Distributed Design for Fair Coexistence in TVWS

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***Abstract*—Very recently, regulatory bodies worldwide started to approve the opportunistic access of unlicensed networks to the TVWS spectrum. Hence, in the near future, multiple heterogeneous and independently-operated unlicensed networks will coexist within the same geographical area over shared TVWS. Nevertheless, the coexistence among heterogeneous unlicensed networks over TVWS represents an open problem, and innovative solutions for handling the coexistence interference are needed to fully unleash the TVWS potentials. Hence, in this paper, we design a coexistence strategy for TVWS scenarios with the following attractive features: i) *fully distributed*, i.e., it avoids the need of centralized interference management; ii) over-the-air communications free, i.e., it avoids the need of direct communications among the heterogeneous networks; iii) *adaptive* to the time- and space-dynamics of the coexistence interference; iv) *selfless*, i.e., it allows a fair TVWS spectrum sharing by accounting for the communication demands of each unlicensed network. These attractive features are obtained by designing a coexistence strategy based on a system of multi-dimensional ordinary differential equations, and by incorporating the trade-off between selfish bandwidth maximization and fair spectrum allocation within the system dynamics. Performance evaluation is conducted through numerical simulations, and the results confirm the attractive features of the proposed coexistence strategy.**

I. Introduction

Regulatory efforts are currently ongoing in many countries to enable secondary (unlicensed) access to the TV White Space (TVWS) spectrum, e.g. IEEE 802.22 [1], IEEE 802.11af [2], IEEE 802.15m [3], ECMA 392 [4], and IEEE SCC41 [5]. The existing rulings [6], [7], [8] obviate the spectrum sensing as the mechanism for the Secondary Networks (SNs) to determine the TVWS availability at their respective locations. In fact, they require the SNs to periodically access to a geolocated database [9] for acquiring the list of TVWS channels free from incumbents along with their qualities.

The standardization of the aforementioned mechanism for incumbent protection along with the excellent TVWS propagation characteristics make the TVWS spectrum highly desirable. Hence, in the near future, multiple heterogeneous and independently-operated SNs are envisioned to share the TVWS spectrum within the same geographical area. Nevertheless, to fully unleash the potentials of TVWS, new challenges must be addressed and solved. In particular, innovative solutions able to handle the coexistence among heterogenous SNs are needed due to the distinguished characteristics of the TVWS scenarios:

- *Dynamic Interference.* In TVWS scenarios, the heterogenous coexistence interference is both time and spatial-variant [10], [11], [12], [13]. In fact, such dynamics depend on several factors, such as the number of SNs roaming within a certain geographic area, the number of users belonging to each SN, the interference range and the traffic/mobility patterns of each SN, as well as the changes in wireless propagation conditions. Hence, any coexistence strategy should be adaptive to such dynamics.
- *Heterogeneity.* The heterogeneity among the different TVWS standards might prevent the adoption of coexistence schemes based on cooperation [14]. Hence, an appealing characteristic of any coexistence strategy is to avoid the need of direct communications among different SNs.

In this paper, we design a coexistence strategy for TVWS scenarios to mitigate the coexistence interference by accounting for all the aforementioned challenges. To this aim, we exploit a recently developed analytical framework for the engineering of decentralized collective decision-making strategies [15], [16], and we model the coexistence problem as a system of multi-dimensional ordinary differential equations describing the evolution of different *populations*. The dynamics within each population model the selfish demand of bandwidth of each SN, whereas the dynamics among different populations drive the system toward a fair bandwidth allocation reducing the coexistence interference. More into the details, the intra-population dynamics implement a decentralized decision making process that leads to the choice of the best available channel that satisfies the SN demand. Also, such collective decision-making process can adaptively break deadlocks in case of same-quality alternatives to guarantee convergence, and achieves a near-optimal speed-accuracy tradeoff, so that a desired accuracy in the decision making is obtained in the least possible time [15]. In this paper, we extend the collective decision making strategy to account for multiple SNs that interact indirectly to choose the best available allocation among different available channels.

The proposed strategy exhibits the following attractive features: $i)$ fully distributed, i.e., it avoids the need of centralized interference management; $ii)$ over-the-air communications free, i.e., it avoids the need of direct communications among the heterogeneous networks; $iii)$ adaptive to the time- and

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space-dynamics of the coexistence interference; iv) selfless, i.e., it allows a fair TVWS spectrum sharing by accounting for the communication demands of each unlicensed network. To the best of our knowledge, this is the first work addressing the secondary coexistence in TVWS with all the above mentioned key features.

The rest of the paper is organized as follows. In Sec. I-A, we discuss the related work. In Sec. II, we describe the network model along with some preliminaries. In Sec. III, we design the coexistence strategy. In Sec. IV, we validate the theoretical framework through a case study, and, finally, in Sec. V, we conclude the paper.

A. Related Work

As mentioned above, very recently the research community started to investigate solutions for the secondary coexistence in TVWS. [17] and [18] address the coexistence between low vs high-power and contention vs reserved-based networks, respectively. The proposed strategies are targeted to specific technologies and, hence, they are not suitable for heterogeneous scenarios such as the TVWS ones. In [13], the intrinsic relationship between environmental and system parameters in affecting the secondary coexistence has been disclosed. [19] and [20] propose an autonomous strategy allowing an arbitrary SN to minimize the effects of the coexistence interference. However, the proposed strategy is selfish, i.e., it optimizes the throughput of a specific SN, regardless of the interference caused on the remaining coexisting SNs. Hence it does not allow to maximize the entire system performance.

II. Model and Preliminaries

We consider multiple heterogeneous SNs operating within the TVWS Spectrum according to the existing regulations and standards. Time is organized in fixed-size slots of duration τ, and by accessing to the TVWS database, any SN obtains the list of channels free from primary incumbents as well as the nominal quality of each channel, i.e., the achievable data-rate in absence of coexistence interference. In the following, we denote the set of incumbent-free channels with $\mathcal{C} = \{1, 2, \dots, C\}$ and the nominal channel throughput (quality) with $\{q_c\}_{c \in \mathcal{C}}$.

Multiple SNs are allowed to operate within the same geographical region. Hence, in a certain time slot k, a channel $c \in \mathcal{C}$ free from primary incumbents can be affected by some interference caused by the coexisting SNs. In the following, we denote the set of coexisting SNs with $\mathcal{N} = \{1, 2, \dots, N\}$, and each SN selects one of the C channels in $\mathcal{C}$ through the distributed strategy described in Section III. To this aim, the following preliminary definitions are needed.

The n-th SN is constituted by a population of nodes. Each node contributes to the channel selection process through the concept of *commitment*. Specifically, a node in favor of using the c-th channel is said to be committed to such a channel. Otherwise, the node is said to be uncommitted. In the following, we denote the fraction of nodes belonging to the n-th SN and committed to the c-th channel at the time slot k as $\psi_c^n(k)$, and the corresponding uncommitted fraction as $\psi_u^n(k) = 1 - \sum_{c \in \mathcal{C}} \psi_c^n(k)$.

By denoting with d_n the overall throughput demand of the i-th SN, i.e, the overall network communication needs in terms of throughput, we have that[1] $\tilde{d}_c^n(k) = d_n \psi_c^n(k)$ represents the *throughput demand committed* to channel c at time slot k. Furthermore, $\tilde{i}_c^n(k)$ denotes the coexistence interference[2] experienced by the n-th SN through channel c at time slot k.

III. Coexistence Strategy Design

To design a coexistence strategy with the mentioned attractive features, we exploit the analytical framework developed in a very recent work on collective decision making [16], and we generalize it to the case of multiple populations. Different populations represent different heterogeneous SNs, and the commitment dynamics among the different populations are designed so that a selfless coexistence solution is obtained. Specifically, each population evolves in time according to five processes driving its commitment dynamics as described in the following. According to this evolution, different heterogenous SNs autonomously (i.e., without direct communications) and distributedly select to use one of the available TVWS channels once its entire population or a sufficient fraction is committed to the same channel.

The five concurrent processes driving the commitment dynamics within the arbitrary n-th SN are:

i) uncommitted nodes spontaneously *commit* to channel c at rate $\gamma_c^n(k)$;
ii) nodes committed to channel c spontaneously *abandon* the commitment at rate $\alpha_c^n(k)$;
iii) nodes committed to channel c recruit uncommitted nodes belonging to the same SN at rate $\rho_c^n(k)$;
iv) nodes committed to channel c are inhibited[3] by nodes belonging to the same SN and committed to channel $\ell \neq c$ at rate $\sigma_\ell^n(k)$;
v) nodes of the n-th SN committed to channel c spontaneously abandon their commitment at rate $\xi_c^n(k)$ due to the coexistence interference[4] experienced on such a channel.

The *intra-population dynamics* modeled by the first four processes drive the system toward a selfish channel selection (channel commitment). In fact, the first four rates do no account for the interference generated by the coexisting networks, i.e., are interference-blind. Differently, the *inter-population dynamics* driven by the last process drive the system toward a fair channel selection by explicitly accounting for the coexistence interference.

As a consequence, the system commitment dynamics can be described by the multi-dimensional discrete-time ODE system

[1] We assume, without loss of generality, that each node belonging to the n-th SN equally contributes to the overall demand d_n.

[2] The coexistence interference can be easily assessed without the need of direct communications among heterogeneous networks [21].

[3] Through inhibition, a node previously committed to a certain channel becomes uncommitted.

[4] Clearly, the experienced coexistence interference is generated by the nodes belonging to the coexisting SNs and committed to the channel c.

$$\begin{cases} \Delta\psi_c^n(k) = \gamma_c^n(k)\psi_u^n(k) - \alpha_c^n(k)\psi_c^n(k) + \rho_c^n(k)\psi_c^n(k)\psi_u^n(k) - \psi_c^n(k)\sum_{\ell\in\mathcal{C}}\sigma_\ell^n(k)\psi_\ell^n(k) - \xi_c^n(k)\psi_c^n(k) \\ \psi_u^n(k) = 1 - \sum_{c\in\mathcal{C}}\psi_c^n(k) \end{cases} \tag{1}$$

(1) shown at the top of the next page, where $c \in \mathcal{C}$ and $n \in \mathcal{N}$. Specifically, the dynamics of $\psi_c^n(k)$ are determined by the five processes described above, and N mass conservation equations constrain the dynamics within feasible bounds.

The ODE system in (1) represents the variation of the population fractions committed to the available channels. The behavior of a single node is instead represented by a Probabilistic Finite State Machine (PFSM) as shown in Fig. 1. Probabilistic transitions between commitment states implement the above-described processes determining the population dynamics. More specifically, a node belonging to the arbitrary n-th population (i.e., n-th SN) can be either uncommitted (state S_U) or committed to a certain channel $c \in \mathcal{C}$ (state S_c). It results that the behavior of each node can be described by a PFSM with $C+1$ states. Three types of transitions drive the commitment process of an arbitrary node:

a) *spontaneous*, i.e., transitions independent from the dynamics of other nodes, and the corresponding rates are $\gamma_c^n(k)$ and $\alpha_c^n(k)$;
b) *interactive*, i.e., transitions depending on the commitment states of the nodes within the same SN, and the corresponding rates are $\rho_c^n(k)$ and $\sigma_c^n(k)$;
c) *interference-driven*, i.e., transitions depending on the interference levels perceived on a channel, and the corresponding rate is $\xi_c^n(k)$. With respect to the intra-population dynamics, such a transition is similar to a spontaneous abandonment of commitment, but is dependent on the traffic generated by other SNs operating on the same channel, as described below.

To account for the TVWS distinctive features, we design the transition rates as function of three key-parameters: i) the nominal channel throughput q_c; ii) the overall throughput demand d_n; iii) the coexistence interference $\tilde{i}_c^n(k)$. Specifically:

$$\begin{aligned} &\gamma_c^n(k) = f_\gamma(\{q_\ell\}_{\ell\in\mathcal{C}}, d_n), \quad \alpha_c^n(k) = f_\alpha(\{q_\ell\}_{\ell\in\mathcal{C}}, d_n), \\ &\rho_c^n(k) = f_\rho(\{q_\ell\}_{\ell\in\mathcal{C}}, d_n), \quad \sigma_c^n(k) = f_\sigma(\{q_\ell\}_{\ell\in\mathcal{C}}, d_n), \\ &\xi_c^n(k) = f_\xi(q_c, d_n, \tilde{i}_c^n(k)) \end{aligned} \tag{2}$$

As discussed in [15], the proposed strategy strongly depends on the functionals defining the transition rates in (2). In this paper, we focus on a *practical* strategy design, i.e., we aim at defining a strategy that can be implemented and adopted in real world scenarios. Hence, in Section IV, we will adopt *simple* functionals not requiring any *a-priori knowledge* about the coexisting SNs.

Furthermore, we note that the proposed strategy is fully distributed, since the intra-population commitment dynamics can evolve independently from each other through local interactions, i.e., through broadcast communications to neighbor nodes [16]. We also note that the strategy does not require

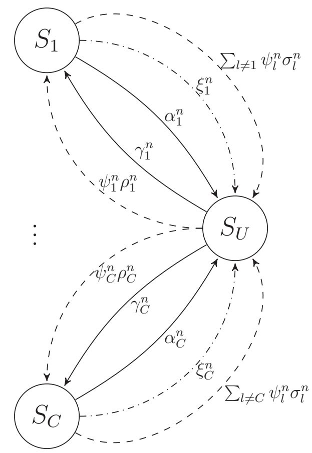

Fig. 1. Probabilistic Finite State Machine (PFSM) describing the commitment dynamics of a node.

any direct communication among heterogeneous SNs, since the inter-population dynamics are driven by a process directly available to each SN, i.e., the coexistence interference.

IV. Case Study

In the following, we evaluate the convergence of the designed strategy toward a fair spectrum allocation with a case study. We consider three performance criteria: i) the quality of the spectrum allocation in terms of both efficiency and fairness; ii) the convergence time; iii) the adaptivity of the strategy to the interference dynamics.

As mentioned in Section III, we focus on a practical strategy design. To this aim, we adopt the following simple functionals not requiring any a-priori knowledge about the coexisting SNs:

$$\gamma_c^n(k) = h_1 \min\{1, q_c/d_n\} \tag{3}$$

$$\alpha_c^n(k) = 0 \tag{4}$$

$$\rho_c^n(k) = \sigma_c^n(k) = \gamma_c^n(k) \tag{5}$$

$$\xi_c^n(k) = h_2 \tilde{i}_c^n(k) = h_2 \max\left\{0, 1 - \frac{q_c}{\tilde{d}_c^n(k) + \tilde{d}_c^{\bar{n}}(k)}\right\} \tag{6}$$

with h_1 and h_2 denoting the probability normalizing constants, and $\tilde{d}_c^{\bar{n}}(k)$ denoting the throughput demand at time slot k of the coexisting SNs different from the n-th and committed to channel c. Note that all the transition rates are constant but the interference-dependent rate $\xi_c^n(k)$. Indeed, intra-population commitment dynamics are based only on the nominal channel throughputs and network throughput demands, and they represent the selfish behavior of the n-th SN trying to converge on a suitable channel c (i.e., $q_c \geq d_n$, see (3)). Note also that we chose a null abandonment rate to obtain full consensus in the SN as a result of the commitment dynamics, following the analytic study[5] presented in [15].

More in detail, the commitment rate γ_c^n drives each population to commit to the channel maximizing the throughput, i.e., it represents the selfish motivation. Additionally, the recruitment rate $\rho_c^n(k)$ and the inhibition rate $\sigma_c^n(k)$ respectively weighted by the fraction nodes of the same SN committed to the same or to a different channel, drive each population to commit to the same channel, i.e., they represent the consensus pressure. Furthermore, the interference rate $\xi_c^n(k)$ is a function of the current interference detected on channel c, which forces each population toward a fair spectrum allocation. Whenever some interference is detected, nodes within a SN tend to leave the channel in search of other alternatives, therefore de-stabilizing the SN allocation on the same channel. The functional (6) allows us to abstract from the particulars of the interference model through a lower bound on the effect of the interference in terms of throughput reduction. Note that, when a direct measure of the channel coexistence interference is available, there is no need of any knowledge about the throughput demands of coexisting SNs. Finally, It is worth noting that the proposed strategy does not lead to consensus if a suitable allocation is not feasible due to limited throughput available on the channels (i.e., $\exists n : d_n > q_c \forall c \in \mathcal{C}$). To counteract this, we let each SN evolve for sufficient time T_c to achieve consensus. If for $\tau k > T_c$ the full demand of all SNs is not satisfied, we force convergence by preventing interference-based transitions (i.e., we set $h_2 = 0$) and letting each SN evolve toward the most profitable solution currently found. With this mechanisms we ensure that consensus is always achieved, although in sub-optimal conditions.

Given the described design, we perform three experiments to evaluate the coexistence dynamics in different conditions.

With the first experiment, we analyze the strategy performance when two TVWS channels are available, namely channels A and B, and two SNs composed by 100 agents/nodes share the channels. The simulation set is as follows: $q_A = 1$, $q_B \in \{0.6, 0.7, 0.8, 0.9, 1\}$, $d_1 = 1$, and $d_2 \in \{0.6, 0.7, 0.8, 0.9, 1\}$, hence obtaining 25 different scenario configurations. For each configuration, we show average figures over 1000 independent runs through interpolated *heat-maps* with Figure 2.

We note that, when $q_B < d_2$, any allocation implies a certain level of interference, as channel B cannot support the demand of any SNs. Conversely, when $q_B \geq d_2$, an interference free allocation does exist. The existence of this threshold effect is evident in Figure 2. Specifically, Panel A shows the average convergence time t_c required to achieve a stable allocation of SNs among the available channels. Fairly low values of

[5]If we neglect interference with other SNs, full consensus can be achieved if the probability of a node to spontaneously abandon commitment is null, as there are no other mechanisms to change commitment state when a population is fully allocated on the same channel. On the other hand, non-null abandonment would preserve a dynamic behavior of the nodes that can explore other alternatives as they become available.

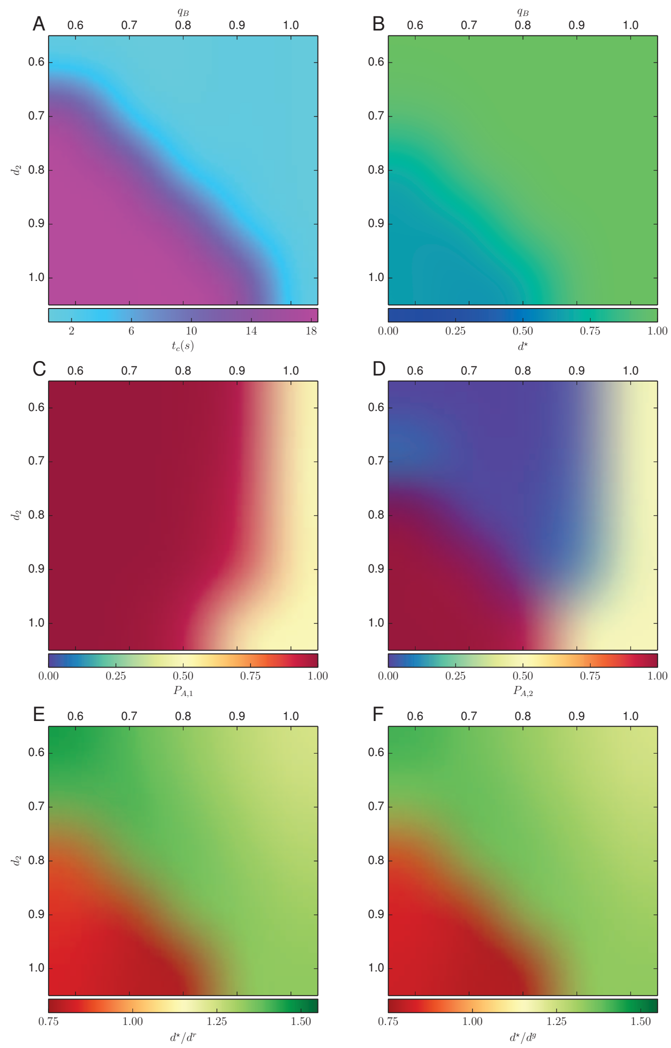

Fig. 2. Coexistence of 2 SNs over two available channels (A, B). Different panels show the metrics computed to evaluate the system behavior observed in multi-agent simulation (1000 independent runs). (A) Convergence time t_c. (B) Normalized achievable throughput $d^\star$. (C-D) Probability of choosing channel A for SN 1 ($P_{A,1}$, panel C) and for SN 2 ($P_{A,2}$, panel D). (E-F) Ratio between the normalized achievable throughput $d^\star$ attainable by the proposed strategy and the normalized achievable throughput attainable through blind random allocation (d^r, panel E) or through random allocation proportional to channel qualities q_A and q_B (d^g, panel F).

t_c are required for convergence when $q_B \geq d_2$ (about $2s$ in average by assuming $\tau = 1$ms), while high values characterize convergence when $q_B < d_2$, suggesting that a stable allocation could be only achieved after the allotted time $T_c = 18s$ during which interference-driven transactions are allowed.

The quality of the final allocation is shown in Figure 2-B as the normalized achievable throughput $d^\star$, i.e., the ratio between the achievable throughput and the overall throughput demand. Also in this case, we observe an optimal behavior for $q_B \geq d_2$, with the strategy achieving the maximum allocated demand $d^\star = 1$. As the quality q_B decreases, the achievable throughput decreases as well, reaching the value $d^\star = 0.625$. This corresponds to both the networks choosing with high probability the best available channel (i.e., A), and it is a result of the dynamics of collective decision making that take place after the coexistence sensing period T_c, which favor the choice of the best option when starting from balanced conditions (i.e., $\tilde{d}_1^c(k) \simeq \tilde{d}_2^c(k), c \in \{A, B\}$). The choice of the low-quality channel is still possible, however, when starting from slightly unbalanced conditions and exploiting stochastic fluctuations.

The probabilities of selecting channel A are shown for SN 1 and 2 in Figure 2-C and -D, respectively. Here, it is possible to notice three different behaviors. As discussed above, (i) when $q_B < d_2$ both SNs select channel A with high probability obtaining sub-optimal fair sharing of the channel; ii) when $1 > q_B \geq d_2$, the optimal allocation is achieved with SN 1 exploiting channel A and SN 2 channel B; iii) when $q_B = 1$, the two available channels are identical and the optimal allocation is achieved with both network choosing either channel with probability 0.5. Overall, the observed behavior is optimal whenever an interference-free allocation is possible, otherwise the proposed strategy leads to a fair distribution of losses between the two SNs.

Finally, in Figure 2-E and -F, we compare the proposed strategy with two stochastic allocation algorithms, namely, *blind random* and *proportional random*, allowing each SN to independently select the channel, regardless of the coexistence interference. With a blind random allocation (panel E), each channel has equal probability of being selected. With a proportional random allocation (panel F), each channel is selected with probability $q_c / \sum_{\ell \in \mathcal{C}} q_\ell$. In Figure 2, panels E and F present the ratios $q^\star/q^r$ and $q^\star/q^g$, respectively. In both cases, a higher performance is expected in the region $q_B \geq d_2$ where the optimal allocation is always achieved, while in the region $q_B < d_2$ the observed performance pays the costs of fairness in the allocation. No significant difference can be appreciated between the two random strategies within the configuration set chosen for this study.

With the second experiment (Figure 3), we analyze the strategy performance in a more interesting scenario, i.e., when three SNs share two available channels. The simulation set is as follows: $q_A = 1$, $q_B \in \{0.6, 0.7, 0.8, 0.9, 1\}$, $d_1 = 0.8$, and $d_{2,3} = d_2 + d_3 \in \{0.6, 0.7, 0.8, 0.9, 1\}$ with $d_2/d_3 = 2/3$. hence obtaining 25 different scenario configurations. For each configuration, we show average figures over 1000 independent runs through interpolated *heat-maps* with Figure 3. Here, each condition features SN 1 with high demand, while SN 2 and SN3 have mid and low values for their demands, respectively.

The convergence time t_c shown in panel A indicates the existence of two regions within the configuration space with high and low values, similarly to the previous case study. Here, however, convergence is achieved within T_c more often, limiting the need to disable the interference-driven dynamics only when there is no interference-free allocation (i.e., $q_b \leq 0.7$ and $d_{2,3} \geq 0.7$). These two zones are visible also in panel B of Figure 3 representing the normalized allocated demand $q^\star$. Note that here an optimal allocation of 1 is never always reached, although average values are very close (often > 0.95). Panel C shows the comparison with the proportional random

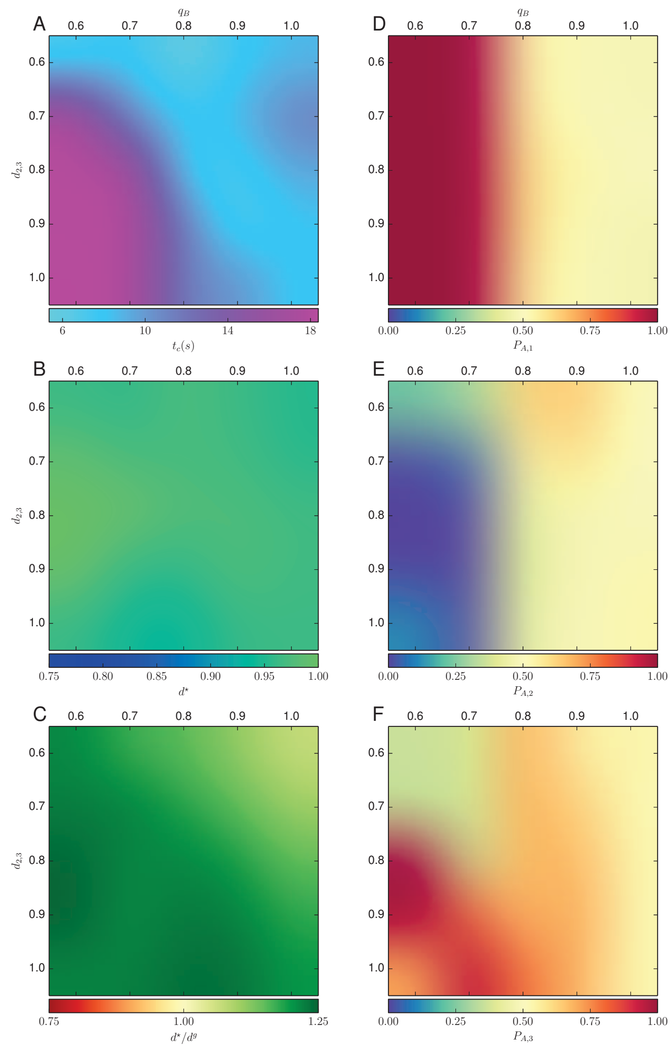

Fig. 3. Coexistence of 3 SNs over two available channels (A, B). Results are the average over 1000 independent runs. (A) Convergence time t_c. (B) Normalized achievable throughput $d^\star$. (C) Ratio between the normalized achievable throughput $d^\star$ and the achievable throughput d^g attainable through random allocation proportional to channel qualities q_A and q_B. (D-F) Probability of choosing channel A for SN 1 ($P_{A,1}$, panel D), for SN 2 ($P_{A,2}$, panel E), and for SN 3 ($P_{A,3}$, panel F).

allocation accounting for quality, through the ratio $q^\star/q^g$. In this case, the proposed strategy displays a large advantage over the random strategy (amounting to 25%).

The behavior of the system is well represented by the probability for each SN to choose channel A, displayed through panels D-F in Fig. 3. When $q_b < 0.8$, SN 1 chooses channel A with high probability, as it is the only one allocating the SN's whole demand. For $q_B \geq 0.8$, both channels represent valid choices, and the probability of choosing either one drops to 0.5 approximately. A complementary behavior is displayed by SN 2, which chooses mostly channel B for $q_b < 0.8$ and selects either channel otherwise. The behavior of SN 3 is more varied, as it mostly pairs with SN2 but when interference is unavoidable. Indeed, in such a case, i.e., when $q_B \leq 0.7$ and $d_{2,3} \geq 0.7$, it is likely to choose A and to pair with SN 1.

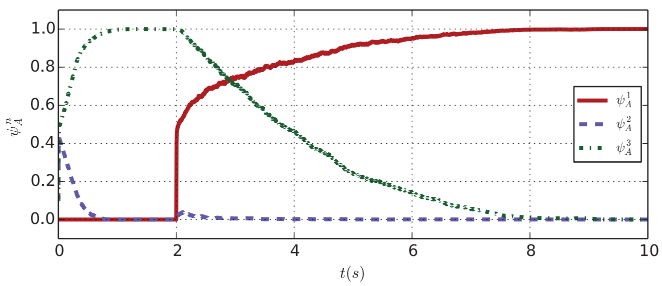

Fig. 4. Adaptivity to interference dynamics. Trajectory of the mean population fractions allocated to channel A for each SNs (100 independent runs). Note that SN 1 is activated only after 2 seconds, and immediately compete for resources with the other SNs.

To further appreciate the properties of the proposed coexistence strategy, we studied the ability of the system to dynamically re-allocate the SNs among the different channels as new SNs appear over time. To this aim, we have performed numerical simulations with two channels (A and B) and three SNs (1, 2 and 3) imposing that SN 1 activation is delayed. We fix both channel qualities ($q_A = q_B = 0.8$) and network demands ($d_1 = 0.8$, $d_2 = 0.48$ and $d_3 = 0.32$). Initially, SN 1 is switched off, and we let SN 2 and 3 find their allocation for the first 2 seconds. In this case, any allocation of SNs to the available channels is acceptable. Then, SN 1 is activated and a new allocation phase takes place, as the high demand of SN 1 prevents its coexistence with another SN on the same channel. We performed 500 independent runs, and a suitable allocation was always found (data not shown). In Fig. 4 we show the percentage of agents committed to the channel A as it varies over time, averaged over a subset of 100 runs in which the initial allocation of SN 2 and 3 consistently exploited two different channels. We note that initially SN 2 occupies channel B while SN 3 goes on channel A. As soon as SN 1 gets activated, it creates interference to the other networks and a re-allocation takes place. Both SN 2 and 3 react to the activation of SN 1, however the network with smaller demand (SN 3 in this case) is mostly influenced and is forced to change channel by the rise of SN 1. Eventually, an optimal allocation could be gained back, with all SNs having their demand satisfied.

V. Conclusions

In this paper, we designed a strategy for secondary coexistence in TVWS scenarios. The proposed strategy exhibits the following attractive features: i) fully distributed; ii) over-the-air communications free; iii) interference adaptive; iv) selfless. Specifically, we exploited and extended an analytical framework based on a system of multi-dimensional discrete-time ordinary differential equations, able to incorporate the trade-off between selfish bandwidth maximization and fair spectrum allocation within the differential system dynamics. Finally, we conducted an extensive numerical evaluation to confirm the benefits of adopting the proposed coexistence strategy in TVWS scenarios. The obtained results demonstrate the achievement of near-optimal performance through a completely decentralized decision process, and open the way for a formal analysis of the properties granted by proposed strategy for the coexistence, which will be targeted in future work.

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