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Comparing Mediated and Unmediated Agent-Based Negotiation in Wi-Fi Channel Assignment

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Abstract. Channel allocation in dense Wi-Fi networks is a complex problem due to its nonlinear and exponentially sized solution space. Negotiating over this domain is a challenge, since it is difficult to estimate opponent's utility. Based on our previous work in mediated techniques, we propose the first two fully-distributed multi-agent negotiations for Wi-Fi channel assignment. Both of them use a simulated annealing sampling process and a noisy model graph estimation. One is designed for Alternating Offers protocols, while the other uses the novel Multiple Offers Protocol for Multilateral Negotiations with Partial Consensus (MOPaC), with experimental promising features for our particular domain. Our experiments compare both proposals against their mediated counterparts, showing similar results on social welfare, Nash product and fairness, but improving privacy and communication overhead.

Keywords: Wi-Fi · Simulated annealing · Automated negotiation

1 Introduction

Wi-Fi channel assignment is clearly a distributed problem, where each access point (AP) may autonomously choose the channel it operates in, and its performance depends both on its choice and the choices of the APs in interference range. In fact, Least Congested Channel search (LCCS) [1], the *de facto* standard for dense, uncoordinated Wi-Fi networks is distributed. But this uncoordinated search often yields suboptimal distributions. In order to solve this, most managed settings design channel distributions for their devices centrally.

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 agents negotiate the distribution of the channels used by the access

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points (APs) of the network, where the objective is to maximize the network throughput. This technique is coordinated and distributed. We proposed a number of approaches, but the complexity of the negotiation domain, along with the difficulty to estimate utility, forced us to resort to mediated settings. The most successful approach was based on simulated annealing [11], which clearly outperformed LCCS, at the cost of a large number of bidding rounds.

In this work, we propose fully-distributed and unmediated alternatives for negotiation in Wi-Fi channel assignment based on our previous techniques. The experimental results (Sect. 5.3) show that mediated and unmediated negotiation approaches are similar in terms of social welfare, nash product and fairness. In addition, we observe an advantage in terms of network efficiency and privacy.

2 Wi-Fi Channel Assignment as a Negotiation Problem

In this section we briefly review the characteristics of the negotiation domain, the problems it presents, and the utility metric we use.

IEEE 802.11 based networks are commercially known as Wi-Fi networks. In the infrastructure mode operation there are two types of devices: access points (APs) and stations or clients(STAs). Each client will connect to an access point in order to communicate with the rest of the network, which will act like a bridge.

One of the reasons for the great popularity of Wi-Fi networks is that users can connect wirelessly over unlicensed frequency bands. The most frequent of these operating unlicensed frequency bands are the so-called 2.4 GHz and 5 GHz frequency bands. For the moment, we focus on the 2.4 GHz (IEEE 802.11n or Wi-Fi 4) one since it is the most congested, where our proposal can be more beneficial, but our work can be easily extrapolated to others. In this frequency band, there are 11 possible channels for each access points and its associated clients, which partially overlap, which makes the problem even more challenging.

To study the problem of Wi-Fi channel assignment, we have modeled Wi-Fi networks by means of geometric 3D graphs. This way, we can keep 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, $E \subseteq \{(u, v) \mid u, v \in V\}$. The vertices represent APs and STAs. The set of edges contains useful signals (signal between a station and its access point) and interfering signals (any signal between two devices that are not communicating). With this graph, we can compute the Signal-to-Interference-plus-Noise Ratio (SINR) for every station as the quotient between the power of the received signal from its access point divided by the sum of the powers of all the interferences plus the thermal noise. SINR is a key performance parameter that will define the throughput. Depending on the SINR, a certain Modulation and Coding Scheme (MCS) can be used. In other words, as the SINR grows, we will be able to use more aggressive coding schemes with less redundancy and more bits per symbol, in exchange. These powers need to be calculated using a specific propagation model. We have used the indoor propagation model proposed by ITU-R in the Recommendation P-1230-10.

Given the above discussion, we formally define different elements of the problem.

– A solution or deal is expressed as a vector $S = (s_1, s_2, s_3, \dots, s_{n_{AP}})$, where each $s_i \in \{1, \dots, 11\}$, represents the assignment of a Wi-Fi channel to the i-th access point.
– The global utility for a solution S is $u(S)$ and can be calculated as the sum of all throughput values. The partial utility obtained by an agent A for a solution S is $u_A(S)$, and can be calculated as the sum of the throughput of all stations attached to the access points depending on the agent A. The opponent utility for an agent A for a solution S is $u_A^o(S)$, and can be calculated as the complementary measure of the previous utility, this is, the sum of the throughputs of all stations attached to access points not controlled by said agent A. These utilities are defined in absolute terms, but can also be expressed in a relative way, normalized.

3 Previous Work

In our previous work on this setting [2,6,11], we used several variations of the simple text mediation protocol [9]. Before we describe our new approach, it is helpful to review a common algorithm family: Simulated Annealing.

3.1 Simulated Annealing

Simulated annealing (SA) [8] is a family of heuristic algorithms. Its goal is to find a global optimal solution in a complex non-linear discrete space, and it is best used when the complete solution space is large and rough, this is, there are many local maxima that make it difficult to find the global optimal solution.

The principle behind SA is to roam across the solution space jumping from one neighbour to another, trying to maximize the utility while being able to escape local maxima. The steps are randomly chosen, and then evaluated. If the candidate yields better utility, it is always accepted. Otherwise, it is decided randomly depending on the current iteration count, and how much worse the new utility is. The exact implementation of simulated annealing depends on the particular problem.

3.2 Mediated Negotiation for Wi-Fi Channel Assignment

Based on simulated annealing, we developed a mediated multi-agent distributed algorithm. It needs a mediator and a number of agents. It works as follows:

1. The mediator starts with a randomly-generated solution, the vector (S_0) and it becomes the current channel vector.
2. In each iteration t, the current channel vector is S_t. The mediator proposes a new candidate S_t^c, changing a random access point to a new random channel.
3. Each agent A either accepts or rejects the candidate S_t^c. Their votes follow the same principle explained in the Simulated Annealing section. They evaluate their own partial utility difference between the new candidate and the current

state, this is $\Delta u_A = u_A(S_t^c) - u_A(S_t)$. With the utility difference and the current temperature (determined by the initial temperature and the cooling schedule), they calculate the probability of acceptance.
4. If all agents have accepted the new candidate S_t^c, it will become the new current state of the algorithm $S_{t+1} = S_t^c$. Otherwise, it will be discarded, maintaining the previous state $S_{t+1} = S_t$. 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 unmediated negotiation approaches, which we propose next.

4 Unmediated Techniques for Wi-Fi Channel Negotiation

We propose the first unmediated negotiation approaches succeeding in this domain. The special characteristics of the Wi-Fi channel domain were preventing the application of state-of-the-art negotiation techniques for these reasons:

1. The high cardinality of the solution space, which makes an exhaustive search unfeasible. For instance, in the biggest scenario in our experiments, a residential building with 40 access points, the number of bids is 11^{40}. This is clearly an obstacle since many negotiation approaches, such as the ones implemented in GENIUS [5], rely on the agent having an ordered set of bids.
2. The lack of negotiation predictability. Being able to estimate the preference profile of the opponents makes it easier to make an effective offer, and it increases the chances of reaching a good outcome more quickly [12]. In our scenario, this problem is, at the same time, twofold. First, the utility space are highly rugged, so linearity, concavity or convexity assumptions are not possible. Second, the estimated utility for the agents depend on the accuracy of the positions of both access points and stations at a given time. Therefore, there is an uncertainty not only about the opponent's utility function, but also about the agent's own one.

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

4.1 Estimating Utility Through the Graph Model

First, in order to address the difficulty of estimating the utility functions ($u_A(S)$ and $u_A^o(S)$), we rely on the graph model.

We assume that each agent can determine the accurate location of their access point and its connected clients, but this is not enough to obtain the estimated throughput. For the rest of positions, agents can use Wi-Fi state-of-the-art localization techniques such as [4,10]. These two sources present results with an average error below 1.7 m. Thus, it is realistic to assume a mixed positioning approach. Each agent will have a different version of the graph, where its access points and stations will have accurately positioned, and the rest of the devices will have an approximate position.

4.2 Simulated Annealing One-Sided Exploration

To allow agents to have a tractable and ordered set of bits to choose from during the negotiation, we leverage the success of the previous approach. The variant of this heuristic executed by each agent, prior to the negotiation, in order to sample the bid space in a directed way, works as follows:

1. Each agent A starts with a randomly-generated current state vector S_0.
2. In each iteration t, the current state is S_t. The agent generates a new candidate as a simple mutation of the current state S_t^c.
3. The agent stores this new candidate S_t^c, its utility for the agent $u_A(S_t^c)$, and the opponent utility $u_A^o(S_t^c)$.
4. The agent calculates the difference of utility $\Delta u_A = u_A(S_t^c) - u_A(S_t)$. With the utility loss and the current temperature, the agent obtains an acceptance probability. If the candidate is accepted, it will become the current state $S_{t+1} = S_t^c$. If it is discarded, the previous state is maintained, $S_{t+1} = S_t$.
5. 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.

The most important part of this variation is to store all the steps, and associated estimated utilities. This allows to have an ordered subset of the bid space that covers a range of aspiration levels for the agent. This detail will enable conventional negotiation strategies to be deployed over this domain.

4.3 Bilateral Unmediated Negotiation

We are going to introduce briefly an example of how to negotiate in the Wi-Fi channel domain using standard techniques, covering the simplest case: a bilateral negotiation. For this part, we have chosen Simple Alternating Offering Protocol (SAOP) [3]. In this protocol, for each round of negotiation, one of the agent proposes a bid, and the other agent evaluates it, accepting it or not. In the next round, their roles will be reversed. The negotiation ends when a bid is accepted by any of the agents or when they reach a fixed number of rounds.

In order to test our annealing exploration and the utility estimation method, we have created a simple agent for SAOP that includes frequently used techniques. It is based on time-dependent agents, which start proposing the bid which yields maximum utility for themselves, but start conceding throughout the negotiation rounds, lowering their utility goals until they reach a common agreement. This simple agent proceeds as follows:

1. The agent runs one or several simulated-annealing-based explorations, according to the technique explained in Sect. 4.2. This is a preparation stage, prior to any communication between agents.
2. Every round, the agent calculates its utility goal. Without loss of generality, in this work we use a linear concession strategy to compute the utility goal at each round.
3. If it is the agent's turn to offer a contract, it extracts the subset of contracts that satisfy its own utility goal and sends the contract with the greater estimated opponent utility. On the contrary, if the agent evaluates an incoming offer, it simply checks if the received contract satisfies the goal.

4.4 Multi-party Unmediated Negotiation

The next objective is to extrapolate this simple approach towards an unmediated negotiation with multiple agents. In this step, we have chosen a new negotiation protocol. 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 and vote them, including a minimum and maximum consensus threshold. This protocol does not require a full consensus, and can be configured to search for multiple partial consensus.

It works in a similar fashion as in the SAOP-based protocol: the agent explores the bid space using SA. Then, for each round, the agents calculate their utility goal. Given an utility goal the agent extracts the subset of bids which satisfy the corresponding goal and propose the one that yields more estimated opponent utility. As a last step, in the voting phase, agents vote using their utility goal, looking for consensus.

5 Experimental Evaluation

5.1 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. Using this building model, we have generated three different buildings, configured with two, four, and six stations per access point, respectively. For each flat, the position of the AP and its STAs follows a uniform distribution in the x and y-axis, and a normal distribution in the z-axis ($\mu = 1.5$ m, $\sigma = 0.5$ m). In summary, our experimental scenarios contain 40 APs distributed along 5 floors and $40 \times 2 = 80$ $STAs$, $40 \times 4 = 160$ $STAs$, or $40 \times 6 = 240$ $STAs$.

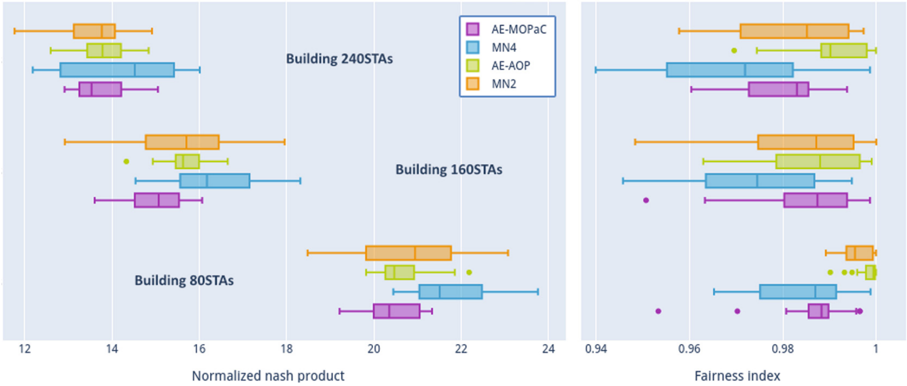

Fig. 1. Normalized nash product ($\sqrt[\text{Number of agents}]{\text{Nash product}}$/Number of stations per agent) and Jain's fairness index for mediated and unmediated negotiations in different buildings according to our experiments.

5.2 Experimental Settings

We summarize here again the techniques used for evaluation, for convenience.

- *Mediated negotiation with two and four agents (MN-2 and MN-4)*: The mediated approach we used in our previous works [2,6,11]. To allow for a better comparison, 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. 4.2, and then we use a bilateral SAOP (Sect. 4.3) for the negotiation.
- *Annealer exploration and MOPaC (AE-MOPaC)*: Again, we perform the initial exploration of the agent utility spaces described in Sect. 4.2, but then we use MOPaC (Sect. 4.4) with four agents for the negotiation.

Agent utility functions were generated making noisy estimations of the real Wi-Fi graph as described in Sect. 4.1. The precision of the unknown devices is modeled adding a random distance determined by a gaussian distribution with $\sigma = 1.7$ in a random direction. These estimations were generated randomly for each agent and trial. Each technique was run for 20 times for the three scenarios described above. All the SA explorations use 3000 iterations and 1 as the initial temperature. We measured measure the following metrics:

- *Social Welfare*: Sum of all throughputs, and global utility of a solution.
- *Communication Overhead*: Number of messages sent during the negotiation.
- *Nash product*: Product of the utility obtained by each one of the agents.
- *Jain index* [7]: Fairness index calculated with all the partial utilities obtained by each one of the agents.

The last two metrics can only be compared with the same number of agents, and for the same distribution of access points between these agents.

5.3 Experimental Results

Table 1, summarize our results. At the same time, we present a graphical summary of these tables in the 1.

The tables show the overall performance of the unmediated proposals is generally similar to the mediated ones (clearly superior to LCCS in our previous work). Communication overhead depends on the protocol. Mediated negotiation requires as many messages as contracts proposed by SA. In our experiments, we have used 3000 iterations for all SA executions. In unmediated negotiations, agents run their annealing exploration processes independently, eliminating this overhead. In this case, the communication overhead depends on the negotiation rounds. We used 50 rounds for our experiments.

With these results, we can tell that unmediated negotiations generally show a similar performance to the mediated counterpart, with clear advantage over the current standard. Unmediated negotiations, however, offer a communication overhead and privacy advantage, at no performance cost.

Table 1. Results for the experiments.

	Social welfare		Nash product		Jain's fairness		Comm. overhead
	Avg	CI	Avg	CI	Avg	CI	Avg
2 stations per access point							
MN-2	1669.85	49.88	$6.97 \cdot 10^5$	$4.16 \cdot 10^4$	0.996	0.001	$3 \cdot 10^3$
AE-AOP	1655.22	23.78	$6.84 \cdot 10^5$	$2.00 \cdot 10^4$	0.998	0.001	$5 \cdot 10^1$
MN-4	1755.00	36.47	$3.63 \cdot 10^{10}$	$3.23 \cdot 10^9$	0.985	0.005	$3 \cdot 10^3$
AE-MOPaC	1646.45	23.94	$2.80 \cdot 10^{10}$	$1.66 \cdot 10^9$	0.986	0.005	$5 \cdot 10^1$
4 stations per access point							
MN-2	2526.87	94.28	$1.58 \cdot 10^6$	$1.12 \cdot 10^4$	0.984	0.007	$3 \cdot 10^3$
AE-AOP	2524.92	43.30	$1.57 \cdot 10^6$	$5.19 \cdot 10^4$	0.986	0.005	$5 \cdot 10^1$
MN-4	2655.90	82.69	$1.89 \cdot 10^{11}$	$2.40 \cdot 10^{10}$	0.975	0.007	$3 \cdot 10^3$
AE-MOPaC	2420.60	45.60	$1.31 \cdot 10^{11}$	$9.63 \cdot 10^9$	0.984	0.006	$5 \cdot 10^1$
6 stations per access point							
MN-2	2526.87	94.28	$1.58 \cdot 10^6$	$1.12 \cdot 10^4$	0.984	0.007	$3 \cdot 10^3$
AE-AOP	2524.92	43.30	$1.57 \cdot 10^6$	$5.19 \cdot 10^4$	0.986	0.005	$5 \cdot 10^1$
MN-4	2655.90	82.69	$1.89 \cdot 10^{11}$	$2.40 \cdot 10^{10}$	0.975	0.007	$3 \cdot 10^3$
AE-MOPaC	2420.60	45.60	$1.31 \cdot 10^{11}$	$9.63 \cdot 10^9$	0.984	0.006	$5 \cdot 10^1$

6 Conclusions and Future Work

Optimizing resource use in wireless networks is a challenging and increasingly critical real-world problem, which we had successfully addressed in the past using mediated negotiation. This paper studies and evaluates the use of distributed negotiation techniques for WiFi-channel assignment. We compare the negotiation-based approaches with our previous mediated approach. Experiments show that the distributed approach is similar to the mediated approach in terms of performance, but involves a privacy and communication overhead advantage.

Although our experiments yield satisfactory results, there are several of research directions. An open challenge of our approach is how to use opponent's bids to refine the utility model throughout the negotiation. We also want to explore different partial consensus formation approaches for MOPaC. Finally, we are interested in evaluating the strategic properties of the mechanisms, to see how they perform when agents may use different strategies to their advantage.

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