Joint Channel and Power Allocation in Tactical Cognitive Networks: Enhanced Trial and Error

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***Abstract*—In tactical networks the presence of a central controller (e.g., a base station) is made impractical by the unpredictability of the nodes' positions and by the fact that its presence can be exploited by hostile entities. As a consequence, self-configuring networks are sought for military and emergency communication networks. In such networks, the transmission parameters, most notably the transmission channel and the power level, are set by the devices following specific behavioural rules. In this context, an algorithm for self-configuring wireless networks is presented, analysed and enhanced to meet the specific needs of tactical networks. Such an algorithm, based on the concept of trial and error, is tested under static and mobile situations, and different metrics are considered to show its performance. In particular, the stability and performance improvements with respect to previously proposed versions of the algorithm are detailed.**

I. Introduction

In recent times, decentralized self-configuring networks (DSCN) have arisen as a possible solution to the growing need of reliable and efficient wireless connectivity. These networks are composed of devices able to self-configure their transmit parameters, normally identified in communication channel, transmit power, modulation and coding scheme, etc.

In extreme conditions, such as emergency or military theatres, there exists an evident necessity for communications that do not rely on the coordination by a central controller. In fact, the presence of such controller can create a weak point in the communication infrastructure, be inefficient with respect to the transmit configuration, or be impractical due to the mission's constraints. Therefore, modern warfare communications can improve their security and efficiency through the deployment of networks composed of devices capable of self-configuring their transmit parameters [1], without any centralized support.

The network topology that mostly fits the requirement of a tactical DSCN is clustered, that is, devices are grouped in small sets named clusters. Each cluster can be considered as an autonomous entity, in which the transmit configuration is selected by the devices belonging to the cluster and it is based on the information available within. Each cluster is managed by a cluster head (CH), that is a device belonging to the cluster which collects the information available and, through a certain decisional process, it selects the configuration to be used by each device.

In the technical literature, several methods have been proposed to efficiently accomplish the configuration selection, see for instance [2]–[11]. In almost the totality of the literature, the most relevant parameters to be chosen are the communication channel (or channels) and the power level.

In [2], the authors propose a distributed power control algorithm to insure a minimum signal to noise plus interference ratio (SINR) level to a set of decentralized links sharing the same channel. A similar problem was tackled in [11], where the authors propose the use of iterative water filling (IWF) to guarantee a certain achievable rate to the links of a completely decentralized networks. The use of IWF is also suggested in [9], [10]. In these works, the authors consider a clustered network in which a device broadcasts allocating its power among the different sub-carriers by employing an IWF technique. In [3], an iterative stochastic algorithm for channel selection was presented under the assumption of incomplete information. This learning algorithm, however, is known to set a probability on the channel to be used, and does not well behave when the number of available channels is minor than the number of potential users. In [5], the authors present a distributed algorithm for channel selection in decentralized clustered networks. Each CH selects the cluster's channel by analysing the whole spectrum in random interval. After each analysis, the channel where the CH observes the minimum amount of multiple access interference (MAI) becomes the chosen one. The underlying assumptions of this algorithm are that the clusters are far enough and mobility is reduced, resulting in a loss of performance in dense and mobile networks. In [6]–[8] the trial and error (TE) algorithm is presented, studied and adapted to wireless decentralized network. In particular, in [6] it is studied in the context of a set of autonomous self-configuring links and in [7] TE's ability of configuring a clustered tactical network is shown. In [8], the authors enhance this algorithm by making it able to encompass different types of designing goals (e.g., maximizing throughput, minimizing the probability of incorrect reception), improving its performance and reducing the unneeded channel switches. However in [8], no thorough test on the effects of the enhancement was provided. Especially, the behaviour of the algorithms in presence of fading channels has never been analysed.

The main contribution of this paper are the following: (i)

we summarize the algorithm presented in [8], namely the enhanced trial and error (ETE), and we specify its parameters in order to be able to efficiently configure a tactical network; (ii) we test the proposed algorithm in a Rayleigh fading scenario and in block fading one; (ii) we show the effectiveness of the algorithm and the improvement with the previous version presented in [7].

The rest of the paper is organized as follows. In Sec. II the details of the tactical network are presented, in Sec. III the game theoretical model of the network described in Sec. II is presented, and its link with the proposed algorithm underlined. In Sec. IV the algorithm is detailed, and its enhancement with respect to TE are remarked and explained. The test scenarios for the algorithms are introduced and described in Sec. V, and the results of such experiments are detailed in Sec. VI. Finally, our conclusions are drawn in Sec. VII.

II. System Model

In this section, we describe the system under consideration and we introduce the notation we use through the paper to indicate the element of the network. Let us consider a certain number of clusters each composed of several transmitter-receiver pairs. Assume that each device in the network has some data to send, i.e., consider the system in a condition of full load. Each of the transmitter-receiver pairs, to which we refer alternatively as a link, wishes to meet a given minimum quality of service (QoS), i.e., a target average SINR in this contribution. The CH accomplishes two functions. On the one hand, it organizes the intra-cluster communications in such a way to avoid any intra-cluster interference. On the other hand, it attempts, relying exclusively on intra cluster available information, to select the best transmission configuration in order to satisfy the SINR constraints for the largest number of links possible, while minimizing the power drained from the batteries. This model is justified by the need of many real world applications for a minimum level of QoS (throughput, delay, bit error rate, packet error rate, etc.), while two of the basic limits of wireless communication are battery consumption and mutual interference. As a consequence, an ideal behavioural rule would satisfy the QoS constraints for the largest set of links in the network, consuming the smallest amount of power.

In our system, we assume the field to be populated with K clusters each composed by L_k links, with a total of L_N links, where $L_N = \sum_{k=1}^{K} L_k$. We denote by $\mathcal{K} = \{1, \ldots, K\}$ the set of clusters and by $\mathcal{L}_k = \left\{\ell_1^{(k)}, \ldots, \ell_{L_k}^{(k)}\right\}$ the set of links in an arbitrary cluster k.

The nodes communicate by sharing the overall spectrum, thus increasing the MAI level. The communication between nodes can exploit C orthogonal logical channels, and we denote the set of channels by $\mathcal{C} = \{1, \ldots, C\}$. The time is considered discrete and indexed by the letter t. We assume that each time instant corresponds to an iteration of our algorithm. Therefore, at each time instant, every CH autonomously selects one channel to be adopted by the transmitters within its area of control for communicating. The channel selected by the k-th cluster for transmission is indicated by $C_k \in \mathcal{C}$. The power is assumed quantized into Q quantization levels. The transmit power used by the m-th link is indicated by $p_m \in \mathcal{P}$, with $= \{1, \ldots, P_M\}$, where P_M is the maximum transmit power, and $|\mathcal{P}|^1 = Q$.

In this work, we consider two different kinds of fading channels: block fading channels, i.e., channels' power gain is both time and frequency invariant for the whole duration of one transmission; Rayleigh fading channels in which the path-loss power attenuation is at each time instant multiplied for the realization of Chi-square random variable. Hence, the power attenuation between the transmitter of m-th the link in the k-th cluster and the r-th receiver of the in the j-th cluster, on the c-th channel is given from:

$$g^{(c)}_{(\ell_m^{(k)}, \ell_r^{(j)})} = \rho^2 \frac{G_{\ell_m^{(k)}} G_{\ell_r^{(j)}} h^2_{\ell_m^{(k)}} h^2_{\ell_r^{(j)}}}{d^4_{(\ell_m^{(k)}, \ell_r^{(j)})}}, \tag{1}$$

where, $G_{\ell_m^{(k)}}$ and $G_{\ell_r^{(j)}}$ represent the antenna gains, $h_{\ell_m^{(k)}}$, $h_{\ell_r^{(j)}}$ the height of the antennas of nodes $\ell_m^{(k)}$ and $\ell_r^{(j)}$ respectively, $d_{(\ell_m^{(k)}, \ell_r^{(j)})}$ is the distance between the two nodes, and ρ is the realization of a stochastic process distributed according to a Rayleigh distribution.

At the receiver side, the interference level perceived by the receiver of link m in cluster k on the selected channel c is evaluated as follows.

$$\mathrm{MAI}_{\ell_m^{(k)}} = \sum_{j \in \mathcal{K} \setminus k} \mathbb{1}_{\{c = c_j\}} \sum_{r \in \mathcal{L}_j} p_j g^{(c)}_{(\ell_r^{(j)}, \ell_m^{(k)})}, \tag{2}$$

where $g^{(c)}_{(\ell_r^{(j)}, \ell_m^{(k)})}$ denotes the channel power gain between the transmitting node of the $\ell_r^{(j)}$-th link, in the j-th cluster, and the receiving node of the $\ell_m^{(k)}$-th link in the k-th cluster, while $\mathbb{1}_{\{\}}$ is the standard indicator function.

The expression of the MAI is used to evaluate the SINR at the receiving nodes. Hence, the SINR level at the receiver of $\ell_m^{(k)}$-th link, in k-th cluster on the selected channel c is given by:

$$\mathrm{SINR}_{\ell_m^{(k)}} = \frac{p_k g^{(c)}_{(\ell_m^{(k)}, \ell_m^{(k)})}}{\sigma^2 + \mathrm{MAI}_{(\ell_m^{(k)}, c)}}, \tag{3}$$

where $g^{(c)}_{(\ell_m^{(k)}, \ell_m^{(k)})}$ indicates channel power gain between the transmitter and the receiver of the $\ell_m^{(k)}$-th link and as usual σ^2 denotes the thermal noise variance.

III. Theoretical Formulation

In this section, we briefly describe the theoretical analysis that is behind the proposed scheme, and we summarize the algorithm. For a more detailed description, the reader is addressed to [8].

[1]The operator $|\cdot|$ denotes the cardinality of the set.

A. Game Formulation:Normal-Form

Game theory is a mathematical framework that enables the designer to model and study conflict situations arising from the interactions between selfish autonomous entities known as players. The DSCN described in Sec. II, in which the CHs are the players, can be mathematically modelled by a non cooperative game. Such a game is commonly represented through its *normal form*. A game in a normal-form is defined by a triplet:

$$\mathcal{G} = \left(\mathcal{K}, \mathcal{A}, \{u_k\}_{k\in\mathcal{K}}\right) \tag{4}$$

where, $\mathcal{K}$ represents the set of players (i.e., the CHs) and $\mathcal{A} = \mathcal{A}_1 \times \mathcal{A}_2 \times ... \times \mathcal{A}_K$ is the joint set of actions with $\mathcal{A}_k = \mathcal{C} \times \mathcal{P}$ (i.e., $a_k = (p_k, c_k)$). As a utility function, we chose the following formulation:

$$u_k(\boldsymbol{a}) = \frac{1}{1 + L_k\beta}\left(1 - \frac{p_k}{P_{\mathrm{M}}} + \beta \sum_{\ell\in\mathcal{L}_k} \mathbb{1}_{\{\mathrm{SINR}_\ell(\boldsymbol{a})>\Gamma\}}\right), \tag{5}$$

where $\beta > K$ is a parameter that tunes the trade-off between satisfying the QoS constraints and the power saving. This utility function follows the general framework described in [8]. It is explicitly designed to be monotonically decreasing with the power consumption p_k, and increasing with the amount of links' constraints satisfied during the transmission. The solution concept for finite games in normal form takes the name of Nash equilibrium (NE) [12]. The NE is defined as an action profile in which no player can improve its utility by unilaterally changing strategy:

Definition 1 (Nash equilibrium (NE) in pure strategies) . *An action profile $\boldsymbol{a}^* \in \mathcal{A}$ is a Nash equilibrium(NE) of game $\mathcal{G}$ if $\forall\ k \in \mathcal{K}$ and $\forall\ a'_k \in \mathcal{A}_k$ it holds that:*

$$u_k(a^*_k, \boldsymbol{a}^*_{-k}) \geq u_k(a'_k, \boldsymbol{a}^*_{-k}), \tag{6}$$

where, as usual we denote by $\boldsymbol{a}_{-k}$ profile of all the players aside k.

In other words, when the network is at a NE, no CH has an incentive in switching channel or modifying the power level.

Generally, a game can have an arbitrary number of NE, thus to differentiate between them we introduce the *social welfare* function $W : \mathcal{A} \to \mathbb{R}^+$ which measures the global performance of each action profile:

$$W(\boldsymbol{a}) = \sum_{k=1}^{K} u_k(\boldsymbol{a}). \tag{7}$$

From [13], we know that the TE algorithm stochastically converges to the NE with the highest social welfare. Hence, it is possible to prove [8] that by means of the utility function (5), if the set of NE of the game $\mathcal{G}$ is non-empty, then the NE with the highest social welfare has the following properties:

- It satisfies the QoS constraints for the largest possible set of links simultaneously satisfiable. The cardinality of this set depends on the constraints of the network (number of nodes, cluster and channels, positions of the nodes, minimum QoS, etc).
- Among the action profiles that satisfy the constraints for the largest possible amount of links, the NE employs the minimum amount of power.
- If there exist different sets of users, with the same cardinality, that can simultaneously satisfy their constraints using the same total power, then the algorithm randomly switches from one to the other, and they are employed with the same probability.

B. Discussion on the utility function

The utility function in (5) needs only intra cluster information to be evaluated. The amount of the power p_k is known at the CH, since its value is part of its decisional process, while the term $\sum_{r\in\mathcal{L}_k} \mathbb{1}_{\{\mathrm{SINR}_r(\boldsymbol{a})>\Gamma\}}$ requires that all links that belong to the cluster feedback one bit to the CH. This feedback mechanism can rely either on a common control channel often available in tactical networks, or on higher level protocols, for instance the ACK/NACK mechanism often operating at the MAC and network level.

Here, for simplicity we chose to directly evaluate the SINR. This performance metric can be estimated by the receivers through several different existing procedures. Alternatively, different types of feedback can be considered, for instance a CRC-based one [7].

IV. Trial and Error

In this section, we briefly summarize the algorithm. The basic idea was firstly introduced by the authors in [13], [14], furthermore, we enhanced the basic idea and specialized the algorithm to fit wireless networks in [6], [8], [15].

A. Basic concepts

In its basic formulation TE is a state machine composed of four states: *content, hopeful, watchful, discontent* [14].

When a CH is in the *content* state, it maintains the previous channel-power setting unless it decides to experiment. This experimentation happens with probability ϵ and it is performed randomly on all possible channels and power levels [6]. According to the result of the experimentation (better or worse performing than the previous configuration), the CH may decide to keep the new configuration or to switch again to the old one.

A CH enters in the *hopeful* state if its performance improves without experimentation, that is, it improves as a consequence of a fortunate modification of the topology of the network. In this case, if the improvement is maintained for two iterations, the CH becomes content again.

Conversely, a CH enters in the *watchful* state if its performance declines without an experimentation, that is, it decreases as a consequence of a unfortunate modification of the topology of the network. If the decline is kept for two algorithm iterations, the CH becomes discontent.

A *discontent* CH performs a noisy search, that is, it tests a channel-power configuration at each algorithm's iteration, choosing randomly among all the possible channels and all the possible power levels. According to the performance of these experimentations, the CH can decide to become content thus arresting the noisy search, or to continue being discontent.

B. Enhancement

The motivations behind the enhancement of TE are: (i) experimenting on different channels may be more harmful, especially in static scenarios, than experimenting new power levels, especially if a lower power level needs to be tested; (ii) Static scenarios require to switch the channels less frequently then mobility ones; (iii) When experimenting, only configurations that can possibly lead to a greater satisfaction should be taken into consideration. Therefore, as described in [8], the proposed modifications act on two levels.

First, the experimentation parameters are differentiated in $\epsilon_p^{(k)}$, which tunes the frequency of testing a new power level, and $\epsilon_c^{(k)}$, which tuned the frequency of testing a new channel level. In fact, to be well performing, the algorithm needs to experiment relatively often new power levels, and to keep the channel scheme as static as possible. Moreover, the value of $\epsilon_c^{(k)}$ is made time-dependent. That is, well performing configurations lead the CH to reduce the frequency of experimentation of new channels. The law under which the value of $\epsilon_c^{(k)}(t)$ is updated is the following:

$$\epsilon_c^{(k)}(t) = \begin{cases} \max\left(\frac{\epsilon_c^{(k)}(t-1))}{2}, \epsilon_c^{\min}\right) & \text{if } \sum_{\ell \in \mathcal{L}_k} \mathbb{1}_{\{\mathrm{SINR}_\ell(\boldsymbol{a}) > \Gamma\}} = L_k \\ \epsilon_c^{(k)}(0) & \text{otherwise} \end{cases} \tag{8}$$

where we set: $\epsilon_c^{min} = \frac{0.001}{K}$, $\epsilon_c^{(k)}(0) = 0.2\frac{C}{K}$. Basically, the law (8) works as follows: if all the links satisfy their constraints, then the frequency of experimentation is divided by two until it reaches a minimum level, otherwise it is set at the maximum level, $\epsilon_c^{(k)}(0)$.

Second, we modify the type of power and channels that can be selected when experimenting. We distinguish among two different types of experimentation, noisy search and content experimentation. When content, if the experimentation is on the channel, every channel can be chosen with equal probability. If the experimentation is on the power levels, if all links satisfy their constraints, then only lower power level are experimented; otherwise, if some links are not satisfied, all power levels are tested with equal probability. During the noisy search, all channels are selected with equal probability, and only maximum power or zero power are tested. For a detailed and thorough description of the enhancements, the interested reader is referred to [8].

V. Scenario Description

In this section, we present and detail the network scenarios adopted to run the simulations and test the performance of ETE. First, we consider a static dense scenario to show the ability of ETE to satisfy the network constraints. Second, we consider a mobile scenario with one cluster moving around four static clusters. In this scenario we focus on the performance improvements brought by the proposed enhancement enhancement. Furthermore, we aim at illustrating that TE is suitable for configuring networks even in mobility, where channels are not time-invariant.

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 1.25 km. In each cluster, 8 nodes are randomly positioned as depicted in Fig. 1. Here, the clusters are not overlapping, nodes belonging to each cluster are coloured with different colours, and the role (transmitter or receiver) is decided once and for all.

B. Mobility Scenario

In this scenario, we compare the performance of ETE with the performance of TE in the presence of a moving cluster. In detail, at times $t = 0$, we set 4 clusters aligned and static, we denote the clusters from the left to the right, as cluster number 1, 2, 4 and 5. A fifth cluster, denoted as cluster number 3, is located far enough to be creating little interference. An instance of this starting situation is depicted in Fig. 2. The scenario remains unvaried until $t = 1500$, when cluster 3 begins to move at constant speed towards the aligned clusters. Since the distance with the other clusters decreases, the amount of mutual interference increases with the time. Around $t = 1875$, the cluster is close enough to create disturbance to eventual clusters that are occupying its same channel. At $t = 2250$, the cluster in mobility is perfectly aligned to the others, it maintains its speed while exiting from the zone in which it creates a sufficient amount of interference around $t = 2575$. Eventually, it reaches the border of the field at $t = 3000$.

In this case the topology is such that, between the four static clusters, there exists an empty space for cluster 3 to pass through. Therefore, when all the five clusters are aligned, no cluster is overlapping with another.

Since here, the number of available channels is restricted to $C = 2$, an optimal allocation scheme is the one which alternates different channels between adjacent clusters.

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 ETE or TE. It evaluates the performance of the selected configuration in terms of satisfaction of the QoS constraints.
- Average power consumption (APC): defined as the average amount of power used by the transmitters in the network to achieve the corresponding satisfaction level.

- Channel switch per iteration (CSpI): defined as the average number of channels that have changed for each ETE or TE iteration and, thus, captures the channel scheme stability.

B. Static Scenario

1) Performance, AS and APC: In this section, we analyse the performance of ETE, in terms of satisfaction and power consumption, applied to the square scenario described in Sec. V-A, and we show the improvement with respect to the standard version of TE.

In the first experiment, we compare the performance, in terms of AS and APC, of TE and ETE in a settings with $\Gamma = 10$ dB, $C = 5$ channels in absence of fading. The results are reported in Fig. 3. In this case, for a similar amount of power spent, ETE is able to satisfy more links.

In the second experiment, on the other hand, we test our algorithms in an analogous scenario with Rayleigh fading. The variance of the Rayleigh random process is set equal to 1. Also in this case, the improvement due to the enhancement with respect to the average level of satisfaction is remarkable.

Notice that, when in presence of fading, both algorithms tend to have a less stable working points. Indeed, the fast modifications in the channel gains' values imply equally fast variations on the optimal working points of the network. From the theory developed in [8], [13], we know that both TE and ETE stochastically implement a globally optimal NE. Hence, the variations of these points modify the decision taken by both algorithms.

In the third experiment, we run 10000 iterations of both algorithms for different amount (from $C = 2$ to $C = 18$) of available channels. For each simulation, we report in Fig. 5 the average satisfaction reached in the network, and the corresponding amount of consumed power. By simple inspection, it can be seen that the enhancement provides the network a gain of one free channel, approximately, consuming a slightly lower level of power.

2) Performance, CSpI: In this section we show the effect of the double epsilon enhancement on the stability of the network. In detail we show that the proposed modification is able to sensibly reduce the amount of unneeded switches without crystallizing the network on inefficient configurations. In order to do this we run 10000 simulation of both ETE and TE for different amount of available channels, from $C = 4$ to $C = 18$. The results are reported in Fig. 6.

In the case in which the channels are not fading, ETE switches its channels at half the speed of TE resulting in a CSpI which is around the half of the one of TE. This effect becomes more remarkable with the growth of the amount of available channels, that is, when the selected configuration is optimal with higher probability.

In the case in which the channels are fading, instead, the amount of changes in ETE increases. This is due to the fact that to achieve a well performing working point, it is necessary to jump often from a channel to another. In other words, it is necessary to follow the variations of the channels and consequent variation of the optimal configuration.

C. Mobility scenario, large topology, SINR based feedback

In this section, we study the performance of the proposed algorithm against the mobile scenario introduced in Sec. V-B, and we show its improvement with respect to the performance of the standard TE.

In Fig. 7, we plot the AS and APC for both TE and ETE as a function of the algorithm's iterations. ETE overcomes the performance of TE in both metrics. This is due to the effect of the stabilization that, when a configuration is well performing, reduces the experimentations. This fact is sustained by the results reported in Fig. 8 and Fig. 9. In both figures, we draw the channel chosen by the CH (each channel is represented by a different colour) and the power used in the cluster for the transmissions (represented by the dimension of the line). We recall that the cluster in mobility is cluster number 3, furthermore in both figures the three black vertical lines demarcate (i) the moment in which cluster 3 begins to be close enough to the aligned clusters, (ii) the instant in which cluster 3 is aligned with the other four clusters, (iii) the moment in which cluster 3 is far enough from the aligned clusters.

In Fig. 8, the channels selected by using ETE are reported. Here, a well performing channel scheme is selected in the very first steps, when cluster 2 switches its channel. The power level decreases since it is not needed to be so high to satisfy the SINR constraints of the nodes. Since the level of satisfaction in the clusters is high, the value of $\epsilon_c^{(k)}$ decreases and the configuration does not change.

On the other hand, in Fig. 9, the channels selected by using TE are reported. Also in this experiment, the algorithm select an appropriate channel scheme at the very beginning, in fact, around iteration $t = 100$ all adjacent clusters are selecting a different channel. However, the value of ϵ is too high for keeping the channel scheme constant, and the channels keep on changing. Moreover, the level of ϵ is too small to let the CH select promptly a good power level, and often a suboptimal (i.e., too high) transmission power is employed.

VII. Conclusion

In this paper, the performance of a resource allocation algorithm for clustered distributed network is studied. Such an algorithm, namely the enhanced trial and error algorithm (ETE), is originated by an enhancement of the trial and error (TE) algorithm [6], [7]. The specific characteristic of the proposed algorithm is to set at the same time a communicating channel and a power level for all the devices within each cluster, exploiting exclusively intra-cluster available information. The main drawbacks of TE are overcome by heuristic modifications of its behavioural rules. The performances of ETE and TE were studied in a static and mobile configuration, both in absence of fading and in presence of Rayleigh fading channels.

In every scenario, the performance of ETE is shown to be superior to the one of TE, in terms of links' constraints satisfaction, total amount of power drained and stability of the channel-cluster association scheme.

Specifically, in the static scenario with non-fading channels, the performance are improved in terms of stability and links satisfaction. When Rayleigh fading is considered, the uncertainty of the channels' gain is subsequently followed by an higher instability of the solution. However, the satisfaction level and the power drain are improved.

In the mobile scenario, all the metrics are improved, in particular it is shown that once an optimal condition configuration is achieved the system does not modify it.

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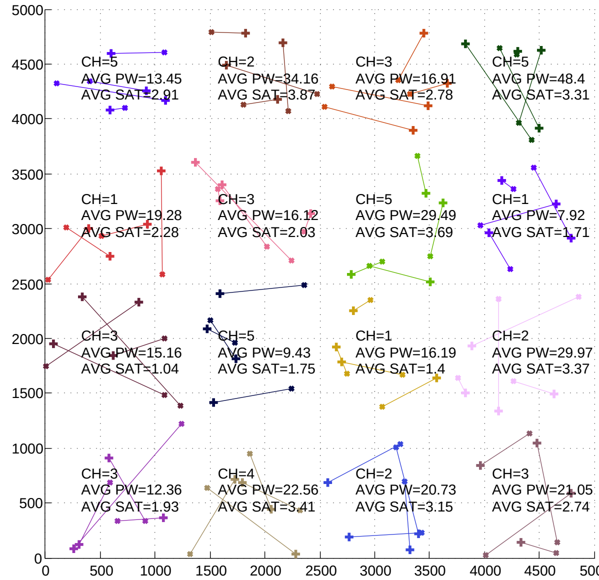

Fig. 1. Square scenario setting with $K = 16$ clusters and $N_k = 4$ pairs. Clusters and nodes are static with SINR-based feedback. CH, AVG PW, and AVG SAT indicate respectively the most frequently selected channel, the APC and the AS.

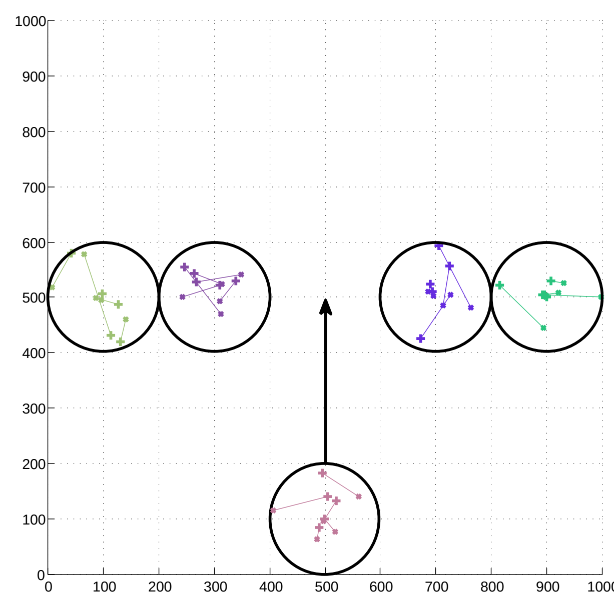

Fig. 2. Cluster positions at the beginning of the mobility scenario with $K = 5$ clusters in a field of 1 km side. Four clusters are static and aligned, the cluster at the bottom is the one in mobility.

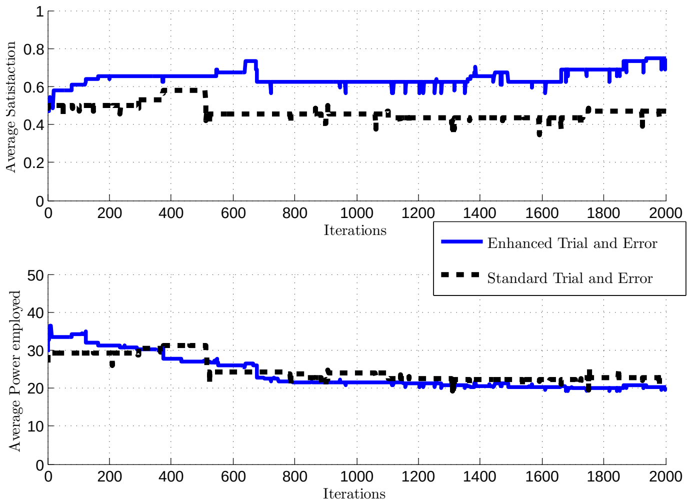

Fig. 3. Average satisfaction and power consumed in the static scenario described in Sec. V-A in absence of fading. The simulation parameters are the following: $\Gamma = 10$ dB, $C = 5$, 2000 iterations. In the upper plot, the blue continuous line represents the average satisfaction reached by employing ETE, the black dashed line the one of TE. In the lower plot, the blue continuous line represents the average power drained by employing ETE, the black dashed line the one of TE.

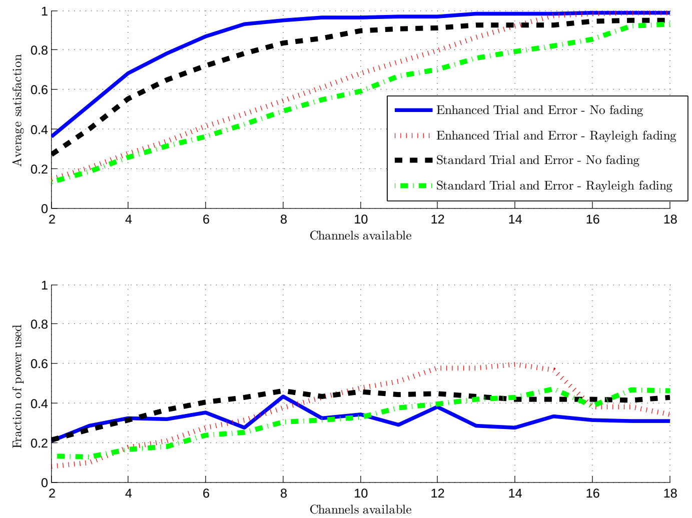

Fig. 5. Comparison between TE and ETE performances in a static scenario, both with Rayleigh fading channels and with block fading ones. In the upper plot, we draw TE and ETE average satisfaction as a function of the available channels. In the lower plot, we draw TE and ETE average consumed power as a function of the available channels.

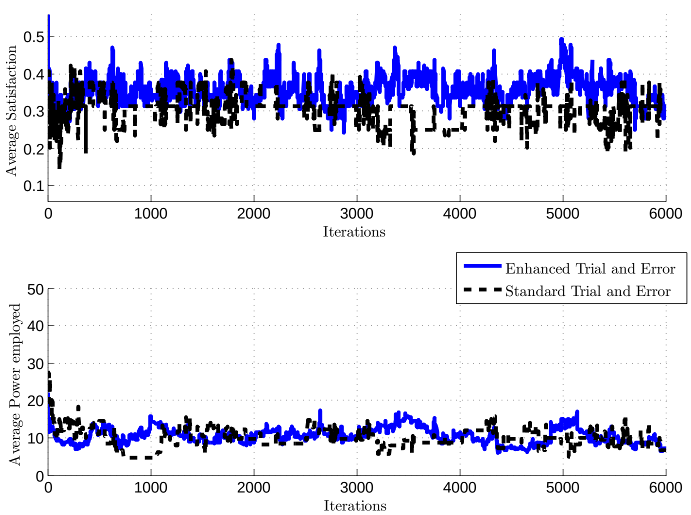

Fig. 4. Average satisfaction and power consumed in the static scenario described in Sec. V-A with Rayleigh fading. The simulation parameters are the following: $\Gamma = 10$ dB, $C = 5$, 6000 iterations. In the upper plot, the blue continuous line represents the average satisfaction reached by employing ETE, the black dashed line the one of TE. In the lower plot, the blue continuous line represents the average power drained by employing ETE, the black dashed line the one of TE.

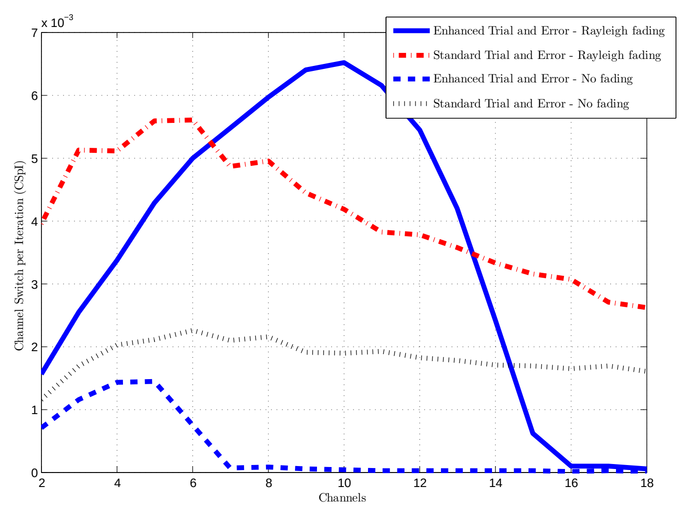

Fig. 6. Channel changes per iteration (CSpI) as a function of the available channels for both ETE and TE in fading and non fading environment.

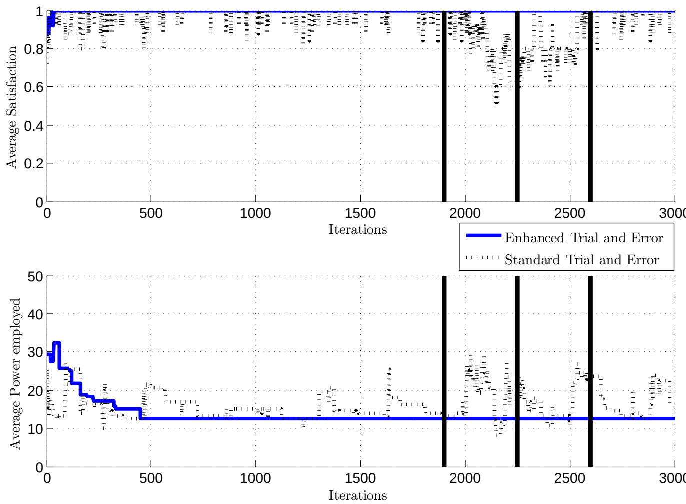

Fig. 7. Achieved AS and APC for both TE and ETE as a function of the iterations for a the mobility scenario. The black vertical lines indicate, approximately, the moment when the moving cluster is close enough to create interference to the others ($t = 1875$), when it is aligned with the others ($t = 2250$) and when it begins to be far enough ($t = 2575$).

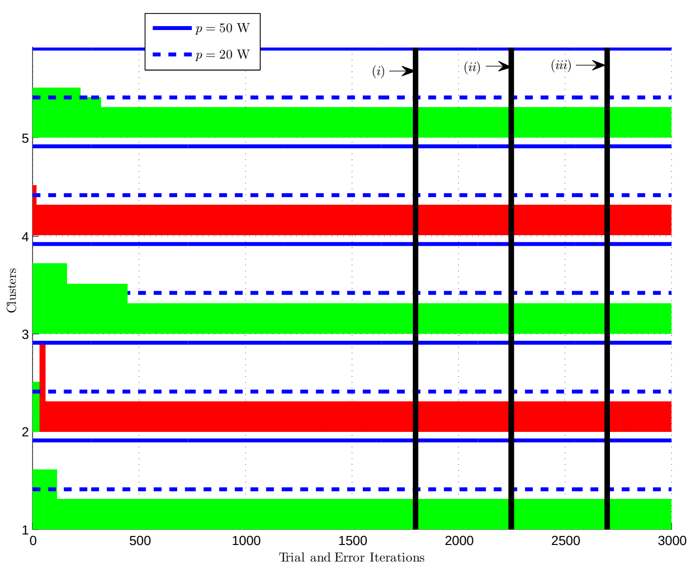

Fig. 8. Progress of the channels for the ETE algorithm in the mobility scenario described in Sec. V-B. To each colour corresponds a channel, the dimension of the line represents the power level chosen for the communication. On the y-axis, the cluster in mobility is represented by the number 3.

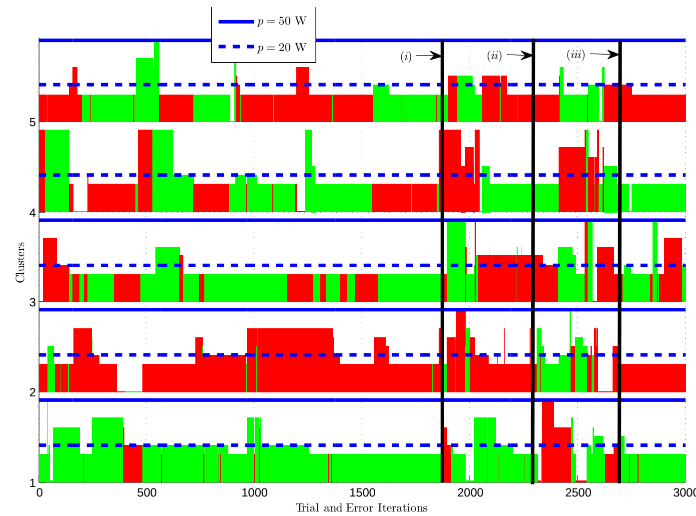

Fig. 9. Progress of the channels for the TE algorithm in the mobility scenario described in Sec. V-B. To each colour corresponds a channel, the dimension of the line represents the power level chosen for the communication. On the y-axis, the cluster in mobility is represented by the number 3.

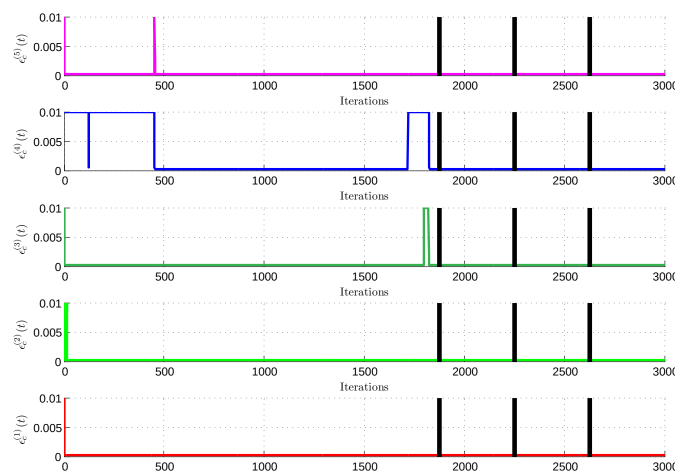

Fig. 10. Value of $\epsilon_c^{(k)}(t)$ versus ETE's iterations in the mobility scenario.