Biologically Inspired Cooperative Spectrum Sensing Scheme for Maritime Cognitive Radio Networks

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***Abstract*—Spectrum sensing is imperative to the success of maritime cognitive radio networks (MCRNs). Spectrum sensing in MCRNs is challenging because of the sea surface movement, the channel interference, and the unstable link quality. Recent research reveals that existing spectrum sensing schemes work well for lower sea states; however, they have failed to perform effectively at higher sea states. There are two disadvantages of performing spectrum sensing at higher sea states: 1) low probability of detection may also cause interference with primary system and 2) energy wastage. In this paper, a biologically inspired cooperative spectrum sensing scheme (BIC3S) is proposed to deal with the reliability and energy consumption challenges associated with the sea environment. It is based on the task allocation model of an insect colony. The proposed BIC3S chooses participating secondary users for cooperative spectrum sensing according to their given sea state. Further, it enables the secondary users to decide whether or not to perform spectrum sensing based on their sea state. Simulation results are presented to demonstrate the performance of the proposed scheme in terms of energy consumption, detection performance, and throughput. It is shown that the proposed BIC3S consumes less energy and, at the same time, achieves higher detection probability and fewer probability of false alarms compared to the existing schemes. Moreover, BIC3S provides better adaptation capabilities for the sea environment.**

***Index Terms*—Cognitive radio network, cooperative detection, maritime communication, spectrum sensing.**

I. Introduction

BROADBAND wireless access becomes an essential part of daily life due to the inventions of new communication devices such as smart phones and other hand-held devices. Maritime broadband access is a relatively unexplored area in comparison with broadband access for land networks. Therefore, deploying wireless technologies for ship-to-shore and ship-to-ship communication system is of significant importance. Current maritime wireless communication systems using either a low-bandwidth licensed very high frequency (VHF) (30–300 MHz) band or satellite communication to satisfy the requirements of International Maritime Organization (IMO) [1]. However, IMO requires wideband and low-cost communication systems for the following reasons:

1) to provide security, surveillance, and better control;
2) better conditions for on-board crews;
3) Internet service for passengers [2].

Novel wireless access mechanisms and improvement on the existing systems are required to improve the maritime services and reduce the communication cost at sea.

Research has been done in the field of maritime communication systems. The first digital VHF network, developed in Norway [3], had data rates of 21 and 133 kbps with a coverage range of 130 km. The system operates in a licensed VHF channel, which results in a narrow bandwidth and a slow communication speed. An 802.16e-based WIreless-broadband-access for SEaPORT (WISE-PORT) was developed in Singapore [4]. It can provide data rate up to 5 Mbps with a coverage range up to 15 km. To provide high speed and low cost for ship-to-shore and ship-to-ship communications, the mesh/ad hoc network based on IEEE 802.16d mesh technology was proposed in a project called TRITON [1]. The authors developed a prototype that operates at 2.3 and 5.8 GHz. Furthermore, the authors in [5] proposed a ship-shore wireless mesh network using long-range wireless networking technologies. A maritime wireless ad-hoc network (MWAN) has been developed with a coverage range up to 70 km in Japan [6]. However, it can provide data rate about 1 kbps, which is not able to satisfy the requirements of high-speed maritime communications. A hybrid network for maritime on-board communications was proposed in [7]. The authors employed ubiquitous technologies on ships to examine connectivity and emergency handling. First, different on-board communication networks were combined by enabling them to cooperate. Second, the smooth integration of different networks was ensured while considering the backward compatibility issues, ease of deployment, and connection to shore via Internet. A detailed summary of systems and networks for maritime communications is presented in Table I.

The above-mentioned systems and networks are designed to provide better data rates, security, quality of service, and low deployment costs. However, it is difficult to find dedicated spectrum to satisfy the requirements of high-speed maritime communications due to congested bandwidth. The devices for a mar-

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TABLE I
SYSTEMS AND NETWORKS FOR MARITIME COMMUNICATIONS

System/ Network	Data rate (upto)	Coverage	Technology
TRITON [1]	6 Mbps	35.3 km	802.16d
MarCom [3]	133 kbps	130 km	Digital VHF
WISE-PORT [4]	5 Mbps	15 km	802.16e
MWAN [6]	1 kbps	70 km	27/40 MHz

itime wireless network on shore may need to coexist with other radio devices installed on land. Additionally, the synchronization of frequency bands is required around the world because ships may travel between countries and continents. Thus, cognitive radio is a promising solution to overcome these challenges in maritime networks, which can access the frequency bands opportunistically [8].

MCRN enables the secondary users (SUs) to communicate over the available spectrum bands. In MCRN, spectrum sensing results are highly dependent on sea environment, specifically on sea state. One way to achieve relatively better results at higher sea states is to increase the sensing time (τ_s). However, there exists a sensing-throughput tradeoff [24], and because of this, the sensing duration cannot be increased beyond a certain limit. Therefore, SUs in MCRN are not always able to perform accurate spectrum sensing, especially at higher sea states. This will result in high miss detections and false alarms. Data transmission is also not very effective at higher sea states because of high path loss.

Similar to MCRN, in insect colonies, the individual insects first analyze the assigned task. After that, the task is performed by many individuals who are better equipped for it. In BIC3S, this natural mechanism has been adopted to introduce an energy-efficient cooperative spectrum sensing scheme for MCRNs. Similar biologically inspired mechanism was earlier used for spectrum sharing in cognitive radio networks in [26].

A. Related Work

Maritime cognitive radio networks (MCRNs) are proposed in [8] to deal with the spectrum issues and to reduce communication cost. MCRN allows efficient utilization of bandwidth and helps to mitigate spectrum scarcity. In MCRNs, spectrum sensing is the key to explore and exploit the opportunities for transmissions. Spectrum sensing is well investigated for terrestrial environment. However, it is a difficult task in MCRN due to the challenges associated with the sea environment. The most common local spectrum sensing schemes include energy detection, matched filter, and cyclostationary feature detection [9]. In multipath fading and shadowing, sensing accuracy can be improved using cooperative spectrum sensing, in which multiple SUs share their local sensing information [10]. There are many improved local sensing schemes [11], [12] and advanced cooperative spectrum sensing schemes [10], [13] proposed in the literature. Spectrum sensing is studied in [14]–[17] by considering unique challenges to MCRN, which includes radio wave propagation over water, surface reflection, and wave occlusions.

Recently, the authors in [8] presented the design requirements of the MCRN to enable cognitive operations in sea environment. It is analyzed to show that there is plenty of unused spectrum at sea. The white spaces available in the sea ranged from tens of megahertz to several gigahertz, including TV, cellular, and maritime white spaces. MCRNs can use these unused frequency bands opportunistically. This not only helps to deal with spectrum scarcity, but also provides a large bandwidth and long-range communications at low cost. However, there are certain challenges associated with MCRN including movement of the sea surface, channel characterization, and unstable link quality.

The use of entropy-based spectrum sensing is investigated for MCRN in [14]. The optimal number of samples is determined for MCRN, and entropy of the received signal is calculated using the optimal number of samples. The entropy value is used as a test statistic to decide the presence or absence of primary user (PU). The idea is further extended to cooperative spectrum sensing in [15], which considers the sea conditions and uses optimal number of samples in entropy detector for local detection. In addition, the throughput is maximized by using the optimal values of k and m for k-out-of-m rule with respect to the sea conditions.

Performance analysis of spectrum sensing in MCRN is presented in [16], in which existing fusion rules for cooperative spectrum sensing are compared to highlight the need of unique cooperative spectrum sensing scheme for MCRN. Feasibility and benefits of MCRN for automatic identification system VHF data link services are discussed in [17]. Further, the performance of energy detection is analyzed for maritime environment.

In summary, existing literature (as shown in Table II) on spectrum sensing in MCRN has considered that spectrum sensing is performed by SUs regardless of the sea conditions. This will result in lower reliability and waste of energy (due to spectrum sensing in poor sea conditions) at higher sea states (sea states are discussed in the next section). Therefore, a general framework for spectrum sensing in MCRN is needed. Unlike prior work in this area, we propose a spectrum sensing scheme in which SUs can decide about participation in cooperative spectrum sensing based on their sensing capabilities in given sea conditions.

B. Contributions

In this paper, we present a biologically inspired cooperative spectrum sensing scheme (BIC3S), which is based on the task allocation model of an insect colony. The BIC3S distributively chooses the participating SUs in cooperative spectrum sensing for MCRN without any need of coordination among SUs. Furthermore, it enables SUs to decide whether or not to participate in cooperative spectrum sensing based on its sensing capabilities. We investigate the detection performance, energy consumption, and throughput for our scheme under different sea conditions. Extensive computer simulations are conducted in order to validate the proposed scheme and to compare with the existing schemes.

The rest of the paper is organized as follows: In Section II, a brief overview of MCRN and channel modeling are presented. Section III presents a system model and spectrum sensing in MCRNs. The relation between task allocation model and spectrum sensing in MCRN is discussed in Section IV. Moreover, proposed BIC3S is presented in the same section. Section V

TABLE II
SPECTRUM SENSING IN MCRN

Ref.	Spectrum sensing	Cooperative	Throughput	Energy efficient	Remarks
[8]	Energy detector				Design requirements of the MCRN are presented
[14]	Entropy detector				The optimal number of samples is determined and entropy of the received signal is used as test statistic
[15]	Entropy detector	√	√		Throughput is maximized by using the optimal values of m and n for m-out-of-n rule with respect to the sea conditions
[16]	Energy detector	√			Performance analysis of existing fusion rules for cooperative spectrum sensing is presented
[17]	Energy detector				Performance of energy detection is analyzed for maritime environment
BIC3S	Energy detector	√		√	Energy efficient cooperative spectrum sensing which provides better adaptation capabilities for the sea environment

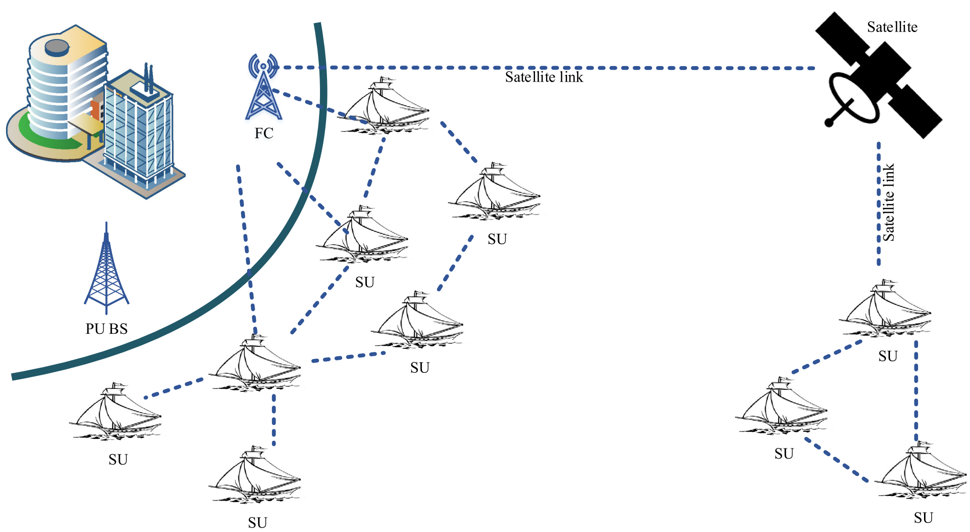

Fig. 1. Architecture of MCRN.

demonstrates simulation results and the conclusions are drawn in Section VI.

II. MCRN AND CHANNEL MODELING

MCRNs can be divided into two types. The first type is the ship-to-ship/ship-to-shore network (close to shore) and the second is the ship-to-ship ad hoc deep-sea network with the support of a satellite communication link, as shown in Fig. 1. Each ship is equipped with devices that are able to perform cognitive radio functions (i.e., they are able to perform spectrum sensing and configure their operating parameters). They periodically sense the radio environment to access the spectrum, which is not used by the PUs. In MCRN, where ships are far from land, it is impossible to access the fusion center using a common control channel. Therefore, satellite links can be used as alternate access routes to the fusion center. In addition to terrestrial CR network spectrum usage, a ship can switch its operating parameters according to sea motion, geographic location, and density of nodes.

Opportunistic spectrum access in CR networks on land is a well-investigated area. However, there are environmental differences between sea and land such as the maritime radio atmosphere (i.e., sea motion and channel model). There are almost no obstacles in the sea, and because the sea's surface is flat, it causes huge path loss due to the negative interference between the line-of-sight path and the reflected path [18]. Therefore, extensive investigations are required for the spectrum access in MCRNs.

A. Channel Model

Unusual challenges arise for MCRNs due to variable channel statistics. The sea surface works as a reflector for radio propagation, and as a result, the signal degrades completely along the path. In a terrestrial environment, there are obstacles of different sizes that result in reflection, refraction, and the scattering of signals in the communication channel. The path loss in terrestrial environments is higher than it is in free spaces and is defined as [19]

$$L_T(d) = L_T(d_o) + 10 \times \alpha \times \log(d/d_o) + X_f^T \tag{1}$$

where d_o is the distance of a reference location with measured path loss L_T, d is the physical distance between the transmitter and the receiver, α is the path loss exponent for the radio environment, and the Gaussian random contributor is X_f^T with zero mean and standard deviation σ_t which represents the fast fading effects. The accurate estimation of the path loss exponent

TABLE III
WMO SEA STATE CODE [20]

Sea state	Wave height (m)	Characteristics
0	0	Calm (glassy)
1	0–0.1	Calm (rippled)
2	0.1–0.5	Smooth (wavelets)
3	0.5–1.25	Slight
4	1.25–2.5	Moderate
5	2.5–4	Rough
6	4–6	Very rough
7	6–9	High
8	9-14	Very high
9	>14	Phenomenal

is a major characteristic of the communication channel. Usually, values of the path loss exponent range from 1 to 4, depending on the physical terrain's features.

The path loss increases with the increase in sea state. A fundamental of propagation analysis for MCRNs is the generation of a random sea surface. Sea movement is described by the sea state divided into ten levels characterized by World Meteorological Organization (WMO) [20]. Table III shows wave height and characteristic for each sea state. Therefore, the path loss in the maritime communication channel during shadowing is defined using wave height as [21]

$$\begin{aligned} L_M(h,f) = \; & L_M(d_o) + 10 \times \{(0.498\log_{10}(f) \\ & + 0.793) \times h + 2\} \times \log_{10}(d/d_o) + X_f^M \end{aligned} \tag{2}$$

where f is the frequency in gigahertz, the observable sea height is h in meters, d is the physical distance between transmitter and receiver, d_o is the distance of a reference location with measured path loss $L_M(d_o)$, and the random variable X_f^M with zero mean and standard deviation is σ_f, which is also represented as a function of wave height:

$$\sigma_f = [0.157f + 0.405] \times h. \tag{3}$$

III. SPECTRUM SENSING IN MCRNS

A. System Model

In our system model, SUs perform spectrum sensing to determine availability of bands for data transmission and can utilize unoccupied PU bands. A centralized MCRN which consists of N_S SUs is considered. For the sake of simplicity, we assume that all SUs use fixed number of samples denote by M for local spectrum sensing. The total number of available channels is K_C which are spread over a wide range of frequencies. Each channel has different channel characteristics. For each channel, the ON–OFF Poisson arrival model is used for the PU activity [22], where P_{ON} and P_{OFF} are the probabilities for which PUs are active and idle, respectively. Moreover, multiple PU networks are considered for detection. Further, we assume that the base station at the shore acts as the fusion center.

We assume $x(t) = \Re\left\{a(t)e^{(j2\pi f_c t+\varphi)}\right\}$ is the PU transmitted signal, where $a(t)$ is a complex base band signal with a bandwidth of B, f_c is the carrier frequency, and φ is the initial phase. The received signal $r_n(t)$ by nth SU can be written as

$$\Psi_n(t) = \Re\left\{a(t) \times h_c(t)e^{(j2\pi f_c t+\varphi)}\right\} + w(t) \tag{4}$$

where $h_c(t)$ is the channel model for cth $\in K_C$, and $w(t)$ is the noise in the absence of PU. The received signal after experiencing the path loss in (2) and noise can be written as

$$\Psi_n(t) = \Re\left\{a(t) \times \sqrt{\frac{G}{L_M}}e^{(j2\pi f_c t+\varphi)}\right\} + w(t) \tag{5}$$

where G is the antenna gain.

The SU carries out spectrum sensing using energy detector. A binary hypothesis model (i.e., the basic model for spectrum sensing by nth SU) is defined as

$$r_n(t) = \begin{cases} w(t), & \text{in the case of } H_0 \\ \Psi_n(t), & \text{in the case of } H_1 \end{cases} \tag{6}$$

where H_0 is the hypothesis that represents the absence of a PU, and H_1 is the alternative scenario.

The energy detector is considered for local sensing. It is known that the energy detector is the simplest detector for the detection of the unknown PU signals. The power of the received signal $r_n(t)$ is estimated over the M samples and received energy ϕ_n by nth SU is given as

$$\phi_n = \sum_{a=1}^{M} |r_n(t)|^2 . \tag{7}$$

For the case when $w(t)$ is circularly symmetric complex Gaussian (CSCG), the probability density function of ϕ_n under the hypothesis H_0 can be approximated by a Gaussian distribution with σ_w^2 mean and $\frac{1}{M}\sigma_w^4$ variance. The probability of false alarm can be given by [24]

$$\begin{aligned} P_f(\theta,\tau) = \; & \Pr[\phi(r_n) > \theta | H_0] \\ = \; & Q\left(\left(\frac{\theta}{\sigma_w^2} - 1\right)\sqrt{\tau f_s}\right) \end{aligned} \tag{8}$$

where $Q(.)$ is the complementary distribution function of the standard Gaussian distribution.

For the signal $x(t) = \Re\left\{a(t)e^{(j2\pi f_c t+\varphi)}\right\}$ and CSCG noise case, the probability of detection can be approximated as [25]

$$\begin{aligned} P_d(\theta,\tau) = \; & \Pr[\phi(r_n) > \theta | H_1] \\ = \; & Q\left(\left(\frac{\theta}{\sigma_w^2} - \gamma_x - 1\right)\sqrt{\frac{\tau f_s}{(2\gamma_x + 1)}}\right) \end{aligned} \tag{9}$$

where $\gamma_x = \frac{\sigma_x^2}{\sigma_w^2}$ (σ_x^2 is the mean of $x(t)$).

B. Centralized Cooperative Spectrum Sensing

In a centralized cooperative spectrum sensing scheme, all cooperative SUs forward their local decisions to a centralized fusion center. A framework of centralized cooperative spectrum sensing for MCRN is shown in Fig. 2. Sea state is incorporated in the centralized cooperative spectrum sensing for MCRN which

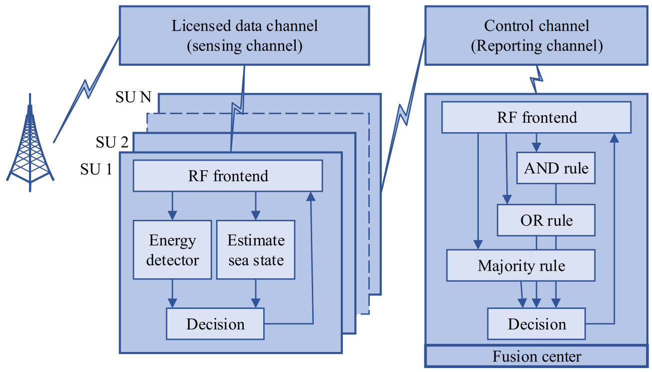

Fig. 2. Framework of centralized cooperative spectrum sensing.

enables SUs to decide whether or not to participate in cooperation. The most commonly used fusion rules are AND, OR, and majority rules for which generalized form is k-out-of-m rule. The fusion center declares a cooperative decision about the PU's presence if k SUs report the PU's presence and PU's absence otherwise. The fusion center forwards the cooperative decision to all individual SUs after applying fusion rules [10]. The probability of detection and the probability of false alarm for k-out-of-m rule are given by [23]

$$G_d = \sum_{b=k}^{m} \binom{m}{b} P_d^b (1 - P_d)^{m-b} \tag{10}$$

$$G_f = \sum_{b=k}^{m} \binom{m}{b} P_f^b (1 - P_f)^{m-b} \tag{11}$$

where G_d and G_f are the global probability of detection and global probability of false alarm at the fusion center.

A list of symbols with description is presented in Table IV.

IV. Biologically Inspired Cooperative Spectrum Sensing for MCRNs

A. Insect Colony Model for Task Allocation

In ant colonies, individual decisions of ants are not very efficient when compared with the ants who collaborate. The collaboration helps them to optimize certain tasks, thereby providing global intelligence. In insect colony model, a task is assigned to multiple ants when it cannot be performed efficiently by a single ant. However, in collaborative groups, each ant has a different capability to perform a particular task. Therefore, in ant colonies, particular tasks are usually performed by those individuals who are best equipped for them. This concept within ant colonies is called division and labor [27].

Each individual in an insect colony has a response threshold for each allocated task. The probability of reacting to a task-associated stimuli is referred to as a response threshold. Each individual performs a particular task only when the task-associated stimuli ψ exceeds the response threshold λ. Therefore, the tendency to respond to a task-associated stimuli is determined by λ. Thus, based on these definitions, the probability of performing a task as a function of ψ and λ can be written

TABLE IV
DEFINITION OF THE VARIABLES USED IN THE MODEL

Symbol	Description
L_M	Path loss in maritime communication channel
d	Physical distance between transmitter and receiver
f	Frequency in GHz
h	Observable sea height
N_S	Number of SUs
K_C	Number of channels
M	Number of samples
P_{OFF}	Probability for which PU is idle
$r_n(t)$	Signal received by SU
ϕ	Test statistic for energy detector
$\tau_{\min}$	Minimum sensing time
σ_x^2	Variance of transmitted signal
σ_w^2	Variance of noise
P_f	Local probability of false alarm
P_d	Local probability of detection
Q_f	Global probability of false alarm
Q_d	Global probability of detection
ζ	Sea state
ϑ	Required sea state to perform spectrum sensing
L	Learning factor
$P_{n\,c}^{\text{sen}}$	Probability of performing spectrum sensing for nth SU on cth channel
$P_{n\,c}^{\text{miss}}$	Probability of miss detection for nth SU on cth channel
η_1	Forget penalty
η_2	Learning reward
D_n	Decision to perform spectrum sensing for nth SU

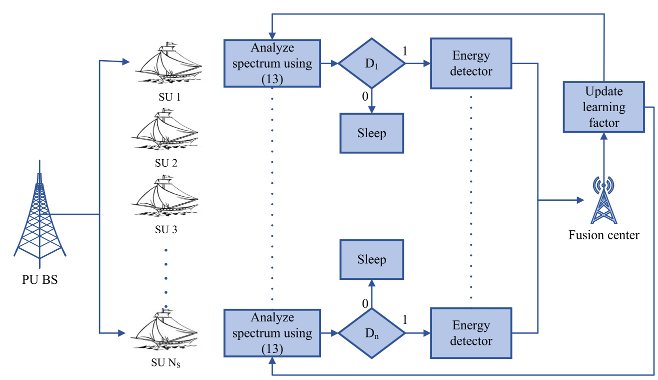

Fig. 3. BIC3S for MCRN.

as [26]

$$P_\lambda(\psi) = \frac{\psi^\rho}{\psi^\rho + \lambda^\rho} \tag{12}$$

where $\rho > 1$ determines the sharpness of the response threshold. It is notable from (12) that the probability of performing a task is close to 1 for $\psi >> \lambda$ and close to zero for $\psi << \lambda$.

Now, a model for task allocation-based spectrum sensing for MCRN is presented by applying the task allocation problem in an insect colony.

B. Biological Task Allocation-Based Cooperative Spectrum Sensing for MCRN

The BIC3S is very similar to task allocation in insect colonies. The block diagram of proposed BIC3S is shown in Fig. 3. In MCRN, each ship can only sense and forward its decision to the fusion center if it is well equipped to perform spectrum sensing under given sea conditions. Similarly, each individual in an insect colony senses the environment for available tasks, and then the task is performed by those individuals who are best equipped for them. The spectrum sensing in MCRN is presented while considering the task allocation problem in Section IV-A as follows.

1) SU is considered as an insect in a colony.
2) Spectrum sensing is considered as a task.
3) Sea state ζ is considered as task-associated stimuli (ψ).
4) The required sea state ϑ for which spectrum sensing can be performed accurately by *n-th* SU is considered as response threshold (λ).

The probability of task performing given in (12) is adopted to introduce the probability to perform spectrum sensing, which enables MCRN to effectively perform cooperative spectrum sensing. It is worth to note that increasing the task associated stimuli in (12) which is the sea state in our case decreases the probability of performing sensing. This is opposite to the insect colony model in [26], where the stimuli increasing improves the probability of performing the task. Therefore, the probability of performing spectrum sensing for *n*th SU on *c*th channel (P_{nc}^{sen}) can be derived from the mapping of an insect colony in an invertible way (opposite to [26]) and MCRN discussed above, written as

$$P_{nc}^{\text{sen}} = 1 - \frac{\alpha(\zeta_c)^{\omega}}{(\zeta_c)^{\omega} + \alpha(\vartheta_{nc})^{\omega} + \beta(L_{nc})^{\omega}} \tag{13}$$

where $\omega > 1$ determines the steepness of the P_{nc}^{sen}. ϑ_{nc} is the required sea state to perform spectrum sensing and L_{nc} is the learning factor. α and β are positive constants for the respective influences of ϑ_{nc} and L_{nc}, respectively.

The learning factor L_{nc} is bounded in $[0, L_{\max}]$. Each SU learns from L_{nc} to remember or forget about the sea state ζ of *c*th channel. The probability of miss detection P_{nc}^{miss} for *n*th SU on *c*th channel is used to determine the upper limit of L_{nc} for sea state ζ. Therefore, the upper limit for each sea state can be written as

$$L_{nc,u} = L_{\max}(1 - P_{nc}^{\text{miss}}). \tag{14}$$

If an SU does not fulfill the requirements of spectrum sensing for a given sea state ζ, then it forgets the sea state and updates the value of L_{nc} as $\min\{0, L_{nc}^{\omega} - \eta_1 P_f\}$. On the contrary, if the SU fulfills the requirements of spectrum sensing for a given sea state ζ, then L_{nc} will be updated and learnt by the *n*th SU. The updated value of L_{nc} can be written as $\max\{L_{\max}, L_{nc}^{\omega} + \eta_2(1 - P_f)\}$, where η_1 and η_2 are the forget penalty and the learning reward, respectively. The forget penalty and learning reward are scaled by P_f and $(1 - P_f)$, respectively, to make these factors according to the probability of false alarm.

Each SU computes the probability of sensing the channel P_{nc}^{sen} before performing spectrum sensing. It enables SU to easily adopt the changes in the sea state and perform spectrum sensing accordingly. We define $\Theta = \zeta_c - \vartheta_{nc}$ as the decision factor for SUs to decide either to perform spectrum sensing or not. If the estimated sea state ζ_c is less than or equal to the response threshold ϑ_{nc}, i.e., $\Theta \leq 0$, then P_{nc}^{sen} is close to one. In this case, the *n*th SU will decide to perform spectrum sensing. On the other hand, if the estimated sea state ζ_c is greater than the response threshold ϑ_{nc}, i.e., $\Theta > 0$, then P_{nc}^{sen} is close to zero. Here, the *n*th SU will decide not participate in cooperative decision. Fig. 4 obtained from simulation shows that with the increase of sea state ζ for a given response threshold ϑ_{nc}, the P_{nc}^{sen} decreases and SU may not perform spectrum sensing. However, energy consumption for cooperative decisions is decreased as *n*th SU is not participating in the cooperation in this situation. The decision D_n of *n*th SU to perform spectrum sensing can be written as

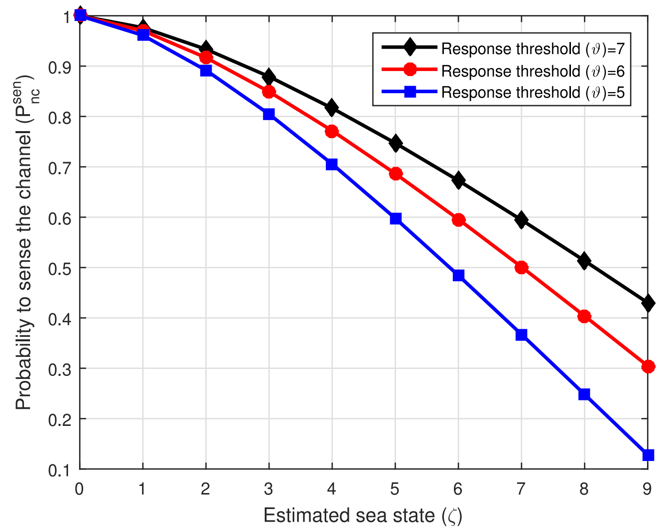

Fig. 4. Probability to sense the spectrum versus sea states.

$$D_n = \begin{cases} 1, & \text{if } \Theta \leq 0 \\ 0, & \text{if } \Theta > 0 \end{cases} \tag{15}$$

where Θ is the threshold to determine either to perform spectrum sensing or not.

The algorithm for the proposed BIC3S is shown in Algorithm 1. In the dynamically changing environment of MCRN, the proposed solution provides better adaptation capabilities. Moreover, the learning capability of the proposed scheme enables SUs to learn about the changing radio environment in MCRN. The fusion of data received from SUs depends on hard and soft local decisions. In this paper, we consider k-out-of-n hard fusion rule based cooperative spectrum sensing as discussed in Section III-B.

C. Energy Consumption and Throughput in BIC3S

Energy consumed by the *n*th SU in BIC3S can be divided into the following modes: sensing, transmitting, receiving, and silent. The energy consumed by the SU depends on the decision on PU activity. There are three possibilities of energy consumption in BIC3S:

Case I: When $\Theta \leq 0$ (in the absence of PU) and no false alarm is generated by SUs, the energy consumed by the *n*th SU to communicate on the channel is

$$E_n^c = E_s\tau_s + E_r\tau_r + E_t(T - \tau_s - \tau_r) \tag{16}$$

Algorithm 1: BIC3S algorithm.

Input: Set $\alpha, \beta, \eta_1, \eta_2, \Theta, \vartheta_{nc}$ $\forall n \in N_S$ and $\forall c \in K_C$
Choose initial L_{nc} $\forall n \in N_S$ and $\forall c \in K_C$
Output: Global decision about presence or absence of PU
for n=1:N_S **do**
  Estimate sea state ζ
  Compute P_{nc}^{sen} using (13)
  if $\Theta > 0$ **then**
    Do not perform spectrum sensing
    Update learning factor by
    $L_{nc} \leftarrow \min\{0, L_{nc}^{\omega} - \eta_1 P_f\}$
  else
    Apply energy detector
    Send local decision to fusion center
    Update learning factor by
    $L_{nc} \leftarrow \max\{L_{\max}, L_{nc}^{\omega} + \eta_2(1 - P_f)\}$
  end if
end for
At fusion center apply k-out-of-m rule to determine global decision

where E_s, E_r, and E_t are the energy consumed in sensing, reporting, and transmission, respectively. T is the frame length and τ_r is the reporting time.

Case II: When $\Theta \leq 0$ (in the presence of PU) and fusion center decides PUs presence accurately, the energy consumed by nth SU is

$$E_n^c = P_s \tau_s + P_r \tau_r. \qquad (17)$$

Case III: When $\Theta > 0$ (in the absence or presence of PU), the sea state is above the response threshold ϑ, nth SU in BIC3S will not perform spectrum sensing and energy consumed E_n^c is negligible small.

Let C_0 be the throughput in of an SU in the absence of PU. When $P_{nc}^{\text{sen}} \geq \Theta$, the practical throughput R_P for an SU with cooperative spectrum sensing is calculated as [28]

$$R_P(\tau_s, \tau_r, \tau_t) = \frac{T - \tau_s - \tau_r}{T} \left\{C_0(1 - G_f)P_{\text{OFF}}\right\}. \qquad (18)$$

As mentioned earlier, P_{OFF} is the probability for which PU is idle.

When $\Theta > 0$, the sea state is above the response threshold ϑ, nth SU in BIC3S will not transmit anything, hence, throughput will be zero.

It is obvious from (16)–(18) that the energy consumption and throughput are functions of τ_s, τ_r, and $T - \tau_s - \tau_r$ when $P\Theta \leq 0$.

V. Simulation Results

In this section, the simulation results are presented and compared with the entropy-based spectrum sensing scheme (E3S) [15] and spectrum sensing maritime scheme (SSMS) [17] for maritime networks. A general network model is considered for the simulations of MCRN. It covers a narrow navigation channel with the traffic separation scheme defined by the IMO. The network consists of one westbound and one eastbound shipping lane in parallel, each with a width of 20 km, and it has a land station, which acts as a fusion center in cooperative spectrum sensing. A similar type of network model was also considered earlier for simulations in [8] and [15]. A simulation environment is developed in MATLAB to evaluate the performance of BIC3S. An energy detector is used as a local spectrum sensing scheme. Unless specifically stated, the number of SUs are assumed to be up to 20 which are uniformly distributed in the network. We consider the one PU for the simulations as we are considering single-band spectrum sensing. It is assumed that SUs are not aware of relevant PU information such as position, moving direction, and velocity. The parameters for learning process are adopted from [26]. The initial learning factor L_{nc} is 2, and the learning reward η_1 and the forget penalty η_2 can initially be in a range of 2–15. If we choose high values for η_1 and η_2, the learning factor will be rapidly changing. On the contrary, for lower values of η_1 and η_2, the learning process will gradually learn. Similar to [26], we set moderate values for both η_1 and η_2 to be 5. The positive constants α and β are set as 5 and 2, respectively. The path loss experienced by each SU depends on the radio environment. Detailed list of simulation parameters is presented in Table V.

TABLE V
SIMULATION PARAMETERS

Parameter	Value
Number of SUs N_S	10 or 20
Number of channels K_C	10
Initial learning factor L_{nc}	2
Forget penalty η_1	5
Learning reward η_2	5
α	5
β	2

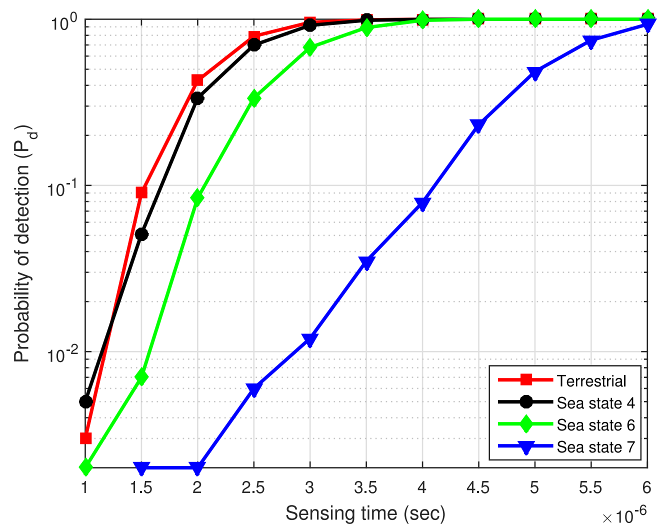

Fig. 5. Probability of detection versus sensing time for MCRN ($P_f = 10^{-1}$).

Fig. 5 shows the probability of detection versus sensing time for the terrestrial network and different sea states. It is obvious in all cases that the probability of detection is increased

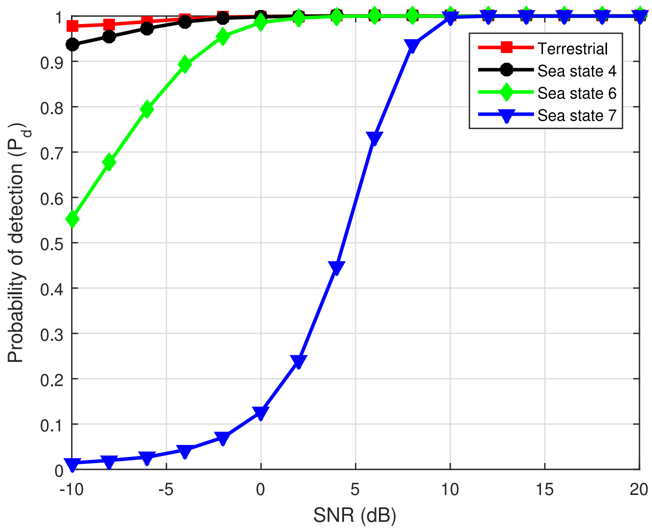

Fig. 6. Probability of detection versus average SNR ($P_f = 10^{-1}$).

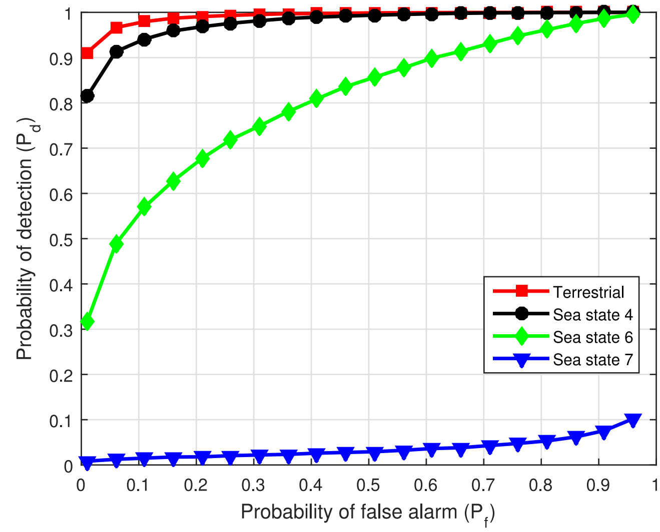

Fig. 7. Probability of detection versus probability of a false alarm (average SNR $= -5$ dB).

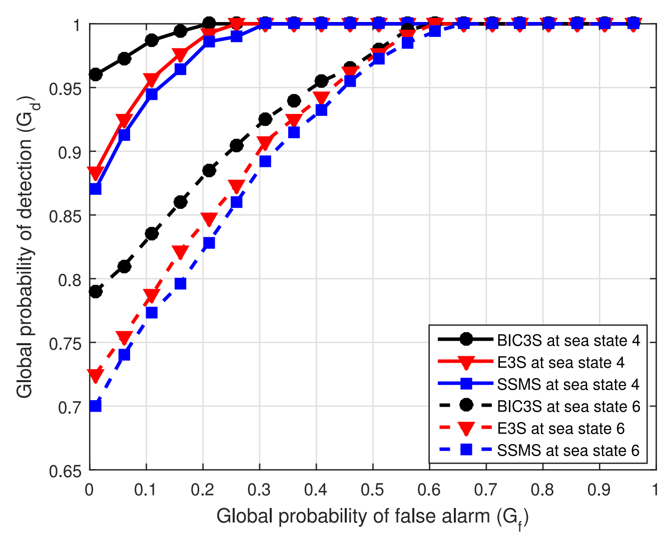

Fig. 8. Global probability of detection versus global probability of false alarm.

by increasing the sensing time. According to the draft IEEE 802.22 standard [29], the probability of false alarm should be less than or equal to 10^{-1}. Therefore, the decision threshold for energy detector is set to maintain $P_f = 10^{-1}$. In MCRN, the sensing time can be increased for higher sea states to satisfy the requirements of the IEEE 802.22 standard. However, a longer sensing time can result in interference with the PU or waste the opportunity to access the spectrum. It is noted that it needs a long sensing time to detect PU for sea states 7 and higher.

The probability of detection is calculated to determine the sensitivity of the energy detector for SNR ranges from -10 to 20 dB. The probability of false alarm is set to 10^{-1} to satisfy the requirements of IEEE 802.22 standard. The cases of terrestrial network, sea states 4, 6, and 7 using an energy detector are considered. Fig. 6 shows that the probability of detection is increased with the increase of SNR. The probability of detection for a given SNR is almost equal in the case of terrestrial network and sea state 4. However, the probability of detection degrades for higher sea states especially in low SNR conditions.

Receiver operating characteristic (ROC) curves are of practical interest in MCRN. Fig. 7 shows the ROC's, i.e., P_d versus P_f for an average SNR -10 dB. The results are shown for the terrestrial network, sea states 4, and 6 using an energy detector. The results reveal that the requirement for the PU protection is satisfied in case of terrestrial network and sea state 4. However, for sea states 6 and above, the energy detector is unable to detect the PU with high probability under low P_f for a given SNR and sensing time.

ROCs for cooperative spectrum sensing in terrestrial network, sea states 4 and 6 are shown in Fig. 8. It is assumed that there are ten SUs participating in cooperation and their SNR varies from -20 to 10 dB. The performance of the proposed BIC3S is compared with E3S and SSMS in MCRN. The spectrum is sensed by each participating SU in the case of both E3S and SSMS; however, in the case of the proposed BIC3S, the spectrum is sensed by only those SUs which satisfy the requirements of sensing. A k-out-of-m fusion rule is applied for BIC3S, where $k = 5$ and $m = 10$. Simulation results show that the probability of detection is higher in the case of BIC3S compared to its competitors. This is due to the fact that the SUs equipped to perform spectrum sensing will produce better and reliable sensing results. Therefore, high global probability of detection can be achieved by using BIC3S. It is also noticed that BIC3S, E3S, and SSMS are still not able to satisfy the requirements of the standard at sea state 6 and above. One way to achieve better sensing results is to increase the sensing time, which means we leave less transmission time resulting in low throughput.

The throughput versus sensing time is considered for the sea states 4, 6, and 7 in Fig. 9(a)–(c), respectively. The results of BIC3S are compared with E3S and SSMS for spectrum sensing in MCRN. The achieved throughput is increased initially with the increase in sensing time, however, increasing the sensing

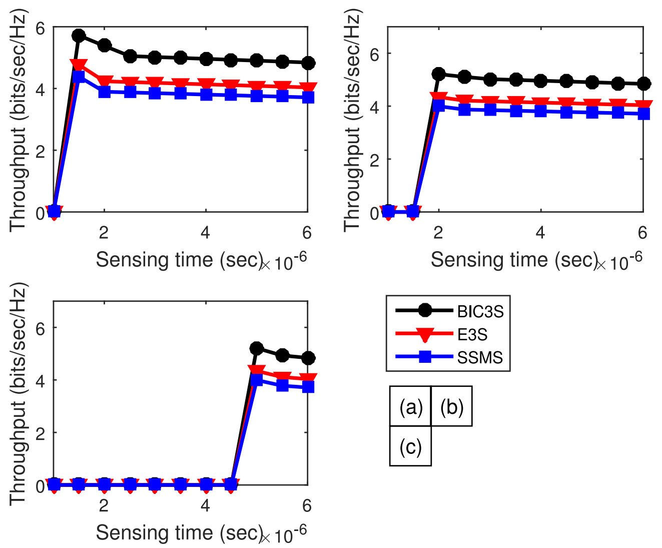

Fig. 9. Throughput as a function of the sensing duration (a) sea state 4, (b) sea state 6, and (c) sea state 7.

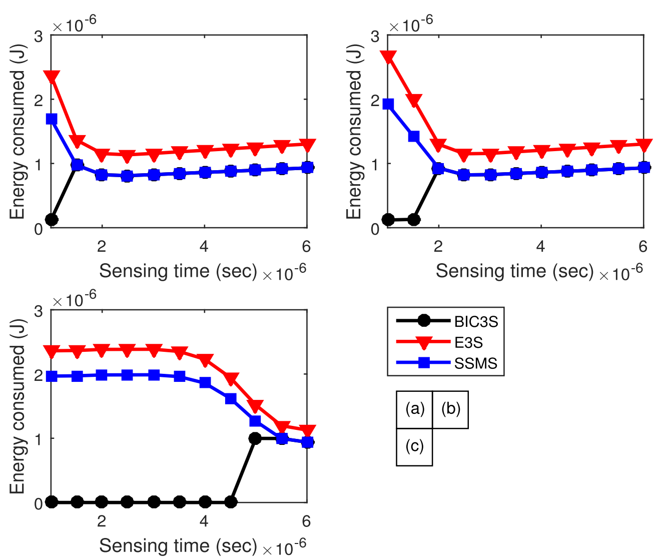

Fig. 10. Energy consumption as a function of the sensing duration (a) sea state 4, (b) sea state 6, and (c) sea state 7.

time will further decrease the throughput in all cases. This is because increased sensing time will result in less transmission time. The throughput for the case of sea state 7 is better at a higher sensing time, but it is not practically possible to sense for long durations. BIC3S pays the cost of this loss of throughput at sea state 7 by consuming less energy and having a low interference at higher sea states when compared with E3S and SSMS.

Energy consumption versus sensing duration is depicted for the sea states 4, 6, and 7 in Fig. 10(a)–(c), respectively. Energy consumption of BIC3S is compared with E3S and SSMS for spectrum sensing in MCRN. It is shown that energy consumption at sea state 4 is close to that of the sea state 6, except from the initial stage. However, energy consumption for the case of

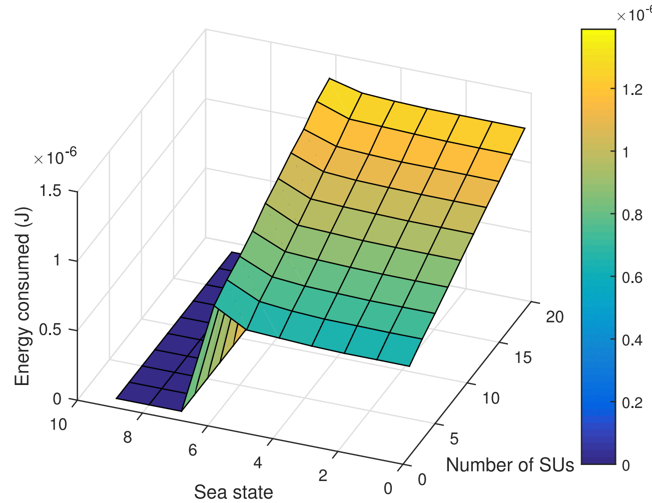

Fig. 11. Energy consumed versus sea state and number of cooperative SUs.

sea states 7 and higher is the main advantage of BIC3S over the E3S and SSMS. From Fig. 10(c), it is clear that BIC3S surpasses the existing E3S and SSMS at sea state 7 with respect to energy consumption.

The energy consumed versus sea states and number of SUs for BIC3S is shown in Fig. 11. It is shown that the energy consumed is increased with the number of SUs. Moreover, increasing the number of cooperative SUs does not only result in less throughput, but also there is no increase in probability of detection at higher sea states. It is evident from the result that energy consumption is near to zero at higher sea states when SUs are not equipped to perform spectrum sensing. This is the main advantage of BIC3S over the existing E3S and SSMS.

VI. Conclusion

In this paper, an energy-efficient biologically inspired cooperative spectrum sensing scheme (BIC3S) is proposed for MCRN. The proposed scheme is based on the biological task allocation model in an insect colony. In BIC3S, the spectrum is sensed by only those SUs which are capable of producing better detection results. The low probability of detection at higher sea states will not only waste energy, and it will also cause harmful interference with PU systems. Simulation results show that BIC3S is energy-efficient for MCRNs, especially under high sea states.

The major advantage of the BIC3S is that it does not include the SUs in cooperation when they are in high sea state conditions. Energy consumption is negligibly small at higher sea states when compared to the E3S and SSMS, and the throughput of the BIC3S is as high as it is for the SSMS and E3S. Moreover, the probability of detection of the proposed scheme is higher than the SSMS.

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