A MAC Level Strategy for Dynamic Resource Allocation in Cognitive Radio Tactical Networks

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Abstract—The ability to continuously self-adapt to the variations of the radio environment will be an interesting issue for future tactical radio networks. Cognitive Radio (CR) is the main enabling paradigm allowing the self-adaptation process in military communications minimizing the human intervention in the network management operations. In this paper we provide a MAC-level solution based on a game theoretic framework that covers these open issues. Thinking to the CR devices in the network as players of the same game, the resource allocation problem can be formulated as a S-Modular Game, since it provides a set of helpful tools aimed at defining multi-objective distributed algorithms in the radio-communications context. On the base of the proposed solution, CR devices are able to hierarchically self-configure the network and share the radio resources in a fair and energy-efficient way. Simulation results presented in this paper has been obtained within the CORASMA project and they show the good performance of the proposed solution for cognitive radio tactical networks.

I. INTRODUCTION

In an heterogeneous and changeable radio environment where a lots of different systems have to communicate sharing the same resources, the possibility to self-organize the exploitation of radio resources is very useful. Thus, the human intervention in the network planning could be minimized by introducing some automatic network functionality, like configuration, management, optimization and healing.

Up to now, on one hand scientific and industrial community has concentrated on bandwidth efficient systems in order to deal with spectrum scarcity, on the other environmental and economics issues drive researchers and manufacturers to consider energy cost of these proposed approaches. In [1], [2], it has been shown that CR could reduce the energy consumption in wireless communications due to the better spectrum usage and to the adaptability of the network to specific environmental conditions.

Due to the need to connect heterogeneous devices in a hierarchical way, self-adapting paradigms started to be applied to heterogeneous tactical radio networks in order to deal with the scarcity of radio spectrum and the increasing data flow requiring an higher robustness to the interference [3]–[6]. As a matter of fact, CR is a promising technology providing a system which can plan, decide and adjust its parameters, observing its internal and external environment. For this reason, in the last years the European Defence Agency (EDA) promoted the Cognitive Radio for Dynamic Spectrum Management (CORASMA) program aiming at studying and testing the capability of Cognitive Radio (CR) to support military communications for heterogeneous network and improve their performance [7]. Medium Access Control (MAC) is the main responsible of the correct execution of several cognitive radio functions like spectrum mobility, channel sensing, resource allocation and spectrum sharing [8].

MAC protocols can be classified in two main categories based on their resources access mode: Direct Access Based (DAB) and Dynamic Spectrum Allocation (DSA). While by the former each node tries to maximize its own target, by the latter the network can optimize the resource usage in an adaptive manner. For this reason, DSA results to be more suitable for a Self-Organizing Network (SON) scenario where an opportunistic and decentralized approach is needed [9]. In DSA-driven MAC protocols each cognitive radio node can adapt its transmission parameters, such as modulation, coding scheme and power transmission, in order to find the optimum configuration for the experimented radio environment. In this context, in the last decade several way to realize DSA has been proposed, such as trial and error solutions [10], algorithms derived from graph theory [11], [12], stochastic theory [13], game theory [14]. Regarding algorithms derived from heuristic [15], [16], in this context they appear to be not suitable due to their prohibitively computational cost and the necessity of a complete knowledge of the network.

In this paper a cognitive MAC strategy that allows CR devices to hierarchically self organize themselves in clusters and share the radio resources in a fair and energy-efficient way exploiting is presented. The proposed solution relies on the non-cooperative game algorithm reported in [14] that has been implemented and integrated into the hi-fi network simulator of the CORASMA project. Thanks to its modular implementation, such simulator allows the evaluation of cognitive solutions in heterogeneous networks at operational level. At the present days, the simulator does not include the satellite component of the network, but such inclusion should be added in the next future. The performance of the solution proposed in this paper has been obtained for a cognitive radio tactical network showing its fairness and goodness, even in case of dense networks with scarcity of radio resources. Moreover, simulation results offer a comparison of

the proposed solution with a canonical allocation methodology. The paper is organized as follows: the reference system model is presented in Section II, while a description of the proposed MAC-level solution is presented in Section III. In Section IV the reference scenarios and results from computer simulation are provided. Finally some conclusions are commented in Section V.

II. SYSTEM MODEL

The strategy proposed in this paper has been thought for a cognitive heterogeneous network, where users, named nodes, communicate in a multi-hop manner. Each node is characterized by a complete radio front-end and therefore it is able to transmit and receive data. As stated in [7] each node is composed by a non cognitive and a cognitive part, as depicted in Figure 1. The non cognitive part, called the Basic Waveform (BW), provides a basic reference waveform that has to be considered as the benchmark for the proposed cognitive solution. This reference waveform is composed by a data plane, i.e. physical (PHY), medium access control (MAC) and network (NET) layers, and the control plane providing the algorithms that manage the parameters used in the data plane. The cognitive part, called Cognitive Plane (CP), is composed by some blocks providing, if enabled, a cognitive way to manage the functions defined in the control plane. Moreover some functionalities like sensing, data and measurements collecting and supervisioning are needed and defined at the cognitive side. The message exchanging between data, control and cognitive plane is done through a common cross-layer interface (XLI). Such node model provides a detailed reproduction of the behavior of a real system at PHY, MAC and NET level. Higher levels are not simulated but traffic generators reflecting their behaviors are used.

In order to allow network coordination and discovery, the system is time-slotted and each node periodically send an ultra-short "HELLO" packet message on a common control channel in order to share with the other neighboring nodes control information. Since common control channel need to be select a priori before network deployment, the satellite link could represent a possible alternative for the implementation of control message exchanging. Even if opportune system adaptation should be taken into account, the exploitation of satellite link should not alter the framework and results proposed in this paper.

Control plane includes a clustering functionality thanks to which nodes are able to organize themselves constituting clusters. Within each cluster, the node experimenting the largest number of neighbors is elected as cluster head (CH). The clustering and cluster head election solution are presented in [17], [18]. During the entire resource allocation strategy of Section IV, each CH is representative for its cluster, selecting the most appropriate radio channel and the best transmission power level on behalf of all the nodes in its cluster.
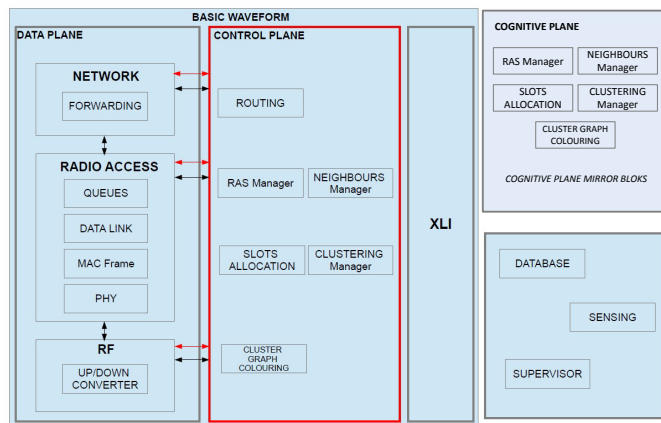

Fig. 1. Node architecture

III. THE RESOURCE ALLOCATION STRATEGY

A. Radio Resource Allocation

The Radio Resource Allocation process is responsible to let each cluster obtain a radio resource, that is a radio channel in the proposed system model. Running this algorithm within a cluster, each CH chooses the current best available channel and notifies it to all the nodes in the cluster and advices the other CHs in the network of its choice. For this reason, each node records one entry per cluster in a dedicated table, named Allocated Resources Table, containing the CH MAC address, radio resource identifier (channel), Time counter and all the other necessary information.

The Radio Resource Allocation algorithm is the following:

- If a CH has no local radio resource, check in the Allocated resources table and then:
  - If there is an unused resource, CH selects that unused resource. Exit.
  - Else for each radio resource:
    * CH determines the ID of the nearest neighboring cluster using that radio resource
    * CH memorizes in the subset C the ID of the identified cluster
  - Then, among all the clusters in C, CH selects the same radio resource of the furthest neighboring cluster. Exit.

Note that in the previous algorithm, distance notations (i.e. furthest, nearest) take into account pathloss measurements among the considered CH and the other nodes in the network. Thus, the link between the considered CH and another one having the highest pathloss value in the Allocated Resources Table will identify the furthest CH for the considered CH. On the contrary, the link with the lower pathloss value will identify the nearest CH for the considered CH.

B. Power-Game

In case of radio resource scarcity, the possible occurrence of inter-cluster interference has to be considered. For this reason, after the execution of the Radio Resource Allocation algorithm, CHs sharing the same resource play the Power-Game algorithm [14]. Such algorithm bases on the game-theoretic framework of the Supermodular Games and it is aimed at minimizing the inter-cluster interference. It has been demonstrated to have always a single Nash Equilibrium [19], to be fast converging and energy efficient [20]. Moreover, thanks to its fully distributed nature, it requires no coordination among CHs to be executed.

Playing the Power-Game, each CH selects the most appropriated maximum transmission power level which will represent an upper bound for the transmission of the nodes belonging to the same cluster. Power-Game is a non-cooperative game that, due to the players behavior, allows to solve problems connected to mini/max optimization and it is demonstrated to have a fast convergence to Nash equilibrium. Such kind of game has been developed according to the mathematical discipline of Game Theory, with particular reference to S-Modular Games [21].

Thank to the implementation of the Power-Game, we can rely on a distributed game-theoretic approach to obtain an energy efficient power allocation method that maximize the Signal to Interference-plus-Noise Ratio (SINR) level received by each user, taking into account throughput fairness among secondary users.

Referring to the game theoretic notation, the Power-Game is a Supermodular game denoted by the set $[N, p_i, U_i]$ where:

- $\mathbf{C} = \{1, ..., C\}$ is the player user set composed by CHs sharing the same radio resource.
- $\mathbf{S} = \{0, p_{max}\}$ is the set of strategies, where the values of allowed transmission power for each player i is $p_i \in \mathbf{S}$.
- U_i is the utility function of player c_i where $i \in \mathbf{C}$.

The utility function can be expressed as:

$$U_i = \log\left(\frac{p_i^t}{I_i^{t-1}}\right) - \Omega_i(p_i^t, I_i^{t-1}) \tag{1}$$

where p is the power selected by CH i at time t and I_i^{t-1} is the interference received by CH i at time $t - 1$. $\Omega_i(p_i^t, I_i^{t-1})$ is the pricing function introduced to let the Nash Equilibrium move toward a more efficient solution. This function generates pricing values on the base of interference generated by nodes of the network. $\Omega_i(p_i^t, I_i^{t-1})$ is strictly increasing with p; the greater is the interference generated by a user transmitting at high power level, the grater will be the value of pricing it will be pay. The pricing function is written as follows:

$$\Omega_i^t = \beta - \delta \exp\left(-\mu \frac{p_i^{t-1}}{I_i^{t-1}}\right) p_i^t \tag{2}$$

where:

- $\beta > 1$ is the maximum pricing value,
- $\delta > 1$ is the price weight of the generated interference,

- $\mu > 0$ is the sensitivity of the users to interference.

Note that parameters β, δ, μ directly act on the rate of convergence of the algorithm and on results accuracy. Since the condition for the existence of the Nash equilibrium is

$$\frac{\partial \Omega_i(p_i^t, I_i^{t-1})}{\partial p_i} = 0 \tag{3}$$

at each time t the power selected by a node is

$$p_i^t = \frac{1}{\beta - \delta \exp\left(-\mu \frac{p_i^{t-1}}{I_i^{t-1}}\right)} \tag{4}$$

Since we assume that the nodes position is not a priori known, at the beginning of the simulation β, δ, μ parameters are initialized to default values in order to ensure accurate results. During the simulation, a control check is performed in order to adapt such parameters values in case of slow convergence. Indeed, the rate of convergence RC of the algorithm respects the following condition:

$$RC \propto \frac{\beta - \delta}{\sqrt[4]{\mu}} \tag{5}$$

IV. SIMULATION RESULTS

A. The considered scenarios

In order to test the proposed strategy, four different scenario configurations have been identified for a 16 km^2 playground. Such scenarios are aimed at highlighting positive outcomes introduced by the cognitive strategy and at providing a comparison of it with the BW results. In defining reference scenarios, three particular features have been taken into account, such as mobility, radio resources availability and presence of interfering harmful nodes.

As far as the mobility is concerned two conditions are taken into account: low mobility (LM) and high mobility (HM). These two conditions differ from one another by the number of mobile nodes in the scenario, while both of them include the presence of static nodes. More in detail, LM1 and LM2 scenarios consist of a mobile cluster of 5 nodes moving through a grid of static clusters (29 nodes); on the other hand, HM1 and HM2 scenarios include in 3 mobile clusters (18 nodes) moving in a playground with 3 static clusters (24 nodes). As for the availability of radio resources, we differentiate scenarios by the number of available radio channels; in LM1 and HM1 scenarios only 3 logical channel are available, while LM2 and HM2 scenarios include 15 logical channel.

Finally, the presence of interfering harmful nodes is modeled including a jammer node that during the whole simulation generates interference on all the available radio channels using a slow frequency hopping scheme. Jammer effects are evaluated in LM2 and HM2 scenarios and therefore they represent high interference cases. The previously described characters of considered scenarios are summarized in Table I.

TABLE I
CONSIDERED SCENARIOS

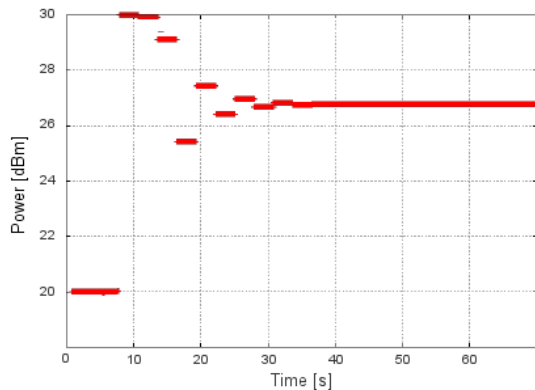| ID Scenario	Mobility	Number of channels	Jammer
LM1	Low	3	No
LM2	Low	15	Yes
HM1	High	3	No
HM2	High	15	Yes

Fig. 2. Scenario LM1: particular of the transmission power level of a node playing power game after 9 seconds of simulation.

B. Performance analsys

Referring to the proposed cognitive solution of Section II and the previously described scenarios, in this section we present the analysis of the simulation results. While analytics results were proposed in [14], in this paragraph we propose the results obtained by the CORASMA simulator. All the simulation results are obtained for both LM and HM scenarios following the MonteCarlo simulation method. All the simulation results have been compared with a non cognitive common waveform, called Basic Waveform (BW) and described in detail by [7].

Confirming [14], the results obtained with the CORASMA simulator demonstrate that the proposed power control algorithm shows a fast convergence to the desired equilibrium point. In Fig. 2 the transmission power level of a CH playing power game in LM1 scenario is reported. During the first 9 seconds of simulation, the considered node uses a 20 dBm of transmission power to communicate with the nodes belonging to its cluster. Afterwords the CH begins to share the same transmission channel with a neighboring cluster and therefore both the CHs starts playing the power game algorithm. For the sake of simplicity, in the following we refer to the actions made by only one CH, since both the CHs will act in the same way due to the fact that both of them are playing the same algorithm. In order to deal with the interference generated by the neighboring cluster, firstly the CH allocates the maximum transmission power level and progressively adapts it during the execution of the power game, converging to the optimal transmission power level that jointly allows intra-cluster communications and minimizes inter-cluster interference.
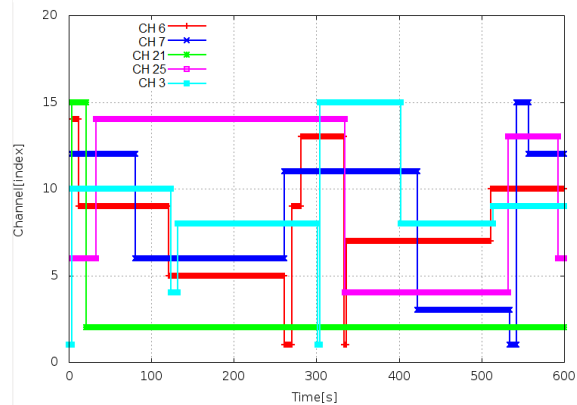

Fig. 3. Scenario HM2: Logical channel occupation of CH nodes during simulation time.

In Fig. 3, each color represents the logical channel occupation of each CH during the simulation for the HM2 scenario. As described in Section IV-B, in this scenario a high interference condition is experimented by the nodes in the network, due to the presence of a frequency hopping jammer operating on all the logical channels, with the exclusion of the control channel. In this context, CH nodes are able to opportunistically adapt channel occupation in order to avoid the interference generated by the jammer, as shown in Fig. 3. Such selection is made by CH nodes trying to minimize channel changes, which increase signaling overhead and latencies. Moreover, the proposed algorithm always provides a feasible channel selection since channel overlapping among the possible 15 colors never happens due to the fact that CH nodes never choose a channel which is already occupied by another node.

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The effective positive outcome obtained thanks to the introduction of the proposed cognitive solution can be noticed in Fig. 4 and Fig. 5, wherein the measured SINR levels for a test node of the LM2 and HM1 scenarios are reported. During the entire simulation time, SINR values measured by a node implementing the proposed cognitive solution (in blue) are almost always better than the ones obtained without the cognitive solution (in red). Moreover, the introduction of the proposed cognitive solution sensibly reduces SINR fluctuations thanks to the actuation of the previously described power control algorithm.

V. CONCLUSION

In this paper, a MAC level strategy for dynamic resource allocation in Cognitive Radio tactical networks has been reported. In this context in addition to an overview of the state of the art, an in-depth description of the system model, including the clustering process and the considered scenarios, is provided. Moreover, an explanation of the proposed resource
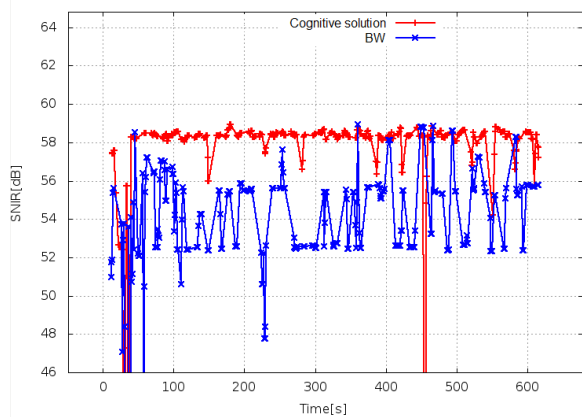
Fig. 4. Scenario LM2: node measured SINR with cognitive solution switched on (red, vertical lined) and off (blue, x symbols).
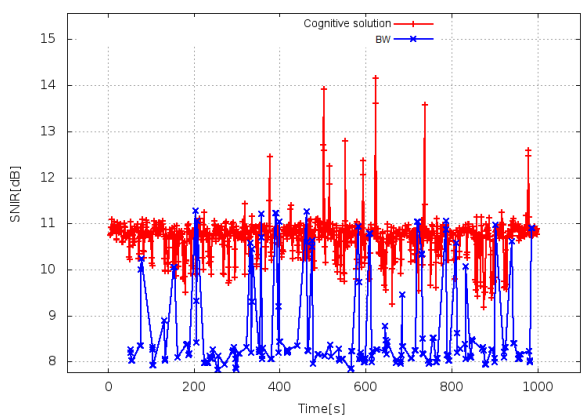

Fig. 5. Scenario HM1: node measured SINR with cognitive solution switched on (red, vertical lined) and off (blue, x symbols).

allocation strategy describes the two forming MAC level algorithms for a fair and energy efficient allocation of radio resources in a tactical network.

Thanks to the analysis of simulation results, the performance of the proposed cognitive strategy are reported, showing an improvement of system performance compared to a non-cognitive strategy case. Moreover, the cognitive solution is able to avoid intentional interference generated by a potential frequency hopping jammer. Finally, the proposed solution is able to efficiently allocate radio resource even in case of scarcity of them, showing a fast rate of convergence.

Such promising results demonstrate the capability of the proposed solution to efficiently allocate radio resources in a cognitive radio tactical network. Therefore, the consequent advancement of this work will be the integration of the proposed MAC level strategy into cognitive radio prototypes based on Software Defined Radio (SDR) in order to obtain network performance by real over-the-air transmissions.

VI. Acknoledgment

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