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A Study of Social-based Cooperative Sensing in Cognitive Radio Networks

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A cognitive radio (CR) is an intelligent radio that reuses frequency band based on dynamic spectrum access (DSA). CR implements spectrum sensing to detect primary users' (PU) presence, and exploits available spectrum without interfering PU. In contrast with local spectrum sensing, cooperative sensing which is implemented by multiple CRs, is more efficient and effective generally.

Previous work on cooperative spectrum sensing in cognitive radio (CR) assumes a default mode that CRs are willing to cooperate for others unconditionally. While this situation does not always hold, the requested CR might reject the cooperation request due to its insufficient energy, or security concerns. In this thesis, we propose a social-based cooperative sensing scheme (SBC) that exploits social ties of CRs on their cooperative sensing. Simulation results show that SBC fulfills improved sensing quality, and the sensing performance of CRs correlate to the social degree and social network topology.

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Contents

1 Introduction

In recent years, the number of wireless portable devices increased drastically, leading to an urgent requirement in wireless spectrum. According to the current regulation of spectrum allocation, considerable spectrum has been allocated to licensed users, such as the military, and most wireless devices can only use the unlicensed spectrum. The current method of spectrum access is called *static spectrum access* (SSA), i.e. the allocated licensed spectrum is always reserved for the licensed users. Even if it is not utilized at present, the licensed spectrum cannot be access by the other users, which results in underutilization of spectrum resources. The research performed by Federal Communications Commission (FCC) shows that, the utilization ratio of licensed spectrum is actually uneven, which the minimum is only 15% [ALV06]. The inefficiency needs to be addressed to meet the growing demand for the wireless spectrum.

In the year 1999, Joseph Mitola III proposed the concept of *cognitive radio* (CR). A cognitive radio is an intelligent radio that reuse frequency band based on *dynamic spectrum access* (DSA). A CR can detect the available channels in its vicinity, then changes its transmission parameters accordingly to avoid interference to the licensed users and also other secondary users. [CoR15]. According to dynamic spectrum access, when the licensed user, aka primary user (PU) does not transmit data through its licensed channel, the unlicensed user, aka secondary user (SU) is permitted to use the idle channel. However, when PU accesses the channel again, SU has to vacate this band. In opportunistic spectrum access, the wireless devices are admitted to access idle frequency band, which is also called spectrum hole.

In order to avoid interfering PU, SU needs to detect whether the licensed spectrum is idle or busy by *spectrum sensing*. Specifically, it analyzes the sample signal from PU, and makes a decision on PU state according to the signal characteristics. When SU discovers an idle frequency band, it will utilize it for its traffic until PU starts to use the channel. If SU can detect the PU signal, it vacates the channel and searches for other idle channels. DSA provides an efficient method in enhancing spectrum utilization, the CRs reuse the licensed channel and relieve overcrowded unlicensed channel.

Previous research show that *cooperative spectrum sensing* improves the sensing accuracy of PU channel compared to *local spectrum sensing* [GaL07, UnV08]. In local sensing, a CR senses the PU channel itself, and determines the PU state based on its own sensing result. In contrast, cooperative sensing suggests several CRs sense the PU channel together, and conclude the final decision by fusing their sensing outcomes. Previous work on cooperative sensing in [ABR11] assumes a default mode that CRs are willing to cooperate for others unconditionally, but this situation does not always hold. As wireless devices are battery-powered, CRs require to consume energy in an effective manner. Moreover, it is not secure to perform unconditional cooperation behaviour.

In this thesis, we exploit the social relations of CRs, to establish a social-based cooperative sensing scheme (SBC). More precisely, the social relationships belong to the users who carry cognitive radio devices. Since wireless devices are held by people, the social pattern of people exerts an influence on wireless communication. For instance, the cooperation tendency between two CRs can be determined by their social ties. CRs tend to cooperate with a close friend rather than a stranger, which coincide with human social feature. In the thesis, by the help of simulations, we evaluate the robustness of SBC when malicious users exist in the network. Additionally, we analyze the effect of CR's social degree on their sensing performance. Furthermore, we discuss the impact of diverse social input on sensing performance of CRs.

The following shows the outline of this thesis,

- In Chapter 2, we introduce the basic knowledge of cooperative sensing and social network analysis (SNA), including the classification, key techniques, gain and overhead of cooperative sensing, as well as the classical graph metrics in SNA. This chapter provides a survey of the background in our research. Moreover, we discuss the related works that exploit social factors in cognitive radio network and other wireless networks.

- In Chapter 3, we describe the system model, including the definition of CR, PU channel, malicious users, and the social-based mobility model of CRs. This chapter elaborates on the construction of the proposed scheme SBC, as well as the operational process of SBC, consisting of three main steps. In addition, we introduce a social-unaware cooperative sensing scheme (RAND) whose performance is compared to our proposal.

- Chapter 4 demonstrates the system simulation and performance analysis. First, we explain the simulation parameters and the metrics used for measuring system performance. Then, we compare and analyze the sensing performance of

SBC and RAND in two scenarios, i.e. various level of maliciousness and diverse value of cooperation threshold. Besides, the influence of CR's social degree on the sensing performance is discussed. Finally, we utilize different network topologies as social graph and analyze its effect on system performance.

- Chapter 5 summarizes the main contribution of the thesis. It highlights the strengths and weakness of our proposed scheme. Furthermore, we discuss the future work on social-based cognitive radio.

2 Background and Related Works

2.1 Cooperative sensing of cognitive radio

A CR is an intelligent radio that is proposed by Joseph Mitola III in 1999. Cognitive radio extends the software radio which enhances the flexibility of personal services [MiM99]. Specifically, CRs can sense the surrounding wireless environment, detect PU presence, and exploit available spectrum without interfering PU.

In order to utilize the idle licensed spectrum, CRs implement spectrum sensing to identify the available licensed spectrum. Cooperative spectrum sensing means several CRs sensing a PU channel collaboratively. Generally, it mitigates the effect of issues in local sensing, such as multipath fading, shadowing, etc. Previous works [ABR11, GaL07] have shown that cooperative sensing enhances the sensing accuracy compared with local sensing, and it brings about overhead at the same time.

Table 1: Spectrum sensing results

H_i	H	Cases
1	1	detected
0	1	collision
1	0	false alarm
0	0	access

Basically, four cases might happen according to the result of spectrum sensing, displayed in Table 1. To be specific, H_i refers to the sensing outcome of CR_i, H

denotes the real PU channel state. 1 and 0 stands for busy and idle state respectively. For instance, "$H_i = 1$ and $H = 1$" implies that the PU channel is indeed busy, and CR_i detects the active state of PU accurately.

In general, the sensing performance of a CR is determined by two parameters, 1) probability of detection (P_d): the ratio of busy channel detected when PU channel is truly busy, 2) probability of false alarm (P_f): the ratio of PU channel alerted to be busy whereas the real state is idle. The following equation gives the definition of P_d and P_f [Mit00],

$$P_d = Probability\{H_i = 1 | H = 1\} \tag{1}$$

$$P_f = Probability\{H_i = 1 | H = 0\} \tag{2}$$

Under an efficient sensing scheme, we expect P_d to be high, that is to say, the collisions between PU and CRs could be alleviated as much as possible. On the other hand, P_f is better to be low, i.e. the idle channel has a high probability to be discovered and accessed by CRs.

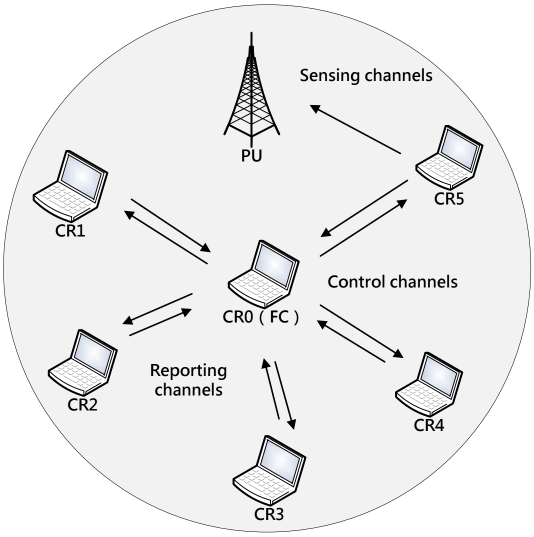
In the following, we first present the taxonomy of cooperative spectrum sensing. Then we discuss the basic components in cooperative sensing. Finally, we briefly introduce the gain and overhead caused by cooperation.

2.1.1 Classification of cooperative sensing

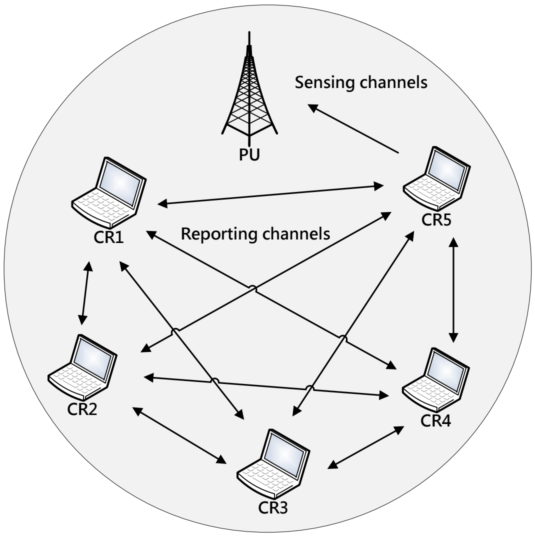
There are three approaches in sharing the collaborative sensing outcomes: centralized [GhS05, VKP05, UnV08], distributed [LYH09], and relay-assisted [GaL07, GgY07, ZhL08]. Figure 1 adapted from [ABR11] illustrates these three models.

i) Figure 1(a) displays the centralized cooperative sensing model [ABR11]. Fusion center (FC) is an entity which plays a central role in controlling and organizing the collaboration. The centralized cooperative sensing process consists of three steps,

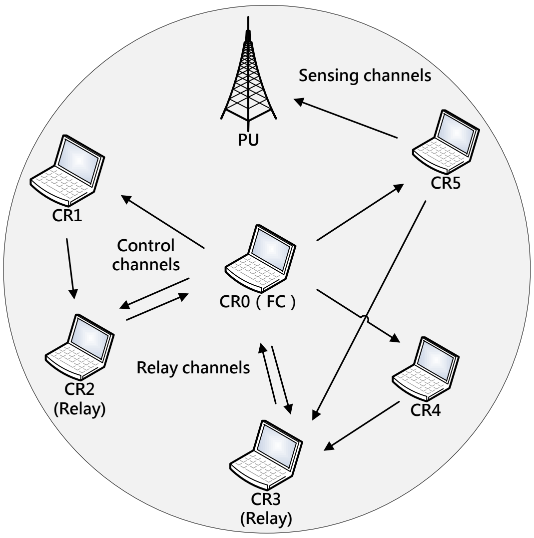
- FC selects the licensed spectrum to be sensed and sends a request to neighbours asking for cooperation.
- The cooperative CRs which respond to the request will sense PU channel independently and report their sensing result afterwards.
- When all sensing outcomes arrive at FC, it fuses the collaborative data using some decision fusion logic, such as AND, OR, MAJORITY, to reach a final outcome, and returns the final outcome to the cooperators separately.



(a) Centralized



(b) Distributed



(c) Relay-assisted

Figure 1: Classification of cooperative sensing [ABR11]

In Figure 1(a), CR0 acts as the FC, and CR1 to CR5 are cooperators of CR0. The physical link between PU and each cooperative CR is called *sensing channel*. FC sends the sensing instruction to the cooperators via a *control channel*, and cooperative CR reports the local sensing result through a *reporting channel*, which may be the same channel as the control channel.

ii) The primary difference between distributed cooperative sensing and centralized cooperative sensing is, the former does not rely on a centralized fusion center to decide the final sensing result. Actually, centralized behaviour also exists in distributed cooperative sensing. Figure 1(b) shows a distributed sensing model [ABR11], CR1 to CR5 are all cooperative CRs, and they operate as their own FC.

Three steps of distributed cooperative sensing:

- Each CR spreads its local sensing outcome to the neighbours within its transmission range.
- Based on its own decision fusion logic, each CR considers both the local sensing result and the received data to conclude a final outcome of PU state.
- Iterate the above steps until converge to a unified decision on PU channel state.

In summary, the CR users communicate continually to generate a unified sensing decision via several times of iteration.

iii) Relay-assisted cooperative sensing applies to the situations when the sensing channel or reporting channel are non-ideal. From Figure 1(c) [ABR11] we can see, CR1, CR4, and CR5 have strong sensing channel but weak reporting channel, hence they request CR2 and CR3 as relay to transmit their sensing data to FC. Apparently, the relay-assisted manner eliminates the negative effect by non-ideal reporting channel, thereby enhancing the global sensing performance.

The physical link from CR2 or CR3 to FC can be called a *relay channel*. Apart from centralized cooperative mode shown in Figure 1(c), relay-assisted cooperative scheme is also appropriate for distributed cooperative sensing.

2.1.2 Key techniques of cooperative sensing

In general, cooperative sensing consists of three steps: local sensing, reporting, and data fusion [ABR11]. In this section, we intend to briefly introduce the essential aspects of cooperative sensing related to our proposed scheme in this thesis.

Sensing techniques i.e. the methodologies of local spectrum sensing. More precisely, it describes how to sense, sample, and process the PU signal for estimating whether PU channel is busy or idle. There are chiefly three techniques: *energy detection* [UnV08] which focuses on the sensed energy, *cyclostationary feature detection* [LCL11] that identifies the PU presence via checking the periodicity in the received primary signal, and *compressed sensing* [WaS98] which is suitable to sense wideband spectrum with less demand of complex hardware.

Since we do not consider the issues in physical layer in this thesis, the local sensing details are not so significant that we do not discuss them in detail. Nonetheless, it is a primary element of spectrum sensing.

Hypothesis testing is to make sure the presence or absence of PU by testing the observed data. We utilize a basic testing method, the Neyman-Pearson (NP) test pertaining to binary hypothesis testing in our scheme. Equation 3 shows the binary hypothesis testing model of the sample signal [ABR11].

$$x(t) = \begin{cases} h(t) * s(t) + n(t), & H = 1 \\ n(t), & H = 0 \end{cases} \tag{3}$$

where $x(t)$ denotes the sample signal that CR received from sensing channel, $h(t)$ denotes the channel gain of the link from PU's transmitter to CR's reciever, $s(t)$ represents the PU signal, and $n(t)$ is the Additive White Gaussian Noise (AWGN) [ABR11]. $H = 1$ and $H = 0$ stands for the presence and absence of PU. Figure 2 illustrates the test criterion. Specifically, if $x(t)$ outweighs the detection threshold λ, then CR regards the PU channel as busy state. Otherwise, PU is supposed to be absent thus CR can try to access the licensed channel.

Control channel and reporting is the channel used for reporting local sensing data to FC or share sensing results with neighbor CRs. As we know, control channel and reporting channel share the same physical end-to-end link, which needs to meet

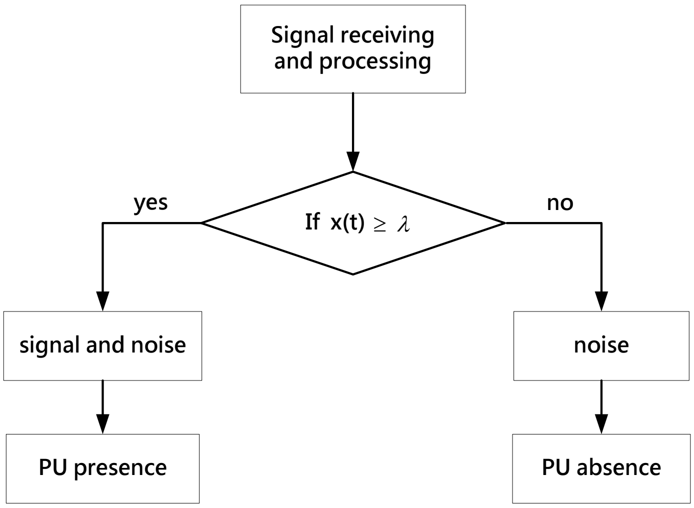


Figure 2: Binary hypothesis testing

the requirements in terms of bandwidth and reliability. The former refers to the maximum data size transferred via this channel, and the latter has relevance to channel impairments, such as multipath fading and correlated shadowing. In other words, the reporting channel bandwidth may fall short of expectation when too many CRs reporting data simultaneously. The network impairments would result in non-ideal reporting channel.

In order to tackle with imperfect reporting channel, Sun et al. propose *a cluster-based spectrum sensing scheme* in [SZL07] that divides CRs into clusters. Each cluster appoints a CR of the most ideal reporting channel as the cluster head, which is responsible for reporting all the local sensing outcomes to FC. That is to say, the members of a cluster just send their local sensing results to the cluster head, and it is only the cluster head reporting data to FC.

Furthermore, *a dynamic multi-user selection based cooperative spectrum sensing (CSS) scheme* is proposed [GYL10] to combat with non-ideal inner-user channels. It is reasonable because the channels between inner members of a cluster are also possible to suffer from network impairments. Considering the defective inner-user channels, the scheme in [GYL10] selects the cluster head dynamically in order to maintain the best reporting function.

A dynamical clustering CSS scheme with bandwidth constraints is proposed in [SuW07] which consider the reliability and bandwidth issues of reporting channel simultaneously. It employs double threshold to screen out dependable CRs. Accordingly, the number of CRs that allowed reporting their local sensing data is reduced, thereby decreasing the transmission bandwidth in reporting channel.

In our work, we investigate the social-awareness in cooperative sensing. To alleviate the system complexity, we assume the reporting channels of our model are error-free channels.

Data fusion In the end of cooperative sensing, the FC requires combining the data and then draws a final decision on PU state. In general, there are two ways to combine sensing outcome: *soft decision* [JuL07] and *hard decision* [ZML09]. The former refers to the cooperative CRs just send their sensing data directly to FC, without processing the data locally. The latter means each CR needs to draw a decision on PU channel locally, before reporting the 1-bit sensing result to FC.

Theoretically, soft decision outweighs hard decision in terms of spectrum sensing accuracy as the FC acquires the entire sensing data when employing soft decision. On the other hand, hard decision entails lower overhead, since each cooperator report 1-bit data solely. To keep our model simple, we consider the case of hard decision.

There are three classical logics of hard decision: AND, OR and K-out-of-N logic. In the following equations, P_d denotes the local probability of detection, and P_f is the local probability of false alarm, N denotes the number of cooperative CRs, $H1$ signifies the PU busy state. We assume the sensing outcomes of cooperative CRs are independent from each other.

- AND logic: it requires all the CRs reporting $H1$ to convince the FC of PU presence. Otherwise, FC regards the PU channel as idle. The global probability of detection Q_d and the global probability of false alarm Q_f are shown below [ZML09].

$$Q_d = \prod_{1}^{N} P_d \tag{4}$$

$$Q_f = \prod_{1}^{N} P_f \tag{5}$$

  According to Equation 4 and 5, Q_d and Q_f both decrease with the rising of cooperator number N when using AND logic. Based on AND logic, CR will not miss any opportunities to access PU channel, but the collision with PU is likely to happen.

- OR logic: the FC determines PU is in busy state as long as a single CR returns $H1$. Accordingly, the global probability of detection Q_d and the global probability of false alarm Q_f are [ZML09],

$$Q_d = 1 - \prod_{1}^{N}(1 - P_d) \tag{6}$$

$$Q_f = 1 - \prod_{1}^{N}(1 - P_f) \tag{7}$$

  From Equation 6 and 7 we can see, Q_d and Q_f both increase with the rising of cooperator number N when using OR logic. Based on OR logic, CR has a high probability to experience false alarms, but the active PU gets noticed effectively.

- K-out-of-N logic: among the total N CRs, if K of them report the PU channel as occupied, then FC regards PU state as busy. The global probability of detection Q_d and the global probability of false alarm Q_f are [PLG09],

$$Q_d = \prod_{1}^{K} P_d \prod_{K+1}^{N}(1 - P_d) \tag{8}$$

$$Q_f = \prod_{1}^{K} P_f \prod_{K+1}^{N}(1 - P_f) \tag{9}$$

  It is worth noting that AND and OR logic are special cases of K-out-of-N logic. If K equals to N or 1, the logic turns out to be AND or OR logic respectively. Moreover, if $K \geq \frac{N}{2}$, it implies only the majority of CRs reporting $H1$, the final outcome could be $H1$.

In our model, we utilize OR logic as the criterion of data fusion because we wish to avoid the collision between PU and CR as much as possible.

2.1.3 Gain and overhead

There is no denying that, the cooperation behaviour among cognitive radios brings about gain and overhead at the same time. In comparison with local sensing, cooperative sensing is beneficial for enhancing sensing accuracy, as the sensing result is not merely determined by one single sensing event at a single location. Besides, cooperation mitigates the influence of multipath fading and independent shadowing to some extent. In addition, it improves system resistance to path loss.

On the other hand, cooperation increases the sensing time and data throughput. Therefore, it needs to fulfil a tradeoff between sensing performance and network throughput. Furthermore, the synchronization among CRs [SoZ08] is also a significant issue because cooperation is based on simultaneous reporting. Specifically, cooperation has the potential to give rise to reporting delay which never incurred by local sensing. Despite cooperative sensing decreases the effect of channel impairments, it still invites spatially correlated shadowing which is caused by closely located CRs [ABR11]. In addition, security is an inevitable overhead raised by cooperation.

In the respect of energy efficiency, a crucial factor of wireless networks, cooperation brings additional energy consumption due to the communication between the transmitter and cooperators. To be specific, two methods can combat this problem: 1) reduce the reporting messages by censoring [SZL07], or 2) reach a balance of the consumed energy and sensing performance, thereby minimizing the energy cost for sensing [PZE10].

In this paper, we propose a social-based cooperative sensing scheme, hence the concentration is upon the social-aware cooperation behaviour. As for the cooperative overheads such as security concerns or reporting delay, we neglect these aspects in this thesis.

2.2 Social network analysis

A *social network* is a group of actors connected by the social relationships between them [JaA06, KDT10]. The two basic elements of social network is the actors, which can be individuals or organizations, and the social ties between them. *Social network analysis* (SNA) is a strategy to investigate the underlying network structure through the use of graph theory [OtR02]. Specifically, SNA focus on the feature of the actors, and what information can be derived from the social ties. SNA is an efficient tool that provides a new perspective for the network designer. For instance, there is a district suffering from an outbreak of infectious disease. If we know the social relations of the people in this district, it is possible to restrain the viral spreading by isolating the most active individuals who might meet numerous people.

In recent years, the online social networks, such as Facebook, Twitter, witness a prosperous development. It also enhances the demand of researching social relationships. SNA has raised tremendous attentions in various research areas: anthropology, biology, communication studies, economics, geography, information science, organizational studies, development studies and so on [ZXS12]. In wireless communication networks, the communication behaviour is basically generated by humans. Therefore, the social factors play an essential role in designing efficient network protocols.

2.2.1 Basic methods of social network analysis

As we know, a network is made up of a set of nodes connected by the links between them. In general, a network can be represented by a graph, in which the node of a network is a vertex in a graph, and the social link between nodes is the edge of the vertices. Table 2 demonstrates the mapping from a network to a graph. We note that the edge could be directed or undirected. For example, if node 1 can reach node 2 unidirectionally, while node 2 has no access to node 1, it could be said node 1 has a directed edge with 2, but not vice verse. On the other hand, undirected edge implies the two nodes know each other mutually. In addition, the weight of an edge stands for the tie strength between two nodes.

Table 2: Mapping from network to graph

Network terminology	**Graph terminology**
Actor/node	Vertex
Interaction/Tie/Link/Connection	Edge (directed, undirected)
Tie strength	Edge weight

Similarly, it is a common way to investigate social network by mapping it into social graph that could be studied with the knowledge of graph theory. Graph theory is a branch of applied mathematics, which targets at the research of graph [RiA11]. In graph theory, the graph features are reflected by metrics, including two categories: local metrics and global metrics. The former concentrates on the properties of single node and the latter describes the characteristics of the whole graph.

In specific, most widely known local metrics are node degree, the shortest path length, betweenness centrality and closeness centrality. In this paper, we generally consider two metrics of the nodes: node degree and the shortest path length from one node to another. For instance, Figure 3 illustrates an undirected graph with eight vertices and nine edges. The weight of each edge is 1. The following gives the definition of two local metrics that we utilized in our system.

- degree: the number of connections with other nodes [RiA11] [KNW11]. As we can see from Figure 3, node 1 is connected with five nodes, so the degree of node 1 is five which is the highest degree of the graph. It implies that node 1 is the most active node in the network.

- the shortest path length: the minimum number of hops that a node reaches another [KNW11]. For example, in Figure 3, the shortest path from node 4 to node 7 is signed as blue line $4 \to 1 \to 6 \to 7$. It could be said the distance between node 4 and node 7 is three.

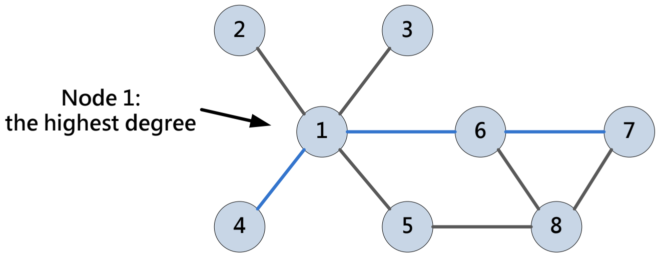


Figure 3: An undirected graph with eight vertices and nine edges

The classic global metrics of a graph include density, radius, diameter, clustering coefficient etc. Next we introduce the global metrics that are used in the system simulation in this paper.

- density: the ratio of existing edges to the overall edges that could exist in the graph [WaF99]. We can see that there are 9 edges in Figure 3, and there could be 28 edges at most if the eight nodes all get connected with any others. Therefore, we calculate the density of this graph via dividing 9 by 28, approximately 0.32.

- diameter: among all the shortest path length between any pairs of nodes in the graph, the maximum length called the diameter [WaF99]. The diameter of the graph shown in Figure 3 is three.

- radius: similar to diameter, the radius also relates to the shortest path length of nodes. A graph radius is the minimum value of all the shortest path length in the graph [WaF99]. Obviously, the radius of the graph shown in Figure 3 is one.

2.2.2 Social-awareness in wireless networks

Given the fact that in most wireless networks, the users are human-centered, and human's behaviour or movement exerts an influence on the network performance. Therefore, it is meaningful to study the social patterns of the people who carry the wireless devices. In particular, considerable research of delay tolerant networks (DTNs) have exploited the social behaviours of nodes to enhance the DTN routing design [ZXS12].

Generally, the nodes of DTN follow a *store-carry-forward* fashion to transmit the data. In specific, the connections between the nodes are not reliable, so that each node has to store the data it has received, carries the data when moving, and forwards them to other nodes which are possible to reach the destination. In other words, the nodes do not get connected continuously, the network topology is dynamic and the network is likely to suffer from long delay. It is obvious that, the routing of nodes plays an essential role in DTN.

Since the social relation of device users have an impact on their behaviour, it is significant to exploit social factors to design the routing protocol in DTN. Various social properties have been utilized in DTN routing, classified into two categories: *positive social characteristics* and *negative social characteristics* [ZXS12].

The *positive social properties* include friendship, community, and centrality etc. The friendship of two nodes reflects their social strength. Based on *homophily phenomenon*, individuals are likely to be friends with people who have the same interests [MSC01]. The nodes in good friendship are more possible to get in touch. Community is a significant concept in sociology, it basically means a group of people living in the same location [McC86]. In addition, a community can refer to a university, company, or even nationality. It is reasonable that people in the same community have a higher sense of identity for each other. For example, it is ordinary that people have a favourable impression of the graduates from their own university, even if they never met each other before. The centrality reflects the importance of a node in the network, in terms of degree, betweenness, and closeness. The nodes of high centralities, i.e. nodes of influence, deserve to be concerned for relay selection [Mar02].

The primary *negative social property* is selfishness, which has been considered in the design of DTN routing protocols [ZXS12]. The selfish node aims at maximizing its own utility regardless of the global performance of the network. In specific, the selfish node in [HXL09] drops the message of others, and always replicates its own data to enhance the delivery of its own messages.

In summary, the social-aware DTNs focus on the design of routing protocols. They exploit positive social properties (such as friendship, community) and negative social properties (such as selfishness) for the sake of data propagation. In our system, we generate a social graph to represent the social ties of nodes. The social features are reflected via the social graph, rather than onefold social property. Furthermore, we build a social connectivity layer to optimally design the cooperative spectrum sensing scheme.

Device-to-device (D2D) communication is an important element of next-generation cellular network, which allows the data to be transmitted between user equipments directly instead of through a base infrastructure [LSC15]. Since it is human beings taking the wireless devices, the interaction of these devices are largely influenced by the social structure of their users. [LSC15] proposes a social-aware D2D resource sharing scheme. The resource allocation, i.e. how to assign the limited spectrum resources among all users, is an essential issue in D2D communications. They utilize the social properties of community and centrality to help allocating resources.

A social-aware scheme for optimizing the traffic offloading process in D2D is proposed in [ZPS14]. Similar to our work, they also exploit two layers, social network layer and physical wireless network layer. The social characteristics are used to maintain a stable transmission link between devices. They generate the social network based on certain context, while we input a social graph to create the social layer.

2.2.3 Related works of social-aware cognitive radio

Currently, there is not abundant work on exploiting social factors into the research of cognitive radio. Generally, the existing research of social-aware cognitive radio are principally about the recommendation of PU channel among CRs.

Li et al. describe a PU channel recommendation mechanism in [LCL11]. Each CR recommends its favourite PU channel to its neighbours based on their social ties, in order to increase the overall utilization of PU channels. In [LSC14], Li et al. introduce the social behaviour propagation in CRNs, on the basis of PU channel recommendation. From a CR's perspective, the channel recommendation from other CRs results in the dynamic preference of PU channels, hence the CR might join another clique to sense its new preferable channel. CR behaviour might propagate through the network. Specifically, Li et al. use a social graph framework to investigate the CR propagation.

Bradai et al. propose a DIStributed channel Selection mechanism for efficient content dissemination in COgnitive RaDio ad-hoc networks (DISCORD) [BAR14]. It employs some centrality metrics, such as node degree and shortest-path betweenness centrality (SPBC) to select the suitable neighbours for content dissemination.

The research described above indeed show the utilization of social network in investigating cognitive radio, but they emphasize on the channel recommendation or content dissemination. However, we intend to design a social-based cooperative spectrum sensing scheme, and to investigate the effect on sensing performance. More precisely, CRs perform collaboration according to their social ties. G*ü*ven et al. introduce a social-aware cooperative sensing scheme [GBA13]. They use the positive social characteristics and negative social characteristics introduced in [ZXS12] to generate the social features of CRs. In contrast, we utilize a social graph, which reflects the real social attributes of human beings. The social graph can be changed at will in our system, that is to say, we can use various types of graph as social input. Furthermore, we build a two-layer structure: a social connectivity layer (SCL) and wireless connectivity layer (WCL), and there are interactions between the two layers. In our scheme, social-based cooperative sensing is performed on WCL, it use the social information of SCL to select cooperators. Besides, we generate a mobility model to control CRs' movement in WCL, which is based on the social ties in SCL.

3 Social-based cooperative spectrum sensing scheme

3.1 System Model

Since wireless communications are mainly human-centred, exploring human factors is significant for the development of wireless communication. Chen et al. present the interplay between social network and technological network in [CCP13], which shows a two-layer structure. We propose a social-based cooperative spectrum sensing scheme (SBC) to analyze the cooperative sensing performance of CRs when they have social ties with each other. Our system consists of two layers, wireless connectivity layer (WCL) and social connectivity layer (SCL).

From Figure 4 we can see, the upper layer SCL displays the social ties among CRs in the cognitive radio network (CRN). More precisely, it is the social relationship between the users who carry the cognitive radio devices. A link in SCL means the two users are friends. The lower layer WCL reflects the wireless communication of CRs. A connection between two devices in WCL suggests that they are inside the wireless transmission range of each other. To our knowledge, most research of cognitive radio only consider the wireless connectivity of CRs. However, we take the social factors into account which offers a new perspective in designing cooperative sensing protocol.

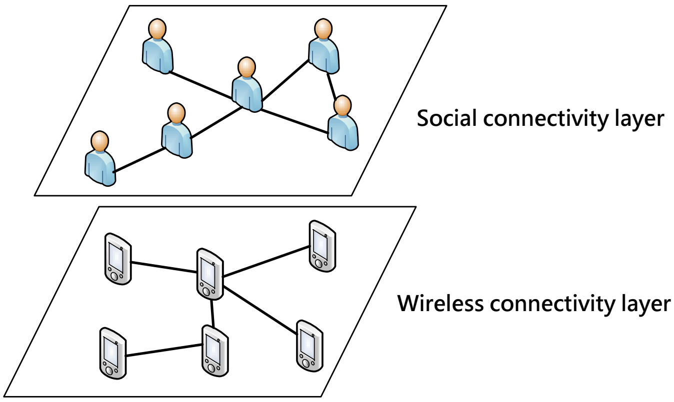


Figure 4: Two-layer structure of SBC.

3.1.1 Wireless connectivity layer

As we introduce before, the system consists of equal sized grids, and the number of grids is N_g. N_{CR} denotes the number of CR users in the system. In each grid, there is only one PU channel, and the CRs can sense for it locally or cooperatively. We assume the transmission range of each CR is limited by the grid it locates. In other words, CRs can only communicate with the companions within the same grid.

The transmitter, i.e. the CR which has a demand to transmit, asks for cooperation from others. Then, the cooperators which have accepted the request, sense PU channel, and report their sensing result to the transmitter. After that, the transmitter plays the role of a FC and concludes a decision on PU state. If it shows idle, only the transmitter is approved to utilize the idle licensed channel. That is to say, we do not consider spectrum sharing issues in the system.

Figure 5 demonstrates an example of wireless connectivity layer. The system consists of four grids and ten CR users totally. There is one PU channel and various number

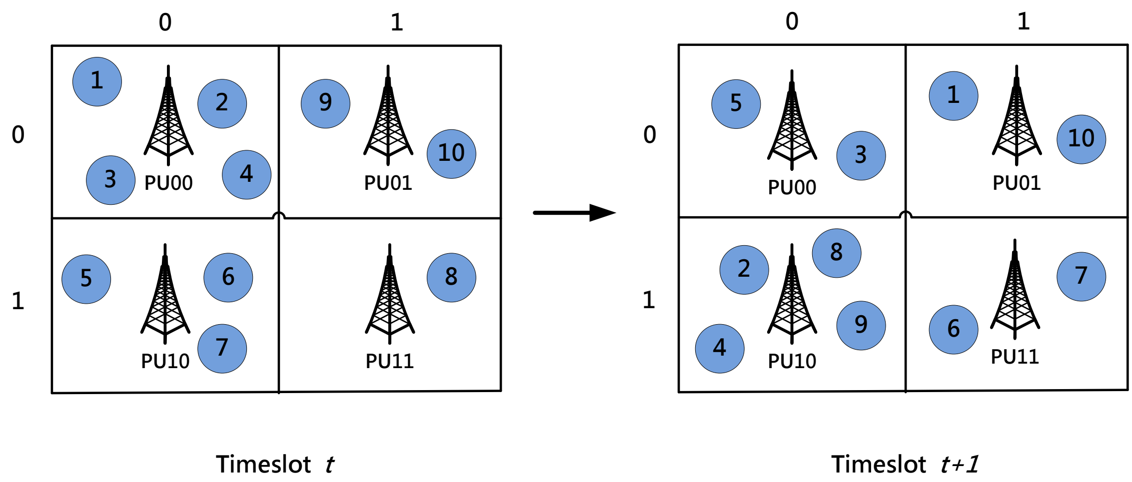


Figure 5: An example of wireless connectivity of CRs.

of CRs in each grid.

At timeslot t, CR_1, CR_2, CR_3, CR_4 all locate at the upper left grid ($Grid_{00}$). If CR_1 plays the role of transmitter, it could ask cooperation from the other three CRs to sense PU_{00}. On the other hand, CR_8, the sole CR in $Grid_{11}$, can only sense PU_{11} itself. At next timeslot $t+1$, as CR_8 moves to $Grid_{10}$, it has three companions that makes it possible to perform cooperative sensing at this point. In summary, we can see from Figure 5, only one licensed channel exists in a grid, and the transmitter is the only CR that can utilize the idle channel. It is worth noting that, CRs' physical position change from timeslot t ro $t+1$. We will discuss the pattern of CR movement in Section 3.1.4.

3.1.2 Social connectivity layer

As stated in Section 2.2, we utilize a social graph to represent the social relations of CRs. Figure 6 displays a simple social graph $G = (V, E)$, where $V = \{v_1, v_2 \cdots v_8\}$, $E = \{e_1, e_2 \cdots e_7\}$. V denotes the set of eight CRs, and E is the set of the links between CRs. The graph G is an undirected graph since we just exploit mutual social relation among CRs. It is reasonable because people generally prefer to help a friend other than someone who do not know them.

In most cases, a graph can be represented by an adjacency matrix $A = [A_{ij}]$,

$$A_{ij} = \begin{cases} w_{ij} & \text{if node } i \text{ is connected node } j \\ 0 & \text{if no connection} \end{cases} \tag{10}$$

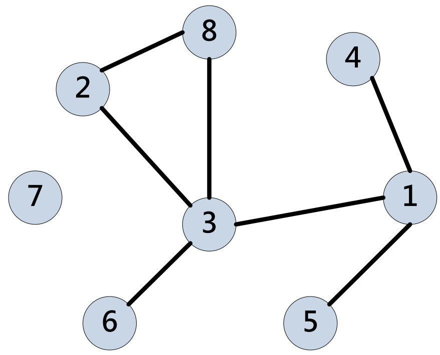


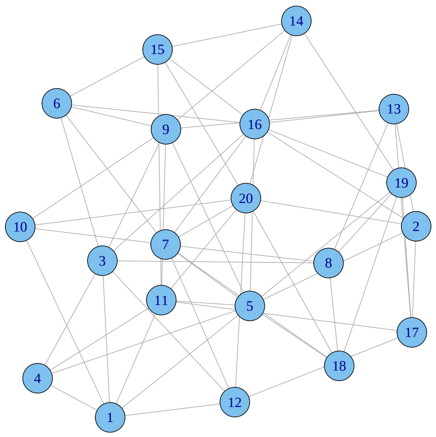
Figure 6: A social graph with eight nodes.

where w_{ij} is the edge weight of node i and j. In our model, we just set all of the edge weights to be 1 if two nodes are linked. Equation 11 demonstrates the corresponding adjacent matrix of the graph in Figure 6. We can see that, CR_7 is an isolated node, therefore the seventh row and the seventh column of the matrix all shows 0 except for $A_{77} = 1$.

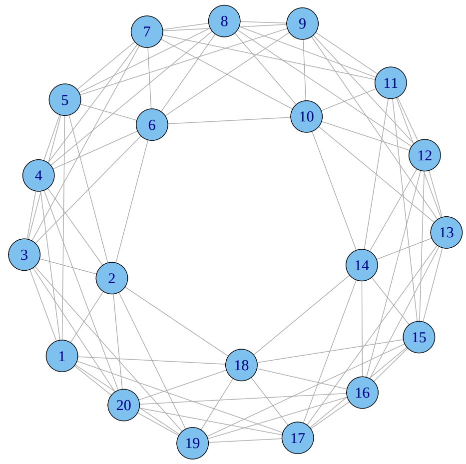
$$\mathbf{A} = \begin{pmatrix} 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{11}$$

We utilize three kinds of graph as the social input, which are *random graph* generated from Erdös and Rényi model, *small world graph* derived from Watts and Strogatz model, and *scale-free graph* created with Barabási-Albert model. The last two graphs reflect some common features of human social networks.

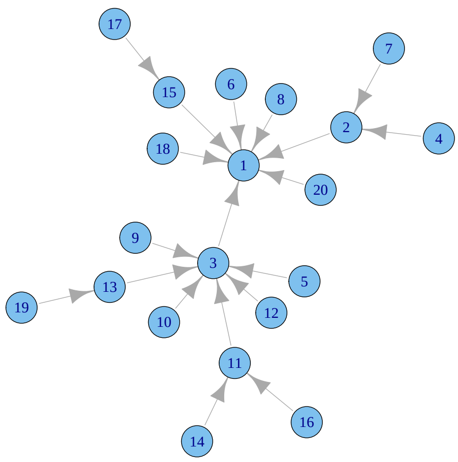
In 1959, Erdös and Rényi propose a random structure of networks [ErR59]. In a random graph, displayed in Figure 7(a), a node is connected to other nodes arbitrarily with the same probability p. Therefore, the structure of random graph does not show apparent feature. Although in real life, human's social network seldom show absolute random topology, it still lays a foundation and a good example for control group in simulation.



(a) Random graph



(b) Small-world graph



(c) Scale-free graph

Figure 7: Three topologies of social networks.

The famous small world effect suggested by Milgram [Mil67] is that, you could acquaint any persons in the world through a few intermediaries. The core concept of small-world refers that there is always a way for two strangers get into contact. It reflects the effect of convergence in social network. In small world graph, the majority of nodes can reach all the others via small number of hops even though they do not have many friends (1-hop neighbours). Small world graph is the transition from regular graph to random graph, proposed by Watts and Strogatz [WaS98], which is illustrated in Figure 7(b).

It's noteworthy that, the node degree of the above two models show a smooth distribution, whereas high-degree vertex is ubiquitous in reality. For instance, the movie stars, celebrities, and politicians obviously know more people and they are better known as well. Barabási and Albert introduced scale-free networks which the node degree shows a power-law distribution [BaA99]. Specifically, in scale-free network which is displayed in Figure 7(c), few nodes possess high degree and the majority of nodes have small amount of direct neighbours. An interesting case is, people who live an active social life may have many friends, but they are more likely to acquaint more friends, aka "Rich-Gets-Richer" phenomenon.

We have introduced some graph metrics in Section 2.2. From the social graphs described above, we extract some local metrics, such as degree and the shortest path length. The social information would be used in designing cooperative sensing scheme.

3.1.3 Model of primary user

The state of PU channel is modelled as a two-finite state machine, where the states are busy and idle, standing for the presence and absence of PU. Busy state suggests that PU is using the licensed spectrum currently, while idle state refers to the PU absence then CRs could utilize the licensed spectrum to transmit data. Figure 8 shows the model of primary user channel.

$P_{idle-idle}$ denotes the probability of PU channel changing from idle state to idle state. More precisely, *idle-idle* means the PU channel was in idle state at last timeslot, and it stays idle at this timeslot. Accordingly, $P_{idle-busy}$ denotes the probability of PU channel transferring from idle state at last timeslot to busy state at this timeslot. It satisfies $P_{idle-idle} + P_{idle-busy} = 1$. On the other hand, when PU channel was busy previously, the probability of tuning into idle state or busy state is represented

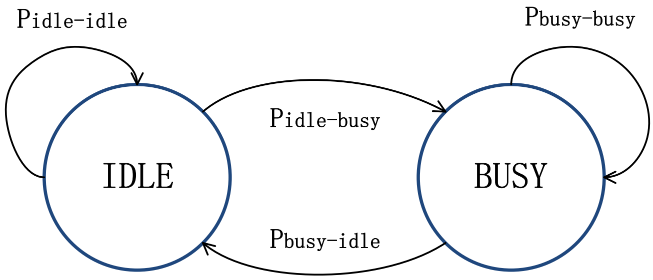


Figure 8: Primary user channel model.

by $P_{busy-idle}$ and $P_{busy-busy}$ respectively. Similarly, $P_{busy-idle} + P_{busy-busy} = 1$. We calculate the probability of PU absence (P_{idle}) and the probability of PU presence (P_{busy}) by computing steady state distribution of a Markov chain,

$$\begin{bmatrix} P_{idle} & P_{busy} \end{bmatrix} \begin{bmatrix} P_{idle-idle} & P_{idle-busy} \\ P_{busy-idle} & P_{busy-busy} \end{bmatrix} = \begin{bmatrix} P_{idle} & P_{busy} \end{bmatrix} \tag{12}$$

where P_{idle} and P_{busy} satisfies Equation 12, and $P_{idle} + P_{busy} = 1$.

3.1.4 Model of cognitive radio and malicious user

A *cognitive radio user*, aka an unlicensed user, is represented as a 5-tuple:

$$cr =< id, D, L_l, L_s, L_w > \tag{13}$$

- id is the identification of each CR. For example, the id of CR_i is i.
- D is the social degree of CR, i.e. the node degree in social graph. It shows the number of friends that a CR has. We consider the 1-hop neighbour in social graph as the CR's friend.
- L_l is the list of social distance. We regard the social distance as the shortest path length of two CRs. The L_l of CR_i stores all of the social distance from CR_i to others. The size of L_l is $N_{CR} - 1$, where N_{CR} denotes the number of CRs in CRN.
- L_s is the list of sensing performance. We propose a scoring mechanism to evaluate the sensing performance of cooperators from the perspective of the requesting CR. The requesting CR, aka the transmitter stores all the sensing score of other CRs in L_s. The size of L_s is $N_{CR} - 1$.

- L_w is the list of *cooperation willingness values*. The L_w of CR_i represents the cooperative tendency from other CRs in terms of cooperating CR_i. Apparently, CR_i prefers the CR which is more willing to cooperate. The size of L_l is $N_{CR} - 1$.

In our model, a CR is a wireless device that carries the social context of its user. With the context stated above, a CR could get the information of its cooperative sensing history with other CRs. For instance, CR_i and CR_j are in the same grid, they would exchange id when communicating with each other. CR_i inquires id "j" in its own list, and then it discovers the cooperative sensing history of CR_j.

In order to create a realistic system, we design the model of **malicious users**. The malicious users are disruptive cognitive radio users, which intend to utilize the network resources as much as possible, but contribute nothing to the system.

Malicious users have the basic properties of CRs, they also carry the 5-tuple context introduced above. However, when a malicious user is requested for cooperation, it always accepts the request, and reports that PU channel is busy without sensing actually. In this manner, the requesting CR would miss the opportunity to access PU channel which is probably not busy.

In the system, we use d_m to denote the density of malicious users, that is, the fraction of malicious users in the CRN.

3.1.5 Mobility model of cognitive radio

In wireless communication networks, the movement pattern of mobile devices exerts a crucial influence on system performance. Thus, the mobility model of wireless devices becomes a study point that attracts significant attention.

In our system, we desire to exploit a social-based mobility model. More specifically, the mobility model changes the physical location of CRs at the beginning of each timeslot, based on their social ties. One CR always set its next destination to the grid where most of its friends are located. Musolesi et al. in [MuM07] propose a community-based mobility model (CMM), which is a primary social-based model. They present a concept of social attractivity (SA).

The SA of an area refers to the attraction of this area in terms of social factors [MuM07]. It is primarily determined by the social strength or social weight from this area. In our system, we define the SA of a grid:

$$SA_{ij} = n_f + 0.5 \times n_{fof} \tag{14}$$

where SA_{ij} denotes the social attractivity of $Grid_{ij}$ in the perspective of CR_k, n_f denotes the number of CR_k's friends in $Grid_{ij}$, and n_{fof} denotes the number of CR_k's friend-of-a-friend in $Grid_{ij}$.

We employ the strength of friendship in $Grid_{ij}$ to represent its social weight with CR_k. It is also ordinary in human society that most people like to stay with friends other than strangers. Since the social tie with a friend-of-a-friend is not that stable compared with a friend, we put a weight of 0.5 on n_{fof} in Equation 14. After acquiring the social attractivity of each grid in the system, we calculate the probability of locating (P_{loc}) of each grid [MuM07],

$$P_{loc}^{ij} = \frac{SA_{ij} + d_{ij}}{\sum_{p=1,q=1}^{N_g}(SA_{pq} + d_{pq})} \tag{15}$$

where P_{loc}^{ij} denotes the possibility that CR_k appoints $Grid_{ij}$ as its next location among the N_g grids which $N_g = p \times q$. Basically, P_{loc}^{ij} is determined by the value of SA_{ij}. $d_{ij} \in (0, 1]$ is a random factor to avoid the denominator of Equation 15 happens to be zero when no CRs existed in $Grid_{ij}$. Additionally, d_{ij} increases the randomness of node mobility. After calculating the P_{loc} of each grid, CR_k sets probabilistically the next destination according to the value of each P_{loc}.

Procedure 1: Social-based Mobility Model Running at Each CR

1: **Begin**
2: Get wireless position of this timeslot
3: Get social relations in social graph
4: **for** Each grid **do**
5: Calculate the social attractivity (SA) according to Equation 14
6: **end for**
7: **for** Each grid **do**
8: Calculate the probability of locating (P_{loc}) according to Equation 15
9: **end for**
10: Assign the wireless position for next timeslot according to P_{loc}
11: **End**

Procedure 1 shows the basic process of social-based mobility model that we utilized. It is worth noting that, the mobility model uses the information from social connectivity layer, but exerts an influence on wireless connectivity layer. Apparently, the social-based mobility model reflects the interaction of the two layers.

3.2 Social-based cooperative sensing algorithm

In this subsection, we introduce the proposed scheme: social-based cooperative spectrum sensing (SBC). CR_i denotes the transmitter, i.e. the requesting CR which asks for cooperative sensing. If it is not specified, CR_i is always regarded as the requesting CR thereafter.

SBC is implemented in the following steps:

- CR_i selects its cooperator set.
- The requested CRs, which receive the request, make a decision on whether to cooperate or not.
- The cooperators, which accept the request, perform local sensing respectively and report their sensing results afterwards.
- Using OR logic, CR_i fuses data and draws a final outcome of PU channel.
- According to the final outcome, CR_i either transmit data via the licensed channel or just stays silent.
- In the end, CR_i updates the cooperative sensing performance of each cooperator.

Figure 9 illustrates the procedure of SBC. Since our focus is on exploiting social relations of CRs into their cooperative sensing process, the steps of *cooperator set selection*, *cooperative sensing*, and *updating the sensing performance score* are of crucial importance that we will explain in detail.

3.2.1 Cooperator set selection

During each timeslot, the spectrum sensing is performed in each grid simultaneously. Each grid selects the transmitter (CR_i) randomly. From the perspective of the CR_i, it expects the cooperator, which assists for detecting PU channel, to be friendly, reliable, and cooperative. Therefore, we design a scoring mechanism to set the standard whether a CR is capable to act as a cooperator. The scoring mechanism

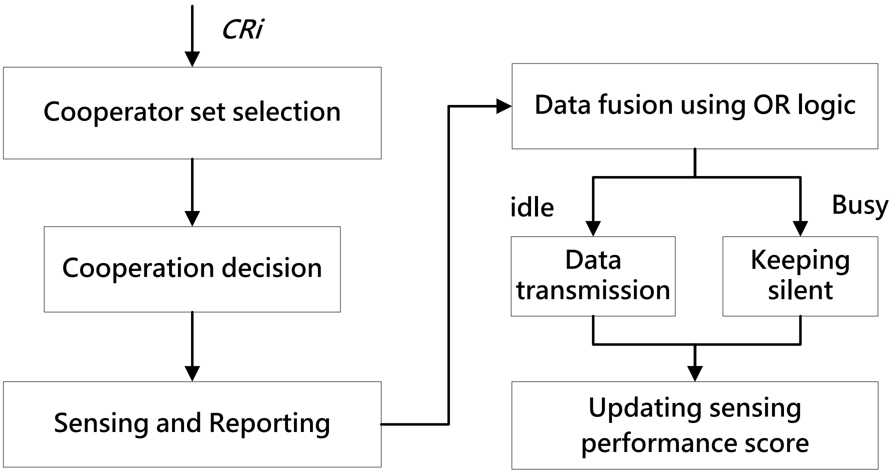


Figure 9: The procedure of SBC.

consists of three aspects: social tie ($l_i(j)$), trust ($t_i(j)$), and cooperation willingness ($w_i(j)$).

- Social tie ($l_i(j)$): In human society, people are more likely to seek help from the individuals of close relationship. The closer the relation between two persons, the stronger social connection they have. If we imitate this phenomenon into CRN, the social tie between two CRs can be determined by their social distance, aka the shortest path length on social network. Apparently, the 1-hop neighbours (friends) in the social graph have the closest relationship. The $l_i(j)$ between CR_i and CR_j is defined as,

$$l_i(j) = \frac{1}{d_{ij}} \tag{16}$$

  where d_{ij} stands for the social distance between CR_i and CR_j, i.e. the shortest path length from CR_i to CR_j in social graph.

- Trust ($t_i(j)$): Govindan and Mohapatra investigate the trust computation in mobile ad hoc networks (MANETs) in [GoM12]. From their work we know that, trust is an important aspect since untrustworthy nodes would bring about considerable damage and affect the quality of data [GoM12]. In this model, we consider the trust of a CR is determined by its previous sensing performance. In other words, CR_i trusts CR_j if the latter reports reliable sensing results with high probability when acting as the former's cooperator. Hence, CR_i would prioritize CR_j when selecting cooperators next time. It coincides with the human communication, people used to judge the dependability of a person based on their previous interaction. The $t_i(j)$ from CR_i to CR_j is,

$$t_i(j) = \alpha s_i^p(j) + (1-\alpha)s_i^r(j) \tag{17}$$

where $s_i^p(j)$ denotes the previous cooperative sensing score of CR_j when it acts as the cooperator of CR_i, and $s_i^r(j)$ is the recent sensing score of CR_j, $0 \leq \alpha \leq 1$ is the weight to tune the priority of previous sensing performance. When the sensing events complete, the system records the sensing result of each cooperator, and evaluate the corresponding sensing performance. Detailed definition of $s_i^p(j)$ and $s_i^r(j)$ will be shown in Section 3.2.3.

- Cooperation willingness ($w_i(j)$): it refers to the tendency that CR_j is willing to cooperate CR_i. From the perspective of CR_i, it prefers those which are less possible to refuse its request as cooperators. Otherwise, it is a waste of energy to send non-responsive requests, particularly for wireless devices. As a consequence, CR_i needs to estimate the cooperation tendency from CR_j before sending a request. We design a simple model to represent the willingness of CR_j:

$$w_i(j) = \frac{N_i^{acp}(j)}{N_i^{req}(j)} \tag{18}$$

where $N_i^{req}(j)$ is the number of requests ever sent by CR_i to CR_j from the very beginning of all timeslots, $N_i^{acp}(j)$ is the total number of acceptance from CR_j responding to CR_i's requests. The ratio shows the acceptance rate of CR_j as a cooperator, which could reflect the future trend to some extent.

After calculating the three scores, the overall score is,

$$S_i(j) = \alpha_l * l_i(j) + \alpha_t * t_i(j) + \alpha_w * w_i(j) \tag{19}$$

where α_l, α_t, and α_w are all in the range [0,1], and satisfies $\alpha_l + \alpha_t + \alpha_w = 1$. They represent the effect of social relation, trust value, and cooperation probability in assessing the selected cooperators.

At the beginning of cooperative sensing, there never occurs cooperation, therefore $t_i(j)$ and $w_i(j)$ must be 0. In order to initiate cooperation, we put all weight to α_l to make the overall score controlled by social ties between CR_i and CR_j completely.

In other words, $\alpha_l = 1, \alpha_t = 0, \alpha_w = 0$ when the number of cooperation (n_{coop}) is less than 2.

As the increasing of n_{coop}, CR_i concerns more about the sensing performance of CR_j in choosing cooperators. After all, the sensing performance plays a fairly crucial role in cognitive radio. Hence, we increase the value of α_t, and decrease α_l gradually. The cooperation willingness accounts for a small proportion, but our focus is on the trust factor.

To restrain the increasing of α_t, in case that the proportion of the other two factors decline too much, we set a minimum value of n_{coop}, denoted by n_{coop}^{min}. Once the number of cooperation between CR_i and CR_j surpasses n_{coop}^{min}, the value of α_l, α_t, α_w are calculated based on n_{coop}^{min} instead of n_{coop}. In other words, the weight of three aspects gets fixed thereafter. **Algorithm 1** displays the tuning of weights in the overall score.

Algorithm 1: Tuning the weights in the overall score.

Acquired information: α_l, α_t, α_w, n_{noop}, n_{coop}^{min}
if $n_{noop} = 0$ or $n_{noop} = 1$ **then**
  $\alpha_l \leftarrow 1$
  $\alpha_t \leftarrow 0$
  $\alpha_w \leftarrow 0$
else if $n_{noop} < n_{coop}^{min}$ **then**
  $\alpha_l \leftarrow \frac{2\times(n_{coop}-1)}{n_{coop}\times n_{coop}}$
  $\alpha_t \leftarrow \frac{(n_{coop}-1)\times(n_{coop}-1)}{n_{coop}\times n_{coop}}$
  $\alpha_w \leftarrow \frac{1}{n_{coop}\times n_{coop}}$
else
  $\alpha_l \leftarrow \frac{2\times(n_{coop}^{min}-1)}{n_{coop}^{min}\times n_{coop}^{min}}$
  $\alpha_t \leftarrow \frac{(n_{coop}^{min}-1)\times(n_{coop}^{min}-1)}{n_{coop}^{min}\times n_{coop}^{min}}$
  $\alpha_w \leftarrow \frac{1}{n_{coop}^{min}\times n_{coop}^{min}}$
end if

According to Equation 19, CR_i calculates the overall score of each CR in its transmission range. Among all the CRs whose score outweighs the cooperation threshold (λ_{coop}), CR_i selects the top N_{coop} CRs as its cooperators. In other words, CR_i can get at most N_{coop} cooperators from the optimal selected CRs, during one cooperative sensing process. Next, CR_i sends a request to each CR that is selected as

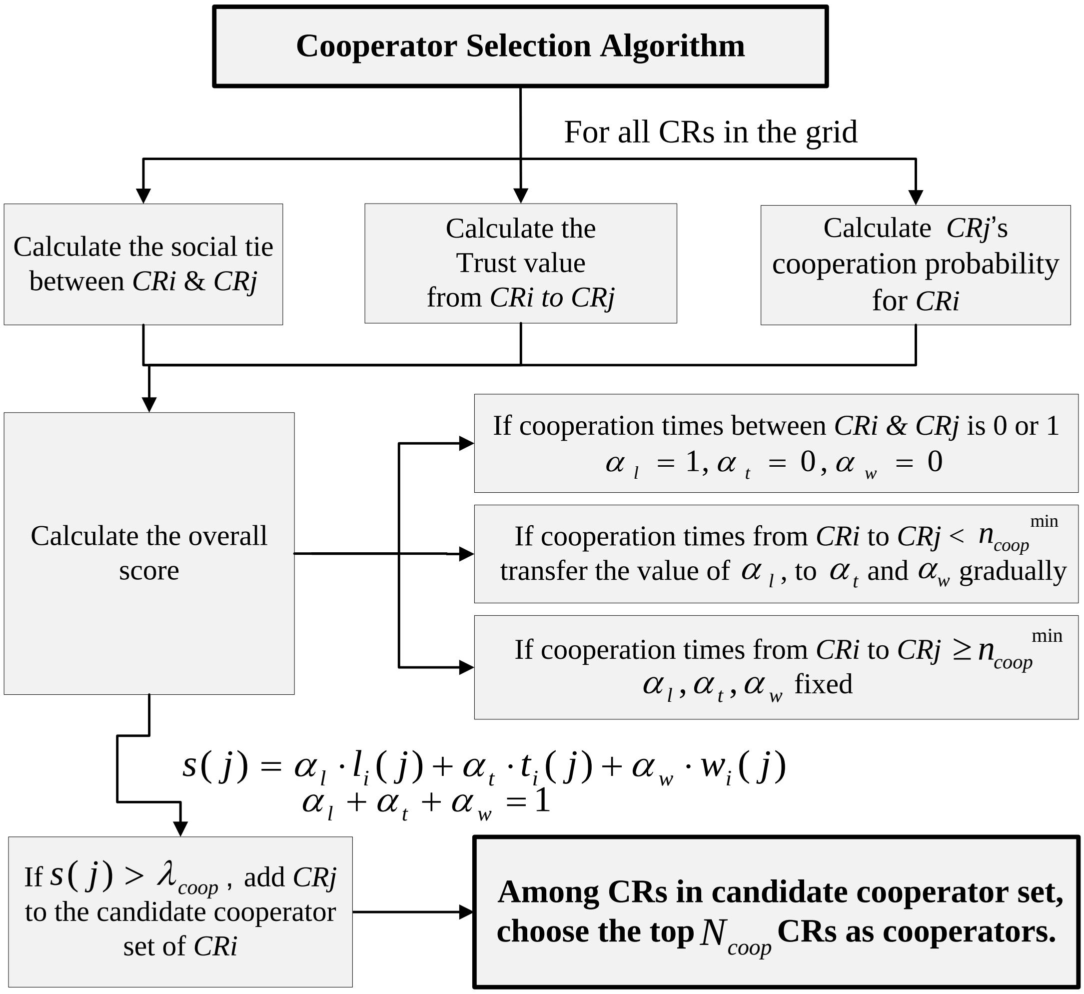


Figure 10: Cooperator selection algorithm.

cooperators, and waits for their sensing results on PU channel state.

All in all, Figure 10 shows the algorithm of cooperator set selection.

3.2.2 Cooperative spectrum sensing

When the requested CR, denoted by CR_j, receive cooperation request from CRi, the possibility that CR_j admits to cooperate CR_i is,

$$p_j^{coop}(i) = \beta * w_j(i) + (1 - \beta) * l_j(i) \tag{20}$$

where $w_j(i)$ denotes CR_i's willingness to accept the cooperation request from CR_j, the definition is shown in Equation 18. $l_j(i)$ represents the social tie between CR_j

and CR_i, which has the same value of $l_i(j)$, shown in Equation 16. $\beta \in [0, 1]$ is the weight of cooperation tendency.

Equation 20 reflects the selfishness of CR_j. We introduce selfishness, one of the typical negative social characteristics in Section 2.2. According to Equation 20, CR_j makes the decision whether to assist CR_i on the basis of the cooperation history from CR_i. For instance, when CR_j acts as the requesting node, it asks CR_i for cooperative sensing. If CR_i always agrees to cooperate, then CR_j would consider it is worthy to help CR_i in return. On the contrary, if CR_i never agrees to help, but still asks CR_j when it needs cooperation, it is fairly worthless for CR_j to help CR_i. Actually, it imitates some respect of human interaction: people seldom help others unconditionally, unless they are of close relationship, or profitable partners.

At the beginning of cooperative spectrum sensing, CR_i and CR_j just cooperate each other for several times. Hence, we use the social tie to initiate the cooperation. In other words, the social strength between CR_i and CR_j determines the cooperation probability of CR_j when they do not cooperate much. Until $w_j(i)$ surpasses a threshold, i.e. the minimum probability of cooperation (p_{min}^{coop}), $p_j^{coop}(i)$ could be totally decided by $w_j(i)$. **Algorithm 2** demonstrates the tuning of weight β, and the calculation of cooperation probability.

Algorithm 2: Tuning the weights in the cooperation probability.

1: **Acquired information:** $w_j(i)$, $l_j(i)$, p_{min}^{coop}
2: **if** $w_j(i) < p_{min}^{coop}$ **then**
3: $\quad \beta \leftarrow \frac{w_j(i)}{p_{min}^{coop}}$
4: **else**
5: $\quad \beta \leftarrow 1$
6: **end if**
7: **According to Equation 20,**
calculate the probability of cooperation from CR_j to CR_i.

If CR_j accepts the request, then it performs spectrum sensing and returns the sensing outcome back to CR_i. Otherwise, CR_j just stays silent and waits for the next request.

3.2.3 Updating the sensing performance score

After CR_i receives all the cooperative sensing outcomes, it fuses the data with OR logic which we have discussed in Section 2.1.2, to conclude a final outcome of PU channel state. If the final outcome shows idle, CR_i accesses the licensed channel to transmit its own data. Otherwise, it waits for the next opportunity. No matter CR_i has utilized PU channel successfully or not, it both needs to record the sensing performance of each cooperator, and update $s_i^p(j)$ and $s_i^r(j)$ of each cooperator accordingly.

Specifically, H denotes the real state of PU channel, H_i represents the final outcome that CR_i concludes, $H_{j,i}$ denotes the sensing outcome from CR_j that reported to CR_i. 1 and 0 stands for the busy and idle state respectively. Based on OR logic, there might happen six cases shown in Table 3.

Table 3: Cooperative spectrum sensing results.

	$H_{j,i}$	H_i	H	Action
Case 1	0	0	0	channel access, success
Case 2	0	1	0	no access
Case 3	1	1	0	no access
Case 4	0	0	1	channel access, collision
Case 5	0	1	1	no access
Case 6	1	1	1	no access

From Table 3 we see, CR_i gets access to PU channel if case 1 or case 4 occurs. Then it knows the real state of PU channel and it can recognize whether the sensing outcome from CR_j is right or wrong. On the contrary, if CR_i do not access the PU channel under the other four cases, it has no idea of the real state. Under such circumstance, the majority of cooperative sensing outcomes is regarded as the PU state [EBK15]. That is to say, if most cooperators consider that PU is busy, then CR_i assumes PU presence ($H_i^{dec} = 1$), and uses the assumption to evaluate cooperators' performance. H_i^{dec} denotes CR_i's decision on PU channel:

$$H_i^{dec} = \begin{cases} 0 & \text{Case 1, 4} \\ \text{Majority in } H_{j,i} & \text{Case 2, 3, 5, 6} \end{cases} \tag{21}$$

The previous cooperative sensing score $s_i^p(j)$ and the last cooperative sensing score $s_i^r(j)$ is calculated as following [GBA13],

$$s_i^p(j) = \frac{s_i^p(j)^* * (n_{coop} - 1) + s_i^r(j)^*}{n_{coop}} \tag{22}$$

where n_{coop} is the number of cooperation ever happened between CR_i and CR_j. $s_i^p(j)^*$ is the former value of $s_i^p(j)$, and $s_i^r(j)^*$ is the former value of $s_i^r(j)$. From Equation 22 we see, the previous score combines the last score to form a new $s_i^p(j)$. The new $s_i^r(j)$ reflects the sensing performance of this timeslot and equals to:

$$s_i^r(j) = \begin{cases} 1 & \text{if } H_{j,i} = H_i^{dec} \\ 0 & \text{if } H_{j,i} \neq H_i^{dec} \end{cases} \tag{23}$$

if CR_j's sensing outcome agrees with CR_i's decision on PU channel, we use 1 to stand for the sensing performance of CR_j, otherwise it is 0. In this way, the CR which always reports correct results or the results in agreement with the majority result, gets higher score in term of the sensing performance. Consequently, CR_i will prioritise this CR as a cooperator thereafter.

3.3 Random-selecting cooperative sensing

We introduce the social-based cooperative sensing scheme (SBC) in the previous subsection, now we describe a random-selecting cooperative sensing scheme (RAND). As the name says, CRs in RAND just select cooperators randomly.

RAND consists of two steps, 1) the transmitter, aka requesting CR (CR_i) selects its cooperators randomly, without considering the social relations, sensing performance of CRs. The maximum number of cooperators is N_{coop}. 2) step 2 is the same as the second step of SBC. The requested CR (CR_j) calculates its cooperation probability according to Equation 20. There is not a step for updating data in RAND, since the CRs are social-unaware, and they do not care about sensing scores. The next section, we compare and analyze RAND and SBC in terms of sensing performance, for the sake of understanding our proposed scheme SBC.

We describe the concept of malicious user in Section 3.1.4. Briefly speaking, a malicious user always accepts cooperative requests and reports the busy state of PU channel. d_m denotes the density of malicious users in cognitive social network. We intend to analyze SBC and RAND in terms of their cooperative sensing performance under malicious user network. Diverse levels of malicious user density is obtained by tuning the value of d_m. Theoretically, SBC can seek out optimal cooperators that make it able to distinguish malicious users, while RAND just chooses cooperators randomly. The effect of malicious user on RAND and SBC will be discussed in the next section.

4 Simulation Analysis

In this section, we provide the simulation results and performance analysis of the proposed cooperative sensing scheme, SBC. In order to compare SBC and RAND under the effect of malicious users, we establish two scenarios to analyze their sensing performance. Additionally, we discuss the effect of CR's social degree on their sensing performance. Furthermore, three kinds of network topologies are utilized as social input, to investigate the effect of social network on the sensing performance of CR.

4.1 Simulation parameter

Table 4 shows the simulation parameters.

Since the CRs are not permitted interfering PU when using licensed channel, it is of importance to avoid the collision between PU and CR. Therefore, we employ OR logic for data fusion. The global probability of detection (Q_d) of the whole system and the global probability of false alarm (Q_f) are calculated based on P_d and P_f, according to Equation 6 and 7 respectively.

$P_{idle-idle}$ represents the probability of PU channel changing from idle state to idle state, and $P_{busy-idle}$ represents the probability of PU channel changing from busy state to idle state, which we have introduced in Section 3.1.3.

We create three levels of malicious user density (d_m), i.e. low, moderate, and high d_m of the CRN to analyze the effect of cooperation threshold (λ_{coop}) on system performance. Once a CR's overall score calculated via Equation 19 outweigh the cooperation threshold (λ_{coop}), it has the quality to be a cooperator.

Here are the metrics we utilize to evaluate the system:

- *Ratio of Malicious User Cooperation* is the ratio of cooperating with malicious users in the network. When the CRN consists of malicious users, it is the pos-

Table 4: Simulation parameters

Parameter	Signification	Value
P_d	Local Probability of detection	0.7
P_f	Local Probability of false alarm	0.1
$P_{idle-idle}$	Probability of PU channel state from idle to idle	0.3
$P_{busy-idle}$	Probability of PU channel state from busy to idle	0.7
N_{CR}	Number of cognitive radio nodes	40
N_g	Number of grids	4
N_{coop}	Maximum number of cooperators	3
N_T	Number of timeslots	10000
α	Weight of previous performance score	0.6
λ_{coop}	Default cooperation threshold if not specify	0.45
$d_m(low)$	Low malicious user density	0.2
$d_m(moderate)$	Moderate malicious user density	0.5
$d_m(high)$	High malicious user density	0.7

sibility of the requesting CR select malicious users as its cooperator. Keeping the ratio as low as possible is desirable.

- *Number of Malicious User Cooperation* is the numerical version of the above metric. When the CRN consists of malicious users, it is the number of malicious users ever selected as cooperators during overall timeslot. Keeping the number as low as possible is desirable.

- *Ratio of Idle Channel Discovered* is the probability of idle channel discovered successfully. The idle channel could be discovered via cooperative sensing or just local sensing by the transmitter; the former is called cooperative discovery and the latter local discovery. Total discovery refers to the summation of cooperative discovery and local discovery.

- *Number of Idle Channel Discovered* is the quantified version of Idle Channel Discovery Ratio. It shows the number of idle channel discovered during all timeslot. Local discovery refers to idle channel detected by local sensing, while cooperative discovery is by cooperative sensing. Their summation constitutes total discovery of idle channel.

- *Probability of Collision*: when CR considers PU is absent but the PU channel is busy in reality, the collision between CR and PU happens. This metric refers to the proportion of collision ever happened during overall timeslots, which could be caused by the result from cooperative sensing or local sensing.

- *Cooperation Request Return*: when CR_i sends a request for cooperation, it might be accepted or rejected. This metric refers to the possibility of rejected cooperation request or accepted request. The sum of reject ratio and accept ratio is always 1.

- *Cooperation Request per Idle Channel Discovery by cooperative sensing* is the fraction of two numbers. The numerator is the number of cooperation requests ever sent during all timeslots, and the denominator is the number of idle channel discovered by cooperative sensing. It reflects the cost of achieving an idle channel through cooperative sensing.

- *Cooperation Request per Idle Channel Discovery by total sensing*: the difference between this metric with the above is that the denominator here is the number of idle channel discovered totally, regardless of local or cooperative sensing. It reflects the cost of achieving an idle channel in the system.

- *Ratio of Cooperation Requests Received by Malicious Users*: when malicious users desire to utilize PU channel, they ask cooperative sensing from other CRs. This metric is the probability that malicious users have received cooperation.

- *Number of Cooperation Requests Received by Malicious Users* is the quantified version of the above metric, i.e. the cooperation times that malicious users have received during all timeslots.

- *Global probability of detection* (Q_d) refers to the ratio of PU's busy state that has been detected during all timeslots. Basically, keeping Q_d as high as possible is the aim of the cooperative sensing algorithm.

- *Global probability of false alarm* (Q_f) refers to the ratio that CR considers PU is in busy state, but PU channel is actually idle, during all timeslots. Basically, keeping Q_f as high as possible is the aim of the cooperative sensing algorithm.

- *Number of Cooperating CRs per Cooperative Sensing Event* (n_{coop}): during an event of cooperative sensing, CR_i sends a request to several CRs respectively, this metric is the number of CRs that admit to cooperate.

- *Average social distance among CRs* is the average value of all the social distance between any pairs of CRs in the network. It reflects the closeness of social relations in CRN.
- *Average social distance from cooperator*: for the pairs of transmitter and its cooperators, we first collect the social distances between all the pairs, and then take an average of them. It reflects the closeness of social relations between the transmitter and its cooperators.
- *Ratio of cooperating with friends* is the proportion of friends in cooperator set from the perspective of transmitter.
- *Ratio of local sensing*: during all the sensing events of CR_i, it could perform cooperative sensing or local sensing. This metric is the proportion of local sensing performed during the total sensing events.

4.2 Performance under malicious network

In this part, we provide the simulation comparison of SBC and RAND when malicious users exist in network, to illustrate the performance improvement from SBC in contrast to RAND. As for the social network input, we utilize a small world graph with link density 0.1.

There are two scenarios to test the effect of malicious users on system performance:

- *Scenario 1: The influence of increasing malicious user density (d_m).*

  Let us review the behaviour of malicious user: as a cooperator, it always accepts the cooperation request and return "1", notifying the PU channel is busy, therefore preventing normal users access to idle channel. As a result, when the density of malicious user (d_m) rises in the network, the system performance would be affected to various extent. In this scenario, we set $\lambda_{coop} = 0.45$ to observe the impact of d_m.

- *Scenario 2: The influence of diverse cooperation threshold (λ_{coop}).*

  In SBC, cooperation threshold acts as a shield for the sake of cooperation quality. Specifically, only the reliable CRs could be selected as cooperators. Too low value of λ_{coop} results in almost all nodes being equally likely to be selected as cooperators, whereas too high value restricts CRs' cooperation behaviour. Therefore, we require to determine an appropriate value of λ_{coop}. In this scenario, we use fixed d_m, which could be low, moderate or high. The values are shown in Table 4.

4.2.1 Influence of increasing malicious user density (d_m)

The array below represent the increasing value of d_m.

$d_m = \{0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7\}$

With the increasing of d_m, more and more malicious users emerge to interfere the system. How does d_m influence the sensing performance is our focus in this part.

Figure 11 shows the ratio of cooperation with malicious users. When d_m is 0, the probability that CR_i (the requesting CR) cooperates with malicious user is 0 both in SBC and RAND. Then, RAND rises dramatically with the increasing of d_m, and SBC also rises, but with a slower rate. For instance, the ratio of malicious user cooperation reaches 0.8 in RAND, but is 0.1 in SBC when d_m is 0.6.

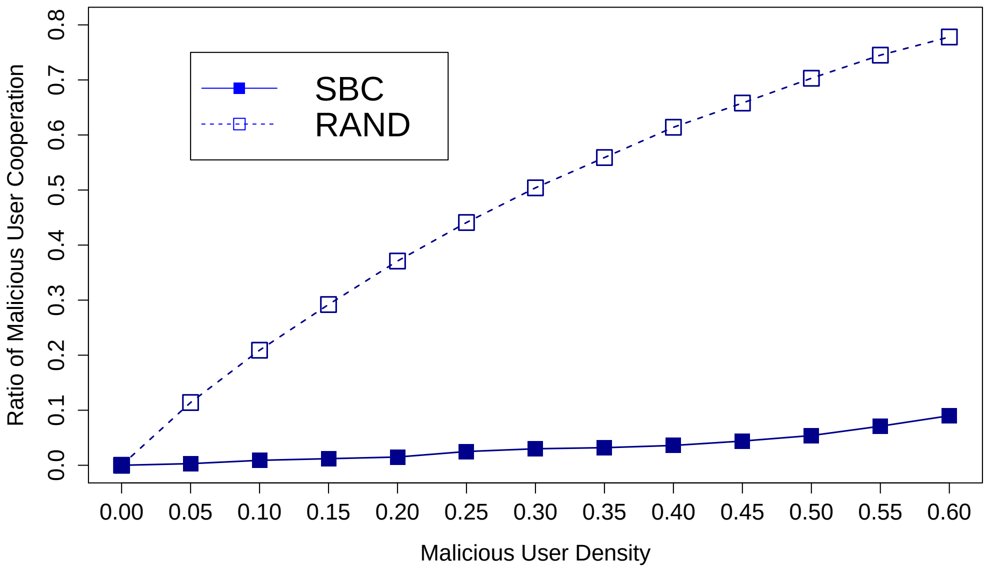


Figure 11: Probability of cooperating with malicious users under various malicious user density

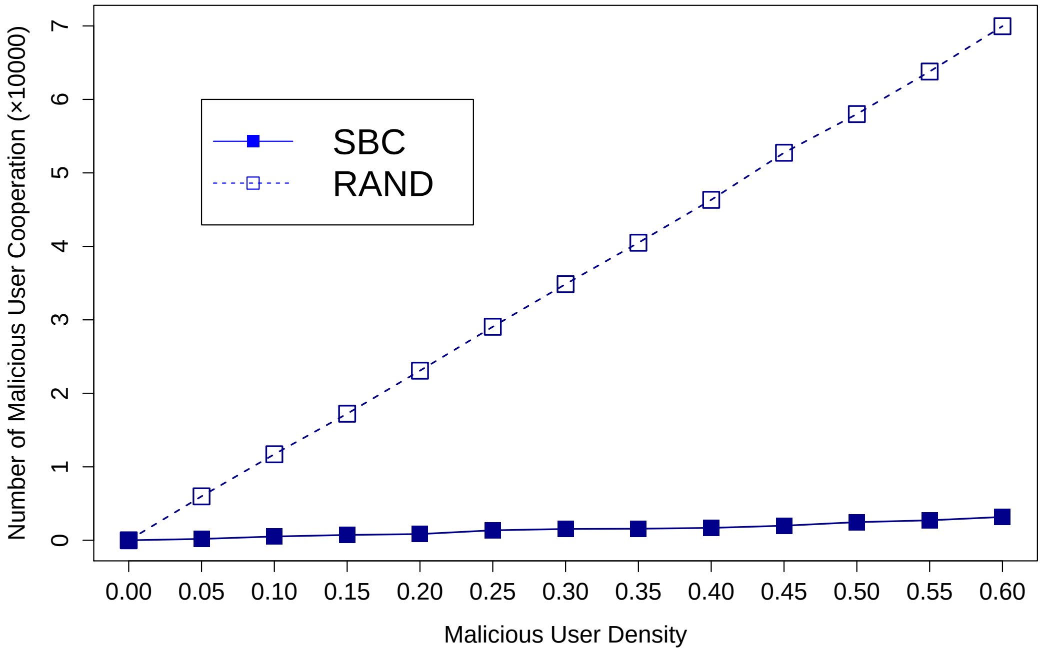


Figure 12: Cooperation times with malicious users under various malicious user density

Figure 12 shows the number of cooperation with malicious users. RAND experiences a linear growth process while SBC is almost unaffected. It is obvious that the fluctuation of SBC and RAND are both similar to Figure 11. That is to say, SBC is more careful of malicious user cooperation whereas RAND just selects cooperators randomly without filtering malicious users.

Figure 13 shows the negative effect of malicious users. When d_m is low, the possibility that discovering an idle channel are similar in SBC and RAND. RAND even discovers more idle channel when no malicious user exists, this is partly due to the effect of λ_{coop} in SBC. More specifically, the number of cooperators are limited by λ_{coop} since only the qualified CRs can be selected as cooperators in SBC. On the other hand, RAND does not have any limit in selecting cooperators as long as the number does not exceed N_{coop}. Therefore, RAND has more chance to get cooperated and further discovers more idle channels when d_m is 0.

However, the ratio of idle channel discovered declines sharply when d_m starts to grow in RAND, which bottoms at 0.02 finally, while the ratio in SBC remain stable at 0.7 to 0.8. It implies that the increasing of malicious user does not affect the idle channel discovery in SBC. From Figure 13 we see, the triangle symbol represents the idle channel discovered by cooperative sensing, whereas the square symbol denotes the idle channel discovered by local sensing and cooperative sensing totally. No matter in SBC or RAND, the cooperative discovery accounts for almost 90% of the total discovery, showing that cooperative sensing takes the overwhelming majority of spectrum sensing. When d_m increases, the proportion of cooperative discovery in SBC descends slightly. It means that with increasing d_m, nodes are forced to local sensing to avoid interaction with the malicious users.

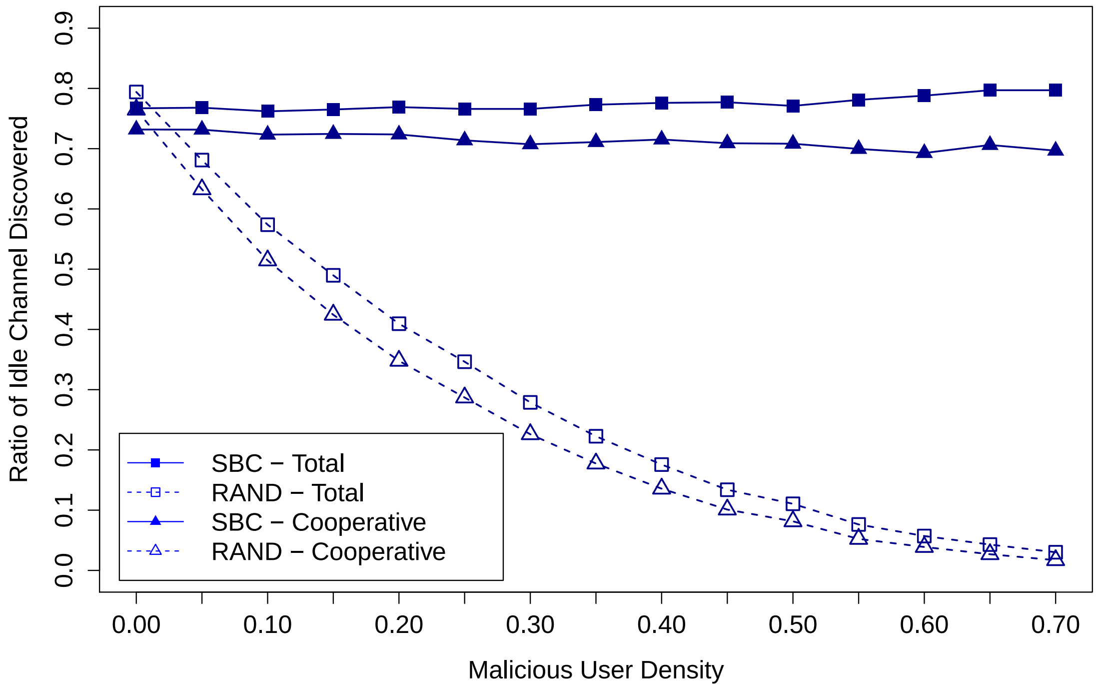


Figure 13: Ratio of idle channel discovered under various malicious user density

Figure 14 demonstrates the numerical result of Figure 13 is consistent with our assumption. The circle solid line shows the number of idle channel discovered by local sensing in SBC, it experiences a almost linear increase with d_m. At the same time, the number of idle discovery via cooperative sensing in SBC decreases with increasing d_m. This is because, the requesting CR cannot find enough reliable cooperators, then, it has to sense itself instead, for the sake of maintaining sensing performance. Therefore, the total idle discovery remains stable regardless of d_m change in SBC.

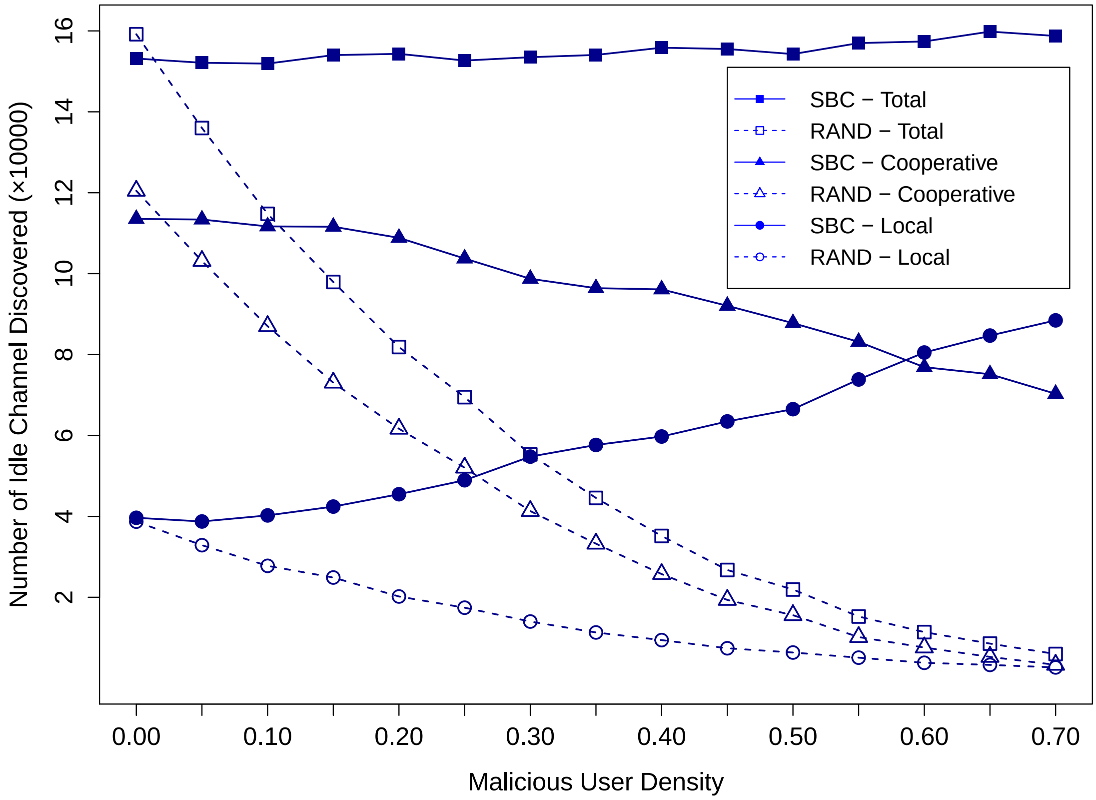


Figure 14: Number of idle channel discovered under various malicious user density

In RAND, the number of local discovery and cooperative discovery both decrease with the inclining of d_m, they tend to 0 when d_m reaches 0.7. In other words, RAND almost cannot discover idle channels at this point. The idle opportunities are occupied by malicious users. All of the data signifies that RAND is not robust to malicious users.

Figure 15 shows probability of collision between CR and PU, consisting of the collision caused by local sensing or cooperative sensing. When PU is actually in busy state while CR's sensing result shows idle, then the collision happens. As can be seen from Figure 15, the probability of collision in SBC is only marginally affected by d_m.

However, the probability of collision via cooperative sensing in RAND falls from 0.06 to 0. It looks that SBC brings more collision than RAND. That is due to the malicious users' behaviour: they avoid the transmitter accessing to PU channel,

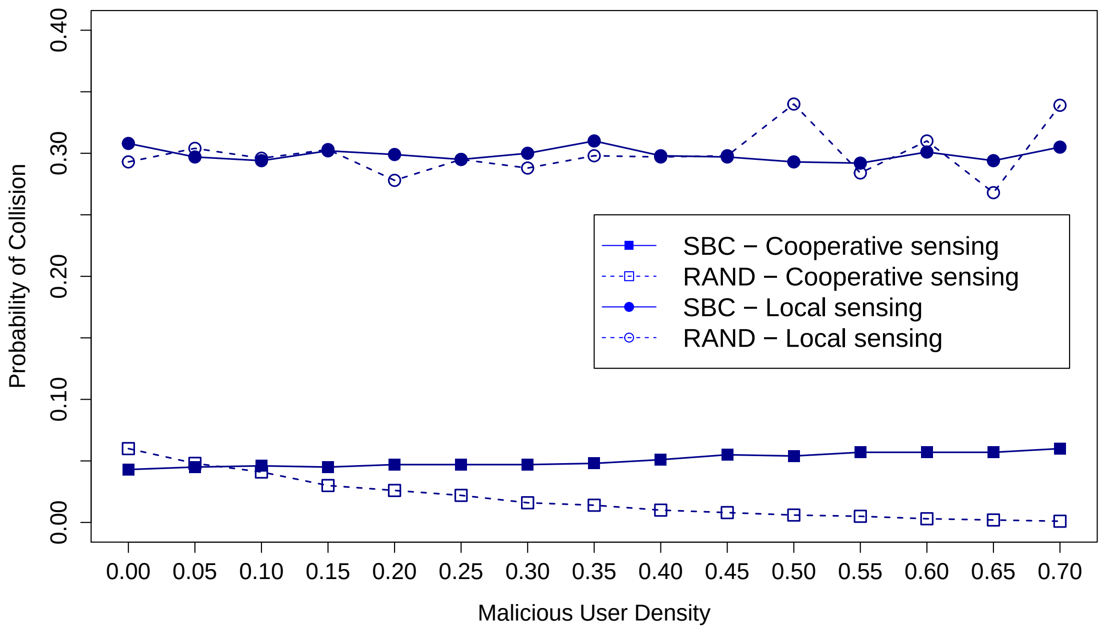


Figure 15: Probability of collision under various malicious user density

decreasing the possibility of collision to some extent. Since RAND cooperates with more malicious users when d_m increases, the collision becomes less likely to happen. Unlike RAND, SBC is able to recognize malicious user and avoid malicious user cooperation, thereby holding a steady collision rate.

In Figure 15, the probability of collision by local sensing in SBC is always nearly 0.3, the difference between 1 and P_d, which verifies our simulation results are accurate. The collision from cooperative sensing is much less than local sensing, showing that cooperation reduces the likelihood of collision.

Figure 16 displays the ratio of rejected requests and accepted requests. Apparently, the summation of reject ratio and accept ratio is always 1 whether in SBC or RAND. At the point d_m is 0, the ratio of cooperation requests accepted by the candidate cooperators of RAND is 0.41, while SBC is 0.84, more than twice of RAND. That is owing to the *cooperation selection algorithm* of SBC, which allows the transmitter to choose the CRs that have lower probability of refusing the cooperation requests.

With increasing d_m, RAND experiences a more steep decrease than SBC in reject ratio, as RAND cooperate more and more malicious user that consequently reduces the reject ratio. Although the reject ratio in SBC also declines, the trend is much

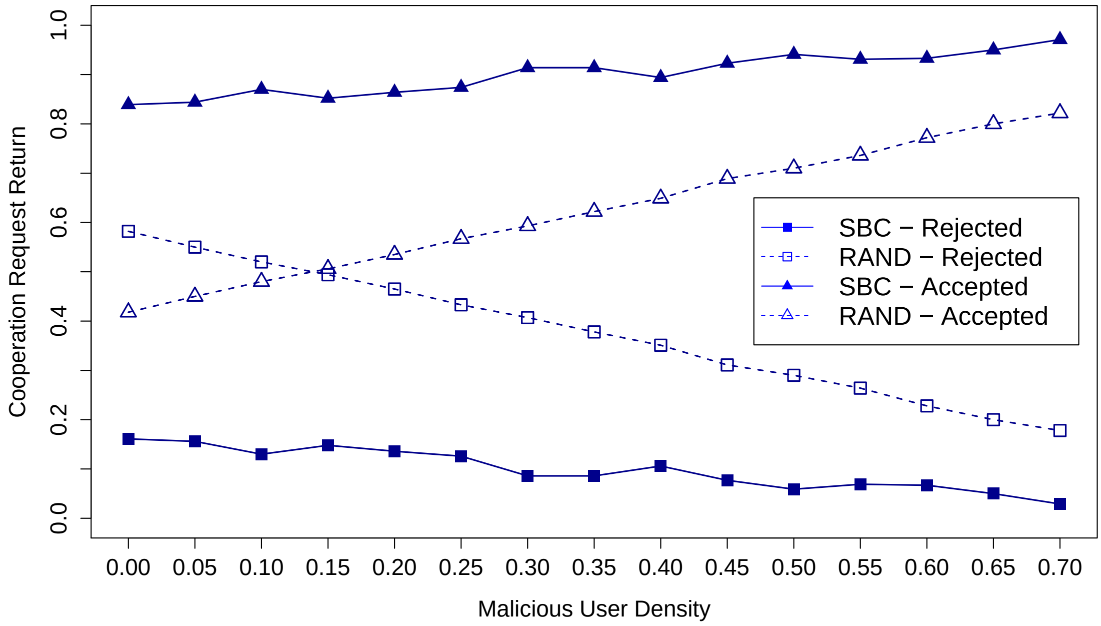


Figure 16: Ratio of rejected or accepted request under various malicious user density

gentler. In other words, SBC can distinguish malicious users so that it still asks cooperation from normal users, while RAND cooperates with more malicious users unconsciously, further decrease the idle channel opportunities for CRs.

Figure 17 shows the number of cooperation requests per idle channel discovered, i.e. the average number of cooperation requests sent to discover an idle channel. The idle channel might be discovered by cooperative sensing or local sensing. The total idle discoveries refer to the summation of cooperative discovery and local discovery. We can see from Figure 17, no matter the idle channel is by cooperative discovery or total discovery, the curves of SBC both descend slightly. On the other hand, RAND witnesses a sharp increase. When d_m is 0.6, it needs to send over 100 requests to detect an idle channel, and it needs 160 requests to discover an idle channel by cooperative sensing. Combing with the results in Figure 16, although RAND gets a low reject ratio, but the cooperation are mainly with malicious users, therefore decrease the sensing efficiency of idle channel.

Malicious users also act as the requesting CR that asks for cooperation. Figure 18 shows the cooperation that malicious users received from other CRs. Specifically,

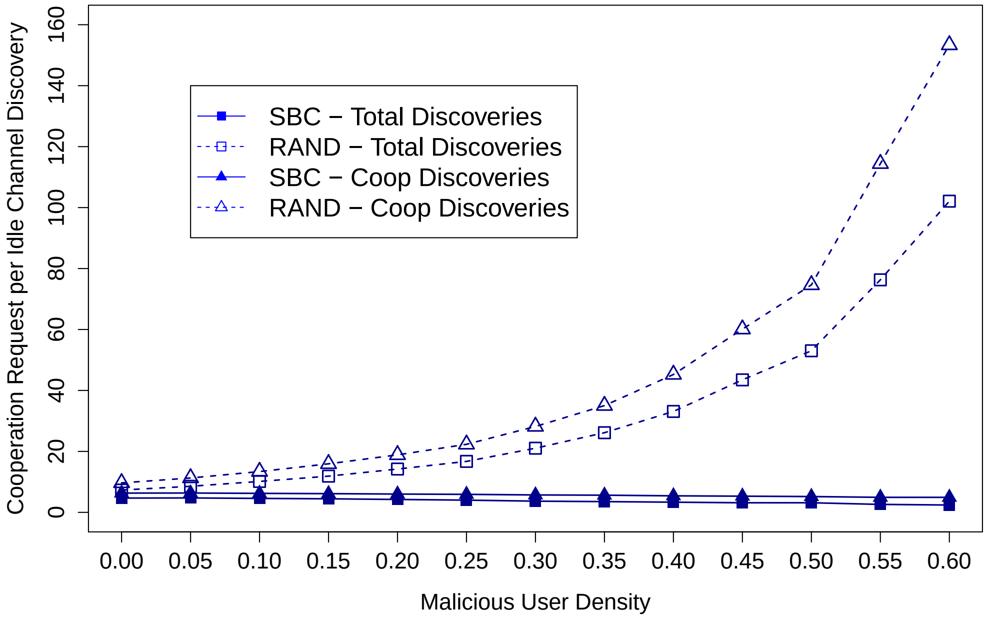
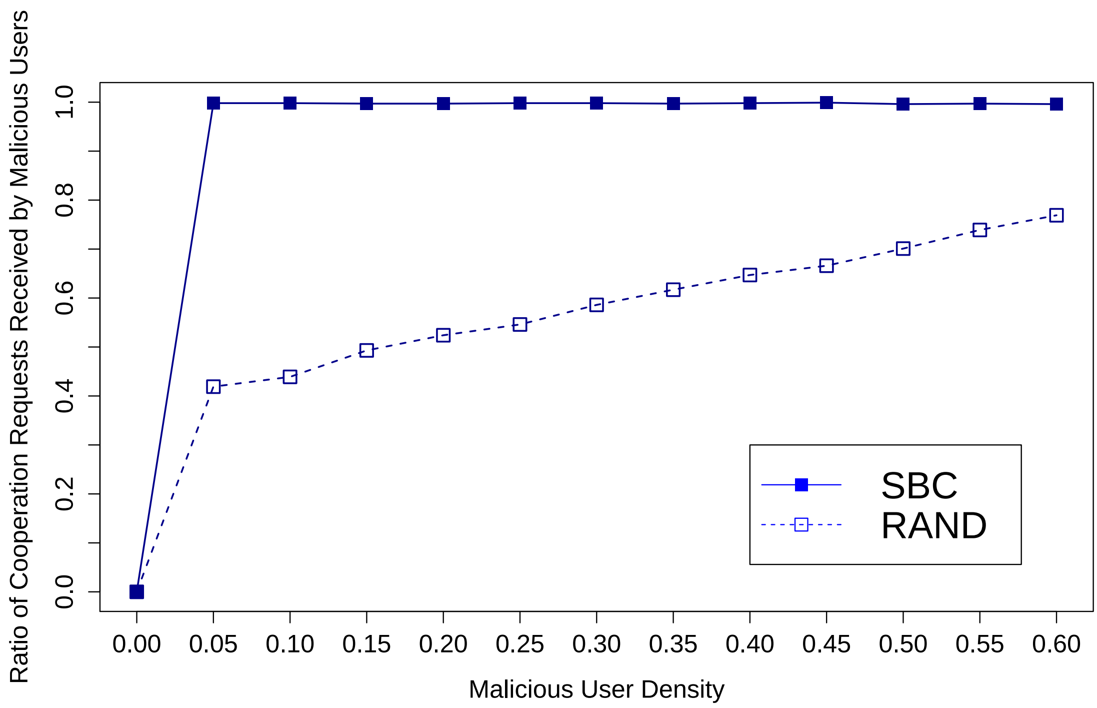


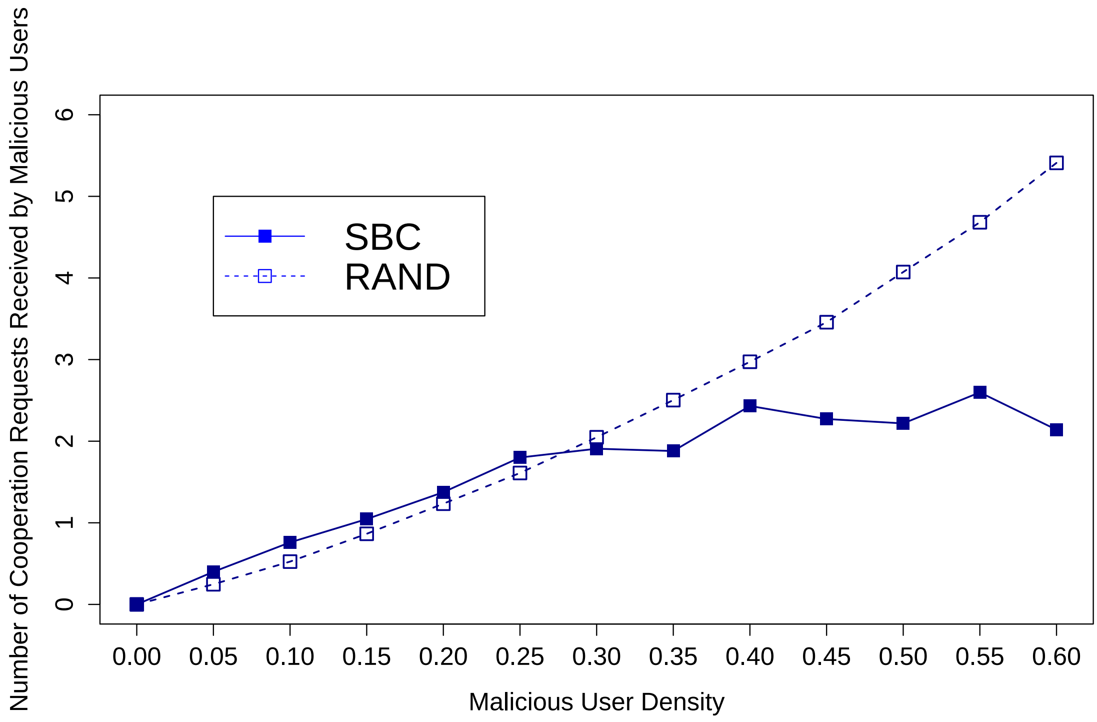
Figure 17: Number of cooperation requests per idle channel discovery under various malicious user density

Figure 18(a) displays the possibility that other CRs agree to cooperate malicious users, they achieve almost 100% support in SBC. That is because the cooperation probability is based on the cooperation tendency of CR_i. For example, if CR_i is a malicious user, it always accepts cooperation requests. When CR_i searches for cooperation as a transmitter, its requests are likely to get accepted. This is due to the candidate cooperators which assumes that CR_i would always support them in return. In contrast, CRs in RAND model just select cooperators randomly. With the increase in d_m, malicious transmitter could find more malicious cooperators, thereby enhancing the ratio of cooperation. In summary, the malicious users in SBC are more able to distinguish the cooperators with lower reject ratio than RAND.

But we do not expect the malicious users receive so much support. Figure 18(b) outlines the actual number of cooperation that malicious users receive: the curve of SBC does not always increase but stays steady later, while the curve of RAND continuously goes up. Overall, despite malicious transmitter in SBC gets higher cooperation efficiency, SBC still ensures that normal users attain more cooperation opportunities.



(a) Ratio of cooperation



(b) Number of cooperation

Figure 18: Cooperation requests received by malicious users under various malicious user density

4.2.2 Influence of diverse cooperation threshold (λ_{coop})

In our experiments, we set λ_{coop} as below:

$\lambda_{coop} = \{0, 0.1, 0.2, 0.3, 0.4, 0.45, 0.475, 0.5, 0.525, 0.55, 0.575, 0.6, 0.7, 0.8, 0.9, 1\}$

when λ_{coop} increases, the standard of being a qualified cooperator is more strict. According to the *cooperator set selection* algorithm in Section 3.2.1, only the CRs whose overall score outweigh λ_{coop} could be selected as cooperators. In this part, our focus is determining the suitable value of λ_{coop}.

Figure 19 shows the ratio of idle channel discovered when malicious user density d_m is low (0.2), moderate (0.5), and high (0.7). Since malicious users restrict the accessing to idle channel, we can see the ratio of idle channel discovery in high d_m scenario is worse than low d_m scenario. For example, when λ_{coop} is 0.2, the ratio of idle channel discovery in low d_m, moderate d_m, and high d_m scenario are 0.58, 0.35 and 0.17 respectively.

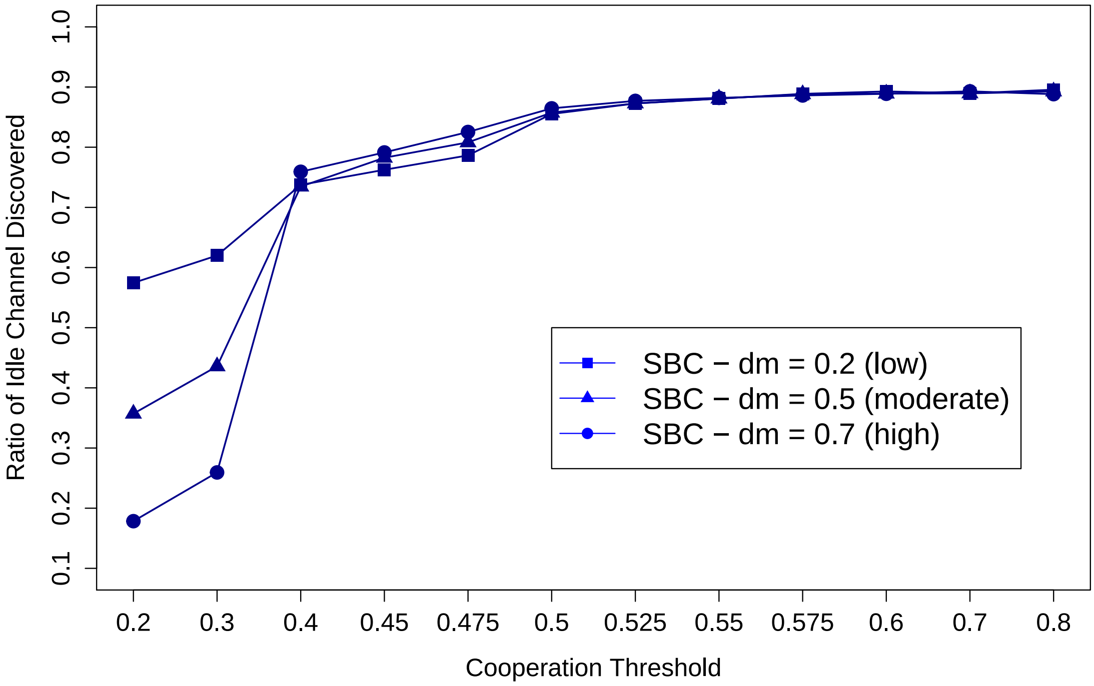


Figure 19: Ratio of idle channel discovered under different cooperation threshold

As the increase of λ_{coop}, the idle discovery ratio all experience an upward trend in three scenarios. When λ_{coop} arrives at 0.4, the ratio under three scenarios all reaches 75%. When λ_{coop} is between 0.4 to 0.525, the ratio converge to 90%, which is the theoretical highest value. However, too high λ_{coop} results in the restriction of cooperation. We set λ_{coop} to be 0.45, for the sake of encouraging CR cooperation behaviour, as well as avoiding a waste of cooperation opportunities.

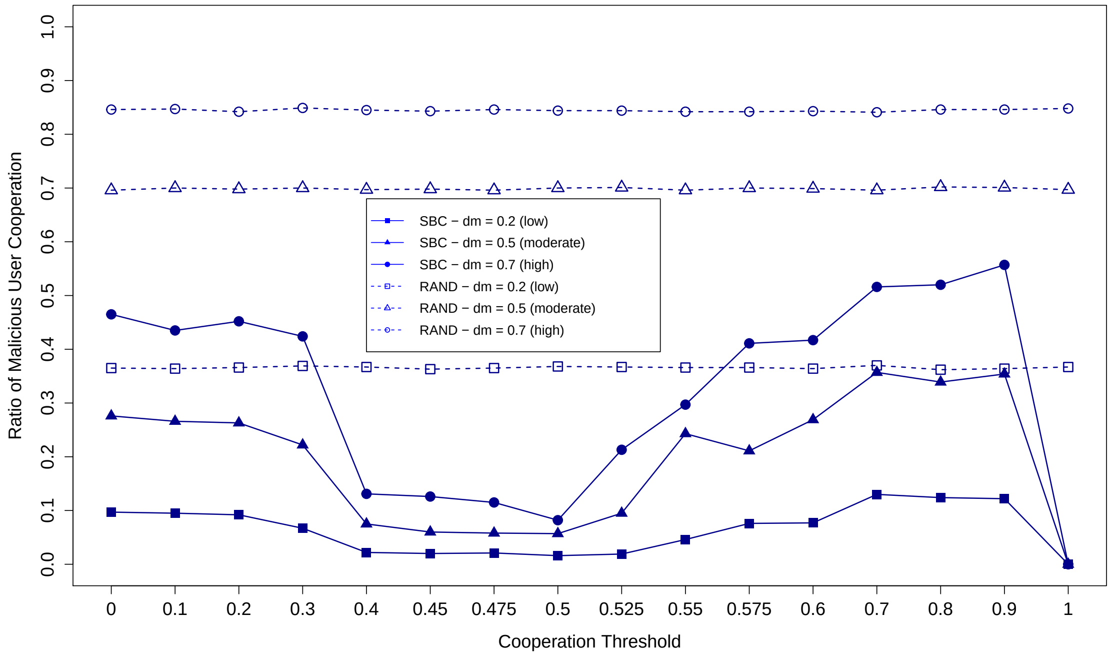


Figure 20: Ratio of malicious users cooperation under different cooperation threshold

Figure 20 shows the ratio of cooperation with malicious users. The three dotted curves of RAND are easy to understand: the higher d_m is, the more possibility of cooperating with malicious users. In comparison, the curves of SBC deserve to be noticed. When λ_{coop} goes up from 0 to 0.4, SBC's resistance to malicious user also increases, hence the ratio of malicious cooperation decreases gently.

When λ_{coop} is between 0.4 and 0.5, the value of y-axis remain stable at the wave valley, showing that λ_{coop} has functioned well here, thereby leading the minimum probability to cooperate with malicious users. However, when λ_{coop} ascends from 0.5, the ratio of malicious user cooperation starts to surge. The reason is that, λ_{coop} turns too high for CR finding appropriate cooperators, thus CRs have to sense themselves instead of cooperative sensing gradually. Moreover, the cooperative behaviour tends

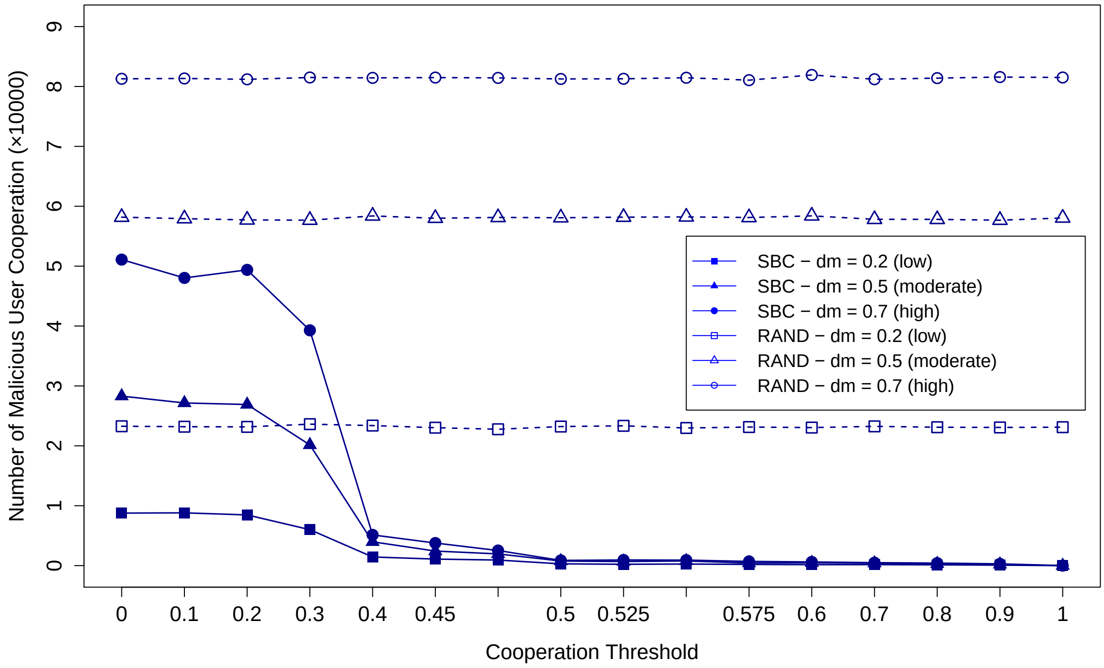


Figure 21: Number of malicious users cooperation under different cooperation threshold

to occur between friends now. In other words, λ_{coop} loses its effects of selecting reliable cooperators, as it restricts cooperation too much. Finally for $\lambda_{coop} = 1$, the ratio drops to 0 suddenly, indicating cooperative behaviour stops at this point. All in all, we select 0.45 as the value of λ_{coop}.

Figure 21 reflects the quantitative characteristics of Figure 20, i.e. the cooperation number with malicious users. When λ_{coop} equals to 0.4, the number of malicious user cooperation plummet to a fairly small value. Furthermore, When λ_{coop} is larger than 0.5, the number of malicious user cooperation almost bottom out at 0. Figure 21 supports our decision to set λ_{coop} as 0.45. Although it might not be the optimal decision, it already meets the requirements: screening out reliable cooperators and not interfere the cooperation behaviour at the same time.

4.3 Effect of social degree on performance

In the last section, we compare SBC and RAND in terms of the robustness in malicious network, i.e. the CRN containing malicious users. Next, we intend to discuss the effect of social degree on CR's sensing performance. In order to get a wide diversity of CRs' social degree, we use scale-free graphs as the social input.

In human society, the people of sociability have more friends, know a wider range of information, and acquire better resources. They look like having advantages in seeking help, in particular. In SBC, the CRs carry social context of their users, which is reflected by social graph. The social degree of CRs shows their sociability: high degree CR have more friends, it means they are social CRs, while low degree suggests relative lonely CRs. In this model, the social degree refers to the number of 1-hop neighbours in social graph, aka the number of friends. The difference between social CR and lonely CR in terms of sensing performance are the main point we discuss in this section.

In order to increase the generality of social graph, we use ten scale-free graphs as input, which have the same graph density 0.05. Figure 22 shows the social degree distribution of the ten scale-free graphs: the x-axis refers to CR's social degree, and the y-axis is the number of CRs which owns the corresponding social degree. According to scale-free feature, only a few nodes have high degree while the majority of CRs just have low degree. Table 5 shows the distribution of number of nodes with each social degree. For example, there are 257 CRs with only one adjacent edge in the social graph. The number of CRs whose degree surpass 5 are lower than 10. Since a scale-free graph has 40 nodes, there are totally 400 nodes taken into account in the simulation. When illustrating the sensing performance of CRs, we take the average value of the CRs in the same degree. That is to say, we just consider the effect of social degree in this section.

Table 5: The number of CRs in differ social degree.

Social degree	1	2	3	4	5	6	7	8	9	10	11
Number of CRs	257	66	33	15	6	4	4	2	3	3	7

Figure 23 shows the number of friends within CR's transmission range, i.e. the same grid it locates. Mobility model changes the physical location of CRs during each timeslot, making them move to the grid where most friends locate. It is obvious that, the friend number is positive proportional to CR's social degree. In other words, high-degree CR have more chances to meet friends and cooperate with them since friends have lower reject ratio. Contrarily, low-degree CRs have low probability of meeting their friends, so that they have to cooperate with unfamiliar CRs.

Our research in this section concentrates on the impact of social degree on performance. For the sake of simplifying our model, we utilize non-malicious network, i.e. d_m equals to 0.

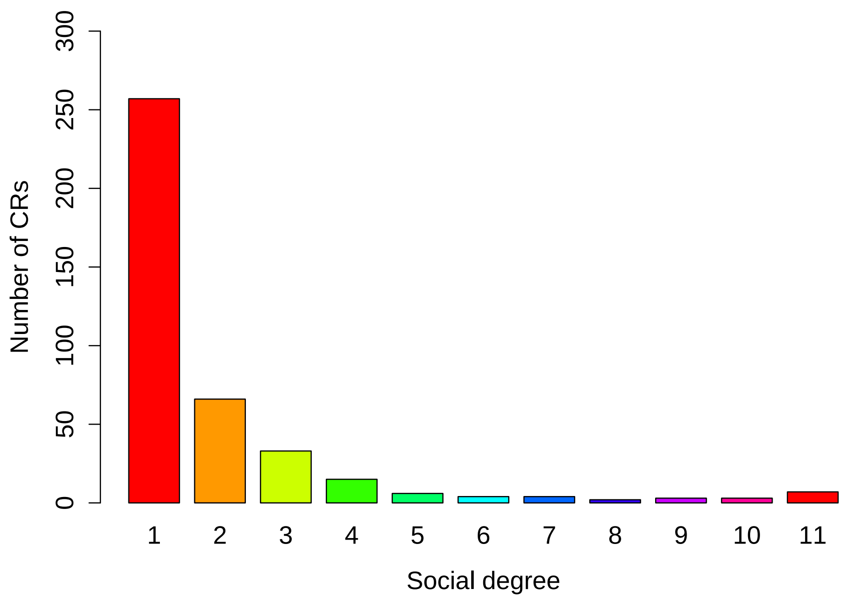


Figure 22: Number of CRs in different social degree

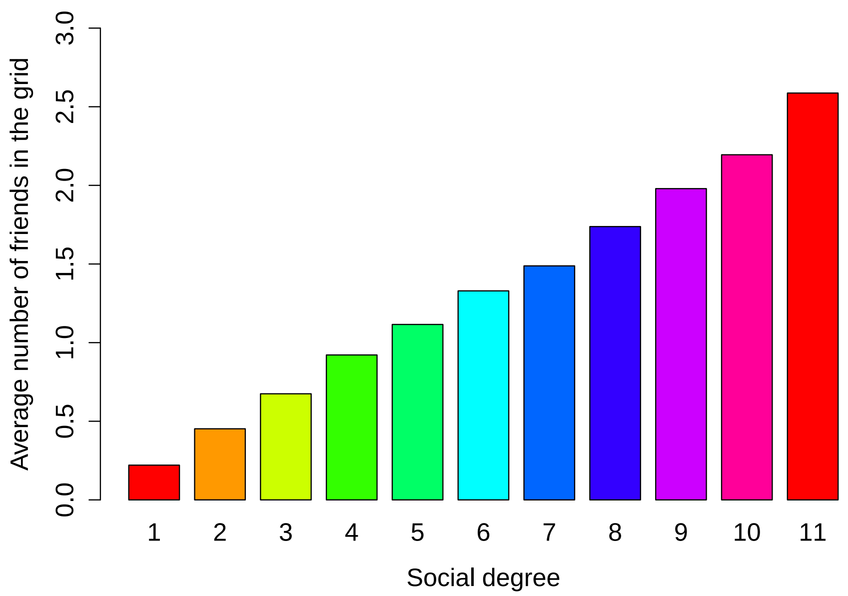


Figure 23: Number of CRs' friends in the same grid

4.3.1 Employing low cooperation threshold

When λ_{coop} is 0, all CRs could select cooperators arbitrarily, regardless of the cooperative sensing quality. In this section, we intend to show the differences of CRs' cooperators in SBC.

Figure 24 (a) and (b) show the global probability of detection (Q_d) and the global probability of false alarm (Q_f) obtained by CRs with diverse social degree. We can see that, the CRs get similar Q_d and Q_f regardless of their social degree. That is due to no limitation in selecting cooperators when λ_{coop} is 0. Therefore, each CR gets similar number of cooperators.

Figure 24 (c) shows the average number of cooperators per cooperative sensing, i.e. when CR_i requests cooperative sensing, the number of CRs accepting its request. The figure illustrates the average value of cooperator number. Theoretically, high-degree CR has more cooperators. But the difference is not apparent. For instance, the 11-degree CR's ($CR_i^{D=11}$) average n_{coop} is 2.42, while leaf node ($CR_i^{D=1}$)'s average n_{coop} is 1.77. Since Q_d and Q_f is positive correlated to n_{coop}, Q_d and Q_f do not show obvious variation with the difference of social degree in Figure 24 (a) and (b).

Figure 24 (d) shows the reject ratio of cooperation requests. The higher social degree is, the lower reject ratio gets. Figure 24 (e) and (f) explain the phenomenon. Figure 24 (e) reflects the social distance from the transmitter CR_i with its cooperator CR_j. According to Equation 20, whether CR_j accepts the request from CR_i depends on their social distance, especially when they have never cooperated before. Consequently, the reject ratio of CR_i is positive proportional to CR_i's social distance with cooperators. High-degree CR in Figure 24 (e) has smaller social distance, thus bringing smaller reject ratio.

Figure 24 (f) illustrates the probability of cooperation with friends. High-degree CR has higher ratio of friend cooperation. We can see from Figure 23 that $CR_i^{D=11}$ has the most number of friends. This implies that they are more likely to meet friends and choose them as cooperators. Accordingly, the social distance from $CR_i^{D=11}$ to cooperators is the lowest, so that its reject ratio of the cooperators is small. On the other hand, it is hard for $CR_i^{D=1}$ meeting the unique friend. $CR_i^{D=1}$ has to cooperate with strangers, resulting in its social distance with cooperators outweigh 3. That is to say, the social gap from $CR_i^{D=1}$ to the cooperators almost reaches 2. Generally, CRs tends to support familiar companions, therefore the reject ratio of $CR_i^{D=1}$ becomes relatively high.

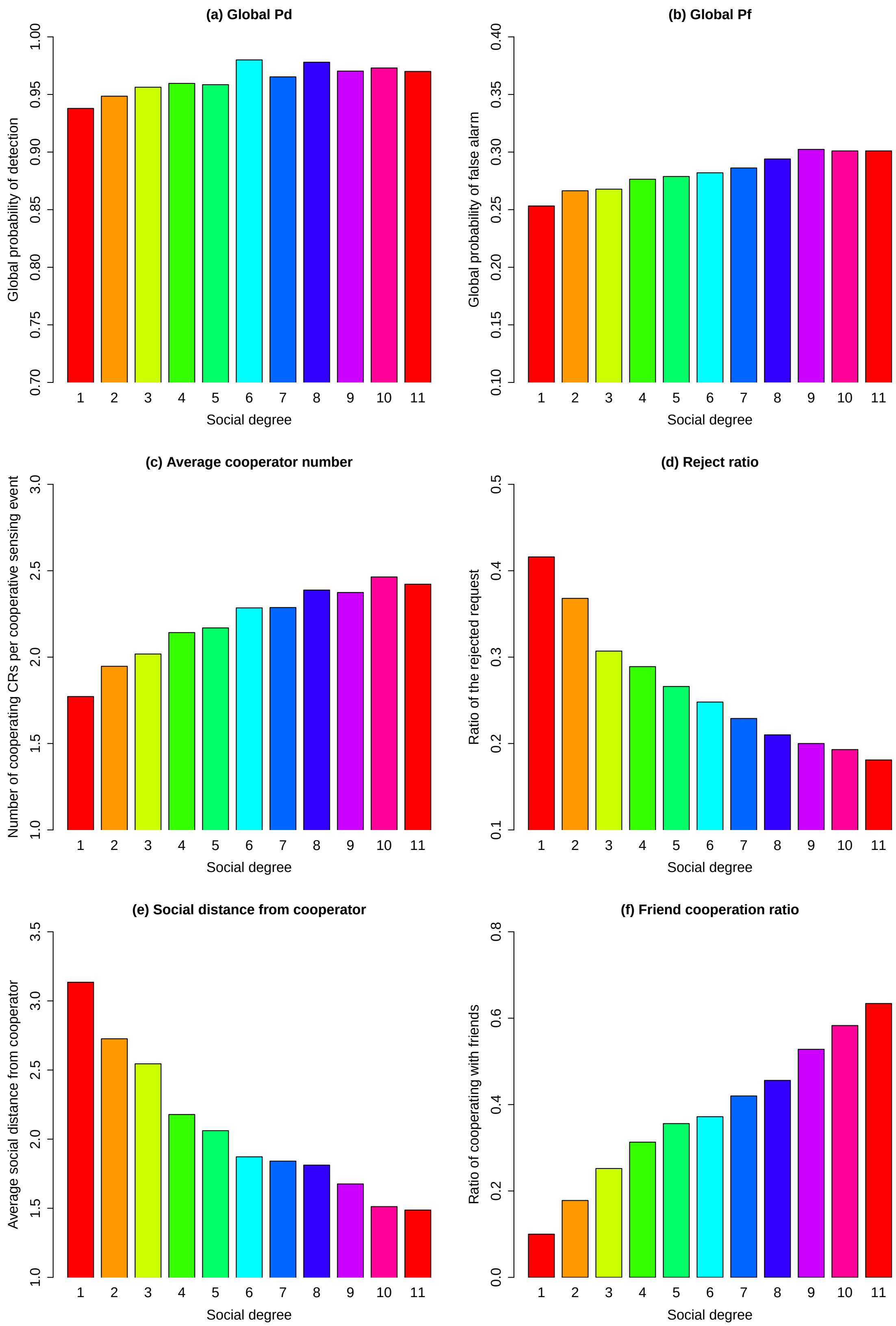


Figure 24: Sensing performance when cooperation threshold is 0 ($\lambda_{coop} = 0$)

Overall, Figure 24 shows that, high-degree CR achieves better cooperation opportunities. Although low-degree CR has got enough cooperation opportunities, it has high probability to be rejected, leading to a waste of resources.

4.3.2 Employing increasing cooperation threshold

In this section, we want to explore how the sensing performance of CRs (low-degree, moderate degree, and high degree) varies with increasing λ_{coop}.

According to the social degree distribution in Figure 22, we define the 1-degree CR ($CR_i^{D=1}$) as low degree CR, the 3-degree CR ($CR_i^{D=3}$) as moderate degree CR, and the 11-degree CR ($CR_i^{D=11}$) as high degree CR. The total number of $CR_i^{D=1}$, $CR_i^{D=3}$, and $CR_i^{D=11}$ is 257, 33, and 7 respectively as shown in Table 5. Thus, the sensing performance shown in Figure 25, 26, 27, and 28 all take the average of the CRs in corresponding social degree.

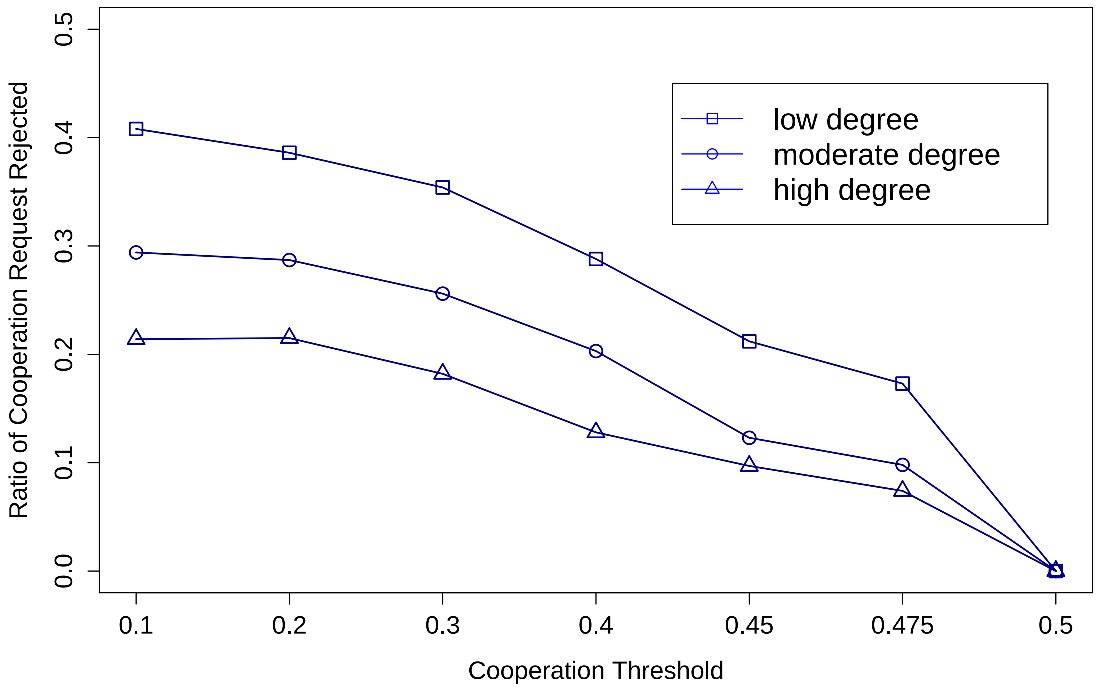


Figure 25: Reject ratio under different cooperation threshold

From Figure 24 (d) we know, the reject ratio is inversely proportional to CR's social degree. In other words, low-degree CRs have higher reject ratio when λ_{coop}

is 0. Figure 25 shows the reject ratio of three types CRs when λ_{coop} rises. More specifically, the reject ratio of $CR_i^{D=1}$ declines with rising λ_{coop}, which means $CR_i^{D=1}$ becomes more able to distinguish satisfied cooperators, thereby reducing the ratio of rejected request. On the other hand, $CR_i^{D=11}$ remains low reject ratio all along, and it still shows a slight decrease. That is to say, the reject ratio of high-degree CR is more stable, it always chooses reliable cooperators. Until λ_{coop} arrives 0.5, the reject ratio of all CRs drop to 0. At this point, all of the CRs just cooperate with friends. The performance of moderate-degree $CR_i^{D=3}$ falls in between $CR_i^{D=1}$ and $CR_i^{D=11}$. Basically, the non-ideal reject ratio of low-degree CR approximates ideal reject ratio step by step with the increasing of λ_{coop}, while high-degree CR shows more stable performance.

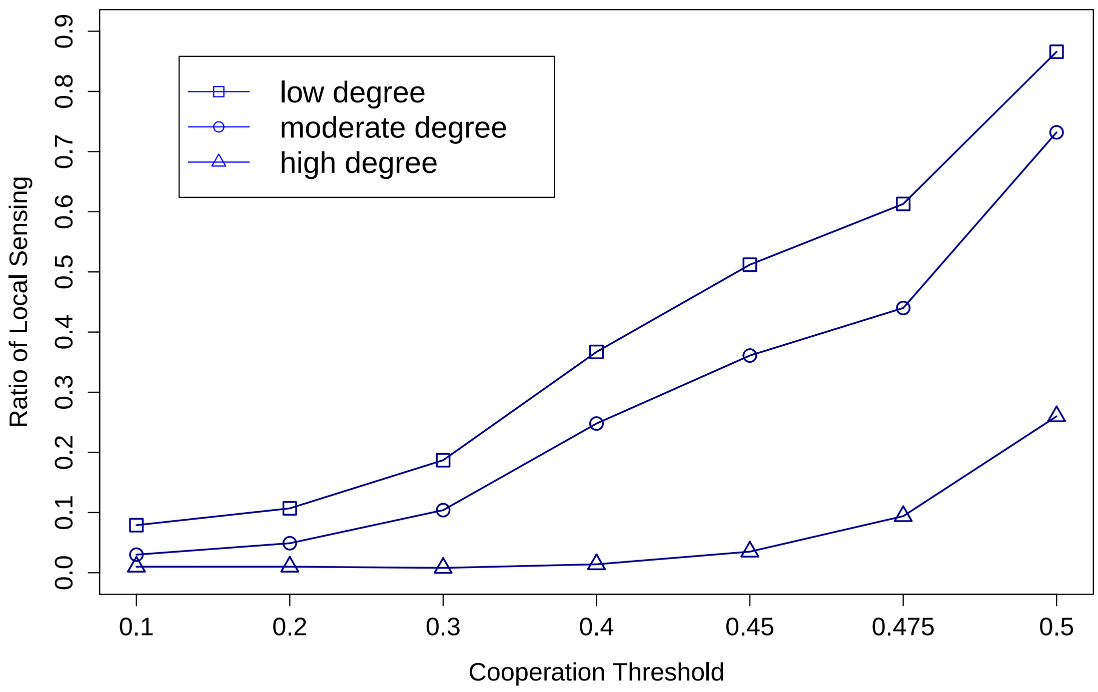


Figure 26: Local sensing ratio under different cooperation threshold

Figure 26 displays the local sensing ratio of different CRs. CR_i has to perform local sensing when all of its cooperation requests suffer from rejection. The local sensing ratio of CR_i refers to the proportion that CR_i does not receive any cooperation but just performs local sensing. With increasing λ_{coop}, the local sensing ratio of $CR_i^{D=1}$ soars compared with $CR_i^{D=11}$. More precisely, $CR_i^{D=1}$ does not have enough suitable cooperators. Therefore, it has to give up cooperative sensing for the sake of maintaining sensing performance. On the other hand, the local sensing ratio of $CR_i^{D=11}$ remains much more stable: it just see a slight increase when λ_{coop} reaches 0.45. The curve of moderate $CR_i^{D=3}$ is between $CR_i^{D=1}$ and $CR_i^{D=11}$. For example, the local sensing ratio of $CR_i^{D=1}$ reaches 86% when λ_{coop} is 0.5, while the local sensing ratio of $CR_i^{D=11}$ is just 26% at the same point.

In essence, λ_{coop} tunes the selection of cooperators. When λ_{coop} is high, it is harder for low-degree CR to find satisfied cooperator meeting the standard. As a result, low-degree CR has to implement local sensing instead. On the contrary, high-degree CR could always find high-quality cooperators, therefore it guarantees reliable co-operation all the time.

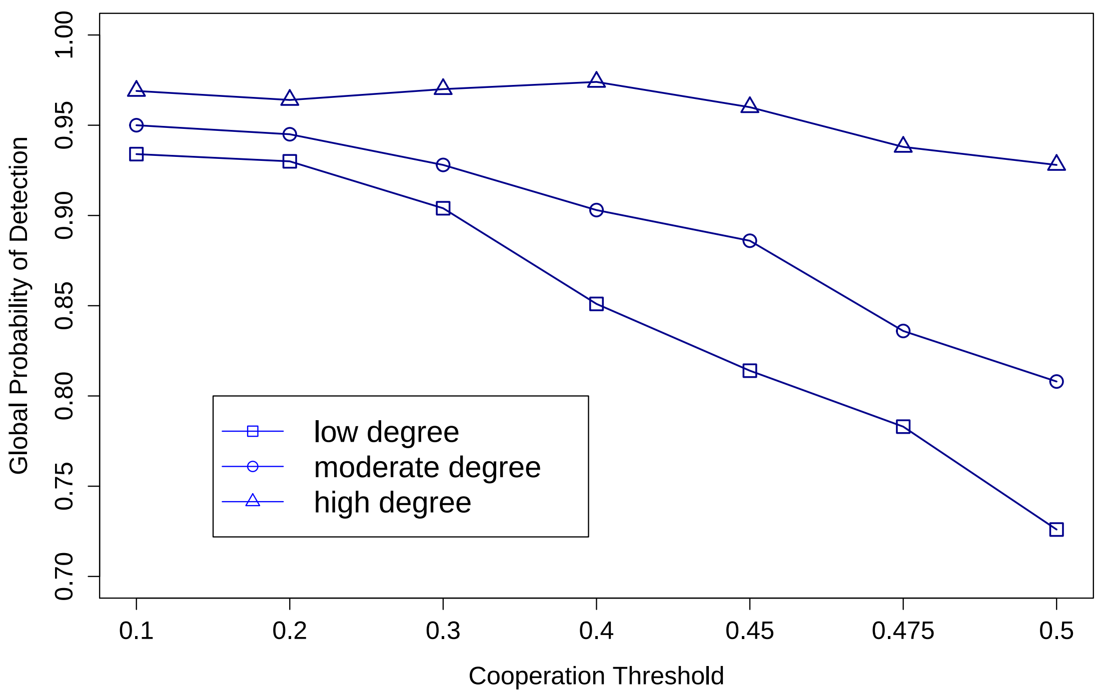


Figure 27: Global probability of detection under different cooperation threshold

Figure 27 shows the variation in global probability of detection (Q_d). Specifically, $CR_i^{D=11}$ keeps higher and steady Q_d, whereas the Q_d achieved by $CR_i^{D=1}$ declines with increasing λ_{coop}. Since the local sensing ratio of $CR_i^{D=1}$ soar, it leads to the decline of n_{coop}, which is directly correlated to Q_d. The curve of moderate-degree CR is in the middle of high-degree CR and low-degree CR.

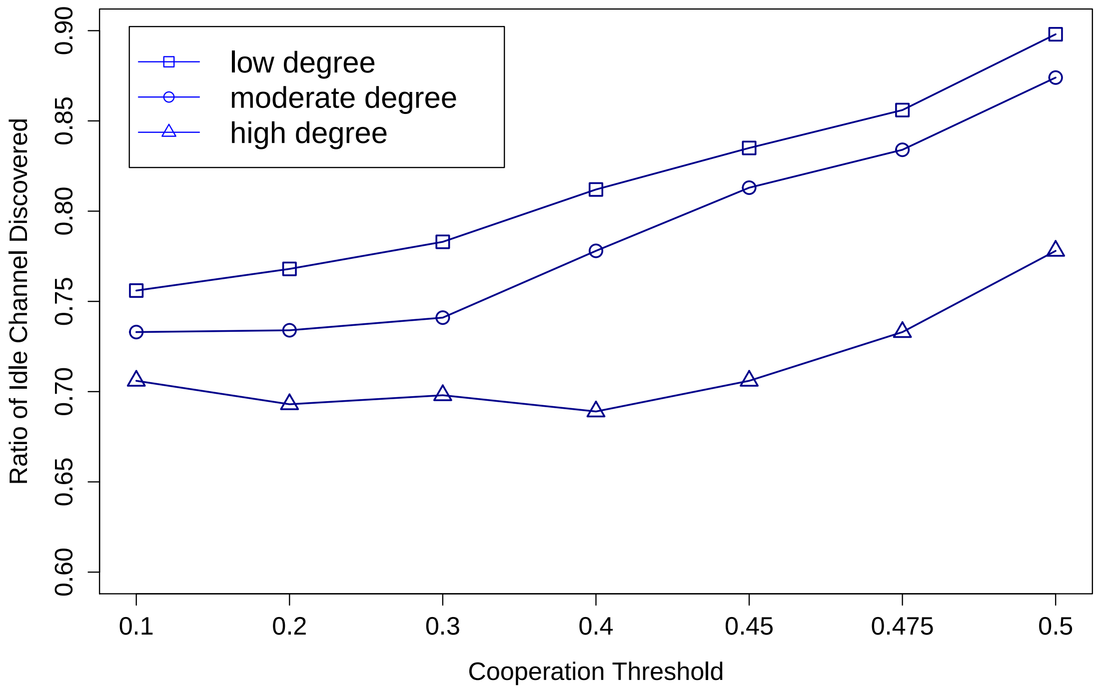


Figure 28: Ratio of idle channel discovered under different cooperation threshold

Figure 28 illustrates the idle channel discovery ratio by different CRs. Apparently, the probability of idle channel detected by $CR_i^{D=1}$ shows an upward trend along with increasing λ_{coop}. It means the sensing performance of $CR_i^{D=1}$ is enhanced by the restriction of λ_{coop}. The fluctuation of $CR_i^{D=11}$ is much gentler: it remains stable until λ_{coop} surpass 0.45, then witnesses a tender incline. The idle channel discovery ratio of moderate-degree CR is always between low-degree and high-degree CR.

In summary, the sensing performance of high-degree CR remains relatively stable, regardless of λ_{coop} changing. $CR_i^{D=11}$ achieves higher cooperative sensing ratio, better probability of detection, as well as lower reject ratio. On the other hand, low-degree CR is sensitive to the variation of λ_{coop}. The high values of λ_{coop} eliminates unreliable cooperators gradually. Due to the lack of suitable cooperators, $CR_i^{D=1}$ has to give up the unreliable cooperation opportunities and turn to sense itself to guarantee sensing performance and energy efficiency. Despite the global probability of detection decreases, $CR_i^{D=1}$ attains better idle channel discovery ratio, as well as decreased reject ratio. The overall sensing performance of $CR_i^{D=1}$ improves. To conclude, when λ_{coop} increases from 0 to 0.5, high-degree CR maintains steady and reliable performance, while low-degree CR loses cooperation opportunities but achieves improved sensing performance.

4.3.3 Employing high cooperation threshold

In this section, we intend to compare the global probability of detection (Q_d) and the global probability of false alarm (Q_f) among CRs of various social degree. Figure 29 shows the sensing performance of SBC when cooperation threshold λ_{coop} is 0.5.

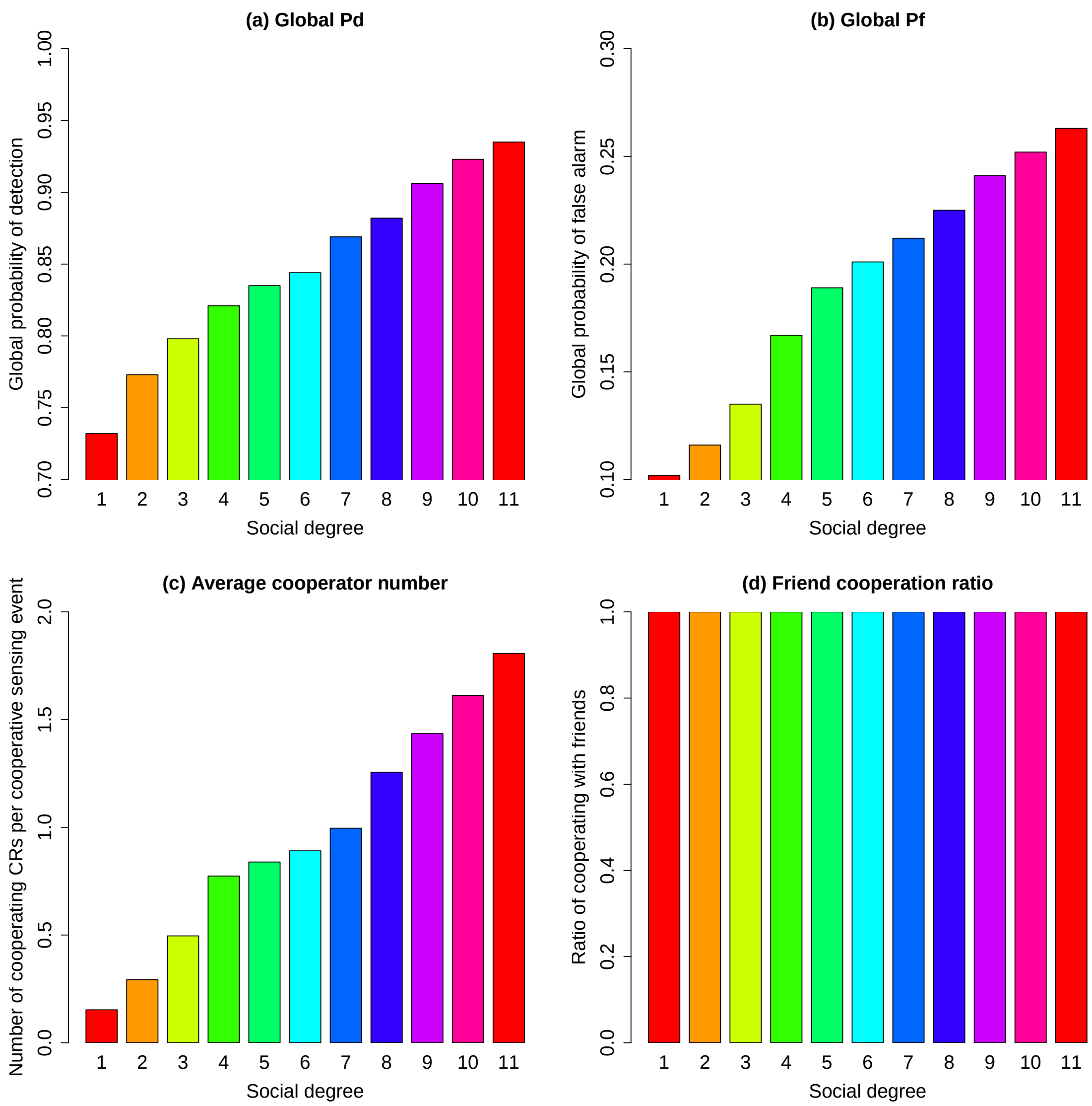


Figure 29: Sensing performance when cooperation threshold is 0.5 ($\lambda_{coop} = 0.5$)

As can be seen from Figure 29 (d), all the CRs only cooperate with friends at this point. In other words, they even do not select a two-hop node, i.e. friend-of-a-friend as cooperator, which is not expected by us. In real life, it is rarely to just ask friends for help. In this condition, we consider CRs' cooperation behaviour are restricted excessively by λ_{coop}. Hence, 0.5 is a high cooperation threshold for the system.

According to Figure 24 (a), the Q_d of CRs does not show substantial distinction because CR_i can select any CRs as cooperators. Under such circumstance, the system cannot recognize malicious users, bringing the hidden risk to itself. Figure 29(a) shows that the Q_d of high-degree CR outperforms low-degree CR significantly. The high-degree CR could always find reliable cooperators, but the low-degree CR has to perform local sensing.

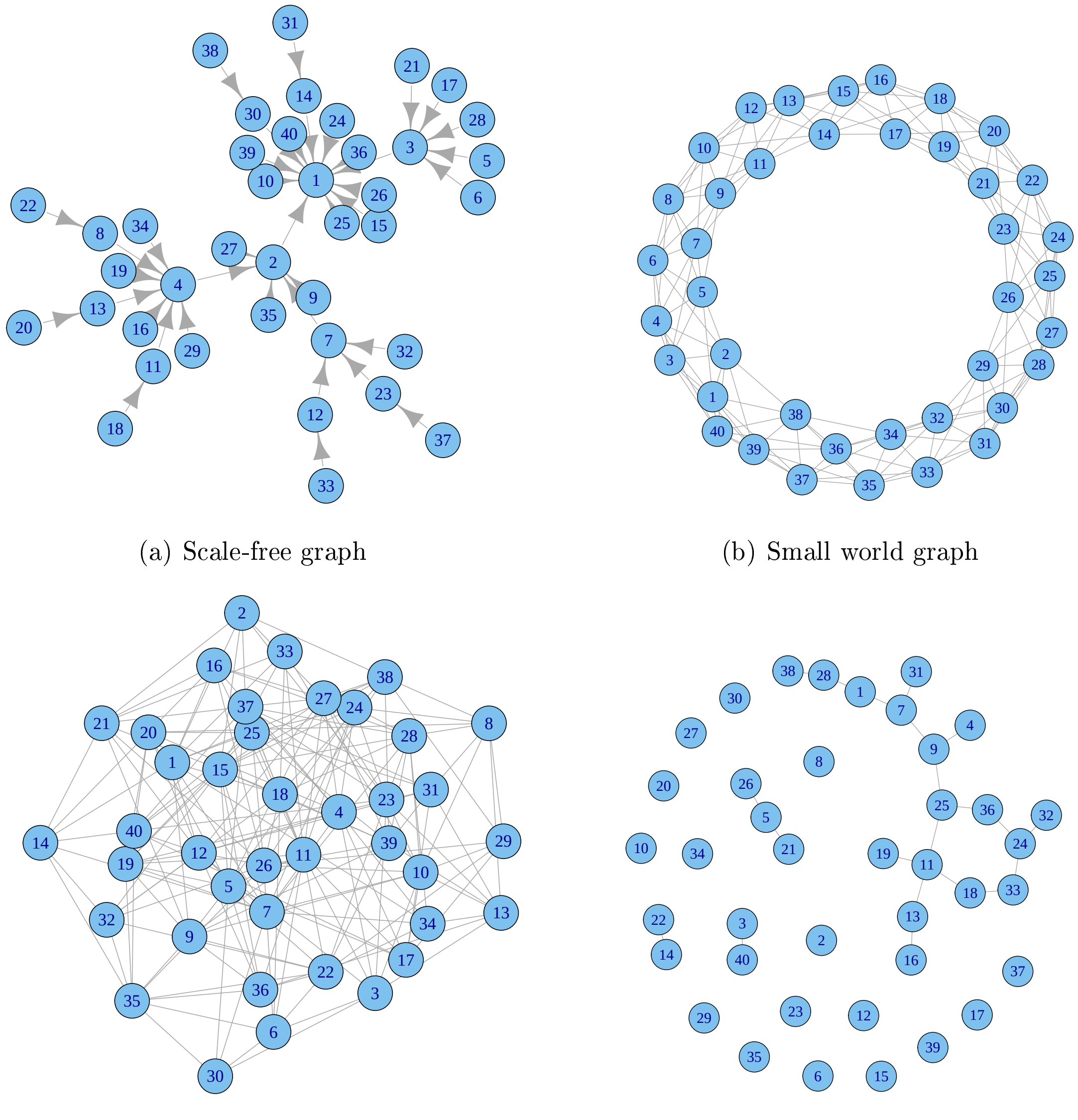
We can see from Figure 29 (c), the average number of cooperators per cooperative sensing of $CR_i^{D=1}$ is only 0.15, that is to say $CR_i^{D=1}$ hardly get cooperated. In Figure 29 (a), the Q_d of $CR_i^{D=1}$ is 0.73, just exceed the local probability of detection ($P_d = 0.7$) for 4.2%, which verifies our analysis: $CR_i^{D=1}$ mainly perform local sensing. Overall, low-degree CR has similar capability of distinguishing malicious user with high-degree CR, but the former's detection performance is far behind the latter's. Since Q_f and Q_d are both directly relevant to the cooperation number, the distribution in Figure 29 (a), (b), (c) are roughly the same.

In conclusion, under the premise in system robustness, the sensing performance of various CRs has positive correlation to their social degree. High-degree CR achieves better sensing performance compared with low-degree CR.

4.4 Effect of social graph on performance

We generate a small world graph as social input in Section 4.2, and a scale-free graph as input in Section 4.3. In this part, we intend to discuss the effect of different social inputs on system sensing performance. Figure 30 shows the four topologies employed in the simulation: scale-free graph, small world graph, random graph, and weak-linked graph.

Figure 31 shows the global metrics of the four graphs. It is clear in Figure 31 (a) that, random graph has the largest density and weak-linked graph has the smallest density. Since graph density is correlated to the number of links, distribution in Figure 31(a) and 31(b) are similar. From Figure 30(c) and 30(d), the former graph shows fairly close connections among the nodes, whereas the latter graph illustrates little links. The graph diameter refers to the largest value among all the shortest path length between any pairs of nodes in the graph. As can been seen in Figure 31



(a) Scale-free graph

(b) Small world graph

(c) Random graph

(d) Weak-linked graph

Figure 30: Four types of social graph

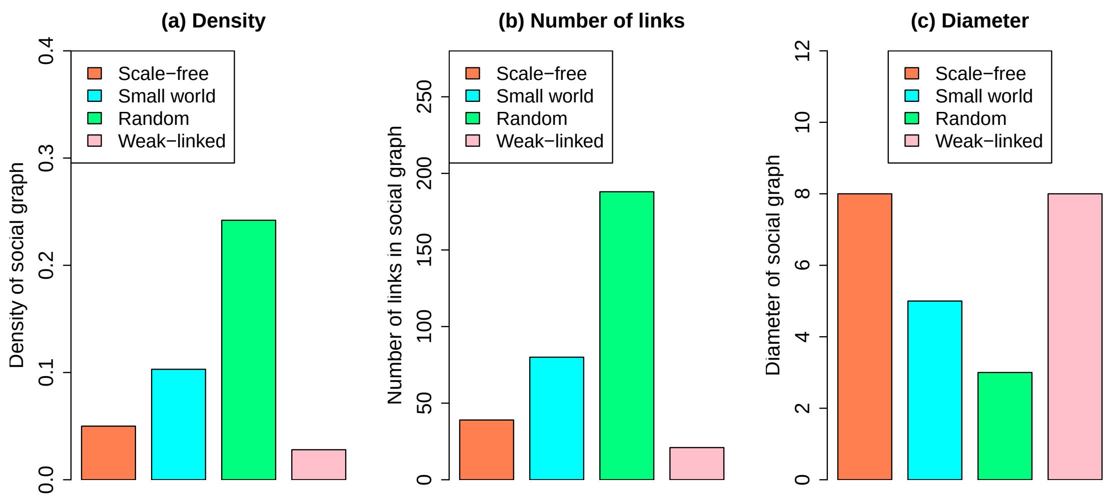


Figure 31: Density and Diameter of four social graphs

(c), scale-free graph and weak-leaked graph have the highest diameter. Specifically, the longest distance from one node to another is 8 in this two graphs. The diameter of small world graph is 5, coincident with the “Six degrees of separation” theory, which says the distance between any nodes in small world graph do not exceed six. Unlike the other three graphs, some nodes in weak-linked graph can never reach the others.

Figure 32 reflects the sensing performance of SBC when applied the above four topologies as social input. In Figure 32 (a), weak-linked graph has the smallest global probability of detection (Q_d). Since the majority of nodes in weak-linked graph are isolated, they have little opportunities to cooperate with friends. Next we analyze the results of weak-linked graph. The average number of cooperators per cooperative sensing of weak-linked graph in Figure 32 (d) is less than 0.5, which means the weak-linked CRs merely get cooperated. Correspondingly, the local sensing ratio (Figure 32 (c)) of weak-linked graph is the highest among all, arrives at 0.77. Furthermore, the average social distance of all CRs (Figure 32 (e)) in weak-linked graph approaches to a relatively high value, as well as the average social distance from transmitter to cooperators (Figure 32 (f)). That is because the CRs have no chance but to cooperate with strangers in weak-leaked graph, leading to the higher social distance between cooperators. Overall, using weak-linked graph as social input results is the most unsatisfactory sensing performance.

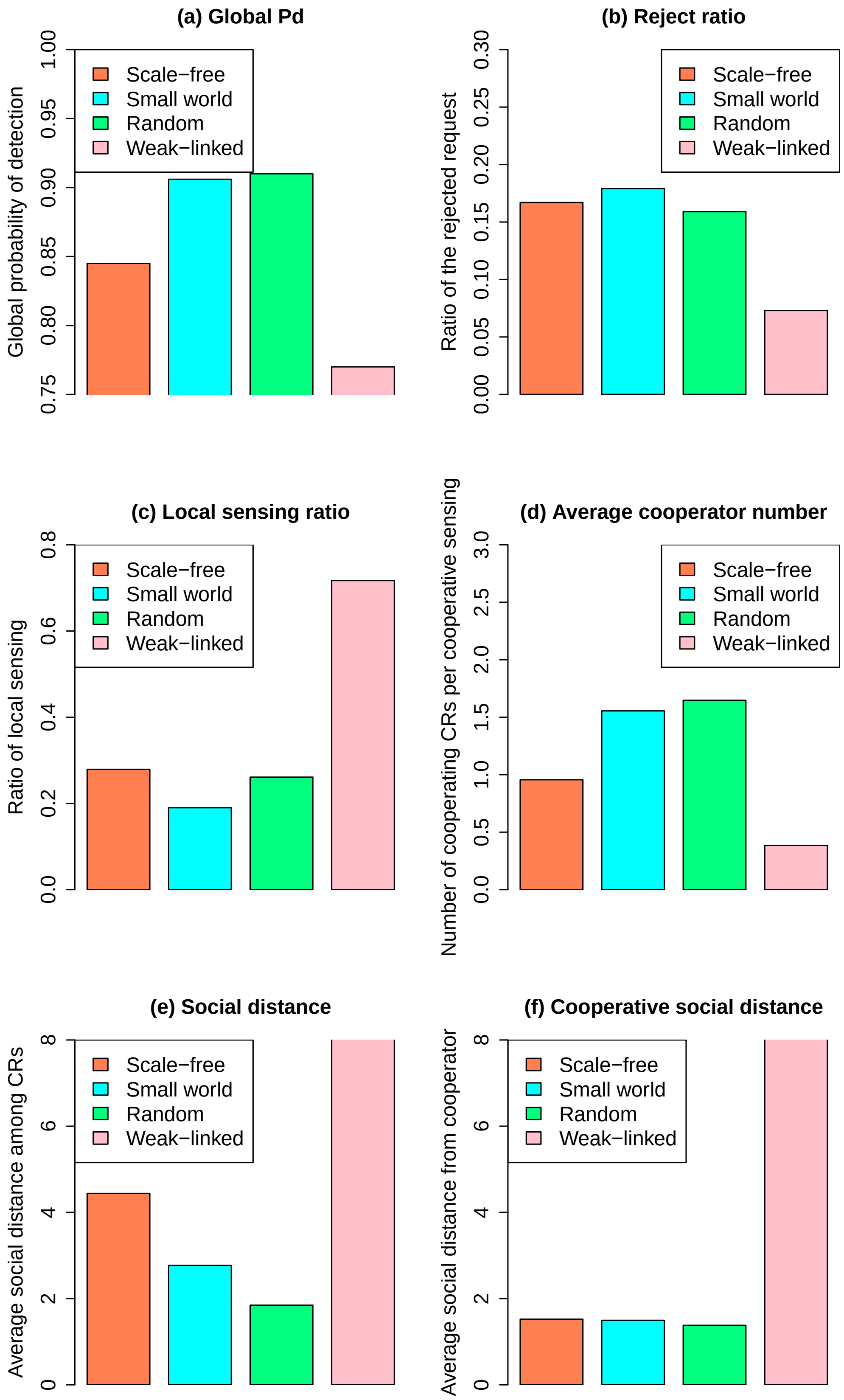


Figure 32: Sensing performance of four social graphs

Next, we compare small world graph and random graph. From Figure 32 (a), the global Pd of the two graphs are similar. It's worth noting that, the density of random graph is twice of small world graph's, but the average cooperation number of the former just surpass the latter by 5.9%, given in Figure 32 (d). It implies that small world performs more efficient selection of cooperators than random. Due to the larger density, the average social distance of all CRs in random graph is less than small world graph, shown in Figure 32 (e). Theoretically, close distance contributes to cooperative sensing, but the local sensing ratio of random is higher on the contrary (Figure 32 (c)). In conclusion, CRs of small world social topology are better at utilizing social relations to assist cooperation. On the other hand, random social relation does not help to acquire cooperation opportunities effectively.

As for the scale-free graph, from Figure 32 (e) we know, the social distance of scale-free graph exceeds small world and random, which is due to its smallest density and highest diameter shown in Figure 31. Since the average social distance among all CRs is relatively high, and they prefer to select close cooperators to prevent rejection, it is harder for scale-free CRs to find suitable cooperators. Therefore, the cooperator number of scale-free is lower than small world and random graph (Figure 32 (d)). Accordingly, the global Pd of scale-free graph is less than the two graphs shown in Figure 32 (a). Owing to the limited number of cooperation, the local sensing ratio in scale-free are larger than small world and random (Figure 32 (c)).

Figure 32 (b) shows the reject ratio of cooperation request. Weak-linked graph appears to have the lowest reject ratio. That is because the CRs are more likely to cooperate with friends, but the ratio of cooperation is rather low in weak-linked graph. Figure 32 (e) demonstrates the average social distance among all CRs in network, and Figure 32 (f) illustrates the average social distance between pairs of transmitters and cooperators. Apparently, cooperative distance is less than social distance. The social distance of scale-free, small world and random graph varies, nonetheless, the cooperation distance are alike owing to the same cooperation threshold λ_{coop}.

5 Conclusion and Future Works

In the current literature of cooperative sensing in cognitive radio, most of the research assume a default mode that the cognitive radio users (CRs) are willing to cooperate with others unconditionally. While this situation does not always hold, the requested CR might reject the cooperation request due to various reasons, such as lack of energy, or security concerns. In this thesis, we propose a social-based cooperative spectrum sensing scheme (SBC), which exploits social relations among CRs to perform cooperative sensing. Specifically, CRs would consider their social ties when selecting cooperators. They also take the previous sensing performance into accounts in cooperator selection, which employs a learning mechanism. That is to say, CRs can distinguish reliable or optimal cooperators based on the past experience of cooperative sensing. The main contributions of this thesis can be listed as follows:

- This thesis integrates two research domains: cognitive radio and social network. We first introduce the background of cooperative sensing in cognitive radio and social network analysis. In specific, we summarize the classification of cooperative sensing and key techniques of cooperation. Moreover, the cooperation behaviour brings about gain and overhead at the same time, which is briefly discussed. As for the social network analysis, we illustrate the classical metrics that are used in our model based on the knowledge of graph theory. Later, we discuss the related works of exploiting social-awareness in wireless networks and social-aware cognitive radio.
- Next, we present the new CRN model and SBC in detail. SBC mainly consists of three steps: cooperator set selection, cooperative spectrum sensing and updating the sensing performance of each cooperator. Furthermore, we describe the malicious user model to generate the simulation environment by tuning the density of malicious users. Then, a random-selecting cooperative sensing scheme is introduced that is used for comparison purposes.
- The simulation concentrates on three aspects: 1) the comparison of SBC and RAND in terms of the sensing performance under different levels of malicious user density. The simulation results suggests that SBC can distinguish malicious users while RAND just cooperates with them unconsciously. 2) We analyze the effect of CR's social degree on the sensing performance. The results demonstrate that high-degree CRs have advantages in cooperative sensing. 3) Finally, we exploit four graphs as the social input of SBC and analyze the effect of social topologies on cooperative sensing.

In summary, we can list the strengths of SBC as follows:

- SBC has a scoring system to rank the candidate cooperators. Owing to this ranking logic, CRs can identify the other CRs who are more willing to cooperate and offer reliable sensing performance. Therefore, it decreases the reject ratio and maintains the sensing performance under non-ideal network environment. It is noteworthy that SBC present a learning mechanism: after each cooperative sensing event, the requesting CR would update and evaluate the sensing ability of its cooperators, as the basis of cooperator selection for next time.

- The CRs in SBC can distinguish malicious users and avoid cooperation with them. If cooperative sensing brings extra overhead due to malicious users, the CRs in SBC would turn to perform local sensing instead, to restrain the deterioration of sensing performance.

- We evaluate the performance of SBC under different social connectivity graphs, such as small world network and scale-free network, which also reflect the social features in human society. Moreover, we employ social-based mobility model to imitate the movement of CRs with human pattern. All of this makes SBC a more realistic system.

On the other hand, there are two main drawbacks of SBC.

- N_{coop}, which denotes the maximum cooperators during one cooperative sensing event, is set to a fixed number. In other words, the limitation of cooperator numbers are the same for all CRs regardless of their social degree. According to the simulation result in Section 4.3, high-degree CR does not need much cooperation but still acquire satisfied sensing performance. Since every single cooperation costs energy, the number of cooperator should be different according with CRs' social degree.

- Our scheme does not encourage cooperation among CRs who have no social ties. If employing a complex network which has a lot of nodes as the social input, it is rare that any pairs of nodes know each other.

There are interesting directions in future research. The energy efficiency is always essential in wireless communication networks. Basically, cooperative sensing costs more energy than local sensing, but it brings about cooperative gain, such as improved sensing accuracy. It needs to make a tradeoff between the energy efficiency and sensing performance of CRN. Theoretically, SBC enhances the energy efficiency as it prevents unreliable cooperation, thus decreases the energy consumed but still guarantees the sensing performance. The energy efficiency in social-based cooperative sensing deserves to be analyzed.

The PU channel recommendation in CRN has been studied in recent years. When there are multiple choices of PU channel in CRN, the CRs exchange the information of favourite PU channel based on their social ties. The recommendation on cooperators among CRs is also interesting to be discussed. Some related works have been applied in delay tolerant network (DTN) [GLZ09], to enable the nodes discover the non-cooperative nodes faster, as well as share the information of cooperative node, such as reliability and so on.

Overall, the thesis provides a new perspective in CR modelling, which exploits social network in cooperative sensing of cognitive radio. We intend to improve the social-based CR model that makes it more realistic, and to promote the development in this new research direction.

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References

ABR11 Akyildiz, I. F., Lo, B. F. and Balakrishnan, R., Cooperative spectrum sensing in cognitive radio networks: A survey. *Physical Communication*, 4,1(2011), pages 40–62.

ALV06 Akyildiz, I. F., Lee, W.-Y., Vuran, M. C. and Mohanty, S., NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey. *Computer Networks*, 50,13(2006), pages 2127–2159.

BaA99 Barabási, A. L. and Albert, R., Emergence of scaling in random networks. *Science*, 286, pages 509–512.

BAR14 Bradai, A., Ahmed, T. and Rachedi, A., Enhancing content dissemination for ad hoc cognitive radio. *Wireless Communications and Mobile Computing Conference (IWCMC), 2014 International pages = 369–374.*

CCP13 Chen, K.-C., Chiang, M. and Poor, H. V., From Technological Networks to Social Networks. *IEEE Journal on Selected Areas in Communications*, 31,9(2013), pages 548–572.

CoR15 Cognitive radio. `http://en.wikipedia.org/wiki/Cognitive_radio`

EBK15 Eryigit, S., Bayhan, S., Kangasharju, J. and Tugcu, T. *IEEE Transactions on Vehicular Technology.*

ErR59 Erdös, P. and Rényi, A., On the evolution of random graphs. *Transactions of the American Mathematical Society*, 5, pages 17–60.

GBA13 Güven, C., Bayhan, S. and Alagoz, F., Effect of Social Relations on Cooperative Sensing in Cognitive Radio Networks. *Communications and Networking (BlackSeaCom), 2013 First International Black Sea Conference on*, pages 247–251.

GgY07 Ganesan, G. and Li, Y., Cooperative Spectrum Sensing in Cognitive Radio, Part I: Two User Networks. *IEEE Transactions on Wireless Communications*, 6,6(2007), pages 2204–2213.

GaL07 Ganesan, G. and Li, Y., Cooperative Spectrum Sensing in Cognitive Radio, Part II: Multiuser Networks. *IEEE Transactions on Wireless Communications*, 6,6(2007), pages 2214–2222.

GLZ09 Gao, W., Li, Q., Zhao, B. and Cao, G., Multicasting in Delay Tolerant Networks : A Social Network Perspective. *Network*, pages 299–308.

GoM12 Govindan, K. and Mohapatra, P., Trust computations and trust dynamics in mobile adhoc networks: A survey. *IEEE Communications Surveys and Tutorials*, 14,2(2012), pages 279–298.

GhS05 Ghasemi, A. and Sousa, E. S., Collaborative spectrum sensing for opportunistic access in fading environments. *2005 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, DySPAN 2005*, pages 131–136.

GYL10 Gao, F., Yuan, W., Liu, W., Cheng, W. and Shu, W., A Robust and Efficient Cooperative Spectrum Sensing Scheme in Cognitive Radio Networks. *Communications Workshops (ICC), 2010 IEEE International Conference on*, pages 640–645.

HXL09 Hui, P., Xu, K., Li, V. O. K., Crowcroft, J., Latora, V. and Lio, P., Selfishness, altruism and message spreading in mobile social networks. *Proceedings - IEEE INFOCOM*, pages 4–9.

JaA06 Jamali, M. and Abolhassani, H., Different Aspects of Social Network Analysis. *2006 IEEE/WIC/ACM International Conference on Web Intelligence (WI 2006 Main Conference Proceedings)(WI'06).*

KDT10 Katsaros, D., Dimokas, N. and Tassiulas, L., Social network analysis concepts in the design of wireless Ad Hoc network protocols. *IEEE Network*, 24,6(2010), pages 23–29.

KNW11 Kayastha, N., Niyato, D., Wang, P. and Hossain, E., Applications, architectures, and protocol design issues formobile social networks: A survey. *Proceedings of the IEEE*, 99,12(2011).

LCL11 Li, H., Chen, C.-f. and Lai, L., Propagation of Spectrum Preference in Cognitive Radio Networks: A Social Network Approach. *2011 IEEE International Conference on Communications (ICC)*, pages 1–5.

LSC14 Li, H., Song, J. B., Chen, C.-f., Lai, L. and Qiu, R. C., Behavior Propagation in Cognitive Radio Networks: A Social Network Approach. *IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS*, 13, pages 646–657.

LSC15 Li, Y., Su, S. and Chen, S., Social-Aware Resource Allocation for Device-to-Device Communications Underlaying Cellular Networks. *IEEE Wireless Communications Letters*, 2337,c(2015), pages 1–1.

LYH09 Li, Z., Yu, F. R. and Huang, M., A cooperative spectrum sensing consensus scheme in cognitive radios. *Proceedings - IEEE INFOCOM*, pages 2546–2550.

Mar02 Marsden, P. V., Egocentric and sociocentric measures of network centrality. *Social Networks*, 24, pages 407–422.

McC86 McMillan, D. and Chavis, D., Sense of community: A definition and theory. *Journal of Community Psychology*, 14, pages 6–23.

MSC01 McPherson, M., L. S.-L. and Cook, J. M., Birds of a feather: Homophily in social networks. *Annual review of sociology*, pages 415–444.

Mit00 Mitola III, J., *Cognitive Radio: An Integrated Agent Architecture for Software Defined Radio*. Royal Institute of Technology, KTH, Sweden, 2000.

Mil67 Milgram, S., The small-world problem. *Psychology Today*, 2, pages 60–67.

JuL07 Ma, J. and Li, Y. G., Soft Combination and Detection for Cooperative Spectrum Sensing in Cognitive Radio Networks. *IEEE GLOBECOM 2007-2007 IEEE Global Telecommunications Conference*, pages 3139–3143.

MiM99 Mitola, J. and Maguire, G. Q., Cognitive radio: making software radios more personal. *IEEE Personal Communications*, 6,4(1999), pages 13–18.

MuM07 Musolesi, M. and Mascolo, C., Designing mobility models based on social network theory. *ACM SIGMOBILE Mobile Computing and Communications Review*, 11,3(2007), page 59.

OtR02 Otte, E. and Rousseau, R., Social network analysis: a powerful strategy, also for the information sciences. *Journal of Information Science*, 28,6(2002), pages 441–453.

PLG09 Peh, E. C. Y., Liang, Y.-C. and Guan, Y. L., Optimization of Cooperative Sensing in Cognitive Radio Networks :. *Structure*, ,c, pages 1–6.

PZE10 Pham, H. N., Zhang, Y., Engelstad, P. E., Skeie, T. and Eliassen, F., Energy minimization approach for optimal cooperative spectrum sensing in sensor-aided cognitive radio networks. *Proceedings of the 5th International ICST Conference on Wireless Internet.*

RiA11 Riaz, F. and Ali, K. M., Applications of Graph Theory in Computer Science. *2011 Third International Conference on Computational Intelligence, Communication Systems and Networks*, pages 142–145.

SuW07 Sun, C., Wei, Z. and Letaief, K. B., Cooperative Spectrum Sensing for Cognitive Radios under Bandwidth Constraints. *Wireless Communications and Networking Conference, 2007.WCNC 2007. IEEE*, pages 1–5.

SoZ08 Song, C. and Zhang, Q., Sliding-window algorithm for asynchronous cooperative sensing in wireless cognitive networks. *IEEE International Conference on Communications*, pages 3432–3436.

SZL07 Sun, C., Zhang, W. and Letaief, K. B., Cluster-Based Cooperative Spectrum Sensing in Cognitive Radio Systems. *2007 IEEE International Conference on Communications*, pages 2511–2515.

UnV08 Unnikrishnan, J. and Veeravalli, V., Cooperative Sensing for Primary Detection in Cognitive Radio. *IEEE Journal of Selected Topics in Signal Processing*, 2,1(2008), pages 18–27.

VKP05 Visotsky, E., Kuffher, S. and Peterson, R., On collaborative detection of TV transmissions in support of dynamic spectrum sharing. *2005 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, DySPAN 2005*, pages 338–345.

WaF99 Wasserman, S. and Faust, K., *Social Network Analysis: Methods and Applications*. Cambridge University Press, 1999.

WaS98 Watts, D. J. and Strogatz, S. H., Collective dynamics of 'small-world' networks. *Nature*, 393,6684(1998), pages 440–442.

ZhL08 Zhang, W. and Letaief, K., Cooperative spectrum sensing with transmit and relay diversity in cognitive radio networks - [transaction letters]. *IEEE Transactions on Wireless Communications*, 7,12(2008), pages 4761–4766.

ZML09 Zhang, W., Mallik, R. and Letaief, K., Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks. *Wireless Communications, IEEE Transactions on*, 8,12(2009), pages 5761–5766.

ZPS14 Zhang, Y., Pan, E., Song, L., Saad, W., Dawy, Z. and Han, Z., Social Network Aware Device-to-Device Communication in Wireless Networks. *IEEE Transactions on Wireless Communications*, 14,1(2014), pages 177–190.

ZXS12 Zhu, Y., Xu, B., Shi, X. and Wang, Y., A Survey of Social-based Routing in Delay Tolerant Networks: Positive and Negative Social Effects. *IEEE Communications Surveys & Tutorials*, 15,1(2012), pages 387–401.

Appendix 1. List of symbols

CR_i	Requesting CR, aka the transmitter
$CR_i^{D=1}$	CR whose social degree is 1, called low-degree CR
$CR_i^{D=3}$	CR whose social degree is 3, called moderate-degree CR
$CR_i^{D=11}$	CR whose social degree is 11, called high-degree CR
d_m	Malicious user density
$d_m(low)$	Low malicious user density
$d_m(moderate)$	Moderate malicious user density
$d_m(high)$	High malicious user density
d_{ij}	Social distance between CR_i and CR_j
D	Social degree of CR
H	Real PU channel state
H_i	Sensing outcome of CR_i
$H_{j,i}$	Sensing outcome from CR_j as CR_i's cooperator
id	Identification of each CR
$l_i(j)$	Social tie between CR_i and CR_j
L_l	List of social distance
L_s	List of sensing performance
L_w	List of cooperation willingness values
n_{coop}	Number of cooperators for cooperative sensing
n_{coop}^{min}	The minimum threshold of n_{coop} in tuning the weight in Equation 19
N_g	Number of grids in the system
N_{CR}	Number of CRs in the system
N_T	Number of timeslots
$N_i^{req}(j)$	Number of requests ever sent by CR_i to CR_j
$N_i^{acp}(j)$	Number of requests accepted by CR_j from CR_i
N_{coop}	Maximum number of cooperators for cooperative sensing
P_d	Local probability of detection
P_f	Local probability of false alarm
$P_{idle-idle}$	Probability of PU channel changing from idle state to idle state
$P_{busy-idle}$	Probability of PU channel changing from busy state to idle state

$P_{idle-busy}$	Probability of PU channel changing from idle state to busy state
$P_{busy-busy}$	Probability of PU channel changing from busy state to busy state
P_{idle}	Probability that PU channel is idle
P_{busy}	Probability that PU channel is busy
$p_j^{coop}(i)$	Possibility that CR_j admits to cooperate CR_i
p_{min}^{coop}	A minimum threshold of $p_j^{coop}(i)$ in tuning the weight in Equation 20
P_{loc}^{ij}	Possibility that a CR set $Grid_{ij}$ as its next location among all grids
Q_d	Global probability of detection
Q_f	Global probability of false alarm
$s_i^p(j)$	Previous cooperative sensing score of CR_j from the perspective of CR_i
$s_i^r(j)$	Recent cooperative sensing score of CR_j from the perspective of CR_i
$S_i(j)$	Overall score of CR_j from the perspective of CR_i
SA_{ij}	Social attractivity of $Grid_{ij}$ from the perspective of a CR
$t_i(j)$	Trust value from CR_i to CR_j
$w_i(j)$	Cooperation willingness from CR_j to CR_i
α	Weight of previous sensing score in Equation 17
α_l	Weight of social relation in Equation 19
α_t	Weight of trust value in Equation 19
α_w	Weight of cooperation willingness in Equation 19
β	Weight of cooperation willingness in Equation 20
λ_{coop}	Cooperation threshold

Appendix 2. List of ABBREVIATIONS

AWGN	Additive White Gaussian Noise
CMM	Community-based Mobility Model
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSS	Cooperative Spectrum Sensing
DSA	Dynamic Spectrum Access
DTN	Delay Tolerant Network
D2D	Device-to-Device
FC	Fusion Center
FCC	Federal Communications Commission
PU	Primary User
RAND	Random-selecting cooperative sensing scheme
SBC	Social-based Cooperative sensing scheme
SCL	Social Connectivity Layer
SNA	Social Network Analysis
SPBC	Shortest-Path Betweenness Centrality
SSA	Static Spectrum Access
SU	Secondary User
WCL	Wireless Connectivity Layer