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On the Partially Overlapped Channel Assignment on Wireless Mesh Network Backbone: A Game Theoretic Approach

Pedro B. F. Duarte[1]*, Zubair Md. Fadlullah[1], Athanasios V. Vasilakos[2], and Nei Kato[1].

Graduate School of Information Sciences (GSIS), Tohoku University, Japan[1]

Department of Computer and Telecom. Engineering, University of Western Macedonia, Greece[2]

E-mail: *burjack@it.ecei.tohoku.ac.jp

***Abstract*—The Wireless Mesh Network (WMN) has already been recognized as a promising broadband access network technology from both academic and commercial perspective. In order to improve the performance of WMNs, extensive research efforts have been dedicated towards finding means to increase the number of simultaneous transmissions in the network while avoiding signal interference among radios. In case of WMNs based on IEEE 802.11 b/g standards, most recent research works have relied upon the usage of orthogonal channels for solving the Channel Assignment (CA) problem. In this paper, we explore the possibility of exploiting Partially Overlapped Channels (POCs) by introducing a novel game theoretic distributed CA algorithm. Our proposed algorithm outperforms both the conventional orthogonal channel approach and the recent heuristic CA algorithms using POC. The proposed algorithm is shown to achieve near-optimal performance in the average case. In addition, the upper bound Price of Anarchy for Multi-Radio Multi-Channel (MRMC) networks is derived to evaluate the effectiveness of the proposed approach.**

***Index Terms*—Wireless Mesh Networks (WMNs), channel assignment problem, partially overlapped channels, game theory, potential games.**

I. Introduction

Recently, Wireless Mesh Networks (WMNs) have attracted tremendous interest from researchers involved in both academia and industry [1]. While a WMN consists of a multi-hop environment, its concept and target differ from those of the conventional Mobile Ad hoc Networks (MANETs). In a typical WMN, there are two types of nodes, namely Mesh Routers (MRs) and Mesh Clients (MCs). MRs are responsible for network routing and bridging while MCs are light-weight nodes performing simple client functions. One key feature of the WMN is the backbone network composed by MRs in which they are usually static and have no constraints on energy consumption. Due to these attractive features, WMNs are expected to appear as a promising technology in the Next Generation Networks (NGNs) in order to deploy ubiquitous Internet access. To promote this phenomenal prospect, a number of standards have already been developed for WMNs for different access ranges, namely IEEE 802.15.4, IEEE 802.11s and IEEE 802.16j [1]. Since IEEE 802.11 is one of the most popular access technologies for commercial end-users, we are interested in WMNs based on this technology.

One of the most promising techniques in Multi-Radio Multi-Channel (MRMC) field is Partially Overlapped Channel Assignment by using IEEE 802.11 b/g technology, which can increase the network throughput by exploiting more simultaneous transmissions. According to this standard, there are eleven channels available for communication on the 2.4 GHz band. By exploiting all eleven channels in a systematic approach to avoid the interference among adjacent channels, we can achieve a higher number of simultaneous transmissions than restricting ourselves with the use of only three orthogonal channels. Note that this approach is not as straightforward as it seems at the first glance. Unless it is carefully planned, adjacent channel interference may become significant in severely degrading network performance instead of improving it.

In this paper, we use game theory to design a systematic approach to utilize partially overlapped channels in WMNs while minimizing the adverse effect of adjacent channel interference. Game theory is a mathematical tool, particularly useful, in the network engineering field to model highly complex scenarios that may include complex traffic models, mobility, unpredictable link quality, in which pure mathematical analysis has met limited success [2]. This mathematical tool provides researchers with the ability to model individual or independent decision makers called "players". Every player interacts with other players and has an impact on their decisions. The dynamics of WMNs and MANETs closely resemble to this observation.

Contributions - Our work investigates the CA problem from the game theoretic perspective, and our main contributions are threefold: (i) we model the interactions among MRs as a de-centralized game, (ii) we derive a negotiation based optimal CA algorithm based upon the properties of a potential game, and (iii) we propose an upper bound for the Price of Anarchy regarding MRMC networks. Through extensive simulations, we compare the game theoretic results against previously proposed heuristic CA algorithms, which includes partially overlapped and orthogonal CA algorithms.

The remainder of this paper is structured as follows. Section II surveys related works on solving MRMC CA problem. Section III identifies and describes the CA problem, and reviews the interference model used in our work. The optimal CA algorithm is described in Section IV. Then, the upper bound of Price of Anarchy is derived in Section V. The performance of the proposed algorithm is evaluated in Section VI, and finally Section VII concludes the paper.

II. Related Works

In 2010, the work conducted by Zhou *et al.* developed fully distributed scheduling schemes, which solve the following three problems for video streaming over multi-channel multi-radio networks: (i) CA, (ii) rate allocation, and (iii) routing and fairness. Instead of focusing on optimal system throughput or scheduling efficiency as with conventional scheduling schemes, this work aimed at achieving minimal video distortion and a level of fairness through integrated media-aware distribution and network resource allocation. This work, however, did not consider the issue of overlapping or non-overlapping channels in formulating the CA problem.

The survey on channel assignment performed by Skalli *et al.* [3] reviews a number of CA schemes using non-overlapping channels. According to this survey, "this (i.e., the use of non-overlapping channels) leads to efficient spectrum utilization and increases the actual bandwidth available to the network". However, the more recent finding by Bukkapatanam *et al.* [4] using numerical analysis demonstrates that the usage of overlapping channels achieves better performance than three non-overlapping channels for the backbone network, expanding the previous work of Mishra [5], [6]. However, none of the these works clearly delineates a novel CA algorithm exploiting POC.

Following the promising trend of using POC, a new heuristic CA algorithms was proposed in [7] and in one of our earlier works [8]. In this paper, we further develop our previous work in [8] by addressing the WMN channel assignment problem from the game theoretical perspective in contrast with a heuristic approach adopted earlier. Game theory has been utilized effectively in wide areas of research, particularly in formulating and solving Economics problems [9], [10]. Using the game theoretical perspective to address complex engineering issues has immensely attracted the attention of prominent researchers in the last decade and its applicability has been abound ever since. More specifically in the context of network communications, there has been a plethora of game theory based work, ranging from power control in cellular radio systems [11] to optimal routing control [12] and use in cognitive radio networks [13]. Readers unfamiliar with Game Theory concepts and its applications are encouraged to study the work in [14], which contains fundamental results in this area and are specially focused on communication applications. Another interesting contribution is worth noting by Meshkati *et al.* [15], who proposed a non-cooperative game theoretic framework, which aims at performing trade-offs among energy efficiency, delay, throughput, and constellation size. This work shows that a user, in order to maximize its utility in terms of energy efficiency, needs to select the lowest modulation level, which can accommodate the user's Quality of Service (QoS) delay constraint. However, this approach missed one important aspect, i.e., it did not take CA problem into account. The work in [16] developed a game-theoretic model for radio resource management in a network architecture, which combines IEEE 802.11 wireless local area networks (WLANs) with IEEE 802.16-based multi-hop wireless mesh infrastructure for relaying the WLAN traffic to the Internet. The formulated game offers the players fair bandwidth allocation and optimal admission control of different types of connections such as WLAN connections and relay connections in an IEEE 802.16 mesh router. In [17], an incompletely cooperative game theory was proposed to improve the system performance of WMNs. In this approach, all the players contend for the channel to transmit real packets always with the optimal strategy. In addition, the works in [18], [19] offers game theory models to address the CA problem in wireless networks.

The afore-mentioned game theoretic approaches, however, do not consider exploiting partially overlapped channels in wireless networks, particularly in WMNs. The research conducted by Zhang and Fang [20] attempts to address this to some extent by presenting a joint solution for channel and power allocation. However, unlike our work, their work focuses on the access network issue instead of the backbone. Recently, Yuan *et al.* [21] also addressed the capacity maximization problem for WLANs exploiting overlapping channels and game theory concepts by using an interesting approach that is not in the scope of our work. They addressed the problem by varying the channel width in order to achieve a fair/optimal resource allocation.

In this paper, we employ game theory concepts to model MRs as decision makers of a cooperative game. The interaction among all MRs can be classified as an *identical interest game* as in [20]. Furthermore, we introduce a negotiation-based CA algorithm that converges to a steady state, in other words a Nash Equilibrium (NE), and as a property of identical interest games, this condition implies achieving an optimum CA.

III. System Model

We may define the CA issue as an optimization problem in terms of mapping available communication channels to network interfaces in order to maximize the communication capacity while minimizing signal interference. Note that Interference range is defined as the distance within which interference occurs.

In a multi-channel environment, four different types of interference and their influence on the network capacity should be addressed. To describe easily, let us consider two pairs of nodes where each pair has a sender and a receiver. Let the sender and receiver of the first pair be S_1 and R_1, respectively. The sender and receiver of the second pair are denoted by S_2 and R_2, respectively. To illustrate our considered system model, first we describe the following terms.

- Co-channel Interference: Co-channel interference occurs in case that all four nodes involved in the afore-mentioned pairs are operating in the same channel. Because of Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA), this type of interference is less harmful for the network capacity than Adjacent Channel Interference. Consider the following scenario: node S_1 is starting to transmit a packet to R_1. It checks if the medium is busy or idle. If it detects that the medium is busy, the node will withdraw its attempt to transmit by postponing it. However, if the medium is idle, it will proceed with the transmission. While S_1 is sending data to R_1, consider a scenario in which S_2 also attempts to send a packet to R_2. S_2 will detect the busy medium. Hence, S_2 will withdraw the transmission attempt and wait over a backoff period. Later on, it will attempt again and if the transmission between S_1-R_1 is already finished, S_2 will finally succeed with the signal transmission to R_2. In this scenario, we have a contention based access.

- Orthogonal Channels: Consider another scenario whereby S_1-R_1 and S_2-R_2 are using two orthogonal channels. Again, S_1 detects an idle medium and starts the packet transmission. Meanwhile, S_2 will also detect an idle medium since it is operating on a distinct channel. Both pairs are able to successfully transmit their packets simultaneously, because there is no overlapping frequency band between those channels. Limitation of this approach is that only three pairs of nodes can communicate in this manner since only three out of the eleven available channels, namely channels 1, 6, and 11, are orthogonal.
- Adjacent Channel Interference: This kind of interference seriously degrades the network capacity. Here, we consider S_1-R_1 and S_2-R_2 assigned to channels 1 and 3, respectively. S_1 begins transmitting first, S_2 will detect an idle medium in channel 3 and also starts to send its packet. However, since channels 1 and 3 share a common frequency band, the receivers will not be able to successfully decode the packets, causing a transmission error that severely degrades the network throughput. It is important to note that the interference range for adjacent channels is inversely proportional to the channel separation.
- Self Interference: Self Interference is defined as a node causing interference to itself due to one of its transmissions. This case will occur in multiple radio nodes using omni-directional antennas. Consider S_1 with two network interfaces. If one interface is assigned to channel 1 and the other one to channel 3, whenever S_1 tries to simultaneously send packets on both interfaces, the Signal to Interference Ratio (SIR) will be degraded no matter where the receiver node is, since channels 1 and 3 are overlapping channels. This type of interference was previously mentioned in [22] and it can be avoided if no node has its interfaces assigned to overlapping channels.

Considering the afore-mentioned types of interference, the authors in [7] developed a schematic procedure for CA. This model is named as I-Matrix and it determines whether it is possible or not to assign channels to a given link exploiting POC. To adopt this model in our work, we need to define one of its main components, namely *Interference Factor* (IF). The *Interference Factor*, $f_{i,j}$, uses, as input parameters, geographical distance and channel separation, and provides the effective spectral overlapping level between channels i and j.

In order to calculate $f_{i,j}$, the experimental measurements showed in [22] [23] are used and scaled by a factor of 10. To achieve an environment as similar as possible as the previous CA scheme, we use the same *Interference Range* (IR) table where $\delta = |i - j|$ denotes the channel separation and $IR(\delta)$ indicates the maximum distance in which there will be interference between channels i and j.

Given the IR table, let d be the distance between transceivers using channels i and j. We define d being zero if the transceivers are in the same node. To calculate $f_{i,j}$ we should consider the three following cases:

TABLE I
INTERFERENCE RANGE (IR)

δ	0	1	2	3	4	5
$IR(\delta)$	132.6	90.8	75.9	46.9	32.1	0

1) $f_{i,j} = 0$: when $\delta \geq 5$ or $d > IR(\delta)$
   In this case, there will be no interference between the radios since either they are assigned orthogonal channels, or they are distant enough not to cause interference.
2) $1 < f_{i,j} < \infty$: when $0 \leq \delta < 5$ and $d \leq IR(\delta)$
   Here, we have two radios assigned to overlapping channels, and the distance between them is within the interference range. Thus, IF should be calculated as the following equation in which $f_{i,j}$ is inversely proportional to the distance between radios.
   $$f_{i,j} = IR(\delta)/d : \qquad (1)$$
3) $f_{i,j} = \infty$: when $0 \leq \delta < 5$ and $d = 0$
   Here, we strictly exclude the case of self interference. Two overlapping channels ($\delta < 5$) will not be assigned at a given node.

By using this interference model exploiting overlapping channels, we can decrease the number of non-interfering links, thereby increasing the network capacity compared to the traditional orthogonal channel approach. In the following section, we use a game theoretic approach to achieve a distributed CA procedure. By modeling the CA as a game, we can use the mathematical results from the game theory to guarantee optimized network performance.

IV. PROPOSED SOLUTION BASED ON GAME THEORY

In this section, we model our MRs as "players". The main objective of such modeling is to derive an optimal CA using the mathematical analyses provided by the Game Theory framework, and then compare this result against existing heuristic algorithms.

Each MR is considered as a *decision maker* of the game, and we model the interactions among them as a Cooperative Channel Assignment Game (CoCAG). The game is composed of a finite set of players, denoted by $\mathbf{A} = \{a_1, a_2, \ldots, a_N\}$ and all the players have a common strategy space $\mathbf{S} = \mathbf{S_i}, \forall i$. In this context, we map the channel(s) assigned to a given MR's radios to its chosen strategy. Formally, the strategy of i^{th} player is $\mathbf{s_i} = \{k_{i,1}, \ldots, k_{i,c}, \ldots, k_{i,|C|}\}$, where $|C|$ is the number of channels for the channel set $\mathbf{C}$ and $k_{i,c}$ is a binary value. $k_{i,c}$ is set to one, if channel c is assigned to one of the player's radio. Otherwise, $k_{i,c}$ is set to zero. The game profile is defined as the Cartesian product of the players' strategy vector, $\mathbf{\Psi} = \times_{i\in\mathbf{A}}\mathbf{s_i} = \mathbf{s_1} \times \mathbf{s_2} \times \cdots \times \mathbf{s_N}$. Note that a game profile includes one strategy for each player. Also, $\mathbf{s_{-i}}$ is specially defined as the strategy set chosen by all other players except player i.

The objective of the game is to maximize the network throughput. We define a joint metric, M_i, for each player i, that translates the network link configuration and topology to a numerical value. This metric is directly proportional to the number of assigned links in each node. Each link's capacity is evaluated according to the number of interfering links. Two topology control factors, k and h, are included, since the network should not be evaluated only by its number of links but also how efficiently these links connect the MRs towards the WMN gateway (GW), *i.e.,* the hop count. M_i is defined as follows:

$$M_i = k\frac{\sum_{j\in\mathbf{C}}\frac{R}{n_j}}{h} \tag{2}$$

where

- k is a connectivity factor set to one, if the node can indirectly reach the GW, zero otherwise.
- R is the link data rate (in Mbps).
- n is the number of interfering links.
- h is the hop count from the node to the GW.

Each player has its utility function dependent on her own strategy and other players' strategy $U_i(\mathbf{\Psi})$, and since we defined a cooperative game, the following holds and U_{NET} stands for utility of the network:

$$U_{NET}(\mathbf{\Psi}) = U_i(\mathbf{\Psi}) = \sum_{i\in\mathbf{A}} M_i, \forall i. \tag{3}$$

Players will negotiate and change their interdependent strategies in $\mathbf{S}$ in order to achieve an optimal value for U_{NET}. Then two important issues arise: (i) whether they ever reach a consensus, or a steady state, and (ii) if the steady state, indeed, exists, how efficient its performance would be.

In Game Theory, *Nash Equilibrium* (NE) is an important concept. The players will meet an agreement if NE exists. Formal definition of NE, as in [14], is described below.

Definition 1. *strategy* $\mathbf{s}^* \in \mathbf{S}$ *is an NE if*

$$U_i(\mathbf{s}^*) \geq U_i(\mathbf{s_i^{'}}, \mathbf{s_{-i}}) \ \forall \ \mathbf{s_i^{'}} \in \mathbf{S_i}, \forall i \in \mathbf{A} \tag{4}$$

According to this definition, no player can benefit by deviating from its strategy if other players do not change theirs. In other words, this result guarantees an agreement for negotiations among players. However, no optimal outcome or fairness is intrinsically guaranteed. Nevertheless, a specific type of games, called *potential games* have useful properties that address the outcome efficiency issue and the existence of NE. For a potential game, the following holds:

- Every finite potential game possesses at least one pure strategy NE [24].
- All NEs are either local or global maximizers of the utility function [24].
- There are well-known learning schemes to reach these function maximizers in the literature, namely *best response* and *better response* (BR) [2] techniques.

Based upon the definition of a potential game, now we have the following lemma.

Lemma 1. *CoCAG is a potential game.*

Proof: A potential game is defined as a game in which a potential function P exists

$$P(\mathbf{s}^{'}, \mathbf{s_{-i}}) - P(\mathbf{s}^{''}, \mathbf{s_{-i}}) = U_i(\mathbf{s}^{'}, \mathbf{s_{-i}}) - U_i(\mathbf{s}^{''}, \mathbf{s_{-i}}) \ \forall \ i, \mathbf{s}^{'}, \mathbf{s}^{''} \tag{5}$$

where $\mathbf{s}^{'}$ and $\mathbf{s}^{''}$ stand for two arbitrary strategies. It is straightforward that the network utility function (3) itself is a potential function for CoCAG. ■

Hence, we have:

$$P = U_i(\mathbf{\Psi}) = U_{NET}(\mathbf{\Psi}), \forall i \tag{6}$$

As a matter of fact, CoCAG is an *identical interest game*, since all the players share the same utility function, which is a strict case of potential games and consequently all of its properties are applicable.

By making use of NE and potential games, we guarantee that our proposed CoCAG approach will converge to an agreement among players and this point will be a utility function maximizer. In the literature, there are two famous learning schemes to accomplish this purpose, namely best response and better response techniques, as expressed in equations (7) and (8), respectively.

$$\mathbf{s_i^{t+1}} = \arg\max_{\mathbf{s}\in\mathbf{S_i}} U_i(\mathbf{\Psi}) \tag{7}$$

$$\mathbf{s_i^{t+1}} = \begin{cases} \mathbf{s_i^{\text{rand}}} & \text{if } U_i(\mathbf{s_i^{\text{rand}}}, \mathbf{s_{-i}}) > U_i(\mathbf{s_i^t}, \mathbf{s_{-i}}) \\ \mathbf{s_i^t} & \text{otherwise} \end{cases} \tag{8}$$

In the former scheme, during its turn to choose a strategy to play, the player searches her entire strategy space and selects the one that yields the best outcome considering the other players' strategy. This scheme provides fast convergence. On the other hand, it requires intensive processing that grows linearly according to the strategy space. In the latter scheme, during its turn, each player selects a random strategy and keeps it as long as it generates a better outcome than the previous one. Thus, better response provides less intensive computation at the cost of a slower convergence to the equilibrium. In other words, there is a trade-off between computational complexity and convergence speed.

Also note that, the equilibrium may occur at the local optimum of the utility function, instead of the global optimum. In this case, the system performance will be trapped in a suboptimal state and, since this is one instance of NE, no node will be able to increase its utility function by changing her strategy. In order to shed some light on this local-global optimum issue, interested readers may be referred to Sec. V.

To avoid the players to be trapped in a suboptimal state, we employ the *smoothed better response* (SBR) learning scheme that was introduced in [25]. We adopt this technique since it is proved to converge, as illustrated in the work of [20]. This method incorporates randomness in the decision process that may lead the convergence to the global NE with a high probability. This uncertainty occurs according to the probability function (9). The player will evaluate the newly chosen random strategy against the previous one, and select the new strategy according to (9):

$$p(\mathbf{s_i^{\text{rand}}}, \mathbf{s_i^t}) = \frac{e^{U_i(\mathbf{s_i^{\text{rand}}}, \mathbf{s_{-i}})/\gamma}}{e^{U_i(\mathbf{s_i^{\text{rand}}}, \mathbf{s_{-i}})/\gamma} + e^{U_i(\mathbf{s_i^t}, \mathbf{s_{-i}})/\gamma}}. \tag{9}$$

Equation (9) is a function of the difference of the utility function given by each strategy. In case the difference is positively high, the player will keep this choice with a high probability. An opposite scenario is also possible, i.e., the player is highly likely to avoid a strategy that provides a much lower utility function. An important analysis occurs for small differences. The player will select one of the strategies almost randomly – by nearly 50%. In this case, even though the players will be able to select a "worse" strategy or not to select a marginal "better" strategy, this behaviour allows the players to move from a local optimum state and to start negotiating towards a new NE. Note that for ($\gamma = 0$), we actually have the better response learning scheme, in which the player "jumps" from one strategy to the other.

In addition, the γ parameter is responsible to control the trade-off between the algorithm's outcome performance and convergence speed. A large smoothing factor provides an extensive strategy search and slow convergence. On the other hand, a small γ restricts the search and improves the convergence speed. In our simulations, we follow the same concept as in [25] that was inspired on the concept of temperature on simulated annealing. Thus, we set $\gamma = 10/k^2$, where k stands for the negotiation step.

We propose the following negotiation based algorithm that converges to NE with a high probability. We assume identical MRs, each of which has a unique identification parameter a_iID for routing purpose. In addition, we generalize the finalization criteria, T, which can be met by following different parameters, e.g., maximum number of negotiations, time limit, or utility function threshold. In this paper, we will employ the maximum number of negotiations as the finalization criteria, T. Now that we have described all the parameters associated with our proposed approach CoCAG, the algorithmic steps are summarized in Algorithm 1.

Algorithm 1 Cooperative Channel Assignment Game (CoCAG)

$\mathbf{s_i} = \{0\}\ \forall a_i \in \mathbf{A}$
while $T = 0$ **do**
  Randomly select a_i with prob. $1/N$
  $\mathbf{s_i^{rand}} \leftarrow$ random strategy $\{k_{i,1}, \ldots, k_{i,c}, \ldots, k_{i,|C|}\}$
  while $\mathbf{s_i^{rand}} \neq$ valid strategy **do**
    $\mathbf{s_i^{rand}} \leftarrow$ random strategy
  end while
  if $p(\mathbf{s_i^{rand}}, \mathbf{s_i^t}) \geq$ random number $[0, 1]$ **then** ▷ Eq. (9)
    $\mathbf{s_i^{t+1}} \leftarrow \mathbf{s_i^{rand}}$
  else
    $\mathbf{s_i^{t+1}} \leftarrow \mathbf{s_i^t}$
  end if
  Broadcast $a_iID + \mathbf{s_i^{t+1}}$
  Update T
end while

In literature, several metrics have been proposed to quantitatively measure algorithms' limitations due to resource constraints, e.g., lack of information for on-line algorithms and lack of unbounded computational resources for approximation algorithms. Regarding the game theory field, an important metric is the cost due to lack of coordination in distributed algorithms. This metric is called Price of Anarchy (PoA), which evaluates the performance loss due to the lack of a centralized coordination. In the next section, the PoA analysis is presented for our proposed CoCAG algorithm.

V. Price of Anarchy Analysis

As previously mentioned, while negotiating strategies, players can be trapped at local optimum points where none of the players are willing to change strategies even if the system performance is yet distant from the desirable global optimum. To quantitatively measure the loss of performance in such scenarios, Koutsoupias and Papadimitriou proposed in [26] the concept of Price of Anarchy dubbed as PoA. When applied to maximization games, PoA indicates the ratio between the global optimum and the worst possible NE that can be interpreted as the system loss due to the lack of a centralized coordination.

Definition 2. *Price of Anarchy*

$$PoA = \frac{max\ U_{NET}(\mathbf{\Psi}')}{min\ U_{NET}(\mathbf{\Psi}'')}, \mathbf{\Psi}', \mathbf{\Psi}'' \in NE. \tag{10}$$

In order to calculate the PoA, the minimum NE can be derived from the following lemma.

Lemma 2. *The worst NE for MRMC networks is the common channel assignment:* $U_{NET}^{CC}(\mathbf{\Psi})$

Proof: If ($n-1$) nodes are connected using the same channel, the n^{th} node can also connect to the network by choosing this channel and increase the utility function (3), which contradicts the NE definition. Hence, the condition that n nodes connect to the gateway should be satisfied. Furthermore, all nodes sharing the same channel yields the highest level of interference which brings (3) to its minimum for the case of n connected nodes. ■

Due to the high complexity of MRMC networks exploiting overlapping channels, to simply derive the maximum NE is arguably unfeasible. Therefore, we provide, in this paper, the PoA resulted from the simulations by using the CoCAG algorithm. In addition, we derive the PoA upper bound for MRMC networks by using the non-interfering links generalization, which is defined in the following lemma.

Lemma 3. *The best NE for MRMC networks is a topology with Non-Interfering links and hop count is the Shortest Path:* $U_{NET}^{NI-SP}(\mathbf{\Psi})$

Proof: In order to derive the maximum NE consider the following illustration. A simple network composed of three nodes (n_1, n_2, n_3) equipped with 2 radios each ($n_i = [r_i^1, r_i^2]$), where r_i^1 represents the channel which the first radio was assigned to . They are positioned in a linear topology and n_2 in the center is the gateway. The maximum NE, according to the utility function (3), will occur when the link between nodes are non-interfering to each other, since none of the nodes will deviate from this state unilaterally and at this point U_{NET} reaches its maximum, $n_1 = [1, 0]$, $n_2 = [1, 8]$, *and* $n_3 = [8, 0]$ *for instance. To extend this illustration for more* *nodes and more generic topologies, we need to address the hop count, since various nodes connecting to the gateway using just non-interfering links is unfeasible considering the channel bandwidth available in IEEE 802.11 technologies. Consequently, in a generic topology containing n nodes, the maximum NE should have just non-interfering links. In addition, the hop count should be the shortest path to the gateway in order to maximize (3).* ■

Note that MRMC networks comprise a wider range of technologies than IEEE 802.11g, covered in this article. Therefore, the assumption of non-interfering links is reasonable when deriving a generic best NE for MRMC. For instance, IEEE 802.11a, which can have up to 12 orthogonal channels, and also networks using directional antennas, can arguably possess just non-interfering links.

Theorem 1. *The upper bound for the PoA in MRMC networks.*

$$PoA = \frac{U_{NET}^{NI-SP}(\mathbf{\Psi})}{U_{NET}^{CC}(\mathbf{\Psi})} \tag{11}$$

Proof: Direct application of Lemma 2 and Lemma 3 ■

VI. Performance Evaluation

In this section, we evaluate our game theoretic CA algorithm. We also compare them against three heuristic algorithms. Two of the heuristic algorithms are based on exploiting POC and the other one is based upon the traditional orthogonal channel approach [27]. The comparison is performed in terms of the utility function and convergence time. Regarding game theoretic algorithms, we exemplify the network reaching the NE through the negotiations among players. Later, we provide the results for the PoA.

The simulation scenario was configured using JAVA as follows. A grid topology is constructed on the backbone. The grid step is set to 120 m, which is the distance between adjacent nodes. The node positioned in the bottom right corner is assumed to be the gateway. IEEE 802.11g is used as the wireless technology. MCS 6 Mbit/s is set as link data rate. In our experiments, we vary the grid size by 9, 12, 16, 20, and 25 nodes.

In Fig. 1, we illustrate the negotiation process reaching the NE. This is a small topology consisting of 5 nodes. We estimate the global optimum using a centralized brute force algorithm. The nodes were placed using a square topology, in which four nodes are located at the corners and one node is positioned at the center. The gateway is positioned at the corner to stimulate a multi-hop topology. We simulate the Smooth Best Response (SBR) learning scheme, which corresponds to CoCAG algorithm, setting $T = 50$ iterations and repeating the simulation using 100 random seeds to calculate the average. The curve SBR_{100} represents the average after 100 simulations. This curve is classified as near-optimal because although the algorithm sometimes reaches global-optimum, it may also generate sub-optimal results when nodes find themselves trapped in a local optimum NE.

In Fig. 2, we compare the outcome of heuristic and game theoretic algorithms. As for heuristic algorithms exploiting

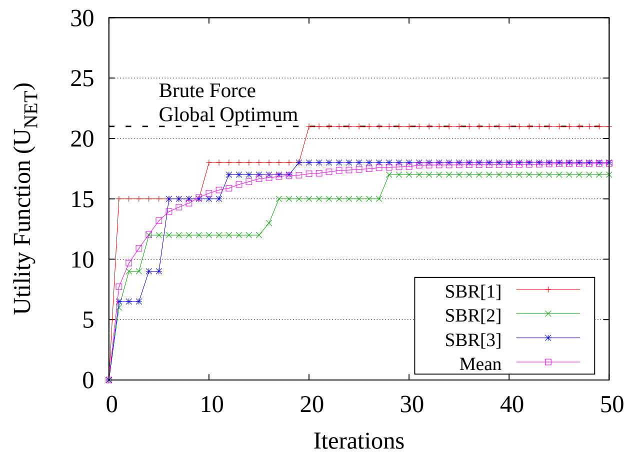

Fig. 1. Channel Assignment Negotiations.

partially overlapped channels, we use two algorithms that are extensively described in our earlier work [8]. The algorithm referred to as Heuristic Partially Overlapped Channel Assignment (HPOCA) was our previously proposed one, and the one named by “original” was originally proposed in [7]. In short, HPOCA measures the traffic load for each link and orders the links in descending order of traffic load. Then, it assigns channels to the ordered links prioritized by higher weights using the same interference model as described in this paper. After this step, the channel assignment is composed of only non-interfering links, however the network fully connectivity is not yet addressed. Later, it addresses the disconnected nodes, by assigning to them channels that will generate only co-channel interfering links, which is less harmful than adjacent channel interference. On the other hand, the “original” algorithm has a different approach. Instead of ordering links, it orders nodes in a descending order of the number of links, i.e., node degree, and it does not take into account the connectivity issue.

In addition to these partially overlapping channel assignment algorithms, we include one more CA protocol called Hybrid Multi-Channel Protocol (HMCP) [27], which uses the traditional non-overlapping CA. Briefly, in HMCP each node uses two radios to communicate. Each radio has different tasks to perform. The first radio uses a fixed channel and is responsible for receiving data while the second radio has a switchable nature, and it changes its channel to reach the neighbors’ fixed radio. Each node maintains the table describing the neighbors’ fixed channel and exploits it to lookup for the destination node’s channel.

First, as expected among the heuristic algorithms given our previous work [8], HPOCA generates the best performance. This result corroborates the simulations from that paper. Second, when comparing game theoretic algorithms, we observe that SBR (CoCAG) algorithm produces a better result than BR, which corresponds to the CoCAG algorithm using Better Response equation (8). This is based on the fact that in average, SBR reached more often the global optimum. SBR and BR are obtained from the average values from 100 repetitions. When we compare HPOCA against the average values of BR and SBR, it has a superior performance than BR and nearly the same as SBR. Hence, we conclude that

HPOCA also has a near-optimal performance.

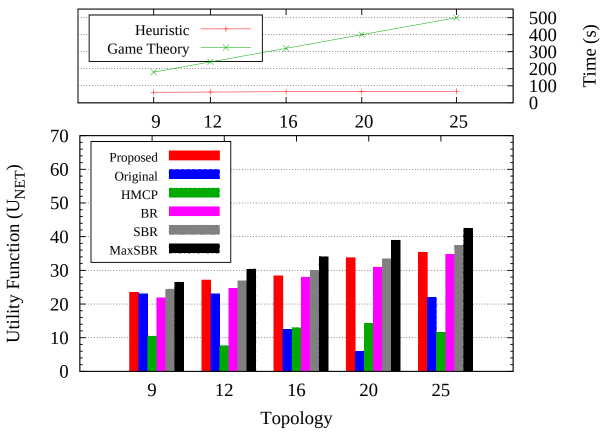

Fig. 2. Channel Assignment Negotiations.

From our simulations, we experimentally derive the global optimum, shown by the MaxSBR. It is important to stress that although the HPOCA does not achieve the optimal results, it has a strong comparative advantage against the game theoretic algorithms, and it has a faster convergence. Due to the numerous negotiation interactions required by the game theoretic algorithms, the proposed algorithm reaches near-optimal performance faster than the former, as shown in Fig. 3.

In order to derive the time performance, we used the following rationale. All the algorithms have two distinct steps, namely negotiation and operation phases. In the negotiation phase, all nodes operate using a common channel to exchange the messages, which guarantees the distributed coordination of the algorithms. This is necessary to avoid deafness problems, i.e., nodes trying to exchange control messages. But, since the nodes are operating in different channels, the message would not be detected by the destination nodes. For HPOCA, the negotiation phase is preceded by the learning phase, in which every node sends the same amount of traffic to the gateway within a sixty seconds window, and the traffic is routed using Optimized Link State Routing Protocol (OLSR). The traffic load for each link is calculated and it will be used as input for the channel assignment algorithm as explained in [8]. During the negotiation phase, for each decision, in other words, for assigning a channel to a link in heuristic algorithms or deciding a strategy in game theoretic algorithms, the nodes have a conservative 200ms window to broadcast their decisions. After assigning channels to all links or after the finalization criteria T is met, the algorithms switch to operation phase. And just at this point, they actually switch channels on the radios.

Regarding the ratio between the best and the worst NEs, we found a considerably high value. The Price of Anarchy for topologies 9, 12, 16, 20 and 25 are found to be 8.72, 9.56, 10.18, 10.76 and 10.96, respectively. It means that the network can be operating approximately 8 to 11 times worse, considering the utility function, when the players are trapped at the worse NE. However, the probability of all the players, after so many negotiation steps, to choose the common channel topology reaching the minimum NE, is extremely low, i.e., nearly impossible. During our extensive experiments, none of the simulations resulted in such an NE. Consequently, this value should be read as a theoretically possible performance difference due to distributed coordination of the algorithm as opposed to the centralized one. In Fig. 4, we also show the upper bound for the PoA resulted from Theorem 1. In this case, since the minimum NE is the same, the maximum NE was improved by using only non-interfering links and the shortest path as hop count, hence yielding a higher PoA.

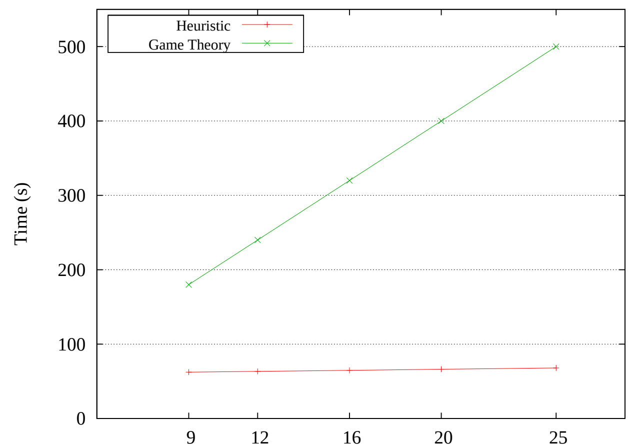

Fig. 3. Convergence Time Performance.

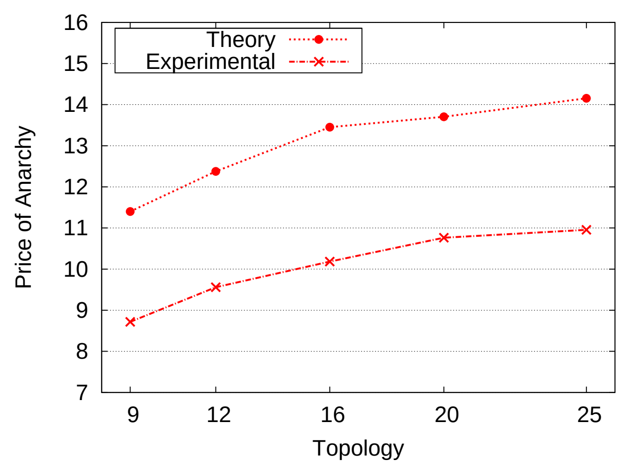

Fig. 4. Price of Anarchy.

VII. Conclusion

In this paper, to solve the channel assignment problem, we envisioned a novel distributed channel assignment algorithm for Wireless Mesh Networks by exploiting partially overlapped channels from a game theoretical approach, which reaches optimal performance. In our algorithm, we exploited partially overlapped channel assignment following the latest research trends in the field. From the simulation results and analysis, we conclude that if well managed, overlapping channels can clearly overcome the overall performance of the prevalent channel assignment strategy using just the three orthogonal channels. Such improvements can be measured as network throughput, channel spatial re-use, and non-interfering links. We also derived the upper bound for the Price of Anarchy for using our proposed approach in Multi-Radio Multi-Channel networks.

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