between the user and the BS, d. If the user is located closer than 18 m to the BS, then the probability is set to 1, otherwise it is calculated as $P_{LoS} = \frac{18}{d} + e^{(-\frac{d}{36})(1-\frac{18}{d})}$. For an urban macro site, the LoS probability is modeled similarly, however, it is, obviously, larger since macro BSs use lower frequencies that are less likely to be blocked than the signals of micro BSs such as mmWaves. The exact formula can be found in [1]. When modeling the channel, a random number for every user and a BS is drawn from a Normal distribution. If the computed LoS probability using d is larger than the randomly drawn number, then the user is assumed to have an LoS link with this BS. The LoS probabilities between a user and every BS are periodically updated. However, 3GPP does not provide any guidelines on how to select a suitable period between two LoS events.

2.2 Proposed Geometric Blockage Model

Any user or object in our scenario can cause a blockage of LoS, including the self-blockage when the user body blocks its own LoS connection to a BS. We model various objects such as humans, buildings, cars, buses that are present in our environment as 3D bodies; specifically, humans as cylinders, similarly to [5], while buildings, cars and busses as rectangular cuboids. Depending on the positions of the user, BS and other objects in the environment, any of them might be blocking the LoS between the user and the BS. To conclude, if there is an LoS between the user and the BS, we check three conditions and obtain the following blockage flag:

$$\begin{gathered} F_{blocked} = \\ F_{obj-close} \land F_{obj-in-between} \land F_{bs-above-border} = \\ (d_{UE-BS} \geq d_{UE-Obj}) \land (\theta_B \leq \varphi_B) \land (\gamma_B \leq \beta_B), \end{gathered} \tag{1}$$

where d_{UE-BS} is the horizontal distance between the user and the BS, d_{UE-Obj} is the horizontal distance between the user and the potentially blocking object as shown in Fig. 1. These Euclidean distances are calculated from user position (x_{UE}, y_{UE}), object position

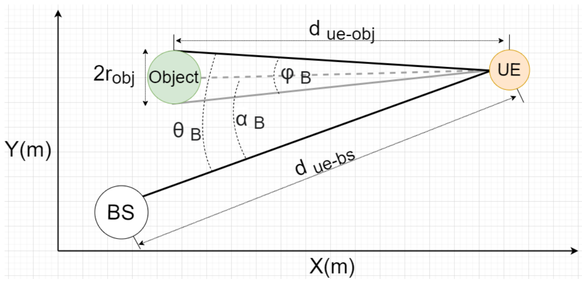

Figure 1: Top view on the positions of the user, BS and the object.

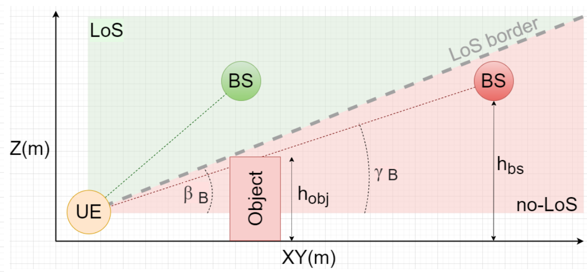

Figure 2: Side view: the user has an LoS with the BS in green, while no-LoS with the BS in red.

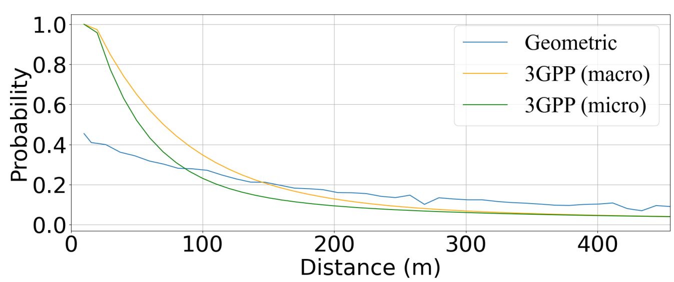

Figure 3: Experimentally computed LoS probabilities for macro and micro BS with 3GPP and geometric blockage models.

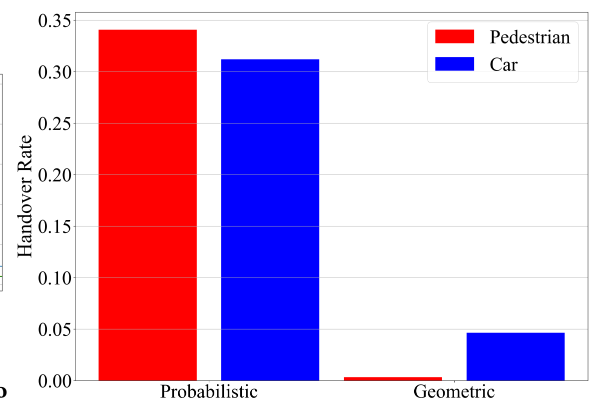

Figure 4: Handover rate per user type with probabilistic and geometric blockage models.

(x_{Obj}, y_{Obj}), and BS position (x_{BS}, y_{BS}) as:

$$\begin{aligned} d_{UE-BS} &= \sqrt{(x_{UE} - x_{BS})^2 + (y_{UE} - y_{BS})^2}, \\ d_{UE-Obj} &= \sqrt{(x_{UE} - x_{Obj})^2 + (y_{UE} - y_{Obj})^2}. \end{aligned} \tag{2}$$

The first condition $F_{obj-close}$ in Eq. (1) checks if a potentially blocking object is located closer to the user than the BS. If not, this object cannot be blocking the LoS. The second condition $F_{obj-in-between}$ looks into the angles θ_B and φ_B (shown in Fig. 1) to infer if the object is located on the LoS line between the user and the BS. If it is fulfilled, the third condition $F_{bs-above-border}$ checks whether the object height is enough to block the LoS line in the z-axis by comparing β_B and γ_B (Fig. 2). If so, the flag $F_{blocked}$ is set to True, otherwise to False. The radius of the object is denoted as r_{obj}, as also shown in Fig. 1. The angle θ_B is calculated from the geometry of the problem as follows:

$$\varphi_B = 2 \cdot \arctan\left(\frac{r_{obj}}{d_{UE-Obj}}\right). \tag{3}$$

We define an auxiliary angle α_B, as shown in Fig. 1, and derive θ_B also using geometry as

$$\theta_B = \alpha_B + \varphi_B/2. \tag{4}$$

To derive α_B, we use the scalar product of the vectors $\mathbf{UE - Obj}$ and $\mathbf{UE - BS}$, which are the vectors between these points, i.e.,

$$\mathbf{UE - Obj} = \begin{pmatrix} x_{Obj} - x_{UE} \\ y_{Obj} - y_{UE} \end{pmatrix} = \begin{pmatrix} x_{UE-Obj} \\ y_{UE-Obj} \end{pmatrix}, \tag{5}$$

$$\mathbf{UE - BS} = \begin{pmatrix} x_{BS} - x_{UE} \\ y_{BS} - y_{UE} \end{pmatrix} = \begin{pmatrix} x_{UE-BS} \\ y_{UE-BS} \end{pmatrix}, \tag{6}$$

where Eq. (5) and Eq. (6) are used to calculate the relative distance between the user and the BS. Now, α_B is computed using the scalar product of both vectors:

$$\alpha_B = \arccos\left(\frac{x_{UE-Obj} \cdot x_{UE-BS} + y_{UE-Obj} \cdot y_{UE-BS}}{d_{UE-Obj} \cdot d_{UE-BS}}\right). \tag{7}$$

The angles β_B and γ_B are computed as follows:

$$\beta_B = \arctan\left(\frac{h_{Obj} - h_{UE}}{d_{UE-Obj} - r_{Obj}}\right), \tag{8}$$

$$\gamma_B = \arctan\left(\frac{h_{BS} - h_{UE}}{d_{UE-BS}}\right), \tag{9}$$

which are used to evaluate the third condition in Eq. (1). If any of the conditions is not fulfilled, then there is an LoS connection between the user and the BS.

Fig. 3 shows the probability of having an LoS with 3GPP model (for macro and micro BS) and with the proposed geometric blockage model (for a user to any BS) at different distances between the user and the BS. For the geometric model, the probabilities are computed experimentally, while for 3GPP as explained in Section 2.1. One can see that the general trend of both models is similar, namely, that the larger the distance, the more likely there is no LoS. Different from 3GPP, with the geometric model not only the distance, but also the user position and the environment around it impacts the probability of having an LoS. The values of LoS probabilities in Fig. 3 cannot be compared directly because the probability with the probabilistic 3GPP model is separate for macro and micro BS, while with the geometric model, the probabilities are computed for the whole scenario with both BS types.

Fig. 4 shows the handover rate per user with the 3GPP handover algorithm for 3GPP blockage model and the proposed geometric model for two user types: pedestrians and cars. With the probabilistic model, the handover rate of pedestrian users is higher than of cars, which is unrealistic. On the contrary, with the geometric blockage model, cars make significantly more handovers than pedestrians. This motivates blockage modeling with 3D shapes.

3 PROBLEM FORMULATION

In this work, we jointly assign users to BSs and allocate resources in proportionally fair manner, as well as aim at reducing the handover rate by keeping it under a certain limit. We take into account the handover overhead in the objective, which is denoted by $\eta_{u,b',b}$. The sets U and B are the set of all users and BSs in the network, respectively, while N_u and N_b are the total number of users and BSs, respectively. We denote by $R_{u,b}$ the per-block rate of user u from BS b and assume that it is the same across all Physical Resource Blocks (PRBs) for one user. The per-block rate $R_{u,b}$ depends on Signal to Interference and Noise Ratio (SINR) and the bandwidth of one PRB (the bandwidth of micro BSs is larger than of macro because of mmWaves). We calculate $R_{u,b}$ using the Shannon's formula, as in [12]. Moreover, we guarantee a minimum required data rate r_u for every user u. There are two decision variables $z_{u,b}$ and $k_{u,b}$ in the optimization problem. The decision variable $z_{u,b}$ is a binary variable that states whether the user u is connected to the BS b or not. If user u is served by BS b, $z_{u,b} = 1$; else $z_{u,b} = 0$. Another decision variable is $k_{u,b}, \forall u \in U, \forall b \in B$, which is integer and states the number of PRBs that the BS b allocates to user u. The optimization formulation is:

$$\max_{z_{u,b},k_{u,b}} \quad \sum_{u\in U}^{N_u}\sum_{b\in B}^{N_b} z_{u,b}\log(R_{u,b}k_{u,b}(1-\eta_{u,b',b})) \tag{10}$$

$$\text{s.t.} \quad \sum_{b\in B}^{N_b} R_{u,b}z_{u,b}k_{u,b} \geq r_u, \quad \forall u \in U, \tag{11}$$

$$\sum_{u\in U}^{N_u}\sum_{b\in B}^{N_b}(z'_{u,b}z_{u,b}) \geq N_u - N_{HO}, \tag{12}$$

$$\sum_{b\in B}^{N_b} z_{u,b} = 1, \quad \forall u \in U, \tag{13}$$

$$\sum_{u\in U}^{N_u} z_{u,b}k_{u,b} \leq K_{PRB_b}, \quad \forall b \in B, \tag{14}$$

$$z_{u,b} \in \{0,1\}, \quad \forall u \in U,\ \forall b \in B, \tag{15}$$

$$k_{u,b} \in \{0, K_{PRB_b}\}, \quad \forall u \in U,\ \forall b \in B. \tag{16}$$

The value of $k_{u,b}$ matters only when $z_{u,b} = 1$, since otherwise the corresponding objective term in Eq. (10) is 0. The objective is to provide proportional fairness, hence the logarithm is under the sums. The handover overhead is considered in Eq. (10) by multiplying user rate with handover efficiency $(1-\eta_{u,b',b})$ since during HIT the user cannot be served. The first constraint (Eq. (11)) ensures that a minimum required rate r_u for user u is provided. Constraint (12) limits the number of handovers per slot in the network[1]. We allow only N_{HO} users to make a handover by forcing $N_u - N_{HO}$ users per slot to stay connected to the same BSs as in the previous slot. Constraint (13) states that each user must be served by exactly one BS. Constraint (14) expresses the fact that every BS has a limited number of PRBs. Note that micro BSs have more PRBs, and each PRB has a larger bandwidth compared to a micro BS.

To account for the data rate reduction during a handover due to a HIT, we consider the handover overhead $\eta_{u,b',b}$ in the objective (Eq. (10)), which can be expressed in terms of the current allocation $z_{u,b}$ and the previous allocation $z'_{u,b}$ as

$$\eta_{u,b',b} = (1 - z_{u,b} \cdot z'_{u,b}) \cdot \frac{T_{HIT}}{T_{slot}}, \tag{17}$$

where T_{HIT} is the interruption time expressed in ms due to a handover and T_{slot} (also in ms) is the slot duration. Note that we need to take $\eta_{u,b',b}$ into account only when $z_{u,b} = 1$, because whenever $z_{u,b} = 0$ the corresponding term in Eq. (10) is 0. In the first slot, we assume that the handover overhead is 0 since the previous allocation is not available. Note that $z'_{u,b}$ is fixed at the current slot, and it is not a decision variable.

This is an integer nonlinear program since both decision variables are integer, the objective and some of the constraints are non-linear. Moreover, the optimal allocation at the current slot depends on the previous allocation because of the handover overhead in Eq. (10). This is an NP-hard problem [18], and the solution via solvers can be obtained within reasonable time only for input set sizes which are not too large. Already for a relatively small network scenario, it is quite computationally intensive to obtain a solution with a solver (Gurobi). Therefore, in this paper, we relax the requirement for the decision variables to obtain only integer or binary values to real numbers from the corresponding intervals. We do this to get a well-performing solution quickly, which is very important when it comes to practical implementation.

4 RELAXED SOLUTION

In this section, we explain how we relax the optimization problem from Section 3 and obtain convex[2] upper bounds for the objective and non-linear constraints.

4.1 Relaxation of integer variables

Both decision variables are integer, hence, they need to be relaxed to take continuous values, so that we can apply an off-the-shelf software for linear problem solving. The decision variables then become as

$$z_{u,b} \in [0,1],\ k_{u,b} \in [0, K_{PRB_b}],\ \forall u \in U,\ \forall b \in B. \tag{18}$$

[1]The slot is the unit of resource allocation in modern cellular networks.
[2]In fact, using these transformations, the terms become linear in our case.

After obtaining a solution to the relaxed problem, the continuous values of the decision variables are rounded to the closest integer. To convert $z_{u,b}$ to an integer value, the largest $z_{u,b}$ for every user u is set to one, while other values are set to 0. To round $k_{u,b}$, we first allocate to every user $\lceil k_{u,b} \rceil$ resources, then we allocate the remaining PRBs of every BS to its connected users one by one starting with the user with the largest decimal part of $k_{u,b}$ as long as there are unused resources left at the BS.

4.2 Transformation of the objective function

We split the objective into three terms, substitute the expression for $\eta_{u,b',b}$ from Eq. (17), and denote the overhead value due to handover as $B = \frac{T_{HIT}}{T_{slot}}$, obtaining

$$\sum_{u \in U}^{N_u} \sum_{b \in B}^{N_b} z_{u,b} \Big(\log R_{u,b} + \log k_{u,b} + \log(1 - B + Bz'_{u,b} z_{u,b}) \Big). \tag{19}$$

The first term $z_{u,b} \log R_{u,b}$ is linear in $z_{u,b}$. By checking the Hessian matrices [4], we infer that the second term $f_2(z_{u,b}, k_{u,b}) = z_{u,b} \log k_{u,b}$ is non-convex and non-concave, while the third term $f_3(z_{u,b}) = z_{u,b} \log(1 - B + Bz'_{u,b} z_{u,b})$ is convex.

To linearize the second term $f_2(z_{u,b}, k_{u,b})$, we first perform a change in variables: $f_2(z_{u,b}, k_{u,b}) = z_{u,b} \log k_{u,b} = z_{u,b} p_{u,b}$, where $k_{u,b} = e^{p_{u,b}}$. To avoid $\log(0)$, we replace $\log k_{u,b}$ with $\log(k_{u,b} + 1)$, which does not impact the final solution. Then we apply an approach for bilinear functions to obtain an upper bound of a product of two variables z and p [8] as

$$V_1 = z^l p + p^l z - z^l p^l, \text{and } V_2 = z^u p + p^u z - z^u p^u, \tag{20}$$

where the corner values of both variables are $z^l = 0$, $z^u = 1$, $p^l = 0$, $p^u = \log(K_{PRB_b} + 1)$ (since $k^l = 0$, $k^u = K_{PRB_b}$), and V_1 and V_2 are the overestimators of the product. The convex overestimator of the product zp is $max(V_1, V_2)$. The relaxed second term then becomes $\log(k_{u,b} + 1) + (z_{u,b} - 1) \log(K_{PRB_b} + 1)$.

The term $h(k_{u,b}) = \log(k_{u,b} + 1)$ is concave in $k_{u,b}$, and we can relax it further, so we apply an approach for univariate functions [8] for concave functions. The linear overestimator of the term is computed as $\hat{h} = h(k^l) + \frac{h(k^u) - h(k^l)}{k^u - k^l}(k - k^l)$. Then we obtain that $\log(k_{u,b} + 1) = \frac{\log(K_{PRB_b}+1)}{K_{PRB_b}} k_{u,b}$. Finally, $f_2(z_{u,b}, k_{u,b}) = \frac{\log(K_{PRB_b}+1)}{K_{PRB_b}} k_{u,b} + (z_{u,b} - 1) \log(K_{PRB_b} + 1)$, which is linear in both $z_{u,b}$ and $k_{u,b}$.

To linearize the third term $f_3(z_{u,b})$, we apply again an approach from [8] for univariate concave functions, where the overestimator is built using the corner values of $z_{u,b}$ (0 and 1) and the value of $f_3(z_{u,b})$ at these points. Then, we obtain a linear overestimator $f_{3,lb}(z_{u,b}) = z_{u,b} \log(1 - B + Bz'_{u,b})$.

Finally, the linear overestimator for the whole objective function from Eq. (10) becomes

$$\max_{z_{u,b}, k_{u,b}} \quad \sum_{u \in U}^{N_u} \sum_{b \in B}^{N_b} \Big(z_{u,b} \log(R_{u,b}) + \frac{\log(K_{PRB_b} + 1)}{K_{PRB,b}} k_{u,b} \tag{21}$$

$$+ (z_{u,b} - 1) \log(K_{PRB_b} + 1) + z_{u,b} \log(1 - B + Bz'_{u,b}) \Big),$$

which is a linear function in both decision variables.

4.3 Transformation of constraints

Similarly, we obtain the upper bound estimators for constraints in Eqs. (11) and (14). By applying the bilinear function approach [8], the constraints (11) and (14) become

$$\sum_{b \in B}^{N_b} R_{u,b}(k_{u,b} + K_{PRB_b} z_{u,b} - K_{PRB_b}) \geq r_u, \ \forall u \in U, \tag{22}$$

$$\sum_{u \in U}^{N_u} (k_{u,b} + K_{PRB_b} z_{u,b} - K_{PRB_b}) \leq K_{PRB_b}, \ \forall b \in B. \tag{23}$$

The relaxed problem formulation consists of the relaxed objective and constraints expressed through Eqs. (21), (22), (12), (13), (23), (18). We convert the initial non-linear integer problem to a linear one with continuous variables, which can be solved quickly with a solver for linear programs.

5 BENCHMARK MODELS

In this section, we describe two benchmark models against which we are going to compare the performance of our approach.

5.1 3GPP-based Handover

Currently, the Make-Before-Break (MBB) 3GPP handover algorithm [2], which terminates the connection with the serving BS only after establishing the connection to the target BS during handover, to reduce HIT, is used in mobile networks. The user periodically measures the channel and sends the measurement report to its serving BS, which contains the signal strength of the serving and neighboring cells. The BS applies Layer-3 filtering and averages RSRP or SINR values over 200 ms [2]. Based on these measurements, the serving BS selects the target BS that should be prepared for a handover. The target BS is selected using an A3 event, which is triggered when a neighboring BS becomes better than the serving BS by a certain margin (e.g., 3 dB) and during a certain period of time (e.g., during 320 ms). The handover and Radio Link Failure (RLF) rates greatly depend on these parameters.

5.2 Adaptive handover parameter benchmark

The authors in [6] adjust handover parameters, like the handover margin (in dB) and Time-to-Trigger (TTT) (in ms), based on the user velocity. They propose to use two thresholds to split users in different groups based on their speed. When the calculated user velocity is bellow 10 km/h, then they set handover margin and TTT to 6 dB and 512 ms accordingly. If the user velocity is in the range between 10 and 45 km/h, then they set the handover parameters to 4 dB and 128 ms. Finally, in case user velocity is above the second threshold of 45 km/h, they select small handover parameters (2 dB and 32 ms) to speed up the handover process and avoid delayed handovers that might result in an RLF.

6 PERFORMANCE EVALUATION

First, we describe the simulation setup. Then, we present results for a smaller network, which is followed by results for a network with a larger number of entities.

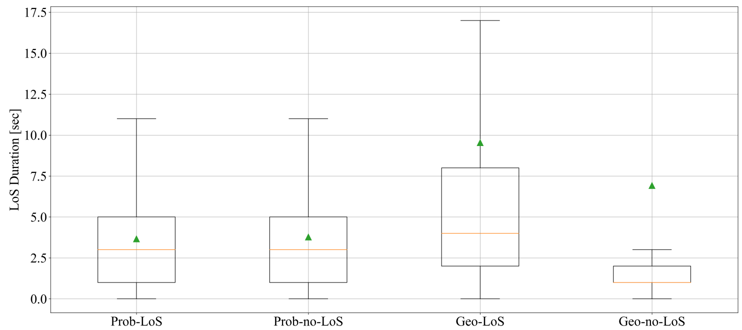

Figure 5: LoS and no-LoS duration with probabilistic 3GPP and geometric blockage models (large scenario).

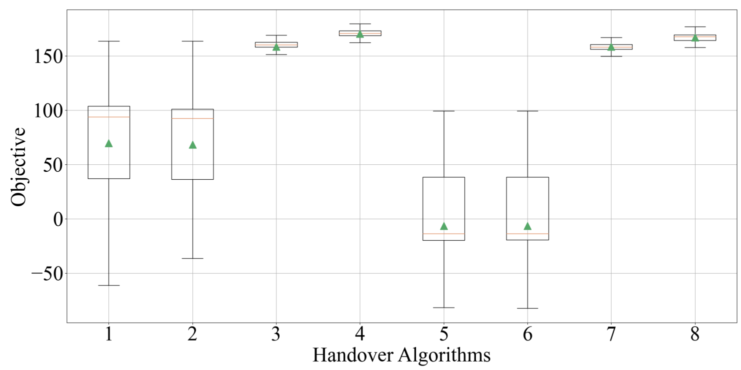

Figure 6: The value of objective function from Eq. (10) for various handover algorithms: 1-Prob-3GPP, 2-Prob-Benchmark, 3-Prob-Relaxed, 4-Prob-Optimal, 5-Geo-3GPP, 6-Geo-Benchmark, 7-Geo-Relaxed, 8-Geo-Optimal (small scenario).

Table 1: Simulation Parameters [1], [2]

Parameter	Value
Carrier frequency (macro)	2.5 GHz
Carrier frequency (micro)	28 GHz
Line of sight update periodicity (3GPP)	1000 ms
Channel measurement periodicity	10 ms
HIT (assuming MBB)	14.5 ms

6.1 Simulation Setup

We consider a two-tier network with urban channel models for macro and micro cells, from 3GPP 5G Release 14 [1]. We model the path loss and shadowing for LoS and no-LoS, as in [1]. We consider the two scenarios: (i) 5 BSs (one macro and four micro) and 10 users; (ii) 15 BSs (3 macro and 12 micro BS) and 45 users. We refer to the first case as *small scenario* and to the second as *large scenario*[3]. Madrid Grid mobility model is used to generate the mobility traces [11] for pedestrian users, bikes, buses and cars that have different velocities, as well as the positions of buildings that might block the LoS. We extend this model with the geometric blockage modeling and we evaluate the performance of our handover approach for various mobility patterns and user speeds. The other simulation parameters are depicted in Table 1. The frequency reuse factor is 1 for scenario (i) and 3 for scenario (ii). We run the simulation over 1000 s.

Our approach is centralized, where an agent runs at a controller and then handover and resource allocation decisions are signaled to all BSs in the network. We compare our relaxed approach against the optimal one, which is obtained using the Gurobi solver. Additionally, we use two other benchmark models, as explained in Section 5; the 3GPP handover [2] and the baseline that adaptively sets handover parameters based on user velocity [6]. To find the solution to the optimal and relaxed problems, we set the handover overhead to 0.9. During simulations, the user does not receive any resources during HIT and RLF for all evaluated algorithms. Moreover, to ensure that the number of handovers is constrained at every time slot, and the signalling resources are not exceeded, we set N_{HO} so that up to 20% of the users can make a handover at every time slot, i.e., $N_{HO} = 0.2N_u$. In the following box plots, the median is denoted as a horizontal orange line and the mean as a green triangle.

6.2 Evaluation of Blockage Duration

We compare the duration of LoS or no-LoS presence with 3GPP-based and the proposed geometric blockage models. LoS and no-LoS duration with 3GPP is 2.6× and 1.8× lower, accordingly, which

[3]We refer to this scenario as *large* to distinguish it from the small scenario with no intention of implying how many users comprise a large network.

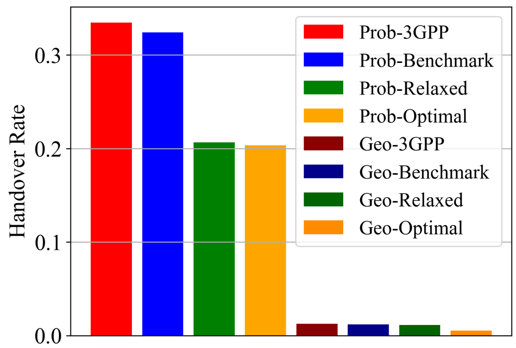

Figure 7: Handover rate (small scenario).

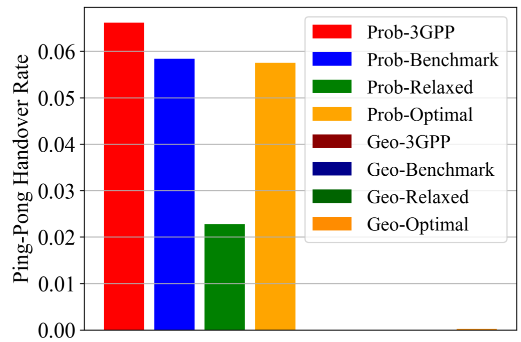

Figure 8: Ping-pong handover rate (small scenario).

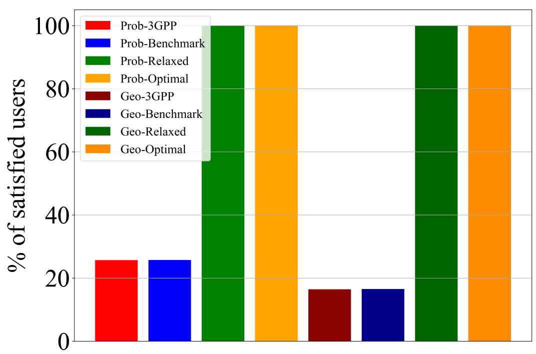

Figure 9: Percentage of users with satisfying data rates.

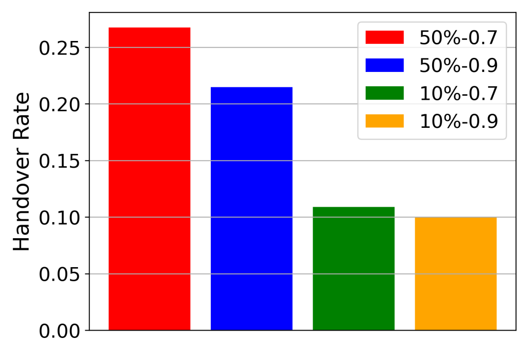

Figure 10: Handover rate for handover count limit N_{HO} (first value in %) and handover overhead B (second value).

leads to more LoS to no-LoS switches and vise versa, which, in turn, causes more handovers as shown in the following. The proposed geometric blockage modeling leads to a more scenario-dependent, and thus, realistic, blockage duration with a larger mean, min and max values, as shown in Fig. 5. Moreover, the LoS duration depends on the user speed, namely, faster users switch from LoS to no-LoS and vice versa more often because they pass more objects by. As a result, the LoS and no-LoS duration has a significantly longer range. In the following subsections, we run the handover algorithms with the 3GPP probabilistic (denoted as Prob. from now on) and our geometric blockage (denoted as Geo. from now on) models to evaluate the impact of the blockage modeling on handover and ping-pong handover rates. Note that if the user makes a handover from the new cell to the old one within three seconds, this handover is classified as *ping-pong*.

6.3 Small Scenario

In this scenario, there are eight pedestrian users, two cars and a bus. Pedestrian users might get on the bus at one of the bus stops with a certain probability according to the traces of Madrid Grid mobility model. We evaluate the performance of 3GPP, the benchmark [6] handover algorithms, as well as the optimal and relaxed solutions.

The relaxed approach provides an upper bound to the optimal one and obtains the mean objective of 269 for both Prob. and Geo for the small scenario. After solving the relaxed problem, the decision variables are converted back to integer to be able to make user assignment and resource allocation decisions. Fig. 6 shows the objective values for various handover algorithms and two blockage models. The optimal (with objective mean of 170 for Prob. and 166 Geo. blockage models) and the relaxed with decision variables converted to integer (with objective mean of 158 for both) solution significantly outperform the 3GPP (with mean of 70 and −6.5) and the benchmark (with mean of 68 and −6.5) approaches. Moreover, the performance of the relaxed approach is within 93 − 96% of the optimal for Prob. and Geo., which is a significant advantage our approach offers.

Fig. 7 and Fig. 8 show the handover and ping-pong rates. The optimal algorithm reduces the handover rate by 40 − 50% compared to both benchmarks (for Prob. and Geo.). For the probabilistic blockage model, the relaxed solution achieves the same handover rate as the optimal, while, for the geometric one, it reduces the handover rate by 13% compared to the baselines. Both the optimal and the relaxed algorithms reduce the ping-pong handover rates significantly, namely, by and 14% and 67%. Interestingly, the relaxed approach reduces the ping-pong handover rate more than the optimal one. With the geometric blockage model, users make significantly fewer handovers because the LoS presence does not switch as often as with 3GPP, and the ping-pong handover rate is very close to 0.

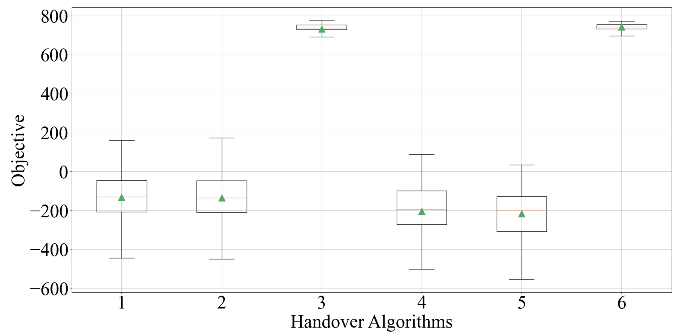

Figure 11: The value of objective function from Eq. (10) for various handover algorithms: 1-Prob-3GPP, 2-Prob-Benchmark, 3-Prob-Relaxed, 4-Geo-3GPP, 5-Geo-Benchmark, 6-Geo-Relaxed (large scenario).

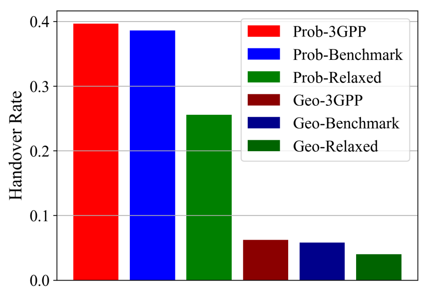

Figure 12: Handover rate (large scenario).

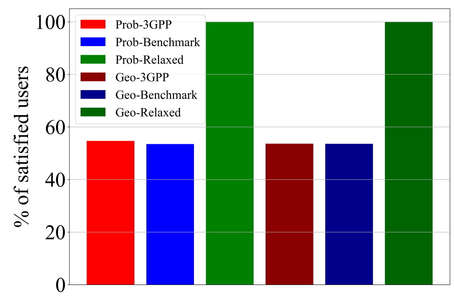

Figure 13: Percentage of users with satisfying data rates.

Another advantage that our approach offers is that we guarantee a minimum required rate per user, which was set to be $4-10$ Mbps, depending on the user. The percentage of users with satisfying data rates is shown in Fig. 9. With 3GPP and the benchmark, just $\approx 20-25\%$ of all users are satisfied, while the proposed optimal and relaxed approaches provide a user satisfaction rate of 100% for both blockage modeling approaches. Thus, additionally to providing proportional fairness, the proposed approach manages to satisfy users' demands and reduce the handover rate.

6.4 Large Scenario

In the larger scenario, there are more users and more BS. The users are divided into 30 pedestrians, 15 cars including public transport in the form of two buses. We compare the same algorithms as for the small scenario except for the optimal solution since it is computationally very expensive to solve an integer non-linear program for a large scenario. The results and the trend is similar to the ones for the small scenario. Fig. 11 shows the value of the objective, where the relaxed proportionally fair approach increases the objective compared to 3GPP baseline from -130 to 732 and from -204 to 742 for each blockage model. Fig. 12 presents the handover rate that is reduced by the relaxed approach by 36% for both probabilistic and geometric blockage models. One can also notice how much the handover rates are affected by blockage modeling. Namely, with the probabilistic model the values are 0.39 with 3GPP and 0.25 with the proposed relaxed approach, while the handover rate is 0.061 and 0.039 with the geometric blockage modeling. This stresses the importance of the appropriate blockage modeling. Fig. 13 shows the percentage of satisfied users, where the relaxed algorithm increases the number of satisfied users by over 40%.

6.5 Impact of handover overhead

Next, we evaluate the impact of handover overhead and the maximum number of users that can handover in a slot on the handover rate for the large scenario. We limit the handover rate by considering the handover overhead in the objective and constraining the number of users that can make a handover per slot to avoid unnecessary handovers. As shown in Fig. 10, the handover rate reduces the larger the handover overhead is and the fewer users are allowed to make handovers by $20-60\%$. This permits the operator to adjust handover rates based on available resources and amount of users.

7 RELATED WORK

First, we describe some related works from blockage modeling, and then we present works related to mobility management.

7.1 Blockage Modeling

The authors in [19] propose a system for indoor THz communication, where they model common blockages such as walls and humans as 3D shapes. They also assume that a human body has a shape of cylinder and the centers of the cylinders (humans) are distributed according to a homogeneous Poisson Point Process (PPP).

PPP-based blockage model is restrictive since in PPP, due to its distribution, it is impossible to have two persons next to each. In reality, users often move in groups or closely to each other, especially in crowded places. Modeling blockages that come from humans and walls allows one to determine whether there is an LoS between the user and the access point or not.

In another work [5], which is the closest blockage modeling work to ours, the authors model human blockages as cylinders in an indoor mmWave network. They model their access points to have a limited field of view. They place blockage bodies uniformly in the indoor area assuming zero or three blockages per squared meter. Differently, we model all components/obstacles of the environment and the network as 3D geometric figures because the users and buildings location depends on the cite features and user mobility patterns. Our model also considers transient blockages from other users on the user of interest. Such blockages increase ping-pong handover rate and should be considered in the simulation scenario. This allows us to study the impact of other users in the network and their trajectories on the user of interest. This way of modeling is, of course, more computationally expensive compared to the 3GPP distance-based probabilistic model because we need to check if any of the objects or users blocks the LoS.

7.2 Handover Management

Various approaches that reduce the handover rate have already been proposed [3], [6], [7], [13], [9]. The authors in [3] and in [14] propose to tune handover margin and TTT based on user speed and measured channel. The authors in [6] also adjust handover parameters based on user speed, as well as cell load and perform load balancing between neighboring cells. However, mapping user speeds to handover parameters is challenging since handovers also depend on the environment and the other users in the network. Handovers in dense scenarios are not only caused by mobility, but also by LoS blockages and load balancing decisions. Therefore, other parameters should be considered to decide if a handover should be triggered and to which target cell. Furthermore, some works like [20], [17] have already used artificial intelligence for handover management using measured RSRP values as an input. However, with artificial intelligence, it is not always clear why a model made a certain decision and if its performance will be stable with a new data distribution. Hence, we formulate an optimization problem to perform user to BSs assignment, fair resource allocation and handover decisions jointly considering measured RSRP values received from all users, available resources at BSs and guaranteeing the minimum required rate. In [16] the authors also formulate an optimization problem with the same decision variables as we do, to perform load balancing in heterogeneous indoor networks. However, they do not consider the handover overhead, nor do they provide a minimum rate guarantee to the users.

8 CONCLUSION

In this paper, we consider the problem of jointly assigning the users to BSs and allocating resources from BSs to the assigned users while providing proportional fairness and guaranteeing a minimum data rate to all users at all times. To model reliably the signal blockages, we use a geometric blockage approach. We formulate an optimization problem, and propose a near-optimal solution which outperforms other benchmark models. We show that our approach reduces the handover rate and increases user satisfaction with the service. In the future, we plan to extend our approach so that it captures dual connectivity as well. Also, we plan to consider the general case of α-fairness.

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