center. This controller is in charge of choosing the proper channel for every AP that it manages, and pushing that configuration into the APs. In this model, there is not a discrete and individual selection of frequencies, but they are proposed by the controller instead; the controller collects information from the APs, and uses that information to come with a global frequency allocation. This fits rather well with the mediated approach we are proposing: the frequency assignment proposal could be determined by a mediator process running in the wireless controller or external to several wireless controllers (one per provider). Even for home wireless networks, the need for Wi-Fi providers in a geographical area to collaborate to enhance the performance of wireless networks has been pointed out [23] and there are ISPs advocating for the central administration of home wireless access points.

4.2 Benchmarking techniques

In addition to the negotiation techniques we propose, presented in Section 3, we have included a comparison with three reference techniques:

- *Random Reference*: as a first base line, in this technique each AP chooses a channel randomly.
- *Least Congested Channel search (LCCS)*: LCCS is the de-facto standard for Wi-Fi channel assignment [2], and its based on each AP sensing the channel occupation and asynchronously choosing the channel where it finds the lowest interferences from other active APs and their clients. We have implemented a coordinated LCCS, where there is a centralized controller which evaluates the proposed changes before actually implementing them, thus preventing utility oscillations. This is a usual implementation in corporate environments.
- *Particle Swarm Optimization (ALPSO)*: additionally to our negotiator based on *simulated annealing*, we wanted to have, as a reference, a nonlinear optimizer using complete information. We have chosen a parallel augmented Lagrange multiplier particle swarm optimizer, which solves nonlinear nonsmooth constrained problems using an augmented Lagrange multiplier approach to handle constraints [13].

4.3 Graph metrics for performance evaluation

Among the aims of this work, we are interested in studying how the structural properties of the network influence the performance of optimization and negotiation approaches used to solve the problem. To this end, we have compared our experimental results with respect to a number of graph metrics selected from the literature. The first two of them are global metrics, while the rest are averages of a centrality metric, a local measure of the importance of a node within a graph:

- *Graph order:* The total number of nodes in the graph.
- *Graph diameter:* The longest distance between any pair of nodes in the graph [21].
- *Average degree centrality:* The degree centrality of a vertex is defined as its number of neighbors. Hence, the average degree centrality is

  $$\frac{\sum_{v\in V}\deg(v)}{|V(G)|}.$$

  By the handshaking lemma $\sum_{v\in V}\deg(v) = 2|E(G)|$, the average degree centrality is related to the density of the graph, defined as the ratio between the actual number of edges and the maximum possible number of edges

  $$\frac{|E(G)|}{\binom{|V(G)|}{2}} = \frac{\sum_{v\in V}\deg(v)}{|V(G)|}\frac{1}{|V(G)|-1}.$$

- *Average closeness centrality:* The closeness centrality of a node v is the inverse of the farness, normalized by the number of other nodes

  $$\frac{|V(G)|-1}{\sum_{w\in V\setminus\{w\}} \mathrm{d}(v,w)}.$$

- *Average eigenvector centrality.* The eigenvector centrality identifies nodes that are connected to many other well-connected nodes. Storing the centralities of the vertices in a vector, this turns out to be the eigenvector associated to the largest eigenvalue of the adjacency matrix of the graph [16].
- *Average betweenness centrality.* The betweenness centrality of a node v is based on the number of shortest paths in the graph passing through that node. In particular, for each s, t different from v, the ratio of shortest paths between s and t containing v is obtained, and these ratios are summed up [16].

One of our hypothesis is that these metrics may be used as a basis for mechanism selection in networked problems involving self-interested parties. In this paper we have used these metrics to compare the relative performance of the benchmarked approaches.

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we describe and discuss the results of our experiments. For the sake of clarity, we initially analyze separately both types of scenarios (random and real-world), and then we study the impact of graph metrics in performance for both types. For all the experiments we show we have performed 20 repetitions.

5.1 Random scenarios

In the first set of experiments, we study the effect of having different number of providers or agents (p) in the 400 random scenarios using SA. APs have been randomly assigned to the p providers. Table 2 shows the average normalized utility (U_n) for these experiments for $p \in \{1, 2, 5, 10\}$. Note that the normalized utility has been computed as the quotient between the sum of the utilities achieved by each node and the number of nodes (graph order). Results show that increasing the number of agents moderately decreases the utility, as the available information for the channel assignment is distributed among a higher number of agents when p increases. From now on, we focus in the two-provider case ($p = 2$) because there are more works in complex bilateral negotiations than for the multilateral case (three or more agents).

Next, we study the performance of the benchmarked techniques (*random*, *LCCS*, *HC*, *SA* and *ALPSO*) in the different scenario categories, recording the achieved social welfare (normalized utility) and fairness as defined in [8]. Figure 4 shows the average normalized utility (U_n) obtained by each technique for all the graphs in each category. Note that the graph categories have been ordered decreasingly according to the mean value of U_n obtained for all the studied techniques (these mean values are represented with a solid horizontal line for each category). Each bar in the figure also includes the 95% confidence interval. In all the studied scenarios, the worst performance is, as it could be expected, the *random*

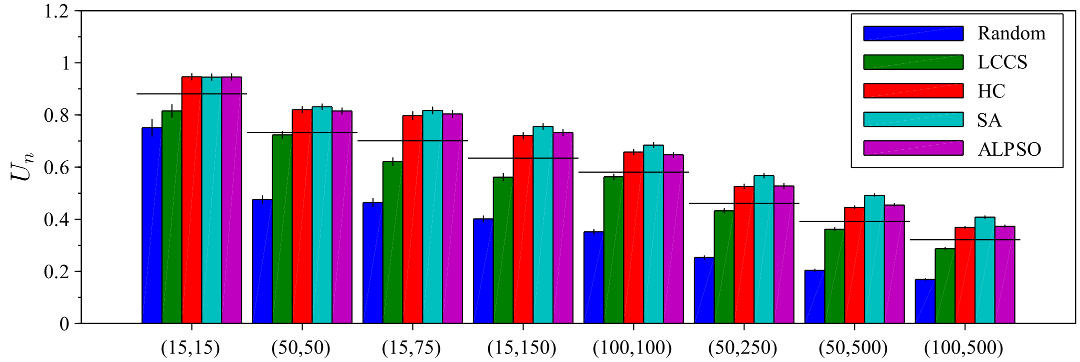


Figure 4: Normalized utility (U_n) for the evaluated techniques in random scenarios.

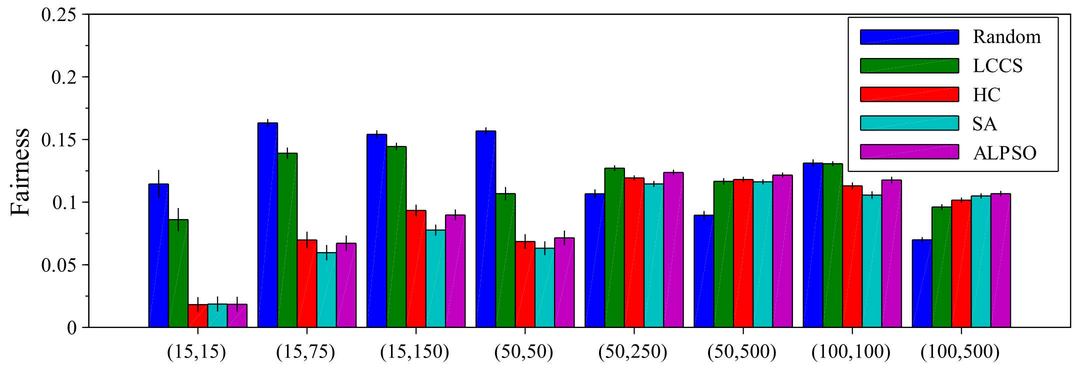


Figure 5: Fairness for the evaluated techniques in random scenarios.

Table 2: Normalized utility for different number of agents (p) in random scenarios using SA.

Scenario	$p = 1$	$p = 2$	$p = 5$	$p = 10$
(50, 250)	0.548	0.538	0.525	0.521
	0.615	0.602	0.596	0.591
	0.618	0.604	0.592	0.587
(50, 500)	0.488	0.482	0.470	0.465
	0.479	0.472	0.462	0.451
	0.547	0.535	0.526	0.521
(100, 500)	0.437	0.427	0.402	0.400
	0.447	0.429	0.425	0.410
	0.411	0.401	0.383	0.384

assignment. The performance of *LCCS* is better than *random* but worse than the rest of techniques. Comparing *HC*, *SA* and *ALPSO* we can conclude that, although their performance is quite similar, *SA* is the best technique for all the scenarios under study (there is a little advantage for the hill climber (*HC*) in the simplest category, but it is not statistically significant). As the scenarios grow more complex, the distance between SA and the rest of techniques increases, which is reasonable since the size of the solution space becomes larger. The increasing distance between SA and HC confirms our hypothesis that these scenarios are highly nonlinear [15]. It is also important to note that, for the more complex scenarios, the *SA* negotiator significantly outperforms the particle swarm optimizer (*ALPSO*). This is a remarkable result, specially taking into account that *SA* reaches the optimum faster than the *ALPSO* optimizer.

Next, we study the performance of the different techniques under study in terms of their fairness (F). We use the definition of fairness given in [8], i.e.:

$$F(u_1, ..., u_N) = \sum_{i=1}^{N} \frac{(u_i - \overline{u})^2}{N},$$

being N the number of nodes (graph order), u_i the utility for node i and $\overline{u}$ the average utility for all nodes. From this definition, note that lower values for F are better. Figure 5 shows the performance in terms of fairness for the studied techniques in the different graph categories. For the simpler graphs ((15, 15), (15, 75), (15, 150) and (50, 50)), *HC*, *SA* and *ALPSO* clearly outperforms the *LCCS* and *Random*. However, this is not true for the more complex scenarios, where there is not a clear ordering but in some cases *Random* is the fairest solution. To explain this behaviour we have to consider both fairness and utility together. As the performance in terms of utility for *Random* is very poor, it is much easier to reach fair (but poor) solutions between nodes. For that reason, we have computed the ratio between the normalized utility (U_n) and the fairness (F) to compare the different techniques, calling this value UF. In Table 3 we show the quotient between UF for the different techniques under study and UF_{SA}, which is the value of UF for *SA*. Values below one in the table mean that *SA* is able to obtain better results. From that table we can conclude that *SA* offers the best results in all cases except for the simplest graphs (15, 15), where *HC* and *ALPSO* slightly outperform *SA*.

5.2 Real-world setting

For the real-world scenarios, Fig. 6 shows the normalized utility (U_n) for the different techniques under study, while Table 4 shows the quotient between UF for the studied techniques and UF_{SA}. Regarding Fig. 6, results show, again, that the annealer *SA* out-

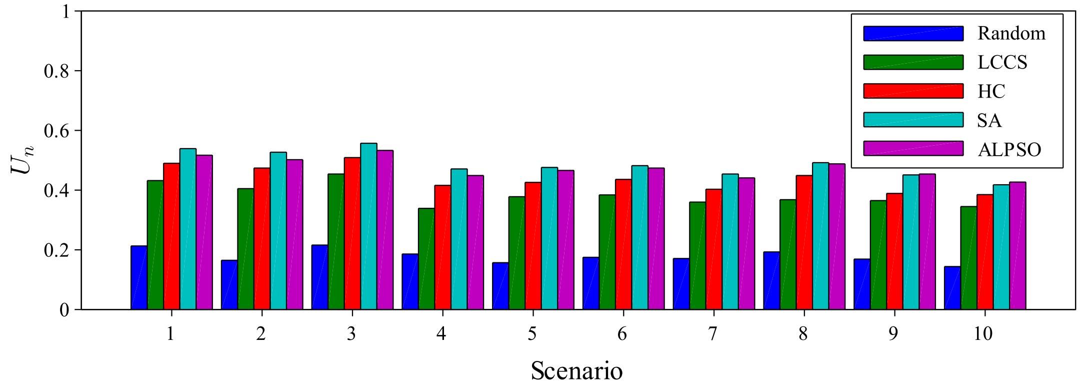
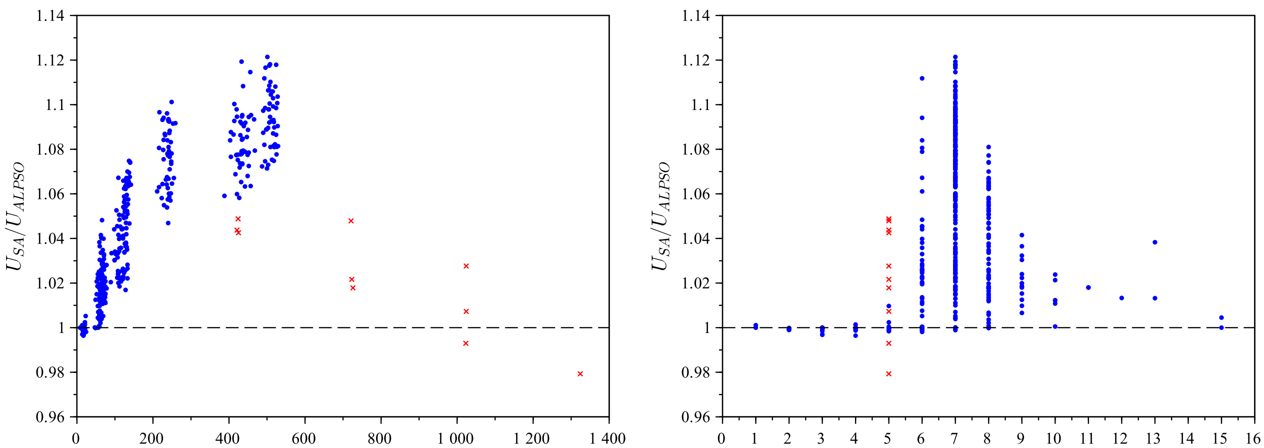


Figure 6: Normalized utility (U_n) for the evaluated techniques in real-world setting.



(a) Order. (b) Diameter.

Figure 7: Utility of SA relative to ALPSO for different graph metrics.

Table 3: UF relative to UF_{SA} in random scenarios.

Scenario	Random	LCCS	HC	ALPSO
(15, 15)	0.13	0.19	1.03	1.01
(15, 75)	0.21	0.33	0.83	0.87
(15, 150)	0.27	0.40	0.79	0.84
(50, 50)	0.23	0.52	0.91	0.87
(50, 250)	0.48	0.69	0.89	0.86
(50, 500)	0.54	0.73	0.89	0.88
(100, 100)	0.41	0.66	0.90	0.85
(100, 500)	0.62	0.77	0.93	0.90

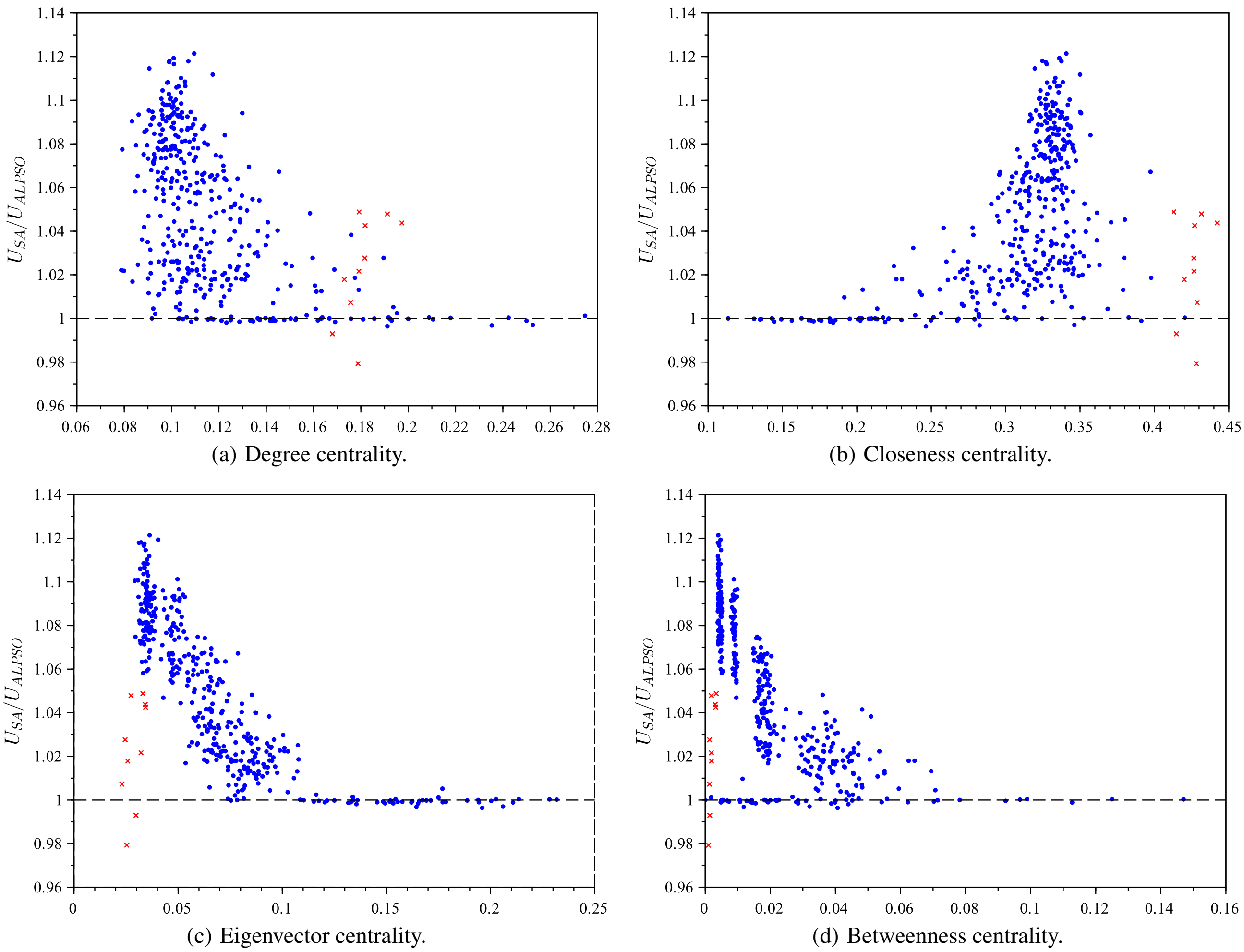
Table 4: UF relative to UF_{SA} in real-world setting.

Scenario	Random	LCCS	HC	ALPSO
1	0.58	0.78	0.87	0.90
2	0.52	0.75	0.89	0.92
3	0.45	0.75	0.83	0.90
4	0.53	0.70	0.81	0.92
5	0.60	0.85	0.89	0.96
6	0.56	0.83	0.88	0.92
7	0.57	0.83	0.88	0.97
8	0.53	0.78	0.84	0.96
9	0.59	0.83	0.86	0.97
10	0.63	0.88	0.91	0.99

performs the *Random* assignment, *LCCS* and *HC*. Comparing *SA* and the complete-information optimizer *ALPSO* we show that their performance in the real-world scenarios are fairly similar, being *SA* slightly better in Scenarios 1-8 and slightly worse in Scenarios 9 and 10. Table 4 shows that if we analyze utility together with fairness, *SA* behaves as the best solution in all the studied real-world settings. For that reason, we can conclude that in the real-world setting the use of *SA* for Wi-Fi channel assignment is advantageous in terms of social welfare and fairness.

5.3 Impact of different graph metrics

In this section, we analyze the results of the best performing approach (*SA*) with respect to the different metrics discussed in Section 4.3. This comparison is done in terms of the normalized utility that the *SA* negotiator obtains relative to the particle swarm optimizer *ALPSO*, i.e. we show the quotient U_{SA}/U_{ALPSO}. We have plotted these results for both random scenarios (blue dots) and real-world scenarios (red crosses). Note that, for all figures, we also include a dashed line that corresponds to the $U_{SA} = U_{ALPSO}$ baseline. Regarding the graph order, in Fig. 7a, for the random scenarios we can see an approximately linear increasing gain for SA, with ALPSO doing better for low-order graphs and SA getting to gains up to 10% for the larger graphs. However, this behaviour does not hold for the real-world scenarios, where the gain decreases



(a) Degree centrality.

(b) Closeness centrality.

(c) Eigenvector centrality.

(d) Betweenness centrality.

Figure 8: Utility of SA relative to ALPSO for different graph centrality metrics.

with the order. From this result we can conclude that the graph order can not be used alone to estimate the gain that can be expected from using *SA*. Figure 7b suggests that there may be optimal values of graph diameter regarding the performance of *SA*. For example, it is reasonable to expect small gains for both low and high graph diameters.

In Fig. 8 we show the gain obtained by *SA* respect to *ALPSO* for the four different centrality metrics defined in Section 4.3. Note that these metrics are defined for each node, so we show their average value for each graph. Examining these figures we can see that all of them show a clear and narrow range of centralities for which the largest gains are obtained. For closeness centrality (Fig. 8b), the results are better for larger average centrality, with the opposite behaviour for the other three types of centrality. Interestingly enough, the eigenvector centrality (Fig. 8c), which is smaller when there are less nodes connected to many well-connected nodes, is the only centrality for which the adequate values lead to *SA* outperforming *ALPSO* in all the random scenarios. The real-world scenarios, however, have very similar values for all the centralities considered, which have led to both gains and losses for *SA*.

6. CONCLUSIONS AND FUTURE WORK

Optimizing resource use in complex networks with self-interested participants is a challenging and increasingly critical real-world problem. This paper studies and evaluates the use of multiagent negotiation techniques for WiFi-channel assignment, which is a realistic problem derived from the popular graph coloring and frequency assignment problems. We compare the negotiation-based approaches with both the *de facto* standard for Wi-Fi channel assignment and a nonlinear centralized optimizer. Experiments show that the negotiation-based approaches outperform the references in both social welfare and fairness.

Although our experiments have yielded satisfactory results, there is still plenty of research to be done in this area. A more in-depth metric analysis is needed, specially to determine if the observed correlations among metrics are inherent or caused by a scenario generation bias. We are also exploring fully-distributed mechanisms based on belief propagation. Finally, we are interested in evaluating the strategic properties of the mechanisms, to see how they perform when agents are allowed to “lie” in their messages in order to try to influence the outcome of the mechanism to their advantage.

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