Received 6 June 2020; revised 3 July 2020; accepted 22 July 2020. Date of publication 29 July 2020; date of current version 11 August 2020.

Digital Object Identifier 10.1109/OJCOMS.2020.3012906

Scalable Learning-Based Heterogeneous Multi-Band Multi-User Cooperative Spectrum Sensing for Distributed IoT Systems

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This work was supported by the Natural Sciences and Engineering Research Council (NSERC) of Canada.

ABSTRACT The emerge of Internet of Things (IoT) brings up revolutionary changes to wireless communications. Cognitive radio (CR) can be seen as one of the prominent solutions to spectrum scarcity in IoT, where multi-band cooperative spectrum sensing (CSS) is the key. However, lack of centralized control and increase in number of devices place a room for many challenges. One of the main challenges is secondary users' (SUs') scheduling to sense a subset of channels in heterogeneous distributed CR networks (CRNs). To overcome the aforementioned challenge, in this paper, we propose a novel heterogeneous multi-band multi-user CSS (HM2CSS) scheme. The proposed scheme allows heterogeneous SUs to sense multiple channels and consists of two stages. We formulate a mathematical model to optimize leader-selection for each channel in the first stage. We then formulate another optimization problem to determine corresponding cooperative SUs to sense these channels in the second stage. After that, diffusion learning is used to decide on the availability of channels. Simulations illustrate that the proposed scheme improves detection performance and CRN throughput, is scalable in terms of detection performance, and provides fair energy consumption for CSS on all channels compared to existing multi-band CSS schemes.

INDEX TERMS Cognitive radio, cooperative communications and distributed processing, heterogeneous networks, Internet of Things.

I. INTRODUCTION

INTERNET of Things (IoT) has brought a rapid increase in the usage of wireless spectrum [1]. Meanwhile, cognitive radio (CR) has drawn attention as a potential technology to address spectrum demands of IoT systems [2]. CR networks (CRNs) allow secondary users (SUs) to opportunistically access the spectrum owned by legitimate/primary users (PUs) without affecting the primary network's transmission [3]. Within CR, spectrum sensing is a key component. By sensing the spectrum, SUs can acquire the knowledge of whether the spectrum is occupied by PUs or not, and hence, utilize the spectrum when it is not used by PUs.

Generally, wide-band spectrum owned by PUs is divided into non-overlapping sub-bands, called channels. This causes a multi-band structure of the spectrum. Due to hardware limitations and energy constraints of IoT devices, instead of sensing all channels, each SU can sense multiple channels and then, exchange the sensed information with other SUs to determine spectrum availability [4]. This process is called multi-band cooperative spectrum sensing (CSS).

Multi-band CSS can be done in centralized or distributed ways [3]. In centralized multi-band CSS, SUs forward locally sensed information to a central entity, also called fusion center (FC). FC controls the system and makes decisions on the availability of channels based on the feedback from SUs. In distributed multi-band CSS, SUs exchange their local observations with corresponding cooperative SUs to determine the availability of channels without an FC. The nature of

IoT systems is distributed [5]. In addition, IoT networks place focus on learning and feedback information about the environment [6]. Therefore, distributed approach tends to be more favorable in the IoT scenario.

The role of learning and adaptation is becoming increasingly essential with IoT. Conventionally, learning implies changes within a system that over time enables it to perform more effectively within its environment by reusing past experiences [7]. However, in this paper, we consider learning as an adaptation process through making adjustments in the locally sensed results within each cooperative SU-cluster in a distributed CRN. Each SU is not only capable of sensing spectrum and experiencing the environment directly, but also receives locally sensed information from its cooperative SUs to process and analyze it [7]. In this way, a common decision about channels' availability is achieved.

In traditional distributed multi-band CSS, SUs sense channels independently, using a single detector type. Then, distributed learning algorithms are used to make cooperative decisions on the availability of channels [3]. However, the nature of IoT comes up with revolutionary ideas. CSS for IoT systems has to consider spectrum analysis, history and prediction, network reconfiguration, hardware limitations, and computational complexity of secondary IoT-nodes [2]. Cognitive IoT systems have to take into account prior information available about the signal carried across the channel. Scalability is another key IoT-driven requirement, which implies network growth with time [5]. SUs deployed in CRNs may have different types of spectrum detectors due to heterogeneous nature of IoT. Nevertheless, supplementary heterogeneous SUs may cause system performance degradation, leading to extra human intervention to get acceptable system performance level back. Therefore, IoT-based multi-band CSS design is very challenging mainly because of SUs' scheduling to sense a subset of channels. Correct choice of cooperative SUs may significantly increase system performance level and reduce latency [8]. Furthermore, heterogeneous multi-band multi-user CRNs place serious challenges in terms of fairness in the cooperative SU-selection process of the IoT system. Therefore, to have stable system performance for all channels, it is essential to study and improve distributed multi-band CSS schemes by considering IoT demands mentioned above.

A. RELATED WORK

There has been a plethora of research efforts in recent years in the area of CSS. This section gives a brief state-of-the-art summary of this field.

To begin with, authors propose an energy-efficient reliable decision transmission scheme for IoT-based CSS in [9]. The proposed scheme has a centralized system model, which uses OR/AND-rule and improves detection probability as well as reduces sensing energy consumption. However, the aforementioned work does not take into account the multi-band approach. Recently, several multi-band CSS schemes are proposed in the literature. Non-uniform sensing duration of multi-band spectrum access is analyzed for centralized CRNs in [10]. Authors in [11] propose an efficient energy detector (ED) based centralized multi-band CSS scheme, which uses detection threshold optimization to minimize sensing energy consumption. A basic centralized multi-band CSS scheme is proposed in [8] to reduce the complexity of the spectrum sensing process. Authors provide a thorough throughput analysis of the proposed system. Nevertheless, all works mentioned above do not take into account either the heterogeneous aspect of SUs or the distributed system topology.

In [12], an optimal multi-band distributed homogeneous CSS scheme is proposed, which maximizes the CRN throughput with constraints on energy and signal processing resources consumed on spectrum sensing. Moreover, in [13], authors propose homogeneous distributed adaptive spectrum sensing strategy (ASSS), which uses PU traffic patterns to determine channels to be sensed in multi-band CRNs. ASSS selects channels to be sensed in an adaptive manner such that the selected channels are more likely to be unoccupied. In [14], a heterogeneous centralized system using k-out-of-K rule is analyzed. Centralized and distributed consensus learning-based heterogeneous CRNs are compared in terms of CRN throughput analysis in [3]. There, using random spectrum sensing strategy (RSSS), cooperative SUs that sense multiple channels are chosen arbitrarily, i.e., in the random manner. Nevertheless, random SU-selection may lead to system performance degradation as the network size increases.

There exists plenty solutions for cooperative SU-selection schemes in single-band CRNs. In [15], a single channel CRN is assumed, where one user is chosen randomly and then, Cramer-Von Mises (CVM) test values are calculated to select cooperative SUs. Only those SUs are selected, for which CVM test values are greater than the calculated threshold. In [16], a distributed heuristic algorithm is proposed to reduce system's energy consumption by minimizing the number of cooperative SUs. However, in this system, SUs located within a certain distance to a PU are not allowed to use the spectrum and act only as sensing units. In [17], we proposed a homogeneous multi-band multi-user CSS (M2CSS) scheme to select multiple SUs to sense channels in distributed CRNs. M2CSS is a two stage process, which consists of selecting a leader for each channel and its corresponding cooperative SUs. We further proposed an enhanced M2CSS scheme to allow new SUs to join and existing SUs to leave the CRN [18]. Both schemes utilize distributed consensus learning based approach. However, these works did not consider SU-selection in the heterogeneous multi-band context.

Concluding, although there exists good literature on CSS, non-arbitrary ways of assigning channels to be sensed by participating SUs in heterogeneous multi-band multi-user distributed CRNs are not considered yet. Therefore, in this paper, we propose a heterogeneous multi-band multi-user CSS (HM2CSS) scheme for distributed IoT systems. The proposed approach is a heterogeneous and scalable scheme based on M2CSS [17]. As discussed previously, the term IoT implies scalability, heterogeneity, and interoperability of connected devices in networks. The proposed HM2CSS scheme provides interoperability of heterogeneous connected devices, i.e., SUs, to schedule sensing task assignments in a scalable distributed CRN. The technical challenge of this work lies in stable system performance levels for scalable and heterogeneous cognitive IoT systems through efficient utilization of resources. Particularly, the existing schemes do not consider optimizing SUs' scheduling to sense multiple channels subject to different sensing capabilities of SUs. The novelty of this scheme is the selection of SUs with different sensing results to improve utilization of IoT systems' resources. In other words, the proposed HM2CSS scheme does not select SUs to be cooperative if they own similar information about the channel. This work differs from the existing scheme by providing a modular two-stage SUs' selection in heterogeneous and scalable IoT systems.

B. CONTRIBUTIONS

The main contributions of this paper are as follows:

- We propose a two-stage HM2CSS scheme for heterogeneous SUs' scheduling to sense multiple channels. We consider heterogeneous information available about channels, where up to 100 SUs have to be assigned to sense multiple channels making this scenario applicable to IoT.
- In the first stage, we propose a modular leader selection approach for channels with heterogeneous information available about them. We formulate separate optimization problems for each detector type that can be integrated into the system in a modular manner and executed concurrently for all channels. Particularly, one module, and hence a detector type, is selected for each channel based on the information available about it.
- We then formulate a unified optimization problem to select corresponding cooperative SUs for all channel concurrently in the second stage. For interoperability, only SUs with similar detector type as the leader's detector and owning different sensed information can be selected for each channel.
- We further utilize diffusion based learning as a unified approach for information exchange between cooperative SUs. This allows to reduce the number of iterations needed to perform the information exchange process, and hence, decrease the learning time compared to the consensus algorithm used in M2CSS.
- Simulations are performed to demonstrate the performance of the proposed HM2CSS scheme. The results are compared to the existing heterogeneous multi-band CSS schemes.

C. ORGANIZATION

The rest of the paper is organized as follows. In Section II, system model is discussed for distributed multi-band CSS with heterogeneous devices. Then, we investigate the proposed HM2CSS scheme thoroughly in Section III. Section IV covers the computational complexity analysis of the proposed HM2CSS scheme. In Section V, extensive simulation results are presented. The proposed distributed HM2CSS scheme is compared to existing distributed and centralized multi-band CSS schemes. Finally, conclusions are made in Section VI.

II. SYSTEM MODEL

We investigate a distributed heterogeneous CRN as illustrated in Fig. 1. There are M PUs in the network, each one having its dedicated channel. Hence, the number of channels is also considered to be M, i.e., $\mathcal{M} = \{m_1, m_2, \ldots, m_M\}$. Each PU is assumed to be either in an active or idle mode. The active mode denotes a PU occupying its channel, while the idle mode means that a PU is not transmitting and hence, this channel can be used by SUs until the PU starts its transmission. We further consider K SUs, i.e., $\mathcal{K} = \{SU_1, SU_2, \ldots, SU_K\}$. In IoT networks, the number of devices is typically higher than the number of channels [19]. Hence, we assume that $K > M$. In addition, SUs have no privileges over the PU transmission in CRNs. In most cases, technical details of the PU transmission are unknown. Only certain significant details may be known at the SU side. PUs can share these details with SUs through a pre-defined agreement. This agreement can allow SUs to use the shared details to improve PUs' detection over the channels and hence, reduce the potential interference levels for both, PUs and SUs [20]. Depending on the sensitivity of an IoT application, the level of shared details may vary. Therefore, in this paper, we consider heterogeneous PUs, i.e., PUs with different technical details of the transmission. We further assume that only certain information is available about the PU transmission at the SU side. Hence, three main channel types considered are with no prior information about a PU signal, with known pilot tone of a PU signal, and the channel with an orthogonal frequency division multiplexing (OFDM) PU signal being sent over it. We assume that M_N is the total number of channels with no information available about them, M_P is the total number of channels with the known pilot-tones, and M_O is the total number of channels known to carry the OFDM signal. This means that $M = M_N + M_P + M_O$.

IoT interconnects heterogeneous applications together, operating concurrently, and provides their interoperability in a scalable network. This means that an IoT system contains more than a single device type, i.e., is heterogeneous in terms of secondary IoT-nodes. For example, smart cars, smart cameras, smart lighting, etc. Therefore, we set the IoT system model in Fig. 1 to be heterogeneous by considering three types of detectors for local spectrum sensing. The detector types considered are ED, pilot tone detector (PD), and OFDM-based detector (OD) [3]. SUs sense channels cooperatively and decide whether they are occupied by PUs or not. For this purpose, each SU is assumed to be equipped

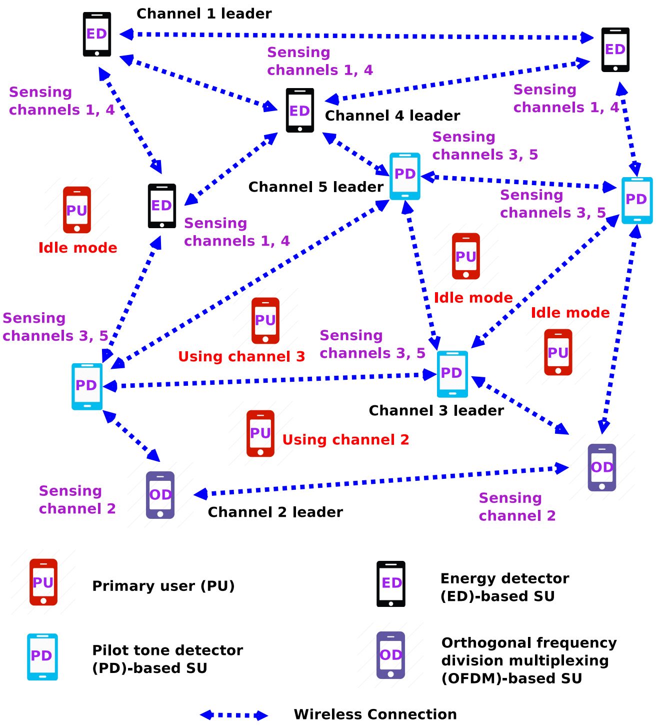

FIGURE 1. Heterogeneous distributed multi-band multi-user CRN topology.

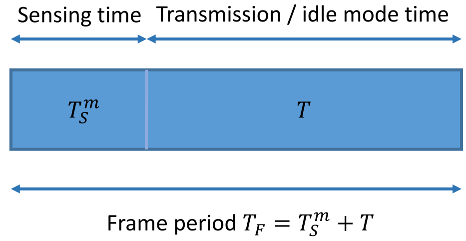

FIGURE 2. The structure of one frame for CSS.

with one detector, such that in total there are K_E ED, K_P PD, and K_O OD-based SUs, i.e., $K = K_E + K_P + K_O$. To determine the availability of channels in the ED-based case, the received signal power is estimated. In the PD-based scenario, the orthogonality property between the pilot tone, i.e., s_p, and the data-carrying signal, i.e., s_d, is used [3], [21]. Hence, in this case, the transmitted PU signal can be seen as $s = \sqrt{\epsilon} \times s_p + \sqrt{1-\epsilon} \times s_d$, where ϵ is the fraction of the total power allocated to the pilot tone. As for the OD-based case, using the knowledge of cyclic prefix and the OFDM symbol length, inherent signal correlation incurred by cyclic prefix repetition is taken into consideration [22]. To this end, we consider two levels of heterogeneity. These are SUs with heterogeneous sensing capabilities, i.e., different detector types, and heterogeneous information available about the channels owned by PUs.

We assume that there is sufficient number of SUs to detect each type of channels in the network. An SU can sense minimum one and maximum I channels, where $I < M$. Each k-th SU performs local spectrum sensing using N_m^k samples for channel m. This means that SUs have to solve multiple binary hypothesis problem [3]:

$$\begin{aligned} H_0^{m,k} &: \mathbf{x}_m^k = \mathbf{w}_m^k \\ H_1^{m,k} &: \mathbf{x}_m^k = \mathbf{h}_m^k \cdot \mathbf{s}_m + \mathbf{w}_m^k, \end{aligned} \tag{1}$$

where $H_0^{m,k}$ and $H_1^{m,k}$ denote the absence and presence binary hypothesis testing of the m-th channel sensed by k-th SU, respectively. $\mathbf{x}_m^k$ is the signal received by k-th SU while sensing the m-th channel, $\mathbf{s}_m$ is the signal transmitted by the m-th PU over the Rayleigh Fading channel with the amplitude gain $\mathbf{h}_m^k$, and $\mathbf{w}_m^k$ is the circularly symmetric complex Gaussian noise with zero mean and $(\sigma_m^k)^2$ variance, i.e., $\mathbf{w}_m^k \sim \mathcal{CN}(\mathbf{0}, (\sigma_m^k)^2\mathbf{I})$.

As shown in Fig. 1, only certain SUs in a CRN can communicate with each other. This is because of the geographic location and fading environment. All PUs and SUs are assumed to be distributed randomly across the area. Furthermore, channel's coherence time is assumed to be larger than the frame period. During a single frame the signal-to-noise ratio (SNR) and position of SUs is considered to be constant. However, these values may change between frames. This means that the location of nodes is not constant. Therefore, each SU is achieving a certain value of SNR for each channel. All SUs participate in the CSS process and have to be aware of the final decision of the availability of channels as well as the priority of SUs' transmission in case channels are unoccupied. Hence, we assume that SUs can route each others information through SU-leaders, where one leader is being assigned for each channel. Fig. 2 illustrates the total frame structure of the CSS process. Let T_s^m denote the total sensing process time, and T be the transmission or idle mode time, depending on the availability of channel m, then T_F is the total period of the frame, i.e., $T_F = T_S^m + T$. The energy consumed to sense and decide on availability of each channel is represented by $E_{m,CONS}$ and can be given as:

$$E_{m,CONS} = \left(P_S \times T_S^m\right) \times Q_m + E_{m,learn}, \tag{2}$$

where P_S is the power consumed on spectrum sensing, Q_m is the number of cooperative SUs sensing channel m, and $E_{m,learn}$ is the total energy consumed on the learning process for the m-th channel. In other words, $E_{m,learn}$ considers the energy spent on exchanging locally sensed data between cooperative SUs and deciding on the availability for the m-th channel. Finally, assuming SUs access M_L channels out of M, global CRN throughput can be defined as:

$$\begin{aligned} R = B \times \sum_{m=1}^{M_L} p_0^m \times \log_2(1 + SNR_{mk}) \times \left(1 - P_f^{mk}\right) \\ + p_1^m \times \log_2(1 + SINR_{mk}) \times \left(1 - P_d^{mk}\right), \end{aligned} \tag{3}$$

where B is channel's bandwidth, p_0^m is the probability that channel m is not used, p_1^m is the probability that channel m is occupied, SNR_{mk} is the SNR value, $SINR_{mk}$ is the signal-to-interference-and-noise ratio (SINR) value, and P_f^{mk} as well

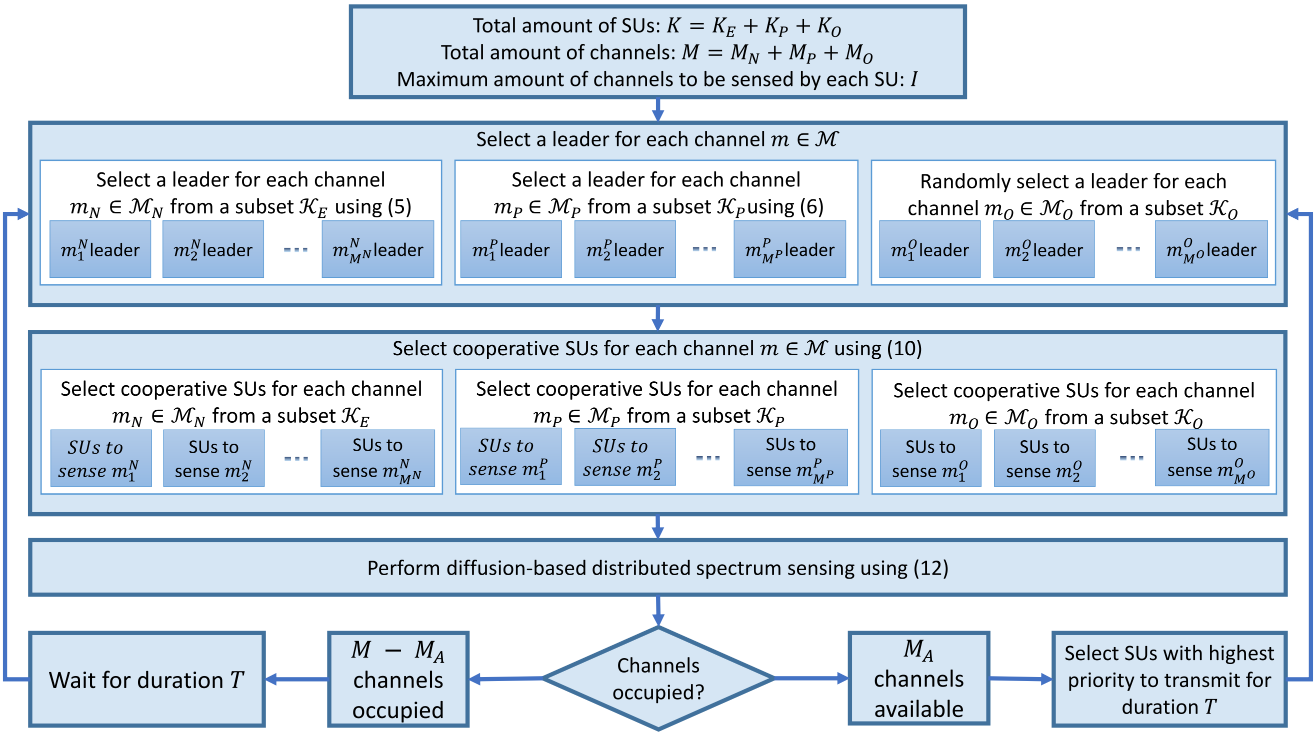

FIGURE 3. A flow chart for the proposed HM2CSS scheme.

as P_d^{mk} are the false alarm and detection probabilities of k-th SU sensing channel m, respectively.

III. HETEROGENEOUS MULTI-BAND MULTI-USER COOPERATIVE SPECTRUM SENSING

In this section, we propose a CSS scheme, called HM2CSS. We select cooperative SUs for distributed multi-band CSS in two stages. Cooperative SUs then sense channels and using diffusion learning algorithm, exchange sensed information and decide on channels' availability. The proposed scheme is designed to enable scalability and improvements for detection performance, enhance CRN throughput, and provide fair sensing energy consumption for all channels.

A flow chart for the proposed HM2CSS scheme is presented in Fig. 3. The first stage of the proposed HM2CSS scheme is to select an SU-leader for each channel $m \in \mathcal{M}$. In case no information is available about a PU signal, i.e., $m_N \in \mathcal{M}_N$, an SU-leader is selected from the ED-based SUs subset, $\mathcal{K}_E \in \mathcal{K}$. If the pilot tone of a PU signal is known, i.e., $m_P \in \mathcal{M}_P$, an SU-leader is selected from the PD-based SUs subset, $\mathcal{K}_P \in \mathcal{K}$. Otherwise, if the signal sent by a PU across the channel is believed to be the OFDM one, i.e., $m_O \in \mathcal{M}_O$, then an SU-leader is selected from the OD-based SUs subset, $\mathcal{K}_O \in \mathcal{K}$. After that, the CVM goodness-of-fit test together with the SU-leaders chosen are used to select cooperative SUs to sense each channel $m \in \mathcal{M}$ as a second stage of the proposed HM2CSS scheme. Similarly to the leaders' choice, cooperative SU-selection depends on the information available about channels, such that in cases no prior information about the signal, the known pilot tone of the signal, and the signal is known to be OFDM, cooperative SUs are chosen to be from the ED, PD, and OD-based SUs subsets, respectively. This is necessary to provide synchronization to the diffusion learning process and use the most out of information available for sensing. The two stages mentioned above are discussed in details in the following sections. After the cooperative SU-selection process is accomplished, diffusion learning is performed by each cooperative SU-cluster to determine whether channels are occupied or not. Those channels, which are determined to be in the idle mode, are available for SUs' transmission, meaning that SUs with highest priorities to use channels can transmit for time duration T. As for the occupied channels, SUs are not allowed to use them. Thus, they have to wait for time duration T and then, repeat the process from the beginning.

A. STAGE 1: LEADER SELECTION

Optimal leader-selection implies determining the best SU to listen to for each channel $m \in \mathcal{M}$. Leaders are responsible to select cooperative SUs for distributed CSS. This is why it is essential to make the correct choice of a leader for each channel. We can define a binary indicator b_{mk} to show, whether k-th SU is chosen as a leader for channel m or not as:

$$b_{mk} = \begin{cases} 1, & \text{if } k\text{-}th \text{ SU is the leader of channel } m \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

1) ENERGY DETECTOR (ED)-BASED LEADER SELECTION

Since ED-based detection is done by estimating the received energy levels whether the noise level is high or low, together with the PU signal it is detected. In case noise level is high and a PU is in the idle mode, an ED-based SU may decide that the PU is present. This is why the SNR value of the channel plays an important role in this type of detection. Let SNR_{avg} be a threshold for the desired and prefixed average SNR value across each channel. Since the test statistics for the ED-based detection is primarily the energy level sensed, for the efficient diffusion process it is important to select cooperative SUs with low correlation in the signal envelopes. This is because lower correlation ensures diversity and results in richer information for cooperative SUs' collaboration. To achieve this objective, we select leaders with SNR values close to SNR_{avg} for channels with no prior information available about them. The optimization problem formulation to select leaders for $m_N \in \mathcal{M}_N$ channels can be defined as follows:

$$\begin{aligned} \min_{b_{m_N k_E}} : & \sum_{k_E=1}^{K_E} \sum_{m_N=1}^{M_N} b_{m_N k_E} \times \left| SNR_{m_N k_E} - SNR_{avg} \right|, \\ \text{s.t.} \quad & C1\colon \sum_{m_N=1}^{M_N} b_{m_N k_E} = c_{kE}, \forall\, k_E \in \mathcal{K}_E, \\ & C2\colon \sum_{k_E=1}^{K_E} b_{m_N k_E} = 1, \forall\, m_N \in \mathcal{M}_N, \end{aligned} \tag{5}$$

where c_{kE} is a binary variable, which takes the value 1 if an SU is a leader of one of the channels from a subset of $\mathcal{M}_N$ and 0 otherwise. C1 ensures that same SU cannot be selected as a leader for more than one channel. C2 confirms that each channel can have one leader.

2) PILOT-TONE DETECTOR (PD)-BASED LEADER SELECTION

For PD-based sensed channels, the orthogonality property between the pilot tone and the data-carrying part of the signal is used for detection. This is why noise existence here is not as crucial as in the ED-based case. Since we own information about the pilot tone of a PU signal, we require a leader with easily detectable pilot tone. Hence, a leader for each channel $m_P \in \mathcal{M}_P$ is selected with highest SNR value. The optimization problem formulation for PD-based leaders' selection can be defined as follows:

$$\begin{aligned} \max_{b_{m_P k_P}} : & \sum_{k_P=1}^{K_P} \sum_{m_P=1}^{M_P} b_{m_P k_P} \times SNR_{m_P k_P}, \\ \text{s.t.} \quad & C1\colon \sum_{m_P=1}^{M_P} b_{m_P k_P} = c_{kP}, \forall\, k_P \in \mathcal{K}_P, \\ & C2\colon \sum_{k_P=1}^{K_P} b_{m_P k_P} = 1, \forall\, m_P \in \mathcal{M}_P, \end{aligned} \tag{6}$$

where c_{kP} is a binary variable, which takes the value 1 if an SU is a leader of one of the channels from $\mathcal{M}_P$ subset, and 0 otherwise. C1 ensures that same SU cannot be selected as a leader for more than one channel. C2 confirms that each channel can have one leader.

3) ORTHOGONAL FREQUENCY DIVISION MULTIPLEXING DETECTOR (OD)-BASED LEADER SELECTION

As for the OD-based detection, using the knowledge of cyclic prefix and the OFDM symbol length, the inherent signal correlation incurred by cyclic prefix repetition is used to detect the PU signal. Since sufficient amount of information is available about the PU signal, there is no need for the specific leader choice because it only increases the algorithm's complexity in this case. Hence, this property of the OD-based scenario allows us to randomly select a leader for each channel $m_O \in \mathcal{M}_O$ from the subset of $\mathcal{K}_O$ SUs.

For all three cases above, SU-leader selection is independent and performed concurrently. This is because only ED-based SUs may be selected as leaders for each channel $m_N \in \mathcal{M}_N$, PD-based SUs for each channel $m_P \in \mathcal{M}_P$, and OD-based SUs for each channel $m_O \in \mathcal{M}_O$. Finally, the problems in (5) and (6) are of mixed integer linear programming (MILP) type. Each one of them includes a linear objective function and constraints. In both problems, all variables are binary. To solve these problems, we adopted the B&B algorithm [23]. The B&B algorithm searches the complete space of solutions for the best one within a given problem. For each iterative search, there exists an incumbent solution, which denotes to the best found feasible solution in the branching tree. If the solution is worse than the existing incumbent solution, then the branch is fathomed. The algorithm stops as soon as no subset is remained, which has to be still fathomed, and the best incumbent solution is denoted as the optimal value.

B. STAGE 2: COOPERATIVE SECONDARY USER SELECTION

The second stage of the proposed HM2CSS scheme is to select SUs for each channel $m \in \mathcal{M}$, which together with SU-leaders cooperatively sense channels. In this paper, the cooperative SU-selection is centralized. It is one of the spectrum management tasks performed by the leaders rather than part of the distributed CSS process. For this purpose, the goodness-of-fit test is used. There are several goodness-of-fit tests in the literature [24]. CVM [25], Anderson-Darling (AD) [26], and Kolmogorov-Smirnov (KS) [27] are the most used ones. Our choice in this paper has fallen on the CVM test for multiple reasons. Firstly, the CVM and AD tests have been proved to be more powerful than the KS test. The main disadvantage of the KS test is low sensitivity to deviations at the tails of the distribution. Secondly, the performance of the CVM and AD tests has been proved to be approximately similar [24]. However, the AD test has a drawback of higher bias. This is because the AD test gives more weight to distribution's tails. In other words, the AD test is more sensitive to noise and fading. This disadvantage makes the AD test difficult in use in realistic situations. Hence, in this paper, we consider the CVM test.

To begin with, locally sensed signals' envelopes for each sample n are calculated as follows:

$$r_k^m(n) = \sqrt{\left(g_{I,k}^m(n)\right)^2 + \left(g_{Q,k}^m(n)\right)^2} \tag{7}$$

where $g_{I,k}^m(n)$ and $g_{Q,k}^m(n)$ are in-phase and quadrature components of the locally sensed signal by *k-th* SU for channel m, respectively. The CVM test matrix is then formed by finding the difference in the correlation of the sensed signal envelopes with the sensed leader ones for all channels. Thus, the CVM test matrix entries are calculated as [17]:

$$T_{j,k} = \frac{1}{12N} + \sum_{n=1}^{N}\left(F_j\left(r_k^m(n)\right) - \frac{2n-1}{2N}\right)^2, \tag{8}$$

where $F_j(.)$ is cumulative distribution function of the received signal by *j-th* SU acting as a leader for channel m, and N is the number of samples used to sense one channel by each SU. For each channel m, test values are computed only for SUs, which are one hop away from the leaders. Otherwise, the test value is set to 0.

Our objective is to select cooperative SUs with highest CVM test values because they provide lowest correlation between SUs' signal envelopes and leaders' signal envelopes. We assume β_{jk} to be a binary variable, which defines whether *k-th* SU is selected for CSS or not as follows:

$$\beta_{jk} = \begin{cases} 1, & \text{if } k\text{-}th \text{ SU is cooperative with leader } j \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Then, an optimization problem for cooperative SU-selection can be formulated as:

$$\begin{aligned}
\max_{\beta_{jk}}:\ & \sum_{k=1}^{K}\sum_{j=1}^{M} \beta_{jk} \times T_{jk} \times a_{jk}, \\
\text{s.t. } & C1: \sum_{j=1}^{M} \beta_{jk} \geq 1, \forall\, k \text{ non-leaders of } \mathcal{M}, \\
& C2: \sum_{j=1}^{M} \beta_{jk} \geq 0,\ \forall\, k \text{ leaders of } \mathcal{M}, \\
& C3: \sum_{j=1}^{M} \beta_{jk} \leq I, \forall\, k \text{ non-leaders of } \mathcal{M}, \\
& C4: \sum_{j=1}^{M} \beta_{jk} \leq I-1, \forall\, k \text{ leaders of } \mathcal{M}, \\
& C5: \sum_{k=1}^{K} \beta_{jk} \leq \frac{K \times I}{M} - 1, \forall\, j \text{ leaders } \mathcal{M}, \\
& C6: L \leq \frac{\sum_{k_E=1}^{K_E} SNR_{jk_E} \times \beta_{jk_E}}{\sum_{k_E=1}^{K_E} \beta_{jk_E}} \leq U, \forall\, j \text{ leaders of } \mathcal{M}_N, \\
& D7: L = (1-p) \times SNR_{avg}, 0 \leq p \leq 1, \\
& D8: U = (1+p) \times SNR_{avg}, 0 \leq p \leq 1,
\end{aligned} \tag{10}$$

where p is the tolerance probability for SNR_{avg}, and L and U are lower and upper bounds for SNR_{avg} of all cooperative SUs of each channel $m_N \in \mathcal{M}_N$, respectively. As it has been mentioned in Section II, only certain SUs in a CRN can communicate with each other. Therefore, a_{jk} is a binary value set to 1 if *k-th* SU can communicate and be selected as cooperative with leader j and 0 otherwise. A list of symbols used in the model and their description is provided in Table 1.

The constraints (C1)-(C5) are introduced to balance energy consumption among all channels and devices fairly. For each T_{jk} matrix column, minimum of 1 (C1) and maximum of I (C3) entries are chosen for the non-leader columns, whereas the minimum of 0 (C2) and maximum of $I-1$ (C4) entries are chosen for the leaders' ones. To limit system's energy consumption, constraint in (C5) sets the maximum number of SUs which can sense one channel to $\frac{K \times I}{M}$. In addition to this, constraint (C6) is introduced only for the channels, which we own no prior information about the signal being carried by them, i.e., ED-based sensed channels. It ensures that the actual average SNR value is dynamic for each channel with the help of lower (D7) and upper (D8) bounds' definitions for the threshold SNR_{avg}. The problem in (10) is also of MILP type with linear objective function and constraints. To solve problem (10), we adopted the B&B algorithm as well. Here, the variables are of binary type.

The problem's output is the optimized cooperative SUs' vector for each channel m as $\mathbf{Q} = [Q_1\ Q_2\ \cdots\ Q_M]^T$, where Q_m is the number of cooperative SUs for channel m and is equal to:

$$Q_m = \sum_{k=1}^{K} \beta_{jk}, \tag{11}$$

where j is the index of the leader for channel m.

In multi-band CSS, we want to achieve and operate in high detection probability and low false alarm probability. In the proposed HM2CSS scheme, we are aiming to achieve it by selecting optimal cooperative SUs rather than putting constraints on the false alarm and detection probabilities. Each selected PU protection level is integrated in the threshold that is compared with test statistics to decide whether the PU is occupying a channel or not. This threshold is proportional to the SNR value at an SU. Hence, without specifying the PU protection level directly in the optimization problem in (10), it still has an influence on the outcome because it depends on the selected threshold at an SU.

The selected cooperative SU-clusters use diffusion learning to exchange the locally sensed information upon which it is decided if PUs are present or not as follows [28]:

$$S_k^m(i+1) = S_{wavg}^m(i) + \mu_k^m \sum_{j=1}^{Q_m}\left(S_{wavg}^m(i) - S_j^m(i)\right), \tag{12}$$

TABLE 1. Description of the symbols used in the model.

Symbol	Description
β_{jk}	binary value set to 1 if *k-th* SU is set cooperative with leader j
T_{jk}	CVM test value between k-th SU and j-th leader
a_{jk}	binary value set to 1 if *k-th* SU can be selected as cooperative with leader j and 0 otherwise
K	total number of SUs in a CRN
M	total number of channels
I	upper limit of number of channels to be sensed by an SU
SNR_{jk_E}	estimated SNR value of k_E-th SU sensing a channel whose leader is SU j
SNR_{avg}	desired and prefixed average SNR value across a channel
L	lower bound for SNR_{avg} of all cooperative SUs of each channel $m_N \in \mathcal{M}_N$
U	upper bound for SNR_{avg} of all cooperative SUs of each channel $m_N \in \mathcal{M}_N$
p	tolerance probability for SNR_{avg}

where S^m_{wavg} is the weighted test statistics' average among received cooperative SUs', S^m_j is the test statistics calculated by the *j-th* SU for channel m, i is the iteration number, and μ^m_k is the learning step size. Reaching consensus point, the point where all cooperative SUs have the same information about the channel, implies performing several iterations. Then, resulted test statistics are compared with the threshold to decide if the channels are occupied or not. Finally, the unoccupied channels can be assigned to SUs with highest priorities for transmitting data.

C. APPLICABILITY OF HM2CSS TO IOT APPLICATIONS

The proposed HM2CSS scheme can be applicable to IoT applications where SUs are typically low-complex nodes with limited power, storage, and processing capabilities. This is because of the following. To begin with, this scheme implies the use of three different detector technologies for SUs. The ED, PD, and OD technologies have different complexity levels and power requirements to perform spectrum sensing. Hence, SUs with limited power capabilities can use the basic ED technology. Medium range SUs can utilize the PD technology, while more sophisticated SUs, such as sink nodes, can have the OD technology incorporated within them. In addition, no information needs to be stored from the previous cycles, which helps in saving the storage space on SUs. Furthermore, the only information that is needed by SUs to implement the proposed HM2CSS scheme is the information about the detector type of the neighboring nodes. Control channels can be used in determining the type of detector for any given SU. For this purpose, each node broadcasts the information about the detector type owned to the neighboring nodes. What is more, not all SUs are involved in the cooperative SUs' selection process. At each cycle of the SUs' selection, different leaders are chosen. The primarily role of SU-leaders is assisting in cooperative SU-selection for their channels. In other words, SU-leaders help in dividing all SUs into cooperative SU-clusters. Finally, to coordinate among heterogeneous SUs distributed in the network, we assume that cooperative SUs are synchronized. Therefore, at least one SU should take over the synchronization responsibility [29]. Here, we assume that SU-leaders' second role is to ensure synchronization. The synchronization of SUs and their information exchange can be done through dedicated control channels.

IV. COMPUTATIONAL COMPLEXITY ANALYSIS OF HM2CSS

A brief analysis of the proposed HM2CSS scheme is presented in this section. To begin with, the leader-selection problems in (5) and (6) are equality constrained optimization problems. First, it is worth mentioning that there exist optimization problem formulations, where all constraints are equality constraints, and the parameters are searched on a set of manifolds that represent these equality constraints [30], [31], [32]. In (5) and (6), we assume that both c_{kE} and c_{kP} are binary variables in C1. We define the constraint to be $\sum_{m_N=1}^{M_N} b_{m_N k_E} - c_{kE} = 0$ and $\sum_{m_P=1}^{M_P} b_{m_P k_P} - c_{kP} = 0$ for the ED-based and PD-based leader selection, respectively. However, by simplifying, we can specify C1 as $\sum_{m_N=1}^{M_N} b_{m_N k_E} = c_{kE}$ and $\sum_{m_P=1}^{M_P} b_{m_P k_P} = c_{kP}$. We can notice that the value of $\sum_{m_N=1}^{M_N} b_{m_N k_E}$ can range from 0 to M_N. Similarly, the value of $\sum_{m_P=1}^{M_P} b_{m_P k_P}$ can range from 0 to M_P. On the other hand, the variables c_{kE} and c_{kP} can range from 0 to 1. C1 constrains the summation of $b_{m_N k_E}$ and $b_{m_P k_P}$ variables to either 0 or 1. Here, we are interested in the variable **b** matrix outcome, which has the size of M_N-by-K_E and M_P-by-K_P in cases of ED-based and PD-based leader-selection, respectively. The objective is that columns and rows of matrix **b** should be orthogonal, meaning that:

$$\mathbf{b} \cdot \mathbf{b}^T = \mathbf{I}, \tag{13}$$

where **I** is the identity matrix. This indicates that the following formulation has limited feasible solution space set and always leads to a feasible solution. The feasible space represents a collection of non-square, i.e., rectangular, matrix **b** permutations. Each permutation represents a product of a permutation square matrix and a projection matrix, which swaps round the basis vectors and then, projects onto the span of the original basis vectors. Hence, the total number of permutations are:

$$n_p^E = \frac{K_E!}{(K_E - M_N)!} \text{ and } n_p^P = \frac{K_P!}{(K_P - M_P)!}, \tag{14}$$

for the ED-based and PD-based leader-selection, respectively. In addition, the number of constraints in both problems grows linearly with the CRN size and number of channels such as:

$$n_c^E = K_E + M_N \text{ and } n_c^P = K_P + M_P \tag{15}$$

for the ED-based and PD-based cases, respectively. Therefore, the computational complexity can be represented as $O(K_E + M_N)$ and $O(K_P + M_P)$ for the problems in (5) and (6), respectively. It is important to note that assuming the same number of ED-based SUs and PD-based SUs, i.e., $K_E = K_P$, and channels they are sensing, i.e., $M_N = M_P$, the complexity of leader-selection for both cases is similar. However, for the OD-based case, the complexity is O(1) because of the arbitrary leader-selection discussed in the previous section.

In the proposed HM2CSS scheme, the optimization problem in (10) is then used to select cooperative SUs. The important part in analyzing the problem in (10) is computational costs as a function of the problem size. The constraints of the optimization problem represent inequalities. Nowadays, the relation between the problem size of an MILP and the average complexity of the solution for such problems is believed to be an open issue [23]. As it has been mentioned in the previous section, the B&B algorithm is used to the problem in (10). In general, the B&B algorithm has the worst case complexity scenario equal to the exhausted search. However, the complexity depends on the input variables and constraints fed to the algorithm.

On the other hand, in the best case scenario, the complexity is linear because simple parallelism and incorporation of heuristics may relax the problem and reduce the tree size [23]. The parallelism mentioned is the ability of the MILP tree nodes to be processed independently. Analyzing the optimization problem in (10), the number of constraints, i.e., n_c, grows linearly with K, M, and M_N as follows:

$$n_c = 2 \times K + M + M_N. \tag{16}$$

Further, we can notice that the number of variables, i.e., n_v, also depends on K and M such as:

$$n_v = M \times K. \tag{17}$$

Therefore, the total complexity of the problem in (10) can be presented as $O((K + M + M_N) \times K \times M)$. We can notice that n_v and n_c do not depend on I, but the number of states, i.e., n_s, depends on I. Hence, the increase in I may lead to computational complexity growth. However, since all variables are binary, the complexity depends on the number of binary input combinations. Moreover, in the formulated problem the constraint matrix is highly sparse, which reduces the computational complexity by $\frac{M-I}{M} \times 100\%$. In other words, the total complexity of the problem in (10) becomes $O((K + M + M_N) \times K \times I)$. Note, for the case when I is relatively small compared to M, the total complexity of the problem in (10) can be approximated to $O((K+M+M_N)\times K)$. It is further important to mention that although equation (10) conducts the selection of SUs belonging to all the three types in one problem, it can conduct the selection of SUs belonging to different types independently. This means that the complexity of an optimization problem can be reduced by running it separately and con-currently for all three types of SUs, if needed.

The computational complexity of the diffusion learning algorithm is another factor of interest. For diffusion learning, the computational complexity can be illustrated in the number of additions and multiplications, which is:

$$n_{add} = 2 \times i \times (Q_m)^2 \text{ and}$$
$$n_{mul} = \Big((Q_m)^2 + Q_m - 1\Big) \times i, \tag{18}$$

respectively. Generally, diffusion learning requires low number of iterations, i.e., i, to reach the consensus (see simulation results section below). The number of iterations and the convergence stability depends on the learning step size, i.e., μ_k^m. The higher the learning step size is, the faster the learning process is. However, high values of μ_k^m may lead to instability. This is why the learning step size is usually chosen between 0 and $\frac{1}{Q_m}$ for fast and stable convergence [7].

The discussion above shows that the problems in (5) and (6) are low in complexity even when the number of channels and the CRN size grows. Therefore, the main concern for the computational complexity is the problem in (10). Reducing the size of the problem formulation can reduce the complexity of the solution. The impact of n_v on the problem solution is higher than the impact of n_c. In this case, a reasonable strategy that can be utilized is the modularity principle [33]. The optimization problem in (10) could be split into several modules each containing smaller values of n_v. Then, the optimal solution for the problems could be found for each of them. However, constructing modules is a challenging task and is out of scope of this paper, but can be left as an open area for further investigation.

It is important to note, that a simple random assignment of SUs to sense particular channels has the complexity of $O(K \times M \times I)$ with the constraint that maximum I channels can be sensed by each SU [13]. This means that the problem in (10) has a higher computational complexity than random assignment. Nevertheless, the problem in (10) allows better system performance as it will be seen in the simulation results section below.

Generally, two-stage optimization problems may lead to a sub-optimal solution compared to joint optimization. However, the reason why joint optimization is not considered in our case is the cooperative SU-selection dependence on leaders. Leaders' selection of the first stage acts as a benchmark in selecting cooperative SUs for the second stage. The second optimization problem has to be solved by leaders only instead of all SUs. Therefore, such a configuration allows complexity reduction of the system in total. Moreover, selecting correct leaders helps in an efficient selection of corresponding SUs, which results in detection performance improvements. As it will be seen in the next section, the two-stage solution in our case is shown to have stable system performance and outperform existing multi-band CSS schemes.

V. SIMULATION RESULTS

In this section, performance of the proposed HM2CSS scheme is investigated. Three different network sizes are

TABLE 2. Number of channels with the certain information available about them.

M	M_N	M_P	M_O
50	20	20	10
25	10	10	5
5	2	2	1

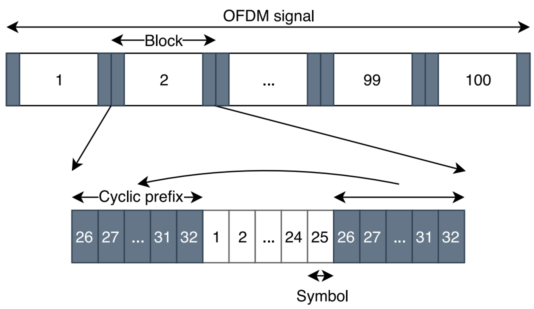

FIGURE 4. The OFDM signal transmission.

considered for simulation results. Those are $M = 50$ channels and $K = 100$ SUs, $M = 25$ channels and $K = 50$ SUs, and $M = 5$ channels and $K = 10$ SUs. In the event that only one network size is used, the $M = 50$ channels and $K = 100$ SUs scenario is assumed. The information available about channels is displayed according to Table 2. PU signals with no prior information are modeled as random Gaussian signals. PU signals with known pilot tones are assumed to have binary phase shift keying (BPSK) modulated pilot tones and the random Gaussian data-carrying signal part, where 10% of the total PU signal power is allocated for the pilot tone part. As for the OFDM PU signals, 16 quadrature amplitude modulation (QAM) is used. As illustrated in Fig. 4, in total 100 blocks are used to construct one OFDM signal, where the number of symbols in one block is assumed to be 32 with the cyclic prefix length of 8 for each block. In all cases, the number of ED, PD, and OD-based SUs are assigned to be approximately 40%, 40%, and 20%, respectively.

The three CRN sizes are considered to demonstrate the trend of the proposed HM2CSS scheme's behaviour in different practical IoT scenarios. For example, 10 SUs and 5 channels can represent a smart home application, 50 SUs and 25 channels can symbolize a smart parking system, whereas 100 SUs and 50 channels can express a smart campus [34], [35], [36]. In an IoT-based CRN, 100 SUs is a reasonable number because many sensor nodes can connect with each one of them. For instance, in a smart campus application, there may be 100 controllers with more than 5000 sensors attached to them [36]. 50 controllers in a smart parking system can connect more than 3000 sensors. In addition, 10 sensor nodes per house can connect more than 4000 sensors in smart homes applications [34]. The assumption that the number of SUs is higher than the available CR channels reflects the scarcity of the available spectrum in future IoT systems and the challenge to fulfill the high spectrum demands of competing SUs.

All the parameters set to the network model are as follows, unless specified. The minimum and maximum number of channels sensed by one SU is set to be 1 and $I = 5$, respectively. We assume that 100 SUs and 50 PUs are randomly distributed in a $1000 \times 1000\text{m}^2$ area. Each SU is achieving a specific SNR value, i.e., SNR_k^m, depending on the location, distance to PUs, and fading and noise conditions. Estimated SNR_{avg} across each channel is assumed to be -10 dB. In addition, we assume a fixed number of samples for each channel for synchronization purposes of the diffusion-based distributed learning. The number of samples sensed by one ED, PD, and OD-based SU per channel are considered $N_{ED} = 2000$, $N_{PD} = 500$, and $N_{OD} = 4000$, respectively. As for the sensing energy consumption, 40 nJ of energy is assumed to be consumed by an SU for sensing one sample [37]. The IEEE 802.22 standard is used as a benchmark for simulation results, according to which the total detection probability should be greater than 90%, while the false alarm probability should be less than 10% [38].

A. DIFFUSION LEARNING ANALYSIS

We compare the proposed HM2CSS scheme with the heterogeneous version of the existing RSSS and ASSS schemes presented in [3] and [13], respectively. RSSS and ASSS are distributed multi-band CSS schemes, which can be implemented in an IoT CRN with heterogeneous devices with hardware limitations. Hence, we believe that RSSS and ASSS are reasonable metrics to compare the proposed HM2CSS scheme with. In this version of RSSS and ASSS, neighboring SUs are selected to form cooperative clusters for each channel with the constraint that ED-based, PD-based, and OD-based SUs are allowed to sense channels with no prior information about the PU signal, channels with known pilot-tones of the PU signal, and channels known to carry OFDM signals, respectively. After that, SUs perform local spectrum sensing. Similarly to HM2CSS, each SU is allowed to sense maximum I channels, and each SU computes the test statistics of its observations. SUs then exchange the local data between each other to achieve a global decision about the availability of channels. In this paper, we assume that it is performed by means of diffusion learning for the sake of similarity in comparison to the proposed HM2CSS scheme. Hence, the first thing to consider is the difference between the diffusion learning process of the proposed HM2CSS scheme and the existing RSSS and ASSS schemes.

Fig. 5 (a), (b), and (c) illustrate the learning process of the proposed HM2CSS and the existing RSSS and ASSS schemes used to select cooperative ED-based SUs to sense channel 2, respectively. Similarly, Fig. 5 (d), (e), and (f) show the proposed HM2CSS and the existing schemes used to select cooperative OD-based SUs to sense channel 5, respectively. It can be observed that one of the main advantages of the proposed HM2CSS scheme is that it does not allow the choice of redundant cooperative SUs, the ones with similar sensed information for the *m-th* channel. After 5 iterations, the consensus point is reached, and results are compared to the threshold to determine the occupancy of channels.

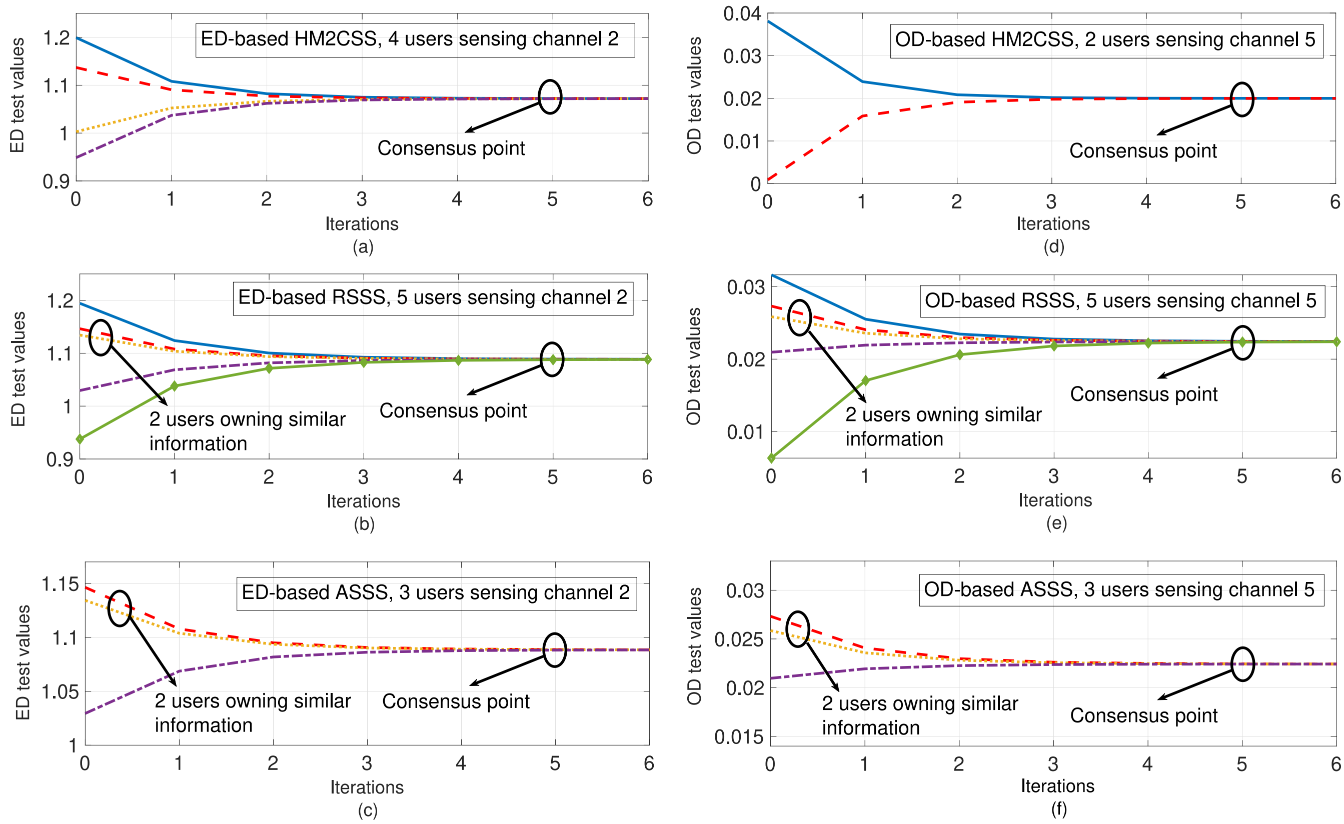

FIGURE 5. The diffusion learning process for: (a) the proposed HM2CSS scheme of ED-sensed channel 2, (b) the existing RSSS scheme of ED-sensed channel 2, (c) the existing ASSS scheme of ED-sensed channel 2, (d) the proposed HM2CSS scheme of OD-sensed channel 5, (e) the existing RSSS scheme of OD-sensed channel 5, and (f) the existing ASSS scheme of OD-sensed channel 5.

It is important to mention that in the proposed HM2CSS scheme, control channels are used for announcing the detector type, selected leaders, their corresponding cooperative SUs as well as the distributed diffusion learning process. However, in the existing RSSS and ASSS schemes, control channels are used for announcing the detector type, selected cooperative SUs, and the distributed diffusion learning process, omitting the leader announcement step. For all schemes, the diffusion learning process is the dominant factor in the communication overhead of control channels. This is because it involves performing several iterations to reach the consensus point. Therefore, the communication overhead over the control channels is almost the same for the proposed HM2CSS and the existing RSSS and ASSS schemes.

B. RECEIVER OPERATING CHARACTERISTICS RESULTS

Fig. 6 represents receiver operating characteristics (ROC) for the proposed HM2CSS scheme. In Fig. 6(a), results for the proposed HM2CSS scheme are compared with the existing distributed RSSS and ASSS schemes. The proposed HM2CSS scheme clearly outperforms the existing schemes. It fulfills the requirements of the global detection probability $Q_d = 90\%$ for the global false-alarm probability Q_f of less than 10% in the cases of $M = 50$ channels and $K = 100$ SUs as well as $M = 25$ channels and $K = 50$ SUs, whereas for the case of $M = 5$ channels and $K = 10$ SUs, $Q_d = 90\%$ is reached for the Q_f value of a bit higher than 10%. Moreover, as the network size increases, the performance of the proposed HM2CSS scheme improves due to a wider variety in selection of cooperative SUs. This makes the system applicable to the future IoT networks as it demonstrates the scalability advantage in terms of detection performance. However, increasing the size of the network decreases system performance for the existing RSSS scheme. This can be explained by the way RSSS is accomplished or, i.e., the way cooperative SUs are being chosen. In RSSS, cooperative SUs are chosen arbitrary, i.e., in a random manner. Hence, the chances to get cooperative SUs with at least one of them to own feasible information for the channel decreases as network size increases. As a result, this leads to system performance degradation. As for the existing ASSS scheme, although its performance tends to slightly improve with increasing the network size due to adaptive principles, it tends to have the lowest performance rate.

Fig. 6(b) shows how changing the maximum number of channels sensed by an SU affects aggregate ROC performance for the proposed HM2CSS and the existing RSSS and ASSS schemes. For the proposed HM2CSS scheme, the enhancement of ROC stops at a certain point of increasing I. This allows us to have decreased energy consumption per SU as additional channels' sensing requires

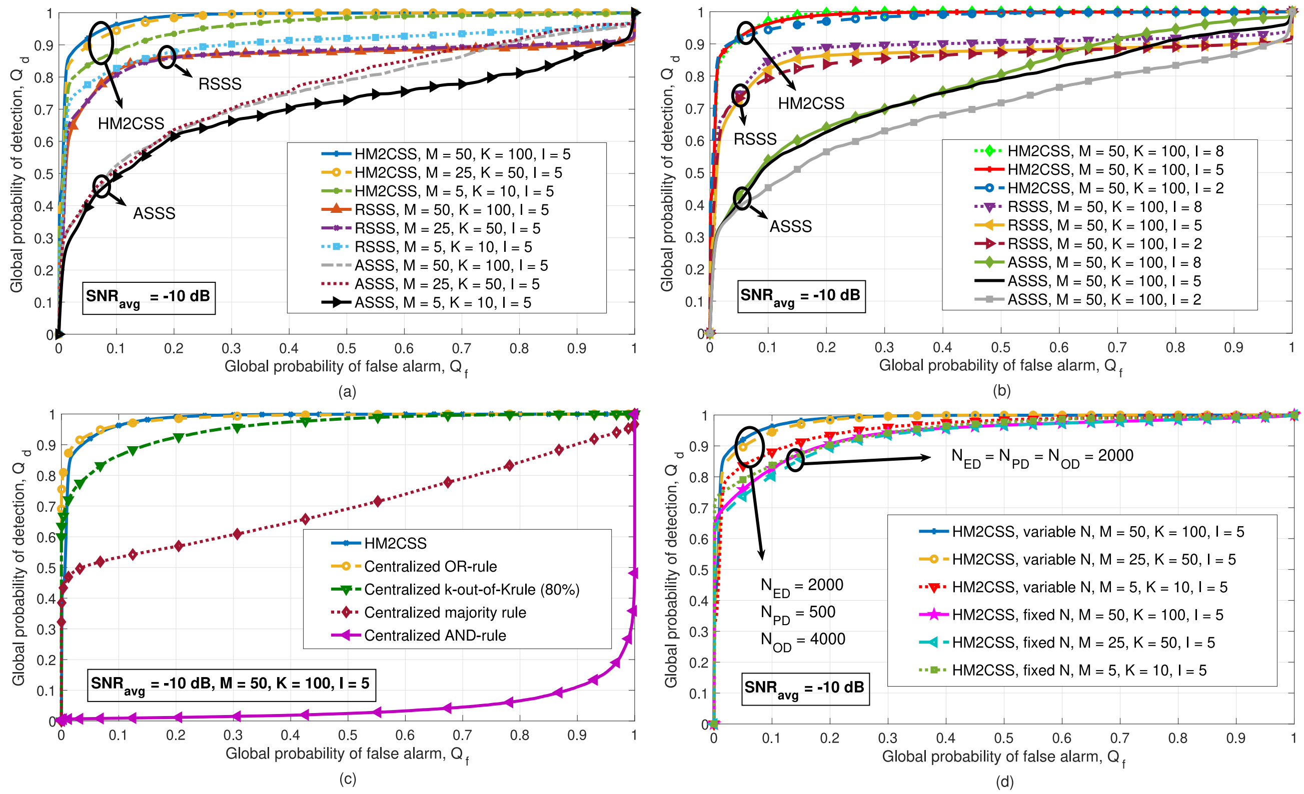

FIGURE 6. Global ROC results: (a) the proposed distributed HM2CSS scheme compared to the existing distributed RSSS and ASSS schemes for different network sizes, (b) the variation of the maximum number of channels allowed to be sensed by one SU for the proposed distributed HM2CSS scheme and the existing distributed RSSS and ASSS schemes, (c) the proposed distributed HM2CSS scheme compared to the existing centralized schemes, and (d) the comparison between fixed and variable number of samples between cooperative SU-clusters for the proposed distributed HM2CSS scheme.

extra power to be consumed on both sensing and transmission processes. The aggregate detection probability for $I = 2$ and $I = 5$ cases is slightly higher than for $I = 8$ when $Q_f \leq 5\%$. This is because the selection of cooperative SUs for the proposed HM2CSS scheme is being optimized. Choosing best 5 channels to be senses by each SU can provide better detection performance than sensing higher numbers of channels as 8 when some of them are in the deep fading state with respect to the SU. This places another advantage for low-power IoT devices, which are not capable of sensing more than a certain number of channels at a time instance. However, for the existing RSSS and ASSS schemes, system performance keeps improving by increasing the number of channels sensed by an SU. The more randomly selected cooperative SUs are chosen, the better system performance is. Randomness of the RSSS process can not guarantee that the selected channels to be sensed by an SU are not in deep fade with respect to it. Hence, choosing more channels to sense can enhance detection performance in this case. Regarding ASSS, as we have seen previously, it allows the choice of cooperative SUs with similar information available about them. This is the main reason that ASSS's performance improves with increasing I.

While Figs. 6(a) and (b) illustrate the proposed distributed HM2CSS scheme with another existing distributed schemes, Fig. 6(c) compares HM2CSS with the existing centralized schemes. In the distributed case, we have assumed that each SU calculates its own test statistics and then, this information is combined by means of the diffusion learning process. As for the centralized case, generally, the combining of locally sensed information can be performed in two ways, i.e., soft and hard combining [14]. In case of soft combining, SUs forward the locally sensed data to an FC without performing any local processing. The processing and decision of the availability of channels is done by an FC. In hard combining, each SU processes the locally sensed information and sends its decision to an FC. Then, an FC combines the received information to achieve a global decision. Generally, soft combining techniques demonstrate better detection performance [14]. However, hard combining techniques allow lower bandwidth utilization. In this paper, we consider combined soft and hard combining in the existing centralized schemes to achieve a trade-off between the detection performance and bandwidth requirements. For a fair comparison, in the existing centralized schemes, we assume that SUs sense channels and then, perform local processing to achieve the test statistics results. After that, they send local test statistics to an FC, which performs further processing. The processing of an FC includes comparing each received test statistics with a threshold and combining the results by means of rules. The OR, 20% k-out-of-K, majority, and AND rules are taken into account for the centralized cases [3], [14]. Typically, the centralized OR and k-out-of-K rules tend to outperform distributed schemes in terms of ROC due to the high control level accommodated by an FC [39]. However, Fig. 6(c) illustrates that the proposed scheme outperforms most of the centralized rules as 20% k-out-of-k, majority, and AND-rule and provides comparable performance to the centralized OR-rule one. Both, the proposed distributed HM2CSS and centralized OR-rule satisfy the condition of $Q_d = 90\%$ at the Q_f value of less than 10%.

Finally, Fig. 6(d) illustrates ROC results for the proposed HM2CSS scheme with variable and fixed number of samples per channel being sensed by each SU. Synchronization during the learning process is an important issue for distributed systems [3]. However, this issue comes within cooperative SUs sensing the same channel. Hence, different channels may be sensed using different number of samples. This represents an advantage to heterogeneous systems as the number of samples needed for different detector types may vary. ROC with fixed $N_{ED} = N_{PD} = N_{OD} = 2000$ results are compared with the allowed variation of $N_{ED} = 2000$, $N_{PD} = 500$, and $N_{OD} = 4000$. In the results of Fig. 6(d), the allowed variation in samples sensed by each detector type proves to enhance ROC performance without disturbing the learning synchronization per cooperative SU-cluster as only similar detector types are chosen as cooperative.

C. AGGREGATE PRIMARY USER PROTECTION LEVEL VS AVERAGE SIGNAL-TO-NOISE RATIO ANALYSIS

In Fig. 7(a), the PU protection level or global detection probability, Q_d, with respect to different values of SNR_{avg} is used to compare the proposed HM2CSS scheme to the existing RSSS and ASSS schemes. The false-alarm probability is fixed and set to 10%. It is clear that for all SNR_{avg} values the proposed HM2CSS scheme outperforms the existing RSSS and ASSS schemes. The global detection probability reaches 90% for the proposed HM2CSS scheme at SNR_{avg} of slightly higher than -12 dB for $M = 50$ channels and $K = 100$ SUs, -12 dB for $M = 25$ channels and $K = 50$ SUs, and -9 dB for $M = 5$ channels and $K = 10$ SUs cases. However, in all three cases the existing RSSS scheme achieves the minimum required global probability of detection at $SNR_{avg} = -8$ dB. It can be concluded that at the SNR_{avg} value of -10 dB, the proposed HM2CSS scheme outperforms RSSS by 14.5%, 12%, and 7.2% for the cases of $M = 50$ channels and $K = 100$ SUs, $M = 25$ channels and $K = 50$ SUs, and $M = 5$ channels and $K = 10$ SUs, respectively. What is more, the existing ASSS scheme does not reach the 90% global detection probability for the global false alarm probability of 10%. For all three network configurations, the existing ASSS scheme has the aggregate detection probability of 80% at $SNR_{avg} = 0$ dB.

Fig. 7(b) discloses the effect of maximum number of channels sensed by one SU, I, by varying SNR_{avg} for the proposed HM2CSS and existing RSSS and ASSS schemes. The values of $I = 8$, $I = 5$, and $I = 2$ are considered for the simulation results. In case of the proposed HM2CSS scheme, increasing I does not have significant impact on the results. For all listed values of I the global detection probability reaches 90% at the SNR_{avg} values under -11 dB. Moreover, at the SNR_{avg} value of -10 dB, all three cases considered have the global detection probability of approximately 95%. This brings an advantage of HM2CSS as in case an SU is not capable of sensing I channels due to power limitations and has to decrease its value, the system performance will not experience sensible changes. Whereas for RSSS, for I values of 8, 5, and 2, the corresponding global detection probability reaches 90% at the values of -9 dB, -8 dB, and -6 dB, respectively. Further, using RSSS, the global detection probability is 86%, 83%, and 78% at the SNR_{avg} value of -10 dB with I values of 8, 5, and 2, respectively. As for the existing ASSS scheme, it does not reach the 90% global detection probability while varying I. For all three network configurations, the existing ASSS scheme has the aggregate detection probability of approximately 50% at $SNR_{avg} = -10$ dB.

Fig. 7(c) illustrates the comparison of the proposed distributed HM2CSS scheme and the existing centralized schemes discussed above. Although at very low SNR_{avg} values centralized OR and 20% k-out-of-K rules tend to outperform HM2CSS, already at SNR_{avg} of slightly higher than -17 dB and -14 dB, the proposed HM2CSS scheme outperforms the 20% k-out-of-K and OR centralized rules, respectively. This can be explained as follows. At very low SNR values, noise level is high, and centralized systems tends to outperform due to high control level provided by an FC. However, at the SNR_{avg} value of -10 dB, the proposed distributed HM2CSS scheme outperforms the centralized OR, 20% k-out-of-K, majority, and AND rules by 5.6%, 15.9%, 75.9%, and more than 5 times, respectively, with the aggregate detection probability of 95%.

Fig. 7(d) shows curves with global false-alarm probability values of 10% and 30%. The enhancement for the proposed HM2CSS scheme is in the similar manner for all three network sizes as the global false-alarm probability increases. Moreover, this enhancement has similar trend of approximately 10% in aggregate detection probability for the SNR_{avg} value of -10 dB. Finally, the increase in system performance can be noticed as the network size grows.

D. THROUGHPUT ANALYSIS

In this section, we compare CRN throughput results of the proposed HM2CSS scheme with existing multi-band CSS schemes. Considering IEEE 802.22 standard, aggregate false alarm probability is set to be 10%. The interference level coming from each PU is set to be -10 dB, while the channel bandwidth and the PU-activity is set to be $6MHz$ and 30%, respectively.

Fig. 8(a) compares the proposed distributed HM2CSS scheme with the existing distributed RSSS and ASSS schemes. Clearly, the proposed HM2CSS scheme outperforms the existing RSSS and ASSS schemes. Already at the global detection probability of 60%, 65%, and 87%, CRN

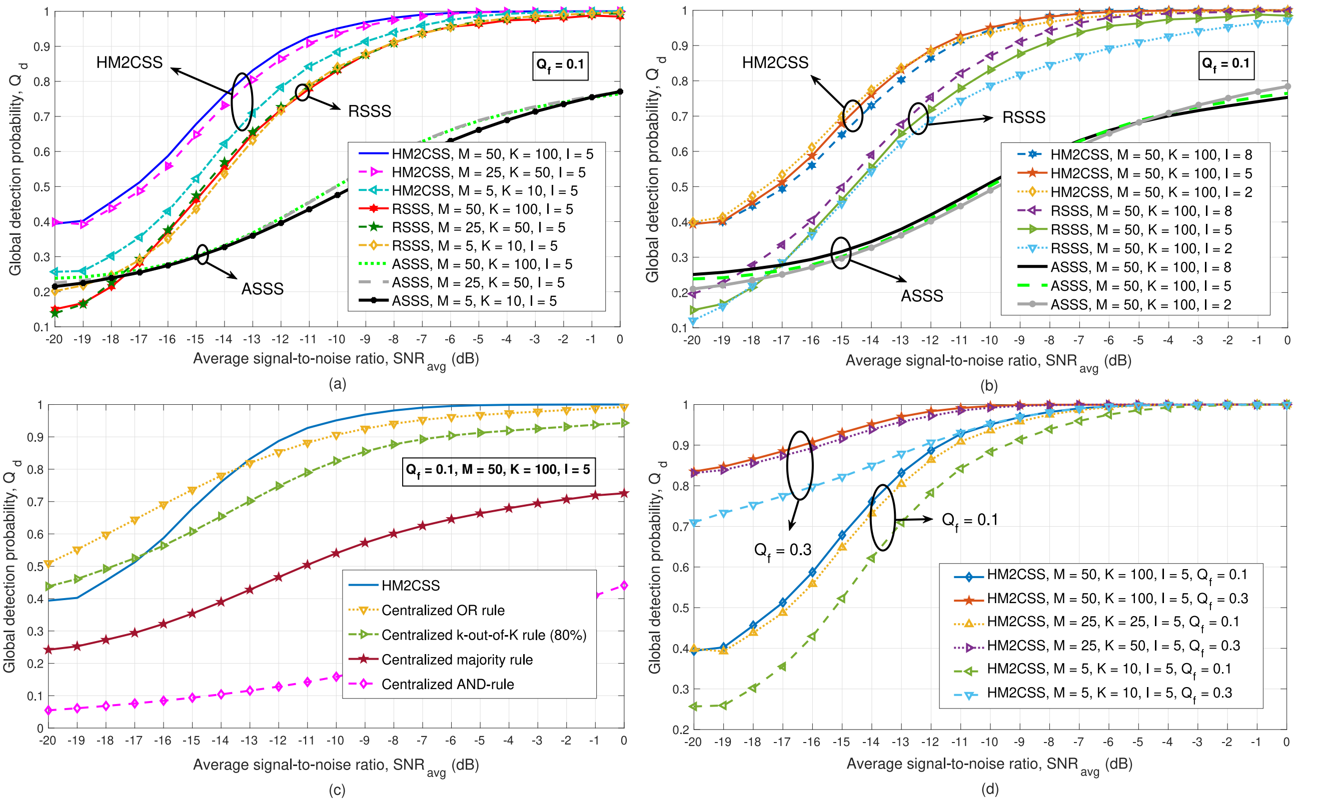

FIGURE 7. Global PU protection level vs SNR_{avg} for: (a) the proposed distributed HM2CSS scheme compared to the existing distributed RSSS and ASSS schemes for different network sizes, (b) the variation of the maximum number of channels allowed to be sensed by an SU for the proposed distributed HM2CSS scheme and the existing distributed RSSS and ASSS schemes, (c) the proposed distributed HM2CSS scheme compared to the existing centralized schemes, and (d) the variation of the global false alarm probability for the proposed distributed HM2CSS scheme.

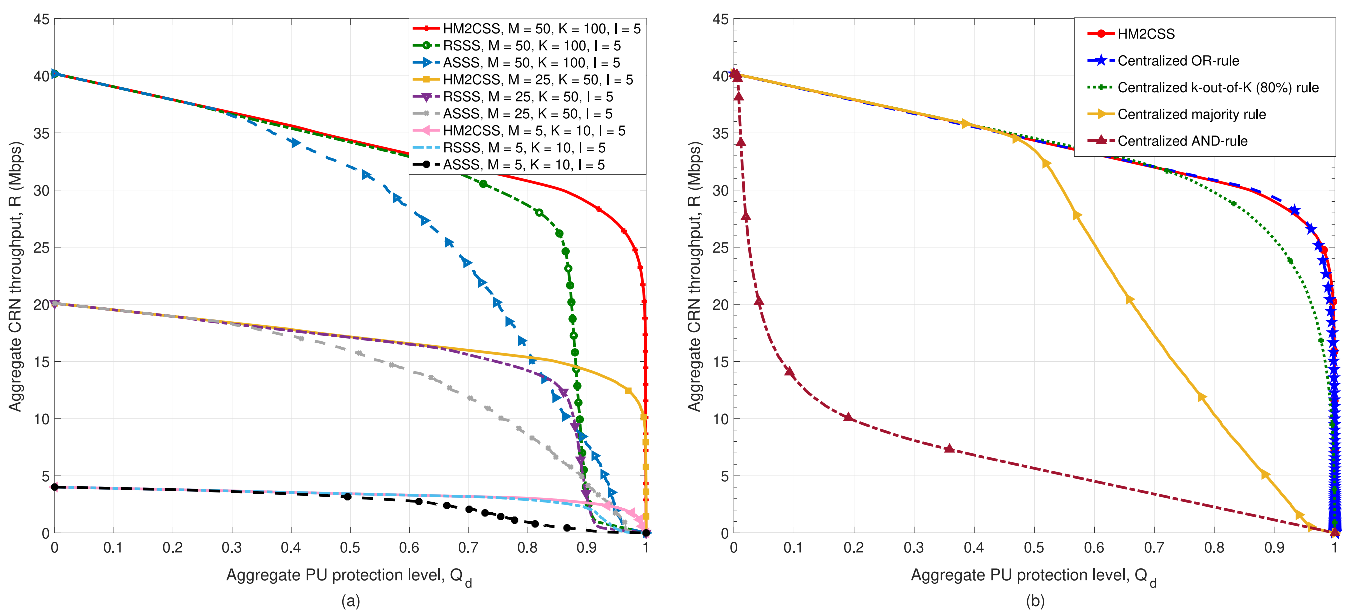

FIGURE 8. Aggregate CRN throughput results: (a) comparison between the proposed distributed HM2CSS scheme and the existing distributed RSSS and ASSS schemes for different network sizes and (b) comparison between the proposed distributed HM2CSS scheme and the existing centralized schemes.

throughput for the existing RSSS scheme starts to degrade with respect to the proposed HM2CSS scheme for the cases of $M = 50$ channels and $K = 100$ SUs, $M = 25$ channels and $K = 50$ SUs, and $M = 5$ channels and $K = 10$ SUs, respectively. Note that for the existing RSSS scheme, the aggregate throughput drops suddenly to very low values

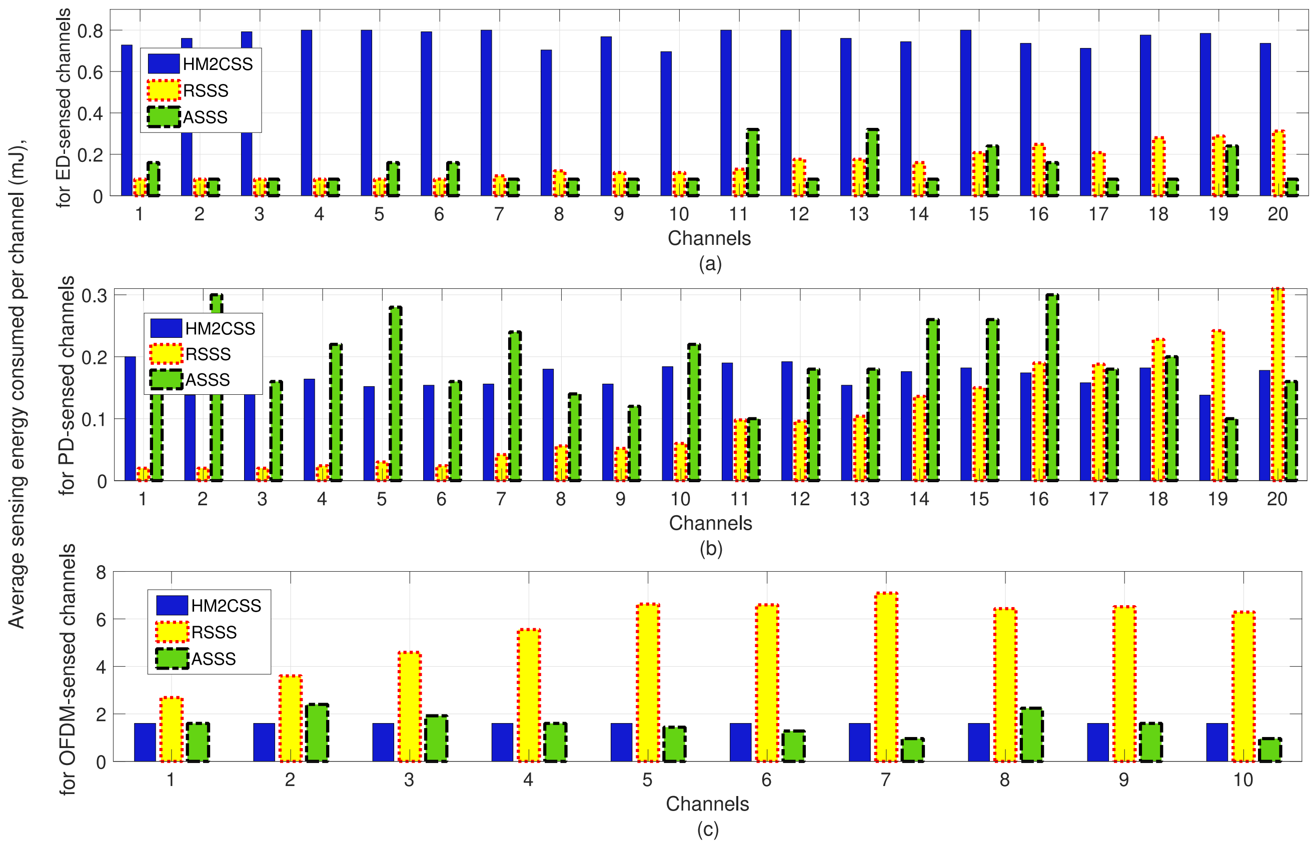

FIGURE 9. Comparison of the proposed HM2CSS scheme with the existing RSSS and ASSS schemes in terms of average sensing energy consumption level per channel for: (a) ED-sensed channels, (b) PD-sensed channels, and (c) OD-sensed channels.

at the global detection probability of approximately 90% for all three networks. However, the proposed HM2CSS scheme maintains smooth logarithmic curves achieving better throughput results by 7.3, 3.6, and 1.4 times for the three network sizes, respectively. In contrast to the existing RSSS scheme, the existing ASSS scheme maintains a smooth logarithmic curve. Its performance starts degrading with respect to the proposed HM2CSS and existing RSSS schemes at approximately 30%, 35%, and 53% aggregate PU protection level for the cases of $M = 50$ channels and $K = 100$ SUs, $M = 25$ channels and $K = 50$ SUs, and $M = 5$ channels and $K = 10$ SUs, respectively. The improvement of the proposed HM2CSS scheme compared to the existing RSSS and ASSS schemes increases as the network size grows. In the proposed HM2CSS, the modularity of the first stage allows to consider different attributes, i.e., characteristics, of three channels/IoT devices types available. As a result, this leads to efficient utilization of resources and hence, boosts the throughput of the whole heterogeneous CRN.

Fig. 8(b) compares the proposed distributed HM2CSS scheme and the existing OR, 20% k-out-of-K, majority, and AND rule centralized schemes. HM2CSS tends to perform in a similar manner to the centralized OR rule, achieving 29 Mbps of aggregate CRN throughput for the global detection probability of approximately 90%. Moreover, HM2CSS outperforms the 20% k-out-of-K, majority, and AND rules by 11.5%, 7.25 times, and 19.3 times, respectively.

E. ENERGY CONSUMPTION ON THE SENSING PROCESS

In both, the proposed HM2CSS and the existing RSSS and ASSS schemes, diffusion learning is used to exchange information between cooperative SUs. Hence, having the same impact on both schemes, for the comparison purposes, the consumed energy on the learning and decision process can be omitted. Therefore, in this section, we focus on the distribution of energy spent on the sensing process among SUs as a result of using a particular CSS scheme. We also focus on differences in the behavior of different detector types, i.e., ED, PD, and OD, for the proposed HM2CSS and the existing RSSS and ASSS schemes. Note that even though both schemes use diffusion learning, the efficiency of the learning is not the same. As we have discussed previously, by efficient diffusion learning we define selecting SUs owning different locally sensed information, i.e., the useful energy consumption. Although energy consumed on the decision may be similar, as we have seen in Section III-A, the efficiency of learning is different.

Fig. 9 illustrates average sensing energy consumption for different channels for the proposed HM2CSS scheme compared to the existing RSSS and ASSS schemes. To begin with, the proposed HM2CSS scheme shows fair distribution of sensing energy consumption across all channels of the same type, while the existing RSSS and ASSS schemes consume more energy on sensing one channel and less on another. This is done through selecting near-equal, depending on availability, number of SUs to sense each channel. However, the existing RSSS scheme selects the number of SUs to sense each channel arbitrarily, i.e., in a random manner. In addition, the existing ASSS scheme does not consider the fairness constraint in its solution. This is why the sensing energy consumed varies. Note that the variation of the average amount of energy consumed for sensing channels 1 to 20 in Fig. 9(a), 21 to 40 in Fig. 9(b), and 41 to 50 in Fig. 9(c) comes from the differences in the number of samples used for each detector type. Higher number of samples needed to sense a channel requires greater amount of energy to perform sensing. Despite the fact that the average amount of sensing energy for ED-sensed channels, i.e., channels 1 to 20, is relatively higher for HM2CSS than for RSSS and ASSS, and the PD-sensed channels has a slight increase in the energy consumption as well, the OD-sensed channels demonstrate reduced energy consumption. This is because the more information is available about the channel, the less number of cooperative SUs are needed to sense it. Finally, aggregate sensing energy consumption of the system depends on the system configuration chosen. This is because different detectors imply different sensing energy consumption. For instance, for sensing one channel, OD-based detector consumes 2 times more energy than ED-based detector, and ED-based detector consumes 4 times more energy than PD-based detector. In addition, aggregate sensing energy depends on the number of nodes selected to sense the channel, which further depends on the particular CSS scheme selected. For the considered system configuration, the aggregate sensing energy for the proposed HM2CSS scheme (35 mJ) is 41.7% less than the existing RSSS scheme (60 mJ). Although the aggregate sensing energy of the existing ASSS scheme (25mJ) is slightly lower than the aggregate sensing energy of the proposed HM2CSS scheme (35 mJ) for the considered configuration, as we have seen in the provided simulation results, this comes at the expense of the overall system performance. In addition, even though the aggregate sensing energy consumption depends on the chosen system configuration, the constraints in the second stage of the SU-selection process for the proposed HM2CSS scheme limit energy consumption independently of the configuration. Therefore, for all system configuration, the sensing energy consumption cannot exceed the maximum allowed sensing limit of the devices.

VI. CONCLUSION

In this paper, we proposed a diffusion learning-based HM2CSS scheme for distributed multi-band CRNs. We formulated a two-stage scheme to provide an efficient cooperative SU-selection for all channels. The first stage consists of forming SU-leaders based on which cooperative SUs are selected in the second stage. Simulation results show that the proposed HM2CSS scheme outperforms the existing multi-band CSS schemes in global detection probability and CRN throughput. Moreover, while the existing distributed scheme's performance starts degrading as network size increases, HM2CSS improves the performance as the system size grows. Hence, HM2CSS is scalable in terms of detection performance, which allows supplementary SUs' addition without extra human intervention needed to keep stable system performance level. The proposed HM2CSS scheme provides fair energy consumption for CSS on all channels. Finally, one of the possible applications for the proposed scheme is smart transportations. Electrical vehicles can be equipped with sensing technologies and small computers, capable of performing the presented optimization problems. Nevertheless, HM2CSS has its own drawbacks yet to overcome as relatively higher computational complexity and power consumption per channel for certain detector types. The scheme may still represent challenges for small IoT devices.

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