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Collaborative Spectrum Sensing Mechanism Based on User Incentive in Cognitive Radio Networks⋆

Masahiro Sasabe*, Nishida Tomohiro, Shoji Kasahara

Nara Institute of Science and Technology, 8916-5 Takayama-cho, Ikoma, Nara 630-0192, Japan

Abstract

In cognitive radio networks (CRNs), it is important for secondary users (SUs) to efficiently reuse spectrum without interfering communication of primary users (PUs). To acquire the communication opportunities, SUs first need become winning, i.e., suppressing its own miss detection probability under the upper limit imposed by PUs. Collaborative spectrum sensing (CSS) is a promising approach to improve the detection performance of SUs, where multiple SUs form a group and share their sensing results. In addition, the probability that winning SUs correctly detect idle state of PUs' spectrum will affect their communication opportunities. We first formulate a global optimization problem as integer linear programming (ILP), which maximizes both the number of winning SUs and average communication opportunities among them. In CSS, we also have to consider the selfishness of SUs because winning SUs will compete with group members to acquire their own communication opportunities. To cope with this competitive problem in addition to scalability problem of the global optimization, we further formulate an individual optimization problem, which can be solved by a user-incentive based CSS mechanism composed of PU selection and group (re)formation among SUs, where communication opportunities are allocated to SUs according to their detection performance. Through simulation experiments, we show the proposed mechanism considering selfishness of SUs is competitive with the existing scheme based on group-level cooperation, in terms of both the ratio of winning SUs and average communication opportunities among them. Comparing with the global optimization, we also show that the proposed mechanism can support larger-scale systems with performance improvement. Finally, we show that the proposed mechanism can achieve stable group formation even under SUs' selfish behavior.

Keywords: Cognitive radio, cooperative communication, collaborative spectrum sensing, game theory, group formation, integer linear programming, user incentive

1. Introduction

The radio resources are essential for wireless communication systems but most frequency bands have already been allocated to various existing systems. It is important to solve the spectrum exhaustion problem and to improve the spectrum utilization, due to the rapid increase in demand on wireless communication. To tackle this problem, cognitive radio has been studied, in which unlicensed users, i.e., secondary users (SUs), utilize the spectrum of a licensed user, i.e., primary user (PU), while avoiding interference in PU's communications [2, 3]. Each SU tries to detect the usage status of the PU's spectrum by spectrum sensing, and attempts to utilize the spectrum only when it judges that the spectrum is idle. Therefore, the accuracy of the SU's spectrum sensing is important to avoid interference in PU's communication and to improve the spectrum utilization.

There are several factors which affect SU's spectrum sensing results, e.g., propagation loss of the PU signal, fading, and noise. Spectrum sensing errors are classified into two types: miss detection and false alarm [4, 5]. The miss detection is a sensing error that an SU recognizes the spectrum of the PU is idle even though it is actually used by the PU. Therefore, it is important for the PU to suppress the probability of miss detection. In this paper, we assume that a PU imposes the upper limit of miss detection probability on SUs. The false alarm is a sensing error that an SU judges the spectrum of the PU is busy even though it is actually unused by the PU. Note that the complementary event of false alarm is the detection of the PU's idle state of the spectrum. Thus, it is important for the SU to improve the probability of idle detection, in order to acquire communication opportunities. From the viewpoint of effective spectrum reuse, we have to simultaneously achieve two goals: 1) increase of the number of *winning SUs*, which can satisfy the upper limit of miss detection probability, and 2) increase of communication opportunities of winning SUs by improving the idle detection probability.

Collaborative spectrum sensing (CSS) has been proposed to improve the accuracy of spectrum sensing [6]. In CSS, multiple SUs share the sensing results and derive a sensing result in a cooperative manner. For example, the collaborative sensing

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*Corresponding author

Email addresses: m-sasabe@ieee.org (Masahiro Sasabe), nishida.tomohiro.nl3@is.naist.jp (Nishida Tomohiro), kasahara@ieee.org (Shoji Kasahara)

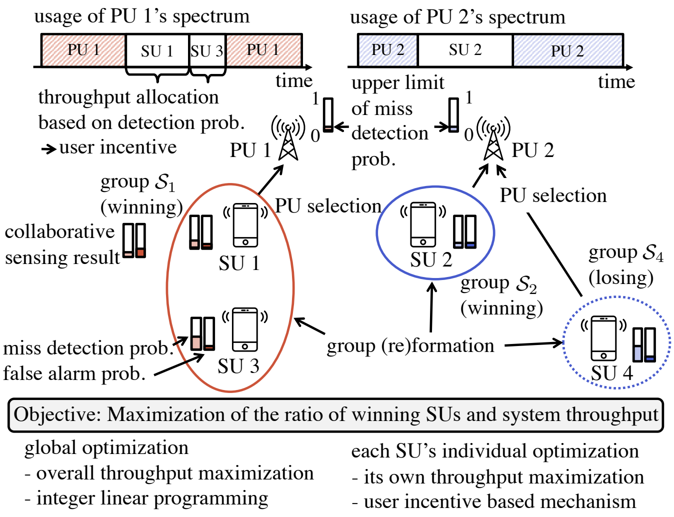


Figure 1: Overview of proposed CSS mechanism.

result based on OR-rule can reduce the miss detection probability with increase of false alarm probability [6]. This indicates that the sensing performance depends on the group formation among SUs [1, 7, 8, 9, 10, 11, 12, 13]. Most of the existing studies focused on group (coalition) formation based on cooperative game theory [14], where SUs in the same group have the same objective to reduce group-level miss detection probability, which will results in acquiring group-level communication opportunity. In addition, if there are multiple PUs, each SU also requires to select an appropriate PU [1, 7, 10, 11].

However, SUs will compete with group members to acquire their own communication opportunities. In addition, the spectrum sensing imposes energy and time consumption on SUs. As a result, it has been pointed out that some SUs may be free riders on others' sensing results [15] and/or gain advantage in spectrum access over other SUs by claiming the channel to be busy (while it is not) [16]. These facts indicate that SUs in the same group (coalition) may not cooperate with each other in the phase of spectrum sharing. To alleviate such SUs' selfish behavior, incentive mechanisms have attracted much attention [15, 17, 18, 19].

As mentioned above, the spectrum sensing requires cooperation among SUs while the spectrum sharing causes competition among them, which makes the design of CSS mechanism more complex. The detail literature review about CSS will be given in Section 2 but there are few work that considers all of the above concerns. In this paper, we establish a CSS mechanism that can maximize both the the number of winning SUs and communication opportunities among them under the consideration of user incentive. Fig.1 illustrates the overview of the proposed CSS mechanism. (The detail explanation will be given in succeeding Sections.) The main contributions of this paper are as follows:

1. We first formulate a global optimization problem for PU selection and group formation, which tries to maximize both the number of winning SUs and communication opportunities among them, which can be reduced to integer linear programming (ILP).
2. To cope with the drawbacks of the global optimization, i.e., scalability problem and lack of a user incentive mechanism, we formulate an individual optimization problem, which can be solved by a user-incentive based CSS mechanism that consists of PU selection and group (re)formation among SUs. In the proposed mechanism, SUs first try to become winning SUs by satisfying PU's requirement of miss detection probability and winning SUs can acquire their communication opportunities according to their detection probabilities.
3. Through simulation experiments in the single-PU cases, we show that the proposed mechanism considering SUs' selfishness is competitive with the conventional CF-PD algorithm, which relies on cooperation among group members, in terms of both the ratio of winning SUs and average communication opportunities among them. Comparing the proposed mechanism with global optimization, we also show that the proposed mechanism can support larger-scale systems with performance improvement.
4. Through simulation experiments in the 2-PUs cases, we demonstrate that the proposed mechanism can not only increase the communication opportunities of winning SUs with high detection performance but also the number of winning SUs with low detection performance. In addition, we also show that the proposed mechanism can achieve stable group formation even under SUs' selfish behavior.

The rest of the paper is organized as follows: Section 2 presents related work. After introducing the system model in Section 3, we propose global optimization and individual optimization in Section 4 and Section 5, respectively. We also show simulation results in Section 6. Finally, conclusions and future work are given in Section 7.

2. Related Work

2.1. Collaborative Spectrum Sensing

There are various studies on CSS [6, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31] and the comprehensive survey can be found in [4, 5]. CSS in CRNs is an effective method to reduce the probability of miss detection of PU's signal by exploiting spatial diversity [20, 21]. There are several fusion rules, e.g., AND, OR, K-out-of-N, and majority rules, to derive a cooperative decision from individual decisions of SUs in CSS [20]. In [6], Ghasemi and Sousa showed that an OR-based fusion method can suppress the probability of group miss detection with the sacrifice of the probability of group false alarm when the number of SUs increases. Liang et al. studied the trade-off between sensing time and throughput [22]. A long sensing time can reduce the false alarm probability but also results in shortening the data transmission time. They formulated the optimization problem for optimal sensing time that takes account of the trade-off. They analyzed how various types of decision functions affect the optimal sensing time and throughput with increase in the number of SUs. Zhang and Letaief proposed CSS based on transmission diversity to suppress the channel errors, which are caused by fading during information sharing about sensing results [23]. In [24], Gupta et al. proposed a two-level decision fusion scheme with collaboration among multiple fusion centers (FCs). In the first-level decision fusion, an FC collects the local decisions from SUs whose decision accuracy is greater than a predefined threshold, and then combines them using the OR-based fusion rule. In the second level decision fusion, all the FCs communicate with each other and combine the decisions using OR rule in order to make a global decision. Finally, they propagate the global decision to all SUs through respective FCs.

2.2. Group Formation

Since CSS requires the collection of individual sensing results from SUs and the distribution of the cooperative decision to SUs, the communication overhead will increase with the number of SUs. To tackle this problem, group formation of SUs for CSS is effective [1, 7, 8, 9, 10, 11, 12, 13]. Such group formation schemes are classified into a centralized approach and a decentralized approach. In the centralized approach, a server that manages SUs derives an optimal group formation by calculating all possible group patterns among all SUs. In [7], a server calculates all possible group patterns among all SUs and forms the group with the highest utility. In the succeeding process, the server continues the same approach until the group formation is completed. In [8], it was reported that the exhaustive search of optimal group formation becomes intractable when the number of SUs is over eight.

In the distributed approach, each SU tries to form a group with neighboring SUs based on its own incentive for CSS. Because of the mutual-dependent situation among SUs, there have been many studies based on game theory [8, 32, 24, 9, 33]. From the viewpoint of spectrum sensing itself, each SU has the same purpose, i.e., success of detection, and thus most of them have applied the coalitional game model in cooperative game theory [14]. Saad et al. proposed a distributed group formation scheme using a game theoretic approach for single-PU CRNs, called *coalition formation with detection probability (CF-PD) algorithm* [8]. In [8], each SU forms a group based on the utility function that exhibits the trade-off between decrease of the group miss detection probability and increase of the group false alarm probability. A coalition-formation (CF) game is a type of cooperative games in which each player participating in the game forms a coalition with other players based on the utility of the coalition [14]. The utility of a coalition cannot be apportioned between the coalition's players in CF-game with NTU [14, 34]. In [32], Balaji and Hota proposed a CSS scheme in which the cost function has been redesigned from [8] to consider the battery power and mobility of SUs. Gupta et al. also proposed a distributed CSS scheme where each group merges with other groups based on the utility function that takes account of throughput and energy/time consumption [24]. In [9], Wang et al. proposed a group formation scheme that considers the limited transmission power and bandwidth of SUs. The group formation among SUs is formulated as an overlapping CF (OCF) game in which it allows each SU to belong to multiple coalitions. In [33], Jiang et al. proposed both the group formation and spectrum sharing by integrating the coalition formation game and transmit time allocation game. Although these distributed group formation schemes are designed for single-PU CRNs, there may be more than one PU in actual systems.

Some group formation schemes in CRNs with multiple PUs have been studied [7, 10, 11, 1]. Jing et al. proposed a group formation scheme for cooperative spectrum prediction in multi-PU CRNs [7]. Each SU predicts the spectrum status of each PU, and selects a PU with the highest spectrum prediction accuracy. For each PU, a group is formed by some SUs in a centralized manner. In [10], a group formation scheme based on sensing accuracy and energy efficiency in multi-PU CRNs was proposed. The groups are formed by using the utility function that takes into account both sensing accuracy and energy required to communication and sensing. Wang et al. studied a distributed cooperative multi-channel spectrum sensing scheme for multi-PU CRNs [11]. Each SU selects the channel with the highest signal-to-noise ratio (SNR) of PU signals and forms a group with other SUs selecting the same channel. In [1], we also proposed a group formation scheme that tries to maximize the SUs' communication opportunities under the assumption that the communication opportunities are equally allocated to SUs that satisfy the PUs' requirement for the miss detection probability.

In this paper, we also consider CSS in CRNs. In most of the existing works, however, SUs in the same group are cooperative with each other and have the same utility function to succeed CSS itself. After CSS, they, however, will be placed in a competitive situation where each of them aims to acquire its own communication opportunities. In this paper, we focus on this users' selfishness and propose a CSS mechanism that takes account of the user incentive. As the main difference from our previous work [1], we newly design the user incentive for joining CSS and add a group reformation scheme that considers users' selfishness.

2.3. Incentive mechanism

Since the spectrum sensing consumes both time and energy of SUs, it has been pointed out that some SUs may not be willing to participate in CSS. To tackle this problem, there are several studies on incentive mechanisms based on game theory [17, 15, 18, 19].

In [15], the authors considered the SUs' selfish behavior called overclaim selfishness (OS) where bad SUs just share dummy or slightly modified sensing results obtained from others and do not conduct sensing by themselves to avoid their own energy consumption. To tackle this problem, they proposed an OS detection scheme and a game theoretical incentive mechanism to enhance cooperation among SUs. However, they did not focus on the detail of SU's utility. In [17], the authors proposed cooperative game based multi-SUs sensing time optimization problem where each SU controls its own sensing time to maximize the cooperative detection probability while minimizing group-level energy consumption. In [18], the authors proposed cooperative spectrum sensing game (CSSG) based on Stag Hunt game. They also considered the data throughput is the utility of SU but assumed that each SU can exclusively access one of sub-bands of the original spectrum. In [19], the authors proposed a pricing scheme where SUs with high sensing accuracy and frequent sensing participation can acquire more reputation, which enable them to use the spectrum in lower prices.

The proposed user incentive is partly similar to some of these existing work. Since the SU's main purpose of joining CSS is acquiring its own spectrum access, we focus on the throughput allocated to each SU, as in [18]. In addition, we also prioritize each SU based on its detection performance, as in [19].

3. System Model

We consider a cognitive radio network consisting of L PUs, labeled from 1 to L, and N SUs, labeled from 1 to N. Let $\mathcal{L} = \{1, \ldots, L\}$ and $\mathcal{N} = \{1, \ldots, N\}$ denote the set of all PUs and that of all SUs, respectively. Fig. 1 is an example of two PUs and four SUs. Suppose that each PU has its own licensed channel. If a PU has multiple channels, the following proposed mechanism can support such situations by regarding the PU as multiple virtual PUs, each of which has a single channel. Each SU recognizes the busy state of PU's spectrum when it detects the PU's signal. Each PU imposes the upper limit of the miss detection probability, χ $(0 \leq \chi \leq 1)$, on SUs [35]. SUs that satisfy this requirement can obtain the communication opportunities. As in [36], we assume a Rayleigh fading environment, where SUs will detect signal by energy detectors and signal transmitted by a node will decrease with distance. Note that the proposed mechanism can also be applied in other noise case, e.g., complex-valued phase-shift keying primary signal and circular symmetric complex Gaussian noise case [22], if both miss detection probability and false alarm probability are given. In the Rayleigh fading environment, In [6], SU i's miss detection probability to PU l, $P^{\text{miss}}_{i,l}$, and SU i's false alarm probability, P^{false}_{i}, are given by

$$P^{\text{miss}}_{i,l} = 1 - e^{-\frac{\lambda}{2}} \sum_{n=0}^{m-2} \frac{1}{n!} \left(\frac{\lambda}{2}\right)^n - \left(\frac{1+\bar{\gamma}_{i,l}}{\bar{\gamma}_{i,l}}\right)^{m-1} \times \left[e^{-\frac{\lambda}{2(1+\bar{\gamma}_{i,l})}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{m-2} \frac{1}{n!} \left(\frac{\lambda \bar{\gamma}_{i,l}}{2(1+\bar{\gamma}_{i,l})}\right)^n \right], \tag{1}$$

$$P^{\text{false}}_{i} = P^{\text{false}} = \frac{\Gamma(m, \frac{\lambda}{2})}{\Gamma(m)}, \tag{2}$$

where m is the time-bandwidth product and λ is the energy detection threshold. Moreover, $\overline{\gamma}_{i,l}$ represents the average SNR of received signal from PU l to SU i, which is given by $\overline{\gamma}_{i,l} = P_l h_{l,i}/\sigma^2$, where P_l is the transmit power of PU l, σ^2 is the Gaussian noise variance, and $h_{l,i}$ is the path loss between SU i and PU l. $h_{i,l}$ is given by $h_{l,i} = \kappa/d^{\mu}_{l,i}$, where κ is the path loss constant, μ is the path loss exponent, and $d_{l,i}$ is the distance between PU l and SU i. $\Gamma()$ is the gamma function and $\Gamma(,)$ is the incomplete gamma function. As a result, $P^{\text{miss}}_{i,l}$ becomes small when the distance between PU l and SU i, called PU-SU distance, is short. On the contrary, P^{false}_{i} is independent of PU-SU distance.

When the SU i's miss detection probability to PU l, $P^{\text{miss}}_{i,l}$, exceeds upper limit χ, SU i should form a group with other SUs and perform CSS to reduce the group miss detection probability. For example, in Fig. 1, both SUs 1 and 3 have higher miss detection probability than χ, and then form group $\mathcal{S}_1$. To form a group, each SU i first requires to discover the candidates of SUs for the group formation. As in [9], we assume that the set of SU i's candidate SUs, $\mathcal{N}_i$, consists of SUs within SU i's transmission range $\tilde{d}$,

$$\tilde{d} = \sqrt[\mu]{\kappa P_{\text{SU}}/\gamma_0 \sigma^2},$$

where P_{SU} is the SU's transmit power to report its sensing result and γ_0 is the minimum average SNR set to be 0 [dB] as in [9]. As in [20, 8, 9], we assume that this communication is conducted through a control channel, which can be temporarily established over ad hoc networks [37] and cognitive networks [38]. In what follows, sensing report error over the control channel will be considered but further consideration is future work. The details of group formation will be described in Section 5.1.

Suppose that each group $\mathcal{S} \in 2^{\mathcal{N}}$ elects an SU called *head* from all SUs of the group. The head collects individual sensing results from other SUs in the group, which are called *members*, and makes a group decision by combining the obtained results. We apply the OR-based fusion rule to the group decision, which is effective to reduce the group miss detection probability.

As in [8], the group $\mathcal{S}$'s miss detection probability to PU l, $Q^{\text{miss}}_{\mathcal{S},l}$, and the group $\mathcal{S}$'s false alarm probability to PU l, $Q^{\text{false}}_{\mathcal{S}}$, are given by

$$Q^{\text{miss}}_{\mathcal{S},l} = \prod_{i \in \mathcal{S}} [P^{\text{miss}}_{i,l}(1 - P_{e,i,k}) + (1 - P^{\text{miss}}_{i,l}) P_{e,i,k}], \tag{3}$$

$$Q^{\text{false}}_{\mathcal{S}} = 1 - \prod_{i \in \mathcal{S}} [(1 - P^{\text{false}})(1 - P_{e,i,k}) + P^{\text{false}} P_{e,i,k}], \tag{4}$$

where $P_{e,i,k}$ is the error probability on the reporting channel between member i and head k, which is given as the error probability of BPSK (binary phase shift keying) modulation in Rayleigh fading environments [39].

$$P_{e,i,k} = \frac{1}{2}\left(1 - \sqrt{\frac{\overline{\gamma}_{i,k}}{1 + \overline{\gamma}_{i,k}}}\right),$$

where $\overline{\gamma}_{i,k}$ represents the average SNR between member i and head k. As in [8], we select the most reliable SU, which has the minimum miss detection probability to the corresponding PU, as the head, in order to avoid the risk that the sensing result of that SU is wrongly reported during the information sharing.

In terms of $P_{e,i,k}$, grouping near SUs can decrease both $Q^{\text{miss}}_{\mathcal{S},l}$ and $Q^{\text{false}}_{\mathcal{S}}$. However, there is a trade-off between $Q^{\text{miss}}_{\mathcal{S},l}$ and $Q^{\text{false}}_{\mathcal{S}}$: Increasing group size $|\mathcal{S}|$ improves $Q^{\text{miss}}_{\mathcal{S},l}$ but degrades $Q^{\text{false}}_{\mathcal{S}}$ [8]. For example, in Fig. 1, we can observe that group formation among SU 1 and SU 3 group decreases (resp. increases) their group's miss detection probability (resp. false alarm probability) to PU 1.

As mentioned in Section 1, each SU can use the PU's spectrum only when it satisfies the PU's requirement for the miss detection probability. As in [8], we call SUs (resp. groups) that satisfy the PU's requirement with CSS *winning* and the remaining SUs (resp. groups) *losing*. In particular, we call a winning SU that does not require to form a group with other SUs *single SU*. For example, in Fig. 1, SUs 1, 2, and 3 are winning while SU 4 is losing. SU 2 is also a single SU.

4. Global Optimization: Maximization of The Number of Winning SUs and Average Communication Opportunities among them

We first focus on global optimization, i.e., maximization of the number of winning SUs and average communication opportunities among them, as mentioned in Section 1. This can be achieved when there is a server that can manage the group formation among all SUs. In what follows, for simplicity of explanation, we assume the single-PU scenario but the problem can be extended to multiple-PUs scenario, with the sacrifice of complexity. The global optimization problem $\mathsf{OP}(\mathcal{N})$ can be formulated as follows:

$$\max \quad N^{-1}\sum_{i\in\mathcal{N}}\mathbb{I}(\widetilde{P}_i^{\text{miss}}\le\chi)(1-\widetilde{P}_i^{\text{false}}) \tag{5}$$

$$\text{s.t.} \quad s_{i,k}=\{0,1\}, \quad \forall i,k\in\mathcal{N}, \tag{6}$$

$$\sum_{k\in\mathcal{N}}s_{i,k}=1, \quad \forall i\in\mathcal{N}, \tag{7}$$

$$\sum_{j\in\mathcal{N}}s_{i,j}s_{k,j}\le a_{i,k}, \quad \forall i,k\in\mathcal{N}. \tag{8}$$

(5) represents the objective function that maximizes the number of winning SUs and average communication opportunities among them. Recall that SUs can acquire the communication opportunities only if they are winning SUs and correctly detect the idle state of PU's spectrum. $\mathbb{I}(\widetilde{P}_i^{\text{miss}}\le\chi)$ is an indicator function: If SU i is a winning SU, $\mathbb{I}(\widetilde{P}_i^{\text{miss}}\le\chi)=1$; Otherwise, $\mathbb{I}(\widetilde{P}_i^{\text{miss}}\le\chi)=0$. If $\mathbb{I}(\widetilde{P}_i^{\text{miss}}\le\chi)=1$, winning SU i can acquire communication opportunities in proportion to probability $1-\widetilde{P}_i^{\text{false}}$.

As in (6), $s_{i,k}$'s ($i,k\in\mathcal{N}$) are binary decision variables that represent group formation: If SU i belongs to group k whose head is SU k, $s_{i,k}=1$; Otherwise, $s_{i,k}=0$. Each SU i can belong to only one group as in (7). Based on $s_{i,k}$, SU i's group-level miss detection probability and group-level false alarm probability can be derived as $\widetilde{P}_i^{\text{miss}}$ and $\widetilde{P}_i^{\text{false}}$, respectively.

$$\widetilde{P}_i^{\text{miss}}=\prod_{k\in\mathcal{N}}\left(1-(1-P_k^{\text{miss}})\sum_{j\in\mathcal{N}}s_{i,j}s_{k,j}\right), \tag{9}$$

$$\widetilde{P}_i^{\text{false}}=1-\prod_{k\in\mathcal{N}}\left(1-P^{\text{false}}\sum_{j\in\mathcal{N}}s_{i,j}s_{k,j}\right). \tag{10}$$

Note that (9) and (10) are equivalent to (3), (4), respectively, under the assumption that error probability on the reporting channel between group member i and head k, $P_{e,i,k}$, is negligible, i.e., $P_{e,i,k}=0$.

(8) represents the possibility of group formation between SU i and SU k. If SUs i and k belong to the same group, $\sum_{j\in\mathcal{N}}s_{i,j}s_{k,j}=1$. Otherwise, $\sum_{j\in\mathcal{N}}s_{i,j}s_{k,j}=0$. As mentioned in Section 3, each SU i can only communicate with neighboring SUs $k\in\mathcal{N}_i$, and thus if $k\in\mathcal{N}_i$, $a_{i,k}=1$, and otherwise, $a_{i,k}=0$.

Although the above optimization problem has nonlinear features, i.e., indicator function and products of binary variables, it can be reduced to ILP, with the help of two kinds of transformation techniques [40]. See the detail in Appendix A. Since ILP is NP-hard, $\mathsf{OP}(\mathcal{N})$ can be solved by existing solver, e.g., CPLEX [41], when N is relatively small.

5. Individual Optimization: User Incentive Based Collaborative Spectrum Sensing Mechanism

The global optimization in Section 4 has not only the scalability problem but also the lack of a user incentive mechanism, which is important for each SU to be willing to join CSS. In CRNs with multiple PUs, the SU's miss detection probability and the PU's utilization of its own spectrum may be different among PUs. Moreover, after SUs conduct CSS, they individually aim to use the idle spectrum, which is a kind of competitive situations. Therefore, it is required for each SU to appropriately select a PU and form a group with other SUs such that it can maximize its own communication opportunities without interfering with the corresponding PU's communication. In this paper, we propose a user incentive based CSS mechanism for multi-PU CRNs, in which communication opportunities are allocated to SUs according to their detection performance. In addition, we also propose a group reformation scheme where SUs try to select better groups based on their own utility.

In what follows, we propose the basis of user incentive based CSS mechanism and selfish group reformation. Finally, we also discuss computation complexity and communication overhead.

5.1. Collaborative Spectrum Sensing Mechanism Based on User Incentive

Each SU i tries to maximize its own communication opportunity $r_{i,\mathcal{S}_i,l}$ while meeting the constraint on the miss detection probability. This can be formulated by the following individual optimization problem $\mathsf{OP}_i(\mathbf{S}_i,\mathcal{L})$, which returns optimal group $\mathcal{S}_i$ and PU l:

$$\max_{\mathcal{S}_i\in\mathbf{S}_i,\ l\in\mathcal{L}_{\mathcal{S}_i,\chi}} r_{i,\mathcal{S}_i,l}, \tag{11}$$
$$\text{s.t.}\ \mathcal{L}_{\mathcal{S}_i,\chi}=\{l\in\mathcal{L}\mid Q_{\mathcal{S}_i,l}^{\text{miss}}\le\chi\},$$

where $\mathbf{S}_i$ is the set of all possible groups for SU i and $\mathcal{L}_{\mathcal{S}_i,\chi}$ is the set of PUs to which SU i's group $\mathcal{S}_i\in\mathbf{S}_i$ can meet the constraint on the miss detection probability.

The objective function is the maximization of SU i's communication opportunity, which can be expressed by the product of three factors:

$$r_{i,\mathcal{S}_i,l}=(1-R_l^{\text{use,PU}})(1-Q_{\mathcal{S}_i}^{\text{false}})\frac{1}{N_l^{\text{group}}}\frac{P_{i,l}^{\text{detect}}}{\sum_{j\in\mathcal{S}_i}P_{j,l}^{\text{detect}}}. \tag{12}$$

Algorithm 1 PU selection and group formation (computation complexity (CP): $O(2^{\overline{W}}L\overline{S}NT)$, communication overhead (CM): $O(\overline{S}(\overline{S}-1)NT)$).

$\forall i \in \mathcal{N}, \mathcal{S}_i = \{i\}$ ▷ Initialization ($\mathrm{CP}: O(N), \mathrm{CM}: -$)
$\forall i \in \mathcal{N}$ discovers their neighboring SUs $\mathcal{N}_i$ ▷ Discovery ($\mathrm{CP}: O(\overline{N}_i N), \mathrm{CM}: O(\overline{N}_i N)$)
for all $i \in \mathcal{N}$ **do** ▷ Trying non-cooperative sensing ($\mathrm{CP}: O(LN), \mathrm{CM}: -$)
  if $\mathcal{L}_{\mathcal{S}_i,\mathcal{X}} \neq \emptyset$ **then** ▷ Winning case ($\mathrm{CP}: O(L), \mathrm{CM}: -$)
    i selects PU by solving $\mathsf{OP}_i(\{\mathcal{S}_i\}, \mathcal{L})$
  else ▷ Losing case ($\mathrm{CP}: O(L), \mathrm{CM}: -$)
    i selects PU according to $\mathrm{argmin}_{l \in \mathcal{L}} P^{\mathrm{miss}}_{i,l}$
repeat ▷ Group update ($\mathrm{CP}: O(2^{\overline{W}}L\overline{S}NT), \mathrm{CM}: O(\overline{S}(\overline{S}-1)NT)$)
  $\mathcal{T}^{\mathrm{winning}} = \{\mathcal{S}_i \mid i \in \mathcal{N}, \mathcal{L}_{\mathcal{S}_i,\mathcal{X}} \neq \emptyset\}$
  for all $i \in \mathcal{N}$ **do** ▷ Trying group update ($\mathrm{CP}: O(2^{\overline{W}}L\overline{S}N), \mathrm{CM}: O(\overline{S}(\overline{S}-1)N)$)
    if $\mathcal{L}_{\mathcal{S}_i,\mathcal{X}} == \emptyset$ **then** ▷ Trying cooperative sensing ($\mathrm{CP}: O(2^{\overline{S}}L\overline{S}), \mathrm{CM}: O(\overline{S}(\overline{S}-1))$)
      i collects $\mathcal{S}_j$ from $\forall j \in \mathcal{N}_i$ ▷ ($\mathrm{CP}: O(\overline{D}), \mathrm{CM}: O(\overline{D})$)
      $\mathcal{W}_i = \emptyset$ ▷ Calculating candidates of cooperation
      for all $j \in \{m \in \mathcal{N}_i \mid \mathcal{L}_{\mathcal{S}_m,\mathcal{X}} == \emptyset\}$ **do** ▷ ($\mathrm{CP}: O(\overline{D}), \mathrm{CM}: -$)
        if $\mathcal{L}_{\mathcal{S}_i \cup \mathcal{S}_j,\mathcal{X}} \neq \emptyset$ **then**
          i adds $\{\mathcal{S}_i \cup \mathcal{S}_j\}$ to $\mathcal{W}_i$
      if $\mathcal{W}_i \neq \emptyset$ **then** ▷ Winning case
        i selects $\mathcal{S}_i$ and PU by solving $\mathsf{OP}_i(\mathcal{W}_i, \mathcal{L})$ ▷ ($\mathrm{CP}: O(2^{\overline{W}}L\overline{S}), \mathrm{CM}: -$)
        i informs $\forall j \in \mathcal{S}_i$ of group merge ▷ ($\mathrm{CP}: O(\overline{S}), \mathrm{CM}: O(\overline{S})$)
        $\forall j \in \mathcal{S}_i$ conducts selfish group reformation (Algorithm 2) ▷ ($\mathrm{CP}: O(2^{\overline{S}}L\overline{S}), \mathrm{CM}: O(\overline{S}(\overline{S}-1))$)
      else ▷ Losing case
        i replaces $\mathcal{S}_i$ with $\mathcal{S}_i \cup \mathcal{S}_j$ such that $j \in \mathcal{N}_i, \mathcal{L}_{\mathcal{S}_j} == \emptyset$, and (3) is minimized, and informs $\forall k \in \mathcal{S}_i$ of $\mathcal{S}_i$
        ▷ ($\mathrm{CP}: O(\overline{DS}), \mathrm{CM}: O(\overline{S})$)
    else ▷ Trying group reformation
      $\forall j \in \mathcal{S}_i$ conducts selfish group reformation (Algorithm 2) ▷ ($\mathrm{CP}: O(2^{\overline{S}}L\overline{S}), \mathrm{CM}: O(\overline{S}(\overline{S}-1))$)
until $\{\mathcal{S}_i \mid i \in \mathcal{N}, \mathcal{L}_{\mathcal{S}_i,\mathcal{X}} \neq \emptyset\} == \mathcal{T}^{\mathrm{winning}}$

The first factor is the probability that the spectrum is unused by PU l, i.e., $1 - R^{\mathrm{use,PU}}_l$. In this paper, we assume that the PU activity follows a simple ON/OFF model [42], where PU l is active (ON/BUSY state) with probability $R^{\mathrm{use,PU}}_l$ and inactive (OFF/IDLE state) with probability $1 - R^{\mathrm{use,PU}}_l$. There has been extensive survey on PU activity models [42]. The second factor is idle detection probability that is the probability SU i can notice the idle state of spectrum, i.e., $1 - Q^{\mathrm{false}}_{\mathcal{S}_i}$. The third factor is the communication opportunity allocated to SU i. Since each group individually conducts the CSS, we assume that communication opportunities are equally allocated to the winning groups with the fraction of $1/N^{\mathrm{group}}_l$, where N^{group}_l is the number of winning groups selecting PU l. On the other hand, in each group, communication opportunities are allocated to each SU corresponding to its own detection performance by taking account of the user incentive, i.e., $P^{\mathrm{detect}}_{i,l} / \sum_{j \in \mathcal{S}_i} P^{\mathrm{detect}}_{j,l}$. For example, in Fig. 1, SU 1 has higher detection probability than its group member SU 3, and thus SU 1 can acquire more communication opportunity than SU 3.

We assume that each SU can obtain or estimate $R^{\mathrm{use,PU}}_l$ and N^{group}_l with the help of existing approaches. For example, an reinforcement learning approach is proposed, which can estimate the PU's spectrum utilization from historical sensing results [43]. On the other hand, the number of winning groups can be directly shared among SUs through the control channel in a multi-hop manner.

The objective function indicates that each SU can maximize its own communication opportunities if it can become a single SU. If the SU cannot meet the constraint on the miss detection probability by itself, it attempts to form a group with other SUs for CSS to meet the constraint. When each SU forms a group with other SUs, the SU with high detection performance can acquire more communication opportunities by forming a group with an SU with low detection performance. On the other hand, there is also user incentive for the SU with low detection performance because it can become a winning SU by forming a group. Recall that the miss detection probability increases with the distance between PU and SU, as shown in (1). As a result, the proposed mechanism encourages each SU close to a PU in forming a group with other SUs away from the PU, and vice versa.

We should note here that the consideration of time and energy consumption for sensing. Although objective function (11) does not directly consider these factors, they will be imposed on SUs. In this paper, we assume that the satisfaction with the expected communication opportunity of winning SU i, $r^*_{i,\mathcal{S}_i,l}$, which is given by (11), exceeds the dissatisfaction with the time and energy consumption. We plan to extend our formulation by

Algorithm 2 Selfish group reformation (computation complexity (CP): $O(2^{\overline{S}} L\overline{S})$, communication overhead (CM): $O(\overline{S}(\overline{S}-1))$).

Require: winning group $\mathcal{S}$

1: **for all** $i \in \mathcal{S}$ **do** ▷ Search for the best group for i $(\mathrm{CP}: O(2^{\overline{S}} L\overline{S}), \mathrm{CM}: O(\overline{S}(\overline{S}-1)))$
2: i calculates new candidate group $\mathcal{S}_i^{\mathrm{A}}$ by solving $\mathsf{OP}_i(2^{\mathcal{S}}, \mathcal{L})$
3: i informs members $\forall j \in \mathcal{S}$ of $\mathcal{S}_i^{\mathrm{A}}$
4: $\mathcal{Y} = \mathcal{S}$
5: **repeat** ▷ Confirm consensus of group reformation $(\mathrm{CP}: O(\overline{S}), \mathrm{CM}: -)$
6: $i \in \mathcal{Y}$
7: **if** $\forall j \in \mathcal{S}_i^{\mathrm{A}}, \mathcal{S}_i^{\mathrm{A}} == \mathcal{S}_j^{\mathrm{A}}$ **then** ▷ Consensus is built
8: $\forall k \in \mathcal{S}_i^{\mathrm{A}}$ replaces $\mathcal{S}_k$ with $\mathcal{S}_i^{\mathrm{A}}$
9: $\forall m \in \mathcal{S} \setminus \mathcal{S}_i^{\mathrm{A}}$ replaces $\mathcal{S}_m$ with $\{m\}$
10: $\mathcal{Y} = \mathcal{Y} \setminus \mathcal{S}_i^{\mathrm{A}}$
11: **else** ▷ Consensus fails
12: $\mathcal{Y} = \mathcal{Y} \setminus \{i\}$
13: **until** $\mathcal{Y} == \emptyset$

taking account of this relationship.

Algorithm 1 shows SU i's control procedure for PU selection and group formation. We also give computation complexity (CP), i.e., the number of calculations, and communication overhead (CO), i.e., the number of communications, in Algorithm 1, which will be discussed in Section 5.3. First, each SU $i \in \mathcal{N}$ forms a group by itself and discovers SUs in its transmission range $\tilde{d}$ as the set of neighboring SUs, $\mathcal{N}_i$ (line 2). Next, each SU i checks whether it meets the constraint on the miss detection probability under single spectrum sensing (lines 3–7). If SU i can become winning, it selects a PU to maximize the expected value of its own communication opportunities by solving $\mathsf{OP}_i(\mathcal{W}_i, \mathcal{L})$ (line 5). Otherwise, it becomes losing and selects a PU with the minimum miss detection probability (line 7).

Each SU $i \in \mathcal{N}$ attempts to update its group $\mathcal{S}_i$ for maximizing its own communication opportunities (lines 10–25). Note that the acting order among SUs in lines 10–25 will be random because each SU acts in a distributed manner. Each losing SU i attempts to perform CSS with other losing SUs (lines 11–23). First, each SU i searches for possible group candidates $\mathcal{W}_i$ for cooperation (lines 13–16). Note that the group candidates must also be losing because winning groups need not to further cooperate with other SUs. If SU i finds appropriate groups with which it can become winning, it selects a PU and forms a group to maximize the expected value of its own communication opportunities by solving $\mathsf{OP}_i(\mathcal{W}_i, \mathcal{L})$ (line 18). Otherwise, it still stays losing and forms a group with a losing group to minimize the group miss detection probability (line 23). In lines 20 and 25, each winning SU i conducts selfish group reformation according to Algorithm 2, which will be described in Section 5.2.

Note that this group updating is repeated until the set of winning groups, $\mathcal{T}^{\mathrm{winning}}$, does not change (line 26). Therefore, there exist two cases after Algorithm 1 has converged. In the first case, all SUs become winning and do not have further incentive to form a new group. In the second case, a part of SUs can become winning and the remaining SUs are forced to remain losing, due to lack of appropriate partner(s). The resulting case depends on not only the locations of PUs and SUs but also the processing order of Algorithm 1 among SUs.

Table 1: Simulation parameters.

Parameter	Value
Simulation region	3 [km] × 3 [km] square area
The number of SUs, N	$2, 3, 4, 5, 6, 7, 10, 15, 20, 30, 40, 50$
Transmit power of SU, P_{SU}	10 [mW]
Transmit power of PU l, P_l	100 [mW]
Gaussian noise variance σ^2	-90 [dBm]
Path loss constant κ	1
Path loss exponent μ	3
Time-bandwidth product m	5
Energy detection threshold λ	21.51 [mW]
False alarm probability P^{false}	0.018 (1.8%)
Upper limit of miss detection probability, χ	0.05
Transmission range of SU, $\tilde{d}$	2,154 [m]

5.2. *Selfish Group Reformation*

Algorithm 1 has the randomness in acting order among SUs (lines 10–25). This may result in different group formation and also leave opportunities for some SUs to improve their own communication opportunities by reforming their groups. Algorithm 2 shows the selfish group reformation with computation complexity and communication overhead. Given winning group $\mathcal{S}$, each SU i in $\mathcal{S}$ individually calculates $\mathcal{S}_i^{\mathrm{A}}$ that maximizes its own communication opportunities (lines 1–3). The group reformation requires the consensus among all SUs that will form the group. From lines 5–13, each SU i confirms the consensus of group reformation. If SU i can build the consensus with all the other SUs in $\mathcal{S}_i^{\mathrm{A}}$, they leave $\mathcal{S}$ and make new group $\mathcal{S}_i^{\mathrm{A}}$ (line 8). The remaining SUs in $\mathcal{S}$ temporarily form independent groups and confirm the possibility of group reformation in the succeeding iterations (line 9). If SU i fails to build the consensus, the group reformation does not occur (line 12).

5.3. *Computation Complexity and Communication Overhead*

We focus on the computation complexity and communication overhead of proposed scheme given by Algorithms 1 and 2. We give the computation complexity (CP) and communication overhead (CM) in Algorithms 1 and 2. Note that T represents the number of repetitions from line 8 to 26 in Algorithm 1. Let $\overline{D}$, $\overline{S}$, and $\overline{W}$ denote the average number of neighboring SUs, that of group members, and that of candidates of group members, respectively. In ordinary cases, the number of PUs is much smaller than that of SUs, ($L \ll N$), and the number of neighboring SUs is limited ($\overline{D} \ll N$). Furthermore, objective function (11) leads to lower $Q_{\mathcal{S}_i}^{\mathrm{false}}$ as in (12), which makes the group size smaller, i.e., $\overline{S} \ll N$ and $\overline{W} \ll N$. As a result, both the computation complexity and communication overhead of proposed scheme are given by $O(NT)$.

We focus on the number of repetitions, T. If the selfish group reformation (Algorithm 2) is not used, Algorithm 1 only applies operations for merging groups. The number of groups starts from that of SUs, N, and each merge operation reduces the number of groups by one. As a result, the merge operation speedily converges. Next, we consider the selfish group reformation. In Algorithm 2, the selfish group reformation replaces an existing group with a group that is more strongly banded together while yields some losing SUs, which will retry the group merge process in Algorithm 1. The convergence property of proposed scheme will be shown in Section 6.5.

6. Simulation Results

We evaluate the effectiveness of the proposed mechanism through several simulation experiments.

6.1. Simulation Settings

We use Netlogo [44] as the simulator. We show the simulation parameters and their default values in Table 1. The values of $N, P_{\mathrm{SU}}, P_l, \sigma^2, \kappa, \mu, m$ are determined according to [8], and the value of $\tilde{d}$ is determined according to [9]. In [8], the authors evaluate the impact of λ on both miss detection probability and P^{false}. We select one of the desirable value of λ, i.e., $\lambda = 21.51$ [m], which can balance between the miss detection probability and P^{false}. Since P^{false} is given by (2), $m = 5$ and $\lambda = 21.51$ results in $P^{\mathrm{false}} = 0.018$. Fig. 2 (resp. Fig. 3) illustrates an example of locations in 1-PU (resp. 2-PU) scenario where 1 PU (resp. 2-PUs) and 18 SUs (resp. 20 SUs) exist. In both scenarios, N SUs are uniformly distributed in the area. As for the PU location, one PU is located at the center of simulation area in the 1-PU scenario. On the other hand, in the 2-PU scenario, two PUs are located at $(0.75, 0.75)$ and $(-0.75, -0.75)$ such that the simulation area can be equally divided by the diagonal line.

We use three evaluation criteria. The first one is the ratio of winning SUs, w, which is the ratio of the number of winning SUs to that of all SUs. The relationship between PU-SU distance and winning frequency is also investigated, where the winning frequency describes how often SUs with certain PU-SU distance can become winning through independent simulation runs. The second one is the average idle detection probability among winning SUs selecting PU $l \in \mathcal{L}$, $1 - \overline{Q}_l^{\mathrm{false}}$, where $\overline{Q}_l^{\mathrm{false}}$ is the average false alarm probability among SUs selecting PU l. As shown in Appendix B, the sum of communication opportunities among winning SUs, i.e., system throughput, can be expressed by $\sum_{l \in \mathcal{L}}(1 - R_l^{\mathrm{use,PU}})(1 - \overline{Q}_l^{\mathrm{false}})$. The relationship between each winning SU's detection probability and throughput will also be shown. The third one is the computation complexity and convergence property. In what follows, we show the average of 5000 independent simulation runs.

Although we will only show the results of the 1-PU scenario and 2-PU scenario, we can qualitatively discuss the tendency of system performance even under scenarios with more than two PUs. First, the ratio of winning SUs is mainly determined by the locations of PUs and SUs. In what follows, we demonstrate that the ratio of winning SUs of the proposed mechanism will show the similar tendency in both scenarios where SUs are located uniformly. Thus, we can expect that the ratio of winning SUs will show the similar tendency even under scenarios with more than two PUs and uniformly located SUs. On the contrary, the system throughput will increase with the number of PUs.

6.2. Performance of Proposed Mechanism in 1-PU Cognitive Radio Network

We first evaluate the effectiveness of the proposed mechanism in 1-PU CRNs by comparing the results with CF-PD [8], which is the CSS scheme designed for 1-PU CRNs. Recall that CF-PD mainly focuses on CSS itself, and thus SUs in a group have the same objective. CF-PD forms groups by taking account of the trade-off between the group detection probability and the group false alarm probability through the following group-based utility function [8]:

$$v(\mathcal{S}) = (1 - Q_{\mathcal{S}}^{\mathrm{miss}}) - C(Q_{\mathcal{S}}^{\mathrm{false}}, \alpha), \tag{13}$$

where $Q_{\mathcal{S}}^{\mathrm{miss}}$ is the group $\mathcal{S}$'s miss detection probability and $Q_{\mathcal{S}}^{\mathrm{false}}$ is the $\mathcal{S}$'s false alarm probability. These are the same as (3) and (4), respectively. Moreover, α is a constraint on the false alarm probability and $C(,)$ represents the cost function for the false alarm probability [8], which is given by

$$C(Q_{\mathcal{S}}^{\mathrm{false}}, \alpha) = \begin{cases} -\alpha^2 \cdot \log(1 - (\frac{Q_{\mathcal{S}}^{\mathrm{false}}}{\alpha})^2), & \text{if } Q_{\mathcal{S}}^{\mathrm{false}} < \alpha, \\ +\infty, & \text{otherwise.} \end{cases}$$

The winning SUs, which meet both constraints on the miss detection probability and the false alarm probability, are defined by the following adjunct utility function [8],

$$u(\mathcal{S}) = \begin{cases} 1, & \text{if } Q_{\mathcal{S}}^{\mathrm{detect}} \geq (1 - \chi) \text{ and } Q_{\mathcal{S}}^{\mathrm{false}} < \alpha, \\ 0, & \text{otherwise,} \end{cases}$$

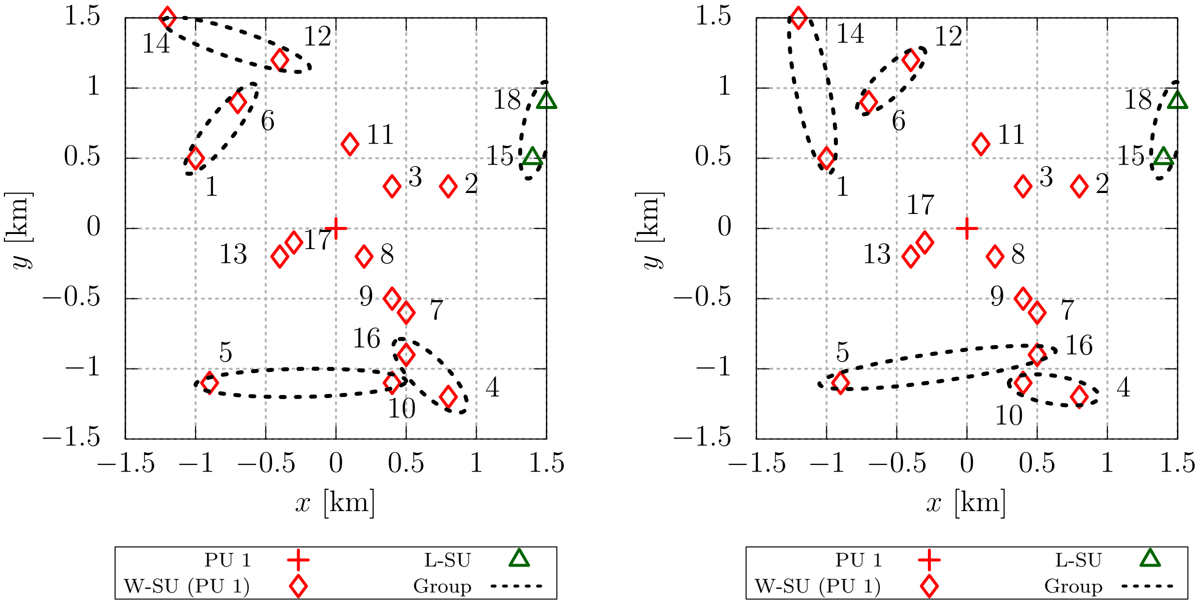
where $Q_{\mathcal{S}}^{\mathrm{detect}}$ represents the group $\mathcal{S}$'s detection probability, i.e., $1 - Q_{\mathcal{S}}^{\mathrm{miss}}$, and χ represents the upper limit of the miss detection probability. If $u(\mathcal{S}) = 1$, group $\mathcal{S}$ is winning. In addition, each winning group performs an adjust operation such that the corresponding group can keep winning with the minimum number of SUs.

In this evaluation, we set the probability that PU 1 uses its own spectrum, $R_1^{\mathrm{use,PU}}$, to be 0.3. To compare the proposed mechanism with CF-PD, we set α of CF-PD to be 0.3, which is the maximum false alarm probability that was observed in the case of the proposed mechanism.

We also show the global optimal solutions, called *Optimal*, which are obtained by solving $\mathsf{OP}(\mathcal{N})$ with the help of existing solver, CPLEX. Note that the optimal solution are obtained in case of relatively small system scale, i.e., $N \leq 10$, due to the computation complexity.

6.2.1. Ratio of Winning SUs

Fig. 4 illustrates the relationship between the number of SUs, N, and the ratio of winning SUs for the proposed mechanism,



(a) CF-PD

(b) Proposed mechanism

Figure 2: An example of PU selection and group formation in 1-PU CRNs when $N = 18$ (W-SU (PU l) means winning SU selecting PU l and L-SU means losing SU).

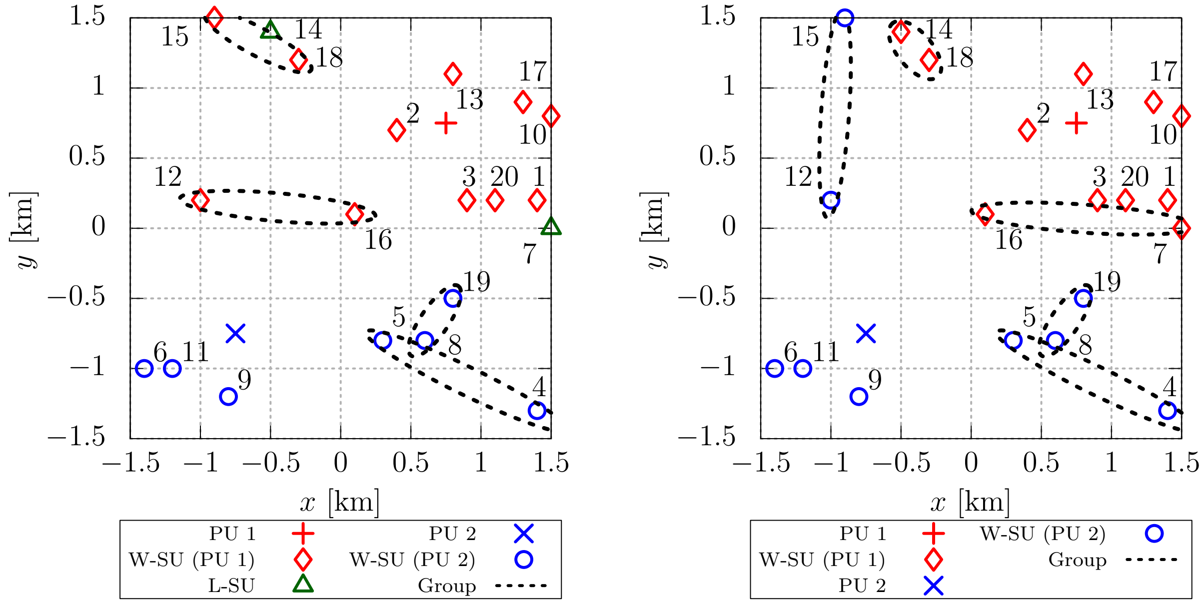
CF-PD, and Optimal. We first focus on the comparison between proposed mechanism and CF-PD. We observe that the performance difference between proposed mechanism and CF-PD is limited but the proposed mechanism can work better than CF-PD when N becomes large, e.g., $N \geq 20$. For example, the improvement ratio becomes about 4% in the case of $N = 50$. To analyze this difference deeply, we further investigate the relationship between upper limit χ of the miss detection probability and the average miss detection probability among winning groups in the case of $N = 50$. The average group miss detection probability of the proposed mechanism is 0.0284, which is closer to the value of χ, i.e., 0.05, compared with that of CF-PD, i.e., 0.0228. In the proposed mechanism, each SU tries to form a group such that the group miss detection probability of group does not exceed χ. CF-PD also guarantees this condition but prefers smaller group miss detection probability according to (13). As a result, in CF-PD, each group tries to include SUs that are close to a PU as shown in Fig. 2a, e.g., SU 1. Such group formation will decrease the chance that SUs distant from a PU become winning SUs. On the contrary, the proposed mechanism can alleviate this problem by introducing the user incentive, which encourages each SU close to a PU in forming a group with other SUs away from the PU, and vice versa, as shown in Fig. 2b, e.g., SU 1.

Next, we focus on the comparison between proposed mechanism and Optimal. We observe that the results of proposed mechanism are 0–15% lower than those of Optimal. This comes from several factors. First, Optimal ignores error probability on the reporting channel between group member i and head k, $P_{e,i,k}$, i.e., $P_{e,i,k} = 0$. Second is the difference of goals between proposed scheme and Optimal. The goal of Optimal is maximization of average communication opportunities among SUs while that of proposed scheme differs among SUs, i.e., maximization of its own communication opportunities. Third, in the proposed mechanism, SUs conduct group formation in a distributed manner with local knowledge and communications. On the contrary, Optimal allows a central server to fully manage group formation among all SUs with global knowledge.

6.2.2. Average Idle Detection Probability

Fig. 5 illustrates the relationship between the number of SUs, N, and the average idle detection probability. As we expected, the average idle detection probability of the proposed mechanism becomes higher than that of CF-PD. (Recall that the group miss detection probability of the proposed mechanism becomes slightly higher than that of CF-PD, under the constraint of χ, as mentioned in Section 6.2.1). In CF-PD, SUs close to a PU want to cooperate together to achieve smaller group miss detection probability. As a result, SUs distant from a PU will be forced to make groups among them, which tends to increase the group size, due to a high miss detection probability of each SU. This results in the decrease (resp. increase) of the average idle detection (resp. false alarm) probability. On the contrary, the proposed mechanism considers the idle detection probability as a part of SU's communication opportunities given by (12). As a result, the proposed mechanism can improve the average idle detection probability, compared to CF-PD. Note that the idle detection probability is identical among SUs as in (2) and the group idle detection probability is mainly determined by the group size as in (4), and thus the improvement is not at major scale, i.e., 0–2%.

Next, we focus on the comparison between proposed mechanism and Optimal. We observe that the results of proposed mechanism shows 0–2% decrease compared with those of Optimal, due to the same reasons as mentioned in Section 6.2.1.



(a) Proposed mechanism without user incentive

(b) Proposed mechanism

Figure 3: An example of PU selection and group formation in 2-PU CRNs when $N = 20$ (W-SU (PU l) means winning SU selecting PU l and L-SU means losing SU).

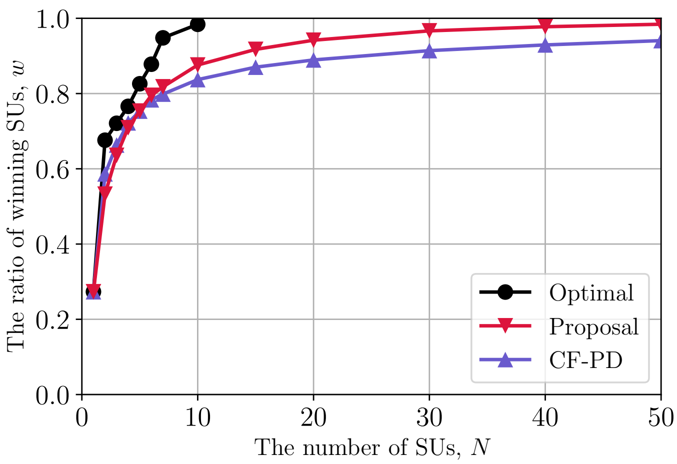


Figure 4: Relationship between the number of SUs, N, and the ratio of winning SUs, w (1-PU scenario).

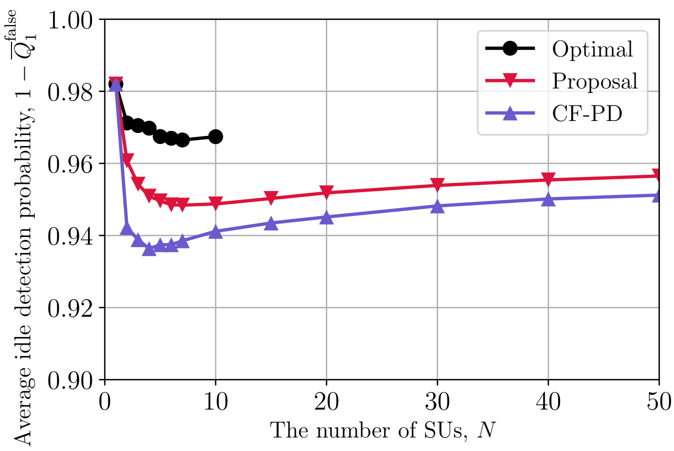


Figure 5: Relationship between the number of SUs, N, and the average idle detection probability, $1 - \overline{Q}_l^{\text{false}}$ (1-PU scenario).

However, we also find a desirable characteristic where the proposed mechanism can support larger-scale systems compared with Optimal, with the help of lower computation complexity and communication overhead. (See the detail in Section 5.3.) Furthermore, the proposed mechanism works better in terms of both the ratio of winning SUs and average idle detection probability with increase of system scale as shown in Figs. 4 and 5.

6.2.3. Relationship between PU-SU Distance and Winning Frequency

Fig. 6 illustrates the relationship between PU-SU distance and winning frequency in the case of $N = 50$. Note that we set the granularity of distance to be 100 [m]: PU-SU distance d_i of SU i is replaced with $d'_i = \lceil d_i/100 \rceil \cdot 100$, e.g., $d'_i = 100$ for $d_i = 50$. We also show the histogram of the number of SUs located at the corresponding distance. We first observe that the winning frequency of both schemes becomes 100% when PU-SU distance is equal or less than 900 [m]. We also find that the proposed mechanism can significantly improve the winning frequency for SUs with larger PU-SU distance, i.e., 1500–2300 [m], compared with CF-PD, with the small sacrifice of winning frequency for SUs with moderate PU-SU distance, i.e., 1000–1400 [m]. As a result, the proposed mechanism can improve the ratio of winning SUs compared to CF-PD as in Fig. 4.

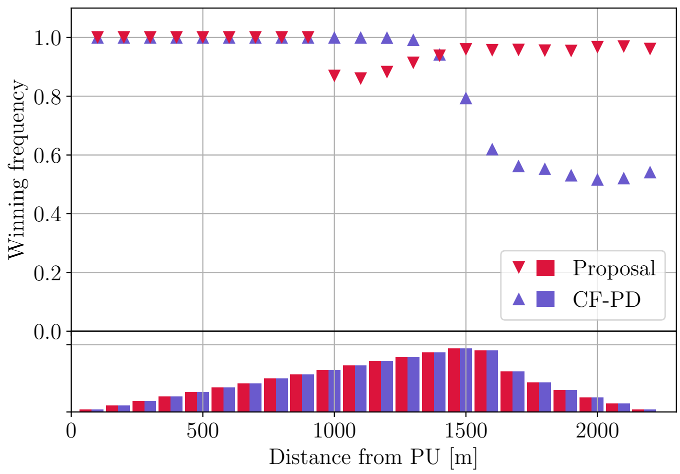


Figure 6: Relationship between PU-SU distance and winning frequency (1-PU scenario, $N = 50$).

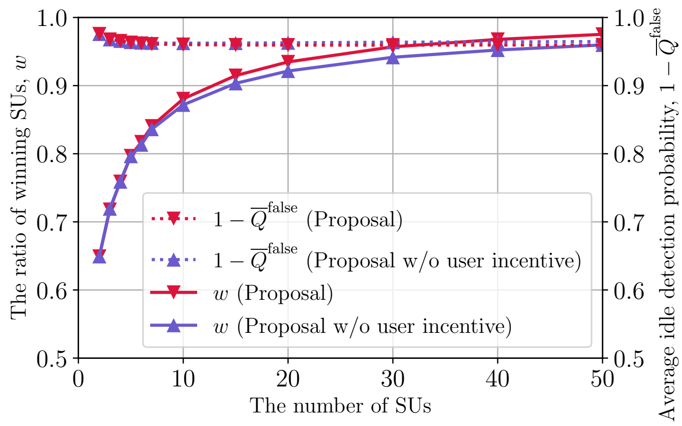


Figure 7: Relationship between the number of SUs, N, the ratio of winning SUs, w, and average idle detection probability, $1 - \overline{Q}^{\text{false}}$, (2-PU scenario).

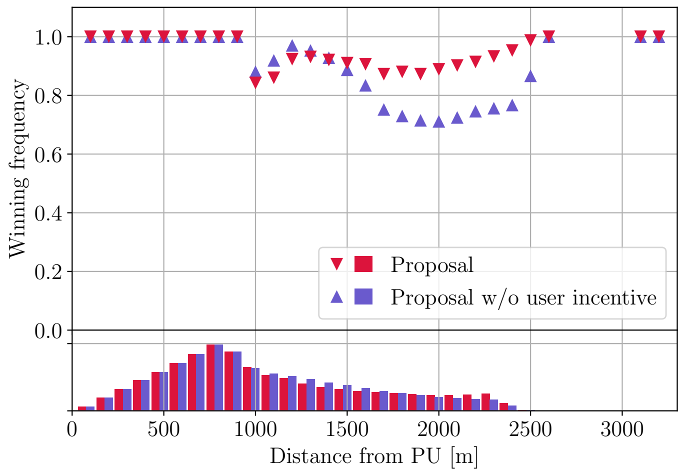


Figure 8: Relationship between PU-SU distance and winning frequency (2-PU scenario, $N = 50$).

6.3. *Impact of Cooperation Based on User Incentive in 2-PUs Cognitive Radio Network*

We evaluate the effectiveness of the proposed mechanism in 2-PU CRNs. For comparison purpose, we use the proposed mechanism without user incentive, which equally allocates communication opportunities to winning SUs, regardless of their detection performance. This can be achieved by replacing objective function (11) of $\mathsf{OP}_i(\mathbf{S}_i, \mathcal{L})$ with the following objective function:

$$\max_{\mathcal{S}_i \in \mathbf{S}_i,\ l \in \mathcal{L}_{\mathcal{S}_i,\chi}} (1 - R_l^{\text{use,PU}})\,(1 - Q_{\mathcal{S}_i}^{\text{false}})\,\frac{1}{N_l^{\text{winning}}}, \tag{14}$$

where N_l^{winning} is the number of winning SUs selecting PU l.

In this subsection, we evaluate through the above mentioned three criteria. In the following evaluation, we set $R_1^{\text{use,PU}}$ and $R_2^{\text{use,PU}}$ to be 0.3 and 0.5, respectively.

6.3.1. *Ratio of Winning SUs and Average Idle Detection Probability*

As mentioned in Section 5.1, the proposed mechanism introduces user incentive, which encourages each SU close to a PU in forming a group with other SUs away from the PU, and vice versa, as shown in Fig. 3b, e.g., SU 12. On the other hand, in the proposed mechanism without user incentive, each SU tends to form the group among nearby SUs as shown in Fig. 3a, e.g., SU 12, because reducing the group false alarm probability has a large impact on maximizing (14).

Fig. 7 illustrates the relationship between the number of SUs, N, the ratio of winning SUs, w, and average idle detection probability, $\overline{Q}^{\text{false}}$, for the proposed mechanism and that without user incentive. Note that $\overline{Q}^{\text{false}}$ is the average of $\overline{Q}_l^{\text{false}}$ among PUs. We observe that the proposed mechanism can slightly improve the ratio of winning SUs, e.g., 1.6% improvement at $N = 50$, and achieves almost the same average idle detection probability, compared to that without user incentive. The main purpose of introducing user incentive is giving motivation to SUs to join CSS. In this evaluation, we assume that all SUs tries to join CSS. This assumption seems to be practical in the proposed mechanism with user incentive because SUs can acquire communication opportunities according to their contribution to detection performance, which will give much motivation to SUs to join CSS. On the contrary, in the proposed mechanism without user incentive, all winning SUs in the same group obtain the same communication opportunities, and thus some SUs with high detection performance may leave the system, due to dissatisfaction with allocated communication opportunities. The impact of user incentive on the communication opportunities of SUs will be given in Section 6.3.2. As in Section 6.2.1, we investigate the relationship between upper limit χ of the miss detection probability and the average group miss detection probability among winning groups in the case of $N = 50$. The average group miss detection probability of the proposed mechanism is 0.033, which is closer to the value of χ, i.e., 0.05, compared to that of the proposed mechanism without user incentive, i.e., 0.027.

Fig. 8 illustrates the relationship between PU-SU distance and winning frequency in the case of $N = 50$. As in Section 6.2.3, Fig. 8 shows the proposed mechanism can significantly improve the winning frequency for SUs with larger PU-SU distance, i.e., 1500–2500 [m], compared with the proposed mechanism without user incentive. Recall that the proposed mechanism without user incentive encourages each SU in forming a group with nearby SUs. If SUs close to a PU make groups among them, it is difficult for SUs distant from a PU to become winning. On the contrary, the proposed mechanism can alleviate this problem by introducing user incentive such that each SU close to a PU wants to form a group with SUs distant from the PU, and vice versa.

6.3.2. Relationship between Detection Performance and Throughput

We use the following time-slot based access model for the usage of PU's spectrum. In each time slot, PU l transmits data according to the probability that it uses its own spectrum, $R_l^{\text{use,PU}}$, and transmission request for each SU occurs with probability 0.1. When multiple winning groups detect the idle state of PU's spectrum, one of the groups is selected at random, and then an SU in the group wins the transmission opportunity based on the contribution to detection performance. If a collision occurs between the PU and SU(s), both of them do not conduct retransmission.

Fig. 9 illustrates the relationship between the detection probability and throughput for each winning SU selecting PU 1 in the case of $N = 50$. We also show the histogram of the number of SUs with the corresponding detection probability (resp. throughput) in the upper (resp. right) area of Fig. 9. As shown in Figs. 9a and 9b, each single SU i with $P_{i,1}^{\text{detect}} > (1-\chi)$ obtains about 0.03–0.04 throughput in both schemes. On the other hand, remaining SUs with $P_{i,1}^{\text{detect}} \leq (1-\chi)$ form a group with other SUs. In the proposed mechanism without user incentive, such SUs obtain almost the same throughput (Fig. 9a). In the proposed mechanism, Fig. 9b shows that SUs with a high detection probability can obtain the high throughput because communication opportunities are allocated to SUs according to their contribution to detection performance. We also confirmed that the similar tendency is satisfied in the case of SUs selecting PU 2.

6.4. Robustness against Selfish Group Reformation

In this subsection, we investigate how the proposed mechanism is robust against SUs' selfish behavior. As mentioned in Section 5.2, the proposed mechanism includes the selfish group reformation scheme where each SU has a chance to remake the belonging group to increase its own communication opportunities. Through simulation experiments, however, we observed that the group reformation occurred at less than 1% of the winning groups, regardless of N. This is because the selfish group reformation occurs only when the SUs joining the new group can build a consensus where all of them can increase their own communication opportunities by the group reformation. This condition is severe and each winning group tends to reach a deadlock. As a result, the proposed mechanism can achieve stable group formation even under SUs' selfish behavior.

6.5. Convergence Property and Adaptability to Environmental Change

Finally, we evaluate the convergence property and adaptability to an environmental change of the proposed mechanism. Note that the convergence property also represents both the computation and communication overhead discussed in Section 5.3. In the proposed mechanism, each SU tries to improve its communication opportunity according to Algorithms 1. We define a time step where one SU conducts group update (lines 11–25 in Algorithm 1). As a result, N time steps corresponds to one repetition of lines 8–26 in Algorithm 1. Fig. 10 illustrates how the ratio of winning SUs, average throughput of winning SUs, and the frequency of group update vary with time step when the PUs' spectrum utilization are initially set to be $R_1^{\text{use,PU}} = 0.3, R_2^{\text{use,PU}} = 0.5$ and change at step 150, i.e., $R_1^{\text{use,PU}} = 0.5, R_2^{\text{use,PU}} = 0.3$.

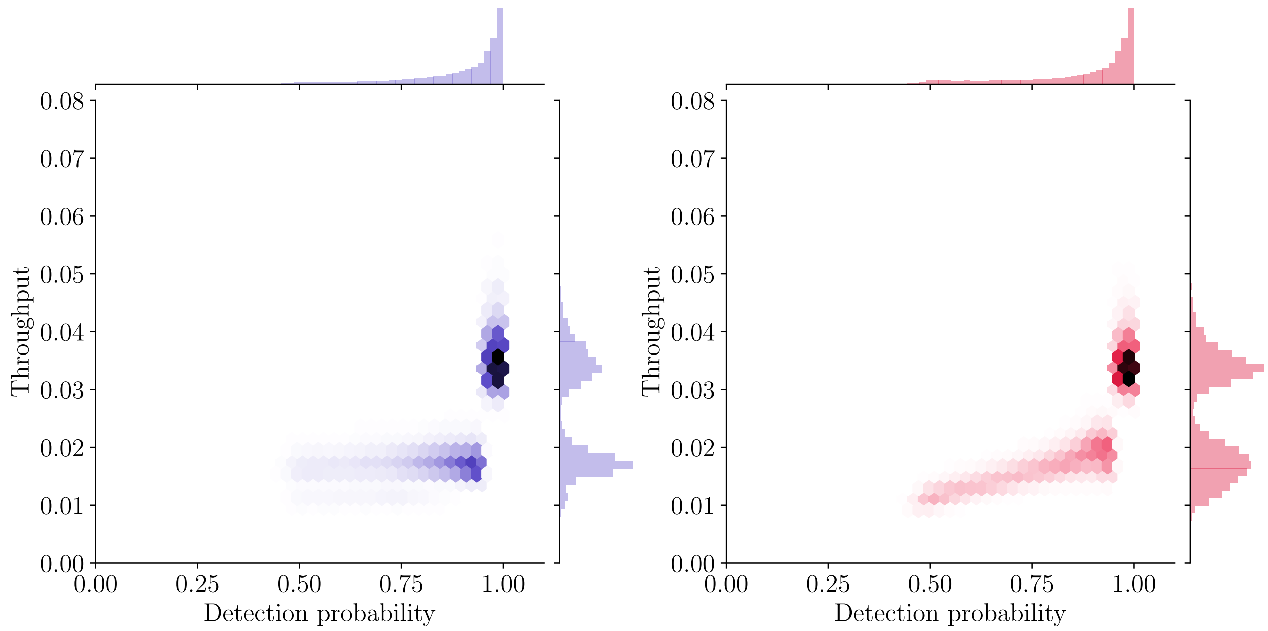
We first evaluate the convergence property by focusing on the first half period of $[0, 149]$. We observe that the total ratio of winning SUs and average throughput of winning SUs for respective PUs almost converges when all 50 SUs try group formation at once, i.e., step 50, which corresponds to $T = 1$. As mentioned in Section 5.3, both computation overhead and communication overhead are given by $O(NT)$ but this result shows that actual value of T is much smaller. Moreover, average throughput of winning SUs for PU 1 can be almost the same as that for PU 2. We also confirm that the system finally reaches the steady state at step 120.

Next, we focus on the remaining half period of $[150, 300]$ to evaluate the adaptability to the environmental change. We find that the proposed mechanism can smoothly converge to the new steady state while keeping the total ratio of winning SUs among two PUs. In ideal, average throughput of winning SUs for PU 1 should be equal to that for PU 2 after the environmental change at step 150, where $R_1^{\text{use,PU}}$ and $R_2^{\text{use,PU}}$ are counterchanged with each other. We, however, observe that there is a gap between average throughput of winning SUs for PU 1 and that for PU 2. This is because some SUs (groups) located near PUs will not be affected by the environmental change. As a result, group update will partially occur among SUs.

7. Conclusion

In this paper, we have tackled the effective spectrum reuse problem in multi-PU CRNs. We have first formulated the global optimization problem as ILP, where the objective function is the maximization of both the number of winning SUs and the average communication opportunities among them. To overcome the drawbacks of the global optimization, i.e., scalability problem and lack of user incentive mechanism, we have also formulated the individual optimization problem, which can be solved by the the user-incentive based CSS mechanism consisting of PU selection and group (re)formation among SUs. In the proposed mechanism, SUs first try to become winning and further aim to acquire more communication opportunities.

Through simulation experiments, we have first showed that the proposed mechanism can increase the ratio of winning SUs



(a) Proposed mechanism without user incentive

(b) Proposed mechanism

Figure 9: Relationship between the detection probability and throughput for PU 1's spectrum (2-PU scenario, $N = 50$).

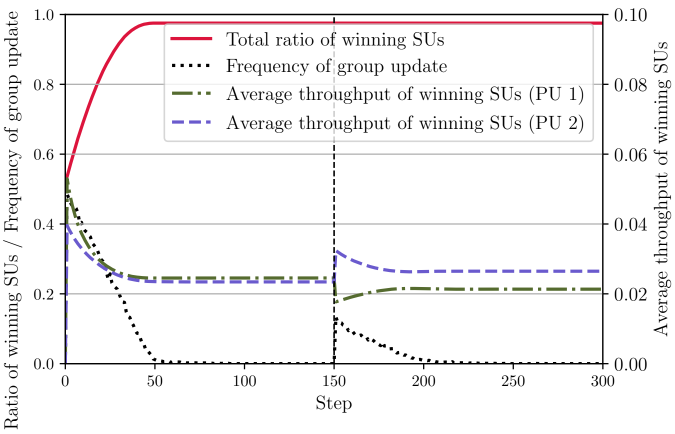


Figure 10: Relationship between the number of step, the ratio of winning SUs, and average throughput among winning SUs (2-PU scenario, $N = 50$).

by 4% and average idle detection probability by 2%, compared to CF-PD. Comparing the proposed mechanism with global optimization, we also have found that the proposed mechanism can support larger-scale systems with performance improvement. We have demonstrated that the proposed mechanism can improve the ratio of winning SUs compared to that without user incentive while allocating the throughput to SUs according to their detection performance. In addition, we have also showed that the proposed mechanism can achieve stable group formation even under SUs' selfish behavior. As future work, we plan to extend the proposed mechanism by considering time/energy consumption, different PU activity models, and multi-channel scenarios.

Appendix A. Linearization of global optimization problem

First, $\mathbb{I}(\widetilde{P}_i^{\text{miss}} \leq \chi)$ $(i \in \mathcal{N})$ can be replaced with binary decision variable $y_i = \{0, 1\}$ $(i \in \mathcal{N})$, which satisfies the following two equations [40]:

$$\widetilde{P}_i^{\text{miss}} \leq \chi + 1 - y_i, \quad \forall i \in \mathcal{N},$$
$$\widetilde{P}_i^{\text{miss}} > \chi - y_i, \quad \forall i \in \mathcal{N}.$$

If SU i is a winning SU, $y_i = 1$. Otherwise, $y_i = 0$. Substituting y_i and (10) to (5), we can update objective function as follows:

$$\max \quad N^{-1} \sum_{i \in \mathcal{N}} \prod_{k \in \mathcal{N}} \left(y_i - P^{\text{false}} y_i \sum_{j \in \mathcal{N}} s_{i,j} s_{k,j} \right),$$

which can be rewritten as

$$\max \quad N^{-1} \sum_{i \in \mathcal{N}} \sum_{l_1=1}^{2} \sum_{l_2=1}^{2} \ldots \sum_{l_N=1}^{2} \prod_{k \in \mathcal{N}} a_{i,k,l_k}, \tag{A.1}$$

where

$$a_{i,k,l_k} = \begin{cases} y_i, & \text{if } i, k \in \mathcal{N}, l_k = 1, \\ -P^{\text{false}} y_i \sum_{j \in \mathcal{N}} s_{i,j} s_{k,j}, & \text{if } i, k \in \mathcal{N}, l_k = 2. \end{cases}$$

Since P^{false} is constant as in (2) and all variables included in (A.1), i.e., y_i, $s_{i,j}$ $(i, j \in \mathcal{N})$, are binary, (A.1) consists of the sum of products of binary variables. $\widetilde{P}_i^{\text{miss}}$ in (9) can also be rewritten as the sum of products of binary variables.

These products of binary variables can be transformed into the combination of linear expressions as follows. If a product of binary variables, which is nonlinear, is given as follows:

$$y = x_1 x_2 \cdots x_k, \qquad x_i = \{0, 1\}, \quad (i = 1, 2, \ldots, k),$$

this can be transformed into the following combination of linear expressions [40]:

$$(k-1) - \sum_{i=1}^{k} x_i + y \geq 0,$$
$$x_i - y \geq 0, \quad x_i = \{0, 1\}, \quad (i = 1, 2, \ldots, k).$$

As a result, all the objective function and constraints can be expressed by linear expressions and all the variables are binary, which indicates $\mathsf{OP}(\mathcal{N})$ is ILP.

Appendix B. Derivation of system throughput in case of individual optimization

In case of the individual optimization approach in Section 5.1, the system throughput can be derived as follows:

$$\begin{aligned}
&\sum_{l\in\mathcal{L}} \sum_{i\in\mathcal{N}} r_{i,\mathcal{S}_i,l} \\
&= \sum_{l\in\mathcal{L}} \sum_{i\in\mathcal{G}_l} r_{i,\mathcal{S}_i,l} \\
&= \sum_{l\in\mathcal{L}} \sum_{i\in\mathcal{G}_l} (1 - R_l^{\text{use,PU}})(1 - Q_{\mathcal{S}_i}^{\text{false}}) \frac{1}{N_l^{\text{group}}} \frac{P_{i,l}^{\text{detect}}}{\sum_{j\in\mathcal{S}_i} P_{j,l}^{\text{detect}}} \\
&= \sum_{l\in\mathcal{L}} \frac{1 - R_l^{\text{use,PU}}}{N_l^{\text{group}}} \sum_{i\in\mathcal{G}_l} (1 - Q_{\mathcal{S}_i}^{\text{false}}) \frac{P_{i,l}^{\text{detect}}}{\sum_{j\in\mathcal{S}_i} P_{j,l}^{\text{detect}}} \\
&= \sum_{l\in\mathcal{L}} \frac{1 - R_l^{\text{use,PU}}}{N_l^{\text{group}}} \sum_{k\in\mathcal{N}_l^{\text{group}}} (1 - Q_{\mathcal{S}_k}^{\text{false}}) \\
&= \sum_{l\in\mathcal{L}} (1 - R_l^{\text{use,PU}})(1 - \overline{Q}_l^{\text{false}}),
\end{aligned}$$

where $\mathcal{G}_l$ (resp. $\mathcal{N}_l^{\text{group}}$) is the set of winning SUs (resp. winning cluster heads) selecting PU l.

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