Improved coexistence between multiple cognitive tactical radio networks by an expert rule based on sub-channel selection

Vincent Le Nir, Bart Scheers

***Abstract*—In this paper, we study the convergence behavior of the coexistence between multiple cognitive tactical radio networks. Each tactical radio network has one transmitter which broadcasts a common information to several receivers sharing the same parallel sub-channels and updates its power allocation autonomously from the other networks owing to a distributed dynamic spectrum management function based on the iterative water-filling principle. It is observed that the algorithm has some convergence issues in the case of strong interference channels. In fact, at each iteration some power is poured in the best sub-channels regardless of the interference caused to the other networks, while they have a better benefit avoiding each other by taking different sub-channels. This motivates the addition of expert rules to the terminals, more specifically the obligation to select by preference a subset of contiguous sub-channels. A first advantage is to give the networks more facility to avoid each other for high target rates and to improve the convergence of the algorithm. Another advantage is to lower the complexity of the algorithm and the waveform model by allocating power only over a subset of the available sub-channels. This is especially true for the selection of a single sub-channel which exhibits a remarkable convergence behavior, and could be seen as an enhanced version of a simple "detect and avoid" strategy. Simulation results are supported by an implementation in the event-driven simulator OMNeT++/MiXiM.**

***Index Terms*—Iterative waterfilling algorithm, tactical networks, broadcast channels, sub-channel selection**

I. Introduction

The distributed power control problem in a frequency selective interference channel has been introduced by Yu et al. [1]. This problem can be modeled as an uncooperative game and can be solved efficiently by the iterative waterfilling algorithm (IWFA). The existence and uniqueness of the Nash equilibrium has been established for two users in a digital subscriber lines (DSL) scenario which exhibits diagonal dominant channel conditions. In [2], the distributed power control problem has been reformulated into an equivalent linear complementary problem (LCP), proving the linear convergence of the IWFA in a DSL scenario for arbitrary symmetric interference environment as well as for diagonally dominant asymmetric channel conditions with any number of users. However, in a wireless scenario in which the channel gains of the interferers could be as high as the channel gains of the direct link, multiple Nash equilibrium solutions exist and no theoretical proof of convergence can be obtained. Moreover, the initial assumption of quasi-static fading channels might be no longer valid in a wireless scenario, therefore robust versions of the IWFA have been introduced in [3], [4], [5], [6], [7] by considering imperfect channel and noise variances information. Simulation results were made under diagonal dominant channel conditions to guarantee the existence and uniqueness of the Nash equilibrium.

Recently, the IWFA has been extended to parallel Gaussian broadcast channels with only common information [8], [9], [10]. In this paper, we study the convergence behavior of the IWFA in parallel Gaussian quasi-static Rayleigh broadcast channels with only common information for the coexistence of multiple cognitive tactical radio networks. For instance, parallel channels represent multiple orthogonal sub-carriers as used in orthogonal frequency division multiplexing (OFDM), or multiple non-overlapping sub-channels. We assume that the links between the transmitters and the receivers exhibit quasi-static fading, i.e. in which the coherence times of the fading channels are larger than the time necessary to compute the algorithm. Such an assumption is motivated by the fact that tactical radio networks using VHF and low UHF bands exhibit long coherence times for low mobility patterns. It is observed that the algorithm has some convergence issues in the case of strong interference channels. This difficulty is inherent to IWFA because at each iteration some power is poured in the best channels regardless of the interference caused to the other networks, while they have a better benefit avoiding each other by taking different channels. However, an optimal multiple access scheme would require some level of coordination in a centralized approach. This motivates the addition of expert rules to the networks, more specifically the opportunity to select a subset of contiguous sub-channels. In this case, the networks can allocate power only over a subset of the available sub-channels, thereby limiting the maximum number of sub-channels needed for transmission. Moreover, the networks can only choose a group of contiguous sub-channels. A first advantage is to lower the complexity of the IWFA by allocating power only over a subset of the available sub-channels. A second advantage is to lower the complexity of the physical layer in the case of a multi-carrier waveform with non-overlapping sub-channels. A third advantage is to give the networks more facility to avoid each other for high target rates and to improve the convergence of the IWFA in wireless channels. Without loss of generality, the sub-channel selection can also be applied to the robust versions of the IWFA in parallel Gaussian interference channels [3], [4], [5], [6], [7].

This paper is organized as follows. First, the system model is presented in Section II. The IWFA in parallel Gaussian broadcast channels with only common information is presented along with the ability to select a subset of contiguous sub-channels at each iteration of the inner loop. Extensive simulation results are provided in Section III for the classic IWFA in parallel Gaussian broadcast channels with only common information and the IWFA in parallel Gaussian broadcast channels with only common information with sub-channel selection. Finally, Section IV concludes the paper.

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This research work was carried out in the frame of the Belgian Defense Scientific Research & Technology Study C4/19 funded by the Ministry of Defense (MoD). The scientific responsibility is assumed by its authors.

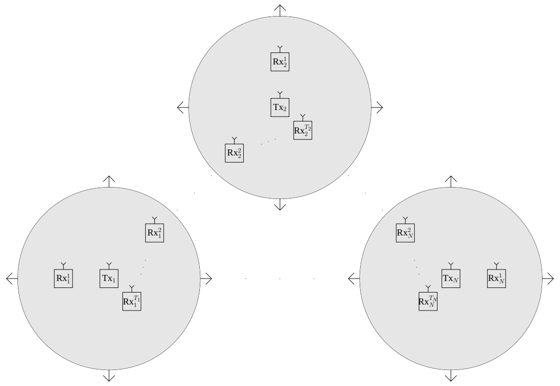

Fig. 1. Scenario considered for the coexistence between tactical radio networks

II. SYSTEM MODEL

The coexistence of multiple cognitive tactical radio networks is shown on Figure 1. The transmission range is represented by the gray area around the transmitter. The different networks can interfere with each other, causing transmission losses if dynamic spectrum management techniques are not implemented. Our goal is to alleviate this problem by equipping each terminal with an algorithm which gives the possibility to optimize its transmission power for each sub-channel. We assume that the links between the transmitters and the receivers exhibit quasi-static fading, i.e. in which the coherence times of the fading channels are larger than the time necessary to compute the algorithm. Such an assumption is motivated by the fact that tactical radio networks using VHF and low UHF bands exhibit long coherence times for low mobility patterns. The received signals $y_{j,it}$ can be modeled as

$$y_{j,it} = h_{jj,it}x_{ij} + \sum_{k\neq j}^{N} h_{jk,it}x_{ik} + n_{j,it} \quad i = 1\ldots N_c,\ j = 1\ldots N,\ t = 1\ldots T_j \tag{1}$$

where N_c is the number of sub-channels, N the number of networks, $n_{j,it}$ the complex noise with variance $\sigma^2_{j,it}$ for the receiver t of network j on sub-channel i, x_{ij} the transmitted signal for network j on sub-channel i, and $h_{jk,it}$ the channel from network k to the receiver t of network j on sub-channel i.

A. Classical IWFA in parallel Gaussian broadcast channels with only common information

We consider the maximization of the aggregate common rate subject to a total power constraint per network

$$\max_{\underline{\underline{\phi}}} \sum_{j=1}^{N} R_{0j}(\underline{\underline{\phi}}) \quad \text{subject to} \sum_{i=1}^{N_c} \phi_{ij} = P_j^{tot}\ \forall j \tag{2}$$

with

$$R_{0j}(\underline{\underline{\phi}}) = \min_{1\ldots T_j} R_{0jt}(\underline{\underline{\phi}}) \tag{3}$$

with

$$R_{0jt}(\underline{\underline{\phi}}) = \Delta f \sum_{i=1}^{N_c} \log_2\Big(1 + \frac{|h_{jj,it}|^2\phi_{ij}}{\Gamma(\sigma^2_{j,it} + \sum_{k\neq j} |h_{jk,it}|^2\phi_{ik})}\Big) \tag{4}$$

and $\underline{\underline{\phi}}$ the power allocation among all sub-channels and networks, $\phi_{ij} = E[|x_i|^2]$ the variance of the input signal on sub-channel i for network j, P_j^{tot} the total power constraint for network j, Δf the sub-channel bandwidth, and Γ the SNR gap which measures the loss with respect to theoretically optimum performance [11]. Moreover, by introducing weight values w_{jt}, with $\sum_{t=1}^{T_j} w_{jt} = 1, \forall j$, (2) can be transformed into the following problem (for more details, see [10])

Find $\underline{\underline{\phi}}^{(\underline{\underline{w}}^{opt})}$ given by

$$\max_{\underline{\underline{\phi}}} \sum_{j=1}^{N}\sum_{t=1}^{T_j} w_{jt} R_{0jt}(\underline{\underline{\phi}}) \quad \text{subject to} \sum_{i=1}^{N_c} \phi_{ij} = P_j^{tot}\ \forall j \tag{5}$$

with

$$\underline{w}_j^{opt} = \min_{\underline{w}_j} \frac{\sqrt{\frac{1}{T_j}\sum_{t=1}^{T_j}[(R_{0jt}(\underline{\underline{\phi}}^{(\underline{\underline{w}})}) - \frac{1}{T_j}\sum_{t=1}^{T_j} R_{0jt}(\underline{\underline{\phi}}^{(\underline{\underline{w}})}))^2]}}{\frac{1}{T_j}\sum_{t=1}^{T_j} R_{0jt}(\underline{\underline{\phi}}^{(\underline{\underline{w}})})} \quad \forall j \tag{6}$$

with $\underline{\underline{w}}$ the weight allocation among all receivers and networks. Maximization of the aggregate common rate subject to a total power constraint per network in a centralized algorithm is an extensive task, since it requires the knowledge of the sub-channel gains from any transmitter to any receiver $|h_{jk,it}|^2$ $\forall i,j,k,t$ and an exhaustive search on w_{jt} $\forall j,t$. Although sub-optimal, a distributed algorithm only requires the knowledge of the sub-channel gains from a transmitter to its own receivers ($|h_{jj,it}|^2, \forall i,j,t$), as well as noise variances of its receivers estimated by spectrum sensing ($\tilde{\sigma}^2_{j,it} = \sigma^2_{j,it} + \sum_{k\neq j} |h_{jk,it}|^2\phi_{ik}$). The distributed algorithm called IWFA for intereference channels [1] and later extended for parallel Gaussian broadcast channels with only common information [8], [9], [10] iteratively updates the power allocation of each network while considering the interference of all other neworks as noise. This process is updated regularly between all the different networks until they reach a Nash equilibrium. Finally, an outer loop minimizes the power while maintaining a target rate for all receivers. Note that some more robust IWFA can also be applied in case of imperfect channel and noise variance information [3], [4], [5], [6], [7]. In this case the SNR gap is increased to assure reliable communication under operating conditions all the time. Under the assumption that each network regards the interference of all other networks as noise, the expression in (2) is the maximization of the aggregate common rate, each common rate being the minimum of a sum of concave functions of ϕ_{ij}. Since the sum and the minimum operations preserve concavity, the objective is concave, and maximizing a concave function yields a convex optimization problem. Considering the classical IWFA in parallel Gaussian broadcast channels with only common information, the Lagrangian function can be written as

$$L(\underline{\lambda}, \underline{\underline{\phi}}) = \sum_{i=1}^{N_c} \left(\Delta f \sum_{j=1}^{N} \sum_{t=1}^{T_j} w_{jt} \log_2(1 + \frac{|h_{jj,it}|^2 \phi_{ij}}{\Gamma \tilde{\sigma}^2_{j,it}}) - \sum_{j=1}^{N} \lambda_j \phi_{ij} \right) + \sum_{j=1}^{N} \lambda_j P_j^{tot} \quad (7)$$

in which $\underline{\lambda}$ are the Lagrange multipliers for all networks. According to [12], the Karush-Kuhn-Tucker (KKT) conditions of the optimization problem can be solved by taking the derivative of the Lagrangian function with respect to ϕ_{ij}

$$\frac{\partial L(\underline{\lambda}, \underline{\underline{\phi}})}{\partial \phi_{ij}} = \frac{\Delta f}{\ln 2} \sum_{t=1}^{T_j} \frac{w_{jt}}{\frac{\Gamma \tilde{\sigma}^2_{j,it}}{|h_{jj,it}|^2} + \phi_{ij}} - \lambda_j \quad . \quad (8)$$

Nulling the derivative gives

$$\frac{\partial L(\lambda, \underline{\underline{\phi}})}{\partial \phi_{ij}} = 0 \Rightarrow \sum_{t=1}^{T_j} \frac{w_{jt}}{\frac{\Gamma \tilde{\sigma}^2_{j,it}}{|h_{jj,it}|^2} + \phi_{ij}} = \underbrace{\lambda_j \frac{\ln 2}{\Delta f}}_{\tilde{\lambda}_j} \quad . \quad (9)$$

For $T_j = 1$, the optimal power allocation corresponds to Gallager's water-filling strategy for parallel Gaussian channels [13]

$$\phi_{ij}^{opt} = \left[\frac{1}{\tilde{\lambda}_j} - \frac{\Gamma \tilde{\sigma}^2_{j,i1}}{|h_{jj,i1}|^2} \right]^+ \quad (10)$$

If $T_j = 1 \; \forall j$, the distributed power control corresponds to the classical IWFA in parallel Gaussian interference channels [1]. For $T_j = 2$, the optimal power allocation corresponds the water-filling strategy for parallel Gaussian broadcast channels with only common information [10]

Find $\underline{\phi}_j^{(w_{j1}, w_{j2})^{opt}}$ $\forall j$ given by

$$\phi_{ij}^{(w_{j1}, w_{j2})} = \left[\frac{1}{2\tilde{\lambda}} + \sqrt{\frac{1}{4\tilde{\lambda}^2} - \frac{(a_{ij} - b_{ij})(w_{j1} - w_{j2})}{2\tilde{\lambda}} + \frac{(a_{ij} - b_{ij})^2}{4}} - \frac{a_{ij} + b_{ij}}{2} \right]^+ \quad (11)$$

with

$$(w_{j1}, w_{j2})^{opt} = \min_{w_{j1}, w_{j2}} \frac{\sqrt{\frac{1}{T_j} \sum_{t=1}^{T_j} [(R_{0jt}(\underline{\phi}_j^{(w_{j1}, w_{j2})}) - \frac{1}{T_j} \sum_{t=1}^{T_j} R_{0jt}(\underline{\phi}_j^{(w_{j1}, w_{j2})}))^2]}}{\frac{1}{T_j} \sum_{t=1}^{T_j} R_{0jt}(\underline{\phi}_j^{(w_{j1}, w_{j2})})} \quad \forall j \quad (12)$$

in which $\underline{\phi}_j$ the power allocation among all sub-channels for network j, $a_{ij} = \frac{\Gamma \tilde{\sigma}^2_{j,i1}}{|h_{jj,i1}|^2}$ and $b_{ij} = \frac{\Gamma \tilde{\sigma}^2_{j,i2}}{|h_{jj,i2}|^2}$. In the general case, the optimal power allocation corresponds the water-filling strategy for parallel Gaussian broadcast channels with only common information [10]:

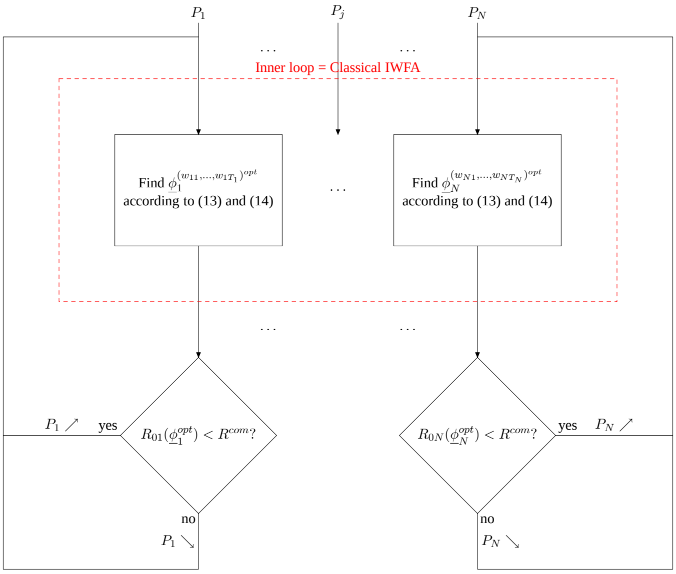

Fig. 2. Distributed power control for the classical IWFA in parallel Gaussian broadcast channels with only common information

Find $\underline{\phi}_j^{(w_{j1}, \dots, w_{jT_j})^{opt}}$ $\forall j$ given by

$$\phi_{ij}^{(w_{j1}, \dots, w_{jT_j})} \text{roots of} \sum_{t=1}^{T_j} \frac{w_{jt}}{\frac{\Gamma \sigma^2_{j,it}}{|h_{jj,it}|^2} + \phi_{ij}} = \tilde{\lambda}_j \quad (13)$$

with

$$(w_{j1}, \dots, w_{jT_j})^{opt} = \min_{w_{j1}, \dots, w_{jT_j}} \frac{\sqrt{\frac{1}{T_j} \sum_{t=1}^{T_j} [(R_{0jt}(\underline{\phi}_j^{(w_{j1}, \dots, w_{jT_j})}) - \frac{1}{T_j} \sum_{t=1}^{T_j} R_{0jt}(\underline{\phi}_j^{(w_{j1}, \dots, w_{jT_j})}))^2]}}{\frac{1}{T_j} \sum_{t=1}^{T_j} R_{0jt}(\underline{\phi}_j^{(w_{j1}, \dots, w_{jT_j})})} \quad \forall j \quad (14)$$

B. Distributed power control for the classical IWFA in parallel Gaussian broadcast channels with only common information

The classical IWFA maximizes the sum rate subject to a total power constraint per network. In practice we want to minimize the power subject to a target rate per network. This can be achieved by a distributed power control similar to [1]. Figure 2 shows the distributed power control for multiple networks. An inner loop determines iteratively for each network the power allocation maximizing the common rate and satisfying its total power constraint. Then, an outer loop minimizes the total powers of the different networks individually such that a common rate constraint R^{com} is achieved. Algorithm 1 provides the power allocation for power minimization subject to a common rate constraint.

C. IWFA in parallel Gaussian broadcast channels with only common information with sub-channel selection

In this Section, the addition of expert rules to the networks is investigated, more specifically the opportunity to select a subset of contiguous sub-channels. In this case, the networks

Algorithm 1 Distributed power control for the classical IWFA in parallel Gaussian broadcast channels with only common information

repeat
  repeat
    repeat
      for $j = 1$ to N
        for all $(w_{j1}, \ldots, w_{jT_j})$
          Calculate $\phi_{ij}^{(w_{j1},\ldots,w_{jT_j})}$ $\forall i$ according to (13)
          if $\sum_{i=1}^{N_c} \phi_{ij}^{(w_{j1},\ldots,w_{jT_j})} < P_j^{tot}$ decrease $\tilde{\lambda}_j$
          if $\sum_{i=1}^{N_c} \phi_{ij}^{(w_{j1},\ldots,w_{jT_j})} > P_j^{tot}$ increase $\tilde{\lambda}_j$
        end for
        Find $\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}$ according to (14)
      end for
    $\times$ times
  until the desired accuracy is reached
  for $j = 1$ to N
    Calculate $R_{0j}(\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}) = \min_{t=1\ldots T_j} \Delta f \sum_{i=1}^{N_c} \log_2(1 + \frac{|h_{i,jj}|^2 \phi_{ij}^{(w_{j1},\ldots,w_{jT_j})^{opt}}}{\Gamma \tilde{\sigma}_{j,it}^2})$
    if $R_{0j}(\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}) < R^{com}$ increase P_j^{tot}
    if $R_{0j}(\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}) > R^{com}$ decrease P_j^{tot}
  end for
until the desired accuracy is reached

can allocate power only over a subset of the available sub-channels, thereby limiting the maximum number of sub-channels needed for transmission. Moreover, the netowrks can only choose a group of contiguous sub-channels. A first advantage is to lower the complexity of the IWFA in parallel Gaussian broadcast channels with only common information by allocating power only over a subset of the available sub-channels. A second advantage is to lower the complexity of the physical layer in the case of a multi-carrier waveform with non-overlapping sub-channels. A third advantage is to give the networks more facility to avoid each other for high target rates and to improve the convergence of the IWFA in parallel Gaussian broadcast channels with only common information in wireless channels.

The sub-channel selection is described as follows. At each iteration of the inner loop in the IWFA in parallel Gaussian broadcast channels with only common information, a network can only use L contiguous sub-channels, with $L \in \{1, N_c\}$. In fact, the network j chooses the subset of contiguous sub-channels exhibiting the maximum common rate

$$l_j^{opt} = \underset{l_j}{max} \min_{t=1\ldots T_j} \Delta f \sum_{i=l_j}^{l_j+L-1} \log_2(1 + \frac{|h_{i,jj}|^2 P_j^{tot}}{L \Gamma \tilde{\sigma}_{j,it}^2}) \quad (15)$$

The optimal subset of sub-channels to be used for the network j is therefore determined by

Algorithm 2 IWFA in parallel Gaussian broadcast channels with only common information with sub-channel selection

initialize $L \in \{1, N_c\}$
repeat
  repeat
    repeat
      for $j = 1$ to N
        $l_j^{opt} = \max_{l_j} \min_{t=1\ldots T_j} \Delta f \sum_{i=l_j}^{l_j+L-1} \log_2(1 + \frac{|h_{i,jj}|^2 P_j^{tot}}{L\Gamma \tilde{\sigma}_{j,it}^2})$
        for all $(w_{j1}, \ldots, w_{jT_j})$
          Calculate $\phi_{ij}^{(w_{j1},\ldots,w_{jT_j})}$ $\forall i \in \mathcal{A}_j$ according to (13)
          if $\sum_{i=1}^{N_c} \phi_{ij}^{(w_{j1},\ldots,w_{jT_j})} < P_j^{tot}$ decrease $\tilde{\lambda}_j$
          if $\sum_{i=1}^{N_c} \phi_{ij}^{(w_{j1},\ldots,w_{jT_j})} > P_j^{tot}$ increase $\tilde{\lambda}_j$
        end for
        Find $\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}$ according to (14)
      end for
    $\times$ times
  until the desired accuracy is reached
  for $j = 1$ to N
    Calculate $R_{0j}(\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}) = \min_{t=1\ldots T_j} \Delta f \sum_{i=l_j^{opt}}^{l_j^{opt}+L-1} \log_2(1 + \frac{|h_{i,jj}|^2 \phi_{ij}^{(w_{j1},\ldots,w_{jT_j})^{opt}}}{\Gamma \tilde{\sigma}_{j,it}^2})$
    if $R_{0j}(\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}) < R^{com}$ increase P_j^{tot}
    if $R_{0j}(\underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}) > R^{com}$ decrease P_j^{tot}
  end for
until the desired accuracy is reached

$$\mathcal{A}_j = \{l_j^{opt}, l_j^{opt} + L - 1\} \quad (16)$$

Algorithm 2 provides the proposed power allocation for power minimization subject to a common rate constraint with sub-channel selection. Note that if $L = N_c$, Algorithm 2 reduces to Algorithm 1 and IWFA in parallel Gaussian broadcast channels with only common information with sub-channel selection becomes the classical IWFA in parallel Gaussian broadcast channels with only common information and distributed power control. The IWFA with/without sub-channel selection are non-optimal solutions of the centralized problem. Similarly to the convergence of the IWFA in non-diagonally dominant channel conditions, the convergence of the IWFA with sub-channel selection cannot be proven theoretically. Therefore, the convergence of the IWFA in wireless channels with/without sub-channel selection will be studied through simulations by an implementation in the event-driven simulator OMNeT++/MiXiM.

III. Simulation results

For the simulations, the log-distance path loss model is used to measure the path loss between the transmitter and the receivers [14]:

$$PL(dB) = PL(d_0) + 10n\log_{10}(\frac{d}{d_0}) \tag{17}$$

with n the path loss exponent, d is the distance between the transmitter and the receiver, and d_0 the close-in reference distance in kilometers. The reference path loss is calculated using the free space path loss formula

$$PL(d_0) = -32.44 - 20\log_{10}(f_c) - 20\log_{10}(d_0) \tag{18}$$

where f_c is the carrier frequency in MHz. The carrier frequency is chosen to be in the very high frequency (VHF) band ($f_c = 80$ MHz). The SNR gap for an uncoded quadrature amplitude modulation (QAM) to operate at a symbol error rate 10^{-7} is $\Gamma = 9.8$ dB. The sub-channel bandwidth is $\Delta f = 25$ kHz, the path loss exponent is $n = 4$, reference distance $d_0 = 0.02$ kilometers and thermal noise with the following expression

$$\sigma_{ij}^2 = -204\text{dBW/Hz} + 10\log_{10}(\Delta f) \qquad \forall i, j. \tag{19}$$

In the first set of simulations, we compare Algorithm 1 with Algorithm 2 with $N = 2$ tactical radio networks, $N_c = 2$ sub-channels and two receivers per network $T_1 = T_2 = 2$ by an implementation in the event-driven simulator OMNeT++/MiXiM. OMNeT++ is an extensible, modular, component-based C++ simulation library and framework, primarily for building network simulators [15]. MiXiM is an OMNeT++ modeling framework created for mobile and fixed wireless networks (wireless sensor networks, body area networks, ad-hoc networks, vehicular networks, etc.) [16]. In this simulation, we have extended the OMNeT++/MiXiM implementation of the classical IWFA in parallel Gaussian interference channels [17] to the IWFA in parallel Gaussian broadcast channels with only common information and sub-channel selection.

Figure 3 shows the scenario used for the simulation. The first network is mobile and follows a pre-defined trajectory with a constant velocity v (about 90 km/h). In this network, node 2 broadcasts a common information to node 0 and node 1 at 64 kbps. The second network remains at the same location during the simulation. In this network, node 5 broadcasts a common information to node 3 and node 4 at 64 kbps. The most critical configuration is obviously reached when the two networks are close to each other, and the interference is maximal. The time interval between two inner loops is set to 0.1s in each network, while the time interval between two outer loops is set to 0.5s with power updates of $10\log_{10}(0.9) \sim 0.46$ dB. The sub-channel gains follow a Rayleigh distribution, i.e. absolute values of random complex numbers whose real and imaginary components are independently and identically distributed (i.i.d.) Gaussian. We assume that the sub-channel gains of the direct channels (node 2 $\rightarrow$ node 0, node 2 $\rightarrow$ node 1, node 5 $\rightarrow$ node 3 and node 5 $\rightarrow$ node 4) do not change during the simulation as the relative doppler is zero. However, the sub-channel gains of the interference channels (node 2 $\rightarrow$ node 3, node 2 $\rightarrow$ node 4, node 5 $\rightarrow$ node 0 and node 5 $\rightarrow$ node 1) have a relative doppler shift $f_d = vf_c/c = 6.67$ Hz, c being the speed of light. The coherence times of the sub-channel gains of the interference channels are given by $t_c = k/f_d$, k begin a constant value between 0.25 and 0.5. Therefore, we assume a block Rayleigh fading distribution for the sub-channel gains of the interference channels, i.e. they are updated according to their coherence time every $t_c = 0.05$s.

Figure 4 shows the evolution of the data rate, the total power and the occupation of the sub-channels versus time of both networks for the classical IWFA in parallel Gaussian broadcast channels with only common information. At the beginning of the simulation, the total power of both networks is maximal, i.e. 10 W. In this case, the difference between the sub-channel gains is negligeable compared to the power being waterfilled, leading to 50% occupation between the sub-channels. As the power is decreasing and as the networks are getting close to each others, the first network tends to take the first sub-channel and the second network tends to take the second sub-channel. However, this transition is a rather slow process and can cause an increase of the total power and a difficulty to stabilize the data rate for both networks. As the interference is strong enough to make both networks choose different sub-channels, the total power and the data rate converge towards stable values althoug the sub-channel occupation shows some convergence issues. These convergence issues are due to the doppler effect on the sub-channel gains of the interference channels and the existence of multiple Nash equilibria. Indeed, these channels are not quasi-static fading channels since their coherence times are lower than the time interval between two inner loops. When the first network moves away from the second, we also see an increase of the total power and a difficulty to stabilize the data rate for both networks.

Figure 5 shows the evolution of the data rate, the total power and the occupation of the sub-channels versus time of both networks for the IWFA with sub-channel selection of a single sub-channel. It is observed that the data rate and the total power are very stable for both networks. The first network takes the first sub-channel while the second network takes the

Fig. 3. Scenario used for the simulation

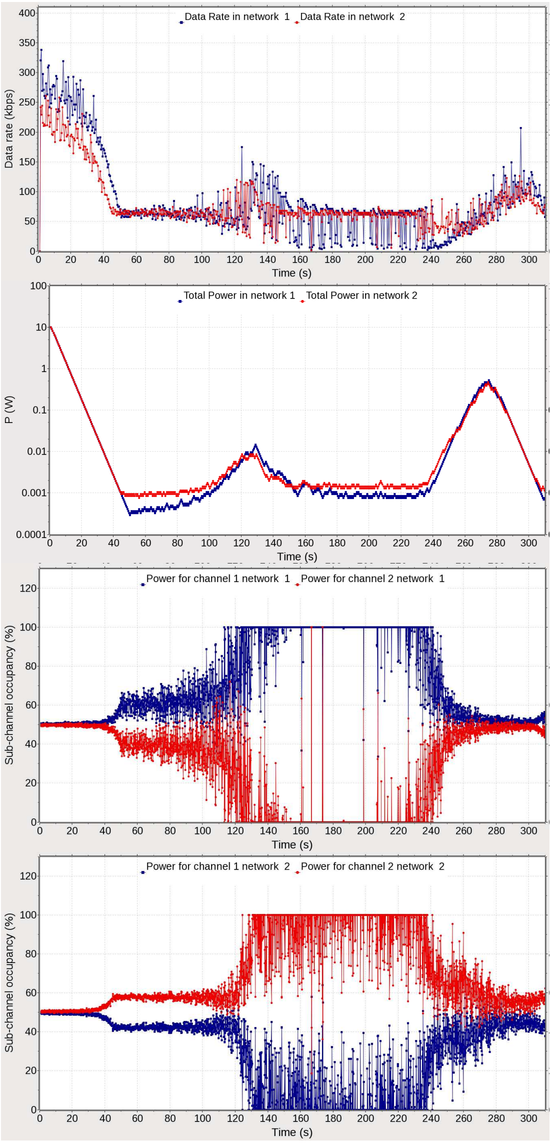

Fig. 4. Data rate, total power and sub-channel occupation for the classical IWFA in parallel Gaussian broadcast channels with only common information with $N = 2$ tactical radio networks, $N_c = 2$ sub-channels and two receivers per network $T_1 = T_2 = 2$

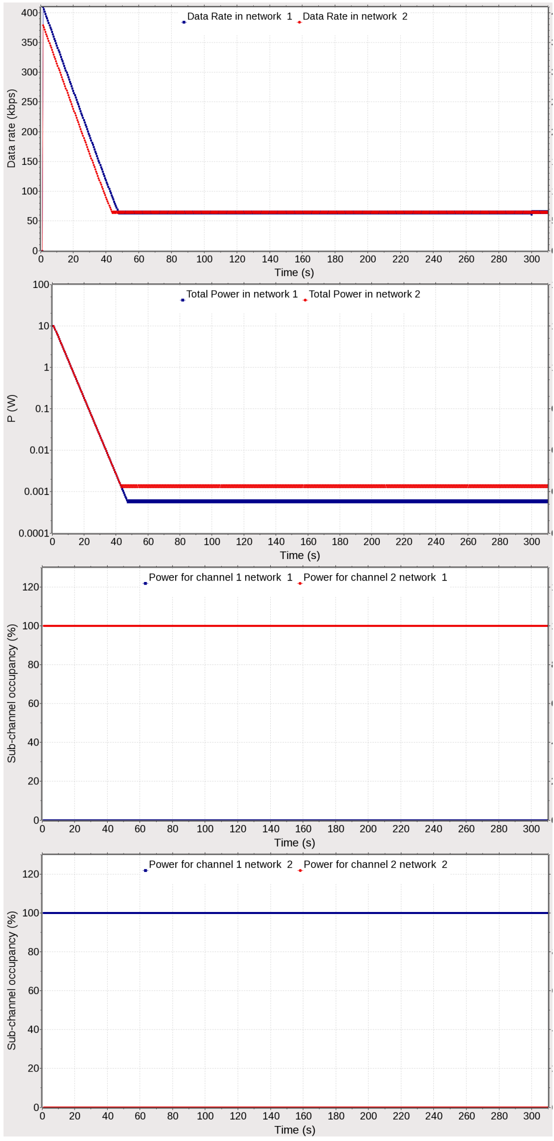

Fig. 5. Data rate, total power and sub-channel occupation for the IWFA in parallel Gaussian broadcast channels with only common information with sub-channel selection of one sub-channel with $N = 2$ tactical radio networks, $N_c = 2$ sub-channels and two receivers per network $T_1 = T_2 = 2$

second sub-channel. In this case, the system is converging rapidly towards one Nash equilibrium and there is no more convergence issues due to the doppler effect on the sub-channel gains of the interference channels.

In the second set of simulations, we compare Algorithm 1 with Algorithm 2 with $N = 2$ tactical radio networks, $N_c = 4$ sub-channels and two receivers per network $T_1 = T_2 = 2$ using the same scenario. Figure 6 shows the evolution of the data rate, the total power and the occupation of the sub-channels versus time of both networks for the classical IWFA in parallel Gaussian interference channels. The data rate and the total power shows better convergence with $N_c = 4$ sub-channels compared to $N_c = 2$ sub-channels on Figure 4. Moreover, the averaged power necessary to achieve the required data rate is lower with $N_c = 4$ than $N_c = 2$ sub-channels owing to the degrees of freedom introduced by the sub-channels. However, the management of the sub-channel powers is more complex as seen on the figure showing the sub-channel occupation versus time. Moreover, some convergence issues appear due to the doppler effect on the sub-channel gains of the interference channels and the existence of multiple Nash equilibria.

The convergence issues can be reduced using a more robust IWFA such as [5], [6]. However, these algorithms either trade performance with robustness or assume a specific distribution of the error process. In [3], [4], the authors proposed to heuristically address the impact of such time-varying uncertainty by introducing a memory parameter at each iteration $\alpha \in (0, 1]$

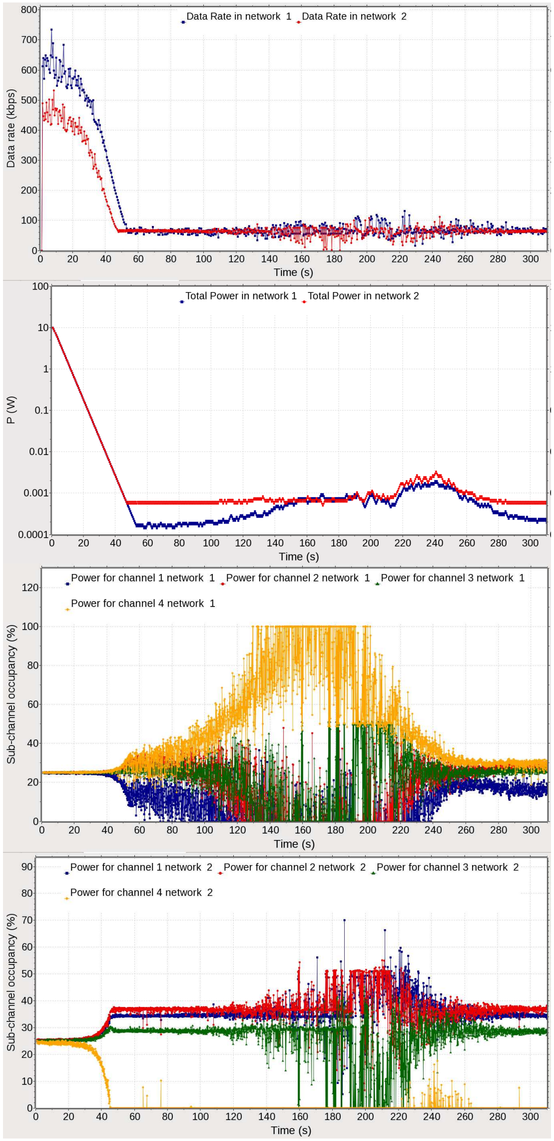

Fig. 6. Data rate, total power and sub-channel occupation for the classical IWFA in parallel Gaussian broadcast channels with only common information with $N = 2$ tactical radio networks, $N_c = 4$ sub-channels and two receivers per network $T_1 = T_2 = 2$

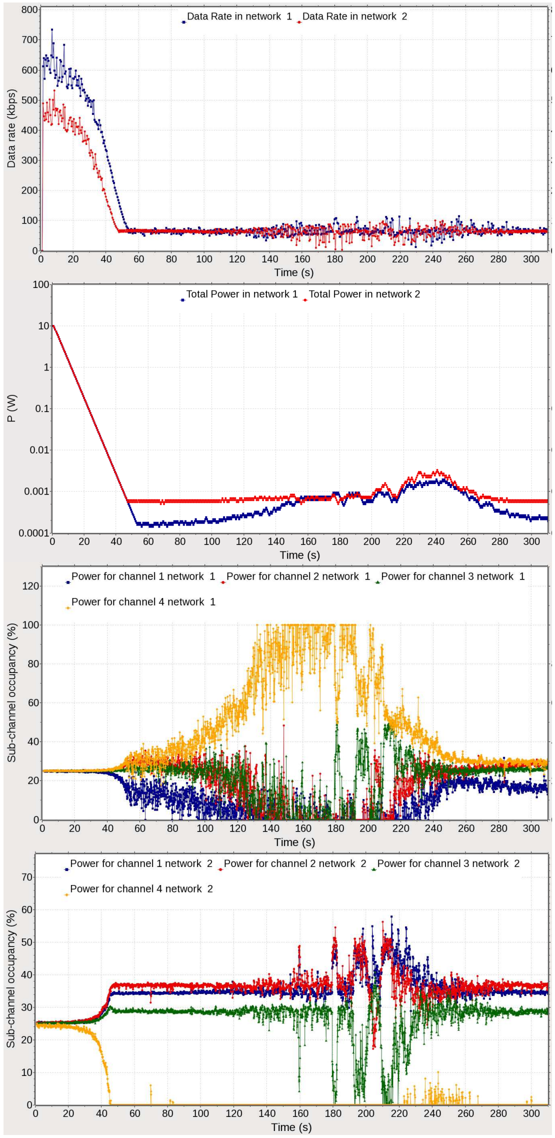

Fig. 7. Data rate, total power and sub-channel occupation for the averaged IWFA in parallel Gaussian broadcast channels with only common information with $N = 2$ tactical radio networks and $N_c = 4$ sub-channels

in the calculation of the transmission power levels

$$\underline{\phi}_j^{(w_{j1},\dots,w_{jT_j})^{opt}}(t+1) = (1-\alpha)\underline{\phi}_j^{(w_{j1},\dots,w_{jT_j})^{opt}}(t) + \alpha\underline{\phi}_j^{(w_{j1},\dots,w_{jT_j})^{opt}} \quad \forall j \tag{20}$$

However, the choice of the memory parameter α is crucial for the convergence and there is no method to find the optimal value. Recently, [7] proposed the averaged IWFA for improved robustness and convergence, showing that if the memory parameter is chosen as a time sequence $\alpha_t = \frac{1}{1+t}$, the transmission power levels are averaged

$$\underline{\phi}_j^{(w_{j1},\dots,w_{jT_j})^{opt}}(T+1) = \frac{1}{T+1}\sum_{t=0}^{T}\underline{\phi}_j^{(w_{j1},\dots,w_{jT_j})^{opt}}(t+1) \quad \forall j \tag{21}$$

In the following simulations, we apply the averaged IWFA to parallel Gaussian broadcast channels with only common information. As shown on Figure 7, the averaged IWFA has better convergence properties than the classical IWFA. As the outer loop is executed every 0.5s and the inner loop ever 0.1s, we choose $T = 4$ to avoid averaging across multiple total power constraints. Indeed, the averaged IWFA is better suited for maximizing the common rates subject to a total power constraint (inner loop) than minimizing the powers subject to common rate constraints (outer loop). Therefore, each memory parameter sequence should be restarted at $t = 0$ whenever the total power constraint is modified. To average across multiple total power constraints, we propose to feed a circular buffer

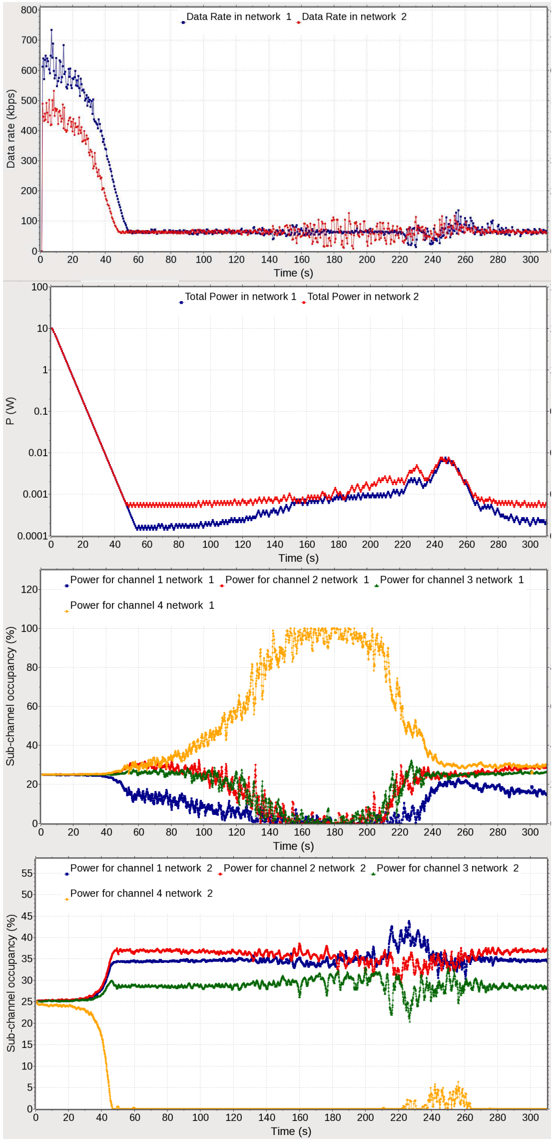

Fig. 8. Data rate, total power and sub-channel occupation for the circular averaged IWFA in parallel Gaussian broadcast channels with only common information with $N = 2$ tactical radio networks and $N_c = 4$ sub-channels

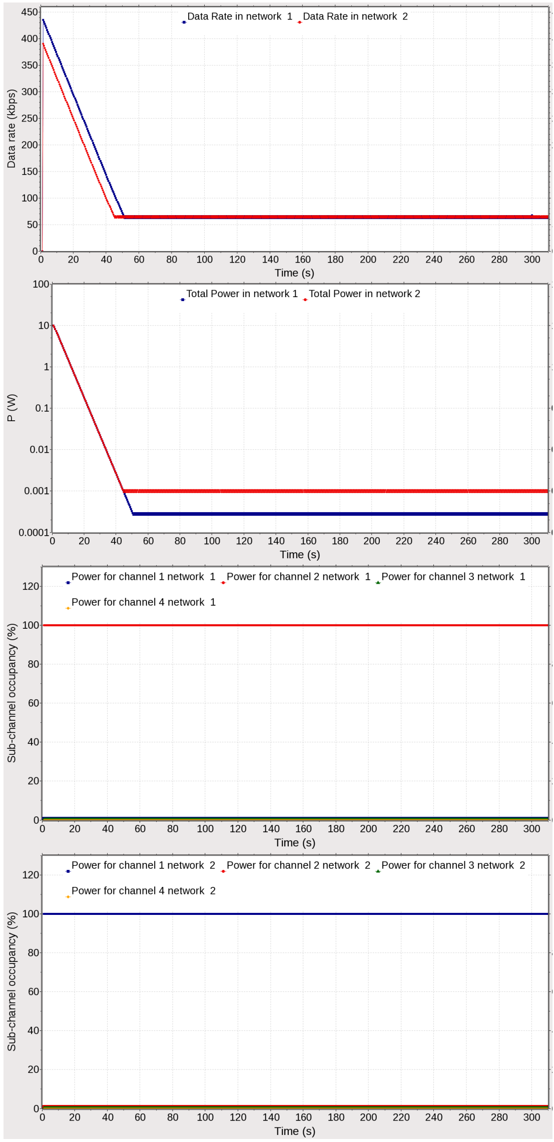

Fig. 9. Data rate, total power and sub-channel occupation for the IWFA in parallel Gaussian broadcast channels with only common information with sub-channel selection of one sub-channel with $N = 2$ tactical radio networks, $N_c = 4$ sub-channels and two receivers per network $T_1 = T_2 = 2$

of length $T + 1$ with the transmission power levels

$$\underline{\phi}_j^{opt}(T+i+1) = \frac{1}{T+1}\sum_{t=i}^{T+i} \underline{\phi}_j^{(w_{j1},\ldots,w_{jT_j})^{opt}}(t+1) \quad \forall i, j \tag{22}$$

We call this algorithm the circular averaged IWFA in parallel Gaussian broadcast channels with only common information. As shown on Figure 8, the circular averaged IWFA with $T = 9$ has also better convergence properties than the classical IWFA and the averaged IWFA.

Figure 9 shows the evolution of the data rate, the total power and the occupation of the sub-channels versus time of both networks for the IWFA in parallel Gaussian broadcast channels with only common information with sub-channel selection of a single sub-channel. The first network takes the second sub-channel while the second network takes the first sub-channel. The system is also converging rapidly towards one Nash equilibrium and there is no more convergence issues due to the doppler effect on the sub-channel gains of the interference channels and the existence of multiple Nash equilibria. One can observe an increased power for both networks of about 1 dB in average compared to Figure 7 and 8 because of the exploitation of a single sub-channel instead of four sub-channels. Therefore, in order to reduce the power when a higher number of sub-channels N_c is available, one might consider to exploit several sub-channels for the IWFA in parallel Gaussian interference channels with sub-channel selection. To summarize, simulation results show that sub-channel selection does not affect drastically the performance of IWFA and in some cases can lead to better performance and a better convergence behavior in wireless channels. This is especially true for IWFA with sub-channel selection of a single sub-channel showing no errors of convergence, which could be seen as an enhanced version of a simple "detect and avoid" strategy.

IV. Conclusion

In this paper, we have studied the convergence behavior of the IWFA in parallel Gaussian quasi-static Rayleigh broadcast channels with only common information for the coexistence of multiple cognitive tactical radio networks. We have investigated the addition of expert rules to the networks, more specifically the opportunity to select a subset of contiguous sub-channels during the IWFA. A first advantage is to lower the complexity of the IWFA by allocating power only over a subset of the available sub-channels. A second advantage is to lower the complexity of the physical layer in the case of a multi-carrier waveform with non-overlapping sub-channels. A third advantage is to give the networks more facility to avoid each other for high target rates and to improve the convergence of the IWFA in wireless channels. In a wireless scenario, multiple Nash equilibrium solutions of the IWFA exist and no theoretical proof of convergence can be obtained. Therefore, the convergence of the IWFA in wireless channels with/without sub-channel selection has been studied through simulations by an implementation in the event-driven simulator OMNeT++/MiXiM. Simulation results show that sub-channel selection does not affect drastically the performance of IWFA and in some cases can lead to better performance and a better convergence behavior in wireless channels. This is especially true for IWFA with sub-channel selection of a single sub-channel showing no errors of convergence, which could be seen as an enhanced version of a simple "detect and avoid" strategy.

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