Comparative Study of Approximation Algorithms and Heuristics for SINR Scheduling with Power Control*

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Abstract. Various recent theoretical studies have achieved considerable progress in understanding combined link scheduling and power control in wireless networks with SINR constraints. These analyses were mainly focused on designing and analyzing approximation algorithms with provable approximation guarantees. While these studies revealed interesting effects from a theoretical perspective, so far there has not been a systematic evaluation of the theoretical results in simulations. In this paper, we examine the performance of various approximation algorithms and heuristics for the common scheduling problems on instances generated by different random network models, e.g., taking clustering effects into account. Using non-convex optimization, we are able to compute the theoretical optima for some of these instances such that the performance of the different algorithms can be compared with these optima.

The simulations support the practical relevance of the theoretical findings. For example, setting transmission power by a square-root power assignment, the network's capacity increases significantly in comparison to uniform power assignments. Furthermore, the developed approximation algorithms are able to exploit this gap providing in general a better performance than any algorithm using uniform transmission powers, even with unlimited computational power. The obtained results are robust against changes in parameters and network generation models.

1 Introduction

Triggered by a seminal work by Moscibroda and Wattenhofer [15], recent algorithmic research on wireless networks has mostly been considering models based on the signal-to-interference-plus-noise ratio (SINR). Using such models, important aspects such as aggregation of interference or different transmission powers are taken into account. Most prominently, approximation algorithms for the combined problem of link scheduling and power control (see Section 1.2) have been considered. However, devising approximation algorithms in a worst-case model

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does not necessarily lead to practical results since the approximation ratio might attain its maximum only in artificially created instances. There has not been a systematic evaluation of the theoretical results in simulations up to now. In this paper, we examine how approximation algorithms that were originally designed in the context of theoretical worst-case analyses perform on randomly generated instances.

We focus on the *capacity-maximization problem*. Given n communication links, each being a pair of a sender and a receiver node, the task is to select a maximum subset of them and assign transmission powers such that the SINR is above some threshold at the receiver of each link in the set. Already Moscibroda and Wattenhofer showed that setting transmission powers appropriately is inevitable for good worst-case performance guarantees in certain networks. For example, for the capacity-maximization problem there are networks in which all n links can be scheduled with the right transmission powers. Restricting all transmissions to use uniform powers even the best solution is hardly better than the trivial one that only selects a single link.

We strive to examine whether these results are particular to the respective worst-case networks or whether similar results can still be observed in randomly generated networks. We tackle these questions from two sides. In the first step, we investigate whether the effect of power control is as important as suggested by theoretical studies. For this purpose, we compare the theoretical optima of several power assignments, including the respective optimal choice. As the involved problems are NP hard, computing each of these optima needs exponential running times. For this reason, in the second step, we focus on approximation algorithms and heuristics that run in polynomial time. We compare the computed approximate solutions with the respective optimum. In both steps, we use non-convex optimization to compute the optimal solution.

1.1 Formal Problem Statement and the SINR Model

We model the interference constraints as follows (cf. [8]). We assume that the network nodes are located in a metric space. In our simulations this is the plane with the Euclidean distance. We model the signal propagation as follows. Assume that some sender s transmits a signal at power level p, then receiver r receives this signal at a strength of $p/d(s,r)^\alpha$. Here, $\alpha > 0$ denotes the path-loss exponent, that is typically assumed to be between 2 and 6. The transmission can be successfully received if its signal-to-interference-plus-noise ratio (SINR) is above some threshold $\beta > 0$. That is, the strength of the intended signal has to be β-times as strong as all simultaneous interfering signals plus ambient noise.

Formally, a set S of sender-receiver pairs (links) is feasible under a power assignment $p\colon S \to \mathbb{R}_{\geq 0}$ if for all $\ell = (s,r) \in S$ the SINR constraint

$$\frac{p(\ell)}{d(s,r)^\alpha} \geq \beta \left(\sum_{\ell'=(s',r') \in S, \ell' \neq \ell} \frac{p(\ell')}{d(s',r)^\alpha} + N \right)$$

is fulfilled, where $N \geq 0$ denotes ambient noise. In the *capacity-maximization problem*, one is given a set $\mathcal{R}$ of n links. The task is to select a subset $S \subseteq \mathcal{R}$ and a power assignment $p\colon S \to \mathbb{R}_{\geq 0}$ such that S is feasible under p. The objective is to maximize $|S|$.

1.2 Considered Approximation Algorithms

For the problem of combined link scheduling and power control a number of heuristic approaches have been proposed to solve this problem exactly [3] or approximately [18,4]. These algorithms, however, rely on stochastic assumptions on the distribution of the network nodes. They do not run in polynomial time or do not provide provable performance guarantees [14].

First theoretical studies of approximation algorithms for link scheduling in the SINR model concentrated on uniform power assignments. Goussevskaia et al. [7] presented an approximation algorithm for the capacity maximization problem that achieves a constant approximation factor with respect to the optimal solution using uniform power assignments. That is, the computed solution is compared to only the ones using the same power for each transmission. A simplified version of this algorithm has been presented by Halldórsson and Wattenhofer [11], which has been implemented for the simulations.

Andrews and Dinitz [1] also gave an approximation algorithm for capacity maximization with uniform transmission powers. Their analysis, however, is with respect to an arbitrary power assignment. The approximation factor is shown to be $O(\log \Delta)$, where Δ is the ratio between the largest and the smallest distance between a sender a receiver. Furthermore, they proved the combined scheduling and power control problem to be NP hard.

Going beyond uniform power assignments, oblivious power assignments have been considered. Here, the transmission power may only depend on the distance between the sender and the respective receiver. The most prominent representatives are linear and square-root power assignments. In a linear power assignment $p(\ell)$ is proportional to $d(\ell)^\alpha$ for all links ℓ. The obtained theoretical results are comparable to the ones with uniform power assignments [5]. Better ones can be achieved using square-root (or mean) power assignments, which set all powers $p(\ell)$ proportional to $\sqrt{d(\ell)^\alpha}$. They have been introduced by Fanghänel et al. [5], who showed that they allow to achieve $\log^{O(1)} n$ approximations for capacity maximization in a bidirectional model. Halldórsson [9] extended this study to the standard directed communication model, giving an $O(\log\log \Delta \cdot \log n)$ approximation algorithm for capacity maximization. Halldórsson and Mitra [10] improved this factor to $O(\log\log \Delta + \log n)$. Up to now, this is the best approximation algorithm using square-root power assignments. Therefore, it has been implemented for our simulations as well.

All oblivious power assignments, however, have the drawback that the approximation factors do and have to depend on Δ. Fanghänel et al. [5] showed that for any oblivious power assignment there are certain network instances in which the optimal solution with arbitrary power assignments is of size $\Omega(n)$. Restricting the transmission powers to the respective oblivious power assignment the optimum degrades to $O(1)$. That means that an algorithm using uniform transmission powers cannot achieve a better worst-case approximation factor than

$O(n)$, which is also achieved by the trivial algorithm that just selects a single link. The first approximation algorithm guaranteeing an approximation factor that is independent of the network was presented by Kesselheim [12]. An extension shows how to deal with restricted transmission powers [16]. We consider the original algorithm for our studies.

1.3 Our Results

One of the most striking results from the design of approximation algorithms is the square-root power assignment. Theoretical studies show that it is superior to uniform and linear power assignments but optimizing the power assignment for the respective instance can still yield better results. Our simulation results support this insight. Using non-convex optimization, we compute the optimal subset of links with respect to arbitrary power assignments and also with respect to uniform, linear, and square-root power assignments. The results indicate that the square-root power assignment is able to partly exploit the potential of power control. That is, the optimal solution is significantly better than the ones using uniform or linear power assignments. However, like in theoretical worst-case considerations, also in our randomly generated instances setting transmission powers yields better results. We carry out these simulations for networks of up to 800 links.

The mentioned computation of the optimal solution is NP hard. Therefore, the computation needs exponential time in general. Also in our simulations, running times get prohibitively large in large instances. For this reason, approximation algorithms have been developed that need a linear or quadratic running time in the number of links. We execute these algorithms on randomly generated instances, consisting of up to 1600 links. These simulations also support the theoretical findings. Algorithms explicitly setting the transmission powers are able to outperform the optimum with uniform power assignments. That is, using power control these algorithms are able to provide better solutions than any algorithm using uniform transmission powers could compute, even with unlimited computational power. However, the theoretical inferiority of the square-root power assignment compared to the constant-factor approximation [12] cannot be observed in the randomly generated instances. Interestingly, all approximation algorithms and heuristics achieve comparable results.

In order to eliminate effects of particular networks or parameters, we repeat all simulations with differently generated networks, with and without clustering. Furthermore, we apply multiple parameter settings. This changes the absolute number of links that can be scheduled. In either case, the relative performance is similar. In particular, the ranking of the algorithms and power assignments is consistent.

2 Generation of Network Instances

For our simulations, we construct network instances applying two different techniques. In each case, we randomly place n sender-receiver pairs in a 1000×1000

square on a plane. These links have length at least 0 and at most L, which is a parameter. Precision for all involved numbers is *double*. Two example networks generated with the two models are depicted in Figure 1.

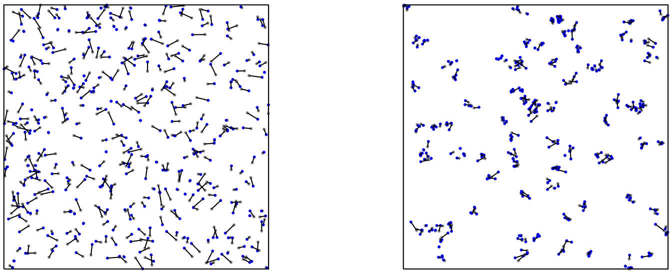

Fig. 1. Two example instance with 400 requests and $L = 50$. Left: Unclustered Network Right: Clustered Network with exponential distribution, $\gamma_c = \gamma_r = 0.2, c = {}^{n}/_{5}$.

The simplest way of construction is an *unclustered network*. Here, we first determine for each link independently the position of the sender node s uniformly in the plane. In the second step, for each sender we place the corresponding receiver r independently. This is performed by selecting a vector k by determining an angle δ uniformly from $[0, 360°)$ and a distance d uniformly from $[0, L)$. The receiver r is then placed by $r = s+k$ if this point lies inside the given 1000×1000 plane. Otherwise, this step is repeated.

Real-world networks typically show clustering effects and that most distances are comparably short. These aspects are taken into account in *clustered networks with exponential distribution* (see, e.g., [17]). We first select c cluster centers independently uniformly at random in the plane. Afterwards, in the vicinity of each cluster center ${}^{n}/_{c}$ sender nodes are placed. For each sender the respective receiver is then placed similarly in the vicinity of its sender. In both steps, an angle and a distance are selected independently. The angle is again chosen uniformly at random from $[0, 360°)$. The distance between the cluster center and the sender is determined using an exponential distribution with mean $\gamma_c \cdot L$. For the distance between the sender and the receiver node, we use an exponential distribution with mean $\gamma_r \cdot L$. If a node lies outside the plane or one of the distances exceeds L, the step is repeated.

All of the results presented in this paper were obtained for clustered networks with $L = 50$, $\gamma_c = \gamma_r = 0.2$, and $c = {}^{n}/_{5}$. The SINR parameters were set to $\alpha = 4$ and $\beta = 1$. In terms of absolute numbers the choice of the network model and its parameters make a large difference in our simulations. However, the relative performances seem to be robust against changes in the model or in the parameters. A further discussion of this issue is deferred to the full version.

3 Comparison of Power Assignments

In order to benchmark different power assignments, we compare the theoretical optima in the respective cases. To do so, we solve the capacity-maximization problem with a fixed power assignment as integer linear program (ILP) as follows. For each link ℓ, we have an indicator variable x_ℓ being assigning the value 1 (accepted) or 0 (rejected). The objective is to maximize the sum of all indicator variables.

$$\max \sum_{\ell \in \mathcal{R}} x_\ell \tag{1a}$$

$$\text{s.t. } \tfrac{p(\ell)}{d(s,r)^\alpha} + M(1 - x_\ell) \geq \beta \left(\left(\textstyle\sum_{\ell'=(s',r') \neq \ell} \tfrac{p(\ell')}{d(s',r)^\alpha} x_{\ell'} \right) + N \right) \quad \text{for all } \ell = (s,r) \in \mathcal{R} \tag{1b}$$

$$x_\ell \in \{0,1\} \quad \text{for all } \ell \in \mathcal{R} \tag{1c}$$

The SINR constraint modeled in Equation (1b) has to be satisfied by each active request ℓ. That is, depending on the binary variable x_ℓ the respective constraint has to be fulfilled or not. To effect this behavior and to receive a linear program so called *big M formulations* are used, setting M to a sufficiently large constant. To ensure numerical robustness, the input for the LP solver was expressed using *indicator constraints*. Internally, the LP solver transforms these constraints and sets suitable values for M.

To optimize over all possible power assignments, we use the following mixed integer linear program (MILP).

$$\max \sum_{\ell \in \mathcal{R}} x_\ell \tag{2a}$$

$$\text{s.t. } \tfrac{p_\ell}{d(s,r)^\alpha} + M \cdot (1 - x_\ell) \geq \beta \left(\left(\textstyle\sum_{\ell'=(s',r') \neq \ell} \tfrac{p_{\ell'}}{d(s',r)^\alpha} \right) + N \right) \quad \text{for all } \ell = (s,r) \in \mathcal{R} \tag{2b}$$

$$0 \leq p_\ell \leq p_{\max} x_\ell \quad \text{for all } \ell \in \mathcal{R} \tag{2c}$$

$$x_\ell \in \{0,1\} \quad \text{for all } \ell \in \mathcal{R} \tag{2d}$$

In this program, we have for each request ℓ a variable p_ℓ specifying the respective transmit power. Again, big M formulations ensure that the SINR constraint is satisfied for each link having $x_\ell = 1$. If $x_\ell = 0$, the SINR constraint does not need to be fulfilled and the power is set to 0.

3.1 Simulation Setting

Our simulations were run with the optimization software CPLEX v12.2. In order to eliminate effects of particular networks or parameters, we repeated all simulations with differently generated networks, with and without clustered structure. Furthermore, we applied multiple parameter settings. Although the absolute number of links that can be scheduled depends greatly on network and parameter settings, the relation between the optima does not change significantly. We ran 10 simulations for each setting and calculated the average result.

With the presented models for the non-convex optimization we computed the optimal subset of links with respect to arbitrary power assignments and also with respect to uniform, linear, and square-root power assignments. For fixed power assignments we were able to calculate optimal results regarding the maximum capacity problem up to a network size of 1600 requests.

The problem gets significantly more involved when attempting to optimize the power assignment. With an increasing number of transmissions it gets rapidly harder to reduce the remaining integer gap. Thus, we set a time limit of 3 hours or accepted the results as the optimal results when the integer gap reduced to a value of less than 3 %. We were able to generate optimal results for networks with less than 200 requests. For networks consisting of more than 200 requests the time limit took effect. That is, the obtained solution is more than 3 % worse than the fractional upper bound at this point. However, we use these solutions for our considerations. This is due to the fact that choosing a much larger time limit could not improve the qualities of the solutions significantly. Furthermore, the solutions obtained up to this point still turned out to be significant since they outperformed the maximal number of scheduled requests achieved with a fixed power assignment.

3.2 Simulation Results

Figure 2 shows the results of the comparison of uniform, linear, and square-root power assignments with the optimized one for network sizes of up to 800 requests. Network instances consisting of 1600 requests did not yield meaningful outputs

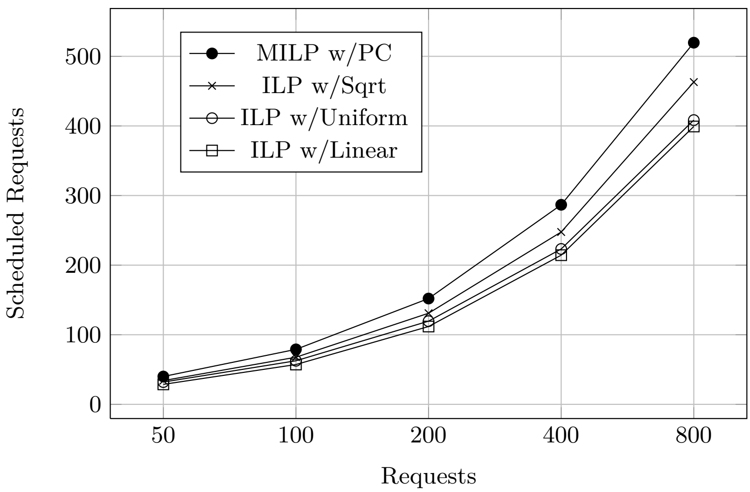

Fig. 2. Comparison of Theoretical Optima (10 test runs)

for the case of power control. The results are given for "standard" parameters but, as further explained in the full version, the ranking of the algorithms and the behavior remained consistent for all tested parameters.

As mentioned in the previous section, the displayed values for the mixed integer linear program are only the best solutions computed within 3 hours. Although these are not necessarily the theoretical optima, they already reveal the potential given by the use of power control. For example, given a clustered network with 800 requests, it can be observed that a linear or uniform power assignment can select about half of the requests on average. The number of requests selected with power control is more than 500 requests on average. Hence, using power control for this parameter setting allows a performance gain of 15 – 17% compared to uniform power assignments. Square-root power assignments are partly able to exploit this potential of power control. The network capacities generated with square-root power assignments are significantly larger than the capacities achieved with a uniform or linear power assignment. Thus, the assumed theoretical advantage of square-root power assignments could clearly be confirmed.

Table 1 presents the remaining integer gap for the MILP approach on a typical network instance. A further interesting fact is presented by the last column of Table 1 giving the ratio between the best achieved ILP solution with a uniform power assignment and the best achieved integer solution of MILP. This ratio stays constant at about 80 % also for larger networks. This suggests that the obtained solutions are nearly optimal ones for the MILP approach.

4 Evaluation of Approximation Algorithms

For our simulations, we implemented the following three algorithms, each being a constant-factor approximation for the respective optimum (see Section 1.2): The algorithm by Kesselheim [12] using power control, abbreviated by *Kess*, the one by Halldórsson and Wattenhofer [11] using uniform transmission powers (HW), and the one by Halldórsson and Mitra [10] using square-root power assignments (HM).

The three employed approximation algorithms have the same underlying working principle. They examine the requests of the network in order of increasing length. A request ℓ' is (tentatively) selected if it satisfies a condition of the form $\sum_{\ell \in \mathcal{L}} w(\ell, \ell') \leq W$, where $\mathcal{L}$ is the set of previously selected links. The weight $w(\ell, \ell')$ and the constant bound W depend on the actual approximation algorithm. Having made this tentative selection, the final solution is computed by

Table 1. Average Optimal Results (10 test runs, time limit: 3h)

Requests	ILP uniform	MILP	MILP + Gap	Ratio ILP/MILP
50	32.0	40.0	40.0	0.80
100	62.6	79.0	79.8	0.79
200	119.5	152	188.3	0.79
400	223.2	286.7	388.1	0.78
800	408.4	519.6	766.9	0.79

choosing a subset of the selection or assigning transmit powers. For the purpose of proving the desired approximation factor, the value W of the selection constraint is chosen very conservatively. In random instances, slight relaxations still result in feasible solutions for most situations. Thus, we implemented an additional binary search to obtain an appropriate bound W. This adapted bound admits better results which are still feasible.

Furthermore we implemented the so-called *MinLoss* and *MaxLoss* heuristics, which are the simplest greedy algorithms for the problem of approximating the capacity-maximization problem with a fixed power assignment. However, they only yield a poor worst-case performance and no non-trivial approximation factors can be proven. The requests are considered in order of increasing (MinLoss) or decreasing (MaxLoss) path loss. This is equivalent to examining the requests in order of increasing request lengths since the path-loss exponent α is fixed. A request ℓ is added to the set $\mathcal{L}$ if all involved SINR constraints are fulfilled afterwards. That is, not only the condition for ℓ is checked but also the ones for all previously added links. For this reason, for the MinLoss or MaxLoss algorithm $O(n^2)$ times the interference between a request and the already assigned requests has to be calculated. In contrast, the remaining approximation algorithms always have to check a single constraint, resulting in $O(n)$ calculations of a constraint. This means that in terms of the required calculation time the MinLoss and MaxLoss algorithms need an additional factor of $O(n)$.

We implemented both heuristics, MinLoss and MaxLoss, both with a uniform and a square-root power assignment. In the following they are referred to as *MinSqrt*, *MinUni* and *MaxSqrt*, *MaxUni*, respectively.

We used Java for our implementations and analyzed network instances with up to 1600 requests.

Simulation Results. The results of 10 test runs are given in Figure 3, comparing the approximation results to the uniform optimum. Interestingly, the uniform optimum achieves results that are similar to MinSqrt, HM and Kess. The previous section showed that the uniform optimum is outperformed by the optima produced with a square-root power assignment or power control. Thus there is still room for improvement for these algorithms. For the sake of clarity, the uniform variants of MinLoss and MaxLoss are not displayed because they are outperformed by their square-root variants.

The weak performance of the MaxLoss heuristic for larger network instances can easily be explained. The MaxLoss heuristic initially examines the longest requests. Due to the fact that with a larger distance between sender and receiver the transmission has to be performed with a higher power value, also the arising interference increases. The reason for the good performance of the MinLoss heuristic, also with a uniform power assignment, is exactly the one why its worst-case performance is very poor. In contrast to the approximation algorithms, that are very conservative, it uses the original SINR constraints. Nevertheless, it also needs a larger computation time as already stated.

Furthermore, we can observe that the HW algorithm achieves much weaker results. Compared to Kess and HM, this is due to the fact that it uses uniform

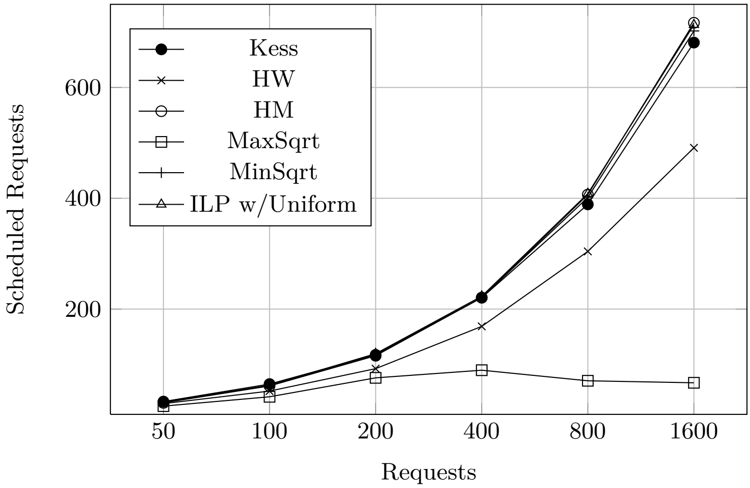

Fig. 3. Comparison of Approximations and Uniform Optimum (10 test runs)

powers, which were shown to be inferior in the previous section. So the weaker performance of a uniform or linear power assignment for the calculation of the maximal network capacity is also revealed by our simulations with the approximation algorithms. This can be observed as well when only comparing MinSqrt to MinUni or MaxSqrt to MaxUni. The variants using a square-root power assignment always outperform their uniform variants. We can even observe that the approximation algorithms using a square-root power assignment or power control, are able to outperform the uniform or linear optimum for some of the smaller instances and can keep up to it in all instances. This means that these algorithms already achieve better results than any algorithm using uniform powers, even one with unlimited computational powers.

However, theoretically, also between these algorithms there were large differences. The Kess algorithm can be shown to guarantee better results than any algorithm using square-root power assignments. Up to now, this cannot be verified by our simulations, where both the Kess and the HM algorithms perform very similarly. Thus, there is still further potential by the use of power control, which is not significantly presented by the implemented algorithms.

A last aspect to be mentioned are running times, as the study of approximation algorithms is motivated by the fact that they ensure a polynomial running time. This discrepancy can also be observed in our simulations. While the running time does not differ significantly for smaller network instances, the required computation time for a network instance consisting of 800 requests differs by a factor of more than 100: Running the approximation algorithms still takes less than a second, whereas solving the ILP takes a minute. The MILP approach using power control does not even complete within days.

Latency Minimization. For our simulations, we focused on the capacity-maximization problem because it is particularly simple to state as an ILP or as and MILP. Practical works, in contrast, often consider the latency-minimization, in which one has to calculate a schedule that serve all requests at least once. Unfortunately, existing approaches [13,6,2] are not able to solve the problem exactly in reasonable time. Furthermore, most approximation algorithms for latency minimization actually solve recursively maximize the use of the first slot.

Nevertheless, we implemented these algorithms as well and observed a similar ranking as for capacity maximization with one striking difference. The MaxLoss heuristics are able to catch up to their MinLoss correspondence. This is due to the fact that the processing order is not as important as for capacity maximization because all requests have to be served anyway.

Further details on these results can be found in the full version. However, dealing with latency minimization mostly remains an interesting topic for future research, because finding the minimum-latency solution within acceptable time still remains an open problem.

5 Conclusion

Our simulations are able to support a number of theoretical findings from worst-case analysis. In particular, square-root power assignments appear to be not only good in theory but also in practice. They originate from theoretical considerations, in which it was shown that they are superior to uniform or linear power assignments. Our simulations confirm this observation. Thus they are an easily implementable alternative that is at least partially able to profit from power control. However, one can get better performances by optimizing the power assignment – both in theory and in simulations.

Comparing the approximation algorithms and heuristics, we can again observe the effects of power control. Algorithms using different transmission powers are in general superior to the ones using uniform power assignments. In particular, we have shown that the developed approximation algorithms can compete with the other approaches in terms of the solution quality. However, they have the advantage that there are guarantees on the performance in any network. Furthermore, structurally they are as simple as the heuristics. Their running times are only quadratic in the network size while the heuristics need cubic running times. Hence, developing approximation algorithms seems to be the right direction.

A last point to be mentioned is that the purpose of the simulations was to study the given algorithms on randomly generated networks in contrast to the worst-case assumptions used in algorithmic theory. This brings about that we neglected modeling issues and carried out the simulations within the same model. It remains an open problem to verify our results in more advanced simulation environments or even in real-world experiments.

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