JOINT ADMISSION AND POWER CONTROL USING BRANCH & BOUND AND GRADUAL ADMISSIONS

By
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The undersigned hereby certify that they have read and recommend to the Faculty of Graduate Studies for acceptance a thesis entitled "**Joint Admission And Power Control Using Branch & Bound and Gradual Admissions**" by **Dimitrios I. Evangelinakis** in partial fulfillment of the requirements for the degree of **Master of Science**.

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Cogito ergo sum (I think, therefore I am).

René Descartes, French Philosopher / Mathematician

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To my alter ego...

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Abstract

Power control has been extensively studied as an important way of mitigating interference and providing minimum signal to interference plus noise ratio (SINR) guarantees. Such formulation of power control is well-motivated in cellular PCS and UMTS, as both voice and streaming media require guaranteed short-term rates. A key difficulty is that the problem can easily become infeasible, implying that some link(s) must be dropped to accommodate the others. Since joint admission and power control is NP-hard, a host of heuristics have been proposed and implemented over the years, mostly based on the concept of gradual removals. More recently, the joint problem was revisited from a better-motivated Lagrangian relaxation / convex approximation viewpoint. In this contribution, we first derive a corresponding branch & bound algorithm that uses convex approximation for the bounding step. This can tackle moderate problem sizes, yielding optimal solution at much reduced average complexity relative to enumeration. Then, we propose a simple gradual admissions policy that appears promising. Simulations suggest that it can attain admission performance on a par with more complex methods, such as convex approximation, which are in turn known to outperform gradual removals.

Introduction

Power control is an important element of modern cellular and ad-hoc wireless networks, as it provides means of balancing interference and frequency reuse versus quality of service (QoS) for the different users, or boosting network-wide performance metrics such as aggregate throughput. Motivated by the need to support voice service and emerging delay-sensitive broadband applications, the most common formulation of power control aims to provide a desired SINR to each link [16, 6]. Depending on the number and geometry of the different transmitter-receiver pairs, the propagation environment, transmit power limitations, background noise level and SINR requirements of the different links, the SINR - constrained power control problem may or may not be feasible. In loaded cells (e.g., urban hotspots) and in certain power-limited long-haul scenarios, infeasibility is the norm rather than the exception. This difficulty is well-known to cellular engineers, e.g., it is often encountered in UMTS deployments.

There are several ways to deal with infeasibility. For delay-tolerant data, one solution is to back-off the individual SINR requirements, or even aim for a weighted sum-rate 'best-effort' solution [8]. This is not acceptable for voice or streaming media, however, which demand low delay and delay jitter and consistently high short-term rate on each active link. With one or more separate channel(s) available, it may be possible to shift part of the demand to another channel. This is a scheduling decision that should be considered jointly with power allocation across links and channels. The third and least desirable (but often the only) option is to exercise admission control - that is, drop one or more links to be able to accommodate the others. If one is forced to drop links, it is of course preferable to drop as few as possible. Unfortunately, deciding which links to drop is not easy, because the choice of powers is heavily dependent on the choice of admitted links, and the joint admission - power optimization problem is NP-hard. In simple words, this means that we cannot hope to solve an arbitrary instance of the joint problem both optimally and efficiently. Yet the joint problem is highly relevant for cellular networks, motivating many practical heuristics [1, 5, 3, 15, 14, 2, 12, 13]. These fall under two broad classes: *gradual removals* (e.g., [1, 5, 3]) until the problem becomes feasible, or *gradual admissions* (e.g., [15, 14, 2, 12, 13]) from the present network operating state, when possible. In both cases, the issue is whether or not to remove or admit a single user, and adjust transmission powers if necessary.

The joint admission and power control problem was recently revisited in [9, 10] from a better-motivated Lagrangian relaxation / convex approximation viewpoint. The main idea behind convex approximation of NP-hard problems is to first try to approximate the NP-hard problem itself (rather than its elusive solution) using a convex problem or a sequence of convex problems. Solution of the latter is then used to guide the search for a good feasible solution of the original NP-hard problem. Convex approximation has produced notable success stories in recent years, and for certain types of problems it can be theoretically motivated - cf. [7] and references therein. Perhaps the most important example is multiuser / multiple-input multiple-output (MIMO) detection.

Besides convex approximation, a branch & bound-based technique known as sphere decoding is the other workhorse of MIMO detection. One may therefore wonder if sphere decoding (or the more general principle of branch & bound) can be successfully ported to our present context. In this contribution, we first derive a branch & bound algorithm for joint admission and power control that utilizes the convex relaxation and approximation in [9, 10] for the bounding step. This can tackle moderate problem sizes, yielding optimal solution at significantly reduced average complexity relative to brute-force enumeration. Then, we propose a very simple gradual admissions policy that appears promising: interestingly, simulations suggest that it can attain admission performance on a par with considerably more complex methods, such as convex approximation, which are in turn known to outperform gradual removals.

Joint Admission and Power Control Formulation

Consider a set of K co-channel links (also called 'users' in the sequel), indexed by $k \in \{1, \cdots, K\}$. Let $p_k \leq P_k^{MAX}$ denote the transmit power, σ_k^2 the received noise power, and c_k the SINR threshold of link k. Let G_{ij} be the link gain / path loss between the transmitter of link i and the receiver of link j. Checking for joint feasibility of all SINR constraints is a relatively simple linear feasibility problem that can be solved in a variety of ways at cubic complexity. Assuming that this is infeasible, the admission control problem can be formulated as

$$\begin{aligned} S_o = & \underset{S \subseteq \{1,\ldots,K\}, \{p_k \in \mathbb{R}_+\}_{k=1}^K}{\operatorname{argmax}} \quad |S| \\ \text{s.t. :} \quad & p_k \leq P_k^{MAX}, \quad \forall k \in \{1, \ldots, K\} \\ & \frac{G_{kk} p_k}{\sum_{l=1, l \neq k}^K G_{lk} p_l + \sigma_k^2} \geq c_k, \quad \forall k \in S \end{aligned} \tag{0.0.1}$$

where argmax should be interpreted as "an argument that maximizes" - there may be multiple solutions. Given a maximal admissible subset of links, it is natural to select an associated power vector that serves them at minimum sum power, in order to limit power consumption and interference to other nearby systems:

$$\begin{aligned} & \min_{\{p_k \in \mathbb{R}_+\}_{k \in S_o}} \sum_{k \in S_o} p_k \\ \text{s.t. :} \quad & p_k \leq P_k^{MAX}, \quad \forall k \in S_o \\ & \frac{G_{kk} p_k}{\sum_{l \in S_o, l \neq k} G_{lk} p_l + \sigma_k^2} \geq c_k, \quad \forall k \in S_o \end{aligned} \tag{0.0.2}$$

If there are multiple solutions to (0.0.1), the power control problem in (0.0.2) should be solved for each one of them to determine a maximal subset of links that requires minimal power (among maximal subsets).

The power control problem in (0.0.2) is a Linear Program (LP) that is easy to solve. The difficulty lies in the subset selection problem in (0.0.1), which is NP-hard. It has been proven in [9] that, instead of first solving (0.0.1) and then (0.0.2), one may *equivalently* solve the following problem to obtain a maximal subset requiring minimal power in one shot:

$$\begin{aligned}
&\min_{\{p_k \in \mathbb{R}_+, s_k \in \{\pm 1\}\}_{k=1}^K} \epsilon \sum_{k=1}^K p_k + (1-\epsilon) \sum_{k=1}^K (s_k+1)^2 \\
&\text{s.t. :} \quad p_k \leq P_k^{MAX}, \quad \forall k \in \{1, \ldots, K\} \\
&\frac{G_{kk} p_k + \delta^{-1}(s_k+1)^2}{\sum_{l=1, l\neq k}^K G_{lk} p_l + \sigma_k^2} \geq c_k, \quad \forall k \in \{1, \ldots, K\}
\end{aligned} \tag{0.0.3}$$

with

$$\begin{aligned}
0 < \epsilon &< \frac{4}{\sum_{k=1}^K P_k^{MAX} + 4} \\
\delta_k &\leq \frac{4}{c_k(\sum_{l=1, l\neq k}^K G_{lk} P_l^{MAX} + \sigma_k^2)}
\end{aligned} \tag{0.0.4}$$

Note that optimization variable s_k in (0.0.3) takes value 1 if user k is dropped (resp. -1 if admitted). For δ_k as in (0.0.4), s_k serves to (de-)activate the corresponding SINR constraint. Also, the cost in (0.0.3) accounts for both admission and power control; ϵ in (0.0.4) is such that the former has full priority over the latter. The problem in (0.0.3) is of course still NP-hard, for it contains the problem in (0.0.1). We can rewrite the problem in the following form:

$$\begin{aligned}
&\min_{\{p_k \in \mathbb{R}_+, \mathbf{S}_k \in \mathbb{R}^{2\times 2}\}_{k=1}^K} \epsilon \sum_{k=1}^K p_k + (1-\epsilon) \sum_{k=1}^K \mathrm{Tr}(\mathbf{1}_{2\times 2} \mathbf{S}_k) \\
&\text{s.t. :} \quad p_k \leq P_k^{MAX}, \quad \forall k \in 1, \ldots, K \\
&\frac{G_{kk} p_k + \delta^{-1}\mathrm{Tr}(\mathbf{1}_{2\times 2} \mathbf{S}_k)}{\sum_{l=1, l\neq k}^K G_{lk} p_l + \sigma_k^2} \geq c_k, \quad \forall k \in 1, \ldots, K \\
&\mathbf{S}_k \geq 0, \quad \mathrm{rank}(\mathbf{S}_k) = 1, \quad \mathbf{S}_k(1,1) = \mathbf{S}_k(2,2) = 1 \quad \forall k \in \{1, \ldots, K\}
\end{aligned} \tag{0.0.5}$$

where matrix $\mathbf{S}_k$ holds the scheduling variables in its off-diagonal elements. By dropping the rank-one constraint, which is the only non-convex constraint, and therefore relaxing the $\mathbf{S}_k$'s off-diagonal elements to lie on the interval $[-1, +1]$, the problem reduces to a Semidefinite Program (SDP):

$$\begin{aligned}
&\min_{\{p_k \in \mathbb{R}_+, \mathbf{S}_k \in \mathbb{R}^{2\times 2}\}_{k=1}^K} \epsilon \sum_{k=1}^K p_k + (1-\epsilon) \sum_{k=1}^K \mathrm{Tr}(\mathbf{1}_{2\times 2} \mathbf{S}_k) \\
&\text{s.t. :} \quad p_k \leq P_k^{MAX}, \quad \forall k \in 1, \ldots, K \\
&\frac{G_{kk} p_k + \delta^{-1}\mathrm{Tr}(\mathbf{1}_{2\times 2} \mathbf{S}_k)}{\sum_{l=1, l\neq k}^K G_{lk} p_l + \sigma_k^2} \geq c_k, \quad \forall k \in 1, \ldots, K \\
&\mathbf{S}_k \geq 0, \quad \mathbf{S}_k(1,1) = \mathbf{S}_k(2,2) = 1 \quad \forall k \in \{1, \ldots, K\}
\end{aligned} \tag{0.0.6}$$

In [9] it was shown that the Lagrangian relaxation in (0.0.6) is equivalent to an interval-constrained linear program, which can be used to derive a lower bound on the objective of (0.0.3). This relaxation, which will be referred to as SLP (Single Linear Program) approximation in the sequel, can also be used to obtain a 'good' feasible solution of (0.0.3), by keeping only those links whose unmodified SINR constraints are satisfied. A better but more complex strategy advocated in [9] is based on a sequence of LP approximations coupled with user deflation - termed LPD (Linear Programming Deflation) in [9]. Here we will employ SLP and LPD to construct a branch & bound algorithm that enables optimal solution at significantly reduced average complexity relative to enumeration.

Branch & Bound

The problem in (0.0.3) comprises positive real and binary variables - it can be viewed as a mixed integer linear program. For fixed admission control variables $\{s_k\}_{k=1}^K$, the corresponding power optimization is easy. All K admission control variables are free in the full problem in (0.0.3). One may define a hierarchy of problems by fixing the values of a subset of admission control variables. For example, the full problem may be split in two subproblems: one in which s_1 is fixed to 1 and another in which s_1 is fixed to -1. Each one of those can be further split by fixing another admission variable, say s_2, etc, thus generating a tree with 2^K leaves. Solving the power control problem for each and every leaf corresponds to enumeration, which has prohibitive complexity. For this reason, we would like to prune entire branches of the tree early on, if possible, without going all the way down to the leaves. The difficulty is that subproblems corresponding to intermediate nodes and especially those close to the root are hard to solve (optimally).

Suppose we can lower-bound the cost of an optimal solution, and also compute a feasible solution for (thus upper-bound the cost of) a subproblem (node in the tree). Note that here we only require lower and upper bounds instead of optimal solution. Ideally, these bounds should be both cheap to compute and tight. These two properties are typically conflicting, and one should trade-off one versus the other for best overall performance. From a conceptual point of view, however, what is important is the following. Assume we have examined a particular subproblem, and the lower bound on its solution is higher than the tightest attainable upper bound from all nodes already examined. Then that subproblem and all its descendants can be safely pruned without loss of optimality. This is because all children are further restrictions of their parent node (each child has one more admission variable fixed relative to its parent), implying that the children's lower bounds must be greater than or equal to the parent lower bound. This implicit elimination is the key to computational savings, and it can be very effective if substantial pruning happens early on in the process.

The worst-case complexity of branch & bound is of course exponential, due to NP-hardness of (0.0.3); but average complexity can be much smaller in practice if the right bounding strategies are employed. For this we use the state-of-art methods in [9]. In particular, SLP is used for lower-bounding, whereas upper-bounding can be done using either LPD or by 'truncating' the solution of SLP as mentioned above - keeping only those links whose unmodified SINR constraints are satisfied.

Branch & bound is usually implemented using a stack to keep track of nodes / branches that require further examination. A skeleton of branch & bound employed for minimization is given next.

Algorithm 1. *Generic Branch & Bound*

1. *Initialize: insert the full problem in the stack, and set* $U = \infty$.
2. *Remove an active subproblem* F_i *from the stack.*
3. *Compute lower bound* $L(F_i)$.
4. *If* $L(F_i) < U$, *obtain a feasible solution* $\bar{\mathbf{x}}$ *for* F_i, *compute its cost* $U(F_i)$, *split* F_i *in subproblems and insert them in the stack. If* $U(F_i) < U$, *also set* $U = U(F_i)$ *and store* $\bar{\mathbf{x}}$.
5. *If the stack is nonempty, go to step 2; else stored solution is optimal.*

Notice that neither the stack input-output discipline (e.g., first-in, first-out), nor the particular way of splitting is specified in the above. Different stack disciplines may be used to affect breadth-first or depth-first search, and the tree itself can be adaptively grown. We use a fixed binary tree and a breadth-first search. A picture is worth a thousand words here - see Fig. 2 for a helpful illustration of the search process.

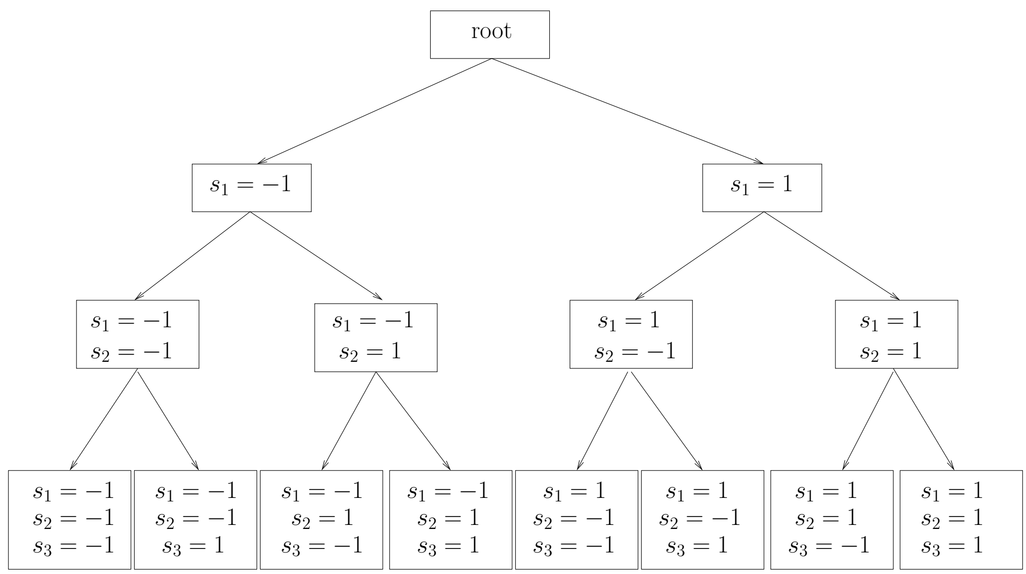

Figure 1: Branch & Bound Search Tree

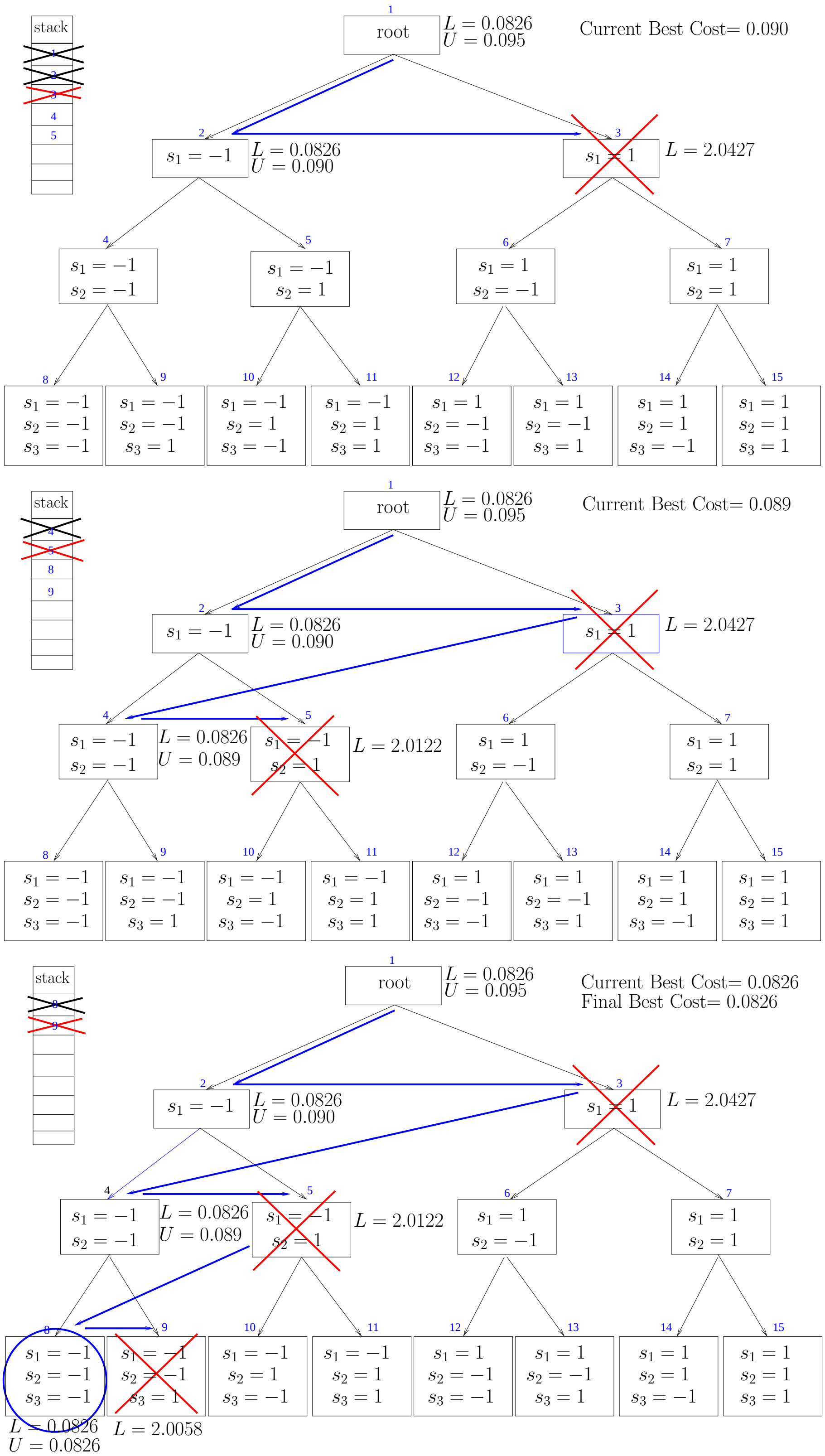

Figure 2: Illustration of search process. Black × means that the node was visited, red × that the corresponding branch was pruned.

Gradual Admissions

In this section, a very simple suboptimal algorithm for (0.0.3) is proposed, based on a gradual admissions strategy. Conceptually, this runs opposite to common approximations based on gradual removals [1, 5, 3]. The idea here is to begin with an empty set and add one user at a time. The new user must be such that the augmented power control problem is feasible, and the user that leads to minimum sum power is chosen in case of multiple candidates. Feasibility can be efficiently checked through a spectral radius computation. Ignoring the individual power constraints for brevity, and considering

$$\begin{aligned} &\min_{\{p_k \in \mathbb{R}_+\}_{k=1}^K} \sum_{k=1}^K p_k \\ \text{s.t. } : &\frac{G_{kk} p_k}{\sum_{l=1, l \neq k}^K G_{lk} p_l + \sigma_k^2} \geq c_k, \quad \forall k \in \{1, \ldots, K\} \end{aligned} \tag{0.0.7}$$

the constraints can be expressed in matrix form as $(\mathbf{I} - \mathbf{\Gamma F})\mathbf{p} \geq \mathbf{u}$, where the inequality applies element-wise, and with obvious notation

$$\mathbf{\Gamma} := \operatorname{diag}(\mathbf{c}), \mathbf{F}(k,l) := \begin{cases} 0, & k = l \\ \frac{G_{lk}}{G_{kk}}, & k \neq l \end{cases}, u_k := \frac{c_k \sigma_k^2}{G_{kk}}. \tag{0.0.8}$$

Problem (0.0.7) is feasible if and only if the spectral radius (maximum absolute eigenvalue) $\rho(\mathbf{\Gamma F})$ is less than one (e.g., see [11]). In this case, $(\mathbf{I} - \mathbf{\Gamma F})^{-1}\mathbf{u} \geq \mathbf{0}$ is the (minimum power) solution of (0.0.7). We thus arrive at the following simple algorithm, which, other than spectral radius computations, never solves an optimization problem.

Algorithm 2. *Gradual Admissions*

1. $S = \emptyset$ *(no user served).*

2. *For* $m \notin S$*, construct* $\mathbf{\Gamma}, \mathbf{F}, \mathbf{u}$ *for* $S \cup \{m\}$*. If* $\rho(\mathbf{\Gamma F}) < 1$*, compute associated power vector* $(\mathbf{I} - \mathbf{\Gamma F})^{-1}\mathbf{u}$ *and check if element-wise power constraints are satisfied. If so, user* m *is a candidate for admission.*

3. *Among all feasible candidates in step 2 above, pick the one that yields smallest sum power and add to* S*.*

4. *Repeat until no other user can be admitted.*

Experiments

We used brute-force enumeration to verify correctness and assess the average complexity improvement of branch & bound approaches relative to exhaustive search. The state-of-art LPD algorithm in [9] was also included as a polynomial complexity baseline as well as GRN-DCPC in [1].

All figures report Monte-Carlo (MC) average results for 200 MC runs. For each MC run, a new problem instance is generated. Transmitter locations are chosen at random from a uniform distribution over a 2km × 2km square. Each receiver is then randomly drawn from a uniform distribution over a disc of radius $400m$ ($300m$ in the 2nd experiment) centered at the respective transmitter. $G_{ij} = 1/d_{ij}^4$, where d_{ij} is the Euclidean distance between transmitter i and receiver j. $P_k^{MAX} = \alpha P_k^{MIN}$, where P_k^{MIN} is the minimum power required for link k to reach minimum operational SINR $c_k = 2dB$ without any interference, $\sigma_k^2 = -60dBm$, and $\alpha = 4$.

Fig. 3 shows the average number of users admitted versus the number of users that request service. Branch & bound and enumeration yield identical solutions, and LPD is close, as expected. Perhaps surprisingly, the simple gradual admissions algorithm meets the performance of LPD.

Fig. 4 (5) shows the mean (resp. maximum) execution time of each algorithm. Note that branch & bound using LPD for upper bounding is two orders of magnitude faster than enumeration, on average, for modest $K = 18$; branch & bound using the simpler and looser SLP for upper bounding is even faster (cf. Fig. 6, which shows that the mean number of nodes examined is similar). Gradual admissions is by far the cheapest option, as expected. Note also the stability of execution times for (worst-case polynomial-time) LPD, whose mean and maximum are very similar.

Finally, Figs. 7 and 8, depict mean and maximum power for all methods considered. Note that the gradual admissions algorithm occasionally serves fewer users than is possible, which explains why its power can be less than that of the optimal solution.

In the second experiment we set $D_{max} = 300m$ in order to decrease interference and consequently increase system's capacity. All the other parameters are those used in the previous setup. Figs. 9 - 13 show the simulation results.

An interesting observation is that as the interference reduces, thus the system's capacity increases, more users can be admitted and consequently more problem subsets must be explored by Branch & Bound. As shown in fig. 14, the more the interference reduces, the more the iterations of Branch & Bound increase.

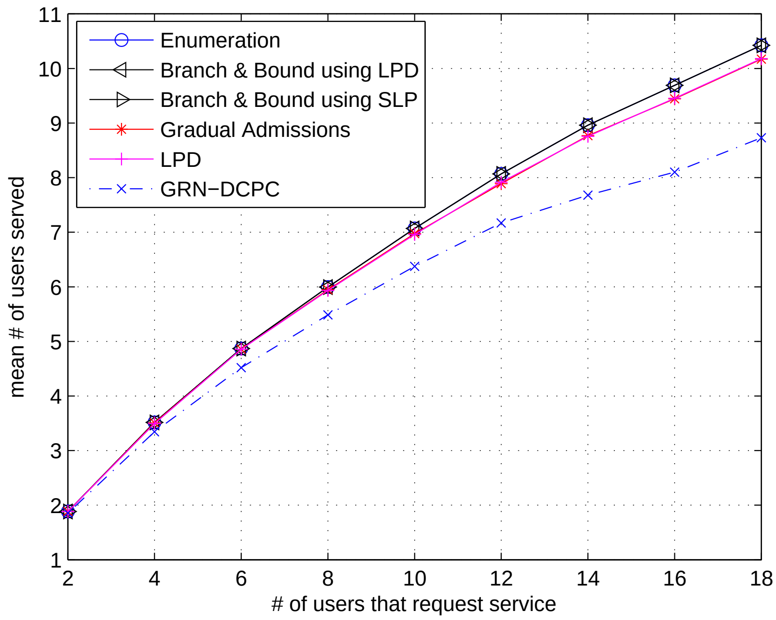

Figure 3: Average # of users served vs K

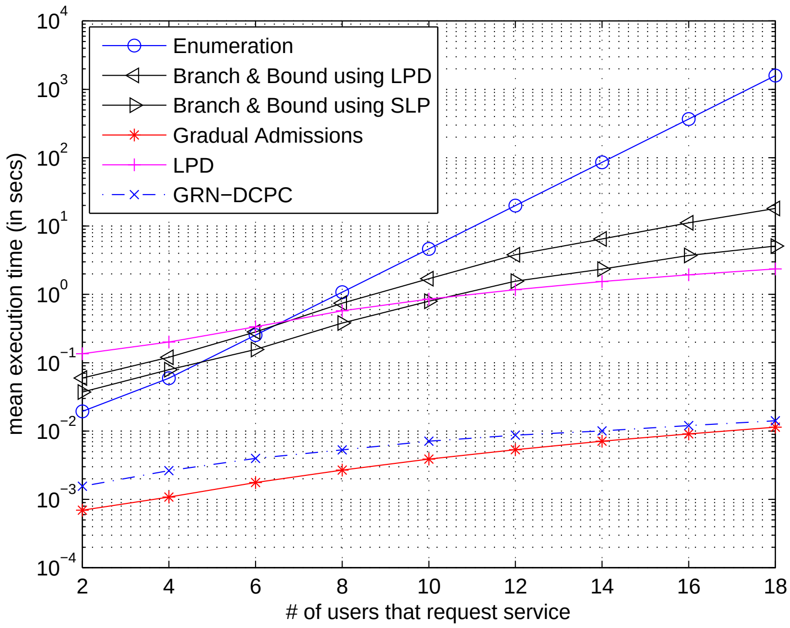

Figure 4: Average execution time (in secs) vs K

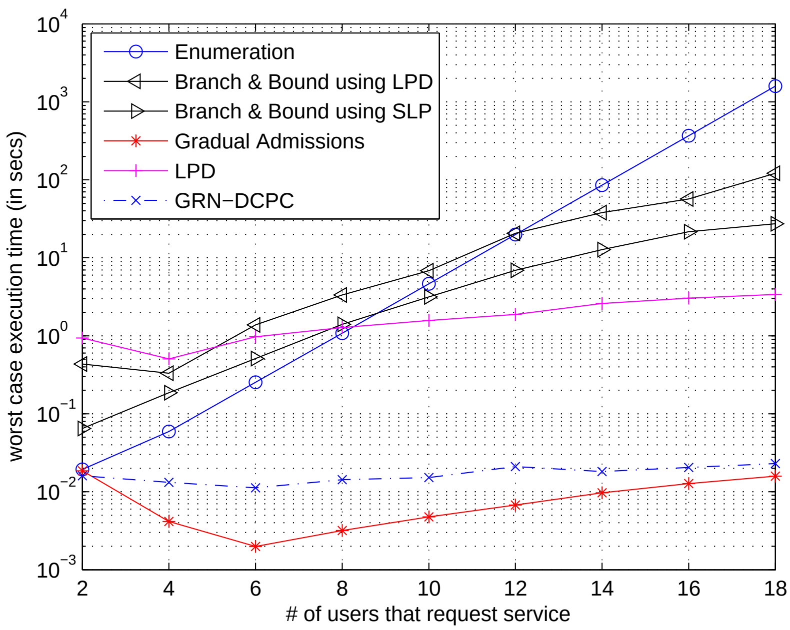

Figure 5: Worst case execution time (in secs) vs K

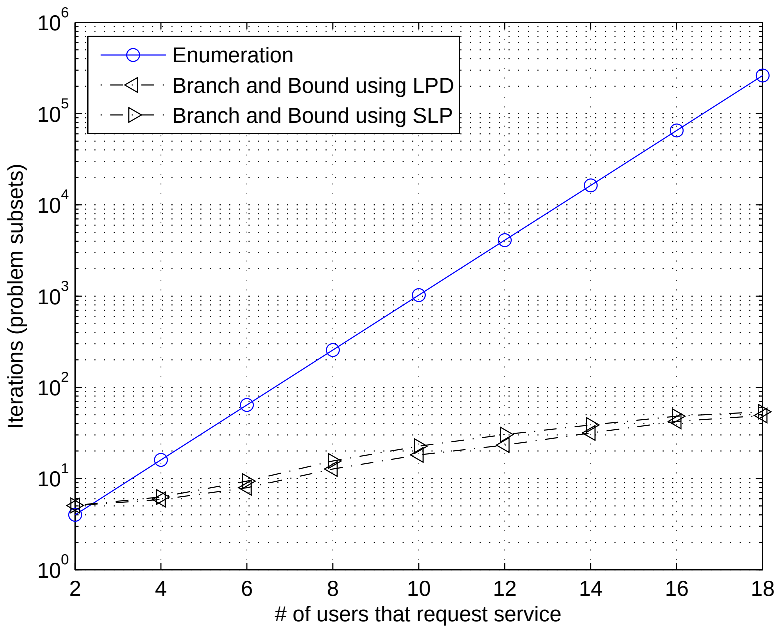

Figure 6: Average # of iterations vs K

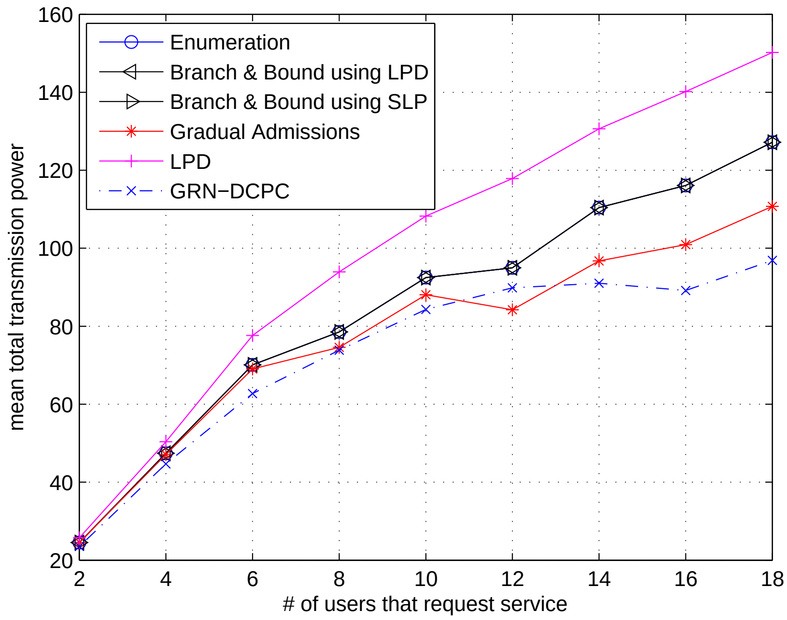

Figure 7: Average transmission power vs K

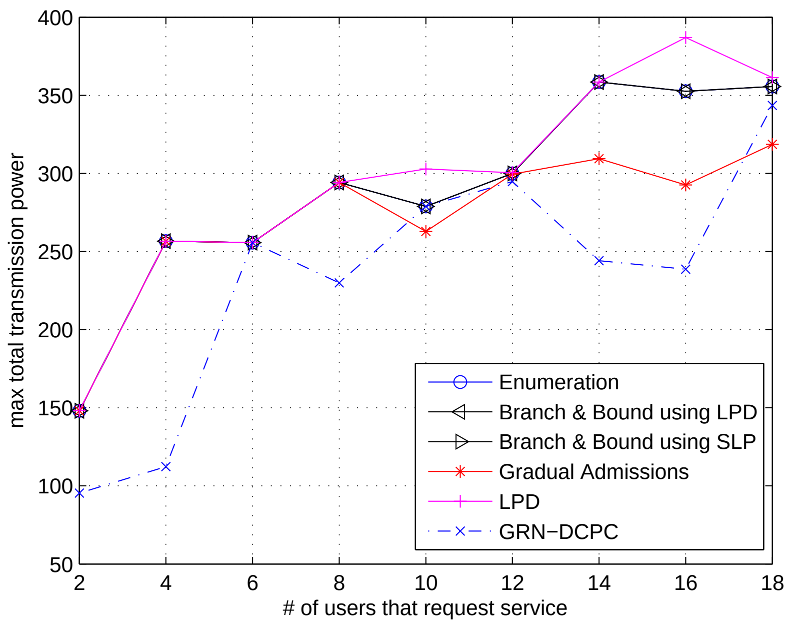

Figure 8: Worst case transmission power vs K

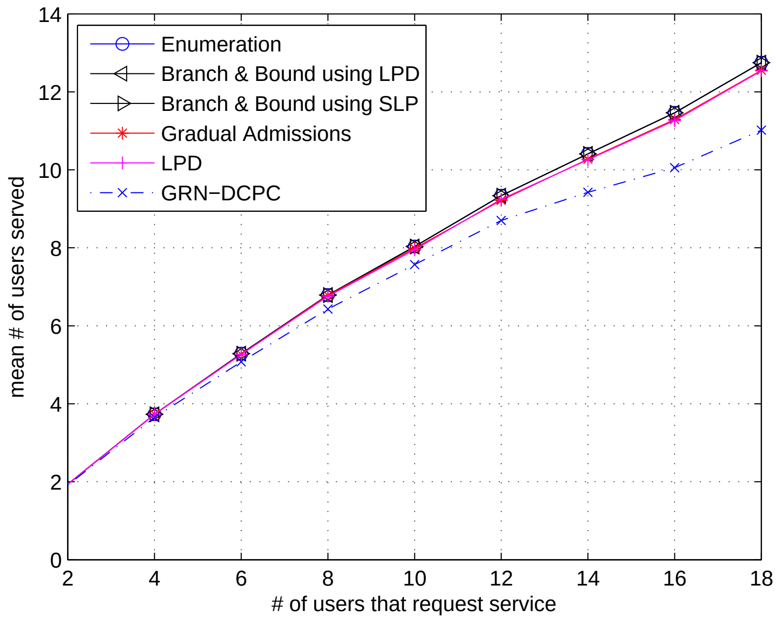

Figure 9: Average # of users served vs K

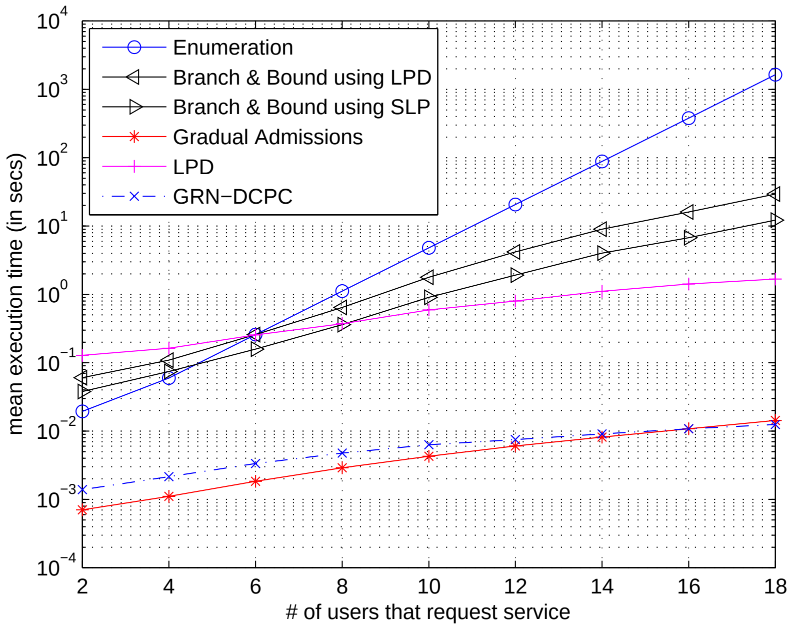

Figure 10: Average execution time (in secs) vs K

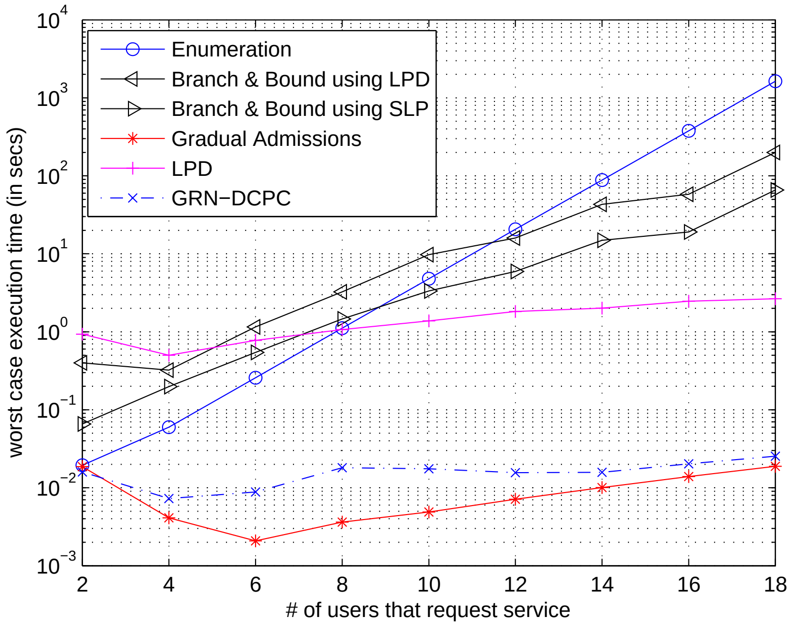

Figure 11: Worst case execution time (in secs) vs K

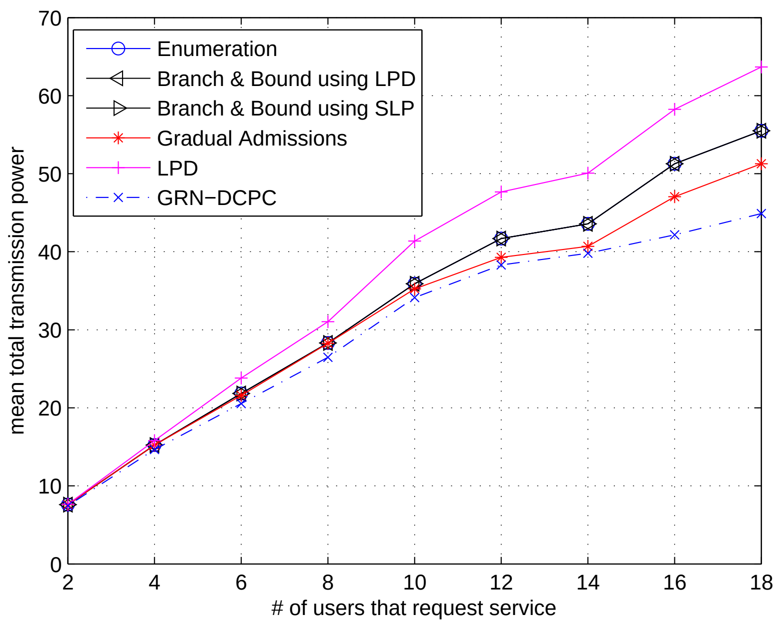

Figure 12: Average transmission power vs K

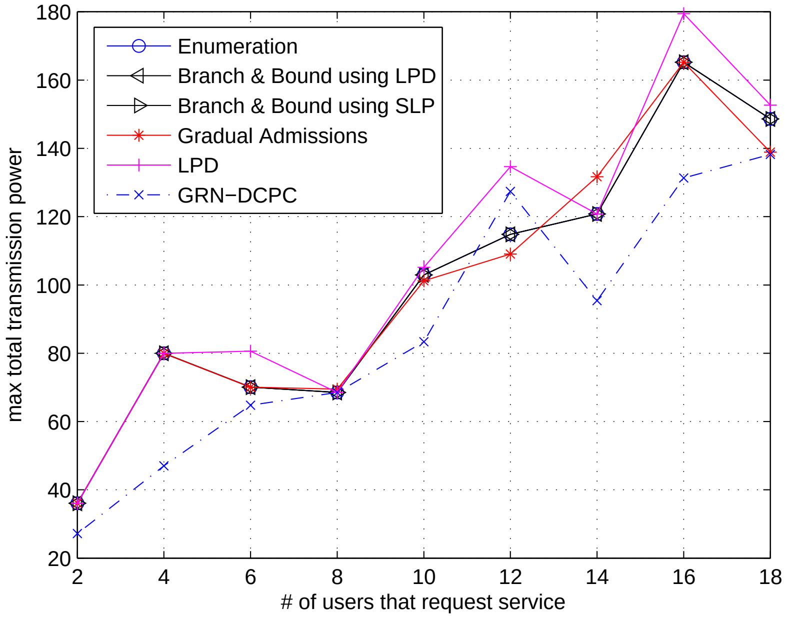

Figure 13: Worst case transmission power vs K

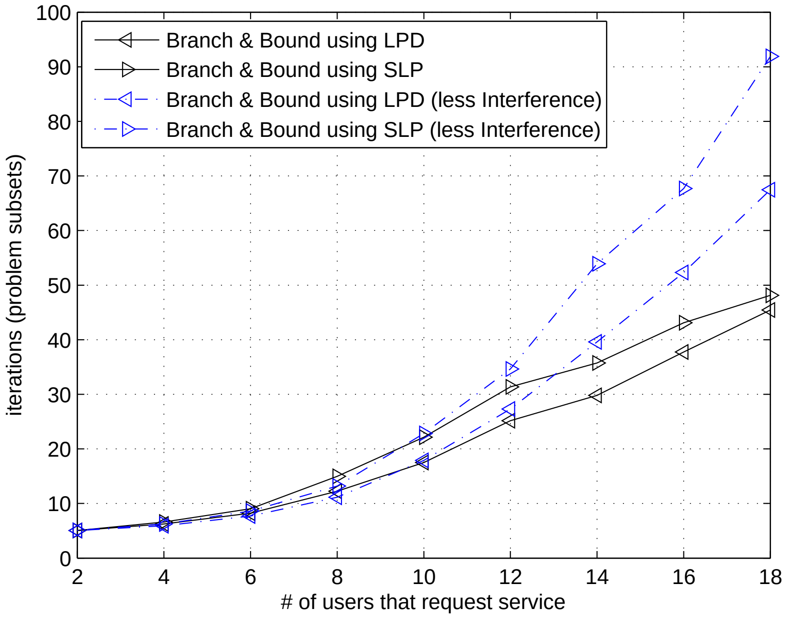

Figure 14: Average # of iterations vs K vs Interference

Conclusion

We have fleshed out a branch & bound algorithm for joint admission and power control, which utilizes the convex relaxation and approximations in [9, 10] for the bounding step. This algorithm can be used to generate optimal solutions at significantly reduced average complexity compared to enumeration, at least for small to moderate problem sizes. It is also possible to trade-off accuracy for speed of computation, by using $U - \epsilon$ instead of U as the branching threshold - this ensures that the final solution will be within ϵ from optimal, see Ch. 10 in [4]. For larger problems, we proposed a very simple gradual admissions policy that appears promising. Our simulations, albeit limited, suggest that it can attain admission performance on a par with considerably more complex methods - such as convex approximation which is known to outperform gradual removals from [9, 10]. A drawback is that the gradual admissions policy proposed here is centralized, whereas convex approximation admits distributed implementation [9, 10].

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