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Distributed Multi-agent Negotiation for Wi-Fi Channel Assignment

Marino Tejedor-Romero[1](✉), Pradeep K. Murukannaiah[2], Jose Manuel Gimenez-Guzman[3], Ivan Marsa-Maestre[1], and Catholijn M. Jonker[2]

[1] University of Alcala, Alcala de Henares, Spain
{marino.tejedor,ivan.marsa}@uah.es
[2] Technical University of Delft, Delft, The Netherlands
{P.K.Murukannaiah,C.M.Jonker}@tudelft.nl
[3] Universitat Politècnica de València, València, Spain
jmgimenez@upv.es

Abstract. Channel allocation in dense, decentralized Wi-Fi networks is a challenging due to the highly nonlinear solution space and the difficulty to estimate the opponent's utility model. So far, only centralized or mediated approaches have succeeded in applying negotiation to this setting. We propose the first two fully-distributed negotiation approaches for Wi-Fi channel assignment. Both of them leverage a pre-sampling of the utility space with simulated annealing and a noisy estimation of the Wi-Fi utility function. Regarding negotiation protocols, one of the approaches makes use of the Alternating Offers protocol, while the other uses the novel Multiple Offers Protocol for Multilateral Negotiations with Partial Consensus (MOPaC), which naturally matches the problem peculiarities. We compare the performance of our proposed approaches with the previous mediated approach, based on simple text mediation. Our experiments show that our approaches yield better utility outcomes, better fairness and less information disclosure than the mediated approach.

Keywords: Wi-Fi networks · Simulated annealing · Automated negotiation

1 Introduction

Automated negotiation enables efficient distributed solutions for problems which are distributed by nature, but that due to their complexity tend to end up resorting to centralized management. A paradigmatic example of such a problem is Wi-Fi channel assignment. The *de facto* standard for dense, uncoordinated Wi-Fi networks is distributed [1], but it usually yields suboptimal allocations. Due to this, most managed settings resort to centralized solutions, which often disregard individual utilities in the search for a global optimum.

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In previous work, we proposed Wi-Fi channel assignment as a realistic and challenging benchmark for complex automated negotiations [2,6,11]. In this setting, different Wi-Fi providers, acting as agents, collectively decide how to distribute the channels used by their access points (APs) to minimize interference between nodes and maximize utility (i.e., network throughput) for their clients, which are different kinds of wireless devices, usually called stations (STAs).

We proposed a number of approaches in the Wi-Fi negotiation setting. However, the complexity of the negotiation domain, along with the difficulty to estimate utility *a priori*, forced us to resort to mediated settings. The most successful approach was based on simple text mediation and simulated annealing [11]. Although the approach clearly outperformed the *de facto* standard, it required a large number of bidding rounds by the agents (on the order of thousands), apart from raising great concerns in terms of communication efficiency and privacy.

In this work, we propose novel distributed negotiation approaches intended for Wi-Fi channel assignment. Further, we want to test the hypotheses that these approaches can be used as an efficient alternative to the centralized ones. This work contributes to achieve this goal in the following ways:

- We describe the Wi-Fi channel assignment as a negotiation problem, and our previous mediated approach (Sect. 2).
- We propose a pre-sampling of the utility space with simulated annealing and a noisy estimation of the Wi-Fi utility function. Then, we incorporate these techniques to two negotiation protocols: Alternating Offers and Multilateral Negotiations with Partial Consensus (MOPaC) (Sect. 3).
- We validate our approaches on a real-world setting modelling a residential building, comparing our negotiation approaches to two reference techniques: the *de facto* standard in Wi-Fi networks based on choosing the least congested channel and our previous work of centralized mediation (Sect. 4).

The experimental results (Sect. 4.3) show that our benchmarked negotiation approaches significantly outperform the *de facto* standard and the centralized mediator in terms of social welfare and Nash product. In addition, we observe better fairness results with the distributed approaches, and a clear advantage in terms of communication efficiency and privacy. The last section includes a summary, concluding remark, and directions.

2 Wi-Fi Channel Assignment: A Challenging Negotiation Domain

We briefly review the previous work on applying negotiation to Wi-Fi channel assignment. First we discuss the peculiarities of the problem and the notion of utility we use (which is based on Wi-Fi throughput), and then we describe the mediated negotiation approach we will compare our proposals with.

2.1 Wi-Fi Performance and Utility

IEEE 802.11 based networks, commercially known as Wi-Fi networks, have greatly changed the way users connect to Internet, mainly due to their infrastructure mode operation. In this mode, Wi-Fi networks are made up of two types of devices: access points (APs) and stations (STAs). More specifically, in infrastructure-mode Wi-Fi networks, each STA is associated with an AP, so that each STA can only communicate directly with its AP, so if two STAs want to communicate, they must communicate by means of, at least, an AP.

One of the reasons for the great popularity of Wi-Fi networks is that they are deployed in unlicensed frequency bands, so anyone can use these bands freely. The most popular examples of unlicensed frequency bands where Wi-Fi networks operate in are the so-called 2.4 GHz and 5 GHz frequency bands. Although our work can be easily extrapolated to the 5 GHz frequency band, we focus on the 2.4 GHz one as it is still the most widely used and congested, so it is the one where our proposal can become more advantageous. We consider the standard IEEE 802.11n (Wi-Fi 4) operating in the 2.4 GHz band. In this context, there are 11 possible channels in which each AP (and, therefore, all their associated STAs) can operate. These 11 channels are not orthogonal, but partially collide, which makes the problem of channel assignment even more challenging.

To study the problem of Wi-Fi channel assignment, we have modeled Wi-Fi networks by means of geometric 3D graphs. Graphs let us to accurately describe the network behavior while keeping the model abstract and reusable. Formally, a graph can be defined as a set of vertices (V) and a set of edges (E) connecting those vertices, $E \subseteq \{(u, v) \mid u, v \in V\}$. This geometric graph has two types of vertices (APs and STAs) and two types of edges—one represents the interfering signals, and the other represents the desired signal between each STA and its associated AP. As a consequence, and using a specific propagation model (we have used the indoor propagation model proposed by ITU-R in the Recommendation P-1230-10), for each STA, the graph model yields not only the power of the signal an STA receives from its AP, but also the power of all the interferences that are received by that STA. Therefore, the graph model will let us to compute the Signal-to-Interference-plus-Noise Ratio (SINR), computed as the quotient between the power of the received signal from the AP divided by the sum of the powers of all the interferences plus the thermal noise. SINR is a key performance parameter that defines the throughput, which is the main performance parameter that defines the quality of service perceived by the final user. In this sense, depending on the SINR a certain MCS (Modulation and Coding Scheme) can be used, as defined in the Wi-Fi 4 standard. For example, as the SINR grows, we will be able to use coding schemes with less redundancy together with digital modulations with a higher number of bits per symbol.

The utility function we use for the negotiation is based on the throughput model for each AP and STA, depending on the chosen channels. The problem settings (high cardinality of the solution space and attribute interdependence) make the utility functions highly complex, with multiple local optima.

2.2 Mediated Negotiation for Wi-Fi Channel Assignment

Given the above discussion, we formally define different elements of the problem. For a channel assignment problem with n_{AP} access points, P is the set of access points. A solution or deal $S = (s_1, s_2, s_3, \ldots, s_{n_{AP}})$, where each $s_i \in \{1, \ldots, 11\}$, represents the assignation of a Wi-Fi channel to the i-th access point.

We assume that there are different network providers (commonly Internet Service Providers, ISPs) or agents. 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.

$A = \{1, 2, \ldots, n_a\}$ is the set containing every agent in the channel assignment problem. The set P is partitioned into n_a subsets, one for each agent. P_a is the subset of access points which belong to agent a.

The utility of an agent depends on the throughput estimated for each solution S. Our model returns the estimated throughput of each access point for the given vector of channels. The global utility for a solution S is U_S and can be calculated as the sum of all throughput values. However, it is more important to define agent-dependant utilities. The utility obtained by agent a for a solution S, $u_{S,a}$, is the sum of the throughput values of the corresponding access points, i.e., the sum of the throughput values for the access points in P_a. The opponent utility, $u^{\mathsf{c}}_{S,a}$, is the sum of the throughput of every access point which does not belong to a, i.e., the sum of the throughput values for the access points in $P - P_a$. Further, for protocols requiring a normalized utility in $[0, 1]$, we can divide the utility by the maximum ideal throughput obtained with no interference whatsoever.

In our previous work on this setting [2,6,11], we used several variations of the simple text mediation protocol [9]. The most successful technique after our previous experiments worked as follows:

1. The mediator starts with a randomly-generated candidate contract (S^c_0). This means to assign each AP a random channel.
2. In each iteration t, the mediator proposes a contract S^c_t to the rest of agents. To generate the next candidate contract S^c_t, the mediator takes the base contract S^c_{t-1} and mutates one of its issues randomly. This corresponds to choosing a random access point and selecting a new random channel for it.
3. Each agent either accepts or rejects the contract S^c_t. To perform this decision, we use a widespread nonlinear optimization technique called simulated annealing (SA) [8]. With this technique, 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 depends on the utility loss Δu associated to the new contract and *annealing temperature* τ, and is equal to $e^{\frac{-\Delta u}{\tau}}$. Annealing temperature begins at an initial value, and linearly decreases over the successive iterations of the protocol.
4. The mediator generates a new contract S^c_{t+1} from the previous contracts and from the votes received from the agents. At time t, if 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. The process moves to step 2.

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

Although the negotiation mechanism above yielded satisfactory results in terms of social welfare, it had a number of limitations. First, since it optimized the sum of utilities, it had a tendency to produce unfair assignments. Second, it needed the agents to vote over thousands of contracts during the negotiation, which involved a significant communication overhead and a potential privacy concern. Our hypothesis is that these limitations can be overcome by using distributed, unmediated negotiation approaches, which we propose next.

3 Unmediated Techniques for Wi-Fi Channel Negotiation

We propose novel approaches for Wi-Fi negotiation. To our knowledge, these are first unmediated negotiation approaches succeeding in this setting.

Our aim is to apply state-of-the art negotiation techniques to the Wi-Fi domain, in order to benefit from the variety of approaches in the literature. However, the peculiarities of the setting prevent the application of most of these techniques. One of the main obstacles is the unfeasibility of performing an exhaustive search over the utility space, due to high cardinality. For instance, in the scenario analyzed in the validation, the number of bids is 11^{40}. Many negotiation approaches, such as the ones implemented in GENIUS [5], rely on the agent having an ordered set of bids, so that it may choose at each step in the negotiation an adequate bid according to the agent's current aspirational level. The other main challenge is how to obtain bids that correspond to "good negotiation moves," and it is related to negotiation predictability. Being able to (partly) predict the preference profile of the other negotiators makes it easier to make an offer that the other party can accept, and increases the possibility of reaching a good negotiation outcome more quickly [12]. This is specially challenging in our scenario for two reasons. First, the utility spaces are highly rugged, so linearity, concavity or convexity assumptions are not possible. Second, the utility for the agents depend on the precise location of APs and STAs at a given time, which may not be known with full precision. Therefore, there is an uncertainty not only about the opponent's utility function, but also about the agent's one.

In the following, we describe the techniques used to overcome these two challenges, and then the protocols used for the negotiation.

3.1 Estimating Utility Through the Graph Model

Although estimating the opponent utility is challenging for the Wi-Fi channel negotiation domain, we need these values for the negotiation. To address this challenge, we rely on the graph model.

We assume that each agent knows the position of their access points, and the position of every client connected to those access points. However, this is not enough to obtain the estimated throughput. We must know the position of all the devices in the Wi-Fi network. For this purpose, agents can use Wi-Fi localization techniques. The state-of-the-art approaches such as [4,10] allow positioning these devices with an error below 1.7 m. Thus, it is realistic to assume that every agent can have their own estimated version of the Wi-Fi graph. Its own access points and devices will have accurate positions, while the rest of the devices have an approximate position. In our benchmarks, we simulate this behaviour, adding a Gaussian noise to the position of the unknown devices. In particular, we add a random distance determined by a Gaussian distribution with $\sigma = 1.7$ in a random direction, following the results described in [4,10].

3.2 Annealing Exploration

To allow agents to have a tractable, ordered set of bids to use in the negotiation, we leverage the success of the previous approach in making an efficient exploration of the utility space in the search for an optimum. Since the annealer optimizer used in [2,6,11] was able to "climb" the utility space from a random contract to an optimum, we are going to use the same approach at each agent individually, to come up with a small subset of bids covering a wide variety of utility values for the agent. The process works similarly as the one described in Sect. 2.2, with a number of minor adjustments due to the fact that now it is an individual process performed at every agent prior to the negotiation:

1. Each agent a starts with a randomly-generated candidate bid ($S_{0,a}$).
2. In each iteration t, the agent generates a simple mutation of the bid $S_{t,a}$, changing only one of the issues to a random value.
3. The agent calculates the utility of the new candidate bid for itself ($u_{S_t,a}$), which depends on the resulting throughput of its access points, and the opponent's utility ($u_{t,a^\complement}$), which depends on the resulting throughput of every other access point that does not belong to agent a.
4. This bid ($S_{t,a}$), its own utility ($u_{S_t,a}$) and the opponent's utility ($u^\complement_{S_t,a}$) are stored.
5. The agent chooses whether to use the candidate bid $S_{t,a}$ as the base bid to generate the next bid $S_{t+1,a}$ or to maintain the previous base bid. This is done by annealing, with a probability depending on the utility loss for the agent associated to the new bid $\Delta u_a = u_{S_t,a} - u_{S_{t-1},a}$ and the *annealing temperature* τ, as described above. The process moves to step 2.
6. After a fixed number of iterations, the agent stops exploring and obtains a set of bids with associated utilities for itself and for the opponents.

At the end of this process, each agent will have sampled its bid space in a directed way, to maximize its utility. Since we store all the history of the annealer exploration process, along with the utility for each bid, we have an ordered subset of the bid space covering a variety of aspiration levels for the agent. This can be used to apply conventional negotiation strategies to this new setting.

3.3 SAOP-Based Unmediated Negotiation

Without a mediator, it is necessary to follow an automated negotiation protocol. Simple Alternating Offering Protocol (SAOP) is a clear example [3]. In SAOP, for each round of negotiation, one of the agents offers a contract, and the other evaluates it, accepting it or not depending on its utility. In the next round, they reverse their roles. The negotiation continues until a contract is accepted.

In order to test our annealing exploration of the contract space and our opponent's utility estimation method, we created a new agent for the SAOP protocol, designed to negotiate on the Wi-Fi channel domain, in a bilateral setting. Our agent's bidding strategy is inspired by time-dependent agents. Time-dependent agents start proposing the bid which yields maximum utility for them, but they make concessions throughout the negotiation rounds, lowering their utility goals. Each agent proceeds as follows:

1. The agent runs one or several simulated annealers, aiming to maximize their own function, according to the technique explained in Sect. 3.2. This is a preparation stage, prior to any communication between agents.
2. Every round, the agent calculates its utility goal. Since the negotiation takes place in a fixed number of rounds, the typical behavior is to start aiming for the maximum utility, lowering the goal as the negotiation advances, in order to achieve an agreement. The utility goal function can be configured, following different strategies, but for simplicity, we are using linear concession.
   - If it is the agent's turn to offer a contract, it extracts the subset of contracts that satisfy the goal. For this subset, it sends the contract with the greater estimated utility for the rest of the agents.
   - On the contrary, if the agent evaluates an incoming offer, it simply checks if the received contract satisfies the goal.

3.4 MOPaC-Based Unmediated Negotiation

Our previous working strategy, mediated negotiation based on simulated annealing, can be generalized to any number of network providers or agents. However, the agent we designed for SAOP works only for bilateral negotiation. To generalize unmediated negotiation for multiple agents, we choose a different protocol that supports multi-party negotiations and enables us to adapt our agent.

We choose the Multiple Offers Protocol for Multilateral Negotiations with Partial Consensus (MOPaC) [13]. In MOPaC, at the beginning of a round, every agent proposes a contract to a common pool. Then, every agent evaluates every contract in the pool, communicating if the vote is positive or negative, and a minimum and maximum consensus threshold. This protocol does not require a full consensus, and can be configured to search for multiple partial consensus.

The first two steps are similar: the agent runs one or several explorations through simulated annealing. Then, for each round, the agent calculates its utility goal, using any configured progression function, linear or not. The biding behavior is also similar: given a utility goal, the agent extracts a subset of contracts which satisfy this goal, and send the one that yields more opponent utility.

In a multi-party negotiation, there is one utility for each opponent. As a last step, in the voting phase, agents vote using their utility goal, looking for consensus.

While MOPaC allows partial consensus, we are, for the moment, forcing a complete agreement. The possibility of reaching several partial agreements can make our approach richer and more versatile, but we are still exploring this idea, as we will cover in the Future Work section.

4 Experimental Evaluation

4.1 Considered Scenario

We conduct our experiments in a realistic scenario that models a 5-floor residential building as a paradigmatic example where multiple Wi-Fi networks coexist. In this setting, each floor has a length, width and height of 40, 30 and 3 m, and there are eight flats in each floor in a 4×2 layout. In each flat, there is one AP and four STAs. Every STA in a flat is associated to the AP from the same flat, even when there are closer APs from contiguous flats. For each flat, the position of the AP and its STAs follows a uniform distribution in the x- and y-axis, but, in the z-axis, the position of each AP and STA is normally distributed in each floor with a mean of 1.5 m and a standard deviation of 0.5 m, being this random height also bounded to the limits of the floor. In summary, our experimental setting consists of 40 APs distributed along 5 floors and $40 \times 4 = 160$ $STAs$, where there are 4 STAs associated to each AP. Figure 1 shows a graphical representation of the experimental layout under study.

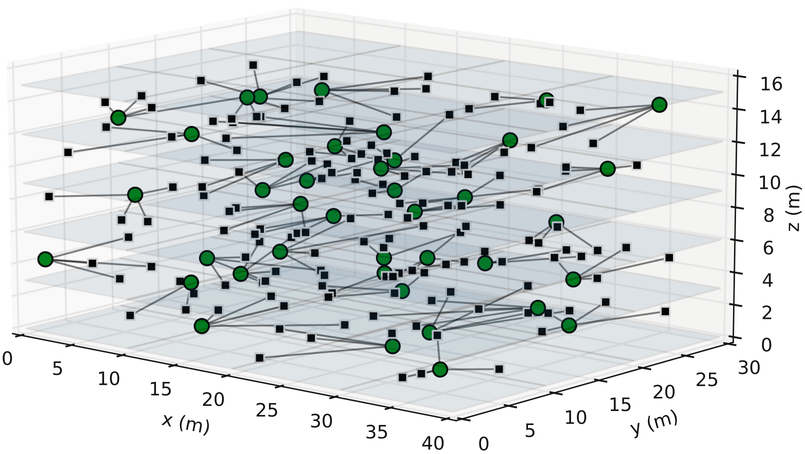

Fig. 1. Considered scenario for experimental evaluation.

4.2 Experimental Settings

The techniques used for evaluation have been described above, but we summarize them here for convenience.

- *Least Congested Channel search (LCCS)*: LCCS is the de facto standard for Wi-Fi channel assignment [1]. It is 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 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.
- *Mediated negotiation with two and four agents (MN-2 and MN-4)*: The mediated approach we used in our previous works [2,6,11], which we described in Sect. 2.2. To allow for a better comparison with the two approaches we propose, we run experiments with two and four agents.
- *Annealer exploration and alternating offers protocol (AE-AOP)*: Here, we perform the initial exploration of the agent utility spaces described in Sect. 3.2, and then we use a bilateral SAOP (Sect. 3.3) for the negotiation.
- *Annealer exploration and MOPaC (AE-MOPaC)*: Again, we perform the initial exploration of the agent utility spaces described in Sect. 3.2, but then we use MOPaC (Sect. 3.4) with four agents for the negotiation.

In all cases, the distribution of APs among the different agents was performed randomly for each trial. Agent utility functions were generated making noisy estimations of the real Wi-Fi graph as described in Sect. 3.1. Again, these estimations were generated randomly for each agent and trial.

Each technique was run for 100 times over the scenario described above. For each run, we measured social welfare, the Nash product, and the Jain index for fairness [7], which is widely used in the wireless network domain. These metrics will be briefly described in the next section.

4.3 Experimental Results

Table 1 summarizes our results. The first measure we can compare is social welfare, measured globally in Mbit/s. It is the sum of the complete throughput vector. LCCS, the de facto standard, obtains the lowest social welfare. The two highest values are from AE-MOPaC, and AE-AOP, which are based on unmediated negotiations with two and four agents, respectively. The corresponding mediated counterparts with two and four agents offer a better social welfare compared to LCCS. However, note that the unmediated negotiation scores higher than the mediated negotiation if we maintain the number of agents; that is, AE-AOP improves MN-2 result and AE-MOPaC improves MN-4 result.

The Nash product and fairness index cannot be compared globally. The Nash product can be compared only between techniques with the same number of agents. In this comparison, the unmediated negotiations obtain approximately 1.5 times the Nash product of the mediated counterpart, which is an important

Table 1. Comparing the proposed decentralized approaches (AE-MOPaC, and AE-AOP) with mediated approaches (MN-2 and MN-4) and the de facto standard (LCCS). Average values (avg) and confidence intervals (CI) are reported.

	Social Welfare		Nash Product		Jain's Fairness		Comm. Overhead
	Avg	CI	Avg	CI	Avg	CI	Avg
LCCS	626.66	9.29	–		–		0
MN-2	637.39	10.88	$9.54 \cdot 10^4$	$3.40 \cdot 10^3$	0.938	0.007	$3 \cdot 10^3$
AE-AOP	787.54	8.85	$1.50 \cdot 10^5$	$3.31 \cdot 10^3$	0.967	0.004	$5 \cdot 10^1$
MN-4	760.24	15.52	$1.08 \cdot 10^9$	$8.80 \cdot 10^7$	0.907	0.011	$3 \cdot 10^3$
AE-MOPaC	817.57	12.85	$1.58 \cdot 10^9$	$1.05 \cdot 10^8$	0.949	0.014	$5 \cdot 10^1$

improvement. Fairness can be compared only between negotiation techniques, leaving LCCS outside of the comparison. Again, it is only fair to compare negotiations with similar number of agents. In this case, we can perceive significant improvements in the fairness of the results using unmediated negotiation over mediated counterparts, although the improvement is more modest.

The communication overhead depends on the protocol. LCCS requires no communication between access points, making it the most simple and lightweight approach. Mediated negotiation requires a number of messages equal to the number of contracts proposed in the simulated annealing process. In our experiments, the communication overhead is 3000 interactions, since we have used 3000 iterations for all the simulated annealing executions. In the unmediated negotiations, agents run their annealing exploration processes independently, eliminating the overhead of 3000 iterations. However, they still need to propose contracts until one of them is accepted. In other words, the communication overhead depends on the negotiation rounds. This parameter is configurable, and we used 50 rounds for our experiments. This is an upper bound, since the actual number of rounds is mostly below 50 rounds, before it reaches the deadline.

5 Conclusions and Future Work

Optimizing the performance of Wi-Fi networks through channel assignment is an example of a distributed critical real-world problem. In the past, we addressed this challenge using mediated negotiation. This paper aims to advance towards a more distributed solution, evaluating the use of fully unmediated negotiation techniques. We compare the negotiation-based approaches with both the *de facto* standard for Wi-Fi channel assignment and our previous mediated approach. Our current experiments show an improvement of performance over the mediated approach in terms of social welfare, Nash product, and fairness.

This paper opens several research directions. First of all, it is important to optimize simulated annealing parameters so we can properly compare the optimal performance of unmediated and mediated negotation techniques. Another open challenge of our approach is how to use opponent's offers to refine our utility model throughout the negotiation. Finally, we would want to explore other strategies and partial consensus formation approaches for MOPaC.

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