On Semi-Static Interference Coordination under Proportional Fair Scheduling in LTE Systems

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***Abstract*—In this paper we consider the design of semi-static inter-cell interference coordination schemes for LTE networks. In this approach, base stations coordinate the power settings per resource block over long time spans such as seconds. In order to optimize the power settings, one needs to employ models which predict the rate of terminals over the next coordination period under the usage of a given power setting. However, these models are typically quite simple and neglect the impact from fading as well as from dynamic resource allocation performed at the base stations on a millisecond base. Ignoring such properties of OFDMA networks leads therefore to suboptimal transmit power settings. In this paper, we study the impact from a *precise* rate prediction model that accurately accounts for fading and dynamic resource allocation. On the down-side, this more precise model leads to a much more involved optimization problem to be solved once per coordination period. We propose two different heuristic methods to deal with this problem. Especially the usage of genetic algorithms results to be promising to counteract the complexity increase. We then study the overall system performance and find precise rate prediction models to be essential for semi-static interference coordination as they provide significant performance improvements in comparison to approaches with simpler models.**

I. Introduction

The current proliferation of smartphones, tablet computers, and mobile usage of laptops have caused an exponentially increasing demand in data traffic for cellular radio networks [1]. To sustain high demands on data traffic, network operators satisfy these requirements with a denser deployment of base stations. For 4th generation networks, such as LTE and LTE-A, this approach is not sufficient as such networks operate with a frequency reuse of one. Hence, neighboring cells transmit in the same frequency band which inevitably causes inter-cell interference. Cell-edge terminals are exposed to this the most.

To mitigate this problem and improve the system capacity, inter-cell interference coordination has been discussed recently as promising solution [2]. According to the time-scale of operation, coordination schemes can be categorized into static, semi-static and fully synchronized approaches [3], [4]. Discussions on interference coordination schemes started with static schemes, where the general idea is to use appropriate transmit power profiles at neighbouring base stations to create spectrum parts where especially cell-edge terminals can gain from a better signal-to-interference ratio. Example profiles are known as fractional frequency reuse or soft-frequency reuse. The configuration of such profiles is usually considered during the network planning phase. As these profiles are not modified over time, we refer to them as *static*. They have the advantage of not having coordination overhead. On the downside, with substantially changing load conditions such static profiles are inferior to dynamic coordination schemes [3]. In contrast, *fully-synchronized* schemes rely on the instantaneous channel quality information (CQI) feedback from the terminals which need to be forwarded to a coordination unit. The coordination unit then computes new transmit power profiles to be fed-back to the base stations. This cycle is re-entered every 10 milliseconds, or faster. It creates obviously high system requirements to be met in terms of communication capacity of the X2 interface as well as regarding the computational capabilities to be provided at the base station. Compared to fully synchronized schemes, *semi-static* approaches [3], [5], [6] have relaxed constraints on the information exchange and computational requirements as the coordination periods are typically in the range of seconds or longer. Such time intervals still allow tracking of terminal positions and consequently adapting to new interference situations in the cell (adapt to changing/dynamic loads). Hence, semi-static coordination techniques can be considered as more suitable coordination approaches for practical deployments.

However, such semi-static approaches are also associated with challenges. Most importantly, for optimizing the power profiles a *precise* model is required that predicts the rates for the next coordination period under some given transmit power and interference level. This is rather difficult to obtain as the radio channel is constantly fluctuating due to fast fading. Furthermore, upcoming 4th generation systems employ at the base station dynamic resource schedulers (such as proportional fair scheduling) which determine the resource allocation on a millisecond base. This dynamic process has a significant impact on the predicted rates as well, as this allocation process provides inherent interference mitigation [7]. Due to these modeling difficulties, rate predictions for semi-static interference coordination schemes are usually based on quite simple models.

In this paper, we deal with the consequences of the usage of such simple models. The contribution of the paper is two-fold. We first discuss a precise model for rate-prediction, which is more involved and can only be solved numerically. In addition, it makes the process of optimizing the power profiles at the coordination unit much more complex. In order to balance this, we study different heuristics for the optimization process and find especially genetic algorithms to be a suitable approach. We then benchmark the combination of the precise model being optimized by genetic algorithms with approaches utilizing the simple model. It turns out that precise models can provide much better system performance due to their efficient allocation of transmit powers among neighboring cells. To the best of our knowledge, these important design aspects of semi-static coordination schemes have not been considered before.

We structure this work as follows. Initially, we present a system model and discuss the problem statement in the context of related work in Section II. Then, we derive the precise rate prediction model in Section III and discuss different heuristics for the subsequent coordination problem in Section IV. The approach is evaluated in Section V. We finally conclude the paper in Section VI.

II. Preliminaries

In this section we first present our system model. We then give a problem statement and discuss state-of-the-art.

A. System Model

We consider a deployment of K cells, where a total of $J(k)$ terminals per cells are actively transmitting and receiving data packets. Each terminal is associated to one base station only. Time is slotted into so called Transmission Time Intervals (TTIs) of duration $T_{\mathrm{TTI}} = 1$ ms, which are index by t. Each base station is connected to the backbone and receives from it data packets destined for the corresponding terminals. In order to transmit these packets over the time-varying wireless channel, a scheduling algorithm within the base station determines the matching of radio resources to packets for the upcoming TTIs. In frequency division duplex (FDD) systems, which most LTE systems utilize, up-link transmissions are handled simultaneously over a different frequency band. In the following, we only focus on the down-link of such a LTE FDD system.

In the down-link each base station utilizes a system bandwidth of B [Hz] with center frequency f_c [Hz] which is split into N disjoint sets of frequency bands of bandwidth $B_n = B/N$ [Hz], also referred to as Resource Blocks (RBs). They are the minimal transmission resources that can be assigned to a terminal within a TTI. Each RB has N_S OFDM symbols per TTI and N_C parallel OFDM subcarriers for payload transmission. Furthermore, base station k can allocate per RB n a variable transmit power p_n^k [W]. However, the total transmit power allocated over all RBs has an upper limit of $P_{\max}$ [W], i.e., $\forall k : \sum_{\forall n} p_n^k (t) \leq P_{\max}$.

In LTE systems neighbouring base stations (of the same network) operate within the same spectrum. This leads to significant inter-cell interference. Hence, the down-link transmission of data is for most terminals in most cells interference-limited (unless the terminals are at the core of a cell) as the signal-of-interest is interfering with signals from neighbouring cells. More precisely, this is dependent on the setting of the transmit powers p_n^k per resource block. Taking the interference-limitation into account, any terminal in the system experiences on each RB a randomly varying signal-to-interference-and-noise ratio (SINR) due to path-loss, shadowing and fading of the signal of interest and interfering signals as well. Denoting by $h_{s,j,n}^2 (t)$, $h_{i,j,n}^2 (t)$ the instantaneous channel gains from the serving and strongest interferer base station to terminal j on RB n, the SINR $\gamma_{j,n} (t)$ is defined as:

$$\gamma_{j,n} (t) = \frac{p_n^s (t) \cdot h_{s,j,n}^2 (t)}{p_n^i (t) \cdot h_{i,j,n}^2 (t) + \sigma^2} , \tag{1}$$

where σ^2 denotes the noise power. The channel gains $h_{s,j,n}^2 (t)$, $h_{i,j,n}^2 (t)$ vary randomly in time, frequency and over different terminals (multi-user diversity) due to fading that is caused by the mobility of terminals and the multi-path propagation environment. We assume a Rayleigh fading model, i.e., the channel gains $h_{k,j,n}^2 (t)$ are exponentially distributed with mean $\bar{h}_{k,j,n}^2 (t)$. Over shorter time spans (i.e., over seconds) the means $\bar{h}_{k,j,n}^2 (t)$ are assumed to stay constant. Furthermore, the fading is assumed to be slowly varying compared to the duration of a TTI. Thus, as terminals report the channel states to the base station in one TTI, these channel state indications can serve as a sufficient prediction for the next TTI. Given these channel state predictions, the base station can employ link adaptation to dynamically adjust the modulation and coding to the instantaneous channel conditions. We denote the function that captures the performance of this link adaptation by $C(\gamma)$. Hence, for the SINR realization $\gamma_{j,n} (t)$ the spectral efficiency with which this resource blocks can be utilized is given by $C(\gamma_{j,n}(t))$. LTE-specific functions mapping the SINR $\gamma_{j,n} (t)$ to spectral efficiency $C(\gamma_{j,n}(t))$ have been reported in [8].

A crucial component determining the performance of LTE systems is the base station scheduler for the down-link. In this work we assume the SINR-based proportional fair scheduling (PFS) algorithm, which is a standard scheduler widely considered in LTE research and standardization. PFS dynamically assigns RBs to the terminals based on their channel quality (CQI) reports per TTI transmitted during the previous uplink (UL) period. However, instead of purely assigning resource blocks based on the instantaneous channel states, PFS normalizes the instantaneous states with the corresponding average SINR and assigns RBs based on these weighted coefficients. Formally, the average channel state from the W last TTIs is given by:

$$\bar{\gamma}_{j,n} (t) = \frac{1}{W} \sum_{i=t-W}^{t} \gamma_{j,n} (i) . \tag{2}$$

Given the instantaneous channel state $\gamma_{j,n}(t)$, the channel weights are defined as:

$$\widehat{\gamma}_{j,n}(t) = \frac{\gamma_{j,n}(t)}{\bar{\gamma}_{j,n}(t)} . \tag{3}$$

Based on the weights $\widehat{\gamma}_{j,n}(t)$ the RBs are now assigned for the upcoming TTI in an opportunistic way, i.e., the terminal j^*

having the highest coefficient $\widehat{\gamma}_{j,n}(t)$ on RB n will be selected for transmission:

$$\forall k, n: \; j_n^*(t) = \arg \max_{j \in \mathcal{J}(k)} \widehat{\gamma}_{j,n}(t) \;, \tag{4}$$

where $\mathcal{J}(k)$ is the set of all terminals belonging to cell k.

B. Problem Statement

In this work, we are interested in the design of a *semi-static* scheme for interference coordination. We propose to adapt the transmit power settings for the base stations over a period T_{IC} that is much longer than a TTI (T_{IC} equalling hundreds or even thousands of TTIs). The rationale for such a design is straightforward. Faster interference coordination creates substantial overhead as information has to be exchanged between base stations. However, the fundamental load situation (the number of the active terminals in the down-link as well as their positions) per cell does not vary drastically on a TTI time scale. Hence, the high overhead might not be justified. On the other hand, if the transmit power settings per base station are not adapted at all, there is a high risk that due to load imbalances this leads to significant performance losses in the network. The semi-static approach balances these two aspects. It is fast enough to cope with load variations but is not creating excessive overhead. Finally, slower power adaptations also allow for more complex computations to be performed in between.

Formally, semi-static interference coordination is defined as an algorithm that decides on the power allocation per resource block and cell p_n^k jointly for a cluster of cells, cf. Fig. 1. These power allocations are valid for a coordination period T_{IC} where we assume that $T_{\mathrm{IC}} \gg 1$ TTI. Furthermore, we assume that the coordination entity can base the power allocation decisions on the average channel state of the terminals with respect to the base stations in the cluster, i.e. $\bar{h}^2_{k,j,n}$.

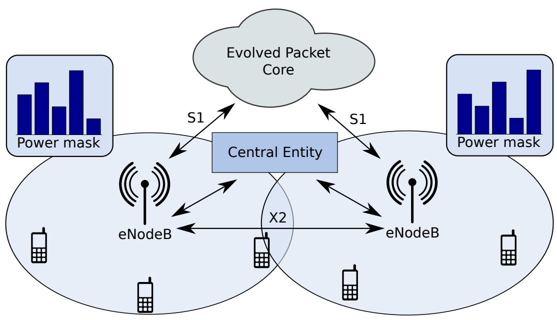


Fig. 1: Schematic overview of the proposed semi-static ICIC.

Although appealing, the design of such a semi-static coordination scheme is significantly complicated by two related issues. Power assignments p_n^k clearly need to be found for the next coordination period such that some objective function of the achieved rates is maximized. However, the rates to be maximized are an expectation over the next coordination period, i.e. we are in principle interested in $\mathcal{R}_{j,n} = \mathrm{E}\left[C\left(\gamma_{j,n}(t)\right)\right]$ for some setting of the transmit and interference power. Nevertheless, the expected rates depend on the distribution of the *scheduled* random SINRs $\gamma_{j,n}(t)$ (where the fast resource allocation at the base station is performing this scheduling). Hence, we need to determine the distribution of the SINRs with respect to the fading (of the signal-of-interest as well as the interference signal) but also with respect to the impact of proportional fair scheduling performed at each base station. This makes the analytical derivation of the expected rates quite involved. In addition, assuming we have such an expected rate expression, we still need to determine the optimal choice of the power allocations p_n^k. As we will see, this is a second major problem as the rate expectations turn out to be highly nonlinear.

In the following, we assume that the interference coordination is performing a max-min optimization of the expected rates of the terminals in the coordination cluster:

$$\begin{aligned} \max \quad & \epsilon \\ \text{s.t.} \quad & \sum_{n=1}^{N} \mathcal{R}_{j,n} > \epsilon \quad \forall k, \forall j \in \mathcal{J}(k), \\ & \sum_{n=1}^{N} p_n^k \leq P_{\max} \quad \forall k. \end{aligned} \tag{5}$$

Note that this choice of objective function is purely for illustration purposes. Any other objective function could also be used based on the contributions that we make in this paper.

C. Related Work

Interference coordination has received significant attention recently due to its beneficial performance impact. In the following we only discuss approaches that also address semi-static coordination. In [3], [9], [5] several schemes are presented with update periods in the range of several hundred TTIs while the base station is assumed to apply opportunistic scheduling during each single TTI. All three approaches rely on a centralized architecture where several base stations are coordinated by a central entity. As objective function pure throughput maximization is considered which is either based on a long-term SINR rate prediction model [3], [9] or on an instantaneous SINR rate prediction model [5]. However, the impact of the opportunistic scheduler is not considered despite the fact that in general long-term SINR based models overestimate the impact of interference for systems operating with dynamic schedulers [10], [11].

A distributed approach for semi-static interference coordination is presented in [6], [12]. The authors propose to update the transmit power settings in a cluster of cells every second while the base stations run a variant of the proportional fair scheduler (α-fair scheduling) for resource allocation per TTI. The interference coordination is performed by a distributed gradient descent method. It runs on top of a stochastic model for the expected rates and approximates the impact of PF scheduling. While the stochastic model accounts for Rayleigh fading for the signal of interest, it does not consider the fading of the interfering signals. The authors furthermore ignore the distribution of the SINR under proportional fair scheduling, only accounting for the rate obtained from the expected base SINR. This leads again to a significant overestimation of the interference impact which we address by an exact model in this paper.

III. Rate Prediction Model

In this section we present two models for the expected rate $\mathcal{R}_{j,n}$ over the period of one coordination cycle. We start with presenting the standard model and later on present our extension.

A. Simplified Rate Prediction Model

The standard model for rate prediction is as follows. The average channel gain values $\bar{h}^2_{s,j,n}$ and $\bar{h}^2_{i,j,n}$ that terminals correspondingly have with their serving base station and interfering ones are used for determining a reference SINR:

$$\widetilde{\gamma}_{j,n} = \frac{p^s_n \cdot \bar{h}^2_{s,j,n}}{p^i_n \cdot \bar{h}^2_{i,j,n} + \sigma^2} \,. \tag{6}$$

By mapping this reference SINR $\widetilde{\gamma}_{j,n}$ to spectral efficiency according to the capacity function $C(\widetilde{\gamma}_{j,n})$, the simplified rate prediction is obtained as:

$$\mathcal{R}_{j,n} = \frac{N_S \cdot N_C}{T_{\mathrm{TTI}} \cdot |\mathcal{J}^{-1}(j)|} C\left(\tilde{\gamma}_{j,n}\right), \tag{7}$$

where $\mathcal{J}^{-1}(j)$ denotes the set of terminals which are in the same cell as terminal j. Note that Equation (7) neither considers the multi-user diversity gain stemming from the PF scheduler nor does it account for the fading of both signals over the coordination period. Moreover, the normalization by $1/|\mathcal{J}^{-1}(j)|$ assumes that each terminal in the cell has equal chances to be scheduled by the PF scheduler, which is not the case. Nevertheless, such simplified models (or derivatives thereof) are commonly used in literature, c.f. [3], [9]. In the following, we use the above mentioned model as a comparison scheme.

B. Precise Rate Prediction Model

For a better rate estimate more details need to be considered, especially regarding fading and scheduling. Let us start with the definition of the following indicator function:

$$M_{j,n} = \begin{cases} 1, & \widehat{\gamma}_{j,n} \geq \max_{i \in \mathcal{J}^{-1}(i) \setminus j}(\widehat{\gamma}_{i,n}) \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

modeling the PFS decision. The function equals one if terminal j has the highest normalized SINR $\widehat{\gamma}_{j,n}(t)$ in the cell. Let $X_{j,n}$ denote the random variable representing the fading SINR $\gamma_{j,n}(t)$ and $f_{X_{j,n}|M_{j,n}=1}(x)$ be the PDF of the scheduled SINR, then from [11] we know for PFS:

$$f_{X_{j,n}|M_{j,n}=1}(x) = \frac{\prod_{\forall i \in J^{-1}(i) \setminus j} F_{X_{i,n}}(\frac{\mathrm{E}[X_{i,n}]}{\mathrm{E}[X_{j,n}]} \cdot x) \cdot f_{X_{j,n}}(x)}{P(M_{j,n}=1)}, \tag{9}$$

where $\mathrm{E}\,[X]$ is the expected value of X. Furthermore, $f_{X_{j,n}}(x)$ and $F_{X_{j,n}}(x)$ are the basic PDF and CDF of the SINR $\gamma_{j,n}(t)$ and are given by [7]:

$$f_{X_{j,n}}(x) = \left[\frac{\sigma^2}{P^i_{j,n} \cdot x_{j,n} + P^s_{j,n}} + \frac{P^s_{j,n} \cdot P^i_{j,n}}{(P^i_{j,n} \cdot x + P^s_{j,n})^2}\right] \cdot \exp\left(-\frac{\sigma^2}{P^s_{j,n}} \cdot x\right), \tag{10}$$

$$F_{X_{j,n}}(x) = 1 - \frac{P^s_{j,n}}{P^i_{j,n} \cdot x + P^s_{j,n}} \exp\left(-\frac{\sigma^2}{P^s_{j,n}} \cdot x\right), \tag{11}$$

where $P^s_{j,n} = p^s_n \bar{h}^2_{s,j,n}$ and $P^i_{j,n} = p^i_n \bar{h}^2_{i,j,n}$ are the average received power of the signal of interest and of the interference at terminal j on resource block n.

From [11] the precise rate expectation $\mathcal{R}_{j,n}$ is then obtained as:

$$\mathcal{R}_{j,n} = \frac{N_S \cdot N_C}{T_{TTI}} \int_0^\infty C(x) \prod_{\forall i \in \mathcal{J}^{-1}(i) \setminus j} F_{X_{i,n}}(\frac{\mathrm{E}[X_{i,n}]}{\mathrm{E}[X_{j,n}]} \cdot x) \cdot f_{X_{j,n}}(x)\, dx. \tag{12}$$

Although there is no closed-form solution to the integral, we can nevertheless obtain the expected rates $\mathcal{R}_{j,n}$ based on (12) by using numerical methods. Especially if we limit the possible realizations for the transmit powers p^s_n and p^i_n, the corresponding expected rates can be precomputed. Finally, note that this analyical model has been validated in [11] as well.

IV. Solving Semi-Static Interference Coordination Problems

It is clear that the solution of the interference coordination problem in (5) is highly non-linear due to the complex expression for the rate predictions of the previous section. Thus, an analytical solution to Problem (5) is infeasible. Hence, semi-static interference coordination problems require heuristic solution strategies for obtaining good solutions. Note in particular that due to the nature of the semi-static approach and the duration of the coordination period T_{IC}, there is significantly more time available for determining good solutions compared to for example resource allocations per TTI [13]. In the following, we study two different heuristic approaches. The first one is a straight-forward reformulation of Problem (5) as integer linear programming (ILP) problem which allows the application of standard solvers like CPLEX [14]. As a second approach we propose the application of genetic algorithms (GA).

A. ILP Reformulation

In order to convert Problem (5) into an ILP, we first discretize the optimization variables p^k_n to a limited set of L transmission power values $p \in \{p_1, p_2, \ldots, p_L\}$. Notice that this allows us to pre-compute the obtainable rates for each terminal $\hat{\mathcal{R}}_{j,n,l_1,l_2}$ from Equation 12 for any combination of transmission powers p_{l1}, p_{l2}. Given the discrete set of power settings and the associated rates, the problem becomes a combinatorial one. In general such problems are known to be hard optimization problems. However, through redefining them to an ILP problem and using state-of-the-art software the considered instances can be solved with a high quality (still at the price of long computation times typically in the range of minutes). The reformulation of Problem (5) as ILP is straightforward:

$$\begin{aligned}
\max \quad & \epsilon \\
\text{s.t.} \quad & \sum_{n=1}^{N}\sum_{l_1=1}^{L}\sum_{l_2=1}^{L} \hat{\mathcal{R}}_{j,n,l_1,l_2} \cdot z_{n,l_1,l_2} > \epsilon \quad \forall k, \forall j \in \mathcal{J}(k), \\
& \sum_{n=1}^{N}\sum_{l_1=1}^{L}\sum_{l_2=1}^{L} p(l_k) \cdot z_{n,l_1,l_2} \leq P_{\max} \quad \forall k, \\
& \sum_{l_1=1}^{L}\sum_{l_2=1}^{L} z_{n,l_1,l_2} = 1 \quad \forall n, \\
& z_{n,l_1,l_2} \in \{0,1\}, \qquad (13)
\end{aligned}$$

The ILP version is now optimized based on the binary variable z. In the following, we use the solution to the ILP reformulation mainly as a benchmarking scheme.

B. Genetic Algorithm Design

Genetic algorithms (GA) are widely used heuristic methods for solving non-linear optimization problems [15]. The basic idea stems from evolutionary theory, postulating the survival of the fittest. Evolution is mimicked by repeatedly applying processes like crossover, mutation and selection to a population of individuals. An individual (genome) possesses some traits, which are encoded into strings (numbers). Applied to our power allocation problem, the set of power allocations (per RB and per cell) p_n^k represents the traits of one individual. When the traits are discrete $p \in \{p_1, p_2, \ldots, p_L\}$, they are referred to as *alleles*. A genome example is represented in Fig. 2. Genomes can be ranked among others by the fitness function. Referring to our optimization Problem (5), the fitness of the genomes is the achieved minimum rate per cell. Natural selection is imitated by selecting with a probability p_c the fittest genomes for crossover. In this way, parent genomes will be able to pass further their good traits to a new generation of offspring. P_r percent of the least-fit individuals from the previous generation are replaced with the newly bred and fittest individuals. In this way a new generation of individuals is created containing both old members from the previous generation and the new ones coming from the crossover and mutation process. If selection and crossover alone are repeatedly applied to individuals, a homogeneous population will be obtained. The lack of diversity is disadvantageous as a homogeneous population limits GAs ability to further explore the solution space. It can lead to a local optimum of the optimization problem. Diversity can be promoted through mutation and a smart initialization of the population. The

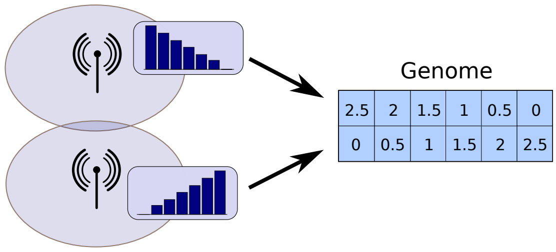


Fig. 2: Genome representation for power masks of two neighbouring cells. Represents p_n^k per resource block of each cell.

Parameter	Value
Number of generations	20.000
Replacement percentage	0.7
Population size	30
Mutation probability	0.05
Crossover probability	0.8
Initial population	20% uniform power mask 20% FR2 power mask 10% stairs power mask 50% random power masks
Selection strategy	Overlapping populations
Crossover type	One-point crossover

TABLE I: Parameters for the genetic algorithm.

mutation operator we use, randomly determines for every gene in the genome whether it should be mutated, according to a mutation probability p_m. If a mutation takes place, the value of the gene is set to an arbitrarily allele, different from the current one. New gene combinations are introduced to the population. Thus, the GA can "escape" from locale optima and converge to a globally better solution. A second approach to support diversity is also initialization with a diverse population. A well selection of individuals for initialization helps also to obtain a fast convergence of the GA. We initialize the population of individuals with power allocations that represent a certain diversity: uniform, frequency reuse two, stair functions and random settings.

Crossover and mutation altogether might produce individuals not fulfilling the optimization problem constraints, i.e., infeasible solutions of the optimization problem. In our case, the transmission power allocated per cell might be higher than the allowed $P_{\max}$. After the crossover and mutation process a correction needs to be applied to the genomes not fulfilling the power constraint. Random alleles are selected and scaled down, until the transmission power constraint is fulfilled. As a stopping criterion the number of generations is selected. The iterative operations of the GA are depicted in Fig. 3. A more detailed discussion of the method can be found in [16]. For an efficient GA run, its parameters need to be tuned. We did a survey on the optimal configuration of GA parameters, the results of the GA optimization parameters is given in Table I. Our implementation is based on the GAlib [17] C++ library. It provides many class objects and tools for usage in the context of genetic algorithms.

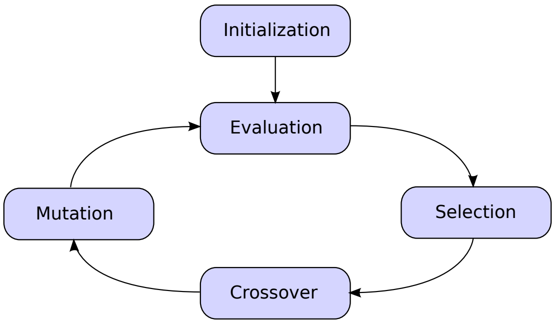


Fig. 3: GA flowchart.

V. Performance Evaluation

In this section we evaluate the performance of the proposed interference coordination scheme. For the evaluations we use a system level simulator based on OMNeT+ [18]. The underlying performance model presented in Section III has already been validated in [11]. Hence, we focus explicitly on the performance impact with respect to interference coordination.

A. Evaluation Methodology

The evaluation is performed in two steps. We start with benchmarking the ability of the GA to reach near-optimal solutions in comparison to the ILP. Note that in this step we only consider the numerical value of the objective function of Problem (5). Thus, we consider the minimal predicted rates ϵ as obtained from both methods. The second part of the evaluation relates then to the simulated system level performance.

As baseline scenario we consider two neighboring cells. Terminals are randomly distributed over the area in between the two base stations as shown in Fig. 4. While the terminals are uniformly distributed over the cell, we consider two specific load scenarios. In the first one, we have a symmetric load. Hence, in each cell 40 terminals are positioned. In the second case we consider an asymmetric load of 15 terminals in the one and 65 terminals in the other cell. For each scenario we evaluated 20 different instances of the random positions of the terminals, referred to as drop. Table II gives more details on the considered parameters for the simulation.

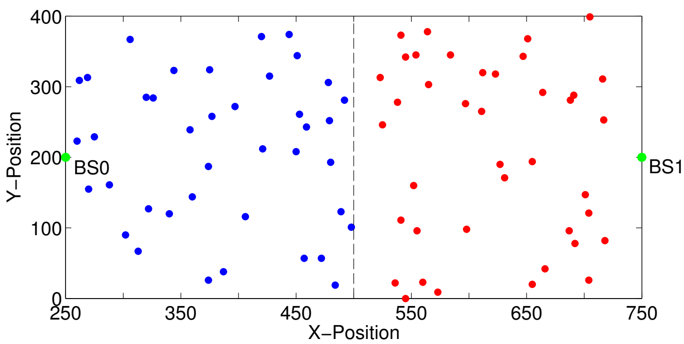


Fig. 4: Example drop of terminals between two BSs.

Parameter name	Value
Simulation Time	5 s
Base station number k	2
Inter-site distance	500 m
Transmission Power $P_{\max}$	20 W
Carrier Frequency	2 GHz
System Bandwidth	5 MHz (25 RBs)
Symbols per TTI N_C	7
Subcarriers per RB N_S	12
Scheduler Window W	1000 TTI
Noise Power σ^2 per RB	-112 dBm
Number of Terminals J	80
Path Loss Model h^2	$35.2 + 35\log_{10}(d)$ [dB] (Urban)
Antenna Pattern	Omnidirectional
Error Model	Exponential Effective SINR
Traffic Model	Full Buffer
Fast Fading Model	Jake's (Sum of Sinusoids)
Background Doppler Freq	5 Hz

TABLE II: Parameters for the system level simulations.

For the system level simulations, we consider two different performance metrics. Our primary metric is the minimal average rate over all terminals as observed during the simulation. In addition, we also consider the empirical CDF of the average rates over all terminals in order to get a more detailed view of the performance of the different approaches. Five different comparison schemes are considered: The solution to the **ILP** based on the detailed rate model of Section III-B, the GA based on the same rate model referred to as **GA precise**, and the GA based on the simple rate model of Section III-A referred to as **GA simple**. Finally, we also consider a **uniform** power profile over all resource blocks in all cells, as well as a frequency **reuse 2**. These last two schemes are static whereas the first three schemes are semi-static.

B. Initial GA Benchmarking

In the first evaluation step, we simply consider the objective function as obtained by the GA in comparison to the solution of the ILP. Recall that both approaches are sub-optimal, nevertheless, the ILP solution is a good indication for the overall achievable performance (as it always considers also the integer-relaxation when searching for near-optimal integer solutions). In the following, twenty different drops are taken into account and for each we obtained the objective function for the ILP solution. Next, we determined for each drop ten solutions by the GA, as the GA is a randomized heuristic. These obtained objective functions were then averaged and 95% confidence intervals were computed.

The resulting performance comparison is given in Fig. 5. Note that the objective values obtained by the GA are nearly as good as the ones from the ILP solutions. The maximal deviation occurred for drop number 3, where the GA value is by 2.6% lower than the ILP solution. Finally, one should note the quite small confidence intervals, indicating a low variance of the results obtained by the GA. We conclude from this that the GA is capable of generating very good power profiles.

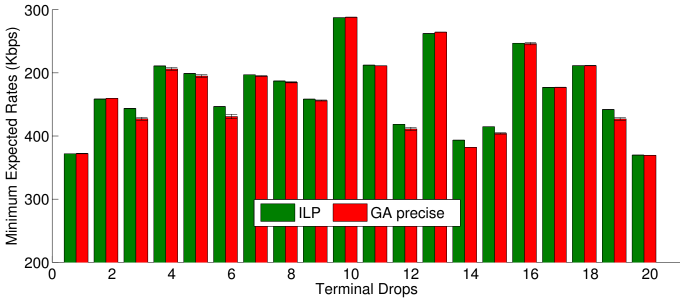


Fig. 5: Comparison of ILP vs. GA scores.

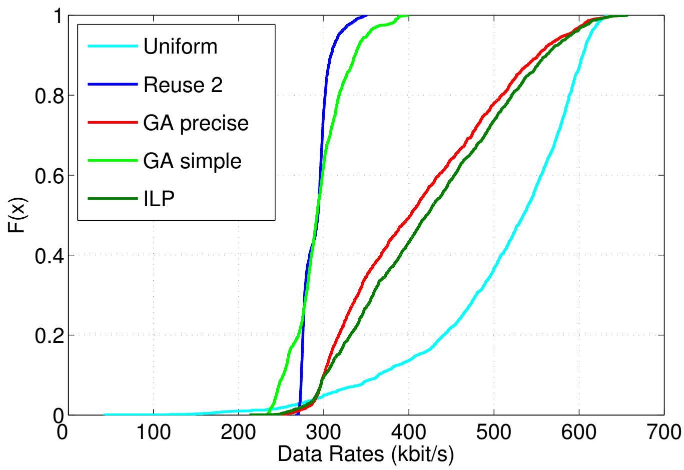
C. Simulation of the Symmetric Load Scenario

As next step we applied the above generated power allocations in the system level simulation. For each drop and power profile we repeated the system level simulation 30 times with different seeds for the random channel generation process. Afterwards, the corresponding average and 95% confidence intervals for the minimum rate per terminal were obtained. These results are given in Fig. 6a. Note that this figure relates to the symmetric load whereas the asymmetric load is discussed in the next subsection.

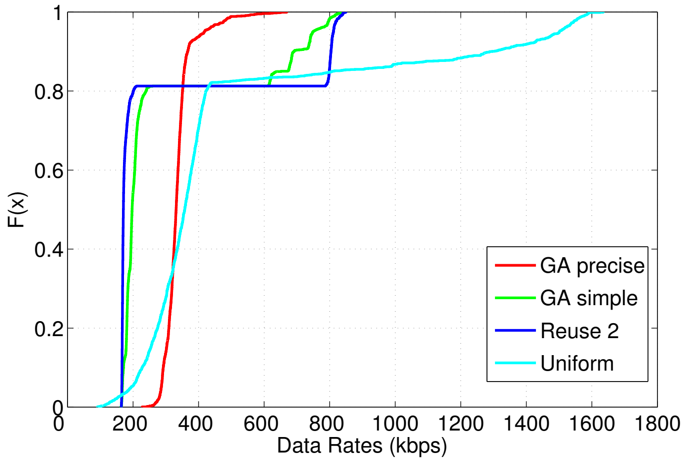
The figure reveals (surprisingly) that in terms of the minimal rates all comparison schemes provide more or less the same performance. The only exception to this observation is the uniform power profile, which provides a much lower minimal rate over all drops. Thus, for a symmetric load scenario, at least under these parameters the cell-edge terminals are treated equally well by the different interference coordination schemes. However, there is still a striking difference in the efficiency of the generated power profiles. This can be seen in Fig. 7a where we show the empirical CDFs over all average rates obtained in the different simulation runs. Here we see clearly a substantial difference between the interference coordination scheme based on the simple model in comparison to the precise model. For example, the best 40% of the terminals receive under a precise model at least an average throughput which is 50% higher. Better overall performance is only provided by the uniform power profile which comes at the cost of having a low cell edge throughput. This performance trade-off is observed often in interference coordination schemes for LTE.

D. Asymmetric Load Scenario

The observations for the symmetric load case become more pronounced in case of the asymmetric loads. Fig. 6b shows the minimal average rates achieved by the different approaches. Here, we observe a significant difference in terms of cell edge performance between the precise and the simple model (at least 50% more rate provided by the precise model). Again, the uniform power profile has the worst performance. Next, if we consider the empirical CDF over all terminal rates in Fig. 7b, we see that the precise model also outperforms the simple model (except for the best 20% of the terminals). We conclude that the usage of a precise performance model is even



(a) Symmetric load scenario.



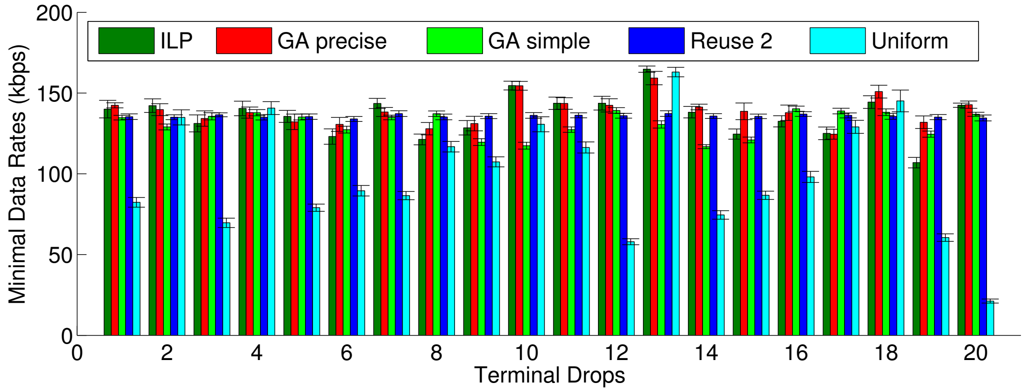
(b) Asymmetric load scenario.

Fig. 7: Empirical CDF of the average rates per terminal.

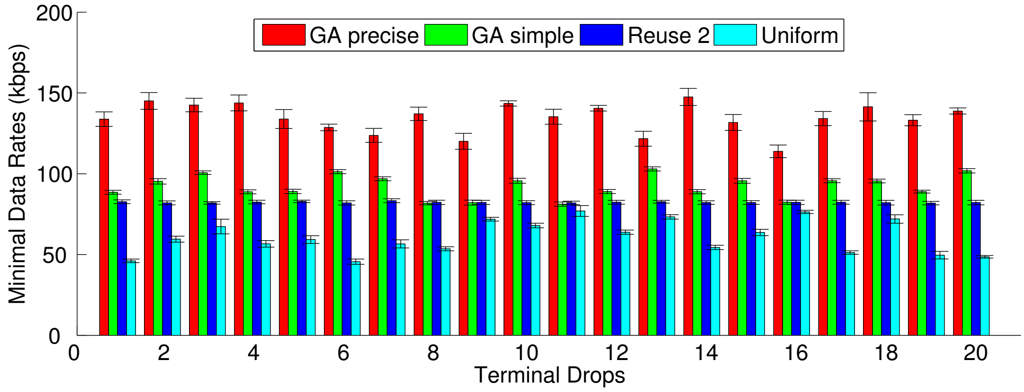
more important if significant load imbalances exist between the cells.

VI. Conclusions

In this paper we have investigated the impact of precise rate prediction models on the design and performance of semi-static interference coordination schemes for LTE networks. Precise rate prediction models allow for an efficient allocation of transmit power among the resource blocks in interfering cells leading to substantial performance improvements in comparison to simpler rate prediction models. However, we find that the computational complexity of the resulting optimization problem increases drastically. The application of genetic algorithms can efficiently mitigate this increase in complexity, as such heuristics generate close-to-optimal solutions while still providing realistic run times. Hence, we conclude that the usage of precise models is essential for semi-static interference coordination schemes. As future work, we are interested in the extension of our analysis to the case of arbitrarily many interferers. In addition, we see significant



(a) Symmetric load scenario.



(b) Asymmetric load scenario.

Fig. 6: Minimal average rates over all terminals for all drops.

potential to drastically reduce the computation times of a genetic algorithm by the usage of graphics processing units and other improvements.

VII. Acknowledgements

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