

A Bio-inspired Solution to Cluster-based Distributed Spectrum Allocation in High-density Cognitive Internet of Things

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Abstract—With the emergence of Internet of Things (IoT), where any device is able to connect to the Internet and monitor/control physical elements, several applications were made possible such as smart cities, smart health care and smart transportation. The wide range of the requirements of these applications drives traditional IoT to cognitive IoT (CIoT) that supports smart resource allocation, automatic network operation and intelligent service provisioning. To enable CIoT, there is a need for flexible and reliable wireless communication. In this paper, we propose to combine Cognitive Radio (CR) with a biological mechanism called Reaction-Diffusion to provide efficient spectrum allocation for CIoT. We first formulate the quantization of qualitative connectivity-flexibility tradeoff problem to determine the optimal cluster size (i.e., number of cluster members) that maximizes clustered throughput but minimizes communication delay. Then, we propose a bio-inspired algorithm which is used by CIoT devices to form cluster distributedly. We compute the optimal values of the algorithm's parameters (e.g., contention window) of the proposed algorithm to increase the network's adaption to different scenarios (e.g., spectrum homogeneity and heterogeneity) and to decrease convergence time, communication overhead and computation complexity. We conduct a theoretical analysis to validate the correctness and effectiveness of proposed bio-inspired algorithm. Simulation results show that the proposed algorithm can achieve excellent clustering performance in different scenarios.

Index Terms—cognitive IoT, cognitive radio, clustering algorithm, bio-inspired solution, spectrum allocation.

I. INTRODUCTION

THE Internet-of-Things (IoT) is a network of interconnected objects including environmental sensors, health monitoring devices, smart meters, home appliances, autonomous cars, and many others [1]. Recently, cognitive IoT (CIoT) emerges to meet the current and even future application requirements and becomes the development trend of IoT. The main idea of CIoT is to enable the IoT to possess the features of smart resource allocation, automatic network operation and intelligent service provisioning [2]. One embodiment of cognition in CIoT is to adapt itself to changes or uncertainties; this requires CIoT devices, that are connected using wireless

communication, to have the capability of efficient spectrum utilization [3].

Cognitive radio (CR) technology, as a promising solution to increase the utilization of scarce radio spectrum, has been widely studied for 5G networks [4][5], Machine-to-Machine (M2M) communications [6] and other scenarios in IoT [7]. The basic concept of CR is dynamic spectrum management, for allocating radio frequency bands [8], which enables wireless devices to have dynamic access to the entire available spectrum. For high-density CIoT deployments, CR could help not only alleviating the issue of spectrum scarcity, but also adapting to the changes of spectrum environment. In this case, CIoT devices can satisfy the communication requirements of varied applications as well as achieve high robustness in a dynamic environment.

However, though CR technology can bring CIoT more flexibility to the dynamic environment, the connectivity of networks may decrease due to the fact that CIoT devices are allocated on varied spectrum bands (channels). Hence, to provide the tradeoff between connectivity and flexibility of the networks, cluster-based spectrum allocation algorithms are proposed [9]. Table I compares the existing representative clustering algorithms regarding spectrum allocation with the proposed bio-inspired algorithm in different aspects. [10] and [11] both use centralized methods to form cluster due to that they need global information. Comparing to centralized spectrum allocation, distributed spectrum allocation can provide more flexibility in the sense it can quickly adjust to the network changes, especially in the distributed scenario where there exists no central controller. Furthermore, according to [12], in most cases, network changes may affect only a local area; in this case, a distributed spectrum allocation can address these changes without performing a large scale adjustment of allocated spectrum. Hence, distributed methods like [13]-[18] are proposed. However, these methods require accurate neighbors' information (e.g., neighbors' available channel list) based on perfect information exchange mechanism (e.g., ideal neighbor discovery scheme) which is not specified in these works. Besides, the requirement for accurate exchanged information will cost wireless devices unacceptable long time to collect enough information when taking into consideration the possible collisions during communications. Particularly, [13] and [14] also require time-synchronization among wireless devices, which is hardly to implement in distributed scenario; [15] requires a reliable signalling mechanism which is imprac-

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TABLE I
SUMMARY OF REPRESENTATIVE CLUSTERING ALGORITHMS

Algorithm	Objective	Method	Neighbors' Information	Global Information	Communication Requirement	Other Requirement
[10]	Enhance the coverage and capacity of cellular networks	Centralized	No	Layout of femtocell and channel gains	Perfect information exchange	No
[11]	Maximize the sum capacity	Centralized	No	CSI	Perfect information exchange	No
[13]	Maintain connectivity in spectrum heterogeneity	Distributed	Yes	No	Perfect information exchange	Synchronization
[14]	Tradeoff between spectrum availability and number of clusters	Distributed	Yes	No	Perfect information exchange	Synchronization
[15]	Tradeoff between spectrum availability and number of clusters	Distributed	Yes	No	Perfect information exchange	Reliable signalling mechanism
[16]	Maximize cluster size in spectrum heterogeneity	Distributed	Yes	No	Perfect information exchange	Two transceivers
[17]	Maximize cluster size in spectrum heterogeneity	Distributed	Yes	No	Perfect information exchange	Synchronization
[18]	Maximize the sum capacity Minimize transmission power	Distributed	Yes	No	Perfect information exchange	No
The proposed	Maximize clustered throughput Minimize communication delay	Distributed	No	No	No	No

tical in dynamic scenario. Other requirement like need of two transceiver per device is claimed in [16], which will result in extra cost like power. Besides, though [17] specifies that neighbor discovery and information exchange can be completed by channel-hopping (CH) mechanism, the assumption of time-synchronization is still impractical; and the algorithm in [17] and [18] may result in **isolated node problem** [19] which means that the formed cluster only contains one node. The isolated node problem drastically decrease the connectivity of the network. Hence, the limitations of these clustering algorithms lead to the lack of practicability.

Challenges in communication and networking (e.g., complexity vs. network size, dynamic nature, resource constraints, heterogeneous architectures, absence or impracticality of centralized control and infrastructure and etc.) have been successfully dealt with by Nature. Indeed, as a result of millions of years of evolution, Nature has yielded many biological systems and processes with intrinsic appealing characteristics that include adaptivity to varying environmental conditions, inherent resiliency to failures and damages, successful collaborative operations based on a limited set of rules [20]. Compared to conventional techniques, bio-inspired algorithms may lead to more effective solutions in areas that include networking, maintenance, control and optimization [21]. Indeed, bio-inspired techniques have been studied for different research fields in communication and networking such as network synchronization [22], cooperation and division [23], resource allocation [24] and routing [25]. With respect to distributed spectrum allocation, there also exist a few notable contributions that use bio-inspired methods in the context of cognitive networks [26]-[28]. For more detailed review of bio-inspired methods, there are two useful survey articles [20], [29]. A theoretical survey article is [20], while [29] focuses more on the practical relevance of bio-inspired solutions. To the best of our knowledge, our proposal is the first that uses a bio-inspired method for cluster-based spectrum allocation with practical assumptions (in opposition to existing methods); these assumptions include (a) there is no central controller; (b)

limited received information, by nodes, may be limited (i.e., not complete); and (c) communication collisions may happen.

In this paper, we propose a bio-inspired algorithm to address the limitations and drawbacks of existing algorithms (Table I) in cluster-based distributed spectrum allocation. The main contributions are as follows.

- We formulate the quantization of qualitative connectivity-flexibility tradeoff problem by considering both clustered throughput and communication delay. We also derive the specific expression of utility function, by which we can compute the optimal cluster size.
- We propose a bio-inspired algorithm to implement distributed cluster formation with tending to optimal cluster size. The proposed algorithm is based on realistic/practical assumptions that include (a) there is no controller; (b) users only use limited received information; and (c) communication collisions can happen.
- We compute the optimal parameter configuration of the proposed algorithm to increase the adaption of CIoT to different scenarios, and to decreases convergence time, communication overhead and computation complexity.
- We provide theoretical analysis and simulations to validate the correctness and effectiveness of proposed algorithm, and proof that the isolated node problem can be addressed in the proposed algorithm.

The rest of this paper is organized as follows. Section II models CIoT and formulates the clustering problem. In Section III, we analyze the problem based on CSMA/CA, and derive the optimal cluster size. We present the bio-inspired algorithm in Section IV. Section V gives analysis and derivation of optimal parameter configuration of the proposed algorithm. In Section VI, we present the theoretical analysis to validate the algorithm. Section VII presents simulation results. Section VIII concludes the paper.

II. DISTRIBUTED CLUSTER FORMATION PROBLEM

A. Network Model

We consider a high-density CIoT with set $\mathbf{U} = \{U_1, \dots, U_N\}$ of users (in this paper, user and CIoT device will be used interchangeably), numbered by set $\mathbf{N} = \{1, \dots, N\}$. The total network bandwidth comprises set $\mathbf{C} = \{C_1, \dots, C_M\}$ of non-overlapping channels, numbered by set $\mathbf{M} = \{1, \dots, M\}$. Denote by $\mathbf{CU}_i \in \mathbf{C}$ the set of locally available channels at each user $U_i \in \mathbf{U}$, $i \in \mathbf{N}$. The spectrum heterogeneity of the environment implies that any two sets \mathbf{CU}_i and \mathbf{CU}_j ($i \neq j$) may be different. It is assumed that there exists at least one common available channel between U_i and U_j for $i, j \in \mathbf{N}$, i.e., $\mathbf{CU}_i \cap \mathbf{CU}_j \neq \emptyset$.

In order to be more resilient to the changes, users in the system employ random access scheme like Distributed Coordination Function (DCF)-based Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) in IEEE 802.11 Standard [30] to transmit messages; thus, time synchronization is not necessarily required among users. It is assumed that each user stays in the system for a long enough duration to accomplish spectrum allocation. Each user operates fully autonomously (without any central controller) and has neither precise knowledge about global information (e.g., channel state and network traffic) nor other users' states (e.g., occupying channel and available channels). That is, each U_i , $i \in \mathbf{N}$, selects its occupying channel (cluster) independently based only on its own local observations (or the parameters that can be measured locally, such as local throughput, local link gains). The only information users can acquire from each other is the information transmitted successfully during the spectrum allocation process.

B. Problem Formulation

The objective is to form cluster-based network where each cluster occupies one channel which is commonly available to all cluster members. Denote by $\{\mathbf{CS}_1, \dots, \mathbf{CS}_K\}$ the set of clusters in which \mathbf{CS}_k , $k \in \mathbf{K} = \{1, \dots, K\}$ represents the set of users belonging to cluster k . Note that each user only belongs to one cluster.

To achieve the maximal throughput, each user needs to choose the 'best' channel (e.g., lower noise and larger bandwidth) in its available channel set. On the one hand, it is likely for a large number of users to choose the same 'best' channel. In this case, users intending to achieve maximal throughput actually receive low throughput because of intense collisions. Considering multi-user transmission contention, the more users occupying the same channel, the more collisions will happen. The *expected* throughput of U_i in \mathbf{CS}_k on C_m is

$$\mathbb{E}[S_{k,i}] = \chi_{m,i} \Gamma(|\mathbf{CS}_k|) B_m \log_2(1 + \gamma_{m,i}), \quad (1)$$

where

$$\chi_{m,i} = \begin{cases} 1, & U_i \text{ occupies } C_m \\ 0, & \text{otherwise} \end{cases},$$

$|\mathbf{CS}_k|$ is the cluster size (i.e., number of users in cluster k), B_m is the bandwidth of C_m and $\gamma_{m,i}$ is the SINR (Signal to Interference and Noise Ratio) in C_m measured by U_i ; $\mathbb{E}[\cdot]$

denotes the expectation function; $\Gamma(\cdot)$ is the decreasing function reflecting the impact of the number of cluster members on the user's throughput. Intuitively, Eq. (1) indicates that users employing random access scheme can achieve high throughput in small-size clusters.

However, on the other hand, the 'best' channels of neighbouring users may be different, which means the commonly available channel of neighbouring users is not the 'best' channel. Hence, occupying the 'best' channel may lead to small cluster sizes and a large number of clusters. In this case, cluster management and inter-cluster communications will generate considerable overhead, especially the communication access delay for inter-cluster communications¹. This indicates that the larger the cluster size is, the less the communication access delay is. The *expected* access delay of U_i in \mathbf{CS}_k can be expressed as follows:

$$\mathbb{E}[D_{k,i}] = \Upsilon(|\mathbf{CS}_k|), \quad (2)$$

where $\Upsilon(\cdot)$ is the function mapping the number of cluster-members to communication access delay.

We define the utility function \mathbb{U}_k of \mathbf{CS}_k as

$$\mathbb{U}_k = \sum_{\{i|U_i \in \mathbf{CS}_k\}} \mathbb{E}[S_{k,i}] - \mathbb{E}[D_{k,i}]. \quad (3)$$

The cluster formation problem can be formulated to maximize the overall utilities of all clusters. More specifically,

$$\max_{|\mathbf{CS}_k|} \sum_{k \in \mathbf{K}} \mathbb{U}_k, \quad (4a)$$

$$\text{s.t.} \quad \sum_{k \in \mathbf{K}} |\mathbf{CS}_k| = N, \quad (4b)$$

$$\mathbf{CS}_k \cap \mathbf{CS}_q = \emptyset, \quad \forall k \neq q, k, q \in \mathbf{K}, \quad (4c)$$

$$\sum_{m \in \mathbf{M}} \sum_{U_i \in \mathbf{CS}_k} \chi_{m,i} = |\mathbf{CS}_k|, \quad (4d)$$

$$|\mathbf{K}| \leq |\mathbf{M}|. \quad (4e)$$

Eq. (4b) indicates that every user must join a cluster. Eq. (4c) ensures that each user belongs to only one cluster. Eq. (4d) indicates that the members of a cluster can occupy only one commonly available channel. Eq. (4e) ensures that the number of clusters cannot be larger than the number of channels.

III. ANALYSIS OF OPTIMAL SOLUTION

We conduct the analysis based on DCF-based CSMA/CA in IEEE 802.11 Standard [30], which is widely used in distributed wireless networks and easy to be adopted and developed.

A. Cluster Throughput

According to Xiao's research [31], which considers backoff counter freezing probability based on Bianchi's model [32], a user employing DCF based CSMA/CA scheme transmits data in cluster k with the probability

$$\tau_k = \frac{1 - p_k^{r+1}}{\left(\sum_{i=0}^r [1 + \frac{1}{1+p_k}] \sum_{j=1}^{W_i-1} \frac{W_i-j}{W_i} p_k^j \right) (1 - p_k)}$$

¹The most common scheme for inter-cluster communication in distributed multi-channel networks is using channel-hopping algorithms [17].

where r is the maximum number of retransmissions before dropping a packet; it is also the maximum backoff stage number. The contention window size W_i at backoff stage i is defined as

$$W_i = 2^i CW_{min} \quad \forall i, 0 < i \leq r$$

where CW_{min} is the minimum contention window size; p_k ($k \in \mathbf{K}$) is the probability that a transmitting user encounters a collision in \mathbf{CS}_k . Since each cluster only occupies one channel, there are $|\mathbf{CS}_k|$ users contending for the same channel in \mathbf{CS}_k , the probability p_k can be expressed as

$$p_k = 1 - (1 - \tau_k)^{|\mathbf{CS}_k|^{-1}}.$$

The probability P_k that a successful transmission occurs in the \mathbf{CS}_k is given by the probability that exactly one user transmits in the \mathbf{CS}_k , on the condition that at least one user transmits, i.e.,

$$P_k = \frac{P_{s,k}}{P_{b,k}} = \frac{|\mathbf{CS}_k| \tau_k (1 - \tau_k)^{|\mathbf{CS}_k|^{-1}}}{1 - (1 - \tau_k)^{|\mathbf{CS}_k|}}.$$

where $P_{s,k} = |\mathbf{CS}_k| \tau_k (1 - \tau_k)^{|\mathbf{CS}_k|^{-1}}$ and $P_{b,k} = 1 - (1 - \tau_k)^{|\mathbf{CS}_k|}$; the unknown τ_k , which can be solved using numerical techniques, is proved to have a unique solution [32].

The *expected* throughput of \mathbf{CS}_k can be expressed as

$$S_k = \sum_{\{i|U_i \in \mathbf{CS}_k\}} \chi_{m,i} P_k B_m \log_2(1 + \gamma_{m,i}). \quad (5)$$

B. Network Access delay

In the case that the source user and destination user are in the same cluster, let $\mathbb{E}[AD_{intra,k}]$ be the expected access delay in \mathbf{CS}_k ; it is defined as the time duration spent for successful packet delivery. According to [31],

$$\mathbb{E}[AD_{intra,k}] = \overline{I}_k \delta + \overline{B}_k T_B + \overline{F}_k T_F,$$

where \overline{I}_k , \overline{B}_k and \overline{F}_k are the average numbers of idle slots (i.e., backoff slots), busy slots (i.e., frozen slots) and retransmissions caused by failed transmission, respectively. δ , T_B and T_F are the time durations of a backoff slot, a freezing backoff counter and a failed transmission, respectively. We have

$$\overline{I}_k = \sum_{i=0}^r \frac{p_k^i (1 - p_k)}{1 - p_k^{r+1}} \sum_{j=0}^i \frac{W_j - 1}{2},$$

$$\overline{B}_k = \frac{\overline{I}_k}{(1 - p_k)} p_k,$$

$$\overline{F}_k = \sum_{i=0}^r \frac{i p_k^i (1 - p_k)}{1 - p_k^{r+1}}$$

and

$$T_B = \frac{P_{s,k}}{P_{b,k}} T_S + \frac{P_{b,k} - P_{s,k}}{P_{b,k}} T_F,$$

where T_S is the time duration of a successful transmission. Note that, δ , T_S and T_F can be obtained according to communication protocol specification.

In the case that the source user and the destination user are not in the same cluster, they use CH to perform inter-cluster communications. To find the destination user, the

source user has to hop between different channels until it finds the destination user. For example, Liu *et al.* [17] require all the cluster heads hop between different channels periodically to allow inter-cluster communication and coordination. However, the performance of the CH scheme in [17] is neither evaluated nor analyzed. Hence, we consider recent SJ-RW CH algorithm [33] as an example to analyze the inter-cluster access delay due to its outstanding performance. According to [34], which also considers the SJ-RW CH algorithm [33], the average access delay \overline{T}_{AD} can be expressed as

$$\overline{T}_{AD} = T_{slot} [ATTR + 1 + \frac{1 - P_{BL}}{P_{BL}} (ASTR + 1)] + \overline{w},$$

where T_{slot} is the length of time slot used for CH scheme; $ATTR$ represents the average number of time slots that users take for achieving the first rendezvous²; $ASTR$ denotes the average number of time slots taken for successive rendezvous (i.e., average interval duration of two successive rendezvous); P_{BL} is the probability that pairwise users establish a communication link during T_{slot} ; and \overline{w} is the average time duration consumed for contention in the rendezvous time slot. Because of space limitation, we do not present the detailed analysis and expressions of these parameters. Simply, $ATTR$ and $ASTR$ relate to the number of available channels (linear increasing relation). P_{BL} and \overline{w} relate to not only the number of available channels but also to the number of contending users; more specifically, a large number of available channels and/or contending users will decrease P_{BL} but increase \overline{w} ³.

The number of contending users outside \mathbf{CS}_k is $N - |\mathbf{CS}_k|$. Hence, the average time spent for the source user and destination user achieving rendezvous using CH can be defined as

$$\overline{T}_{inter} = \overline{T}_{AD} (N - |\mathbf{CS}_k|, \frac{\sum_{\{i|U_i \in \mathbf{CS}_k\}} |CU_i|}{|\mathbf{CS}_k|}),$$

where $|CU_i|$ is the number of available channels of U_i . Note that [33] proposes a routing scheme with CH to help the source user and destination user communicate by the aid of the routing user, for the sake of analysis, we consider the case of one time routing with routing delay being $2\overline{T}_{inter}$. Indeed, the more channels that are available to the source user, the larger the probability that the source user can make a direct communication with the destination user. Hence, the average time duration needed by the source user to locate the destination user can be expressed as

$$\mathbb{E}[AD_{inter,k}] = \frac{\sum_{\{i|U_i \in \mathbf{CS}_k\}} |CU_i|}{M |\mathbf{CS}_k|} \overline{T}_{inter} + 2(1 - \frac{\sum_{\{i|U_i \in \mathbf{CS}_k\}} |CU_i|}{M |\mathbf{CS}_k|}) \overline{T}_{inter}.$$

The *expected* access delay of \mathbf{CS}_k can be expressed as

$$\mathbb{D}_k = \frac{|\mathbf{CS}_k|}{N} \mathbb{E}[AD_{intra,k}] + \frac{N - |\mathbf{CS}_k|}{N} \mathbb{E}[AD_{inter,k}]. \quad (6)$$

²In CH schemes, a sender and a receiver are described as *Achieve Rendezvous* if they hop on the same channel in the same time slot.

³Referring to [34] for more details.

Accordingly, Eq. (3) can be written into

$$\begin{aligned} \mathbb{U}_k = & \sum_{\{i|U_i \in \mathbf{CS}_k\}} \chi_{m,i} P_k B_m \log_2(1 + \gamma_{m,i}) \\ & - \frac{|\mathbf{CS}_k|}{N} \mathbb{E}[AD_{intra,k}] - \frac{N - |\mathbf{CS}_k|}{N} \mathbb{E}[AD_{inter,k}]. \end{aligned} \quad (7)$$

Thus, the theoretically optimal solution corresponds to the resolution of the optimization problem (Eq. (4)) after replacing \mathbb{U}_k (in Eq. (4a)) by the expression in Eq. (7).

C. NP-hardness

The optimal cluster configuration of Eq. (4) which yields the highest system utility could be found using an exhaustive search. For N users and M channels, the number of possible solutions to form clusters is given by

$$M^{\mathcal{B}_N} \approx O(M^{N^N})$$

where \mathcal{B}_N is the Bell Number of N .

The number of possible cluster configurations grows exponentially with the number of users. Accordingly, the computation complexity will also increase exponentially with the number of users when computing the optimal cluster configuration. Hence, it is impractical to do exhaustive search for computing the optimal cluster configuration.

If we only take channel throughput into consideration, the cluster formation problem can be constructed by a weighted bipartite graph $\mathcal{G}(\mathcal{V}, \mathcal{E}, \mathcal{W}, \mathcal{B})$ on the basis of the given users. The set of vertices \mathcal{V} is partitioned into two disjoint sets \mathcal{U} and \mathcal{C} with $\mathcal{U} \cup \mathcal{C} = \mathcal{V}$, such that \mathcal{U} corresponds to users while \mathcal{C} corresponds to the set of channels. \mathcal{E} is the set of edges between these two disjoint sets \mathcal{U} and \mathcal{C} . \mathcal{B} is the weight set of \mathcal{C} which corresponds to the bandwidth of channels. \mathcal{W} is the weight set in which each weight is a non-negative value assigned to each edge. Hence, the weighted edge $w_{m,i}$ represents the channel throughput $\chi_{m,i} B_m \log_2(1 + \gamma_{m,i})$ of U_i on C_m . The optimal clustering problem can be formulated as follows:

$$\max \sum_{m \in \mathbf{M}} \sum_{i \in \mathbf{CS}_k} w_{m,i} \quad (8)$$

However, Eq. (8) has been proved to be an NP-hard problem [35]. Note that Eq. (4) is a harder problem than Eq. (8), which indicates Eq. (4) is also an NP-hard problem.

IV. BIO-INSPIRED SUBOPTIMAL CLUSTERING ALGORITHM

In a high-density CIoT, it is practically essential to find a reasonably good solution that can be obtained fast. In biological systems, the pattern formation is spontaneous and can adapt to changes in the environment. In this section, we propose a bio-inspired distributed clustering algorithm, which enables distributed implementation and guarantees convergence to a reasonably good solution. More specifically, we consider a biological mechanism called reaction-diffusion [36] to perform distributed clustering.

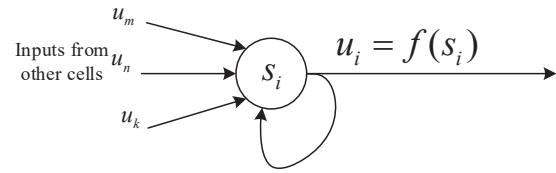


Fig. 1. A typical cell in CNN.

A. Conventional Reaction-diffusion Model

Let us start with a brief introduction of the conventional reaction-diffusion mechanism. Reaction-diffusion was proposed by Turing [36] in 1952 to explain the formation of patterns in biological systems, especially to explain spatial concentration patterns with features known from biological systems involving two substances: the *activator* and the *inhibitor*, which both diffuse within the system boundaries. The state of each point of the system depends on the relative concentration of the activator and inhibitor at its location. Denote by $a(x, y, t)$ and $h(x, y, t)$ the concentration of the activator and inhibitor respectively in the system at location (x, y) and time t , the reaction-diffusion mechanism is described in terms of second order partial differential equations ([36],[37]) of the form

$$\begin{aligned} \frac{\partial a}{\partial t} &= f(a, h) + D_a \nabla^2 a + S \\ \frac{\partial h}{\partial t} &= g(a, h) + D_h \nabla^2 h \end{aligned}$$

where ∇^2 is the Laplacian operator with respect to the location (x, y) , f and g are nonlinear functions describing reaction dynamic, D_a and D_h are the diffusion rate of the activator and the inhibitor respectively. S is the amount of stimulus.

The reaction-diffusion mechanism can be applied to simpler cellular automaton models such as the Cellular Neural Network (CNN) [38]. A CNN is an array of identical systems, which are only locally connected. A typical cell in a CNN can be depicted in Fig. 1, in which, the state s_i , of cell i at time $t + 1$ depends on its output u_i at time t and on the activatory and inhibitory inputs it gets from neighboring cells.

B. Modified Model for Distributed Clustering

A conventional reaction-diffusion model applied in CNN system can be modified to model distributed cluster formation in high-density CIoT, as follows. In our model, a cell corresponds to a user, and the output u_i represents the utility of the current cluster (channel) evaluated by U_i . To get the ‘inputs’ from other users on the current channel, any user must broadcast the evaluated utility of the current channel. To relieve broadcast collisions caused by simultaneous transmissions, we use backoff scheme in 802.11 DCF to regulate broadcasts. That is, each user randomly choose a backoff counter number from $[0, CW_{bc,m}]$. If the backoff counter decreases to zero, the user starts to broadcast, or it will freeze its backoff counter when it senses other user transmitting. Due to the absence of feedback regarding the reception of a broadcast message,⁴ users continue to send broadcast messages intermittently, regardless of the

⁴In fact, in typical wireless communications, broadcast messages are not acknowledged in order to avoid the ACK implosion problem.

success of their transmissions. Note that any user re-chooses a new backoff counter number after operating a broadcast and continues the backoff-transmit process.

To update the utility of the current channel, we modify the original Reaction-Diffusion equations to a simple but controllable and effective one that can be formulated as

$$u_{m,i}(t + \Delta_m) = u_{m,i}(t) - D_m u_{m,i}(t) + \sum_{j \neq i, j \in \mathbf{N}_{m,i}(t + \Delta_m)} \rho_{ij} u_{m,j} \quad (9)$$

where $\mathbf{N}_{m,i}(t + \Delta_m)$ is the set of users that U_i receives broadcast messages successfully from on C_m during t to $t + \Delta_m$, D_m is the diffusion rate on C_m , Δ_m is the diffusion interval which is the time duration each user waits to update the utility by using Eq. (9), and ρ_{ij} is the stimulus coefficient which can be expressed as

$$\rho_{ij} = \kappa_{ij} + \frac{B_m}{\sum_{n \in \mathbf{CU}_i} B_n}$$

where κ_{ij} is the preference factor; it reflects the intention that U_i wants to stay with U_j . B_m is the bandwidth of C_m that U_i currently stays on; $u_{m,j}$ is the utility estimated and transmitted by U_j on C_m . The reaction-diffusion principles are translated in the process of updating the utility. That is, the more broadcast information U_i successfully receive, the more accumulated ‘stimulus’ will be added on its $u_{m,i}(t + \Delta_m)$, which means the better the current channel is. On the contrary, if broadcast collisions occur frequently or if few broadcasts are transmitted on the current channel, the added ‘stimulus’ cannot counteract the diffused utility, the $u_{m,i}(t + \Delta_m)$ will decrease. Furthermore, if the traffic of U_i heavily relies on user U_j or the quality of communication link between U_i and U_j is better, ρ_{ij} is large and more ‘stimulus’ will be added on $u_{m,i}(t + \Delta_m)$, which attracts U_i to join the cluster of U_j .

C. Description of the Proposed Algorithm

To achieve optimal cluster configuration, each user need to hop between different channels to evaluate the quality of the current cluster and decide whether to join it or hop to another. We use the *stay probability* $P_{m,i}$ to describe the intention that U_i wants to stay on channel C_m after updating $u_{m,i}(t + \Delta_m)$, which can be formulated as

$$P_{m,i} = \begin{cases} 1, & u_{m,i}(t + \Delta_m) \geq \underline{u}_{m,i} \\ 1 - \exp(-|u_{m,i}^*(t + \Delta_m)|), & u_{m,i}(t + \Delta_m) < \underline{u}_{m,i} \end{cases} \quad (10)$$

where $u_{m,i}^*(t + \Delta_m) = \frac{u_{m,i} - u_{m,i}(t + \Delta_m)}{u_{m,i} - D_m u_{m,i}(t)}$.

In Eq. (10), $\underline{u}_{m,i}$ is the utility value threshold that is

$$\underline{u}_{m,i} = \frac{\overline{u}_{stm,m} [x_{m,i} - z_{\frac{\alpha}{2}} \sqrt{x_{m,i} (1 - \frac{x_{m,i}}{S_m^*})}]}{D_m^*},$$

where $x_{m,i}$ is the number of stimulus utility during $(t - \Delta_m, t)$ on C_m , S_m^* and D_m^* will be detailed in Section V, $z_{\frac{\alpha}{2}}$ is α -percentile of standard normal distribution, more specifically, $z_{\frac{\alpha}{2}} = 3.291$ for $\alpha = 1\%$ and $z_{\frac{\alpha}{2}} = 1.960$ for $\alpha = 5\%$; and $\overline{u}_{stm,m}$ is an average value of stimulus utility computed by a

sliding window which consists of the last s diffusion intervals, i.e.,

$$\overline{u}_{stm,m} = \frac{\sum_{i=0}^{s-1} \sum_{j \neq i, j \in \mathbf{N}_{m,i}(t + \Delta_m - i \Delta_m)} \rho_{ij} u_{m,j}}{\sum_{j=0}^{s-1} |\mathbf{N}_{m,i}(t + \Delta_m - j \Delta_m)|}.$$

Eq. (10) indicates that, when the quality of the current channel tends to get stabilized or better (i.e., the evaluated utility is larger than the dynamic threshold), U_i wants to stay. On the contrary, if the quality of the current channel gets worse, U_i prefers to leave, and the worse the state is (i.e., the more the reduced utility is), the stronger the desire that U_i wants to leave (i.e., the less the $P_{m,i}$ is). Note that, if the user needs to hop to another channel with $1 - P_{m,i}$, it will hop on the channel that has the maximum updated utility value expect the current channel.

V. OPTIMAL CONFIGURATION OF PARAMETERS

In order to make the proposed distributed clustering algorithm more tractable, necessary parameters should be computed and optimized. In the proposed algorithm, the necessary parameters to be determined are $CW_{bc,m}$, Δ_m and D_m .

According to Eq. (7), the main factor that affects the utility of the cluster is the cluster size. Indeed, Eq. (7) can be divided in to two parts: the expected throughput and the expected access delay. The ideal solution is to find a optimal cluster size that maximize \mathbb{S}_k but minimize \mathbb{D}_k . Then, the optimal cluster size $|\mathbf{CS}_k^*|$ that maximize \mathbb{U}_k can be represented as

$$|\mathbf{CS}_k^*| = \operatorname{argmax} \mathbb{U}_k = \operatorname{argmax} (\mathbb{S}_k - \mathbb{D}_k). \quad (11)$$

$|\mathbf{CS}_k^*|$ can be computed by any user using numerical techniques according to Eq. (7), due to the limited space, we do not present details. Since U_i can only know its own local available channels, we assume that during the clustering process U_i holds the belief that users in the same cluster with it have the similar available channels. Hence, we replace $\frac{\sum_{\{i|U_i \in \mathbf{CS}_k\}} |\mathbf{CU}_i|}{|\mathbf{CS}_k|}$ with $|\mathbf{CU}_i|$ when computing $|\mathbf{CS}_k^*|$.

On the one hand, in order to achieve the optimal cluster configuration, users pursue large utility value by using Eq. (10), which increases the amount of the diffused utility according to Eq. (9); on the other hand, to maintain cluster-based network stability, the received stimulus utility is supposed to counteract the diffused utility. Let us assume that users form an optimal cluster by satisfying Eq. (11), then the size of the formed cluster is $|\mathbf{CS}_k^*|$. Let $P_{bc,s,k}^*$ be the probability that a collision-free broadcast occurs with the cluster size of $|\mathbf{CS}_k^*|$. Different from intra-cluster communication after cluster formation, during the cluster formation process, users broadcast their estimated utility by Eq. (9) on (in) the current channel (cluster) with a backoff counter chosen randomly from $[0, CW_{bc,m}]$, without binary exponential backoff, then the probability $P_{bc,s,k}^*$ can be represented as

$$P_{bc,s,k}^* = P_{s,k}(r = 0, |\mathbf{CS}_k| = |\mathbf{CS}_k^*|).$$

A. Optimal $CW_{bc,m}$

The parameter $CW_{bc,m}$ mainly affects the probability $P_{bc,s,k}^*$ during the cluster formation process, that is, for the same cluster size, different $CW_{bc,m}$ can decrease or increase $P_{bc,s,k}^*$, which further leads to a decrease or increase on the amount of stimulus utility. A large $P_{bc,s,k}^*$ can result in a large amount of stimulus utility, and thus will increase the evaluated utility of \mathbf{CS}_k . Besides, according to Law of Large Numbers, $\forall \epsilon \in \mathbb{N}^+$, $\lim_{S \rightarrow \infty} P(|X - P_{bc,s,k}^*S| < \epsilon) = 1$, which indicates that the more frequency of receiving stimulus utility, the more precise the X is statistically (i.e., to determine $X = P_{bc,s,k}^*S$), and the more accurate estimation on $|\mathbf{CS}_k|$ is⁵. Hence, with the optimal cluster size $|\mathbf{CS}_k^*|$, the optimal $CW_{bc,m}$ is

$$CW_{bc,m}^* = \operatorname{argmax}_{P_{bc,s,k}^*} (|\mathbf{CS}_k^*|). \quad (12)$$

Eq. (12) can be solved by numerical techniques after $|\mathbf{CS}_k^*|$ being worked out.

B. Optimal Δ_m

During the cluster formation process, users update the utility every duration of Δ_m . Intuitively, users may receive more stimulus utility using large Δ_m or less stimulus utility using small Δ_m . To better evaluate current cluster and achieve higher utility, it seems better for users to choose a large Δ_m . However, a large Δ_m can decrease the frequency of updating utility, which costs long time for completing cluster formation. To end this up, we calculate the optimal Δ_m , denoting Δ_m^* , with guaranteeing required confidence level.

Let us assume the event that a successful (i.e., collision-free) broadcast occurs be B and the event that others (i.e., a failed broadcast or no broadcast) occur be O. Then, in every relative slot (the length of relative slot is varied according to occurring event), during cluster formation process, either B occurs in \mathbf{CS}_k^* with the probability $P_{bc,s,k}^*$ or O occurs with the probability $1 - P_{bc,s,k}^*$. Let us define X_i be

$$X_i = \begin{cases} 1, & \text{B occurs} \\ 0, & \text{O occurs} \end{cases},$$

then $X_i \sim b(X_i, P_{bc,s,k}^*)$, where $b(x, p)$ is the 0-1 distribution.

Let us define that $X = \sum_{i=1}^S X_i$, which means X is the frequency of B occurring during S relative slots. Then, X follows the Binomial Distribution, i.e., $X \sim B(S, P_{bc,s,k}^*)$. According to Central Limit Theorem, when S is large enough, X tends to follow Normal Distribution, i.e., $X \sim \mathcal{N}(\mu, \sigma^2)$, where the expectation μ is $P_{bc,s,k}^*S$ and the variance σ^2 is $P_{bc,s,k}^*(1 - P_{bc,s,k}^*)S$.

Let us define that $Y = \frac{X}{S}$, according to the characteristics of normal distribution, we have $Y \sim \mathcal{N}(\frac{\mu}{S}, \frac{\sigma^2}{S^2})$. This can be transformed into standard normal distribution as

$$\frac{Y - P_{bc,s,k}^*}{\sqrt{\frac{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)}{S}}} \sim \mathcal{N}(0, 1).$$

⁵Actually, the proposed algorithm does not need to directly estimate $|\mathbf{CS}_k|$, but indirectly estimate $|\mathbf{CS}_k|$ by evaluating whether the amount (mainly the frequency) of stimulus utility reaches the required level (i.e., the diffused utility is equal to or less than the received stimulus utility).

Let us define H_0 and h_0 be the event that $Y = P_{bc,s,k}^*$ and the event that Y is supposed to be $P_{bc,s,k}^*$, respectively. Then, the $P\{h_0|H_0\}$ can be represented as

$$P\{h_0|H_0\} = \int_{\underline{\theta}}^{\bar{\theta}} \frac{1}{\sqrt{2\pi\varpi}} \exp\left(-\frac{(x - P_{bc,s,k}^*)^2}{2\varpi^2}\right) dx = 1 - \alpha. \quad (13)$$

where $\varpi = \sqrt{\frac{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)}{S}}$, $\bar{\theta} = z_{\frac{\alpha}{2}}\varpi + P_{bc,s,k}^*$ and $\underline{\theta} = -z_{\frac{\alpha}{2}}\varpi + P_{bc,s,k}^*$.

Hence, when the confidence level is $1 - \alpha$, the confidence interval is $(-z_{\frac{\alpha}{2}}\sqrt{\frac{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)}{S}} + P_{bc,s,k}^*, z_{\frac{\alpha}{2}}\sqrt{\frac{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)}{S}} + P_{bc,s,k}^*)$. More specifically, Eq. (13) indicates that when the statistic Y fluctuates within $(-z_{\frac{\alpha}{2}}\sqrt{\frac{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)}{S}} + P_{bc,s,k}^*, z_{\frac{\alpha}{2}}\sqrt{\frac{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)}{S}} + P_{bc,s,k}^*)$, we believe that statistic X , referred as the frequency of receiving stimulus utility, is equal to $P_{bc,s,k}^*S$ with the probability of $1 - \alpha$. Let us define $\phi = \frac{X - \mu}{S}$ be the statistically frequency error ratio of receiving stimulus utility, thus the frequency error ratio threshold can be represented as $\bar{\phi}$. Then, the optimal number of S^* can be derived as

$$S^* = \lceil \frac{z_{\frac{\alpha}{2}}^2 P_{bc,s,k}^*(1 - P_{bc,s,k}^*)}{\bar{\phi}^2} \rceil. \quad (14)$$

If we believe that $X = P_{bc,s,k}^*S^*$ when X fluctuates within $(P_{bc,s,k}^*S^* - z_{\frac{\alpha}{2}}\sqrt{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)S^*}, P_{bc,s,k}^*S^* + z_{\frac{\alpha}{2}}\sqrt{P_{bc,s,k}^*(1 - P_{bc,s,k}^*)S^*})$, the number of backoff slots and failed transmission slots will be $(1 - \tau_{bc,k}^*)|\mathbf{CS}_k^*|S^*$ and $(P_{bc,b,k}^* - P_{bc,s,k}^*)S^*$, thus Δ_m^* can be represented as

$$\Delta_m^* = \lceil \delta_{bc}(1 - \tau_{bc,k}^*)|\mathbf{CS}_k^*|S^* + T_{bc,F}(P_{bc,b,k}^* - P_{bc,s,k}^*)S^* + T_{bc,S}P_{bc,s,k}^*S^* \rceil, \quad (15)$$

in which

$$\tau_{bc,k}^* = \tau_k(r = 0, CW_{min} = CW_{bc}^*, |\mathbf{CS}_k| = |\mathbf{CS}_k^*|),$$

$$P_{bc,b,k}^* = P_{b,k}(r = 0, CW_{min} = CW_{bc}^*, |\mathbf{CS}_k| = |\mathbf{CS}_k^*|);$$

$T_{cb,S}$ and $T_{bc,F}$ are time duration spent for successful and failed transmission of broadcast message, which can be obtained from specific communication configuration.

Eq. (14) and (15) indicate that, if we want a more precise estimation on the frequency of receiving stimulus utility, we need to use smaller $\bar{\phi}$ which will result in larger Δ_m^* .

C. Optimal D_m

According to Subsection V.B, users in the formed cluster receive totally $P_{bc,s,k}^*S^*$ times of stimulus utility during diffusion interval Δ_m^* . Hence, we can compute D_m^* by

$$D_m^* = (\bar{\kappa}_i + \frac{B_m}{\sum_{n \in \text{CU}_i} B_n})P_{bc,s,k}^*S^*, \quad (16)$$

where $\bar{\kappa}_i$ is the average value of U_i 's $|\mathbf{CS}_k^*|$ largest preference factors.

Note that the optimal parameters are computed once user complete sensing the environment (e.g., available channels and corresponding bandwidths, etc.), thus makes these optimal

parameters fixed during the cluster formation process, which drives users to reach the optimal cluster configuration.

VI. THEORETICAL ANALYSIS

In this section, we first study the correctness and effectiveness of the proposed distributed cluster-based spectrum allocation algorithm; then we show the computation and communication complexity of proposed algorithm. Finally, we proof that the proposed algorithm can solve the isolated node problem in clustering.

A. Correctness and Effectiveness

Any user will encounter in total three kinds of updating states when using Eq. (9) for cluster formation: i) the stable utility, ii) the increasing utility and iii) the decreasing utility; which are correspondingly caused by three cases: a) the accumulated stimulus utility during Δ_m^* counteracts the diffused utility, b) the accumulated stimulus utility exceeds the diffused utility and c) the accumulated stimulus utility is less than the diffused utility.

Theorem 1: The proposed algorithm guarantees that users will finally form an stable cluster configuration no matter how they go through these three kinds of updating states.

Proof: According to Eq. (9), the discrete utility updating process can be viewed as the number sequence u that satisfies $u(n+1) = Du(n) + U$ where $U \in \mathbb{R}^+$ and $D \in (0, 1)$. Then, the general term of the sequence can be expressed as $u(n) = (u(0) + \frac{U}{D-1})D^n - \frac{U}{D-1}$. Due to the fact that D is less than 1, $\lim_{n \rightarrow \infty} u(n) = \frac{U}{1-D}$. Hence, the final utility of C_m can be derived as

$$\lim_{t \rightarrow \infty} u(t) = \frac{\sum_{j \neq i, j \in \mathbf{N}_{m,i}(t)} \rho_{ij} u_{m,j}}{D_m}.$$

Theorem 2: The proposed algorithm always drives users to a suboptimal clustering configuration no matter how they go through these three kinds of updating states.

Proof: As can be easily found, the unstable states ii) and iii) that respectively caused by cases b) and c) mainly relate to insufficient received stimulus utility during Δ_m^* . According to the subsection V.B, the frequency of receiving stimulus utility is $P_{bs,s,k} S^*$. Thus, the more $P_{bs,s,k} S^*$ will be, the more received stimulus utility will be. Eq. (12) guarantees that $P_{bs,s,k}$ will reach its maximum value $P_{bs,s,k}^*$ when using CW_{bc}^* under configuration of $|\mathbf{CS}_k^*|$. That is to say, for fixed CW_{bc}^* , $P_{bs,s,k}^*$ will decrease when the cluster size tends to be either more or less than $|\mathbf{CS}_k^*|$. Then, starting from the initial updating, the initial cluster configuration may contain three kinds: $|\mathbf{CS}_k| = |\mathbf{CS}_k^*|$, $|\mathbf{CS}_k| < |\mathbf{CS}_k^*|$ and $|\mathbf{CS}_k| > |\mathbf{CS}_k^*|$. According to Eq. (10), the first kind will result in state i) but the last two kinds will lead to state iii). If it is $|\mathbf{CS}_k| > |\mathbf{CS}_k^*|$, in average $|\mathbf{CS}_k| P_{m,i}$ will leave C_m , which will increase $P_{bs,s,k} S^*$ and therefore the utility of C_m will increase, until it reaches its maximum value. If it is $|\mathbf{CS}_k| < |\mathbf{CS}_k^*|$, either state ii) or iii) will happen. That is, if other users continue to hop on this channel, $P_{bs,s,k} S^*$ will increase to the maximum;

or all users on C_m will hop on other channels due to the utility continuously decreasing. In this case, the channel that is available to more users is more likely to form a stable cluster. ■

B. Computation Complexity

Let us assume that users spend averagely $\overline{K_c}$ slots on each channel to update the utility before getting convergent. According to the analysis in Section V, when $|\mathbf{CS}_k|$ trends to be $|\mathbf{CS}_k^*|$, the utility of C_k trends to be maximized and \mathbf{CS}_k trends to be stable. Hence, the closer $|\mathbf{CS}_k|$ is to $|\mathbf{CS}_k^*|$, the less slots users spend for formation of stable cluster. Besides, nearly all the users need to visit all their respective available channels to determine the optimal cluster configuration, thus users totally spend $M\overline{K_c}$ slots for getting convergent. Hence, except for the computation of the optimal parameters at the initial stage, users need to update the utility $M\overline{K_c}$ times by computing Eq. (9). Then, the computation complexity is $O(M|N - \sum_{k \in \mathbf{K}} |\mathbf{CS}_k^*| |)$.

C. Communication Complexity

We refer to the communication complexity as the amount of communication involved in the cluster formation process before convergence. According to the proposed algorithm that users need to broadcast messages intermittently by randomly choosing a backoff counter number from $[0, CW_{bc,m}]$, the average interval of broadcasting is $\frac{CW_{bc,m}}{2}$. Let us assume that users broadcast average $\overline{k_{bc,m}}$ times during Δ_m^* on C_m , then the average amount of broadcasting on each channel is $\frac{\sum_{m \in M} \overline{k_{bc,m}}}{M}$, which is assumed to be represented as $\overline{K_{bc}}$. Based on the fact that the more users on the current channel, the more collisions will occur, and the more frozen slots users spend to backoff; thus users broadcast less messages on the current channel. Hence, total broadcast amount can be represented as $\frac{M\overline{K_{bc}}}{N}$. As $\overline{K_{bc}}$ will increase when the computation amount of updating utility increases, the communication complexity can be represented as $O(\frac{M^2}{N} |N - \sum_{k \in \mathbf{K}} |\mathbf{CS}_k^*| |)$.

D. Isolated Node Problem

The proposed algorithm can solve the isolated node problem that is mentioned in [19]. The isolated node problem, which can be viewed as the single-node cluster, will reduce connectivity of networks. As is a fact that in the proposed algorithm, stable clusters maintained by enough amount of received stimulus utility. That means, when a single user hops on a channel where there exist no stimulus, the utility of this channel will decrease to zero if no other users will hop on this channel. According to Eq. (10), before the user's utility of the channel decreasing to zero, it will hop to another channel on which it can receive stimulus (i.e., broadcast message).

VII. PERFORMANCE EVALUATION

In this section, we demonstrate the practicability of the proposed algorithm in adapting to different scenarios. We

first investigate the performance of the proposed algorithm with considering both spectrum homogeneity and spectrum heterogeneity; then, we compare the proposed algorithm with two spectrum allocation algorithms regarding clustering in communication overhead and convergence time.

A. Simulation Setup

We employ DCF based CSMA/CA to operate broadcast in proposed scheme, as well as in comparing algorithms [17][18]. The main simulation parameters and corresponding values are shown in Table II. All users are located randomly in a field of $500 \times 500 \text{ m}^2$, and each has a transmission range of 700 m.

TABLE II
MAIN SIMULATION PARAMETERS AND VALUES

Parameter	Value
SINR threshold	-7 db
Power of Gaussian white noise	-174 dBm/Hz
Tx power of user	-50 dbm
Backoff slot	20 μs
Short inter-frame space (SIFS)	10 μs
Distributed inter-frame space (DIFS)	50 μs
Length of broadcast message	128 bit

B. Example

We show an example of cluster formation process using the proposed bio-inspired algorithm in Fig. 2, where there exist 100 users and 5 channels. The channel bandwidth is shown

on the figure, e.g., ‘CH3=25M’ means that the bandwidth of Channel 3 is 25MHz. In Fig. 2, the black number in the colored circle represents the number of users located on the channel characterized by this color and the grey number represent the value rounded to integer of average utility. Fig. 2 (a), (b), (c) and (d) represent clustering results of first iteration, 5 iterations, 15 iterations and 25 iterations, respectively. In first iteration, the utility is initialized to maximize Eq. (7). Then the utility is updated by using Eq. (9) to evaluate the quality of the cluster (channel).

C. Adaptive Cluster Formation Simulations

We consider different scenarios where there exist 5 channels (i.e., $M = 5$) and 10 channels (i.e., $M = 10$) respectively, and both are with the numbers of users are 100 (i.e., $N = 100$) and 150 (i.e., $N = 150$). The bandwidth of these channels are not all the same. More specifically, in $M = 5$ scenario, there are three 10M-channels, two 15M-channels and one 25M-channel; in $M = 10$ scenario, there are five 10M-channels, three 15M-channels and two 25M-channels. Besides, we also consider both spectrum homogeneity and spectrum heterogeneity; in spectrum homogeneity all users have same available channels but in spectrum heterogeneity users have different available channels. Specifically, the ration of user’s available channels to total channels is 0.6 in spectrum heterogeneity and there exists at least one common channel between different users.

Fig. 3 (a) and (b) show the simulation results of cluster size and average utility variation with increasing iterations in

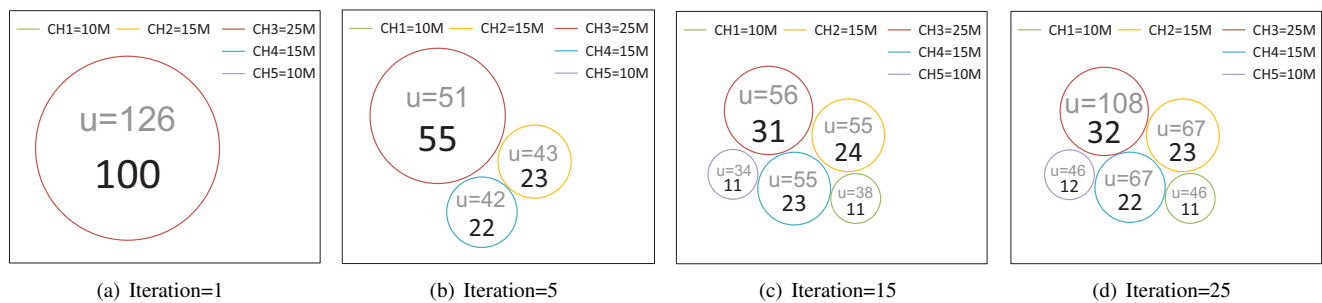
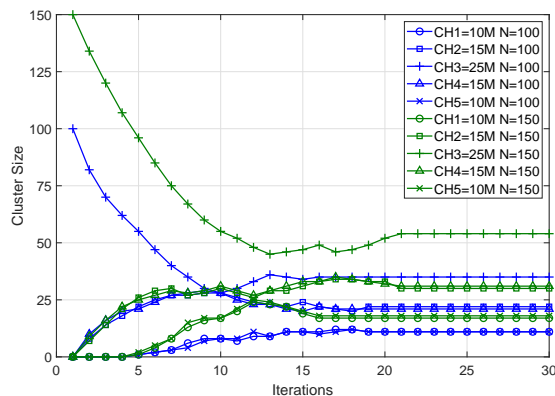
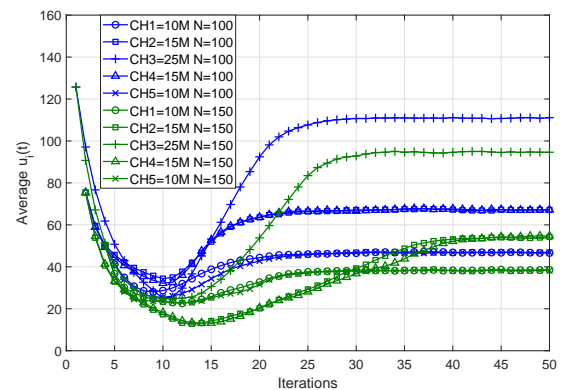


Fig. 2. Example of cluster formation process where $N = 100$ and $M = 5$



(a) Cluster size variation with increasing iterations in $M = 5$ scenario



(b) Average utility variation with increasing iterations in $M = 5$ scenario

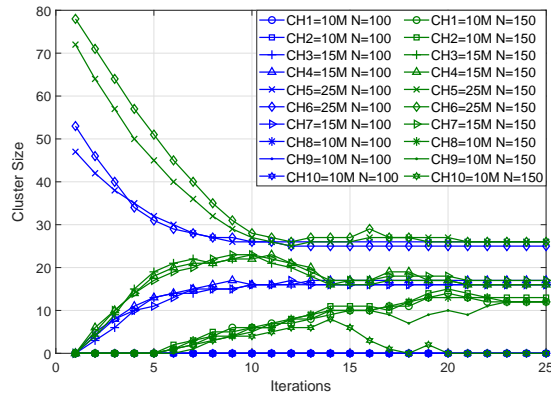
Fig. 3. Simulations of $M = 5$ scenario in spectrum homogeneity

spectrum homogeneity scenario where $M = 5s$, respectively. The average utility is computed by the users on the channel, which indicates the average utility is zero if no user is located on the channel. From Fig. 3 (a), one can find that (1) cluster size of Channel 3 (CH3) drops and (2) cluster size of other channels increase. Such results can be interpreted as follows. All users first choose the 'best' channel (i.e., CH3) that has largest initial utility, but when they all step into the cluster formation process using update rules (i.e., Eq. (9)), some of the users hop on other channels according to $P_{m,i}$ in Eq. (10). Besides, the number of each cluster in $N = 150$ is larger than that in $N = 100$, which shows the adaption performance of the proposed scheme. In Fig. 3 (b), the average utility of every channel first decreases then increases. The reason is that, according to Eq. (9) and Eq. (16), the updated utility will decrease if the cluster size is not the optimal (i.e., the diffused utility is larger than the received stimulus utility); then, according to *Theorem 2*, users tend to form a suboptimal cluster which will result in receiving more stimulus, and thus the average utility increases. It can be observed that the average utility of every channel in $N = 150$ is less than that in $N = 100$. This is due to the fact that when $N = 150$, the number of users need to be located on each channel is

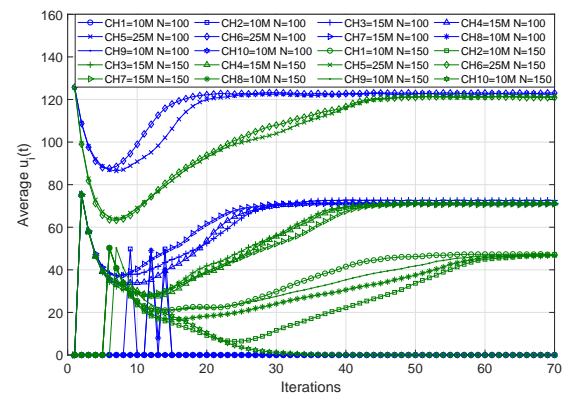
much larger than the optimal cluster size computed by Eq. (11). Correspondingly, it costs more iterations to accomplish cluster formation when $N = 150$, which can also be observed in Fig. 3 (a) and (b).

Fig. 4 (a) and (b) show the simulation results about cluster size and average utility variation with increasing iterations in spectrum homogeneity scenario where $M = 10$, respectively. In Fig. 4 (a), when $N = 100$ the final cluster configuration is composed of CH3, CH4, CH5, CH6 and CH7, which indicates the other channels are 'empty channel' that no user is located on to form clusters. This is because the number of user (i.e., $N = 100$) matches the total sum of optimal cluster size of CH3-CH7. However, when $N = 150$, only the CH10 is the 'empty channel' that is failed to form a cluster⁶. The reason is similar with that in $N = 100$, which is that the number of user (i.e., $N = 150$) matches the total sum of optimal cluster size of CH1-CH9. Besides, one can find from Fig. 4 (b) that the convergence time of $N = 100$ is less than that of $N = 150$. This is mainly because that more users need to be located on more channels to form clusters and thus results in more

⁶In fact, the 'empty channel' can be any channel with bandwidth of 10M. This indicates the 'empty channel' may be not CH10 in some other simulations.

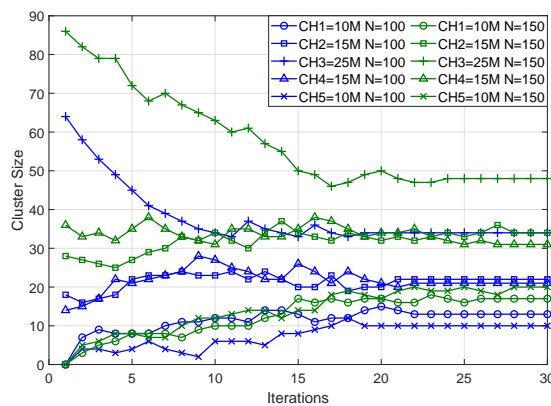


(a) Cluster size variation with increasing iterations in $M = 10$ scenario

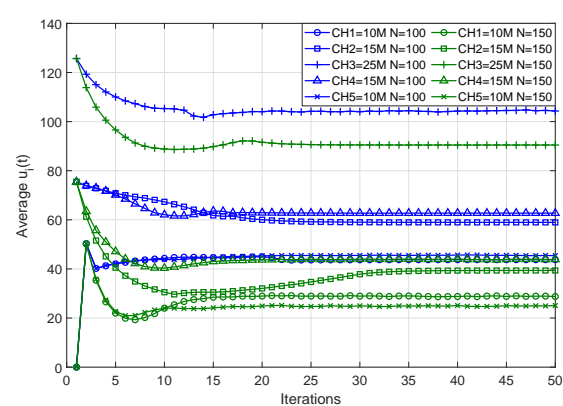


(b) Average utility variation with increasing iterations in $M = 10$ scenario

Fig. 4. Simulations of $M = 10$ scenario in spectrum homogeneity

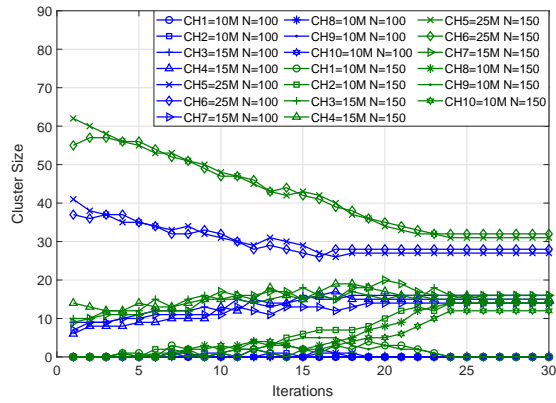


(a) Cluster size variation with increasing iterations in $M = 5$ scenario

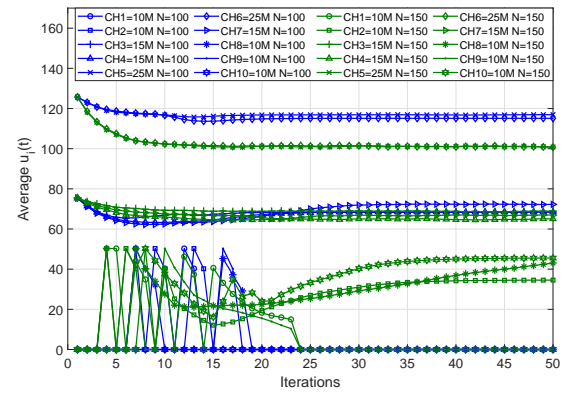


(b) Average utility variation with increasing iterations in $M = 5$ scenario

Fig. 5. Simulations of $M = 5$ scenario in spectrum heterogeneity



(a) Cluster size variation with increasing iterations in $M = 10$ scenario



(b) Average utility variation with increasing iterations in $M = 10$ scenario

Fig. 6. Simulations of $M = 10$ scenario in spectrum heterogeneity

iterations of updating utility.

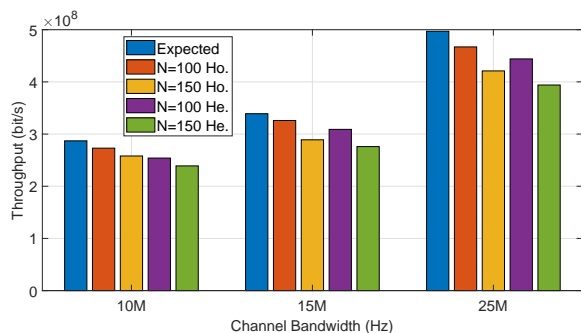
Fig. 5 (a) shows the cluster size variation with increasing iterations when $M = 5$ in spectrum heterogeneity scenario, in which the cluster size fluctuates more in general than that in spectrum homogeneity scenario; while the average utility changes less than that in homogeneity scenario in Fig. 5 (b). The can be explained by the fact that not all users choose the same channel at first due to the spectrum heterogeneity. Hence, users on all other channels except CH3 receive more stimulus at first than that in spectrum homogeneity. However, the spectrum heterogeneity leads to more updates of utility to regulate users hopping on the final cluster.

Fig. 6 (a) shows the cluster size variation with increasing iterations when $M = 10$ in spectrum heterogeneity scenario. Comparing Fig. 6 (a) with Fig. 4 (a), one can find that the final cluster size is generally larger in Fig. 6 (a) than that in Fig. 4 (a) due to that limited channels in spectrum heterogeneity makes users failed to ‘choose’ the ideal one. Fig. 6 (b) shows the variation of average utility with increasing iterations, in which during first several iterations the average utilities of 10M-channels fluctuate more than that in Fig. 4 (b), which can also be explained by the limited channel choices in spectrum heterogeneity.

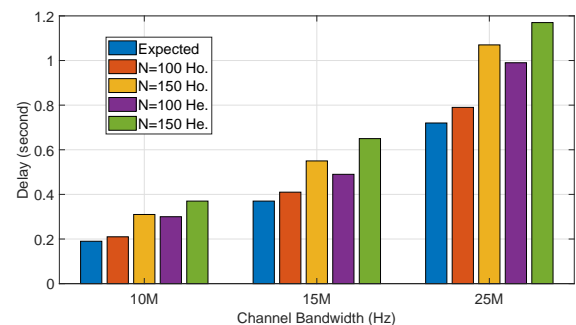
D. Evaluations of throughput and delay

In this subsection, we evaluate the throughput and delay performance respectively in both spectrum homogeneity and heterogeneity scenarios with $M = 5$, $N = 100$ and 150 (i.e., the scenarios are same with Fig. 3 and Fig. 5).

Fig. 7 shows the variation of throughput (a) and delay (b) with channel bandwidth. We observe that the throughput and delay performance, when $N = 100$ in spectrum homogeneity, is most close to the expected performance. The expected performance is achieved by allocating optimal number of users, which is computed by Eq. (11) on the channel (cluster). When $N = 150$, due to the limited number of channels ($M = 5$), the proposed algorithm allocates more users, than the optimal number of users, on the channel (cluster); this results in more collisions causing, thus, a throughput decrease and a delay increase. Fig. 7 (a) shows that throughput increases with bandwidth (see Eq. (5)). Fig. 7 (b) shows that the delay increases with bandwidth; this can be explained by the fact that larger bandwidth attracts more users to form larger size clusters causing, thus, more collisions. In the case of spectrum heterogeneity (i.e., different available channels for users), the cluster size may be not as ‘optimal’ as in the case of spectrum homogeneity. Hence, in general the performance in spectrum homogeneity is better than that in spectrum heterogeneity.



(a) Channel Bandwidth vs. Throughput



(b) Channel Bandwidth vs. Delay

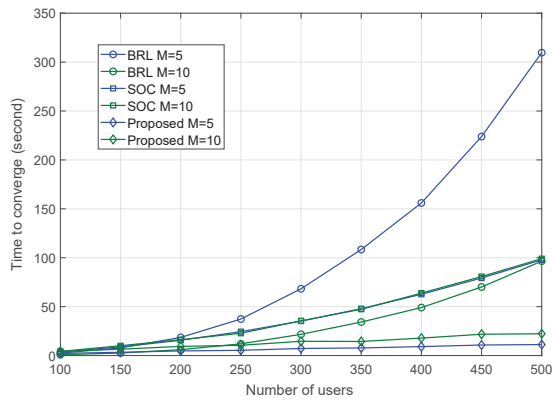
Fig. 7. Simulations of Channel Bandwidth vs. Throughput and Delay

E. Communication Overhead and Convergence Time

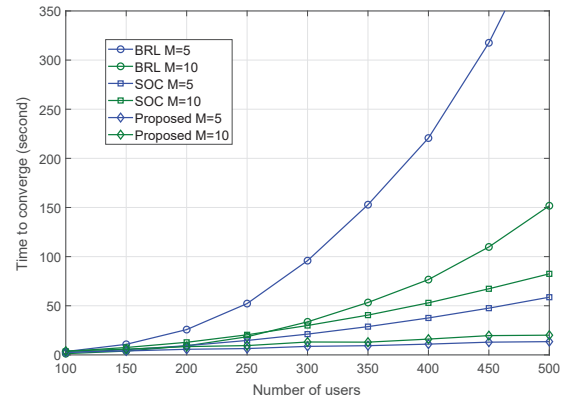
In this subsection, we compare the proposed bio-inspired algorithm with two classic algorithms which are called RBL [18] and SOC [17], in communication overhead and convergence time, respectively. In RBL, D2D users share the spectrum source distributedly by using Bayesian coalition game combined with reinforcement learning, in which a coalition can be viewed as a cluster. The coalition formation process can be summarized to three stages: (1) each user should broadcast its information (e.g., occupied channel, mode, desired base station and etc.) to all other users; (2) one proposer user is randomly selected to propose a new coalition configuration to cluster members, the cluster members need to accept or reject the proposal according to the expected reward computed by using reinforcement learning; (3) the proposer user needs to broadcast the decided coalition configuration to all other users. The stage (2) and stage (3) compose the repeated game loop. In SOC, the clustering problem is formulated as a bipartite graph problem, for which two kinds of tradeoff between number of common channels in a cluster and the cluster size are proposed by using principles of maximum edge biclique graphs and maximum one-sided edge biclique graphs, respectively. To fit the research context in this paper,

we choose the SOC algorithm using the principle of maximum one-sided edge biclique graphs. The cluster formation process in SOC is as follows. At first, each user needs to search for its neighbors by channel-hopping and informing the channel availability; then, each user broadcasts its biclique information to its neighbors. After receiving biclique information from neighbors, the user computes the best biclique and informs its neighbors of the updated cluster membership and the common channel list. Finally, the user whose biclique is selected by its neighbors broadcast all received biclique information to avoid the information inconsistency problem due to limited transmission rang of users in a cluster, and the cluster is formed.

Fig. 8 (a) and (b) show the simulation results of convergence time vs. number of users in both spectrum homogeneity and heterogeneity scenarios. From Fig. 8, one can find that the proposed bio-inspired algorithm consumes the least time to converge comparing with the other two algorithms, especially when the number of user is larger than 200. Generally speaking, the SOC consumes less time to converge than BRL in both spectrum homogeneity and heterogeneity scenarios for $M = 5$ and $M = 10$. The main reason is that, users in BRL need to propose and responds to the proposal, which involves more

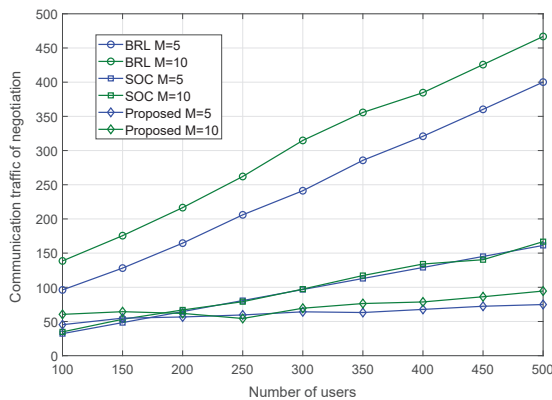


(a) Convergence time vs. number of users in spectrum homogeneity

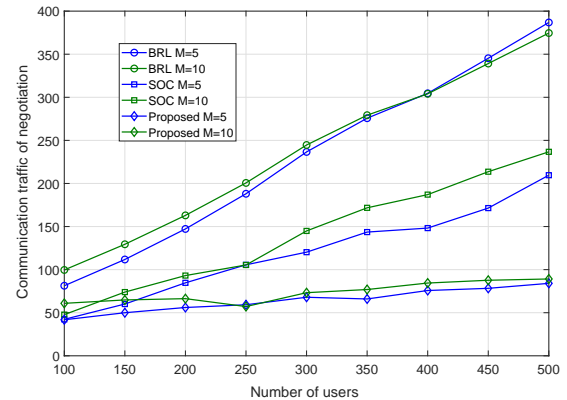


(b) Convergence time vs. number of users in spectrum heterogeneity

Fig. 8. Simulations of convergence time vs. number of users



(a) Communication overhead vs. number of users in spectrum homogeneity



(b) Communication overhead vs. number of users in spectrum heterogeneity

Fig. 9. Simulations of communication overhead vs. number of users

communications (this can be also reflected by simulations in Fig. 9) and thus will lead to more collisions (the collision is severer in $M = 5$ than that in $M = 10$ due to higher user density on each channel in $M = 5$) and communication delay. Besides, in spectrum homogeneity scenario convergence time of $M = 5$ is nearly equal to that of $M = 10$ in SOC. This is because of the channel-hopping scheme designed in SOC that all users need to be time-synchronized so that they can hop on the same channel in same time slot. Hence, all users are in same channel when they exchange information, which indicates that they do not need to hop on different channels. However, in spectrum heterogeneity scenario, users with SOC in $M = 10$ consume more time to converge than that in $M = 5$ due to the fact that they need to hop on different channels to exchange information.

Fig. 9 (a) and (b) show the simulation results of communication overhead vs. number of users in spectrum homogeneity and heterogeneity scenarios. The communication overhead is represented by the communication traffic of negotiation before convergence, specifically, it means the average number of exchanged messages involved in cluster formation process. From Fig. 9, even though the communication overhead of the proposed algorithm is little more than that in SOC when N is less than 200, the overhead is much less comparing with the other two algorithms when N is larger than 200. The main reason that the proposed algorithm consumes less time is that, users using proposed algorithm do not entirely rely on the precise information exchange among them to operate clustering, they also acquire knowledge from ‘collisions’, which means that more collisions represent worse channel quality.

Generally speaking, the simulation results show that in high-density networks, the proposed algorithm outperforms the other two algorithms in both convergence time and communication overhead.

VIII. CONCLUSION

This paper proposes a novel bio-inspired algorithm to distributedly allocate spectrum in cluster-based architecture for CIoT. The connectivity-flexibility tradeoff problem is first formulated by the aim of maximizing clustered throughput and minimizing communication delay. Then, the optimal cluster size is computed by maximizing the formulated utility function that considers possible communication collisions in practice. The bio-inspired algorithm is proposed to regulate CIoT devices to be allocated on spectrum by forming cluster distributedly with tending to optimal cluster size. To provide the adaption of the CIoT to different scenarios and better clustering performance, the optimal parameter configuration is analyzed and derived. Theoretical analysis and simulations validate the proposed algorithm.

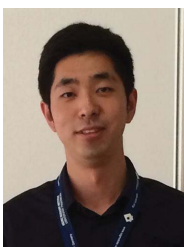
ACKNOWLEDGMENT

This work is supported in part by National Natural Science Foundation of China, under grant No. 61471376.

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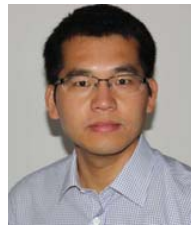
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