Rate and UE Selection Algorithms for Interference-Aware Receivers

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Abstract—In cellular communications, user equipment (UE, i.e., mobile device)-side interference cancellation (IC) along with multicell coordinated scheduling can significantly reduce the effect of the downlink intercell interference. To aid UE-side IC, a study item, called network-assisted interference cancellation and suppression (NAICS), has been initiated for Long Term Evolution (LTE) Advanced Release 12. Among NAICS receivers, this paper considers a receiver with interference-aware successive decoding (IASD) capability, which is one of the most advanced UE-side IC techniques. The IASD achievable transmission rate is dependent on the interferer transmission rate. Thus, coordination among multiple cells for rate and UE selection would be necessary for the overall network performance enhancement. In this paper, we consider a single dominant interference model and propose an optimal single-user rate selection algorithm based on the belief-propagation framework. In the multi-user-per-cell case we propose several UE and rate selection algorithms and analyze their performance.

I. INTRODUCTION

In the emerging fourth generation (4G) cellular systems, intercell interference is a major limiting factor on the network downlink performance. Various schemes of interference avoidance and mitigation have been proposed in literature [1] and used in practical systems [2]. Network-side coordination and scheduling are primary techniques for interference avoidance. For instance, the Coordinated Multipoint Transmission (CoMP) framework of 4G LTE Release 11 considers coordination and scheduling among multiple base stations to improve the performance of cell-edge users [3]. However, even with state-of-the-art interference avoidance techniques such as CoMP, the level of residual interference is substantial, which is the major drawback of network-side solutions.

On the other hand, the downlink intercell interference can be mitigated at a UE side. Conventionally, at a UE receiver, a downlink interfering signal is treated as Gaussian noise and its discrete and coded nature are ignored. To handle intercell interference properly, more advanced UE-side interference mitigation needs to be supported by standards. To this end, a study item, called NAICS, has been initiated for LTE Advanced Release 12. Among NAICS receivers, the IASD receiver decodes and cancels the interference signal utilizing the most advanced receiver technique, and thus, increases the achievable transmission rate substantially [4]. Given a constant interfering signal power, the maximal achievable rate of an IASD receiver is highly dependent on the interference modulation and coding scheme (MCS). Therefore, along with IASD, coordinated scheduling of UEs and their MCSs among adjacent cells may achieve a substantial gain in the overall network performance.

In this paper, we consider a cellular network with IASD UE receivers, where each UE is subject to downlink interference from one of the neighboring cells (the dominant interferer), and propose cooperative multicell scheduling algorithms for the network utility maximization. A similar problem has been considered in [5] for wireless networks, where a single receive node per transmit node is assumed and a conventional belief propagation algorithm is applied to solve the MCS selection problem. The authors of [5] claim that their proposed approach finds an optimal MCS assignment in most cases, which is demonstrated through simulations. In this paper we take a different approach in solving the MCS selection problem for the case of a single UE per cell. A modified max-sum-based algorithm is proposed. It is analytically shown that the proposed algorithm always finds the global optimal solution. We also study a more general problem for multiple UEs in each cell (which happens e.g. in cellular networks), and propose algorithms for joint UE/MCS selection.

The paper is organized as follows. In Section II the system model is described. In Section III the rate selection problem for a single UE per cell is studied, and the existent algorithm from [5] and the proposed optimal algorithm are discussed. Section IV considers UE and rate selection algorithms in the case of multiple UEs per cell. The numerical simulation results are presented in Section V. Section VI provides conclusions of this paper.

II. SYSTEM MODEL

We consider a coordination set of $n$ cells $\{C_1, C_2, \ldots, C_n\}$ in a cellular network. At any particular time frame cell $C_i$ is serving $|C_i|$ UEs: $C_i = \{U_{i1}, U_{i2}, \ldots\}$. Only one UE $u_i \in C_i$ has an active downlink connection in each cell $C_i$ (per time slot and frequency slot). We denote the (index of) dominant
interfering cell for UE $U_{ij}$ as $\inf(U_{ij}) \equiv \inf(ij)$. Let $r_i \equiv r_{C_i}$ be the downlink transmission rate (in bits per second) of $i$-th cell (which goes to user $u_i$). $r_i$ can take values from a finite set $\mathcal{M}$ of MCSs. The lowest and the highest rates in $\mathcal{M}$ will be denoted as $r_{\min}$ and $r_{\max}$, respectively.

The system model with interference can be described as follows. Let $P_i$ be the transmitter power of cell $i$, let $G_{i,jk}$ denote the channel gain from the transmitter of cell $i$ to UE $U_{jk}$ in cell $C_j$. Let $N_{jk}$ be the thermal noise power at UE $U_{jk}$. Assuming slow flat fading channel, the achievable rate region of $U_{jk}$ without interference cancellation is given by

$$r_j \leq \log(1 + \rho_{jk}),$$

$$\rho_{jk} = \frac{G_{i,jk}P_i}{\sum_{i \neq j} G_{i,jk}P_i + N_{jk}}, \quad (1)$$

IASD receiver can expand this region by performing decoding and cancellation of some interfering signals. Since joint decoding requires substantial computational complexity, cancellation of just one (dominant) interference signal is considered here. The theoretical limit of the rate region expansion is given by the multiple access channel (MAC) region

$$r_j \leq \log(1 + \hat{\rho}_{jk}),$$

$$r_j + \inf(U_{jk}) \leq \log(1 + \hat{\rho}_{ij} + \hat{\rho}_{\text{int}(U_{ij}),j,k}),$$

$$\hat{\rho}_{ij} = \frac{P_i}{\sum_{i \neq j} G_{i,jk}P_i + N_{jk}}, \quad (2)$$

where $\inf(U_{jk})$ is the transmission rate of the interfering cell $\inf(U_{jk})$. The theoretical IASD achievable rate region is the union of the regions given in (1), (2). It sets a maximal possible rate $r_j$ for any value of the interfering rate $\inf(U_{jk})$. The practically achievable value of $r_j$ may be smaller, but it can still be described by some function of $\inf(U_{jk})$.

Suppose $\inf(U_{ij}) = k$, then we assume that $u_i$’s reliable rate is limited by $r_i \leq f_{u_i}(r_k)$. Rate constraint curve $f_{ij} \triangleq f_{U_{ij}}(r_{\text{int}(U_{ij}))}$ is a non-negative non-increasing function of $U_{ij}$’s dominant interferer rate. Real constraint curves are estimated and updated based on channel state information (CSI) feedback, with more feedback required for more accurate estimation. Note that since $r_k \in \mathcal{M}$, the $U_{ij}$’s performance is fully characterized by a finite set of $(r_k, r_i)$ pairs, as shown by the points on the plot of $f_{ij}(r_k)$ (Fig. 1).

Let $w_{ij} \equiv w_{U_{ij}} \forall i \in [1..n], j \in [1..|C_i|]$ be non-negative scheduling weights of users $U_{ij}$. The choice of UE’s weights is problem specific: for instance, if the network utility function is the total throughput then all weights are equal to 1; if proportional fair scheduling is used then each weight is inversely proportional to the average UE’s transmission rate over some number of the latest time slots. Then the multicell scheduling problem for each time and frequency slot can be formulated as a constrained optimization problem

$$\max_{u_i, r_i} \sum_{i=1}^{n} w_{ij} r_i,$$

such that $r_i \leq f_{u_i}(r_{\text{int}(u_i)}) \quad \forall i \in [1..n],$$

$$u_i \in C_i, r_i \in \mathcal{M} \quad \forall i \in [1..n].$$

(3)

We will also make use of some auxiliary notation. By the interference set of cell $C_k$ we shall mean the indices of UEs whose dominant interferer is cell $k$: $\text{iset}(k) = \{i, j \mid \inf(U_{ij}) = k\}$. By $\text{ngth}(k)$ we denote the set of adjacent cells to cell $C_k$. By $1\{A\}$ we denote the indicator function, which is 1 if $A$ is true, and 0 otherwise. We use $f_{U_{ij}}^{-1}(r_i)$ to denote the inverse function of $f_{U_{ij}}$. It shows the highest rate of $\inf(U_{ij})$ that is compatible with rate $r_i$ of $U_{ij}$:

$$f_{U_{ij}}^{-1}(r_i) \triangleq \max \{r_{\text{int}(U_{ij})} \in \mathcal{M} : f_{U_{ij}}(r_{\text{int}(U_{ij}))} \geq r_i\}. \quad (4)$$

If for some $x \in \mathcal{M}$ $f_{U_{ij}}^{-1}(x)$ is not defined, then we assume that $f_{U_{ij}}^{-1}(x) = -\infty$.

III. THE CASE OF SINGLE UE PER CELL

In the case of single UE per cell the interference structure of the problem can be represented as a directed graph, where nodes correspond to cells $C_i$, and each node $C_i$ has exactly one incoming edge from the node, corresponding to the $u_i$’s dominant interferer $\inf(U_{ij})$. An example of such a graph is shown on the left side of Fig. 2. Generally, the graph may contain more than one connected components. As shown in [5], each connected component contains at most one cycle.

A. The original max-sum algorithm

Linearity of the objective function and sparsity of the constraints (dependencies between variables) allows applying the max-sum message passing algorithm, described in [6], [7], to our problem in (4). This approach is proposed in [5]. The algorithm is a log-domain variation of the max-product
algorithm, which is in turn an instance of the belief propagation (BP) algorithm. BP is widely used in machine learning for performing inference on graphical models, such as Bayesian networks and Markov random fields. The general max-sum algorithm tries to find a variables assignment which maximizes an additive objective function of the variables (logarithm of the joint distribution in random graphical models), conditioned on the dependencies between them according to some graph structure. The algorithm is iterative and local: on each iteration it computes and passes messages between neighboring (dependent) variables. Hence, it does not need a centralized server to operate. The overall computation requirements and signaling overhead are distributed over multiple BSs.

The problem in (4) can be reformulated in a way as follows:

$$\max_{r_i \in M} \sum_{i=1}^{n} (w_i r_i + 1 \{ r_i > f_u, (r_{int(u_i)}) \} P_i).$$  

(6)

Here $P_i$ is a negative number representing a penalty, i.e. decrease in the objective function, for a violation of the constraint $r_i \leq f_u, (r_{int(u_i)})$. The penalties are problem dependent, e.g. large negative values, such as $P_i = -10r_{max}$, do not allow any violations. On the other hand, smaller negative values, such as $P_i = -r_{max}$, or smooth functions, like $P_i = -\exp(r_i - f_u, (r_{int(u_i)}))$, correspond to soft constraints.

BP algorithms operate on an undirected bipartite graph (the right side of Fig. 2) called factor graph with two kinds of nodes: variable nodes (v-nodes), corresponding in our case to variables $r_i$, $i \in [1..n]$, and functional nodes (f-nodes), corresponding to the additive terms in the objective network utility function $g_i(r_i) \equiv w_r r_i$ and $h_i(r_i, r_{int(u_i)}) \equiv 1 \{ r_i > f_u, (r_{int(u_i)}) \} P_i$, $i \in [1..n]$. In the bipartite graph the v-nodes and f-nodes are represented by circles and squares, respectively.

The conventional max-sum algorithm is described in detail in Algorithm 1. Since each cell has one UE, iset(i) holds only cell indices $iset(i) = \{ j \in [1..n] : intf(u_i) = i \}$. Let $m_{r_i h_j}$ be the message going from v-node $r_i$ to f-node $h_j$, and let $M_{h_j r_i}$ be the message going in the opposite direction. Both $m_{r_i h_j}$ and $M_{h_j r_i}$ are vectors with $|M|$ components indexed by $r_i \in M$. In the max-sum the $M$-messages are calculated from the $m$-messages by using the max operation, and the $m$-messages and the beliefs $p_i$ are calculated from the $M$-messages by using the sum operation. $p_i(x)$ represents the belief that in a maximizing variables assignment $r_i = x$, and $r_i^*$ is the value of $r_i$ with the maximal belief.

Algorithm 1 Max-sum for 1 UE per cell

For all $i \in [1..n], j \in iset(i) \cup \{ i \}, r_i \in M$ do $m_{r_i h_j}(r_i) \leftarrow 0$ end for

repeat

For all $i \in [1..n]$ do $M_{h_j r_i}(r_i) \leftarrow \max_{r_i} h_i(r_i, r_{int(i)}) + m_{r_i h_j}(r_i)$ $M_{h_j r_i}(r_i) \leftarrow \max_{r_i} h_i(r_i, r_{int(i)}) + m_{r_i h_j}(r_i)$ end for

For all $i \in [1..n]$ do $m_{r_i h_j}(r_i) \leftarrow g_i(r_i) + \sum_{k \in iset(i) \cup \{ j \}} M_{h_k r_f}(r_k)$ \forall j \in iset(i) \cup \{ i \}$ $m_{r_i h_j}(r_i) \leftarrow m_{r_i h_j} - \max_{r_i} m_{r_i h_j}(r_i)$ \forall j \in iset(i) \cup \{ i \}$ $p_i(r_i) \leftarrow g_i(r_i) + \sum_{k \in iset(i) \cup \{ j \}} M_{h_k r_f}(r_k)$ $r_i^* \leftarrow \arg \max_{r_i} p_i(r_i)$ end for

until convergence in $p_i(r_i)$ or maximal allowed number of iterations

Output $\{ r_i^* \}_{i=1}^{n}$

It is known that on trees (i.e. graphs without cycles) the max-sum algorithm always converges in no more than $n$ iterations, and the resulting assignment is optimal (maximizes the objective function) [6]. On graphs with cycles, there is no guaranteed convergence in general. However, once the algorithm converges on a graph with only one cycle, the resulting variable assignment is always optimal [8]. Although in [5] it is claimed that the max-sum algorithm converges to the optimal solution in most cases, this convergence is not guaranteed even for graphs with one cycle.

B. An optimal scheduler

We propose an Algorithm 2 that can be applied to some subgraph $S \subseteq [1..n]$ of the factor graph, when the conventional max-sum (Algorithm 1) does not converge on this subgraph. The idea is to choose an arbitrary v-node $r_b$ in this subgraph cycle, and to fix the rate $r_b$ to some value $x \in M$. After that, Algorithm 1 is performed, with two exceptions:

- no messages are sent to the v-node $r_b$, and
- all the messages going from the v-node $r_b$ correspond to the assignment where $r_b = x$ is the only possible value for $r_b$: $m_{r_b h_j}(x) = 0, m_{r_b h_j}(y) = -\infty \ \forall y \neq x$.

This virtually destroys the v-node $r_b$ and modifies $r_b$’s neighboring f-nodes $h_j$ so that they emit constant messages to their remaining neighbors. This is equivalent to breaking the cycle in the subgraph and turning it to a tree (Fig. 3). On a tree Algorithm 1 always converges to an optimal solution. Therefore, we find an optimal assignment of other variables (given $r_b = x$) in the subgraph and the corresponding value of the network utility. Trying out all possible values for $r_b$, we can find the largest network utility possible for the original subgraph $S$ and the corresponding optimal rates assignment.

Algorithm 2 guarantees to find an optimal solution at the cost of increasing the complexity at most by factor of $|M|$. The messages corresponding to different values of $r_b$ can be calculated simultaneously (in parallel) in a decentralized manner as in the original max-sum algorithm.
Now let us consider the general problem in (3) with multiple UEs per cell. UEs in the same cell may have different neighboring cells as their dominant interferers. In this section we consider several algorithms, which are suboptimal in the sense that they do not always find the best UE/rate selection. We shall consider decentralized algorithms, which can be efficiently performed by several cells with only local information exchange. Note, that the algorithms in this section output some UE selection, and can be improved by adding Algorithm 2 as a post-process, since Algorithm 2 finds the best rate selection given a UE selection.

A. Greedy scheduling

The easiest way to solve (3) is to greedily choose the best available rate/user combination in each cell after another (Algorithm 3). The algorithm starts with the most conservative rate selections in all cells $r_i = r_{\text{min}}$. It traverses the cooperation set several times, in each cell selecting the user which allows the highest achievable weighted rate (given the rates and UE of all the other cells).

B. Loosest constraint UE selection/max-sum rate selection

Another possibility is to select UE in each cell without regard to the other cells rates. As we want as few rate constraints violations as possible, we may want to try choosing the UE with the greatest (in some sense) rate constraint function, i.e. with the loosest constraint. Algorithm 4, that we propose, for each cell chooses the UE which has the largest weighted constraint $w_{ij} f_{ij}(x)$ at some fixed point $x$. $x$ can be the average rate estimation (in simulation we use $x = (r_{\text{min}} + r_{\text{max}})/2$). For this UE selection Algorithm 2 is run to find the corresponding rate selection.

Unlike other schedulers, this algorithm performs UE and rate selection separately. That significantly reduces the computational complexity and scheduling time.

C. Max-sum

The max-sum algorithm can also be used in the case with multiple UEs per cell and UE scheduling weights. We reformulate the problem as follows:

$$
\max_{u_i, r_i} \sum_{i=1}^{n} \left( w_{u_i, r_i} + \sum_{j=1}^{\left| C_i \right|} I\{u_i = j\} \left( r_i > f_{u_i, i}(r_{\text{int}(u_i)}) \right) P_i \right) 
$$

$$
r_i \in M, u_i \in C_i \quad \forall i \in [1..n].
$$

(7)

The interference graph and the factor graph representation of the problem are presented in Fig. 4. In the interference graph the incoming edge for each UE goes from the dominant interfering cell. In the factor graph there are v-nodes $r_i$, $u_i$ and a f-node $g_{ij}(r_i, u_i) = w_{u_i, r_i}$ for each cell. Each cell $C_i$ also contains one f-node $h_{ij}(r_i, u_i, r_{\text{int}(u_i)}) = \{u_i = j\} \{r_i > f_{u_i, i}(r_{\text{int}(u_i)})\} P_i$ for each UE $U_{ij} \in C_i$. The f-nodes $g_{ij}, h_{ij}$ are connected to the v-nodes $(r_i, u_i)$ and $(r_i, u_i, r_{\text{int}(u_i)})$, respectively.

As before, the messages, going to/from a v-node, are vectors of the dimension corresponding to the number of possible values of the v-node, i.e. $|M|$ for r-node, and $|C_i|$ for u-node. The messages and the rate/UE beliefs are calculated following the ordinary BP rules similar to those in Algorithm 1 according to the factor graph on Fig. 4. The algorithm stops after fixed number of iterations (unless it has converged earlier) and outputs the UE and rate assignment with the maximal belief for each cell. The rate selection in each cell is truncated to the closest point without any constraints violation.
The performance evaluation showed that in the 40 random realizations of the network, which were generated by Algorithm 4, showed the best results. It outperforms the other algorithms by 5–15 percent and has little extra computational complexity (≈ 4|M|^2) per cell per iteration and convergence in < 20 iterations) in addition to that of the simple greedy scheduler. Note, that the resulting utility increases with the number of UEs per cell for all schedulers, since increased diversity of constraint functions allows to find a better combination of compatible cell rates.

VI. CONCLUSIONS

We proposed several distributed algorithms for cooperative multicell rate and UE scheduling of IASD UEs. For the case of one UE per cell, an optimal rate selection algorithm was proposed based on the max-sum algorithm. In the multi-user case, the max-sum algorithm was extended to incorporate the UE selection, and several other suboptimal algorithms were also proposed. A weighted multiuser version of this algorithm was designed. The performance evaluation showed that in the multiuser case the separated UE and MCS selection results in the largest weighted network utility out of all the algorithms proposed.

REFERENCES