Nonlinear negotiation approaches for complex-network optimization: a study inspired by Wi-Fi channel assignment

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Abstract. In this paper, we study a problem family inspired by a prominent network optimization problem (graph coloring), enriched and extended towards a real-world application (Wi-Fi channel assignment). We propose a utility model based on this scenario, and we generate an extensive set of test cases, against which we run both a complete information optimizer and two nonlinear negotiation approaches –a hill-climber and an approach based on simulated annealing (SA). We show that, for the larger-scale scenarios, the SA negotiation approach significantly outperforms the optimizer while running in roughly one tenth of the computation time. Also, we point out interesting patterns regarding the relative performance of the two approaches depending on the properties of the underlying graphs.

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 structures). An important sub-class involves autonomous, self-interested entities (e.g. drivers in a transportation network). The self-interested nature of these entities 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 [1], 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 process in scenarios where it is necessary to find an agreement quickly and with conflicting interests involved [2]. Potential applications of automated negotiation range from e-commerce [3] to task distribution problem solving, resource sharing or cooperative design [4]. 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 [5].

We want to explore the possibilities of using non-linear negotiation techniques [6] to solve complex network problems involving self interested parties. To this end, we are working on the problem of frequency assignment in Wi-Fi infrastructure networks. In this problem, different Wi-Fi providers have to collectively decide how to distribute the channels used by their APs 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 is strongly related to the Frequency Assignment Problem (which has been extensively studied from the perspective of discrete optimization), to the prominent mathematical graph coloring problem [7], and to distributed constraint optimization models [8].

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, and that network properties have an impact on the relative performance of the different techniques. This work contributes to achieve this objective in the following ways:

– We model the problem of Wi-Fi channel assignment, using an abstract model based on a multilayer graph and a nonlinear utility model (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, we select a set of metrics based on graph theory to analyze them, and we perform extensive experimentation on this set of instances, comparing our negotiation approaches to two reference techniques: a random channel assignment and a complete-information nonlinear optimizer based on particle swarms (Section 4).

The experimental results (Section 5) show that one of the benchmarked negotiation approaches (single text mediation with simulated annealing) significantly outperforms the optimizer for the larger-scale scenarios, both in computation time and social welfare. Also, interesting patterns regarding the influence of network properties on the relative performance of the approaches are identified. The last section summarizes our contributions and sheds light on future lines of research.

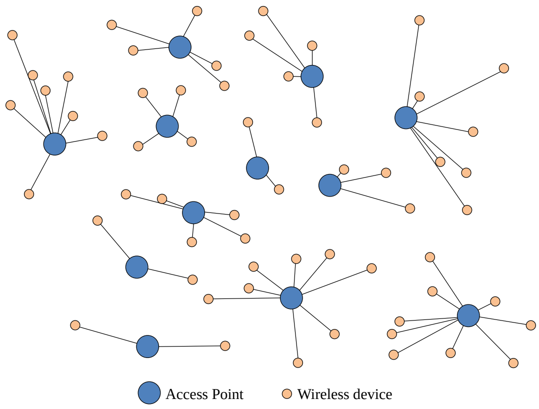

Fig. 1. Wi-Fi architecture.

2 Problem Modelling

2.1 Wi-Fi architecture

IEEE 802.11 technology, commercially known as Wi-Fi, is a very popular and widespread technology, whose most used standard operates commonly in the 2.4 GHz frequency band. Due to the high number of Wi-Fi devices that coexist in these frequencies, this band is usually congested, a situation often worsened by other devices like Bluetooth, ZigBee, microwave ovens, baby monitors or cordless phones. For those reasons, it is of paramount importance that Wi-Fi devices smartly manage the use of the radio spectrum. The 2.4 GHz band is divided into 11 partially overlapped channels [9], so it is important to choose the most advantageous one to minimize interferences.

The most widely deployed Wi-Fi architecture is infrastructure mode, where there are two types of devices in the network: access points (APs) and wireless devices (WDs) such as laptops, smartphones... In infrastructure mode, wireless devices are wirelessly connected to a single AP, which is generally a wireless router, and are able to communicate to other devices only through that AP. For that reason, WDs are also called clients. In Fig. 1 we show a graphical representation of a scenario with 12 APs and 60 WDs.

2.2 Modelling based on a multilayer graph

Graphs are one of the most commonly used tools for modelling the frequency assignment problems, because of the relation of this problem to the graph coloring problem, which has been widely studied by the mathematical community [7]. In graph coloring, an abstract graph is considered, defined by a set of vertices along with some edges connecting them, and the objective 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

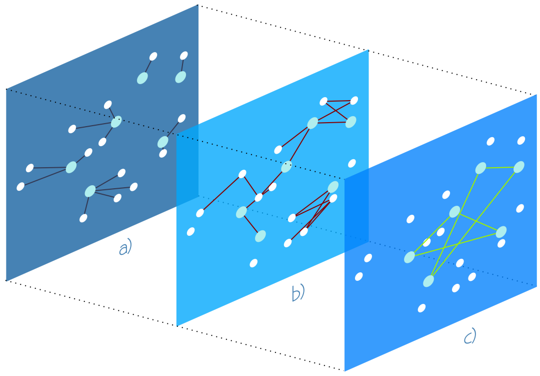

Fig. 2. Multilayer graph model.

model, graph nodes 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. [10] 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 a multilayer network graph [11], where each layer represents a different relationship between network elements, as shown in Fig. 2. In this graph we can distinguish two types of vertices: APs and WDs. *Layer a* captures the infrastructure links between Wi-Fi APs and WDs, i.e. the links shown in Fig. 1. 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 *layer a* will use the same channel (color) to communicate. On the other hand, *layer b* captures the potential interferences between nearby vertices. To be more specific, *layer b* 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. In Section 2.3 we describe the interference model in more detail. Finally, *layer c* captures the idea that usually there is a small number of communication providers to which the APs belongs to. This last layer is the key to model the automated negotiation, since the fact that a provider may choose to sacrifice the throughput of a given access point in favor of others is what will enable the existence of utility trade-offs during negotiations.

2.3 Interferences and utility of the solutions

To model interference power between two elements, we weigh each edge of the interference graph (*layer b* in the multilayer model) based on three factors:

1. We consider a weight for each color pair ij that we have called the co-channel index, which can be understood as the interference between color i and color j. It is worth noting that the usual coloring problem only takes into account the particular case of interferences between vertices of the same color, while our extension of the problem allows considering also interferences between adjacent colors or 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 for this index in [9], where authors provide a matrix where each value (i, j) represents the interference, as seen in channel i, motivated by a transmission on channel j.
2. We consider the distance between edge endpoints. This way, the weight assigned to a colored edge ij will be different depending on how far apart its endpoints are, following the propagation model described in [12]. This represents another extension to the usual coloring problem, because now vertices have also certain positions and this means that our graph is no longer abstract but geometrical.
3. We include the effect of the amount of data into the weights, including a factor (called activity index) that accounts for the fact that a higher bandwidth data flow will occupy the wireless channel a higher fraction of the time. In other words, higher bandwidth flows will generate more harmful interference signals, as they will occupy the spectrum for a higher ratio of time.

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. 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 have used the concept of utility, which is closely related to the perceived throughput and $SINR$. According to [13], 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 seen 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 [14]. 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.

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 a quite wide field [15] but most authors agree that a negotiation problem can be characterized by a negotiation domain (who negotiates and what to 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 [16]. 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 two network providers (commonly Internet Service Providers, ISPs), thus APs belong to one of the providers. Each provider only has control over the channel assignment for its own access points. According to this situation, $P = \{p_1, p_2\}$ will be the set of agents that 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, from the classical alternating offers model [17] to auction-based protocols [18]. From the assumption that the negotiation scenarios coming from Wi-Fi channel assignment will be highly nonlinear, and according to the discussion in [6], we have chosen a simple text mediation protocol [19]. 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 (i.e. the providers).
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 mechanism to be used by the negotiating agents and the mediator.

3.3 Decision Mechanisms

For the mediator, we have implemented a single-text mediation mechanism [19] 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^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.
- *Annealer (SA):* In this case, we use a widespread nonlinear optimization technique called *simulated annealing* [19]. 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 [20], and are the basis for several of other works [6]. Furthermore, as discussed in [19], 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.

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 [21]. We have also made the assumption that both APs and clients are randomly distributed throughout the environment, and that clients associate to the AP which is closer to them. With these assumptions, we have generated scenarios varying the number of APs (15, 50 and 100) and the number of clients per AP (1 and 5). For each of these combinations of parameters we generated 50 different graphs, for a total of 300 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). Keep in mind that there is more variability on the number of APs and clients than the one suggested by the parameter set, since we removed from the scenario any AP which had no nearby clients, and vice versa. Finally, for each scenario, we randomly assigned half of the APs to each provider.

4.2 Analysed techniques

In addition to the negotiation techniques under study, presented in Section 3.3, we have included a comparison with two reference techniques:

- *Random Reference*: as a first base line, in this technique each AP chooses a channel randomly.
- *Particle Swarm Optimization (ALPSO)*: additionally to our negotiators 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 [22].

4.3 Graph metrics for performance evaluation

One of the long-term purposes of our work is to study how the network structural properties of a problem influence the performance of optimization and negotiation approaches used to address it. To this end, we have selected a number of graph metrics from the literature to analyze our experimental results. The selected metrics are the following:

- *Graph order:* the number of nodes in the graph.
- *Graph diameter:* the longest distance between any pair of nodes in the graph [23].
- *Wiener index:* gives a measure of graph complexity from the distances in the graph. It is computed as $W(G) = \frac{1}{2}\sum_{i=0}^{|N|}\sum_{j=0}^{|N|} d(n_i, n_j)$, where $d(n_i, n_j)$ is the shortest distance between nodes [24].

- Graph density: the ratio between the number of edges in the graph and the maximum possible number of edges (that is, for a fully-connected graph).
- Clustering coefficient: a measure of the degree to which nodes in a graph tend to cluster together. The cluster coefficient of a graph is computed as the average of the local clustering coefficient of its nodes, which is the ratio between the number of links between a node's neighbors and the maximum possible number of links between them (that is, if they were fully connected).
- Average betweenness centrality. Centrality metrics measure the importance of a node within a graph. In particular, betweenness centrality of a node is the ratio of shortest paths in the graph which traverse the node [25].

One of our long-term hypothesis is that these metrics may be used as a basis for mechanism selection in networked problems involving self-interested parties. As a first step in this track, 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 each of the aforementioned 300 scenarios, we did 20 repetitions with each of the benchmarked techniques, recording the achieved social welfare (sum of utilities for both providers) and the computation time.

Firstly, we study the performance of the evaluated techniques in the different scenario categories according to the scenario generation parameters (number of APs and number of clients per AP). Table 1 shows the average utility obtained by each approach for all the graphs in each category. We can see that, for the less complex scenarios, all approaches but *random* perform reasonably well, with a non-significant little advantage for the hill climber (*HC*). As the scenarios grow more complex, we can see the performance of the *random* approach turns worse, which is reasonable since the size of the solution space becomes larger. We can also note significant increasing distance between the performances of the hill climber and the annealer (*SA*) negotiators. This confirms our hypothesis that these scenarios are highly nonlinear [19]. We can also see 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. Table 2 shows the average computation times for both approaches. We can see that, in the largest scenarios, the SA negotiator is roughly 10 times faster than the complete information optimizer.

To account for the diversity of scenarios within each category, we have analyzed the results of the best performing approach (SA) against the complete-information reference (ALPSO) with respect to the different metrics discussed in Section 4.3. Figure 3 shows, for each metric, the ratio between the average utility achieved by SA in the 20 runs for a given graph, and the average utility obtained by ALPSO for the same graph (hence the dashed line in the figures

Table 1. Utility for different techniques.

(APs,WDs)	Random		HC		SA		ALPSO	
	avg	std	avg	std	avg	std	avg	std
(15, 15)	12.45	1.90	15.88	0.02	15.86	0.04	15.86	0.03
(15, 75)	30.57	5.18	52.53	1.35	53.85	0.50	52.95	0.93
(50, 50)	29.17	4.15	50.40	0.89	51.08	0.52	50.06	0.98
(50, 250)	60.28	9.44	125.24	4.71	134.96	2.34	125.51	3.80
(100, 100)	45.37	5.48	84.90	2.39	88.33	1.52	83.53	2.25
(100, 500)	86.21	11.68	188.13	7.93	208.23	4.33	191.43	6.25

Table 2. Run time (in seconds) for different techniques.

(APs,WDs)	HC		SA		ALPSO	
	avg	std	avg	std	avg	std
(15, 15)	0.53	0.21	0.64	0.22	0.25	0.19
(15, 75)	5.79	1.22	5.96	1.23	5.86	2.00
(50, 50)	5.22	1.16	5.40	1.17	11.91	5.02
(50, 250)	69.39	6.44	69.32	6.36	285.89	74.37
(100, 100)	22.01	2.96	22.15	2.99	108.14	31.39
(100, 500)	330.38	17.23	326.90	16.61	3225.63	817.93

corresponds to the ALPSO 1.0 baseline). We can see there is an approximately linear increasing gain for SA with graph order, with ALPSO doing better for low-order graphs and SA getting to gains up to 10% for the larger graphs (Figure 3a). This is coherent with the results in Table 1. We can see an inversely proportional trend with the average betweenness centrality (Figure 3b). The SA negotiator performs better for low centrality values, which seems reasonable because in these graphs there will be more peripheral nodes (i.e. with less interfering nodes) than central nodes (i.e. with more interfering nodes), which should make negotiations easier. The same reasoning explains the results with respect to density (Figure 3c). The negotiator fares better in the less dense graphs (i.e. where there are less interference links).

There are other interesting patterns arising from the metrics analysis. For instance, Figures 3d and 3e suggest that there may be optimal values of graph diameter and graph cluster coefficient, respectively, regarding the performance of the SA negotiator. However, further analysis would be needed to rule out other possible explanations. For instance, it is reasonable to expect very little room for improvement of the negotiator in the extremely high clustering coefficient cases (almost complete graph, all nodes interfere with each other).

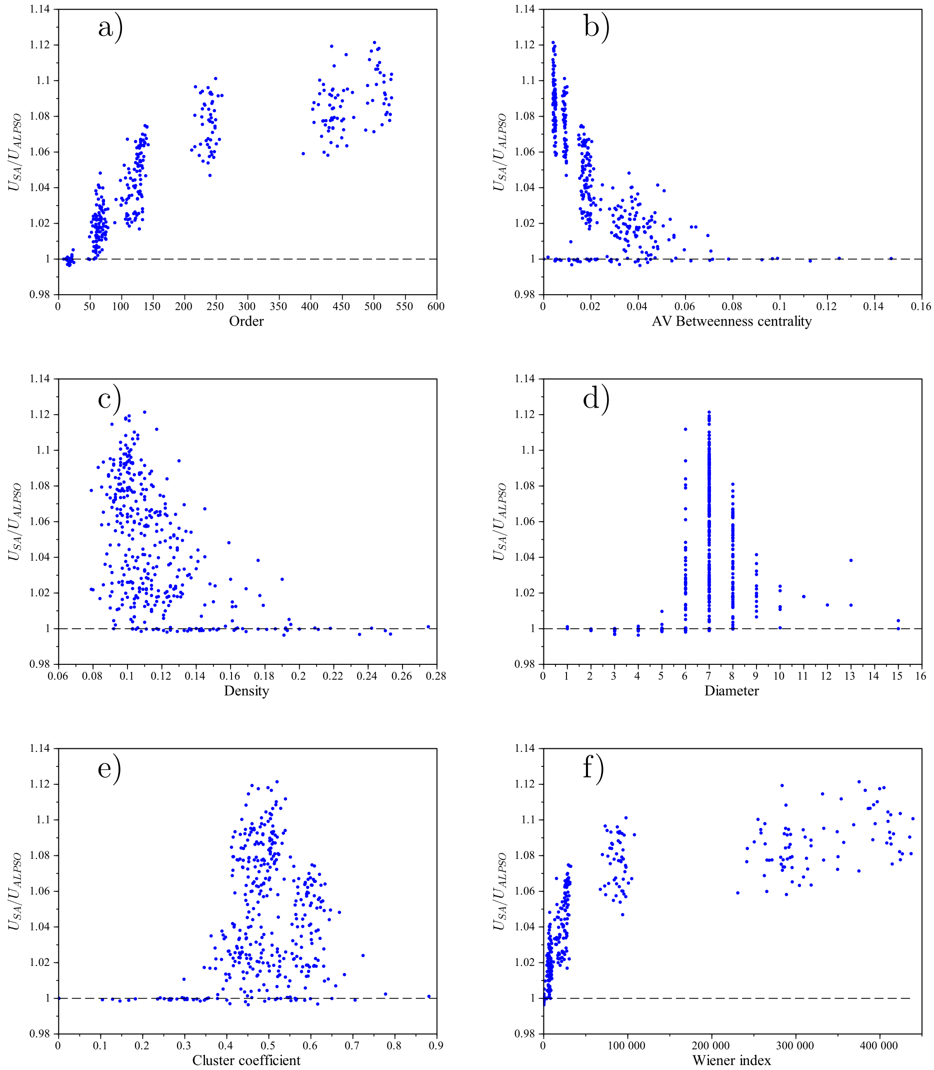

Fig. 3. Utility of SA relative to ALPSO for different graph metrics.

6 Conclusions and future work

This paper presents a problem inspired by an extension of the prominent graph coloring problem, enriched towards a real application domain (Wi-Fi channel assignment), which has been extensively studied from the discrete optimization perspective, but has not received attention from the negotiation community. We study a negotiated approach to address this problem, which is, to our knowledge, the first attempt to apply nonlinear negotiation techniques to real complex network scenarios. Experiments show that our approach based on simulated annealing significantly outperforms the optimizer used as a reference in both social welfare and computation time. This is a relevant result, since scalability is the main drawback to apply negotiation approaches to complex systems.

Although our experiments yield satisfactory results, there are still a variety of avenues for further research. As discussed in the previous sections, a range of bilateral and multilateral negotiation protocols and agent decision mechanisms can be studied. 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. Finally, we are interested in fully-distributed negotiations, where the need for mediation can be substituted by a form of distributed social choice.

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