SOM-Based Leader Selection Strategies for Cooperative Spectrum Sensing in Multi-Band Multi-User 6G CR IoT

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***Abstract*—In 6G Cognitive Radio Internet of Things (CR-IoT) networks, multi-band spectrum sensing cooperatively provides access to extensive spectrum resources. The suggested learning-based multi-band multi-user cooperative spectrum sensing (M2CSS) scheme addresses intelligent spectrum access challenges. A cooperative strategy is introduced into a dueling deep Q network to facilitate multi-user reinforcement learning. This study selects the most suitable IoT secondary users (SU) to sense channels using the proposed learning-based M2CSS scheme. With the restriction that each IoT SU can serve as a front-runner for a single network and that there will only be one leader for individual frequency, the proposed work expresses an optimization difficulty in choosing leaders through k-means and SOM, who can efficiently interact with other SUs. Next, choose matching cooperative SUs for each frequency and express additional optimization problems. Following this phase, a subset of cooperative secondary users (SUs) senses frequencies and employs accurate knowledge to determine the channels' availability in a distributed manner. The simulation findings demonstrate significant improvements in detection performance, preventing the misuse of specific devices, providing reliable sensing data over extensive IoT connections, and achieving energy efficiency—all essential for IoT implementations. These advantages make the proposed M2CSS system suitable for the massive machine-type communications anticipated in 6G IoT scenarios.**

Keywords*—Cooperative spectrum sensing; reinforcement learning; k-means leader selection; self-organizing map

I. Introduction

The concept of cognitive radio (CR) involves a communication device that can recognize and adapt to the spectral characteristics of its surroundings. By utilizing the spectral gaps (or holes) that approved consumers, also referred to as primary users (PUs), do not use, CR skill makes it possible for no licensed or secondary users (SUs) to identify these accessible portions of the spectrum [1]. Four distinct stages or functions are involved in the operation of spectrum reuse in a cognitive radio network (CRN): spectrum sharing, spectrum mobility, spectrum sensing (SS), and spectrum decision. A crucial step in identifying particular or additional PUs is SS, which indicates whether the sensed spectrum is engaged or unoccupied [2]. This mission is typically performed in particular groups, but the current multiband SS paradigm uses multiple bands that aren't always attached [3]. Demand for spectrum is rising because of the appearance of the Internet of Things (IoT), sixth generation (6G), past systems, and big data [4]. Spectrum scarcity and underutilization issues may be resolved with the help of CR skills [5]. Secondary users (SUs) in CRNs resourcefully contact the spectrum without intrusiveness through the broadcast of legitimate or PUs [6]. Each SU might have to sense every channel in single-band cooperative spectrum sensing (CSS). On the other hand, because of constraints on hardware and power consumption, each SU in multi-band CSS is given access to a subset of channels. By enabling access to a large spectrum with less difficulty and computational expense, this can significantly improve system performance. Additionally, low hand-off frequency, high throughput, and decreased sensing energy consumption are provided by multi-band CSS [7]. This essay focuses on multi-band CSS to enhance detection performance in CRNs and optimize SU scheduling for sensing a subset of channels.

Most previous methods only consider one user, which has fewer sensing capabilities than a real multi-user or multi-channel environment. As a result, SUs use a fully distributed model for multi-user spectrum access [8], which entails creating a deep multi-user reinforcement learning technique [9]. Multi-band CSS can be divided into centralized and distributed types [5]. SUs send multi-band, centralized CSS information, including multiple channels' worth of locally observed data, to an FC (fusion center) [10]. The fusion center used this information before deciding which channels were available. CRNs are bounded by limitations of the centralized method, including high latency and a single point of failure. [11]. SUs share local observations of several channels with neighbors in a multi-band distributed CSS to facilitate cooperative decision-making. Wireless sensor networks, mesh networks, Mobile ad-hoc networks, Vehicular ad-hoc networks, Flying Ad-hoc networks, etc., remain a few examples of disseminated CRNs [12]. Distributed CRNs are especially well-suited for newer Internet of Things applications like public safety networks and habitat monitoring. In disseminated CRNs, SUs typically have constrained computational and battery resources. Therefore, when developing multi-band CSS schemes for distributed CRNs, trade-offs must be made between energy resources, computational capacity, and performance limitations.

A difficulty with multi-band CSS is the development of SUs to detect radiofrequency (RF) in specific networks in distributed CRNs. Depending on the channel state data, SUs may be able to sense channels in different ways. Consequently, if multiple SUs have similar locally sensed information, selecting cooperative SUs efficiently to sense a subset of frequencies can lower sensing overhead and enhance organization presentation [13]. The CRN's size grows when new SUs join the existing SUs. New SUs must be given multiple channels to divide the sensing load equally between the original and new SUs in the network. To do this, research on the topic is essential. The actions and residual energy of the previous frame determine each frame's initial energy level. In addition to being sporadic and unpredictable, the electrical energy obtained from the harvested RF may not always have enough power to optimize throughput. Therefore, the CRN must be energy efficient to balance the amount of energy harvested with the energy consumed during sensing and transmission activities. There is a sensing-throughput trade-off [14] in typical cognitive radio networks (also known as unconstrained energy counterparts), which depends on sensing accuracy and sensing time. However, the results of the sensing process (i.e., the sensing duration and accuracy) are energy-constrained in the context of the energy harvesting CRN, making the energy harvesting-based CRN (EH-CRN) a scenario with increasing complexities. The SS is the primary mechanism that enables spectrum findings, which is not possible without all other CR functions. It is the driving force behind concentrating solely on this component of CR. In [15–16], it has developed into a method that enhances spectral efficiency by providing access to SH, or vacant frequency bands, during intermittent times.

The primary objective of this research is to develop and analyze an efficient SS framework for CRN in 6G-enabled Internet of Things (6G CR-IoT) environments that addresses critical spectrum scarcity challenges through opportunistic spectrum access while ensuring minimal interference to licensed users. The SOM-based cooperative SS technique carries out this function by having the CRN node sample the targeted spectrum in the range of 0.1 to 1 THz and determine whether or not an incumbent signal is present. SS seeks to reduce any interference that the incumbent might encounter from CRN nodes, in addition to identifying resources that are easily accessible. As a result, the SS scheme that the CR nodes use for identification significantly impacts the CRN and its performance, regardless of the incumbent network's licensing status. By allowing IoT devices to strategically access and share available spectrum resources while utilizing the improved capabilities of 6G networks, 6G CR-IoT seeks to address significant issues with spectrum scarcity.

A. Study Organization

The following sections are organized as follows: Section II provides the literature survey with existing gaps. Section III emphasizes the detailed proposed model with suitable diagrams and mathematical equations. Section IV gives the experimental results with four sub-sections under it, and Section V concludes this research.

II. Literature Survey

Recently, studies have been carried out to improve multi-band CSS performance in CRNs [2, 5, 8–26]. The type of CRN—decentralized or centralized—and the particular techniques used by different authors determine how effective these systems are. Most multi-band CSS schemes in the existing literature were created with centralized CRNs in mind. Through simultaneous optimization of the detection inception, a multiband multi-user scheme is proposed in [17] to maximize the throughput of a centralized CRN with imperfect sensing information. A centralized CRN-based multi-band CSS scheme proposed in [18] overcomes the issues of spectrum resources and limited energy. The plan uses wireless occurrence dynamism gathering and maximizes throughput by optimizing sensing time. For centralized CRNs, an ideal multi-band CSS scheme with chance disruptions is put forth in [19]. The method reduces interference to PUs while optimizing CRN throughput. For centralized CRN, a multi-band sensing time-adaptive structure is also suggested in [20] to increase throughput and lessen interference to PUs. An artificial immune procedure built on the clonal selection theory is used to overcome this obstacle. Responsive hand-off in expression is reduced in centralized multi-band CRNs according to [21]. Sample-based sensing is an effective method for this purpose. In [22], the authors details that to maximize detection performance, the smallest number of SUs is chosen to sense frequencies based on the network situation. Centralized CRNs in [23] suggested a sub-Nyquist multiband CSS protocol to lower the overhead of computation and transmission using resident sub-Nyquist samples. For centralized CRNs with malevolent users, a multi-band CSS scheme is suggested in [24]. To limit the throughput of CRNs and counteract the threat of malevolent attackers, the authors devised an optimization problem. To improve system performance, a multiband CSS scheme based on deep learning is suggested in [25] for centralized CRN. This scheme allows SUs to sense networks independently and forecast the effects of indolent forecasting on the frequency of state-owned during the opening period. As a result, sensing requires less energy. Two secreted coatings, each containing 40 neurons, are used in the implementations for this purpose. The algorithms broadly impact the performance of centralized CRNs, and it continues to be exceptional as the CRN's dimension grows. Due to their computational intensity, these processes can result in growth that is above average, as evidenced by higher SUs and dispersed CRNs.

The investigations in [26] specifically pinpoint the ideal sensing policy. They are an expansion of [26] that establishes the ideal detection threshold and sensing policy for enhancing the anticipated throughput while taking collision limits and energy causality into account. To increase average throughput while preserving energy, the relationship between the ideal sensing length and the matching sensing threshold was looked at. Based on the energy arrival rate and the correlation of the primary traffic, the theoretical maximum throughput of the SU in an energy harvesting-based system is considered, considering energy causality and collision constraints. The trade-off between SS and SU throughput is examined in [27] for a typical energy-unconstrained CRN. This maximizes both the average throughput and the harvested energy by optimizing the decision-making time. Based on it, the work [28] aims at proposing an optimum sensing time for the overlay energy harvesting (EH) CRN, in order to improve SU throughput and the harvested RF energy. Additionally, [29] performs the optimal SS and SU transmissions so as to maximize the residual energy. A common obstacle detected in these works is the unpredictable nature of energy derived from ambient RF sources and the inability of it to always provide the maximal throughput in EH-CRNs. The SU split the channel into two sub-channel sets. One is used to detect the PU, while the other is used to record the RF of the PU signal. To ensure throughput, gathered energy is supplied in the transmission slot to offset sensor energy loss. Nevertheless, there is no mention of the specific energy source used for data transmission. In summary, although a significant amount of research has been done on non-arbitrary ways to assign channels for sensing by involving SUs in disseminated CRNs, these schemes are not remarkably scalable because of their limited computational capabilities. All cognitive radios participate in CSS by measuring the licensed spectrum and making autonomous decisions. Typically, the cognitive radio network is made up of multiple SUs and PUs, with the goal of the SUs being able to share multi-channel spectrum properties with the PUs without interfering with the PUs. Every SU optimizes its own SS performance while exchanging sensing data with the others. SU cannot be sure of the channel environment and is unable to choose until after trying a few times to sense a new channel. As a result, the partial observability issue can be resolved by modeling the channel exchange as a Markov chain. Every SU is synchronized with the designated time slot. The sensing data and the information broadcast historically are the two periods that make up the time slot structure. Every SU in the system independently senses the slot at the start of the sensing historical event. Subsequently, the SU merges data with received data and transmits its sensing data to other users. Every SU, then sends out its decision. An acknowledgment signal is sent to confirm the accomplishment or failure of the broadcast before the sensing period ends.

III. Research Methodology

A. Model Creation

The system model is created in this section by assigning base stations to secondary users, calculating the received powers, visualizing the network deployment, and generating random coordinates for both primary and secondary users. Using the existing k-means clustering, this section divides both new and current secondary users into various clusters according to their coordinates. It also selects new secondary users' leaders using proposed self-organizing maps. SS is carried out in this part by comparing secondary users' received power from base stations with a sensing threshold. The sensing result array indicates identified primary users with a value of 1.

B. Proposed SOM-Based Leader Selection

Choosing a leader involves determining which SU on each channel m is the best to listen to. Leaders must also select cooperative SUs for sensing each channel. Let, SNR_mk and SNR_avg represent the SNR standards of the k^{th} SU sensing the m^{th} channel, respectively, the preferred and attached thresholds for the normal SNR value across different frequencies. The channel m leader must establish a minimal association between its indication wrapping and the signal envelopes of the SUs to choose cooperative SUs with distinct nearby sensed data. The leader for each channel is the SU whose SNR is near SNR_avg, as defined in Eq. (1) and Eq. (2):

$$\propto_{mk} = \begin{cases} 1, & if\ K^{th}\ SU\ is\ a\ leader\ for\ channel\ m \\ 0, & otherwise \end{cases} \quad (1)$$

The following is a definition of the optimization problem preparation for a similar collection of channel leaders:

$$\min_{\propto_{mk}}: \sum_{k=1}^{K}\sum_{m=1}^{M} \alpha_{mk} \times \left|SNR_{mk} - SNR_{avg}\right|$$

Subject to: C1 : $\sum_{m=1}^{M} \propto_{mk} = c_k, \forall\, k,$

C2: $\sum_{k=1}^{k} \alpha_{mk} = 1, \forall\, m,$ (2)

The binary variable $c_k$is equivalent to 1 if the k^{th} SU is a leader for a channel and 0 in all other cases. C1 ensures that a single SU can't simultaneously be chosen as a leader for multiple channels. C2, on the other hand, affirms that a single leader is selected for every channel. Combining these two restrictions ensures that every cooperative cluster has a distinct leader and channel.

C. Reinforcement Learning (RL) for Resource Allocation

According to the power received from the primary user, this section allocates available secondary users to primary users. Users who have been allotted are shown. This section applies a reinforcement learning algorithm to maximize resource distribution for every secondary user. The Q-learning algorithm trains a Q-table and mimics the environment to obtain rewards. Based on the rewards, the Q-table is updated, and metrics like energy consumption, false alarm rate, throughput, and probability of detection are calculated. A new line of inquiry for addressing SOM issues is the development of reinforcement learning (RL) techniques. The RL techniques shown in Fig. 1, don't need any prior understanding of the system model and can adjust to the spectrum environment. Because it is model-free, Q-learning is a significant reinforcement learning subfield with extensive applications in various settings. Finding the Q value for every state-action pair is the primary goal of Q-learning, a value iteration technique. Every SU uses the Q-learning approach, and based on recent action-observation experience and past channel occupation history, decides whether to sense the channel. Q-learning is effective when the state and action spaces are small.

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indicates the state space, $A \in \{1,\cdots,N\}$ indicates the action space, $R \in \{0, 1\}$ indicates the instant reward, and S' indicates the next state. Every time slot begins with the current state (S), which comprises all the previous observations and decisions.

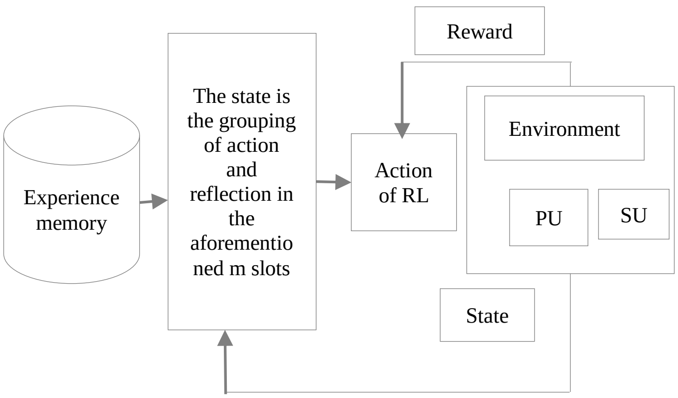


Fig. 1. RL framework for CRN.

The Q network takes the S as an input and predicts what the best action, A, should be as an output, which denotes A sensing of a particular channel at time slot t. The system may reach the next state after taking action A and receive a reward instantly. At last, the time slot record is saved in memory D, and it iterates again to D. And the experience memory is filled according to the random sampling. It samples m records (S, A, R') using experiences sampled from memory D to derive the current target Q estimate. The associated in Eq. (3) is given as:

$$y=R+\gamma \max_{a'} Q(S_{t+1}, a'; \theta_i^-) \tag{3}$$

The reinforcement output, denoted by y, is determined by the new experience. The approximation function created through prior expertise is represented by Q (S_{t+1}, a' ; $\theta{-}i$), where S_{t+1} is the novel state resulting from action a, assuming the state S_t , and t is the time interval. The weightiness of the Q-network charity to calculate the objective at repetition i is represented by θ_i^-, and the discount rate is denoted by γ. The loss function, which is expressed in Eq. (4) and Eq. (5), is the mean right-angled error between the value of the impartial purpose and the assessment of the definite purpose.

$$L_i(\theta_i) = E[(R_{t+1} + \gamma \max_{a'} Q\,(S_{t+1}, a'; \theta_i^-) - Q(S_t, A_t; \theta_i))^2] \tag{4}$$

$$\nabla_{\theta i} L_i(\theta_i) = E\left[\left(\left(R_{t+1} + \gamma \max_{a'} Q\,(S_{t+1}, a'; \theta_i^-) - Q(S_t, A_t; \theta_i)\right) \nabla_{\theta i} Q(S_t, A_t; \theta_i)\right]\right) \tag{5}$$

where, the estimate purpose designed by old understanding is represented by Q (S_{t+1}, a'; $\theta{-}i$) and the estimate purpose designed by new understanding is represented by Q (S_t, A_t; θ_i).

IV. Results and Discussion

The states of the proposed M2CSS are the grouping of the operator's state on respective frequency, and the user's relationship to the PU, SU, data 1, data 2, and CBS, as shown in Fig. 2. Two simulated networks with different user and channel counts are employed to achieve accurate sensing in many user scenarios. The network implementation should take less time to yield positive outcomes.

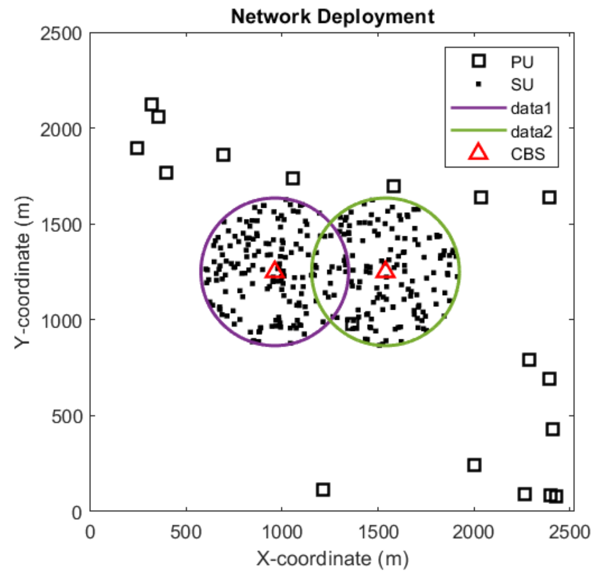


Fig. 2. M2CSS network deployment.

D. K-means for Leader Selection (KMC)

This stage uses similarities to classify recently joined SUs in the system that are interested in common assemblies. Fig. 3 shows the organization process when new SUs attempt to intersect the CRN. The primary justifications for utilizing KMC in this work are its simplicity, speed, and low complexity. To locate the centroids in KMC, the maliciousness of the exercise set under consideration is computed. The centroids then state that the unlabeled set is confidential. The classifier in this study is created utilizing historical data from operational cooperative SUs. To classify the joining SUs, one needs to determine the centroids of each class. The CVM test results of current SU leaders are the lowest, and their SNR values are relatively close to the average SNR for each channel. Non-leaders, on the other hand, have larger SNR value spreads and high CVM test values. This implies that the training set should form two distinct clusters. Fig. 3 displays the filtered data as well as the current data points. Eigen vectors and values of the new and old data points were used to generate distribution contractions for them. The distributions differ from one another. Outliers must therefore be removed from freshly acquired data points. Fig. 3 shows the data points for leaving cooperative SUs. Interestingly, two separate SUs do not align with two marked departing data points.

E. SOM Leader Selection

Consequently, the data points from the operational cooperative SUs were split into two classes (see Fig. 4). The RL algorithm is utilized to do this. Channel leaders make up Class 1, and non-leaders make up Class 2. These class centroids serve as reference points for classifying new data instances. This procedure aids in distinguishing new data from Class 1 samples.

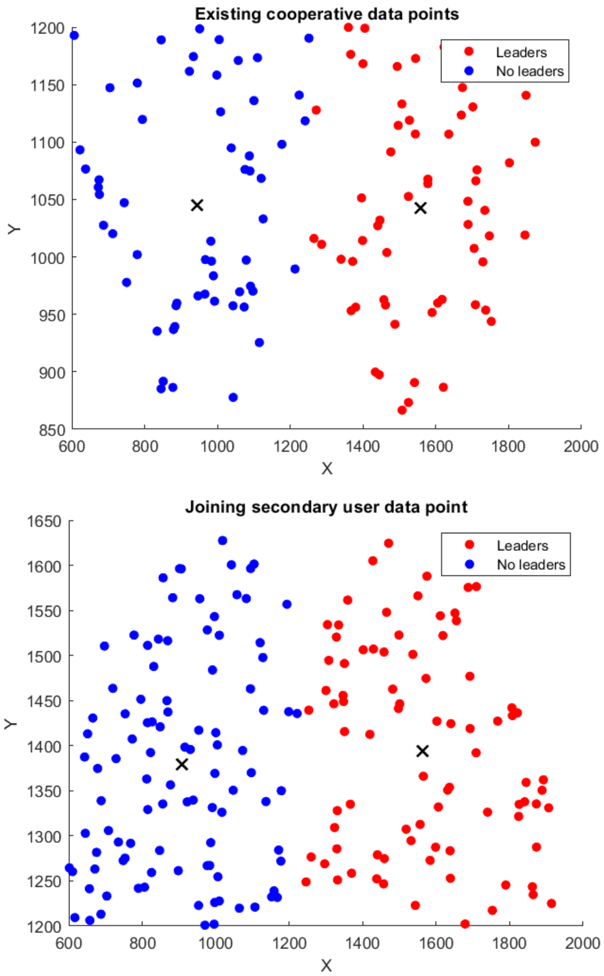
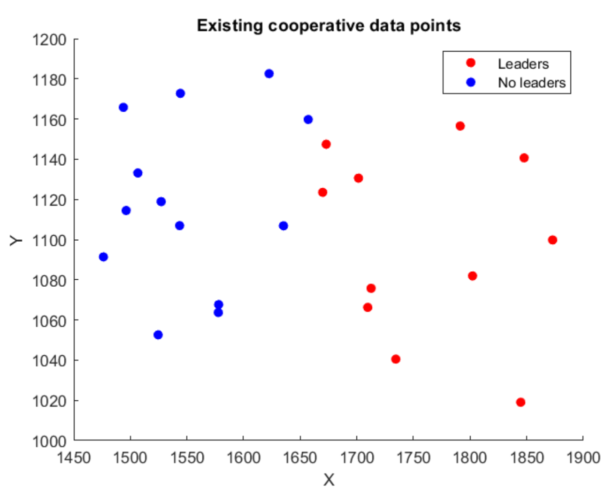
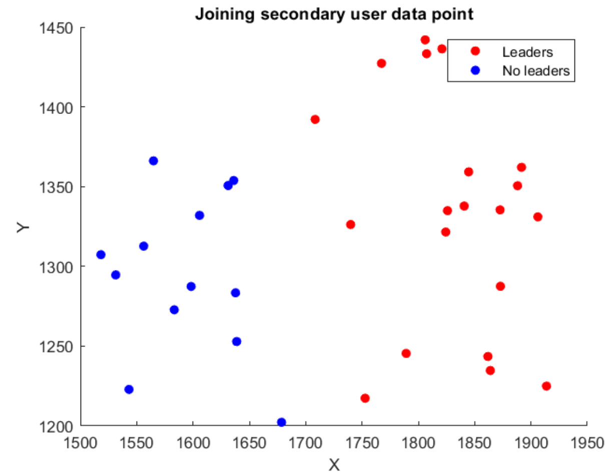


Fig. 3. K-means leader selection.



(a)



(b)

Fig. 4. (a) Leader selection with SOM, (b) No-Leader selection with SOM.

F. SNR Distribution of the Secondary Users

The SNR for secondary users is determined as defined in Eq. (6), where $received\_power\_SU\_bs$ is the established control of the secondary consumer from the base station, and $noise\_power$ is the noise power. When the sensing duties were distributed, the number of SUs sensing each frequency increased. This may result in the system using more energy. The incorporation of multiple SUs into the system can cause average SNR levels to surpass acceptable limits, resulting in compromised detection capabilities. Therefore, for a few freshly selected SUs, testing the average channel SNR condition and lowering the minimum required is necessary. If they find another channel, new SUs might not have to bother about sensing this one. This will enable the performance and energy to be recovered (see Fig. 5).

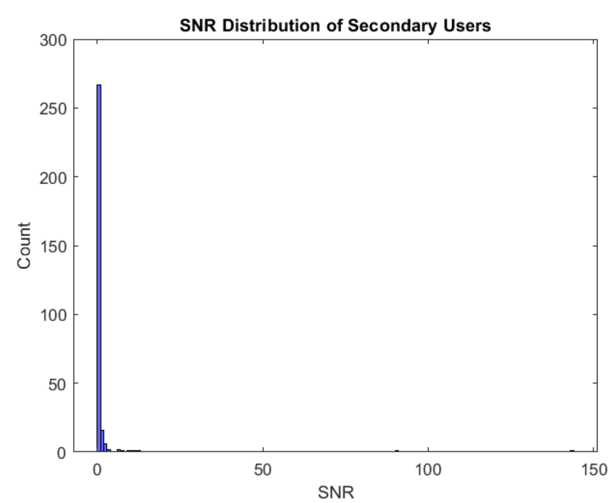


Fig. 5. SNR distribution of SU.

$$SNR_{SU} = \frac{received\_power\_SU\_bs}{noise\_power} \tag{6}$$

G. Resource Allocation

For illustration, it is considered that the user is distributed by channel with 10 joining and 10 existing SUs. Fig. 6 displays training data points or the data from the cooperative SUs currently used for sensing channels. The proposed work considers two features, resource allocation and SNR values, and defines a data point as a pair of binary feature standards for SU sensing at the m^{th} frequency represented in Fig. 7. Both characteristics are scaled to depict the data points accurately. The disseminated version procedure for channel 2 of the recommended M2CSS and EM2CSS arrangements and the current multi-band schemes, RSSS, and ASSS, are shown in Fig. 8, Fig. 9, and Fig. 10. To simulate CRN systems, λmax is considered the learning rate, without losing generality. The suggested M2CSS and EM2CSS schemes establish the minimum and maximum K×I values for the number of designated SUs that can intelligently set a channel.

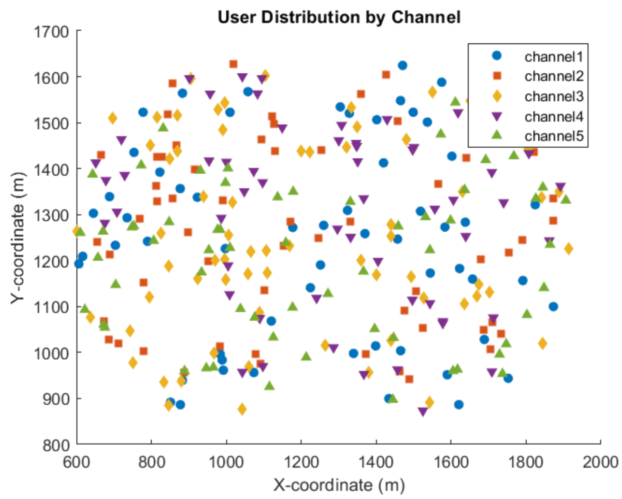


Fig. 6. User distribution by channel.

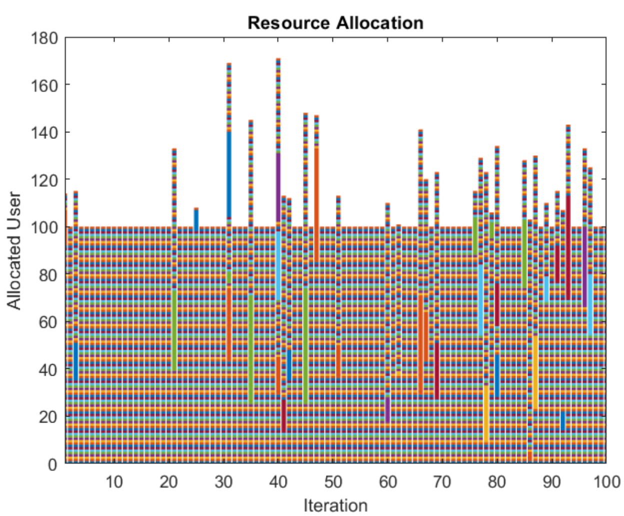


Fig. 7. Resource allocation for SU.

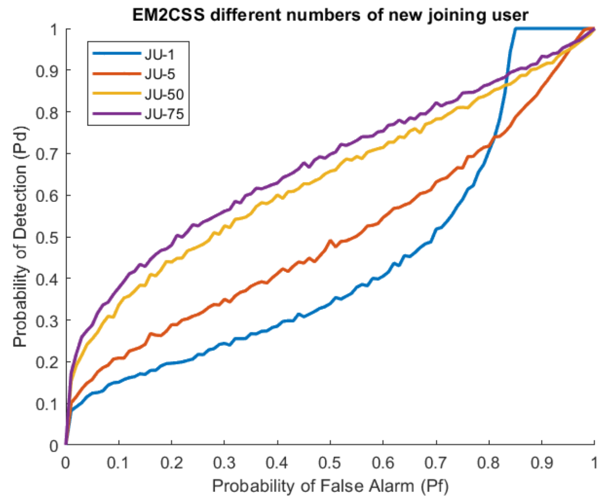


Fig. 8. EM2CSS with different numbers of SU.

Before estimating each cooperative SU separately, ASSS selects them at random. Determining the test statistics and sensing a few examples based on the estimate. If the examination indicators are exceeding a specified boundary, SU is supposed to be able to sense primary user activity on the channel and execute preparation. It eliminates the need to sense that channel in any other way. Because of the approximation of the SUs' procedure in ASSS, there are generally fewer SUs in ASSS. SUs that were predicted to have poor sensing performance are dropped. RSSS selects cooperative SUs at random. Consequently, in M2CSS, EM2CSS, RSSS, and ASSS, respectively.

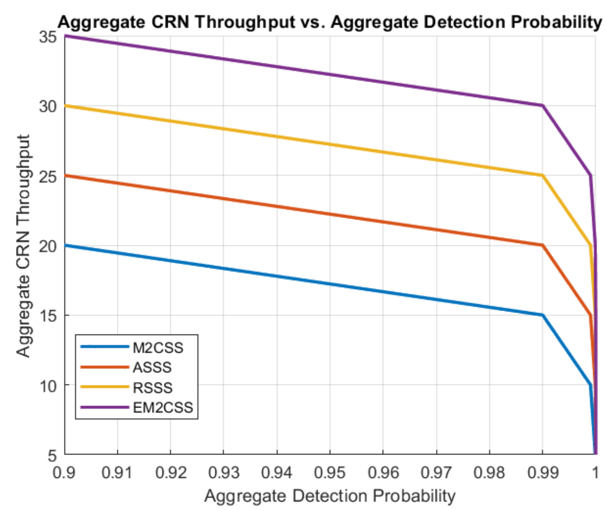
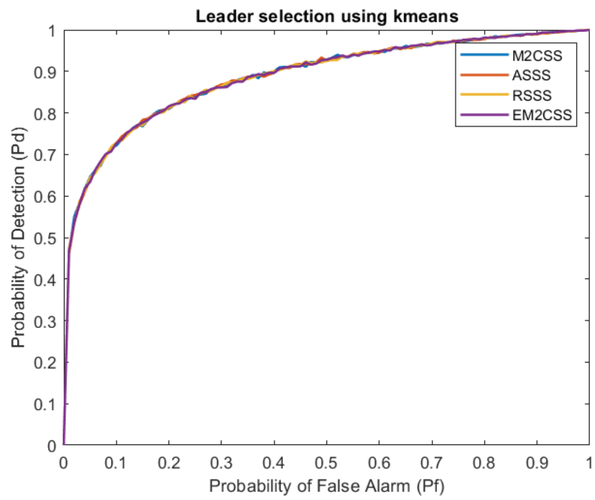


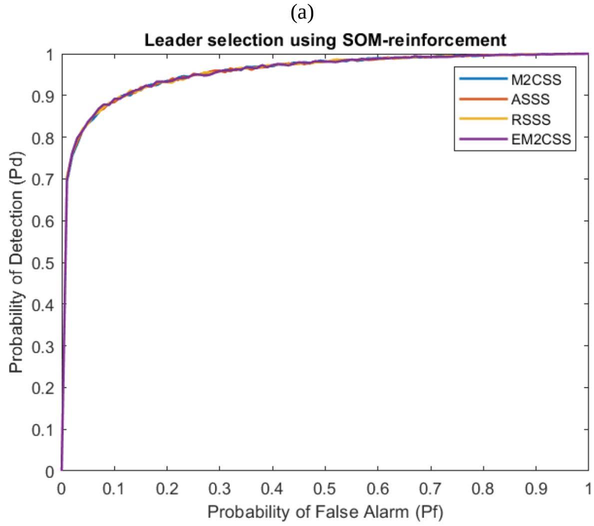
Fig. 9. CRN throughput for SOM leader selection.

A significant benefit of the proposed M2CSS and EM2CSS schemes is that they do not select dismissed cooperative SUs or those through comparable identified material for the m^{th} channel. Nevertheless, when SUs are chosen by popular RSSS, SUs with comparable information may be chosen randomly, as the first selected SU possesses comparable sensing information, as seen in Fig. 9. In contrast, the third selected SU does not have original statistics for the alteration procedure.

This could result in increased computational complexity and expenses related to energy usage. The consensus point is reached in each case after 14 iterations, and the channel occupancy is calculated by comparing the obtained results to the threshold. The throughput results demonstrate that EM2CSS performs significantly better than M2CSS, and for all network sizes considered, both schemes provide excellent CRN throughput consequences.



(a)



(b)

Fig. 10. (a) ROC with different CRN schemes using k-means, (b) ROC with different CRN schemes using SOM.

Proceeding with the additional indicator, the CRN throughput presentation of the current schemes varies. For lower and higher CRNs, the combined PU throughput is compared to the combined untrue distress possibility (also called the PU security level). At a 10% false alarm probability, the most significant combined throughput is attained by the proposed EM2CSS scheme. Additionally, the M2CSS scheme achieves the same false alarm rate. However, it is achieved when the current ASSS scheme is used with the same false alarm possibility. The ROC curve in Fig. 10(a) and Fig. 10(b) shows that leader selection through SOM helps in achieving high probability of detection with less value of probability of false alarm as compare to existing k-mean. Therefore, the proposed EM2CSS structure fulfills the highest requirements of PU throughput in both inferior and superior CRN configurations. The combined sensing energy usage of the larger CRN's current RSSS and ASSS systems, as well as the indicated EM2CSS and M2CSS schemes.

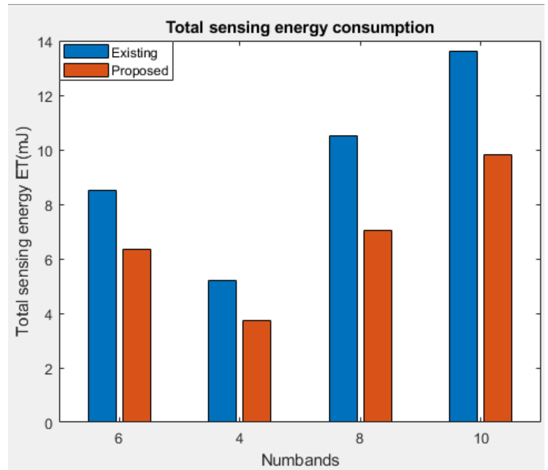


Fig. 11. Total energy consumption.

The scheme's ability to drop SUs sensing specific frequencies with low-slung expected values correlates with this lowest value. On the other hand, the current RSSS scheme uses the most total energy for sensing. The highest energy consumption in RSSS is caused by randomly selecting cooperative SUs with no restriction on the number of SUs sensing each channel. Furthermore, by relaxing cooperative SUs, EM2CSS offers the benefit of distributing the sensing load among already-existing and newly joined SUs. Reduced energy consumption for sensing is made possible by the distribution of the sensing load. It is for this reason that Fig. 11 shows that EM2CSS uses less sensing energy than M2CSS. As a result, the suggested EM2CSS enables respectable levels of sensing energy consumption and outstanding classification presentation in terms of discovery and quantity.

V. Conclusion

The SOM-based multi-band CSS schemes M2CSS and EM2CSS, which have been proposed to disseminate 6G-enabled IoT CRNs, are discussed in this study. The proposed M2CSS architecture addresses two critical optimization challenges: intelligent cluster leader selection across frequency bands and dynamic secondary user accommodation within 6G CR-IoT networks. To choose a leader for every frequency and consistently accommodate SUs, the proposed work developed two optimization problems for the suggested M2CSS scheme. These problems are solved by the reinforcement learning algorithm in the EM2CSS scheme to offer a more effective and simplified method for allocating connection SUs to allocate a subsection of frequencies intelligently. The system architecture incorporates energy-efficient mechanisms that preserve network performance while reducing power consumption—a crucial requirement for resource-constrained IoT devices in 6G networks. The system has been relaxed to minimize energy consumption without compromising performance, and the joining SU selection process has been optimized to detect specific channels. Compared to the currently offered multi-band CSS schemes, reproduction consequences show that the recommended M2CSS arrangements select SUs through distinct nearby sensed evidence to preserve an effective agreement variation procedure and high-performance stages in lower and higher 6G IoT CRNs. While the proposed MBMU-CR IoT framework is demonstrated via simulations, extending the work to hardware implementation could introduce additional complexity, but would significantly enhance the evaluation under real-world conditions. Incorporating the concepts of joint sensing and communication, along with integrated sensing and communication, can significantly enhance the performance of the proposed M2CSS.

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