Multi-Agent Nonlinear Negotiation for Wi-Fi Channel Assignment

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ABSTRACT

Optimizing resource use in complex networks with self-interested participants (e.g. transportation networks, electric grids, Internet systems) is a challenging and increasingly critical real-world problem. We propose an approach for solving this problem based on multi-agent nonlinear negotiation, and demonstrate it in the context of Wi-Fi channel assignment. We compare the performance of our proposed approaches with a complete information optimizer based on particle swarms, together with the *de facto* heuristic technique based on using the least congested channel. We have evaluated all these techniques in a wide range of settings, including randomly generated scenarios and real-world ones. Our experiments show that our approach outperforms the rest of techniques in terms of social welfare. The particle swarm optimizer is the only technique whose performance is close to ours, but its computation cost is much higher. Finally, we also study the effect of some graphs metrics on the gain that our approach can achieve.

Keywords

Nonlinear negotiation, Wi-Fi channel assignment, graph coloring

1. INTRODUCTION

In the last years, complex networks have attracted a lot of interest within the AI community, both due to the inherent challenge of some network-structured optimization problems (e.g. to be NP-hard) and due to the enormous potential for real-world applications (many important real-world problems have network structure). An important sub-class involves autonomous, self-interested entities (e.g. drivers in a transportation network), which tend to cause the network to deviate from socially-optimal behaviour.

Taking this into account, it is not surprising that problems which combine a networked structure and self-interested parties have been drawing attention from the AI community. Different fields of research are working on the challenges these problems raise, but, so far, with only mixed success. Optimization techniques are especially suited to address large-scale systems with an underlying network structure, usually with a “divide and conquer” approach. However, their performance severely decreases as the complexity of the system increases [24], and with the presence of autonomous entities which deviate from the globally optimal solution, thus harming the social goal. Automated negotiation has proven to be valuable to support decision-making processes in scenarios where it is necessary to find an agreement quickly and with conflicting interests involved [25]. Potential applications of automated negotiation range from e-commerce [20] to task distribution problem solving, resource sharing or cooperative design [27]. One of the most important advantages of automated negotiation is that it takes into account the conflict of interests from the beginning. This enables finding more stable solutions (agreements) which make participating agents less prone to deviating from the socially optimal solution to favour their privately optimal solution. Although there is significant work on game theory and bargaining in complex networks, the nonlinear negotiation community has made only few, very specific incursions in complex networked problems [3].

Wi-Fi technology, based on the IEEE 802.11 standard family, has become an omnipresent technology in our daily lives. The 2.4 GHz wireless frequency band is the most common band where Wi-Fi operates, and is divided into 11 partially overlapped frequency channels [22]. Due to the high number of Wi-Fi devices together with many other technologies and devices that operate in the same band we have to accurately choose the frequency channel where an access point should operate in. The main purpose of this paper is to explore the possibilities of using non-linear negotiation techniques [19] to solve complex network problems involving self interested parties like the problem of frequency assignment in Wi-Fi infrastructure networks. In this setting, different Wi-Fi providers, acting as agents, have to collectively decide how to distribute the channels used by their access points in order to minimize interference between nodes and thus maximize the utility (i.e. network throughput) for their clients. This is a particularly interesting problem, since it belongs to the family of Frequency Assignment Problems (which has been extensively studied from the perspective of discrete optimization) and it is strongly related to the prominent mathematical graph coloring problem [28] and to distributed constraint optimization models [11].

More specifically, we want to test the hypotheses that our nonlinear negotiation approaches can be used as an efficient alternative to centralized, generic optimization tools. This work contributes to achieve this goal in the following ways:

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- We model the problem of Wi-Fi channel assignment as a graph coloring problem (Section 2).
- We propose to solve this problem using nonlinear automated negotiation techniques, and define the corresponding negotiation scenario (Section 3).
- We generate a large set of scenario instances for this problem including both random and real-world settings, and we perform extensive experimentation on these sets of instances, comparing our negotiation approaches to three different reference techniques: a random channel assignment, the *de facto* standard in Wi-Fi networks based on choosing the least congested channel and a complete information nonlinear optimizer based on particle swarms (Section 4).

The experimental results (Section 5) show that our benchmarked negotiation approaches significantly outperform the reference approaches in both random scenarios and real-world settings in terms of social welfare and fairness. Also, we identify interesting patterns regarding the influence of graph properties such as the order, the diameter or some well-known centrality metrics on the relative performance of the approaches. The last section includes a summary of the paper, some concluding remark and briefly describes possible future lines of research.

2. PROBLEM MODELLING

2.1 Graph modelling

Graphs are one of the most commonly used tools for modelling frequency assignment problems, because of the relationship between them and the graph coloring problem, which has been widely studied by the mathematical community [28]. In graph coloring, an abstract graph is considered, defined by a set of vertices along with some edges connecting them, and the goal is to assign one color to each vertex, in such a manner that the minimum possible number of colors should be used, while avoiding monochromatic edges. In the commonly used model for frequency assignment, graph vertices represent elements that should be assigned a frequency while edges represent element pairs that should not be assigned the same frequency. This way, colors act as frequencies and hetero-chromatic edges guarantee element pairs with different frequencies. Although widely used, Tragos et al. [5] conclude that the model is not accurate enough, because it does not reflect all the information. For instance, the authors suggest that the information regarding adjacent channel interferences should be incorporated into the graph.

To model the Wi-Fi channel assignment problem we propose to use two different graphs. In both graphs, there two different types of vertices: access points (APs) and wireless devices or clients (WDs). Note that APs are typically wireless routers and WDs can be laptops, smartphones... that are able to communicate with other WDs only through the AP which they are associated to. The first graph, called connectivity graph (G), captures the association links between APs and WDs. Note that every WD is associated to its closest AP, and that, since APs are the ones who set the channel to be used by their associated clients, all nodes connected in graph G will use the same channel (color) to communicate. The second graph, called interference graph (I), links node pairs where the distance between them is below the corresponding interference radius R (that depends on the sensitivity of the receiver): AP–AP pairs will be linked provided that the distance condition is met, AP–WD pairs only when the device is not associated to that AP, and WD–WD pairs only if both devices are associated to different APs, since the communications among the elements connected to the same AP are coordinated and do not interfere. The next section describes the interference model in more detail.

2.2 Interferences and utility of the solutions

The weight of the edges in graph I represents the interference between the nodes they link and it can be computed, for a node operating in channel i and the other node operating in channel j (i and $j \in \{1, \ldots, 11\}$), as:

$$I_j = P_t + G_t + G_r - L - P_{loss} + W(i,j) + \psi,$$

where P_t stands for the transmission power (in dBm), G_t (G_r) stands for the transmission (reception) antenna gain (in dB) and L stands for losses due to walls, windows and other obstacles in the propagation (in dB). $W(i,j)$, called the co-channel index, can be understood as the interference between color i and color j. This index includes the interferences not only between adjacent colors but also between colors in a certain distance range, to take into account the partial overlapping between frequency channels in Wi-Fi. To model this effect, we have used the values obtained in [22]. On the other side, ψ, called activity index, accounts for the fact that a higher bandwidth data flow will occupy the wireless channel a higher fraction of the time. Finally, P_{loss} stands for propagation losses (in dB) and has been computed according to [10], that defines signal losses in the 2.4GHz frequency band as:

$$P_{loss} = 7.6 + 40 \log_{10} d - 20 \log_{10}(h_t h_r),$$

where d is the distance between interfering nodes, in meters, and h_t (h_r) is the transmission (reception) antenna height, also in meters.

Once there is a model for interfering signals, the signal to noise ratio for terminal i ($SINR_i$) can be computed as the ratio between the received desired signal and the sum of the received undesired interferences, i.e.

$$SINR_i = \frac{P}{\sum_{j=1}^{M} I_j},$$

being P the power of the desired signal and M the number of interference signals (I_j) that are received.

Note that each AP will have a $SINR$ value for every terminal that is associated to it. In that case, we will assume that its $SINR$ will be the minimum of all of them, which is in fact the worst case.

To quantify the goodness of the different network colorings, we consider that the utility of an AP is closely related to the perceived throughput and $SINR$. According to [1], in a wireless network the throughput equals a maximum value when the $SINR$ is over a certain value $SINR_{max}$ and monotonically decreases with the reduction of $SINR$ until an insufficient value of $SINR$, called $SINR_{min}$, is reached, when the throughput falls to zero. We can consider the utility perceived by node i (U_i) as a normalized throughput, so it can be defined as a value ranging from 0 to 1, with 0 corresponding to the situations when there is a very low-quality reception and the devices cannot keep connected (throughput equals to zero), and 1 corresponding to the case when the signal quality is excellent (throughput equals to its maximum value). Threshold values for $SINR$ have been defined from the values presented in [9]. Finally, the utility value for a specific provider P_i (U_{P_i}) is computed as the sum of the utility values for all its APs and the clients associated to these APs.

With the aforementioned description, we can formally formulate the problem as follows. Given a geometric graph G, together with a spectrum of $k = 11$ colors (channels) endowed with a $k \times k$ matrix W of interferences between them, the goal is to determine a k-coloring c for the AP-vertices of G such that the sum of utility values for all the nodes in the graph (APs and WDs) is maximized, i.e., achieving the maximum

$$\max \left\{ \sum_{i \in V(G)} U_i(G, W, c) \;\mid\; c \text{ is a coloring of } V(G) \right\},$$

where $V(G)$ denotes the set of vertices of G and $U_i(G, W, c)$ denotes the utility for the vertex i of graph G under the coloring c, for a spectrum matrix W.

3. AUTOMATED NEGOTIATION TECHNIQUES FOR CHANNEL SELECTION

In this work, we propose to tackle the network-structured channel assignment problem in Wi-Fi using automated negotiation techniques. Automated negotiation is quite a wide field [6] but most authors agree that a negotiation problem can be characterized by a negotiation domain (who negotiates and what they negotiate about), an interaction protocol (which rules govern the negotiation process), and a set of decision mechanisms or *strategies* that guide the negotiating agents through every phase of the interaction protocol [7]. In the following we define our particular negotiation problem along these three dimensions.

3.1 Negotiation Domain

For the scope of this work, we assume a multiattribute negotiation domain, where a deal or solution to the problem is defined as the set of attributes (*issues*), and each one of them can be in a certain range. In our case, for a channel assignment problem with n_{AP} access points, a solution or deal S can be expressed as $S = \{s_i | i \in 1, ..., n_{AP}\}$, where $s_i \in \{1, \ldots, 11\}$ represents the assignation of a Wi-Fi channel to the i-th access point.

In this work, we assume that there are different network providers or agents (commonly Internet Service Providers, ISPs), thus APs belong to one of the agents. Each provider only has control over the channel assignment for its own access points. According to this situation, the agents will negotiate the channel assignment. Finally, each one of these agents will compute its utility for a certain solution according to the model described in the previous section. The problem settings (high cardinality of the solution space and attribute interdependence) will make the utility functions highly complex, with multiple local optima.

3.2 Interaction Protocol

There are many interaction protocols for negotiations in the literature, from the classical alternating offers model [26] to auction-based protocols [12]. From the assumption that the negotiation scenarios coming from Wi-Fi channel assignment will be highly nonlinear, and according to the discussion in [19], we have chosen a simple text mediation protocol [15]. In its simplest version, the negotiation protocol will be as follows:

1. It starts with a randomly-generated candidate contract (S_0^c). This means to assign each AP a random channel.

2. In each iteration t, the mediator proposes a contract S_t^c to the rest of agents.

3. Each agent either accepts or rejects the contract S_t^c .

4. The mediator generates a new contract S_{t+1}^c from the previous contracts and from the votes received from the agents and the process moves to step 2.

This process goes on until a maximum number of iterations is reached. The protocol, as defined, is rather generic and must be completed with the definition of the decision mechanisms to be used by the negotiating agents and the mediator.

3.3 Decision Mechanisms

For the mediator, we have implemented a single-issue mutation mechanism [15] for the generation of new contracts, which works as follows:

- If at time t all agents have accepted the presented contract S_t^c, this contract will be used as the base contract S^b to generate the next contract S_{t+1}^c. Otherwise, the last mutually accepted contract will be used.

- To generate the next candidate contract S_{t+1}^c, the mediator takes the base contract S_b and mutates one of its issues randomly. In our case of study, this would correspond to choosing a random access point and selecting a new random channel for it.

- After a fixed number of iterations, the mediator advertises the last mutually accepted contract as final.

For the agents, we have considered two different mechanisms to vote about the candidate contracts S_t^c:

- *Hill-climber (HC):* In this case, the agent behaves as a greedy utility maximizer. The agent will only accept a contract when it has at least the same utility for her than the previous mutually accepted contract. The first contract proposed by the mediator is accepted by default.

- *Annealer (SA):* This negotiation mechanism, that we first proposed in [15] and was further refined in [18] and [17], uses a widespread nonlinear optimization technique called simulated annealing (SA) [14]. The mechanism is similar to HC, but when a contract yields a utility loss against the previous mutually accepted contract, there will be a probability for the agent to accept it nonetheless. This probability P_a depends on the utility loss associated to the new contract Δu and also depends on a parameter known as *annealing temperature* τ, so that $P_a = e^{\frac{-\Delta u}{\tau}}$. Annealing temperature begins at an initial value, and linearly decreases to zero throughout the successive iterations of the protocol.

The choice of these two mechanisms is not arbitrary. *Simulated annealing* techniques have yielded very satisfactory results in negotiation for nonlinear utility spaces [18, 17], and are the basis for several of other works [19]. Furthermore, as discussed in [15], the comparison between *hill-climbers* and *annealers* allows to assess whether the scenario under consideration is a highly complex one, since in such scenarios greedy optimizers tend to get stuck in local optima, while the *simulated annealing* optimizer tends to escape from them.

4. SCENARIOS, BENCHMARKS AND METRICS

4.1 Considered scenarios

In this paper, we make the common assumption that Wi-Fi nodes (APs and clients) are static elements. As in our problem there is not any element that evolves with time, we deal with the problem of evaluating the performance of a particular channel assignment strategy by means of the computation described in Section 2.

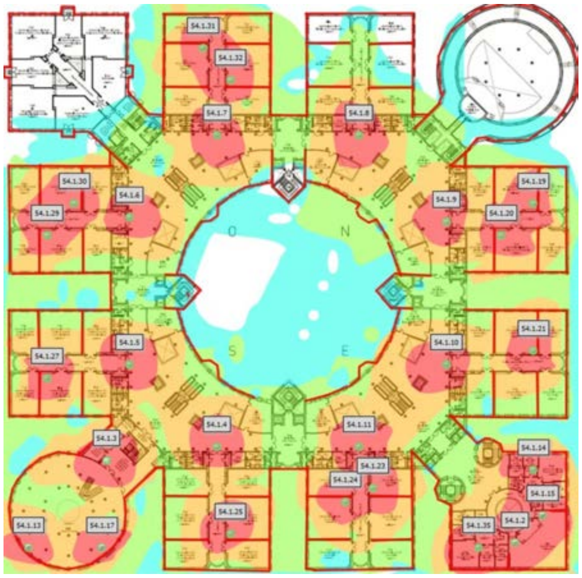


Figure 1: Polytechnic School building plan.

Moreover, the choice of the configuration parameters for the studied scenarios has been driven by considering typical or reasonable power transmission and sensitivity parameters from a realistic point of view [4]. We have made the assumption that clients associate to the AP which is closer to them. Finally, for each scenario, we randomly assigned half of the APs to each agent.

With these assumptions, we have performed experiments both in randomly generated scenarios where APs and clients are randomly distributed throughout the environment, and in a real-world setting. For the random scenarios we have generated scenarios varying the number of APs (15, 50 and 100) and the number of clients per AP (1, 5 and 10). Combining these parameters, we have generated eight categories with 50 different graphs per category, for a total of 400 scenarios. This allowed us to have a wide range of problem sizes (from tens of nodes to roughly one thousand nodes), and also a wide diversity (due to the randomization of node placement).

For the real-world setting, we have made use of the real layout of the first floor plant of our building, the Polythecnic School of the University of Alcala. The sides of this square-shaped building are approximately 130 meters long. In Fig. 1 we provide the plan of this building, where the real positions of deployed APs are displayed with green dots and where signal coverage ranges from red (high coverage) to light blue (very low coverage). In this figure we can observe that the floor is equipped with 26 APs. Note that the center of the plan represents a central courtyard, so it has low signal coverage. For the position of WDs we have considered that we have users attending classes in classrooms and also some students are located randomly in the building (resting, in the cafeteria, studying...). For this last group of students, we have considered that there are 100 students randomly located in the building following a uniform distribution. For the students in classrooms, we have tested several scenarios varying randomly the ratio of classrooms being used Ψ, with $\Psi \in [0.25, 0.5, 0.75, 1.0]$. As there are 48 classrooms in the building, we have considered scenarios with 12, 24, 36 and 48 classrooms. For each classroom, we have deployed 25 students in each one randomly using a normal distribution around the center of each classroom and a standard deviation normalized to the size of the scenario of 0.05. In Table 1 we show a summary of the real-world scenarios under study. Finally, as the specific random classrooms in use could affect the results,

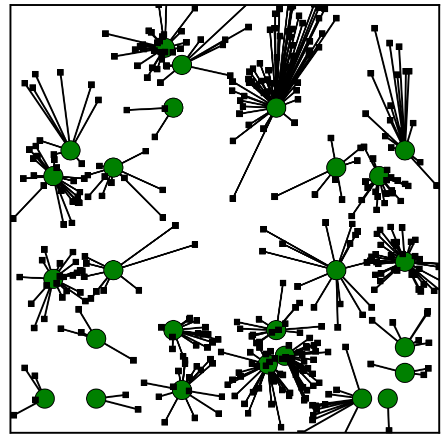


Figure 2: Connectivity graph G for Scenario 1.

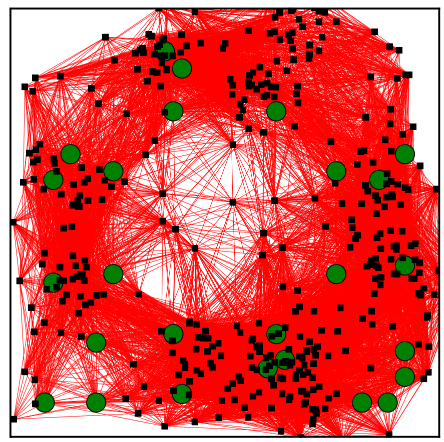


Figure 3: Interference graph I for Scenario 1.

we have tested three experiments for each value of Ψ (except for $\Psi = 1$ because all classrooms are in use in this setting), for a total of 10 deployments. As an example, Figure 2 shows the association between APs and WDs (graph G according to Section 2.1) of Scenario 1, while Fig. 3 shows the potential interferences between network elements (graph I in Section 2.1). In both figures, APs are represented by green circles and WDs by small black squares.

It is in this real-world setting where the role of the mediator can be more easily understood. In contrast to home and legacy wireless networks that provide access via independent wireless APs, enterprise wireless networks, like the one just described, make use of a centralized entity, known as wireless controller. A wireless LAN controller is used in combination with protocols such as Lightweight Access Point Protocol (LWAPP) or Control And Provisioning of Wireless Access Points (CAPWAP) to manage access points in large quantities by the network administrator or network operations

Table 1: Summary of scenarios of the real-world setting.

Scenario	Ψ	# Classrooms	# WD
1, 2, 3	0.25	12	400
4, 5, 6	0.5	12	700
7, 8, 9	0.75	12	1000
10	1.0	48	1300

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*

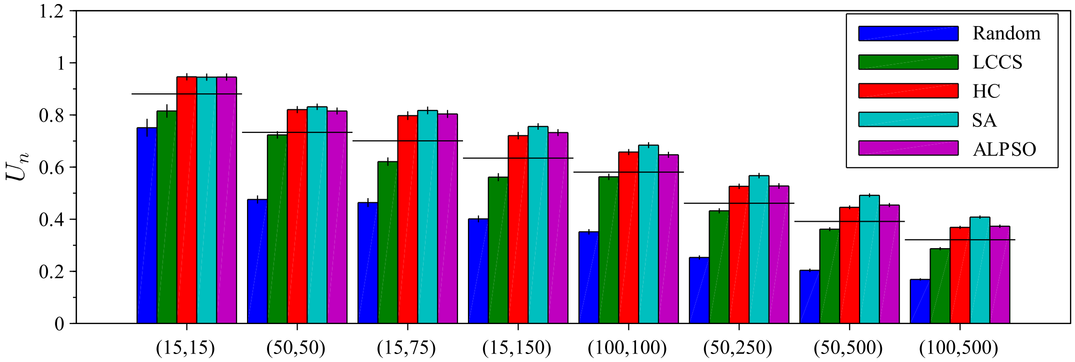


Figure 4: Normalized utility (U_n) for the evaluated techniques in random scenarios.

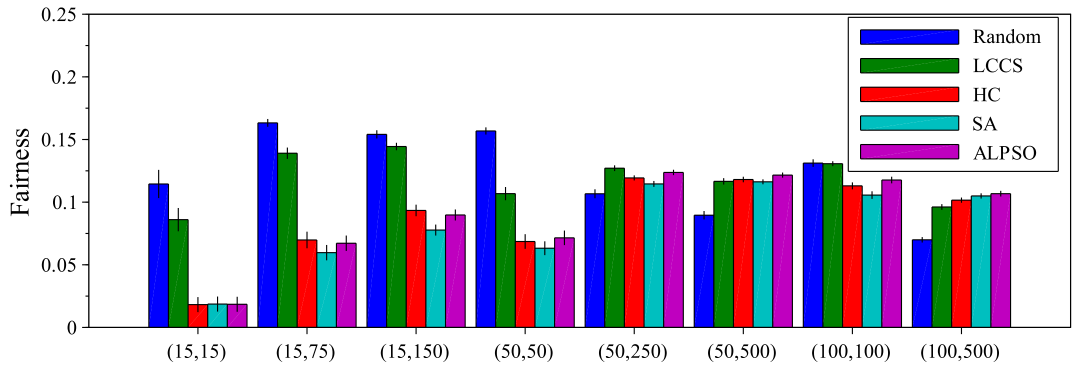


Figure 5: Fairness for the evaluated techniques in random scenarios.

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-

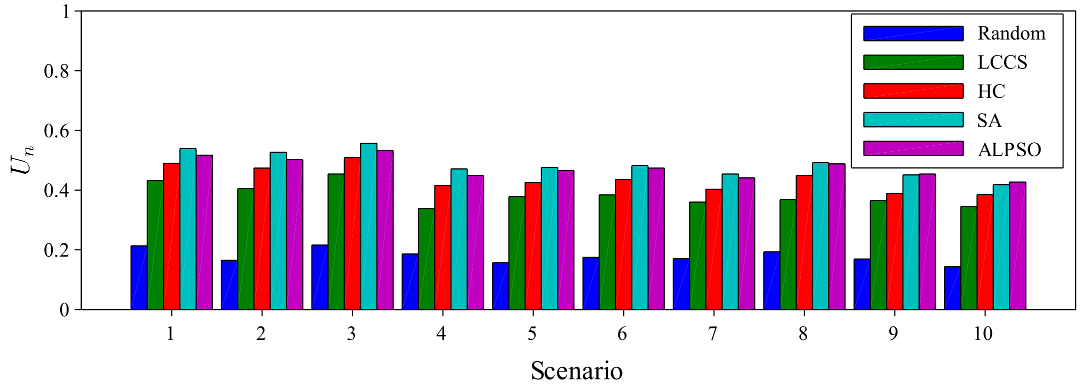


Figure 6: Normalized utility (U_n) for the evaluated techniques in real-world setting.

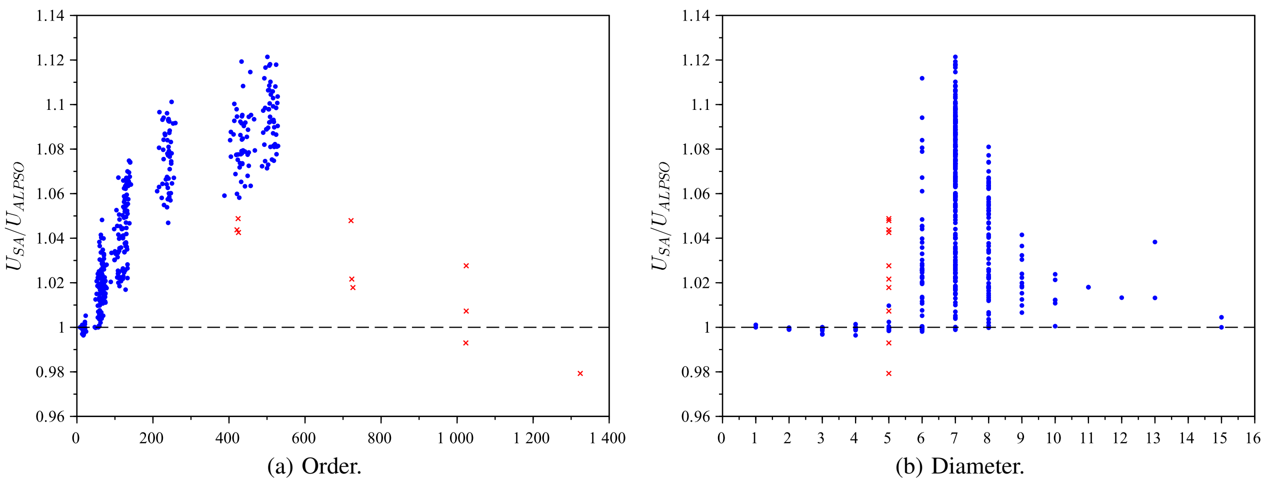


Figure 7: Utility of SA relative to ALPSO for different graph metrics.

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

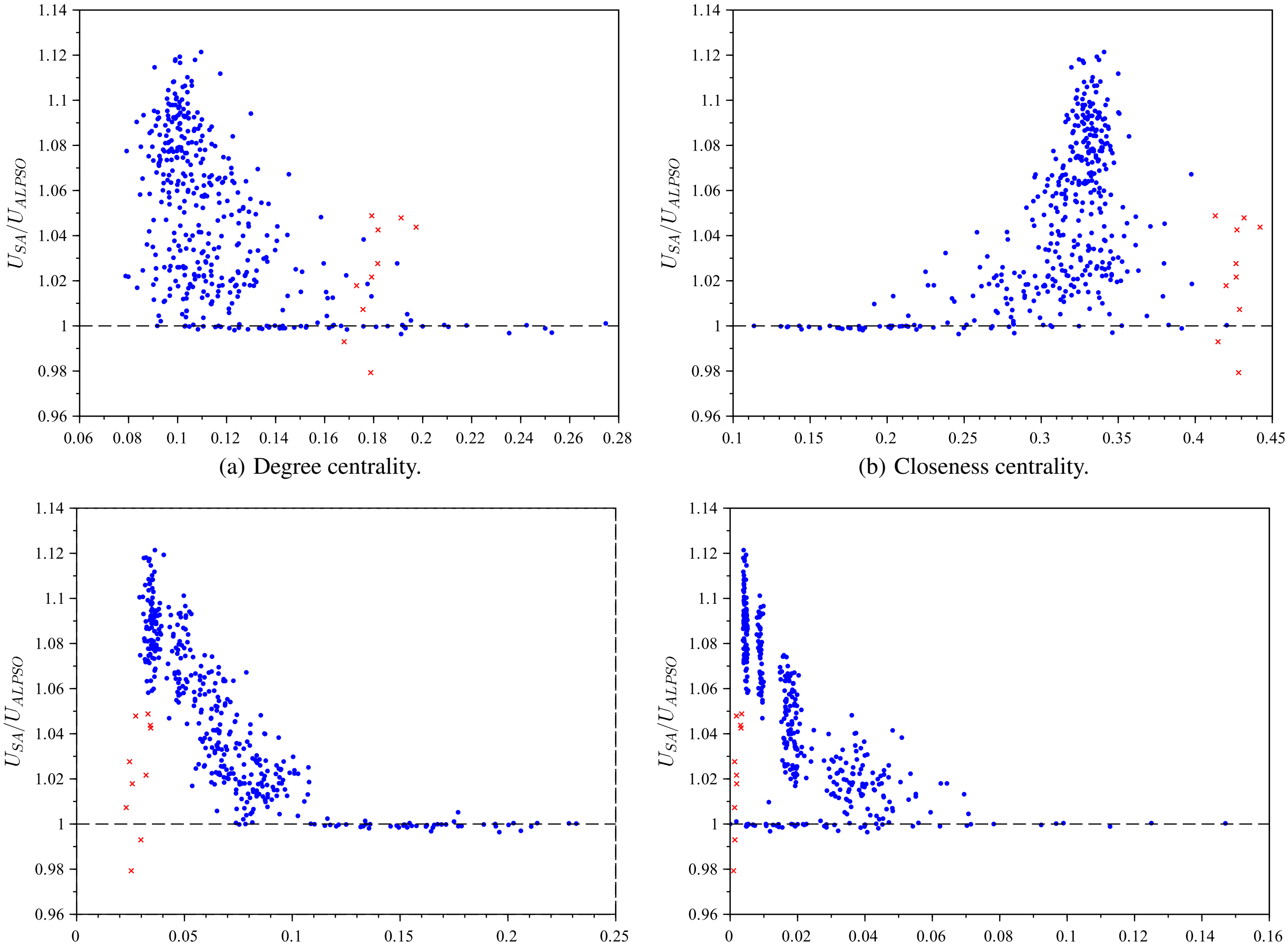
Table 4: UF relative to UF_{SA} in real-world setting.

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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