Immune System-inspired Evolutionary Opportunistic Spectrum Access in Cognitive Radio Ad Hoc Networks

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Abstract— **Underutilization of licensed spectrum stimulates the opportunistic spectrum access (OSA) paradigm that aims to enable unlicensed users to detect and access the temporarily unused spectrum bands so as to enhance overall spectrum utilization. However, the realization of these paradigms entails several difficulties such as self-organization of unlicensed users, self-regulation of communication parameters, and self-adaptation to time-varying radio environment. In nature, biological systems intrinsically have these great abilities that can be modeled and adopted to overcome the difficulties posed by opportunistic spectrum access. In this paper, a new Immune system-inspired Evolutionary Opportunistic Spectrum Access (ESA) protocol is introduced. Based on the *self-nonself detection and clonal selection principles in immune system*, ESA allows unlicensed users to separately detect, share, and access the available spectrum bands without interfering the licensed users. The overall ESA operations do not need for any priori information about the access statistics of licensed users and also do not need for any coordination and message exchanges among the network nodes. In addition, unlike the existing works, ESA does not require any dedicated control channel in the entire network. Furthermore, ESA also exploits the contention among the nodes and their mobility, if exists, towards accelerating the evolution in the system, and hence, yielding higher overall spectrum utilization. Performance evaluation results show that ESA achieves high throughput under various network conditions.**

Index Terms— **Cognitive radio, spectrum sharing, spectrum management, immune system, clonal selection.**

I. INTRODUCTION

UNDERUTILIZATION of wireless spectrum stimulates cognitive radio ad hoc networks (CRAHNs) aiming to enable unlicensed ad hoc users to opportunistically access unused licensed spectrum [1]. The term Opportunistic Spectrum Access (OSA) [3] is broadly used to identify a such kind of overlay spectrum access, in which unlicensed users, i.e., secondary users (SU) detect and access the temporarily unused spectrum bands legitimately licensed to primary users (PU). OSA mainly includes three operations:

- *Spectrum opportunity identification* (SI) aims to identify and intelligently track temporally unused spectrum bands to allow each SU to decide whether a spectrum band is temporally accessible or not.
- *Spectrum sharing* (SS) enables SUs to intelligently allocate the spectrum opportunities to minimize perceived interference level so as to maximize utilization.
- *Spectrum access* allows SUs to access the identified spectrum opportunities to maximize the throughput achieved.

Beside its promising spectrum utilization capabilities, OSA incurs many additional challenges on the conventional access technologies. For example, SI includes scanning and sensing the available channels to determine whether a channel is accessible. However, this process brings significant overhead into the secondary communication in terms of time and energy consumption. Moreover, SI is prone to some inaccurate observations of SUs about channel availability. These wrong observations may impose excessive interference on the licensed communication. Unshared spectrum opportunities may also yield high interference among the SUs and the overall spectrum utilization inevitably decreases. Thus, the efficient SI, SS, and spectrum access mechanisms are imperative to allow SUs to effectively communicate over the temporarily unused spectrum bands [2].

In nature, biological systems maintain their normal operations in absolutely random and continuously changing environments by means of their *self-organization*, *self-adaptation*, and *self-regulation* capabilities. For example, immune system is a natural defense mechanism to protect organism against pathogens. The aim of immune system is to detect and eliminate the pathogens. Immune system first reliably detects and discriminates the pathogens from self-molecules of the body, e.g., other blood cells or beneficial vitamins and minerals. These operations are intrinsically exposed to many detection and discrimination faults as well. However, immune system can amazingly tolerate the possible detection and discrimination faults via *self-nonself identification mechanism* [4].

Immune system has also an evolutionary instrument called *clonal selection mechanism* (CSM) allowing its cells called B-cells and T-cells to dynamically change their genetic shapes to genetically recognize and eliminate the pathogens. CSM can also improve its genetic recognition talent such that as diversity of infections increases, the organism and immune system become more robust toward a large set of new infections.

Clearly, the capabilities of immune system give great inspiration for the development of many efficient evolutionary algorithms such as network intrusion detection [5], multi-objective function optimization [6], [7] and fault diagnosis

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[8]. Moreover, based on natural immune system principles, in [9], distributed node and frequency rate selection (DNRS) algorithm is proposed for energy-efficient and reliable communication in wireless sensor networks. In this paper, to harness the great natural capabilities of immune system we develop an evolutionary opportunistic spectrum access (ESA) algorithm.

A. Related Work

Various OSA protocols in current literature are generally categorized according to their control information exchange strategies divided mainly to two different types. In [10], [11], [12], and [13], a dedicated control channel is used to exchange control information. However, a single dedicated control channel may be a bottleneck when primary users frequently use this channel. In [14], [15], time slots are divided into control and data phases. In the control phase, control information are exchanged using a single dedicated channel. However, in the data phase, data transmission is carried out using the channels negotiated in the control phase. In this approach, the dependency to a single dedicated channel is alleviated because of exchange of only the control information on the single control channel.

In addition to control information exchange strategies, the existing OSA protocols also differ in terms of SI strategies. In fact, some can identify spectrum opportunities [10], [11], [12], [14], while others acquire this information from an external entity. However, dependency on an external entity is a major barrier for the realization of OSA in CRAHNs.

Beside the existing OSA algorithms, some bio-inspired mechanisms are also developed for some spectrum sharing and management problems in cognitive radio based OSA scenarios. In our previous works, some biological systems are investigated to discover their promising properties that can be harnessed to develop efficient algorithms in cognitive radio networks (CRN) [17]. Based on the task allocation phenomenon in an insect colony, a spectrum sharing mechanism is proposed to enhance spectrum utilization [16]. In [18], similarly, some resource allocation mechanisms adopted from insect colonies are used for cognitive wireless networks.

None of the existing OSA protocols simultaneously provides SI, SS, and spectrum access. Lack of a spectrum sharing mechanism severely reduces the spectrum utilization. These protocols are also subject to possible congestion in the single control channel. Moreover, they consider highly static network models in which a fixed number of immobile nodes opportunistically access the available spectrum bands which is not practical for CRAHNs.

B. Contributions

In this paper, immune system based Evolutionary Opportunistic Spectrum Access (ESA) protocol is introduced. Based on the principles of self-nonself identification and CSM, ESA concurrently provides efficient SI, SS and spectrum access operations for SUs in CRAHNs. The salient features of ESA are outlined as follows:

- Unlike all the existing OSA mechanisms using single dedicated control channel that may hamper all SU communications, ESA enables SUs to use all available channels to exchange control information.
- ESA is error-tolerant to provide the resilient identification of all spectrum opportunities despite potentially erroneous spectrum sensing measurements.
- ESA allows SUs to employ optimal spectrum sharing and access strategies to maximize overall spectrum utilization.
- ESA quickly incorporates the changes in the network like node mobility or new node arrivals adaptively.
- ESA is an evolutionary algorithm that can surprisingly improve its performance as contention and also interference among SUs increase. This is a fascinating feature for OSA domain such that undesirable situations such as interference or node mobility can be harnessed to improve network robustness via the evolution of network nodes.
- ESA is an autonomous algorithm that does not need any coordination among network nodes for SI and SS and it also does not need any priori information about the channel access statistics of primary users.

The remainder of this paper is organized as follows. In Section II, we discuss the analogies and similarities between immune system and OSA. Based on these similarities, in Section III, we introduce an evolutionary OSA model and ESA protocol operations. In Section IV, we present the performance evaluation results, which are followed by the concluding remarks given in Section V.

II. IMMUNE SYSTEM AND OPPORTUNISTIC SPECTRUM ACCESS

Here, we first introduce the immune system, then, discuss its relation with OSA.

A. Biological Immune System

The natural immune system is a complex defense mechanism that protects the organism from hazardous molecules or micro-organisms. This complex task can be accomplished by specific blood cells called B-cells and T-cells in immune system. When an organism is exposed to antigen molecules, B-cells and T-cells cooperatively detect and eliminate the antigens through *self-nonself detection* and *CSM* [6].

Self-nonself detection mechanism can be considered as a distributed detection mechanism in which B-cells are envisaged as small independent detectors that diffuse through the organism in the blood [4]. Detection of antigens can be achieved when the genetic shape of an B-cell chemically matches with an antigen genetic shape. However, due to the huge diversity in B-cell genetic shapes, it is highly likely for B-cell to match with the self-cells of the organism. Although this is a fatal dilemma for the organism, immune system has the great error-tolerance capability to avoid this fatal dilemma. This is accomplished through thymus that is an organ and includes most self-molecules of the organism and in which B-cells genetically mature. During this maturation process, if an B-cell matches with some self-molecules in the thymus, it is eliminated to avoid eliminating self-cells of the organism.

While the self-nonself detection mechanism discriminates antigens from self-molecules of the organism, CSM concurrently allows B-cells to recognize genetic shape of antigens by means of *affinity maturation* and *hypermutation* phenomenon. Hypermutation separately enables each antibody to change its genetic shape. As the genetic change can improve the matching between the antibody and antigen, affinity maturation process allows the B-cells having the best matching with the antigen to proliferate so as to genetically recognize and eliminate the antigen. The genetic shape of B-cells that having the best matching with the pathogen can be considered as an *elitist genetic shape* that is no longer mutated and is memorized by continuously proliferating in the course of life time. This *elitist selection mechanism* provides great robustness for organism. Moreover, this mechanism gives great inspiration for the development of immune system based multi-objective function optimization algorithms [6], [7]. Next, we introduce some advantageous analogies between immune system and OSA.

B. Immune System and Opportunistic Spectrum Access

Although OSA seems different from the natural immune system, they have great deal of intrinsic analogies in terms of operation principles. When immune system encounters a molecule, it determines whether this molecule is a nonself harmful pathogen by means of *self-nonself identification mechanism*. If the molecule is determined as a pathogen, immune system recognizes and eliminates the pathogen using *clonal selection mechanism*. Similar to self-nonself identification in immune system, OSA needs a detection mechanism to identify spectrum opportunities. Moreover, similar to clonal selection in immune system, OSA also needs a selection mechanism to enable each SU to choose and access a set of spectrum opportunities so as to maximize spectrum utilization.

In addition to the operational analogies, some attributive analogies between immune system and OSA are as follows:

- Immune system is a highly robust system since it is diverse and error-tolerant. For OSA, it is also essential to provide robust opportunistic spectrum access via diversity and error tolerance. Diversity in channel availability improves the OSA performance in terms of achieved throughput and interference level. Error tolerance in channel sensing provides great robustness in terms of interference level incurred on primary users.
- Immune system is adaptive to recognize and learn new infections. Immune system achieves this adaptivity by improving useful genetic shapes and discarding useless or dangerous ones. Similarly, OSA should be adaptive to recognize and learn channel access pattern of primary users. This can be accomplished by discarding useless channels, on which primary user activities are high, and selecting other fruitful spectrum channels on which primary user activities are minor.
- Immune system is a fully autonomous system which does not need any central control to perform its fascinating steps. Similarly, OSA needs autonomous operations to alleviate the coordination latency overhead and to make spectrum access more robust.

In order to harness the operational and attributive advantages of immune system, we establish the following analogies between immune system and OSA outlined in Table I.

TABLE I
RELATION BETWEEN IMMUNE SYSTEM AND CRN.

Immune System	**Opportunistic Spectrum Access**
B-cell	Secondary user
Genetic shape of antibody	Frequency hopping sequence of SU
Antigen	Spectrum opportunity
Self-nonself identification	Spectrum opportunity identification
Clonal selection via somatic hypermutation and affinity maturation	Spectrum sharing and access

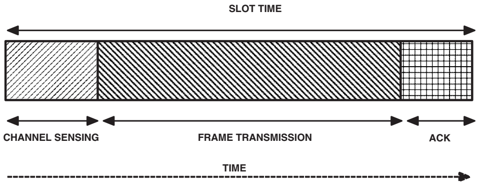

Fig. 1. The time slot structure of a secondary user.

III. IMMUNE SYSTEM BASED EVOLUTIONARY OPPORTUNISTIC SPECTRUM ACCESS

In this section, we present Immune System Based Evolutionary Opportunistic Spectrum Access (ESA) protocol based on the analogies between immune system and OSA. Before giving the details of ESA, we introduce the network model and assumptions and also give a brief overview for ESA.

A. Network Model and Assumptions

We consider a network model in which entire spectrum is divided into number of N non-overlapping orthogonal channels having the same bandwidth. Number of M mobile SUs may randomly arrive or depart without any need for a negotiation among SUs. Slot timing is broadcast to SUs by the primary system. Each slot lasts for $\tau\ seconds$. ESA splits a time slot into three phases as shown in Fig. 1. In the channel sensing phase, each SU randomly selects a number of channels less than N and senses them using the energy based channel sensing [20]. In the data transmission phase, each SU intending to transmit makes data transmission. After the data transmission phase, each SU sent data packet waits for an ACK frame from its receiver SU. Each of these three phases consecutively occur in every $\tau\ seconds$.

All SUs use fixed length frequency hopping sequences (FHS). FHS_i denotes the FHS of SU_i composed of K distinct frequency channels where $K \leq N$. In each time slot, SU_i consecutively hops on FHS_i to transmit or receive data frame. As will be detailed in Section III-D, each transmitter SU can handshake with a receiver SU to tune its FHS.

B. ESA Overview

ESA concurrently perform SI, SS and spectrum access operations. It enables each SU to resiliently identify all spectrum opportunities based on the entropy based channel availability information acquired by channel sensing. This information can be reinforced to tolerate possible channel sensing errors. Based on the channel availability information, each SU generates its

FHS including the channels on which PU activities are minor maximizing overall spectrum utilization.

For spectrum sharing and access, ESA allows each SU to mutate its FHS separately to generate an optimal spectrum sharing and access performance based on a clonal selection based distributed immune algorithm. For this optimization, each receiver SU first interacts with the environment by means of channel sensing and listening and receiving. This interaction lasts for a *mutation interval* that is a specific number of slots and preselected by ESA. During the mutation interval, each receiver SU gathers information from the radio environment to infer which of its frequency hops are exposed to interference. Based on this information, it mutates its FHS at the end of the mutation interval. If a receiver SU does not receive any interference, it stops the mutation operation on its FHS and its FHS becomes an *elitist* FHS. When all receiver SUs have an elitist FHS, the spectrum sharing process converges to a global optimum point maximizing the spectrum utilization.

Next, we detail the ESA operations for SI, SS and spectrum access, which can also be seen in Fig. 3.

C. Spectrum Opportunity Identification

SI in ESA is based on the principles of self-nonself identification in immune system. Immune system enables each B-cell to separately discriminate a harmful pathogen from self-cells of the organism. This discrimination is based on natural maturation process in which each B-cell is matured to infer whether it is useful to eliminate pathogens. This provides great error-tolerance for the identification errors by reinforcing the information about self and non-self cells. Similar to immune system, ESA allows each SU to separately infer whether each spectrum channel can be useful for transmission or not. This is accomplished by the *spectrum opportunity maturation process*. This process empowers each SU_i to reinforce channel availability information for each channel j as follows.

- Whenever SU_i senses channel j, it keeps a channel availability information about channel j using its *idle and busy counters*, i.e., I_i^j and B_i^j, respectively.
- If SU_i senses channel j as idle, it updates the idle counter I_i^j as $I_i^j = I_i^j + 1$.
- If SU_i senses channel j as busy, it updates the busy counter B_i^j as $B_i^j = B_i^j + 1$.
- Based on the updated I_i^j and B_i^j, SU_i computes the probability, i.e., p_i^j, that channel j is available for SU_i, as follows
$$p_i^j = \frac{I_i^j}{I_i^j + B_i^j} \tag{1}$$
- To characterize the uncertainty in the availability of channel j, SU_i also computes *channel identification entropy*, i.e., H_i^j, for channel j as follows
$$H_i^j = -\Big(p_i^j log_2(p_i^j) + (1-p_i^j) log_2(1-p_i^j)\Big) \tag{2}$$
- SU_i computes H_i^j for all available channels and sorts H_i^j, $\forall j$ in ascending order and accordingly, generates the set T_i that includes the channel IDs arranged according to the sorted channel identification entropies.
- T_i includes all channel IDs for SU_i from the most accessible to the least accessible such that $T_i(1)$ is the ID of a channel that is the most useful and accessible for SU_i to maximize spectrum utilization.

Next, ESA spectrum sharing, access method is presented.

D. Spectrum Sharing and Access

Based on the principles of CSM in immune system, ESA allows each SU to separately share and access the spectrum opportunities that are identified by SI given above. In immune system, to recognize and eliminate a pathogen, each B-cell mutates its genetic shape in a way that it improves some genetic patterns having best matches with the genetic shape of the pathogen. Genetic mutations are based on the some interactions between B-cells and the pathogen. As these interactions increase, the rate of the genetic mutations also increases to recognize and eliminate the pathogen. Similarly, ESA allows each SU to generate a frequency hopping sequence (FHS) like the genetic shape of B-cells. Let FHS_i is the frequency hopping sequence of SU_i. Each FHS is a fixed length string composed of some channel IDs. Similar to a B-cell in the immune system, each SU_i can mutate FHS_i based on the some interactions with the radio environment such as listening it or transmitting to an intended receiver.

ESA provides the receiver centric spectrum sharing such that each receiver SU mutates its FHS to avoid possible interferences and to share the spectrum opportunities efficiently. The interference avoidance can be only possible for each SU if it can gain a FHS not overlapping with other SU's FHSs via mutations. In Fig. 2, mutations for M receiver SUs are observed. The mutations can be modeled as an optimization process subject to

$$\text{minimize} \ \sum_{i=1}^{M} \sum_{j \neq i}^{M} \sum_{l=1}^{K} \Big[1 - \text{sgn}\Big(|FHS_i(l) - FHS_j(l)| \Big) \Big] \tag{3}$$

where $sgn(.)$ is the sign function M is the number of receiver SU in the environment, K is the number of channels in each FHS and $FHS_i(l)$ denotes the l^{th} channel of the FHS sequence of SU_i. ESA performs this optimization process similar to the clonal selection based optimization procedures [6], [7] and each SU_i separately performs the following operations,

- During a *mutation interval*, SU_i senses the radio environment and receives the transmissions from the transmitter SUs to infer the interferences on its frequency hops.
- SU_i determines its frequency hops on which it perceives interference from the radio environment. This means some overlapping frequency hops among some SUs.
- If SU_i receives interference on some of its frequency hops, it randomly mutates these hops on FHS_i by randomly flipping these frequency hops.
- If SU_i does not receive any interference on its all frequency hops, it sets its frequency hopping sequence FHS_i as an elitist FHS. Similar to clonal selection based optimization algorithms [6], [7], elitist set selection allows the convergence of the spectrum sharing algorithm.

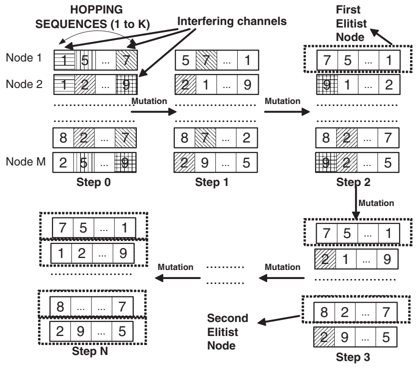

Fig. 2. Spectrum access and sharing by the mechanisms of FHS generation using mutation and elitist selection.

- Until all FHS become elitist, the mutations continue.

After each FHS becomes the elitist, the spectrum sharing operations are naturally terminated. At the optimal point, since all frequency hops do not overlap, SUs can no longer collide and interfere with each other providing significant spectrum utilization for the opportunistic communication. All mutation and elitist FHS selection operations are illustrated in Fig. 2.

In addition to the simulation analysis given in Section IV for the convergence of the spectrum sharing, here, we also briefly prove it as follows. Let us assume that we concatenate all FHS sequences of receiver SU to form a single large FHS sequence, i.e., $\overline{\text{FHS}}$=(FHS$_1$ FHS$_2$...FHS$_L$), where L is the number of receiver SUs. Since each FHS has the length K, the length of $\overline{\text{FHS}}$ is KL. We also assume that there exists an optimal sequence $\overline{\text{FHS}}_{opt}$ with length KL that can optimize the objective function given in (3). Hence, if there are c mismatches between $\overline{\text{FHS}}_{opt}$ and $\overline{\text{FHS}}$, the probability of convergence, i.e., P_c, can be given as [19]

$$P_c = \frac{c!}{K(K^2 - K)^c} \tag{4}$$

P_c shows that the spectrum sharing algorithm is convergent. However, elitist set selection is imperative for the convergence of all immune system based optimization algorithms [19]. Since the mutations are separately performed and elitist FHSs are dynamically generated by each SU, immune system based algorithm strictly converges to the global optimal point. Convergence of artificial immune system algorithms requires a strict elitist selection mechanism [19] such that the artificial immune system algorithm is convergent if an elitist set selection mechanism is used. Hence, due to its elitist FHS selection mechanism ESA is also a convergent algorithm. Although its convergence is not analytically proved in the paper, by means of the simulation results in the performance evaluation part, it is easily shown that ESA is convergent.

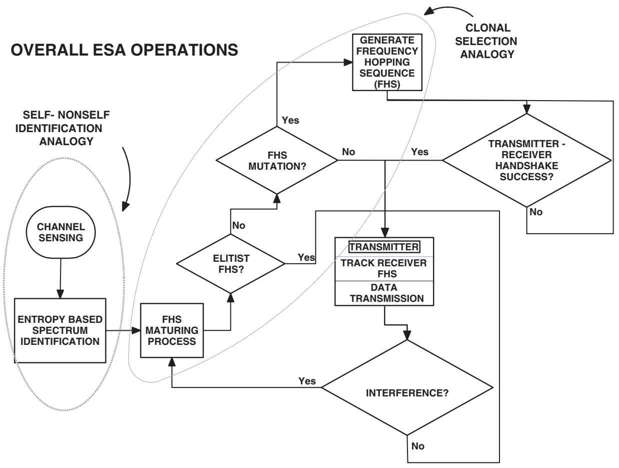

Fig. 3. Overall ESA operation is illustrated with SI, SS, and spectrum access. All protocol steps can be easily tracked and it is seen how and which parts of ESA operation gives inspiration from the principles of immune system.

TABLE II
COMPARISON OF DISTRIBUTED OSA MAC PROTOCOLS [21].

Protocol	**Spec. ID.**	**Spec. Sharing**	**CC Type**	**Scan**	**# of RFE**	**MRCC**
DOSS [10]	√	-	Dedicated	√	3	-
SCA-MAC [22]	-	-	Dedicated	√	2	-
C-MAC[12]	√	-	Dedicated	√	1	-
AS-MAC [11]	√	-	Dedicated	√	1	-
ESCAPE [23]	-	-	Dedicated	√	1	-
DC MAC [24]	-	-	Dedicated	√	1	-
HC-MAC [13]	-	-	Dedicated	√	1	-
BB-OSA [25]	-	-	Dedicated	-	1	-
OS-MAC [26]	-	-	Dedicated	-	1	-
HD-MAC [14]	√	-	Split Phase	√	1	-
SRAC [15]	-	-	Split Phase	-	1	-
Evolutionary Spectrum Access (ESA)	√	√	***MRCC***	√	***1***	√

For the spectrum access, each transmitter SU also generates FHS including some channels on which PUs do not frequently transmit. In the first phase, each transmitter SU struggles to handshake its intended receiver SU. For this handshake, each transmitter user transmits a Request-To-Sent message (RTS) in a way that it hops on its FHS. When the transmitter SU achieves to deliver a RTS packet, its intended receiver immediately sends a CTS frame including its FHS. This allows the transmitter SU to handshake with its receiver and to track its FHS. However, as presented above, the receiver SUs mutate their FHSs. Therefore, the previously achieved handshakes between the transmitter and receiver SUs are corrupted in the case of the mutations in the FHS of receiver SUs. In this case, the transmitter SU retries to handshake with its receiver SU. However, once the receiver SUs complete the spectrum sharing operation such that all FHS become elitist, SU handshakes no longer suffer from the mutation in receiver SUs.

IV. PERFORMANCE EVALUATION

In this section, the performance of the ESA algorithm is investigated. We first present an overview of the existing OSA techniques in the current literature, and discuss the advantages of ESA with respect to them. Then, we present simulation experiment results of ESA protocol in terms of wide range of performance metrics. Finally, we perform numerical error tolerance analysis of ESA to the inaccuracy in SI process.

A. Overview of Existing OSA Mechanisms

The performance analysis is made for comparison with other OSA protocols. In [21], a comprehensive performance comparison of the existing solutions are presented. In Table II, the existing OSA algorithms are compared with ESA according to their various properties such as dedicated channel type and number of radio-front-ends [1].

As observed in Table II, ESA has a number of advantages with respect to others. First of all, ESA is a unique protocol concurrently performing SI and SS, in addition to default CR functionalities such as channel scanning for spectrum sensing. ESA has also a completely different control information exchange strategy from other OSA such that ESA enables the control information exchanges using all available channels, i.e., multiple rendezvous control channel (MRCC) [21], while others use a single control channel, which would be a major barrier under congestion by PU transmissions. Furthermore, ESA requires only a single radio-front-end (RFE) since it splits the channel sensing and data transmission phases in time domain. Consequently, ESA unifies several salient features.

B. Simulation Experiments

Here, we show the performance of ESA and compare it with generic OSA methods capturing the main features, i.e., SI and SS. The ones making only SI identify the available spectrum channels ordered with respect to entropy and choose K of them. The ones additionally making SS choose the spectrum channels collaboratively with each other but without changing the resulting sequences over time. Simulation experiments are performed in MATLAB. Unless otherwise explicitly stated, in total $N = 10$ channels are used among 10 nodes, half of which are ad hoc opportunistic transmitters and each transmitter is assumed to have a specific target receiver with a single-hop networking topology. The nodes use $K = 6$ hops in FHS and listens to 6 channels in order to collect the entropy information as explained in Section III. The channels are assumed to be independent with bandwidth $B = 1$. Throughput performance of ESA is measured in terms of PU channel access probability, number of channels available, number of SUs. In addition, the fairness analysis of ESA, its collision probability as well as its performance under high node mobility are also presented.

1) Throughput vs. PU channel usage: We vary the PU channel access on-off probability and observe the effect on throughput. It is expected that the nodes using the PU channels are affected much more than the ones utilizing the channels that PU does not reside in. As shown in Fig. 4(a), throughput achieved with ESA is much higher than both cases that do not intelligently share the available channels. In addition, ESA is not affected by increasing PU channel access probability due to its evolutionary mechanism which converges to an optimal spectrum access as explained in Section III. The observed advantages are because of adaptive use of channels in order to utilize spectrum holes by using entropy information and distributing the acquired resources in an efficient manner.

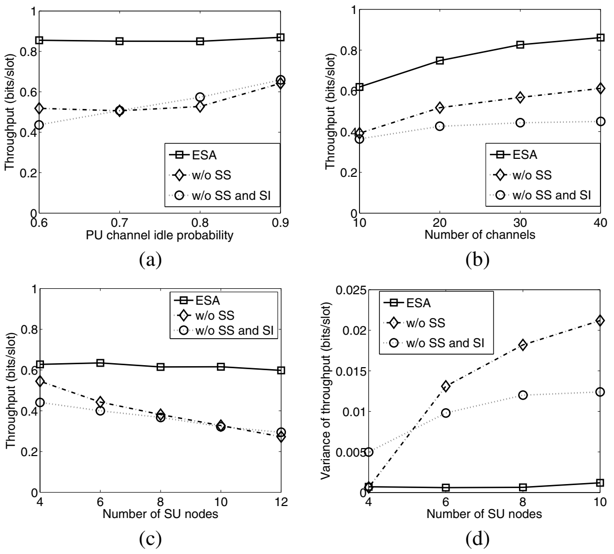

Fig. 4. The throughput and the fairness of ESA algorithm compared with the algorithms making only SI and making SI and SS. The throughput for (a) varying primary user channel idle probability where $N = 40$, (b) varying number of channels used, (c) varying number of nodes in the network, and (d) the fairness for varying number of nodes.

2) Throughput vs. Number of available channels: Secondly, the effects of changing the number of channels on the throughput are observed. As it can be clearly seen in Fig. 4(b), overall throughput increases with the number of channels as expected. However, in all cases, the full utilization of the channel resources is best exploited by ESA algorithm with SI and SS incorporated. The reason is that with a balanced and adaptive use of resources overall throughput is leveraged.

3) Throughput vs. Number of SUs: Throughput performance of evolutionary and bio-inspired nature of ESA algorithm is observed by varying the number of nodes. In any biological process the self-adaptation achieves efficient response to the dynamically varying size of the system autonomously.

As it is observed in Fig. 4(c), ESA without SI and SS are severely affected by the increasing number of contending SUs. However, due to CSM, the collisions among the new SUs are mitigated, and the high throughput is maintained regardless of the increasing demand.

4) Fairness: Here, we investigate the fairness performance of ESA protocol in terms of opportunistic distribution of spectrum resources. The variance of the throughput achieved by individual SUs is used as the fairness metric. As shown in Fig. 4(d), if SS and SI were not used, the throughput variance significantly increases with the number of SUs. As also outlined in Table II, this is, in fact, the case of majority of the existing OSA mechanisms in the literature. However, ESA protocol, with its immune system-inspired SI and SS mechanisms, maintains relatively constant and very low throughput variance. This reveals that ESA provides fair share of spectrum as well.

5) Collision Probability: In Fig. 5, overall collision probability is observed during a course of ESA operation. As explained in Section III, ESA enables receiver SUs to hypermutate their FHS to optimally share the available spectrum

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[1] A more comprehensive performance comparison of these existing mechanisms can be found in [21].

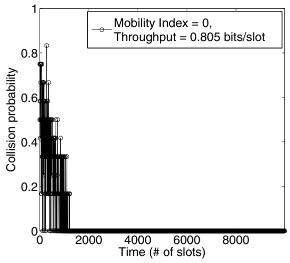
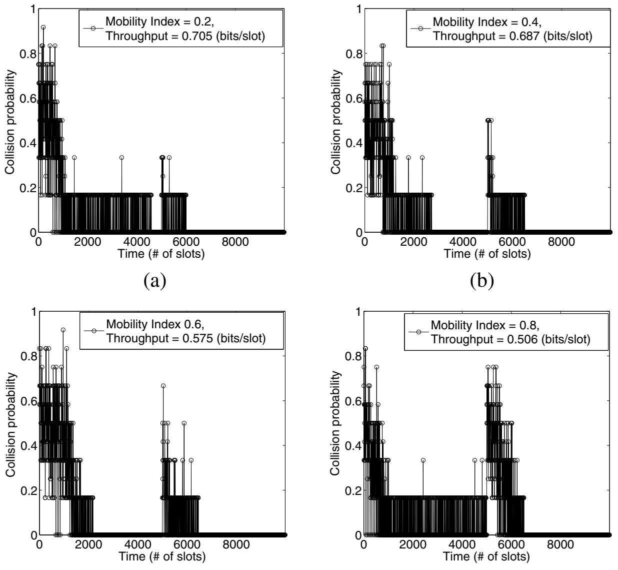


Fig. 5. Collision probability, and the convergence of ESA algorithm.



(a) (b)

(c) (d)

Fig. 6. The throughput performance with respect to the effect of mobility over time. (a) Mobility index = 0.2 (b) Mobility index = 0.4 (c) Mobility index = 0.6 (d) Mobility index = 0.8.

bands with the minimum collision probability. This optimal point can be easily observed in Fig. 5 such that ESA completely avoids all possible collisions and reaches to the optimal point in which SUs no longer observes collisions. Note also that in Fig. 6, all x-axes implicitly correspond to time since the duration of each time slot is fixed to a τ $seconds$. For example, τ is selected as $1ms$, the convergence of ESA can be achieved within approximately 5 $seconds$. Hence, based on the evolutionary mutation mechanisms over FHS of SUs ESA significantly improves overall collision probability regardless of initial state of the network.

6) Node Mobility: Here, we investigate the effects of mobility in the CRAHNs on the performance of ESA protocol. To this end, we define an evaluation variable, i.e., *mobility index* representing the ratio of the mobile SUs in the network. Here, a number of SUs randomly change their locations with a random velocity. Hence, as the mobility index increases, the network becomes more mobile. In Fig. 6(a),(b),(c), and (d), the variation of the collision probability with time for the case of mobile nodes with a varying mobility index value is shown.

In Fig. 6(a), the network is initially set as immobile and the mobility index is set as 0 for a specific number of slots. In this interval, ESA completely avoids overall collision probability after approximately 5000 time slots. After the convergence, the 20% of the nodes start moving, i.e., the mobility index 0.2. At this point (approximately between slot 4000 and 5000), previous FHS are invalidated by the SU mobilities and collision arises. However, ESA can easily recover the network from the collisions by re-initiating evolutionary hypermutations as observed Fig. 6(a).

In Fig. 6(b), (c), and (d), the same immobile and mobile network states are consecutively set using the mobility index 0.4, 0.6, and 0.8, respectively. As the mobility index increases, the achieved throughput decreases, due to inevitable but temporary collision. However, in all cases, the ESA protocol operation converges to very low collision probability case regardless of the mobility level in the networks.

Moreover, an evolutionary feature of ESA can be observed in the convergence behavior in Fig. 6(b), (c), and (d). If the convergence time lasts for relatively a long time in the immobile phase of the network, the network converges more quickly after the mobile phase of the network. Conversely, if the convergence lasts for a small amount of time, it struggles for a relatively longer time to converge to a low collision state. This is an evolutionary mechanism such that the robustness against the undesirable situations such as node mobility and interference can be improved with more exposition to these undesirable situations for a relatively long time.

C. Error-tolerance to Inaccuracy in Spectrum Identification

Since spectrum sensing process is prone to false alarm and mis-detection probabilities, SI needs to be resiliently performed in order not to interfere PUs and to maximize spectrum utilization. Similar to error-tolerant self-nonself identification mechanism in immune system, ESA allows each SU to separately tolerate the identification errors by reinforcing the information about SI. Here, we analytically investigate this case using the Gaussian channel model.

When a SU senses a channel, the received signal can be evaluated as [20]

$$x(t) = \begin{cases} n(t), & H_0 \\ s(t) + n(t), & H_1 \end{cases} \tag{5}$$

where H_0 and H_1 are the hypotheses corresponding to idle and busy channel cases, respectively. $s(t)$ is the communication signal and $n(t)$ is a zero-mean Gaussian noise.

The output of the energy detector, i.e., Y, has the Chi-square distribution that can be approximated as a Gaussian distribution [20]

$$Y \approx \begin{cases} \mathcal{N}(n\sigma_n^2, 2n\sigma_n^4), & H_0 \\ \mathcal{N}\Big(n(\sigma_n^2 + \sigma_s^2), 2n(\sigma_n^2 + \sigma_s^2)^2\Big), & H_1 \end{cases} \tag{6}$$

where n is the number of samples, σ_s^2 and σ_n^2 are the variance of signal $s(t)$ and noise $n(t)$. If we assume that a PU accesses the sensed channel with probability p_a, using (6) false alarm p_f and mis-detection p_m probabilities can be given as

$$p_f = p_a\bigg(1 - Q\Big(\frac{\lambda - n(\sigma_n^2 + \sigma_s^2)}{\sqrt{2n(\sigma_n^2 + \sigma_s^2)^2}}\Big)\bigg) \tag{7}$$

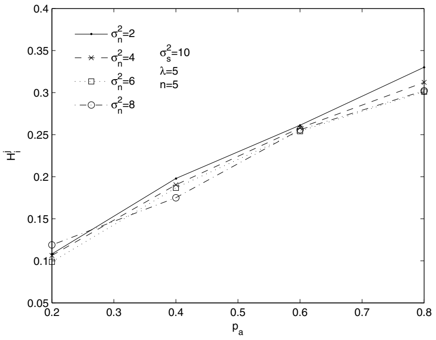


Fig. 7. H_i^j with respect to varying p_a for different σ_s^2 to show the error tolerance capability of ESA.

$$p_m = (1 - p_a) Q\Big(\frac{\lambda - n\sigma_n^2}{\sqrt{2n\sigma_n^4}}\Big) \tag{8}$$

where $Q(.)$ is the Q-function and λ is the detection threshold of the energy detector. In order to show the error tolerance of ESA to potential inaccuracies in spectrum identification process, in Fig. 7, we plot the spectrum identification entropy for a channel, i.e., H_i^j in (2), with respect to channel access probability of PUs for this channel, i.e., p_a. Despite increasing p_a and channel noise variance σ_s^2, ESA provides the resilience SI. For the case in which p_a is high, H_i^j becomes also high. However, as p_a decreases, H_i^j becomes smaller. This allows each SU to separately identify the spectrum opportunities with smaller H_i^j in which PU activities are minor. Entropy-based SI is not affected by the probabilities of false alarm and mis-detection in channel sensing although noise variance increases. This shows the error tolerance capability of ESA to the inaccuracy in SI.

V. CONCLUSION

In this paper, we introduced a new bio-inspired OSA mechanism, i.e., immune system-inspired evolutionary spectrum access (ESA), for CRAHNs. We have shown that immune system-inspired opportunistic access mechanism has many advantages coming naturally form the inspired process. The efficient, fair and high-level usage of resources are succeeded by ESA with the mechanisms of inspired self-nonself detection and clonal selection. These natural methods make the system self-organized, self-adapted and self-regulated resulting in an evolutionary OSA system. Furthermore, unlike the existing OSA mechanisms, ESA does not require a single dedicated control channel. The performance analysis results show that ESA provides more fair and effective utilization of communication channels where SUs try to use the channels in a cognitive sense without disturbing PU. In addition to this, performance of ESA is not affected by the high traffic load incurred by the nodes, instead, the system evolves faster with the presence of high contention and converges to an optimal state earlier especially in the case of high node mobility.

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