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Swarm Intelligence Based Dynamic Control Channel Assignment in CogMesh

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***Abstract*—In this paper we address the control channel assignment problem in a cognitive radio based wireless network, namely the CogMesh. Such a network is featured by the dynamic spectrum sharing of the secondary users coexisting with the primary users. The opportunistic nature of the spectrum utilization among the secondary users makes a global control channel infeasible. The self-coordination of the network, hence, becomes a challenge task. Considering the fact that common channels may temporarily exist among a local group of secondary users, we propose an adaptive approach that selects local common control channels independently by each secondary user according to the qualities of the detected spectrum holes and the choices of its neighbors. To achieve this, a swarm intelligence-based algorithm is used to facilitate the common control channel selection. The idea is to use HELLO messages periodically broadcasted by neighbors as the pheromone to rank the common channels so as to expedite the channel selection process. The algorithm is completely distributed and therefore scalable. Moreover, it is simple, flexible, adaptive, and well balanced on the exploitation and exploration of the radio resources. The behaviors and performance of the proposed algorithm are verified by simulation.**

I. Introduction

Aiming at providing ubiquitous wireless communications, the *CogMesh* is a new concept of heterogeneous wireless mesh networks integrating legacy wireless networks as well as cognitive radio (CR) networks [1]. A CR network within a CogMesh networking scenario is a *dynamic spectrum access* (DSA) network where the *secondary users* (SU) of the spectrum opportunistically access the spectrum holes based on the activities of the *primary users* (PU) as well as the radio environment. According to the taxonomy of the DSA defined in [2], a CogMesh network can be described by a hierarchical model using a hierarchical access structure.

As an important application of the CR [3], the DSA plays a key role to improve the spectrum efficiency and solve the spectrum scarcity problem. However, since it is still in its infancy, many research challenges remain. To name a few, robust spectrum sensing, spectrum access modeling, resource allocation and optimization, protocol design, etc. We study the control channel assignment problem of the SUs in a CogMesh network.

The channel assignment problem has been studied in various DSA systems [4]-[7]. Following the conventional approach in multi-channel systems [8], the majority of the DSA systems uses a dedicated global control channel to coordinate the channel allocation [4], [5]. It is obviously not realistic in an opportunistic DSA system since there is no permanent channel for SUs. The control channel assignment, therefore, becomes a key problem in such a system. Zhao et al. [6] dealt with this problem through a group coordination solution, in which a common control channel is only required locally in a coordination group, which is formed by neighbors sharing common channels. Bian et al. [7] used the concept of the segment, which is a group of nodes who share common channels along a routing path, to organize control channels. In previous work, we tackled this by a cluster-based approach [9]. The local users sharing common channels form a dynamic one-hop cluster and the spectrum is managed by cluster heads.

In this paper, we propose a control channel assignment solution based on the idea of the swarm intelligence. The *swarm intelligence* is a well established science biologically inspired by the collective behavior of social insects, for instance, ants or bees solving complex tasks like building nests or foraging [10]. It is based on the principle of the division of labor where the higher efficiency is achieved by specialized workers performing specialized tasks in parallel. The advantages of swarm intelligence techniques are scalability, fault tolerance, parallelism and autonomy. Swarm intelligence algorithms have been successfully employed in telecommunication networks for the performance improvement of routing protocols [11], [12]. Recently, its applications have been found on spectrum sensing and resource allocation in the CR networks [13].

In a typical swarm intelligence algorithm, an agent deposits a small amount of pheromone on a trail and the trail with higher pheromone level becomes the choice of the working trail. This distributed optimization approach relies on the cooperation of agents to achieve the common optimization goal with a collective complexity out of individual simplicity. Considering each SU in a CogMesh network as a simple agent and its choice on the control channel as the pheromone, the swarm intelligence matches the dynamics in the CogMesh network very well. We use the concept of the *channel cloud*, which is a collection of SUs connected by a common control channel in one or multiple hops, to manage the CogMesh network. The underlying principle is to make the channel clouds evolve with the radio environment in a desired way aiming at less common control channels in the network. Clearly, control messages running over few channels reduces the control overhead and delay.

The contributions of this paper include:

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1) To the best of our knowledge, it is the first paper applying the swarm intelligence-based algorithm to solve the control channel assignment problem in CR networks. Although the similar problem has been studied by Pollin et al. [14] using Q-learning algorithm, our approach is different from them by emphasizing the node collaboration, leading to less complexity.
2) A distributed algorithm is proposed with several attractive features: using the simple cooperation among neighbors to achieve the optimal use of dynamic channels; balancing the exploration and exploitation of radio resources by a stochastic method. Compared to other approaches, it is scalable, self-organizing, overhead reduced, and most importantly, adaptive.

The remainder of this paper is structured as follows. In Section II we describe the system model and assumptions. Next, we introduce the concept of the master channel. Then in Section IV, a swarm intelligence-based master channel selection algorithm is proposed. After discussing the properties of the proposed algorithm in Section V, we study its performance in Section VI by simulation. The conclusion and future work are provided in the last section.

II. System Model

In this paper we use a distributed algorithm to dynamically select a common control channel by a SU based on the measured channel quality and the choices of its neighbors. It is essentially a cross-layer approach focusing mostly on the lowest two layers, and the layer 2 is our main reference point. Since the only information needed from the physical layer is the available spectrum holes over time, a simplified physical layer model capable of detecting spectrum holes accurately and periodically is assumed.

The network is constructed by PUs and SUs, whose definitions can be found in [15]. A SU is allowed to access a spectrum hole only when causing tolerant interference to the PUs working nearby on that hole. The tolerant interference can be well described by the *interference temperature* [3], a metric proposed to quantify the interference in a radio environment. Although it has recently been abandoned by the FCC due to the practical reason, the concept itself remains of great help to the research community.

According to the tolerant interference of PUs on different frequency bands, spectrum holes are detected through the spectrum sensing performed at the physical layer. Although the spectrum hole and channel are two different concepts, without losing generality, we assume that one spectrum hole holds one channel, and the frequencies of spectrum holes are fixed in the spectrum space. In the following of this paper, a channel implies a spectrum hole available at a specific frequency band. For each SU, the result of the spectrum sensing is the available channels and their associated qualities. For simplicity, we number the channels according to their frequency bands and assume equal bandwidth in each channel. The goal of the control channel assignment is to use the best channel as the control channel as possible in order to increase the system efficiency.

We assume that the spectrum holes detected by a SU change over time with a relatively slow rate. Moreover, the users in the network move only at low speeds. These assumptions imply a relatively stable network topology, allowing the proposed algorithm to keep pace with the ever-changing radio environment. A CogMesh networking scenario is shown in Fig. 1, where the PUs present in the network randomly in time. Once activated, a PU occupies a frequency band in a given area where the SUs should carry out their power control accordingly on this band in order to avoid hampering the communication of the PUs. Complying with this rule, the channel quality model of the SU is defined, which is related to the distance to the PU. Using the Friis free space propagation model [16] to calculate the receiving interference, the metric of the channel quality is defined as the maximum transmitting power a SU can apply to a given channel so that the interference imposed to the receiver of the PU does not exceed the tolerant threshold. The interference temperature model is therefore reflected in the channel quality model. A table is held in each SU, storing the channel quality information of each channel, and being updated periodically by the spectrum sensing process.

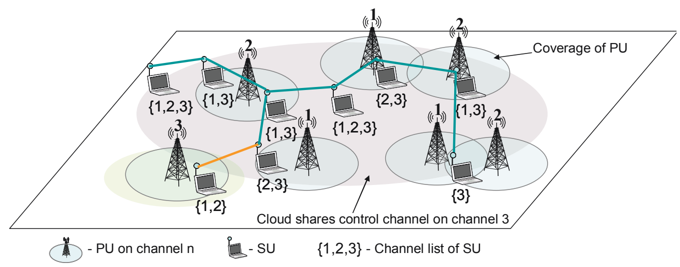

Fig. 1. A CogMesh network.

An additional assumption is the perfect spectrum sensing performed by each SU. This implies the communications among the SUs are not falsely recognized as PU signals. To achieve this, a synchronized spectrum sensing process is required. We assume a certain mechanism to achieve the synchronization of nodes for the spectrum sensing at the physical layer and signaling at the MAC layer. The detail of this mechanism is out of the scope of this paper. Moreover, for brevity, we use the user to stand for the SU in the remainder of this paper.

III. Master Channel Concept

According to the channel quality, a user chooses a channel as its control channel, namely the *master channel*, for signaling. The key idea is to have the neighbors chose as much as possible the same master channel, thus alleviating the signalling efforts. In case that two neighbors use different master channels, a proper listening rule can be used to do the neighbor discovery orderly on other channels according to their channel qualities. Once a neighbor is detected, the proposed algorithm is run to negotiate a common master channel among most of the neighbors. Accordingly, channel clouds are formed and evolved with a trend to form few clouds in the network as possible. As a result, few signalling efforts are required to let control messages traverse the network.

To setup the master channel, we assume the following neighbor discovery process in this paper. Supported by the layer 2 or 3, a user periodically broadcasts HELLO messages over the master channel. The HELLO message includes the information of the user's master channel and all other available channels with the quantized quality values. The neighbors of the user listen to their master channel in the most of time for HELLO messages, and shift the listening to other channels with probabilities proportional to their channel qualities for a given period in a repeating manner. Once the channel information is exchanged among the neighbors, a common master channel shared by the neighbors will be negotiated by the proposed algorithm. We describe the algorithm in the following section.

IV. Master Channel Selection

The basic idea of the algorithm is to let a user select a channel with a good enough quality, meanwhile preferred by most of its neighbors, as the master channel. The good enough quality means the quality of the chosen channel ranks higher among the available channels. The reason to choose a better channel as the control channel is straightforward: transmission failures are reduced. The channel quality is measured in the spectrum sensing process and presented by a single value Q, which is a non-negative real value inversely proportional to the accumulated interference imposed by the surrounding PUs in a given time window. A higher Q indicates a better channel quality. To simplify the algorithm, we use a step function to quantize the Q value as shown in Eq. 1.

$$Q = q_i; \quad \text{if } \gamma_i \leq P < \gamma_{i+1} \tag{1}$$

for $i = 0, ..., M-1$, where P is the measured power, q_i is the quantized value according to the stage i, γ_i is the stage threshold, and M is the stage size. We define $\gamma_M = \infty$.

The preference of the neighboring nodes on the master channel is reflected by the number of neighbors who choose the same master channel. A straightforward way to present the preference is to count the choices of neighbors in the neighbor list. However, we use a different approach that reflects the freshness of the neighbor's choice. In each user, we maintain a probability p for each channel, and update its value once receiving a HELLO message. The p value is the probability that a channel will be selected as the master channel. For the channel list, we have:

$$\sum_i p_i = 1; \quad \text{for } i = 1, ..., N$$

where p_i is the probability for the channel i, and N is the total channels in the network. Periodically, a user updates its master channel according to its p list.

The problem now becomes how to determine the p value of each channel according to the Q list of a user and its neighbors. The p list, which is updated frequently by the change of the channel quality and the choices of neighbors on the master channel, becomes the key parameter to reflect the radio environment and determine the master channel. By presenting the p list properly, a trade off between the exploitation and exploration of radio resource can be achieved. In the following, we apply the swarm intelligence to achieve this goal.

A. Swarm Intelligence Algorithm

In our network, each user acts as an agent, which uses the HELLO message as the pheromone. A user receiving a HELLO message updates its p list as follows. The channel equal to the master channel of the broadcasting neighbor receives a positive reward with an amount proportional to the difference of the Q values between the neighbor and the local user's master channel. All other channels receive negative rewards to make the sum of all p equal to one. It is a process in which the neighbor invites the user to move to the same master channel. A master channel shift happens if sufficient pheromone is accumulated on a non-master channel. On the other hand, the channel quality will be affected by the PUs and thus changed over time. The user itself updates the p list periodically according to the refreshed Q list. It acts as the disturbed factor to push the master channel back to the best quality channel. The amplification of disturbed factor makes the master channel evolve with the radio environment.

The algorithm works as follows. At the beginning, p is chosen proportional to the quality of each channel. Then, assume the user U_A with the master channel C_i receives a HELLO message from its neighbor U_B, whose master channel is C_j. Assume the Q value of C_i on the user U_A is Q_i, and Q value of C_j on the user U_B is $\overline{Q}_j$. The parameter p_j, which is the p value of C_j on the user U_A, is updated by:

$$p_j = p_j + r(1 - p_j); \tag{2}$$

where r is a parameter determined by $\Delta Q = \overline{Q}_j - Q_i$. That is:

$$r = f(\Delta Q); \quad \text{where } r \in [0, 1] \tag{3}$$

The r function in Eq. 3 is a monotonically increased function. We prefer to give the weights to different ΔQ values by a nonlinear function, i.e.:

$$r = [\arctan(A * \Delta Q) + B)]/C; \tag{4}$$

where A, B, and C are the constants affecting the converging rate of the algorithm. The proper values of A, B, and C depends on the requirements on the adaptability and stability of the control channel.

For all channels other than C_j, their p values on the user U_A are updated by:

$$p_k = p_k(1 - r); \quad \text{for } p_k \in \{p_l | l = 1, ..., N;\ l \neq j\} \tag{5}$$

Due to the channel fading, interference and collision problems, a user may miss some HELLO messages, leading to the

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adaptive problem of the algorithm. To solve this, we introduce a self-updating mechanism. Periodically, the user U_A evaluates its channel list, choosing the best quality channel to update according to Eq. 2-5. That is the p value of the best quality channel is updated by Eq. 2, and the p values of other channels are updated by Eq. 5. Note that Eq. 4 in this case can take a different function other than the neighbor updating case.

As we can see, the Q value is reflected in the parameter r. Different r functions make the p value susceptible to either the neighbors' pheromone or the channel quality of its own. An online learning strategy can be applied here to tune the parameters in the r function so that the user's desire on either the exploitation of most common channels or the exploration of the best quality channels can be reflected.

V. Discussion

The proposed algorithm has several advantages. First, it is independent of a specific physical and MAC layer. As a result, it can be easily integrated into heterogeneous wireless networks. Secondly, the algorithm is flexible in the sense that the parameters of the algorithm can be tuned to suit different network scenarios, for instance, adapting the HELLO message broadcasting rate to the radio environment change. Moreover, the algorithm provides a stochastic method to exploit and explore the radio resources.

Note that several factors affect the performance of the algorithm. First of all, the sensing capability of the physical layer determines how well the Q value reflects the radio environment and in turn the quality of the p value. Then, the choice of the parameters, including the HELLO message broadcasting rate, the self-update rate, the mapping of the channel quality to the Q value, and the choice of the r function in Eq. 3, determine the adaptability of the algorithm to the radio environment. Furthermore, the HELLO messages certainly contribute to the control overhead in the system. The broadcasting rate needs to be controlled in order to achieve a balance between the overhead and the adaptivity of the algorithm. The frequency occupancy pattern of the PU can be used to control the HELLO message broadcasting rate.

Since the p value reflects the channel quality and willingness of the users to utilize the channels, it has added values for clustering, routing, and data transmission. We proposed a cluster based network architecture in [1]. The p value can ease the cluster management in such a network, and then improve the spectrum efficiency. A routing protocol integrating the p value will be more intelligent to adapt to the radio environment, and therefore be more flexible and robust. In addition to using the p value to choose the control channel, the neighbor SUs can use it to select the transmission channel as well, therefore increasing the spectrum efficiency.

VI. Simulation Study

The simulation is setup as follows. As shown in Fig. 1, we randomly place a set of PUs and SUs in a 600m $\times$ 600m 2-dimensional playground. The maximum reach range of a PU is set to 200m and that of a SU is set to 100m. N channels are available in the network. A PU randomly picks up one channel as the working channel at one time. We assume an interference-free condition among the SUs. Therefore the channel quality is only related to the presence of the PUs. Moreover, we use the path loss model proposed in Section II to calculate the channel quality.

The time of the simulated network is divided into a contiguous sequence of time periods. Each period is an independent cycle, in which the spectrum sensing, HELLO message broadcasting, and p value updating are performed orderly. The parameters of the r function in Eq. 4 is set as follows: $A = 0.1$, $B = 1.5$, and $C = 4$ for ΔQ in the given range. This setting makes the r more sensitive to smaller ΔQ. At the end of each cycle, the SU makes the master channel selection decision. We collect the statistic data at the end of each cycle to analyze the algorithm behavior and performance.

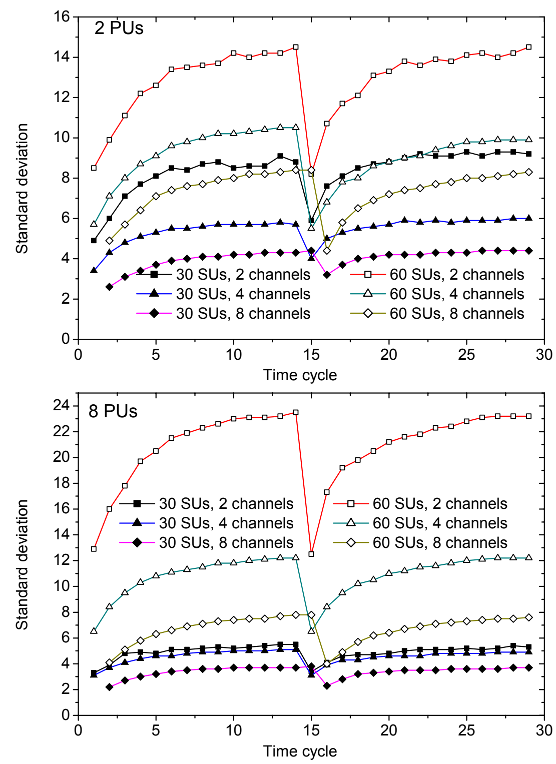

Fig. 2. STD of channel cloud per channel, stationary scenario.

The simulation process consists of two working scenarios. In the stationary scenario, each PU fixes its operating channel, while in the dynamic channel scenario, a PU hold its operating channel for a given period and then shift to another randomly chosen channel. We use the standard deviation (STD) of the SU number distributed on each channel to measure the trend to share the common master channels, and the percentage of the SUs who use the best quality channel as the master channel to show the quality of the master channel selection. A large STD means the sizes of channel clouds are not evenly distributed. Therefore more users are aggregated to few large clouds.

Fig. 2 shows the evolution of channel clouds in terms of

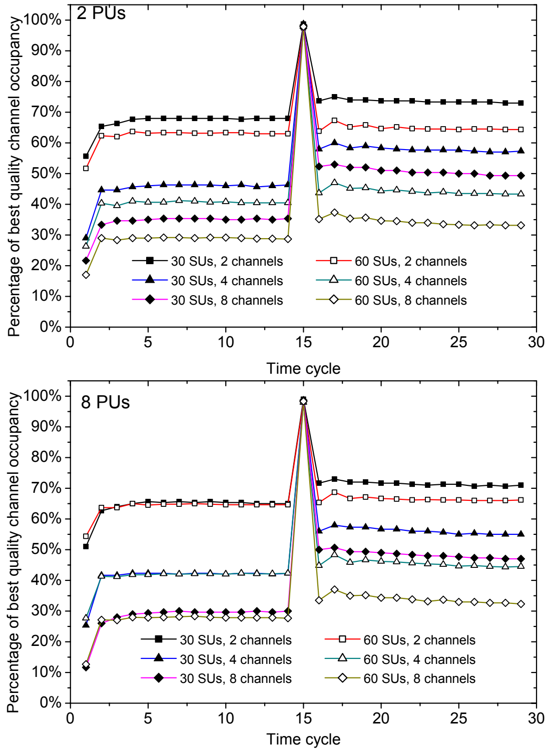

Fig. 3. Percentage of SUs taking best quality channel as master channel, stationary scenario.

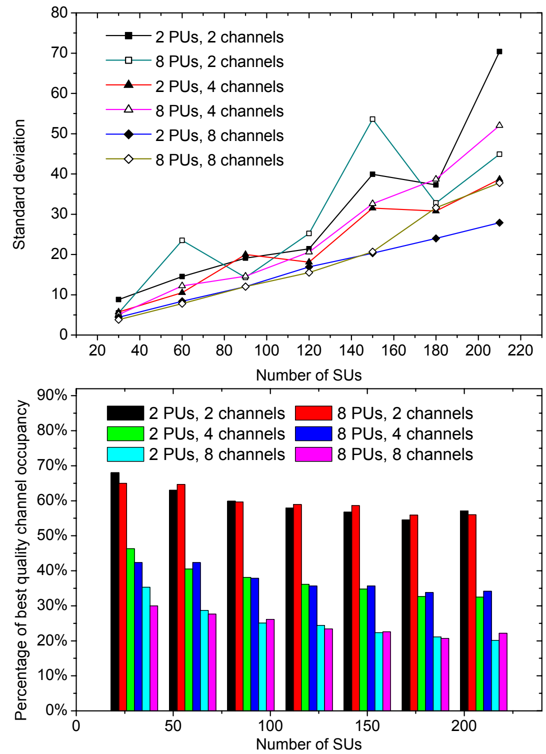

Fig. 4. STD and percentage as a function of SU number, stationary scenario.

time cycles. As seen from the figure, the algorithm takes a few time cycles to converge to a stable state, in which the STD of the channel clouds on each channel is relatively high in all cases. Fewer available channels results in a higher STD. This is because the SUs have fewer channels to stay when the available channels are fewer. Moreover, the STD increases as the SUs increases, because more SUs shift to fewer master channels. Comparing two figures in Fig. 2, as the PUs increase, the STD difference among different SU populations become larger when the available channels are few (e.g. two), but that difference becomes smaller as the available channels increase.

In Fig. 2, an abrupt drop of the STD is observed at the time cycle of 15. It is caused by the process that all SUs update their p lists simultaneously according to their own Q lists. In the simulation we set the simultaneously self-updating of the SUs so that this phenomenon can be emphasized. Since the self-updating forces the SUs change their master channels, large clouds are broken to small ones, leading to the decreasing of the STD. The jump in Fig. 3 can be explained by the same reason.

Fig. 3 shows the percentages of the SUs who take the best quality channel as the master channel. First, we observe the trend of the SUs adapting to their best quality channels. The percentage is high when there is few available channels, but decreases as the available channels increase. The reason for this behavior is that the SUs have more channels to choose when the available channels increase. This is also confirmed

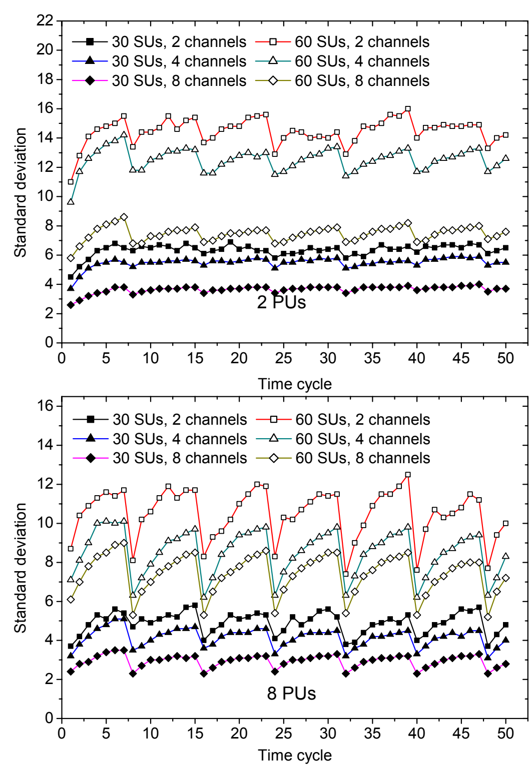

Fig. 5. Dynamic behavior of algorithm, dynamic scenario.

in Fig. 2, where the STD is lower when the available channels increase. An interesting point in this figure is that after the jump point at the time cycle of 15, more SUs take the best channel as the master channel, meaning the algorithm takes the channel quality of the user itself into account. Another observation is that the difference of the percentage is small in terms of the PU number. It is around 65% in the two channel case, 40% in the four channel case, and 30% in the eight channel case.

Fig. 4 shows the algorithm behaviors corresponding to different SU populations. As seen from the figure, the STD is high in all cases, meaning the algorithm works well. The STD increases as the SUs increase. It implies more SUs are aggregated to few common master channels. As the number of SUs increases, the percentage of the best quality channel occupancy decreases slightly. For fewer available channels, that percentage is higher. However, the correlation of the percentage and the PU number at the same channel size is not strong here.

The dynamic behaviors of the algorithm are shown in Fig. 5. The PUs in this simulation setup change their operating channels every 8 time cycle simultaneously. As seen from this figure, in both cases after the changing, the STD turns to a high stable value shortly, meaning the SUs are aggregated to few common master channels quickly.

VII. Conclusion

We propose a swarm intelligence-based approach to solve the common control channel assignment problem in the CogMesh networking scenario, in which, a SU is capable of sensing the radio environment and broadcasting its sensing result to its neighbors periodically through specific HELLO messages. Such messages are used as the pheromone to influence the common control channel selection performed autonomously by each SU. The balance is therefore made between the channel quality and the common choices of the neighboring users. This distributed approach is suitable for solving a large scale optimization problem through the node cooperation based only on local information. Its performance is verified by simulation. As a learning technique, it has inherent relationship with other learning strategies, for instance, Q-learning. From now on, it is worth extending the current work to other learning strategies in order to apply the algorithm to more complex CR-based networks. This will be addressed in our future work.

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