Channel and power allocation algorithms for ad hoc clustered networks

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***Abstract*—In the context of mobile clustered ad hoc networks, this paper proposes and studies a self-configuring algorithm which is able to jointly set the channel frequency and power level of the transmitting nodes, by exploiting *one* bit of feedback per receiver. This algorithm is based upon a learning algorithm, namely *trial and error*, that is cast into a game theoretical framework in order to study its theoretical performance. We consider two different feedback solutions, one based on the SINR level estimation, and one based on the outcome of a CRC check. We analytically prove that this algorithm selects a suitable configuration for the network, and analyse its performance through numerical simulations under various scenarios.**

I. Introduction

In recent times, the interest for technological solutions which allow communications to happen in difficult conditions, e.g. without the aid of a central controller, has gained much momentum. The development of cognitive radios (CR), devices able to sense their environment and to modify their configuration in accordance, has made this a reality.

On operational theatres, the presence of a fixed central controller infrastructure, for instance a base station, configuring the whole network is difficult to implement and is not desirable for the weakness it presents against potential enemies. Moreover, one can expect future equipments on the battlefield to be able to exploit the free spectrum to communicate and to keep their transmit power as low as possible. The goal is both minimizing their spatial frequency footprint, avoiding to pollute transceivers from other networks, and reducing the battery drain while achieving a certain Quality of Service (QoS). The concept of cognitive, self-configuring *ad hoc* network, thus, is a candidate solution to all of the above challenges.

In our work, we consider clustered *ad hoc* networks where the nodes are grouped into subsets (clusters), each of which is led by a cluster head (CH). We assume that all the clusters share the same frequency band, each CH being in charge of allocating sub-channels of the common resource to the multiple transmitter-receiver links that need to be operated within its cluster.

The CH, basically, fulfils two purposes: (i) it selects a frequency-channel and a power level to be employed by the devices within its control zone, (ii) it manages the intra-cluster communication by allocating logical sub-channels to each link. Thus, we can consider our system as locally centralized, and globally distributed. In order to do so, we assume that the CH only relies on local information, without any form of cooperation or explicit coordination with the other CHs. This reduces the amount of signalling demanded and makes the network more resistant to jamming attacks. For the same reasons, we need to minimize the amount of feedback between the CH and the nodes under its control.

The closest works to ours are [1], [2], [3] and [4]. In [1] an algorithm for interference avoidance is presented assuming an underlying clustered *ad hoc* network. The algorithm sets the frequency channel, leaving to the CH the duty to choose the power based on the needs of the cluster's devices. The authors assume the clusters to be far apart one to each other in such a way that the interference created form one cluster to another does not depend on the actual transmitter location. In [2], authors consider and present a trial and error (TE) algorithm, and analytically study its convergence properties. There, the scenario under analysis is composed of a group of communicating links, without considering the structure of a clustered network. In [3], authors suggest the use of iterative water filling (IWF) to allocate sub-channels and power in order to achieve a certain QoS, measured in terms of achievable rate. The authors assume a system with low interference, i.e., interferers very distant from each other, such that the convergence of the IWF could be insured. In [4], authors consider a clustered network where, in each cluster, a single transmitter broadcasts to the other nodes. In this work, each transmitter allocates its power using an IWF strategy aiming at maximizing the weighted mean of the throughputs. In a clustered network with many transmitters and only one decision maker, it is not practical to implement such a water-filling strategy. Indeed, this would require all the receivers to feedback to the decision maker their channel state information. Thus, this strategy requires a large amount of signalling to allow the CH to evaluate the correct power allocation. Moreover, there exists a sufficient literature, e.g. [4], [5] and [6] showing that, in decentralized networks, the operating point achieved through IWF is often less efficient than the one achieved through spectrum segregation, i.e. forcing each link to operate only on a small fraction of the available bandwidth.

In our paper, we present and detail an algorithm which, when employed by all the CHs, is able to set the network channel and power configuration by exploiting the information of only one bit feedback per receiver. This algorithm, namely trial and error learning algorithm, has been studied in [2] under the assumption of a static scenario (i.e., time invariant channel, fixed power gains and network topology), with the transceivers aiming at achieving a certain SINR to fulfil a given QoS. In this paper, we study several scenarios taking into consideration cluster mobility as well as more realistic communication performance metrics. We show the capability of the proposed algorithm to statistically steer the network into a state where clusters next to each other employ different channels.

Therefore, the main contributions of this paper are the following: (i) we detail a self configuring algorithm by defining all its parameters; (ii) we study its behaviour under several scenarios; (iii) we compare two ways of measuring transmission success, either by comparing the estimated SINR to a target or by considering packet integrity through cyclic redundancy check (CRC) of the transmitted packet; (iv) through numerical simulations, we estimate the optimal number of spectral resources, (i.e., channels) the network should be providing for the algorithm to well perform.

The paper is organized as follows. In Sec. II we present the general model of an *ad hoc* network and provide its associated game-theoretical model in Sec. III. In Sec. IV we briefly describe the resource allocation algorithm and we show the test bench scenarios in Sec. V providing the results of the experiment in Sec. VI. Finally, we conclude our work in Sec. VII.

II. System Model

In this work, we consider a network populated with K clusters, each of which composed by N_k links (transmitter-receiver pairs), with $N_N = \sum_{k=1}^{K} N_k$. Let $\mathcal{K} = \{1, 2, \ldots, K\}$ indicates the set of clusters and $\mathcal{N}_k = \{\ell_1^k, \ell_2^k, \ldots, \ell_{N_k}^k\}$ the set of links within an arbitrary cluster k. The nodes communicate by sharing a common spectrum, thus creating mutual interference. The overall spectrum is divided into C channels, and we denote by $\mathcal{C} = \{1, 2, \ldots, C\}$ the set of available channels. Each cluster, say k, is managed by its CH, which selects its transmission setting, i.e., a channel $c_k \in \mathcal{C}$ and a power level p_k, to be used by all the devices belonging to the cluster. The power level p_k is chosen among a finite set of possible power levels $\mathcal{P} = \{0, \ldots, P_{\text{MAX}}\}$, where P_{MAX} is the maximum amount of power that can be used by a transmitter device. The CH divides the selected channel, c_k, into N_{sc} orthogonal logical sub-channels and assigns them to the links to avoid intra-cluster interference. Assuming a time division multiple access scheme (slotted frame), each CH allocates to each link a set of sub-channels per slot, as depicted in Fig. 1. We define by $\mathcal{S}_\ell$ the set of sub-channels allocated to link ℓ and by s_ℓ an arbitrary element of $\mathcal{S}_\ell$. In every cluster we also assume that the transmit power on each sub-channel is constant for all the links.

We consider flat and block fading channels, i.e., channels power gain is both time and frequency invariant for the whole duration of one transmission. As such, the level of multiple access interference (MAI) in each sub-channel suffered by a receiving node, for instance the receiving node of link ℓ_m^k, on the sub-channel s is given by the sum of the interference created by all the transmitters which employ the same sub-channels at the same time, that is:

$$MAI_{(\ell_m^k, s)} = \sum_{x \in \mathcal{K} \setminus k} \mathbb{1}_{\{c_k = c_x\}} \sum_{l \in \mathcal{N}_x} \frac{N_x}{N_{sc}} p_x g(l, \ell_m^k) \mathbb{1}_{\{s_\ell^t = s\}}. \tag{1}$$

In (1), $g(l, \ell_m^k)$ indicates the channel power gain between the transmitting node of link l and the receiving node of link ℓ_m^k, and $\mathbb{1}_{\{\}}$ is the indicator function. Therefore, the level of the SINR experienced by the receiver of link ℓ_m^k on sub-channel s is given by:

$$\text{SINR}_{(\ell_m^k, s)} = \frac{N_k}{N_{sc}} \frac{p_k g(\ell_m^k, \ell_m^k)}{\sigma^2 + MAI_{(\ell_m^k, s)}}, \tag{2}$$

where $g(\ell_m^k, \ell_m^k)$ indicates link ℓ_m^k power gain, which is modelled by the two-rays model [7], i.e.

$$g(\ell_m^k, \ell_l^j) = \frac{G_{\ell_m^k} G_{\ell_l^j} h^2_{\ell_m^k} h^2_{\ell_l^j}}{d^4_{(\ell_m^k, \ell_l^j)}}. \tag{3}$$

In (3), $G_{\ell_m^k}$ and $G_{\ell_m^j}$ represent the antenna gains, $h_{\ell_m^k}$, $h_{\ell_l^j}$ the height of the antennas of nodes ℓ_m^k and ℓ_l^j respectively, and $d_{(\ell_m^k, \ell_l^j)}$ is the distance between the two nodes. In order to study the performance of the network, we assume the queue of each transmitter to be not empty, i.e., we analyse the system in a fully loaded situation.

For the sake of simplicity, we consider an uncoded binary phase shift keying (BPSK) modulation scheme for each sub-channel transmission. Since the transmitters may use multiple sub-channels per link to perform their communication, we introduce an equivalent SINR that accounts for all the sub-channels in order to assess the link performance. We define our equivalent SINR based on a bit error rate (BER) point of view. Here, we consider the interference as Gaussian noise, thus, the equivalent SINR may be expressed, by applying uncoded BPSK BER formula, as:

$$\text{SINR}_{\text{eq}}(\ell_m^k) = \text{erfc}^{-1}\left(\frac{N_k}{N_{sc}} \sum_{s \in \mathcal{S}_\ell} \text{erfc}\left(\text{SINR}_{(\ell_m^k, s)}\right)\right), \tag{4}$$

where erfc is the complementary error function.

III. Game Formulation

In this section, we model the scenario presented in Sec. II under a normal-form formulation [8].

A. Normal-Form

A game in a normal-form is defined by a triplet:

$$\mathcal{G} = \left(\mathcal{K}, \mathcal{A}, \{u_k\}_{k \in \mathcal{K}}\right) \tag{5}$$

where, $\mathcal{K}$ represents the set of players, $\mathcal{A} = \mathcal{A}_1 \times \mathcal{A}_2 \times \ldots \times \mathcal{A}_K$ is the joint set of actions with $\mathcal{A}_k = \mathcal{C} \times \mathcal{P}$, i.e., $a_k = (p_k, c_k)$. Since the utility is a measure of the individual quality of the chosen action, its formulation strongly depends on the type of feedback chosen. Here, we formulate our utility function as

$$u_k(\boldsymbol{a}) = \frac{1}{1+N_k\beta}\left(1 - \frac{p_k}{P_{\text{MAX}}} + \beta \sum_{x\in\mathcal{N}_k} \text{Feedback}_x(\boldsymbol{a})\right), \tag{6}$$

where Feedback$(\boldsymbol{a})$ is a one bit value, which depends on the nature of the feedback chosen in the network, as described in the following section. This utility function is chosen to be monotonically decreasing with the power consumption p_k, and increasing with the number of successful transmission Feedback$_x(\boldsymbol{a})$. The parameter β tunes the interest we have in satisfying the constraints over the power consumption.

Definition 1 *(Interdependent game). The game $\mathcal{G}$ is said to be interdependent if for every not empty subset $\mathcal{K}^+ \subset K$ and every action profile $\boldsymbol{a} = (\boldsymbol{a}_{\mathcal{K}^+}, \boldsymbol{a}_{\mathcal{K}\setminus\mathcal{K}^+})$such that $\boldsymbol{a}_{\mathcal{K}^+}$ is the action profile of all players in $\mathcal{K}^+$, it holds that:*

$$\exists i \notin \mathcal{K}^+, \exists \boldsymbol{a}'_{\mathcal{K}^+} \neq \boldsymbol{a}_{\mathcal{K}^+} : u_i(\boldsymbol{a}'_{\mathcal{K}^+}, \boldsymbol{a}_{\mathcal{K}\setminus\mathcal{K}^+}) \neq u_i(\boldsymbol{a}_{\mathcal{K}^+}, \boldsymbol{a}_{\mathcal{K}\setminus\mathcal{K}^+}). \tag{7}$$

In the following, we assume that game $\mathcal{G}$ is interdependent. This is a reasonable assumption, since, physically, this means that no cluster is electromagnetically isolated. Under a normal-form formulation, the solution concept used is the Nash equilibrium (NE), which we define as follows:

Definition 2 *(Nash equilibrium in pure strategies). An action profile $\boldsymbol{a}^* \in \mathcal{A}$ is a NE of game $\mathcal{G}$ if $\forall\ k \in \mathcal{K}$ and $\forall a'_k \in \mathcal{A}_k$*

$$u_k(a_k^*, \boldsymbol{a}_{-k}^*) \geq u_k(a'_k, \boldsymbol{a}_{-k}^*). \tag{8}$$

Generally speaking, a game can have an arbitrary number of NE, thus, to measure the efficiency of each one, we introduce the *social welfare* function, defined by the sum of all individual utilities: $W(\boldsymbol{a}) = \sum_{k=1}^{K} u_k(\boldsymbol{a})$.

B. QoS and Feedback Strategies

In this work, we express the QoS constraints in terms of SINR, which means that we fix a given SINR target for each link. For simplicity sake, this value will be assumed here constant, i.e. equal to Γ, for all links. As explained in the previous section, the utility function design (6) allows the system to take these constraints into account.

We discuss now two different feedback strategies that can be applied in real systems.

1) SINR-based feedback: This is the first strategy that naturally arises, given that the QoS is expressed in terms of SINR. Most of communication systems estimate the received SNR based on pilot sequences, and thus the SINR when MAI is present. Relying on this capability, we define the feedback as:

$$\text{Feedback}_x(\boldsymbol{a}) = \mathbb{1}_{\{\text{SINR}_x(\boldsymbol{a})>\Gamma\}}. \tag{9}$$

This formulation was proposed and studied in [9]. There, authors proved that with a utility function such as (6), the action profile which maximizes the social welfare is the one which (i) maximizes the number of links which simultaneously satisfy the SINR condition, (ii) minimize the network power consumption. Tuning the parameter β allows to favour either the QoS constraints satisfaction for large β values, or the consumed power for small β values.

2) CRC-based feedback: Usually, communication systems implement a CRC to check the integrity of the received packets. From this information, it is thus possible to infer the quality of the communication link, and this allows us to consider another kind of feedback defined as:

$$\text{Feedback}_x(\boldsymbol{a}) = \mathbb{1}_{\{\text{CRC}_x(\boldsymbol{a})=0\}}. \tag{10}$$

Here, the receivers feedback a 1 if the packet is received without errors and a 0 otherwise. Note that, in this case the result in [9] does not apply, especially since the CRC is a stochastic function of the action profile $\boldsymbol{a}$. In this case, the theoretical framework is not able to predict the exact point of convergence of the algorithm. However, simulation results, illustrated in Sec. VI, indicate that this way of evaluating the feedback results in better performance.

IV. Trial and Error

In this section, we briefly summarize the TE algorithm, introduced in [10], [11], and applied to wireless networks in [2]. TE is a state machine which selects, in a fully decentralized way, a strategy for a player such that, when every player is using the same scheme, the system is at an optimal NE a large proportion of the time with high probability. A state of a player k is defined as a triplet $z_k = (m_k, \bar{a}_k, \bar{u}_k)$, where m_k, $\bar{a}_k$ $\bar{u}_k$ represent, respectively, the mood, the benchmark action and the benchmark utility of player k. There are four possible moods, each implying a different behaviour and depending on different responses by the network.

- **Content**

If player k is content, then it plays action $\bar{a}_k$ with probability $(1-\epsilon)$, and another action (chosen randomly according to some probability distribution) with probability ϵ. Here, $0 < \epsilon < 1$, namely the experimentation probability, is a parameter of the system. Numerical simulations suggest $\epsilon = \frac{0.02}{K}$ as a value with a good trade off between stability and experimentation. At each iteration, each player compares the actual utility u_k with the benchmark utility $\bar{u}_k$. There are four possible outcomes: (i) if $u_k > \bar{u}_k$, and it did not experiment, i.e., $a_k = \bar{a}_k$, player k mood becomes *hopeful*, (ii) if $u_k > \bar{u}_k$, and it experimented, i.e., $a_k \neq \bar{a}_k$, then, with probability $\epsilon^{(F(u_k(a)-\bar{u}_k))}$, a_k becomes the new benchmark action, and u_k the new benchmark utility; (iii) if $u_k < \bar{u}_k$ and $a_k = \bar{a}_k$, then the player mood turns to *watchful*; (iv) if $u_k \leq \bar{u}_k$ and $a_k \neq \bar{a}_k$, then nothing changes. Here $F(\cdot)$, is a non increasing function as explained in [11].

- **Hopeful**

If player k is hopeful it evaluates its utility u_k and compares it with the benchmark utility $\bar{u}_k$. If $u_k \geq \bar{u}_k$, then the player mood becomes *content* and the benchmark u_k becomes the new benchmark utility. If $u_k < \bar{u}_k$, then the player becomes *watchful*.

- **Watchful**

If player k is watchful it evaluates its utility u_k and compares it with the benchmark utility $\bar{u}_k$. If $u_k < \bar{u}_k$, then the player mood becomes *discontent*. If $u_k \geq \bar{u}_k$, then the player becomes *hopeful*.

- **Discontent**

If player k is discontent, it experiments a random action a_k, and evaluates its corresponding utility u_k. Then, with probability $\epsilon^{G(u_k)}$ the player mood becomes *content*, with a_k and u_k as new benchmark action and utility. Here, $G(\cdot)$, is a non increasing function as explained in [11].

A. Trial and Error Properties

The theoretical properties of TE have been thoroughly analysed in precedent works. In this section, we report two among the most relevant results with our notations.

Theorem 1 *Let $\mathcal{G}$ be an interdependent game, and let it have at least one NE and let each player employs TE, then a NE that maximizes the social welfare among all equilibrium states is played a large proportion of the time.*

This theorem, shown in [11], states that the algorithm does not only look for individual optimality (the NE) but, among the states individually optimal, it searches the one which maximizes the global outcome.

Theorem 2 *Let $\beta > K$ and let game $\mathcal{G}$ be interdependent with at least one NE. Then, TE converges to the NE where the number of links satisfied is maximized and the power employed to obtain this result is minimized.*

This result, proven in [9], shows that TE is able to selects among all the possibilities an optimal working point for the network under analysis, at least for a large proportion of the time.

V. Scenario Description

The scope of this section is to present and describe the scenarios used to run the simulations and study the performance of TE. First, we consider a static dense scenario. Second, we consider a mobile scenario with one cluster moving around four static clusters. We aim at illustrating that TE is suitable for configuring networks even in mobility, where channels are, thus, no more time-invariant. In the following, we set $\beta = K + 1$, to comply with the conditions in Theorem 2.

A. Static Scenario

In this scenario, we consider a square field of 5 km per side populated with $K = 16$ equally dimensioned square clusters, each of which has a side of $\frac{5}{4}$ km. In each cluster, 8 nodes are randomly positioned as in Fig. 2. The clusters are not overlapping, the nodes belonging to each cluster are coloured with different colours, and the role (transmitter or receiver) is decided once and for all. In this scenario, each cluster has $N_{sc} = 8$ sub-channels, which are randomly associated with the links. This means that, between two TE loops there will be three time slots, and three feedbacks. For each of these packets $\frac{N_{sc}}{N_k} = 2$ sub-channels are randomly assigned for each link.

B. Mobility Scenario

In this scenario, we evaluate the performance of TE in the presence of a moving cluster. We assume $K = 4$ clusters to be aligned and sharing the spectrum while a fifth cluster is far enough to be creating little interference. An instance of this starting situation is depicted in Fig. 3. In this case the topology is such that, between the four static clusters, there exists an empty space for the fifth cluster to pass. Therefore, when all the five clusters are aligned, no cluster is overlapping with another. This happens after around 2250 iterations. Later, the cluster in mobility reaches the end of the field after 3000 iterations. Here, the number of available channels is restricted to $C = 2$.

VI. Simulation Results

In this section, we evaluate the performance of the TE for the scenarios introduced in Sec. II according to some metrics defined in the following section.

A. Performance Metrics

In order to evaluate the performance and the behaviour of the proposed algorithm, we have selected the following metrics:

- Average satisfaction (AS): defined as the average number of positive feedbacks the receivers send to their CH, for each iteration of the TE. It evaluates how much the algorithm enables to satisfy the criterion selected by the feedback (either SINR or CRC).
- Average power consumption (APC): defined as the average amount of power used by the transmitters in a cluster to achieve the corresponding satisfaction level. It captures how much power is consumed per cluster.
- Packet error rate (PER): defined as the average dropped packets, it helps evaluating the link quality and thus if the algorithm is correctly configuring the network.
- Channel switch per iteration (CSpI): defined as the average number of channels that have changed for each TE iteration and thus captures the channel allocation stability.

B. Static Scenario, SINR-based Feedback

In this section, we analyse the performance of TE, in terms of satisfaction and power consumption, applied to the square scenario described in Sec. V-A. Here, receivers feedback their satisfaction based on the comparison between the received SINR and the threshold Γ, fixed in the simulation equal to 10 dB.

In Fig. 4, we plot AS in the network and the APC by the nodes as a function of the iteration number. As we can see, full satisfaction is not reached. This is due to the scarcity of resources in the network that does not permit full satisfaction. This can be understood intuitively since, in a network with $K = 16$ clusters sharing $C = 5$ channels, each cluster has on the average two neighbour clusters which employ the same channel.

In Fig. 2, we show the node localizations on the field and the corresponding links with the AS and APC along with the most often chosen channel for each cluster. Note that having the same channel as the most used ones does not imply a collision, since the channels might be used in different time slots. On the contrary, having two different channels as the most used one implies no interference for a large part of the simulation.

C. Mobility Scenario

In this simulation, we refer to the scenario presented in Sec. V-B. First we consider the case where receivers feedback their satisfaction based on the comparison between the received SINR and the threshold $\Gamma = 10$ dB. Then, we consider the case where receivers send a CRC-based feedback.

In Fig. 5, we plot the global performance of the system in terms of AS and APC. It is possible to see the drop down of the system performance after 2000 iterations. The algorithm reacts by increasing the power level and by modifying the channel configuration. The satisfaction level, then, increases when the algorithm rearranges the channel and power allocation scheme in order to suit the new topology. Note that, when the mutual interference is too high, TE turns off one cluster by selecting zero power. The rationale behind this is that, if the desired level of SINR is not reachable by the current topological configuration, then the algorithm prefers to stop one of the clusters to improve the individual utility. When the algorithm reaches a different channel assignation pattern it is, again, possible to achieve a higher level of satisfaction.

In Fig. 6, we plot the AS and APC in a similar scenario, where the feedback is based on the evaluation of a CRC over a packet of 256 bytes. Note that, here, the reaction to the approach of the moving cluster appears to be a sudden increment in the power level. The power level increment is larger then when using an SINR-based feedback. Intuitively, this is due to the fact that the CRC test is more tolerant on the SINR decrement than the SINR test. Therefore, the transmission power increment is more effective to insure the compliance with the constraints when considering a CRC-based feedback than when considering a SINR-based one.

In Fig. 7 we plot a summary of the simulation run. Here each colour represents one of the possible two channels, while the height of the bins represents the used power. The static clusters are indexed with numbers 1, 2, 4, and 5 and the moving cluster is indexed with the number 3. When the system reaches time instant (i) the 3rd cluster is close enough to create interference to the other clusters. This forces the system to reorganize the power-channel pattern. When the moving cluster is completely aligned with the others (ii) the system starts working in an orthogonal way and the power starts decreasing. At (iii) the cluster is far enough to stop creating interference.

D. Static Scenario, CRC-based Feedback

In this section, we analyse the performance, in terms of satisfaction and power consumption when the TE is applied to the square scenario described in Sec. V-A. We recall that, in the following graphs, the upper curve measures the AS, where the feedbacks are calculated with a CRC on the received packets. We recall that in this simulation each packet is considered to be 256 bytes long. In Fig. 8, the performance of such a system is summarized. The upper curve represents the AS reached in the network, while the lower curve represents the APC. Note that, it is not possible to directly deduce the PER from the satisfaction. Especially, low levels of AS do not automatically translate into high levels of PER. This is because, when the transmitter is employing zero power, which may happen especially if the satisfaction level is low, the feedback is zero, but it cannot be considered as an unsuccessful transmission. Therefore, to evaluate the PER, we need to reduce the level of no-satisfaction of the amount of time the transmitters were using zero power. On the other hand, a high level of AS, can guarantee a high number of packets received correctly, which translates in a low PER. In this system, simulation results indicate an average PER $= 2.8\ 10^{-3}$. Note that, when we employ an SINR-based feedback, we obtain PER $= 0.23$, which is much higher for equivalent average employed power.

In Fig. 9, the performance of the algorithm on a single node is reported. It is possible to see that, generally, most of the transmitted packets are correctly received. Moreover, it appears that packets errors increase during some particular time windows, i.e., errors appears in burst. This is probably due to a change in the network (for instance another cluster start employing the same channel) which makes the power-channel pair chosen by the CH inappropriate for the transmission.

E. Channel Switch per Second

The stability of a network configuration is an important parameter to evaluate the performance of a self configuring algorithm. TE attempts to steer the network to a NE, which is inherently stable point. Nonetheless, the stochastic nature of TE, the incompleteness of the information and the lack of CH cooperation leave space for interference and collisions. To evaluate this instability we have defined the CSpI metric in Sec. VI-A. To compute it, we run 20 simulations on the scenario described in Sec. V-A and we count the number of time a CH switches its channel. We performed this evaluation both in the case of a SINR-based feedback and of a CRC-based feedback and found $\text{CSpI}_{\text{SINR}} = 4.5\ 10^{-3}$ and $\text{CSpI}_{\text{CRC}} = 4.3\ 10^{-3}$. As we can see the results are very close one to each other. This is due to the fact that avoiding other clusters interference is important independently from the nature of the feedback. As a consequence, in both cases clusters try to employ good (low interference) channels.

F. Average Satisfaction Versus Available Channels

Here, we aim at evaluating the variation of TE's performance as a function of the available channels. In this simulation we use the scenario depicted in Sec. V-A, where we set a CRC-based feedback. In this scenario, we have $K = 16$ clusters and we vary the number of available channels for the network from 4 to 18. For each of this values, we run 20 tests, each of which lasts 6000 TE iterations. We recall that, three packets are sent for each iteration, and each packet has 256 bytes length. The result is depicted in Fig. 10. It is possible to see that the curve does not reach the full satisfaction. This is due to the stochastic nature of the algorithm. Since clusters are experimenting, and the CH have no way of cooperating one with each other, a certain, even if low, level of unsatisfaction is unavoidable. From these results, it appears that the optimum number of channels should be 10. Here, we mean optimum as the minimum number of channels needed to keep the network satisfied at least 90% of the time.

VII. Conclusion

In this paper, we have presented and studied the performance of a resource allocation algorithm, namely the trial and error (TE) learning algorithm. We have shown that it is effectively capable of setting the transmission parameters (channel and power) of clustered *ad hoc* network, using only one bit feedback per receiver. This feedback must be an evaluation of the quality of the transmission link. In our settings, we have proposed two different types of feedback strategies: one based upon the measurement of the SINR at the receiver, the other reporting the CRC check status of the transmitted packet over the link.

In a crowded network, when several clusters try to share a few spectral resources, TE is able to find a setting such that the largest part of the cluster fulfils its QoS constraints, employing a low level of power. The clusters which are not able to fulfil their QoS constraints are automatically turned off, saving battery power and avoiding useless interference.

When clusters are moving, the changes in the topology force the algorithm to react quickly and to find a different channel and power allocation scheme, such as to satisfy the new conditions. This may be done by a temporary increase in the power level, or in a reorganization of the channel assignment.

Several paths could be followed to extend this contribution. Experimentation parameters which adapt on the satisfaction levels, for instance, could be used to let the algorithm discriminate between almost static or high mobility situations. Moreover, a study on a more effective probability distribution for the experimentation, and on the effect of the values of the parameters ϵ and β could bring insight on ways to improve the performance. Finally, the case when an action profile depends upon stochastic parameters would need to be investigated to study convergence properties of the game when CRC-based feedback is used.

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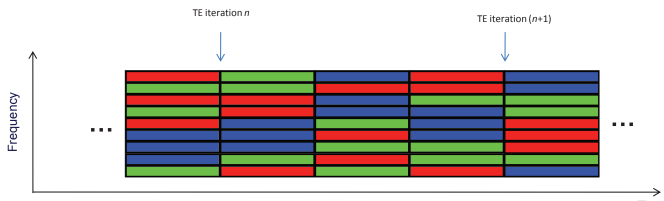

Fig. 1. Sub-channel assignment instance. At each different colour corresponds a different link.

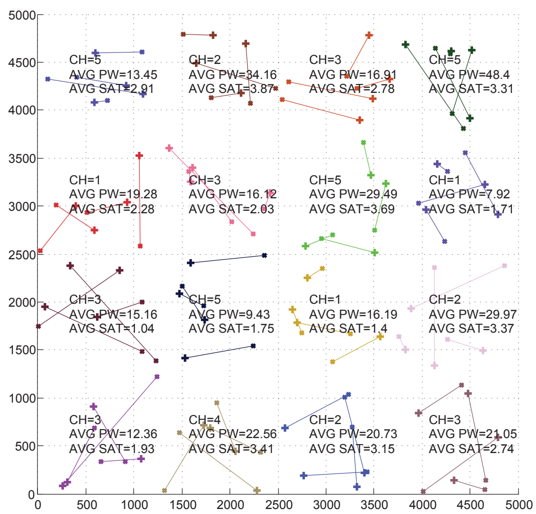

Fig. 2. Square scenario setting with $K = 16$ clusters and $N_k = 4$ pairs. Clusters and nodes are static with SINR-based feedback. CH, AVG PW, and AVG SAT indicate respectively the most frequently selected channel, the APC and the AS.

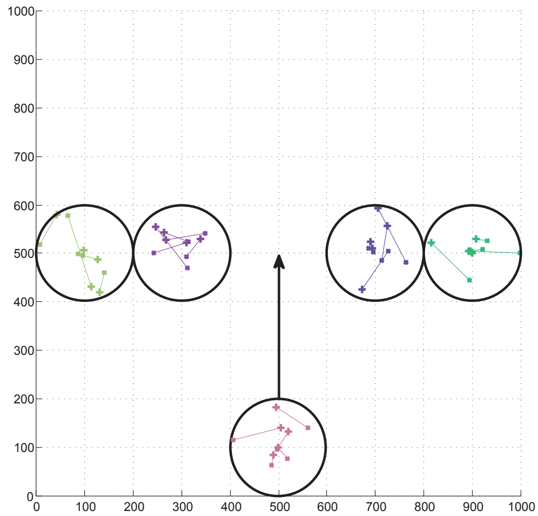

Fig. 3. Cluster positions at the beginning of the mobility scenario with $K = 5$ clusters in a field of 1 km side. Four clusters are static and aligned, the cluster at the bottom is the one in mobility.

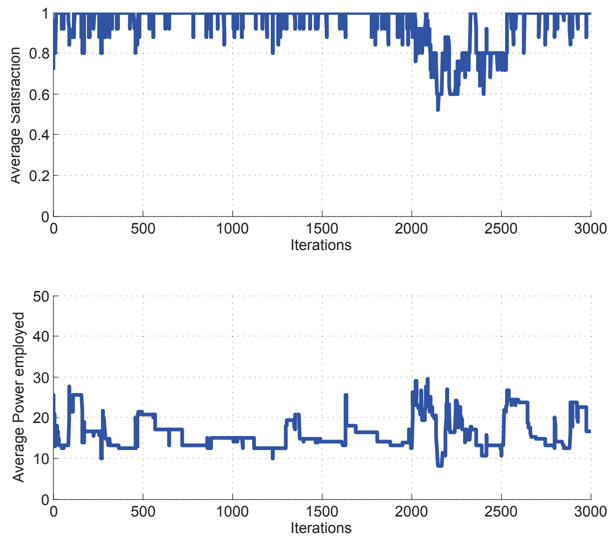

Fig. 5. Achieved AS and APC as a function of the TE iterations for a the mobility scenario, with SINR-based feedback.

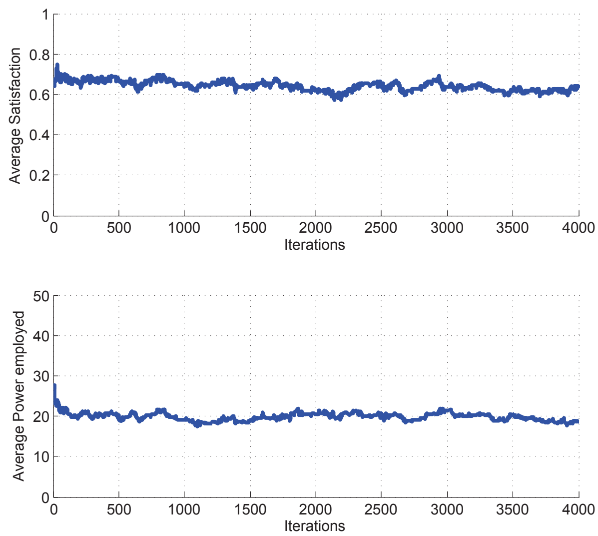

Fig. 4. Achieved AS and APC as a function of the TE iterations for a square static scenario, with SINR-based feedback.

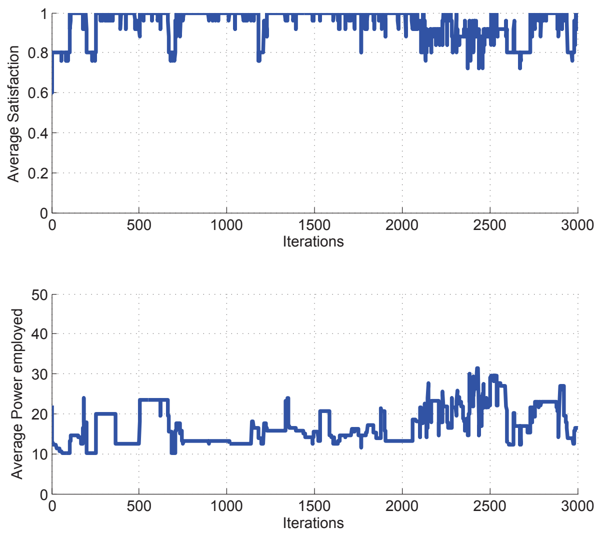

Fig. 6. Achieved AS and APC as a function of the TE iterations for a the mobility scenario, with CRC-based feedback.

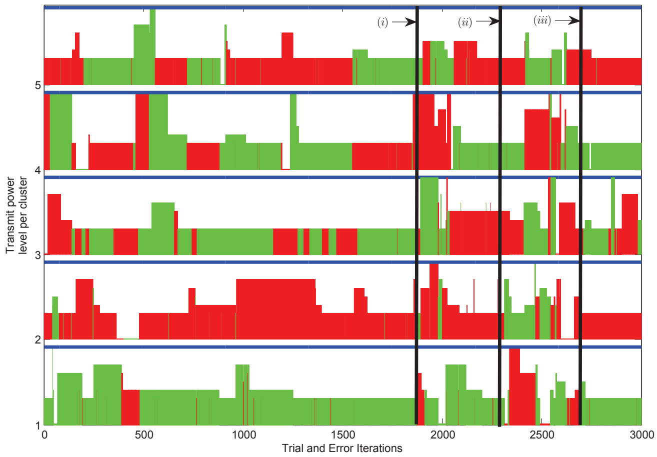

Fig. 7. Channel-power allocation as a function of the TE iterations for the mobility scenario with two channels. Each colour represents a different channel, and the heights of the graph the transmit power level. Clusters $1, 2, 4, 5$ are static, cluster 3 is in mobility. (i) beginning of the interference from the 3rd cluster, (ii) Five clusters are aligned, (iii) end of interference from the 3rd cluster. The blue solid lines represent $P_{\text{MAX}} = 50$W.

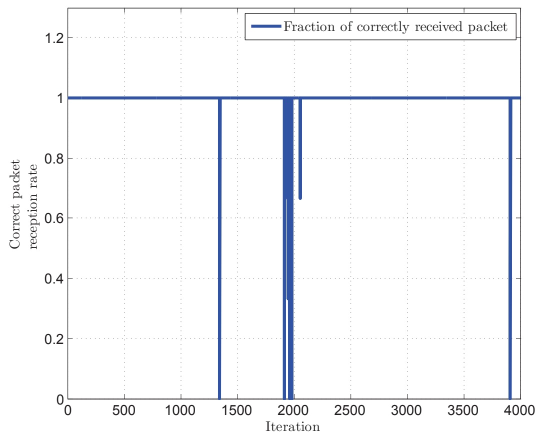

Fig. 9. Fraction of packet correctly received. Single node CRC outcome for scenario V-A, CRC-based feedback.

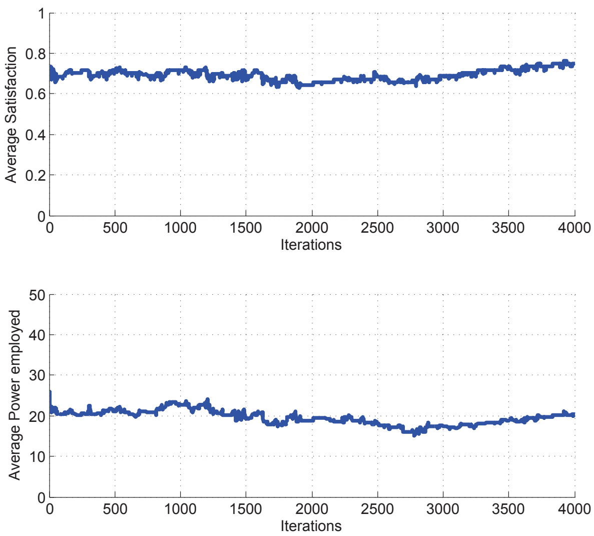

Fig. 8. AS and APC as a function of the TE iterations for a square static scenario, with CRC-based feedback.

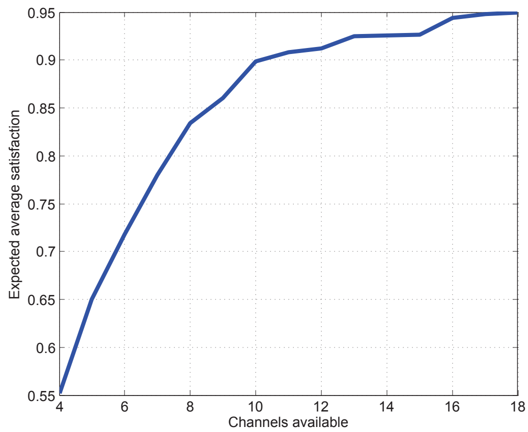

Fig. 10. Expected satisfaction versus available channels. This plot has been realized assuming a square field as the one described in V-A, assuming a SINR-based feedback.