國立交通大學

電信工程研究所

碩 士 論 文

針對感知無線網路設計之分散式多通道偵測策略

Design of Distributed Multi-channel Sensing Strategies for Cognitive Radio Networks

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中 華 民 國 100 年 6 月

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摘　　要

為了提升頻譜使用效率，近年來已經有許多致力於感知無線電(Cognitive Radio)的研究。在分散式的感知無線電網路中由於硬體的限制，對於感知無線電使用者而言，偵測所有頻帶在實作上是不太實際的。因此，部分可觀察馬可夫決策程序(Partially Observable Markov Decision Process, POMDP)可用於部分可觀察的環境中，提供感知無線電使用者關於網路環境的充分資訊。現有以 POMDP 為基礎的通訊協定，為了提升頻譜使用機會以及系統效能而使用了通道聚集的技術。然而，頻譜偵測所需的時間並未被考慮，在實際的環境中當通道數目增加時，過多的偵測時間冗餘將無可避免地導致頻譜機會的損失。因此，在此論文中，在考量頻譜偵測時間冗餘的情況下，我們提出了隨機式多重頻帶偵測(Stochastic Multiple Channel Sensing, SMCS)之通訊協定，以讓感知無線電使用者能夠根據部分觀察的通道狀態，針對聚集吞吐量(Aggregated Throughput)最大化做出最佳決策。藉由我們所提出的 SMCS 通訊協定，感知無線電使用者能夠快速地適應多變化的環境，這是因為多重通道偵測的最佳決策是動態調整的。除此之外，通道偵測的問題也進一步延伸至不完美偵測的情境，這將大幅降低吞吐量，因為主要使用者和感知無線電使用者之間可能會發生封包碰撞。因此，為了改善碰撞問題，感知無線電使用者除了通道選擇之外，還必須決定通道偵測的時間長度。我們提出了兩階段式的隨機式多重頻帶偵測(TSMCS)之通訊協定以將感知無線電使用者的聚集吞吐量最大化並且還能達到主要使用者服務品質的要求。關於不完美偵測的問題將被證明是凸性最佳化問題，因此藉由使用迭代式次梯度法(Iterative Approach with Subgradient)，將能有效地解決此問題。模擬結果顯示我們所提出的 SMCS 和 TSMCS 通訊協定皆能有效地讓感知無線電使用者的聚集通吐量最大化。

Design of Distributed Multi-channel Sensing Strategies for Cognitive Radio Networks

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ABSTRACT

A great amount of research has devoted to cognitive radio (CR) in recent years in order to improve spectrum efficiency. In decentralized CR networks, it is not realistic for the CR users to sense the entire spectrum in practice due to hardware limitations. Consequently, the partially observable Markov decision process (POMDP) can be utilized to provide the CR users with sufficient information in partially observable environments. Existing POMDP-based protocols adopt channel aggregation techniques in order to improve spectrum opportunities and system performance. However, the required time for channel sensing is neglected, which is considered inevitable to result in large sensing time overhead and spectrum opportunity loss in realistic environments with increased number of the channels. In this thesis, based on the partially observable channel state information in consideration of sensing overhead, the stochastic multiple channel sensing (SMCS) protocol is proposed to conduct the optimal channel selection for maximizing the aggregated throughput of the CR users. By adopting the proposed SMCS protocol, the CR users can highly accommodate themselves to the rapidly varying environment since the strategy for channel sensing is dynamically adjusted. Moreover, the channel sensing problem is further extended to the imperfect sensing scenario, which can severely degrade the throughput due to packet collision between the primary users (PUs) and the CR users. Consequently, in addition to channel selection, it is required for the CR users to determine the channel sensing time in order to address the collision problem. The two-phase SMCS (TSMCS) protocol is proposed to maximize the aggregated throughput of the CR users while still fulfilling the PUs' QoS requirements. The problem associated with imperfect sensing is proved to be a convex optimization problem and can therefore be efficiently solved by exploiting iterative approach with subgradient method. Numerical results show that the proposed SMCS and TSMCS protocols can effectively maximize the aggregated throughput for decentralized CR networks.

誌　　　謝

每年六月盛開的鳳凰花，彷彿是在提醒學子們畢業時節的到來，但這對於今年的我來說，卻具有著不同意義，因為它將為我學生生涯的終章劃下美麗的休止符。在研究所階段，因緣際會下成為 MINTer 的新成員，初次參與實驗室聚餐時聽著畢業學長們分享畢業心得的情景，至今仍是記憶猶新。兩年的時光轉眼間飛逝而去，已來到了自己發表感言的時刻。首先要感謝在研究上給予我諸多指導的 方凱田 教授，早在我參與大學部專題時期就擔任我的指導老師，創意啟發式的教導風格，讓學生們有絕對自由發揮的空間，即使在我研究方向不對之時，也不曾表現出不悅的神情，反倒是用一句句「再看看」來暗示我此路不通，是該是回頭的時候了。在老師的指引下，我終於步上屬於我的研究之路，並且一圓我出國參加研討會的夢想，最後也讓我能夠順利地在畢業典禮來臨之前完成口試。心存感激自己能夠遇到這麼好的老師，也希望自己有符合老師對我的期望。在研究所期間的這兩年，我也漸漸領悟老師堅持無為而治的理念。老師從不要求同學們要常到實驗室做研究，但在最後緊要的絕殺時刻，MINTers 總是能夠繳出漂亮的成績單，讓老師有怎麼改都改不完的期刊，這使我學會了如何在研究過程中做自我要求。

由衷感謝 MINTers 夥伴們(仲賢、建華、志明、添壽、文俊、柏軒、佳仕、子皓、其懋、俊宇、萬邦、承澤、瑞鴻、惟能、昭華、宥儒、裕平、修銘、智偉、景維、治緯、唯慶)在我研究所時期的相伴，除了給予我在解決研究問題的方法，吃飯時間也不忘邀約我一起去學校餐廳吃飯以及打打嘴砲歡樂一下。希望畢業後就業中的學長們在職場上都能展現 MINTer 一流的絕殺實力；正在當兵以及即將畢業的夥伴們，往後邁入生命中的另一個階段後，祝福你們都能夠開創出自己的一片天地；將來要繼續在實驗室打拼的學長們以及學弟妹們，相信你們一定能夠在研究方面有更加傑出的成果。

除此之外，還要感謝到瑞典做交換學生時認識的查默思酒吧團(Chalmers 98)，與你們一起當背包客在歐洲自助旅行的時光，至今仍難以忘懷，尤其是那些說不盡、令人驚奇的經驗，相信那都會是我們永遠共同美好的回憶，也希望團員們將來鴻圖大展後，能夠有機會再聚在一起，組成環遊世界豪華旅遊團。最後要感謝從小到大家人們默默給予我支持以及關心，也期許自己將來在新的階段，能夠完成下一個里程碑。

徐劭凱　謹誌　于新竹國立交通大學

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Chapter 1

Introduction

According to FCC [1], a large portion of priced frequency spectrum is underutilized in most of time and location, i.e. known as spectrum holes. However, there still exists the spectrum scarcity problem due to the increasing spectrum demand for the operations in unlicensed bands. In order to address the problem, the conventional approaches with static spectrum management are suggested to be adjusted. Cognitive radio (CR) [2] is an emerging technique exploited for dynamic spectrum access (DSA) such that the CR users are capable of opportunistically accessing the unused spectrum in licensed bands. As a result, not only the spectrum scarcity problem over the unlicensed bands can be alleviated, but also the spectrum efficiency over the licensed bands can be significantly improved [3]. The IEEE 802.22 [4] is a standard that allocates the TV broadcast spectrum on a license-exempt basis, which is considered a realization of the CR concept. In order to prevent the primary users (PUs) from being interfered in licensed bands, the CR users are required to perform spectrum sensing before opportunistic spectrum access.

In addition to centralized CR networks [5], there is also a great amount of research that has devoted to the studies of decentralized CR networks [6, 7, 8, 9, 10]. In such circumstance, the CR users have to perform spectrum sensing individually without acquiring the information about spectrum holes from centralized base stations. However, it is considered not realistic to assume the CR users to possess the full knowledge about the entire network due to hardware limitations and power constraints, especially the case that the spectrum of the primary network is comparatively wide. Therefore, the partially observable Markov decision process (POMDP) can be utilized to model partially observable CR networks. With single channel operations, the POMDP-based DSA MAC protocols are proposed to provide the CR users with the optimal policies for achieving maximum throughput [11] [12] and minimum waiting time during spectrum handoff [13]. In [14], the authors further extend the problem to the case that the CR users are capable of simultaneously accessing multiple channels while still limiting the maximum number of channels that can be operated at each specific time instant. However, the required time for channel sensing in those works is not taken into consideration, which is crucial in practice.

As a matter of fact, it is inevitable to introduce excessive sensing time when CR users are conducting wide spectrum. The more channels they sense, the more sensing time they spend. Consequently, there exists a trade-off between spectrum opportunity exploration and sensing time overhead. A cognitive hardware-constrained MAC (HC-MAC) protocol for conducting decisions on spectrum sensing and accessing is proposed in [15] in consideration of sensing time overhead. The authors assume that the joint distribution of the correlated channels are known to the CR users while the assumption is considered impractical in realistic environments. Furthermore, in consideration of the sensing time overhead and the characteristics of the channels at stationary state, the optimal policies for multiple channel sensing are proposed in [16]. However, the changes in the channel states over sensing slots are not well considered, which causes the non-negligible interference to the PUs. Therefore, a stochastic multiple channel sensing protocol is proposed in our previous work [17] in order to address the aforementioned problems. In [18], the authors extend the network model to the scenario that the PUs are unslotted based and then provide the CR users with the optimal strategy for maximizing throughput. Even though the sensing time overhead is taken into consideration in those protocols, the CR users' sensing outcomes are assumed to be perfect by performing spectrum sensing with a fixed sensing period, which is considered impractical in realistic circumstances that the CR users may receive the signals from the PUs with low SNR due to path loss or noisy channel. Consequently, the problem of sensing errors caused by imperfect sensing is not well addressed.

Under the imperfect sensing scenario, the CR users' spectrum sensing consists of the probabilities of mis-detection and false alarm. From the PUs' point of view, the lower probability of mis-detection, the better transmission reliability they have. However, the CR users are required to spend more time on channel sensing, which reduces the remaining time for access and increases the probability of false alarm. The design problem of the optimal sensing time in consideration of imperfect sensing is studied [19]. In [20], the problem is further extend to the POMDP framework for both single and multiple channel operations. The proposed strategy determines the optimal sensing time for each channel individually based on the fact that the decision on each channel can be considered independent from each other. However, the overall sensing time overhead is not taken into consideration, which leads to the performance degradation in realistic circumstances due to the highly correlation among the decisions on the sensing time for each channel. In [21], the sensing time overhead is taken into consideration in the formulated POMDP problem. However, only the case in single channel operations is considered, and the proposed policy is not applicable to multiple channel operations. In consideration of sensing time overhead and multiple channel operations, the problem of finding the optimal sensing time is studied in [22], but the proposed approach can only be exploited in the case that there are two primary channels, which is not suitable for generalized networks with multi-channel.

In this thesis, under the consideration of sensing time overhead, the stochastic multiple channel sensing (SMCS) protocol is designed to conduct the optimal policies based on partially observable channel state information with perfect sensing outcomes. In the proposed SMCS protocol, the CR users can highly accommodate themselves to the rapidly varying network environment since the channel selections for multiple channel sensing are dynamically adjusted over time slots. Furthermore, considering the feasible techniques for multiple channel sensing, two cases with wideband and narrowband sensing techniques are studied. In the wideband sensing case, the CR users are capable of sensing multiple target channels simultaneously with a fixed sensing time overhead [23, 24]. On the other hand, the channel sensing has to be sequentially conducted among target channels in the narrowband sensing, and the required time is aggregated with the increasing number of the sensed channels. The optimal policies are designed based on the CR users' sensing technique, and the maximum aggregated throughput can be achieved by adopting the SMCS protocol. Moreover, in order to provide the CR users with simplified decision-making process, the SMCS protocol with long-term statistics (SMCS-L) is proposed. In the SMCS-L protocol, the strategy for multiple channel sensing is determined based on the steady-state statistics and therefore has the lower implementation complexity.

In addition to the perfect sensing scenario, the problem of performance degradation caused by sensing errors in the decentralized CR networks is studied. Under the imperfect sensing scenario, the CR users' action-taking can be divided into two steps as follows: (a) select the candidate channels for channel sensing; and (b) determine the required time for multiple channel sensing. Consequently, the POMDP problem becomes a joint optimization problem with multi-variable. However, the decisions on the sensing time among channels are highly dependent on each other, which makes it difficult for the CR users to find the optimal policy. Therefore, in order to address the problem, a two-phase SMCS (TSMCS) protocol is proposed by dividing the original problem into two subproblems without the loss of its optimality. Since the computational complexity of the

TSMCS may be high as the number of the channels increases, the SMCS protocol with sub-optimal approach (SMCS-S) is proposed to facilitate the problem-solving. Moreover, the TSMCS protocol with long-term statistics (TSMCS-L) is proposed to simplify the decision-making process, which is based on the steady-state statistics as similar to the approach in the SMCS-L protocol. Numerical results are presented to illustrate that both the proposed SMCS and TSMCS protocols are applicable to capture the rapidly varying opportunities of spectrum holes and maximize the aggregated throughput in the decentralized networks. Moreover, the SMCS-L, TSMCS-S, and TSMCS-L effectively balance the trade-off between the complexity reduction and performance maintenance.

The rest of this thesis is organized as follows. Section 2 formulates the considered problem on a POMDP basis. The proposed SMCS and TSMCS protocols for solving the problems under the perfect and imperfect sensing scenarios are described in Section 3. Section 4 illustrates the performance evaluation for the proposed SMCS and TSMCS protocols. In the end, the conclusions are drawn in Section 5.

Chapter 2

Problem Formulation

In this section, based on the preliminary concept of the POMDP framework, the design problem of channel sensing strategy will be formulated as a POMDP problem and considered under perfect sensing scenario and further extended to imperfect sensing scenario. For further details about POMDP, it is suggested to refer [25]. Considering that the PUs are accessing the primary network with wide spectrum that is divided into N channels each with identical bandwidth B. The PUs are permitted to access these channels according to the centralized channel assignment provided by the base stations. On the other hand, the CR users are unlicensed in the primary network and can only opportunistically access the unused channels if the PUs are absent. The queue capacity for the PUs is considered to be infinite, and the PUs are always preemptive when accessing, i.e. the CR users must evacuate themselves from the channels whenever the PUs are present. Both the primary and CR networks are time-slotted based on the same time slot duration T_s, and the PUs' channel allocation is conducted at the beginning of each time slot. In order to prevent the PUs from being interfered, the CR users are required to perform channel sensing before accessing. Each CR user is equipped with single transceiver, which means that channel sensing and accessing cannot be conducted simultaneously. Furthermore, it is feasible to satisfy the throughput requirement of the CR users by adopting spectrum aggregation techniques such as discontinuous orthogonal frequency division multiplexing (OFDM). In this thesis, considering that the CR users' objective is to maximize the aggregated throughput over current time slot, the impact of current action on future reward is beyond the scope of this thesis.

2.1 Multiple Channel Sensing Techniques

According to the channel access scheme in the primary network, the multiple channel sensing techniques adopted by the CR users can be classified into wideband sensing and narrowband sensing with the definitions as follows.

Definition 2.1. Wideband Sensing (WS) is a sensing technique that senses multiple channels simultaneously.

Definition 2.2. Narrowband Sensing (NS) is a sensing technique that senses multiple channels sequentially.

Among simultaneously WS techniques, the OFDM-based energy detector is the most frequently used for application due to its feasible implementation in practice. It can be applied to the CR users' multiple channel sensing if the primary network adopts the orthogonal frequency-division multiple access (OFDMA) scheme. Consequently, the CR users are capable of simultaneously sensing multiple channels. The required time for wideband sensing τ^w can be obtained as [26]

$$\tau^w = \frac{N_s(MN_f + N_{cp})}{f_s} \tag{2.1}$$

where

$$\begin{cases} N_s: & \text{number of OFDM blocks} \\ M: & \text{maximum number of channel operation} \\ N_f: & \text{number of subcarrier per channel} \\ N_{cp}: & \text{length of cyclic prefix} \\ f_s: & \text{sampling freqency} \end{cases} \tag{2.2}$$

On the other hand, considering the general case that the OFDMA scheme is not necessarily adopted by the PUs, the WS techniques become inapplicable for the CR users. Instead, the sequentially NS techniques are utilized, which means that the CR users have to sense the target channels in sequence. In practice, the CR users can adopt the carrier sense multiple access for NS, which is similar to the scenario in WLANs that each decentralized node verifies the traffic absence on the shared channel before transmission. However, noted that the sensing time overhead in the NS τ^n is accumulated with the increasing number of the channels to be sensed and can be written as $L\tau^n$, where L represents the number of the sensed channels and τ^n denotes the required sensing time for each channel. From the CR users' point of view, more opportunities may be acquired when sensing more channels. However, it is considered impractical to sense all the channels in realistic circumstances due to excessive sensing time. As depicted in Fig. 2.1, the CR user chooses the first and ith channels to sense in the first time slot and finds that only the ith channel is unoccupied. Consequently, the CR user can only access one channel for data transmission which results in the normalized throughput $B(T_s - 2\tau^n)/T_s$. Considering the case that the CR user decides to explore more unoccupied channels by spending more time on channel sensing, four channels are sensed in the next time slot. The sensing results show that both the second and Nth channels are unoccupied, and the CR user can therefore access these two channels with channel aggregation, which is expected to increase its performance.

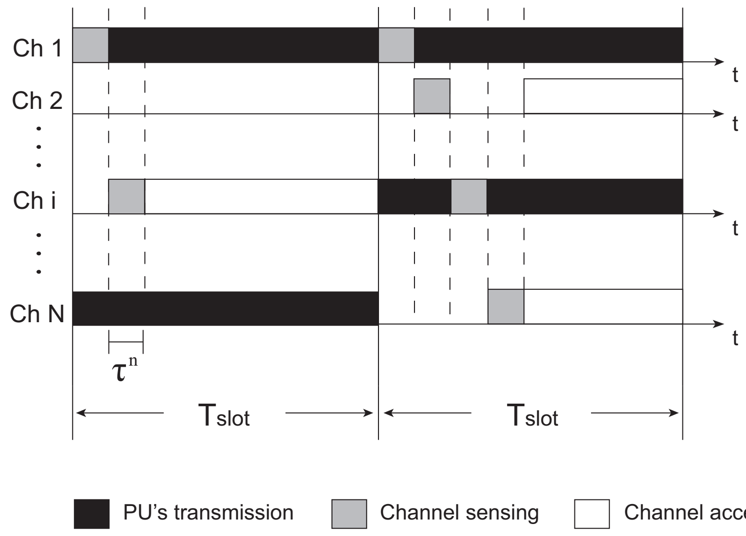


Figure 2.1: An example to illustrate the spectrum opportunity and sensing overhead.

However, the remaining time for data transmission in this time slot is significant reduced, and the resulting throughput becomes $2B(T_s - 4\tau^n)/T_s$. Therefore, there exists a trade-off between spectrum opportunity exploration and sensing time overhead for each CR user.

2.2 POMDP Framework

In the decentralized networks, the CR users are not able to acquire full information about the PUs' presence during channel sensing period due to the limited capability of spectrum sensing and the aforementioned sensing trade-off. Consequently, the CR users' channel selection for multiple channel sensing can be modeled as a POMDP problem.

The POMDP framework considers a realistic scenario that only partial information from environment is acquirable. It is formally described as a tuple (S, A, T, O, Ω, R), where S is a set of states, A is a set of actions, T is a set of state transition probabilities, O is a set of observations, Ω is a set of observation probabilities, and R is a set of immediate rewards for evaluating decision-making. However, the user still fails to determine the optimal decisions due to the fact that the observations acquired by the user are considered insufficient to precisely reveal the past information of the process. In order to

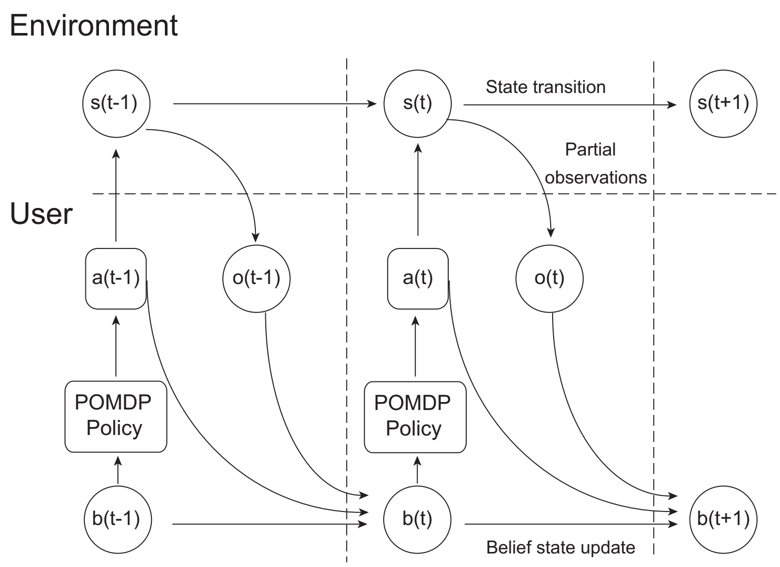


Figure 2.2: Interaction between user and environment in POMDP framework.

address the problem of environmental uncertainties, the belief state b is introduced and developed to capture the current state of the realistic environment. It provides a sufficient statistics about history such that the user can have a better understanding of the realistic environment. With the assistance of the belief state, the decision-making process is facilitated, and the belief state is therefore considered essential and beneficial to the user even through current state is not fully observable. Fig. 2.2 depicts the interaction between the user and the environment in the POMDP framework during state transitions. As can be seen in the figure, the future belief state $b(s')$ can be updated by the current observations $o(t)$, action $a(t)$, and belief state $b(s)$, which is attributed to the Markovian nature of state transition. Moreover, based on the current state $s(t)$ of the realistic environment, the immediate reward $R(t)$ can be calculated after action $a(t)$ execution.

With the knowledge of POMDP framework, the CR users' channel selection for multiple channel sensing is modeled as follows. From the CR users' perspective, each channel is either unoccupied or occupied by the PUs and can therefore be modeled as a two-state Markov process. Specifically, $s_i(t)$ is defined as the state of the ith channel in the tth time slot, where $s_i(t) = 0$ and $s_i(t) = 1$ indicate that the channel is idle and busy respectively, where $i = 1, ..., N$. Since the spectrum of the primary network is divided into N channels, there exist 2^N possible combinations of the entire network states. For ease of representation, the state vector of the entire network in the tth time slot is written as $\vec{s}(t) = [s_1(t), ..., s_i(t), ..., s_N(t)]$, where $s_i(t) \in S$ and S is the set of channel states. Furthermore, based on the PUs' dynamic occupancies on each channel, the state transition probability of the ith channel can be formulated as $T_i(s, s')$, where $s, s' \in S$ and

$$T_i(s, s') \triangleq P(s_i(t+1) = s' | s_i(t) = s) \tag{2.3}$$

At the beginning of each time slot, the CR users have to select their candidate channels for multiple channel sensing, which can be modeled as an action-taking process in the POMDP framework. $a_i(t) = 1$ and $a_i(t) = 0$ indicate the ith channel is selected to be sensed or not in the tth time slot. Then, the action vector of the multiple channel sensing can be written as $\vec{a}(t) = [a_1(t), ..., a_i(t), ..., a_N(t)]$, where $a_i(t) \in A$ and A is the set of all possible sensing actions. Since the channel states of the entire network may not be fully observable, each CR user can only acquire partial observations after action execution. The observations on N channels are denoted as $\vec{o}(t) = [o_1(t), ..., o_i(t), ..., o_N(t)]$, where $o_i(t) \in \{0, 1\}$ represents the observed channel state of the ith channel in the tth time slot, i.e. the sensing outcome of the ith channel. Noted that $o_i(t) \in O$, where O denotes the set of all possible sensing outcomes. As mentioned before, in order to ensure the optimality of the decision-making process, each CR user has to maintain its internal belief states which can be regarded as its understanding of uncertain channel states and plays an important role in PODMP framework. In the tth time slot, the belief state of the ith channel in state s is denoted as $b_i(s)$, where $b_i(s)$ is located within the interval $[0, 1]$ and $\sum_{s \in S} b_i(s) = 1$. Furthermore, the updated belief state vector $b_i(s')$ can be acquired from the former observations $\vec{o}(t)$, action $\vec{a}(t)$, and belief state $b_i(s)$. The updating process can therefore be written and derived by adopting the Baye's rule as [25]

$$
\begin{aligned}
b_i(s') &= P(s'|b_i(s), a_i(t), o_i(t)) \\
&= \frac{P(o_i(t)|s', a_i(t), b_i(s))P(s'|a_i(t), b_i(t))}{P(o_i(t)|a_i(t), b_i(s))} \\
&= \frac{P(o_i(t), s', a_i(t)) \sum_{s\in S} P(s'|a_i(t), b_i(s), s)P(s|a_i(t), b_i(s))}{P(o_i(t)|a_i(t), b_i(s))} \\
&= \frac{\Omega(s', a_i(t), o_i(t)) \sum_{s\in S} b_i(s)T_i(s, a_i(t), s')}{P(o_i(t)|a_i(t), b_i(s))}
\end{aligned} \tag{2.4}
$$

where $P(o_i(t)|a_i(t), b_i(s))$ is a normalizing factor and can be obtained as

$$P(o_i(t)|a_i(t), b_i(s)) = \sum_{s'\in S}\sum_{s\in S} \Omega(s', a_i(t), o_i(t))b_i(s)T_i(s, a_i(t), s') \tag{2.5}$$

Noted that $\Omega(s', a_i(t), o_i(t))$ indicates the probability that the CR users observe $o_i(t)$ given that $a_i(t)$ is performed and s' is the resulting state, which can be written as

$$\Omega(s', a_i(t), o_i(t)) = P(o_i(t)|a_i(t), s') \tag{2.6}$$

Due to the fact that the channel state transitions of the primary network are independent from the CR users' actions, (2.4) can be further reduced as

$$b_i(s') = \frac{\Omega(s', a_i(t), o_i(t)) \sum_{s\in S} b_i(s)T_i(s, s')}{\sum_{s'\in S}\sum_{s\in S} \Omega(s', a_i(t), o_i(t))b_i(s)T_i(s, s')} \tag{2.7}$$

In order to provide the CR users with the measurement for evaluating policy-making, the immediate reward $R(s, a_i(t))$ is defined based on the action execution and the channel states as

$$R(s, a_i(t)) = \begin{cases} 1, & \text{if } s_i(t) = 0 \text{ and } a_i(t) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.8}$$

It can be seen that the CR users can obtain a unit reward from the channel that is sensed idle. Noted that there is no penalty to the CR users. However, since the realistic channel states of the network are not fully observable for the CR users, the reward cannot be calculated. Fortunately, with the assistance of the belief states, the expected reward $r(t)$ can still be obtained by the CR users as

$$r(t) = \sum_{i=1}^{N} \sum_{s \in S} b_i(s) R(s, a_i(t)) \tag{2.9}$$

As a result, the CR users' policy is to take the action such that the maximum expected reward can be achieved, and the optimal policy $\pi(t)$ for multiple channel sensing can be written as

$$\pi(t) = \arg\max_{\vec{a}(t)} r(t) \tag{2.10}$$

From (2.10), it can be seen that the optimal policy is expected to be time-varying, and the CR users are required to dynamically adjust the policy in order to accommodate themselves to the rapidly varying environment. In consideration of the reliability of sensing results, both the perfect and imperfect sensing scenarios are studied in the following subsection.

2.3 Spectrum Sensing Scenarios

2.3.1 Perfect Sensing

When the CR users are geographically close to the PUs, the received signals from the PUs are expected to have higher signal-to-noise ratio (SNR), which provides the CR users with reliable detection so that the sensing outcomes can be considered perfect. Under such perfect sensing scenario, the CR users can acquire the accurate information about PUs' presence on the sensed channels after channel sensing. Since the CR users' aggregated throughput depend on the idle probabilities of N channels in the primary network, the current belief for the idle state $b_i^0(t) = b_i(s_i(t) = 0), i = 1, ..., N$ are utilized in the action-taking problem which can be formulated as

Problem 1. Find the optimal channel selection for multiple channel sensing.

$$\max_{\vec{a}(t)} \quad \frac{T_s - \sigma}{T_s} \sum_{i=1}^{N} a_i(t) b_i^0(t) \tag{2.11}$$

$$s.t. \quad \begin{array}{ll} \sum_{i=n}^{n+M-1} a_i(t) = M & \text{, if wideband sensing} \\ L(t) = \sum_{i=1}^{N} a_i(t) \leq M & \text{, if narrowband sensing} \end{array} \tag{2.12}$$

where

$$\sigma = \begin{cases} \tau^w & \text{, if wideband sensing} \\ L(t)\tau^n & \text{, if narrowband sensing} \end{cases} \tag{2.13}$$

Noted that the expected reward of the ith channel is equal to zero if $a_i(t) = 0$ since the CR users are not allowed to access the target channels without performing channel sensing. The former product term in (2.11) denotes the normalized data transmission time in consideration of sensing time overhead. Moreover, (2.12) defines the constraints of **Problem 1** in the WS and NS cases. M represents the CR users' capability of channel operation, i.e. the maximum number of channels can be operated at the same time, where $1 \leq M \leq N$ in general. Considering that the OFDM technique is adopted for the WS, the channels to be sensed must be contiguous due to implementation feasibility of the OFDM in practice. Consequently, there exist $N - M + 1$ combinations of the channel selection for channel sensing. For instance, considering that $N = 3$ and $M = 2$, the CR users can choose either the 1st and 2nd channels or the 2nd and 3rd channels for multiple channel sensing.

On the other hand, in the NS case, $L(t)$ denotes the number of the candidate channels in the tth time slot and is associated with the accumulated sensing time overhead σ.

Since the channel sensing is individually and independently conducted on each channel, the channels to be sensed can be discontiguous. As a result, all possible combinations of the channel selection can be derived as

$$combinations[L(t) = 1] + ... + combinations[L(t) = M] = \sum_{i=0}^{M} \begin{pmatrix} N \\ i \end{pmatrix} \tag{2.14}$$

Considering the special case that the CR users have full capability of spectrum sensing, i.e. $M = N$, (2.14) can further derived as $\sum_{i=1}^{N} \binom{N}{i} = 2^N$ by applying the Binomial Theorem $(x + y)^n = \sum_{i=0}^{n} \binom{n}{i} x^i y^{n-i}$ with $x = y = 1$ and $n = M$. It is equivalent to the case that the CR users determine to sense or not for each channel and there exist 2^N combinations of the sensing decisions on N channels.

2.3.2 Imperfect Sensing

In the cases that the CR users are far from the PUs or interfered by the noisy channels, the received signals from the PUs may have low SNR, which results in inaccurate sensing outcomes when channel sensing, i.e. imperfect sensing. Consequently, it is inevitable for the CR users to cause the interference to the PUs. In order to avoid it, the PUs' QoS requirements are taken into consideration in the CR users' decision-making process. Considering the PUs set different requirements for successful data transmission on the channels, i.e. the constraint on the probability that the PUs are not interfered by the CR users during transmission, the CR users must avoid mis-detection when opportunistic spectrum access in order to meet the PUs' requirements. Mis-detection describes the case the the CR users consider that the PUs are absent from the target channel after channel sensing while the PUs are actually active. In such case, due to the PUs' unexpected presence, the packet collisions between the PUs and CR users may occur and severely degrade system performance. Specifically, the PUs' requirements for detection probabilities on N channels are denoted as $[P_1^d, ..., P_i^d, ..., P_N^d]$. On the other hand, false alarm is the case that the CR users declare the PUs' presence on the target channel but the PUs are actually absent, which causes unnecessary loss of spectrum opportunity. Consequently, from the CR users' perspective, the lower false alarm probability, the higher probability that they can access the unused channels. By adopting energy detector for determining the presence of the primary signals with circularly symmetric complex Gaussian (CSCG) [19], the CR users' false alarm probability on Nth channel can be derived as

$$P_i^f(\gamma, P_i^d, \tau_i, fs) = Q(\sqrt{2\gamma + 1}\; Q^{-1}(P_i^d) + \sqrt{\tau_i f_s}\gamma) \tag{2.15}$$

where γ, τ_i, and f_s denote SNR level, sensing time for the ith channel, and sampling frequency respectively. Noted that $Q(x)$ is the Q-function for simple transformation of normal cumulative distribution function as

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp -\frac{u^2}{2} du \tag{2.16}$$

As can be seen in (2.15), given the PUs' requirement P_i^d, P_i^f is an decreasing function as the sensing time increases. In other words, the CR users can avoid false alarm when spending more time on channel sensing. However, the remaining time for data transmission within the time slot is reduced. Therefore, the sensing time for each channel should be taken into consideration in the action-taking process of the POMDP problem. Consequently, based on the current belief states, the optimization problem under the imperfect sensing scenario can be defined and formulated as

Problem 2. Find the optimal channel selection and the corresponding sensing time for multiple channel sensing.

$$\max_{\vec{a}(t)} \quad \frac{T_s-\sigma}{T_s}\sum_{i=1}^{N} a_i(t)(1-P_i^f(\gamma,P_i^d,\tau_i,fs))b_i^0(t) \tag{2.17}$$

$$s.t. \quad \left.\begin{array}{l} \sum_{i=n}^{n+M-1} a_i(t)=M \\ \tau_1^w=...=\tau_i^w=...=\tau_N^w=\tau^w \\ 0\leq\tau^w\leq T_s \end{array}\right\} \text{if wideband sensing} \tag{2.18}$$

$$\left.\begin{array}{l} L(t)=\sum_{i=1}^{N} a_i(t)\leq M \\ 0\leq\tau_i^n\leq T_s,\forall i \\ \sum_{i=1}^{N}\tau_i^n\leq T_s \end{array}\right\} \text{if narrowband sensing} \tag{2.19}$$

where

$$\sigma=\begin{cases}\tau^w & \text{, if wideband sensing} \\ \sum_{i=1}^{N}\tau_i^n & \text{, if narrowband sensing}\end{cases} \tag{2.20}$$

τ_i^w and τ_i^n denote the selected sensing time for the ith channel in the WS and NS cases, respectively. Noted that the sensing time in the WS case should be identically selected among M consecutive channels due to simultaneous channel sensing. On the other hand, in the narrowband sensing case, since the channel sensing is sequentially conducted, the CR users are allowed to select different sensing time for each channel. $(1-P_i^f(\cdot))$ represents the probability that no false alarm occurs on ith channel, which means that the channel is expected to be available for opportunistic access in consideration of the protection to the PUs. As mentioned before, the PUs on N channels may have different QoS requirements, i.e. the detection probabilities, so the CR users have to find the optimal sensing time that can jointly meet the PUs' requirements among the target channels. As a result, the CR users' actions in **Problem 2** can be regarded as a joint design problem of both the channel selection and the sensing time decision for multiple channel sensing.

Chapter 3

Proposed Protocols for Multiple Channel Sensing

In this section, the stochastic multiple channel sensing (SMCS) and two-phase stochastic multiple channel sensing (TSMCS) protocols are proposed to assist the CR users to determine the channel sensing among multiple channels based on the POMDP framework under the perfect and imperfect scenarios, respectively. Furthermore, the SMCS and TSMCS protocols with long-term statistics (SMCS-L and TSMCS-L) are designed for the purpose of implementation complexity reduction, and the TSMCS protocol with sub-optimal approach (TSMCS-S) is proposed to reduce the computation complexity of the TSMCS protocol.

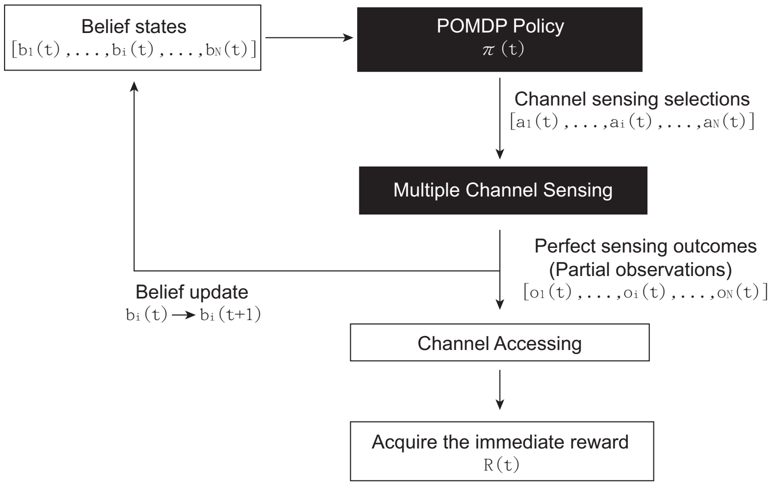


Figure 3.1: The flow chart of the proposed SMCS protocol under the perfect sensing scenario.

3.1 SMCS Protocol under the Perfect Sensing Scenario

3.1.1 Protocol Overview

Under the perfect sensing scenario, the proposed SMCS protocols are designed to address **Problem 1**, which is composed of the sensing and accessing stages. Fig. 3.1 illustrates the flow chart of the proposed SMCS protocols. In the first stage, based on the current belief states, each CR user has to determine the group of the candidate channels to be sensed. After that, the CR users perform multiple channel sensing on those candidate channels. Once the CR users have recognized the current spectrum opportunities, i.e. the unoccupied channels, multiple channel access with channel aggregation are conducted in the second stage. Furthermore, the CR users obtain their immediate reward over the current time slot. Noted that since the channel states of the network are only partially observable, the CR users have to update their internal belief states all the time such that they can have the sufficient information about the realistic environment for the POMDP policy-making.

3.1.2 Wideband Sensing

By combing (2.11) with the constraint for the WS in (2.12), the expected reward in tth time slot can be reduced as

$$\frac{T_s-\tau^w}{T_s}\sum_{i=1}^{N}a_i(t)b_i^0(t)=\frac{T_s-\tau^w}{T_s}\sum_{i=n}^{n+M-1}b_i^0(t)\triangleq R(t,n) \tag{3.1}$$

where n denotes the starting channel index of the WS, i.e. the smallest channel index within the sensing range. The equality in (3.1) is attribute to the fact that the reward of the ith channel is zero if $a_i(t)=0$. Consequently, the optimal channel selection for the WS can be obtained by comparing the expected reward over all the possible combinations of the channel selection. Then, the optimal channel selection is to choose the channels with indices from n^* to n^*+M-1. Once the optimal POMDP policy is decided, the multiple channel sensing will be conducted. Furthermore, based on the actions and observations, the belief states can be updated as

$$b_i^0(t+1)=\begin{cases} p_{00,i} & \text{, if } a_i(t)=1 \text{ and } o_i(t)=0,\\ p_{10,i} & \text{, if } a_i(t)=1 \text{ and } o_i(t)=1,\\ b_i^0(t)p_{00,i}+(1-b_i^0(t))p_{10,i} & \text{, if } a_i(t)=0 \end{cases} \tag{3.2}$$

where $p_{00,i}=P(s_i(t+1)=0|s_i(t)=0)$ and $p_{10,i}=P(s_i(t+1)=0|s_i(t)=1)$. Noted that the belief states of the unobserved channels are updated according to the Markov chain. The proposed algorithm for solving **Problem 1** in the wideband sensing case is shown as **Algorithm 1**. Considering the special case that the CR users have the full capability for wideband sensing, i.e. $M=N$, the POMDP problem is reduced to the Markov decision process (MDP) problem since the channel states of the entire network are fully observable for the CR users. In such case, the CR users' optimal policy is always to sense all the channels and access the unoccupied channels based on their full information about the

Algorithm 1: SMCS Protocol for Perfect Wideband Sensing

Input: $b^0(t)$

Output: $b^0(t+1), \vec{a}(t), \vec{o}(t)$

```
begin
    for n = 1 to N − M + 1 do
        R(t,i) = ((T_s − τ^w)/T_s) Σ_{i=n}^{n+M−1} b_i^0(t)
    n* = arg max R(t,n)
    for i = 1 to N do
        if n* ≤ i ≤ n* + M − 1 then
            a_i(t) = 1
        else
            a_i(t) = 0
    for i = 1 to N do
        if a_i(t) = 1 then
            if o_i(t) = 0 then
                b_i^0(t+1) ← p_{00,i}
            else
                b_i^0(t+1) ← p_{10,i}
        else
            b_i^0(t+1) ← (p_{00,i}, p_{10,i})
```

PUs' presence.

3.1.3 Narrowband Sensing

In the NS case, since the required sensing time is proportional to the number of the channels to be sensed, the group size of the target channels in the tth time slot $L(t)$ should be properly chosen in the POMDP policy-making. Let $L^*(t)$ be the optimal number of channels to be sensed that maximizes the expected throughput over the tth slot. Due to the dynamic environment, $L^*(t)$ is expected to be dynamically adjusted over time slots. Since the action for each channel is either 1 or 0, the problem can be formulated as a Binary Linear Programming (BLP) problem. In general, the BLP problem can be solved via exhaustive search. However, it becomes difficult and complicated as M increases since the computational complexity of the exhaustive search is $O(2^n)$ due to 2^n possible combinations of the actions. Therefore, instead of applying the exhaustive search, a computational complexity-reduced algorithm is proposed in order to solve the problem more efficiently. The detailed steps of the proposed algorithm for perfect narrowband sensing is described as follows.

- First of all, in order to realize the efficient search, N channels are sorted by the expected idle probability in descending order based on the current belief states and represented as $\vec{p}^n(t) = [p_1^n(t), ..., p_i^n(t), ..., p_N^n(t)]$, where $p_1^n(t)$ is the highest idle probability among N channels. Then, the expected reward $R(t, L)$ when choosing the first L channels in $\vec{p}(t)$ to sense can be formulated as

$$R(t, L) = \frac{T_s - L\tau^n}{T_s} \sum_{i=1}^{L} p_i^n(t) \tag{3.3}$$

where $L = 1, ..., M$. Noted that τ_n is considered unique among N channels due to the identical channel bandwidth. Therefore, the optimal solution can be written as

$$L^*(t) = \arg\max_{L} R(t, L) \tag{3.4}$$

$L^*(t)$ can be obtained by computing the values of $R(t, L)$ with all possible L, where $0 \leq L \leq M$. Once $L^*(t)$ is obtained, the first $L^*(t)$ channels in $\vec{p}^n(t)$ are chosen as the candidate channels for channel sensing. The reason is that the CR users expect to gain greater reward by accessing the channels with higher expected idle probabilities. Noted that the proposed algorithm significantly reduces the computational complexity from $O(2^n)$ to $O(n)$ compared with the exhaustive search since the optimal solution to the problem can be found by M times search in (3.4).

- Once the channel sensing is conducted, the CR users acquire the sensing outcomes, i.e. observations $\vec{o}(t)$, and are allowed to access the unoccupied channels with channel aggregation technique. Meanwhile, the reward can be calculated according to the accessing results.
- The updating process of the belief states is as similar to (3.2). A brief summary about the proposed algorithm for perfect narrowband sensing is shown in **Algorithm A2**.

3.1.4 Stationary Strategy

In addition to the performance-oriented schemes, the SMCS protocol with long-term statistics (SMCS-L) is proposed to provide the CR users with the simplified decision-making process. The main idea of the SMCS-L protocol is to determine a fixed group of the candidate channels for multiple channel sensing at the beginning of the CR device operation, and the policy is designed based on the long-term statistics about the idle

Algorithm 2: SMCS Protocol for Perfect Narrowband Sensing

Input: $\vec{b}^0(t)$
Output: $\vec{b}^0(t+1), \vec{a}(t), \vec{o}(t)$
begin
  $\vec{p}^n(t) \leftarrow \vec{b}^0(t)$
  for $L = 1$ *to* M **do**
    $R(t, L) = \frac{T_s - L\tau^n}{T_s} \sum_{i=1}^{L} p_i^n(t)$
  $L^*(t) = \arg\max(R(t, L))$
  $\vec{a}(t) \leftarrow L^*(t)$
  for $i = 1$ *to* N **do**
    if $a_i(t) = 1$ **then**
      if $o_i(t) = 0$ **then**
        $b_i^0(t+1) \leftarrow p_{00}$
      else
        $b_i^0(t+1) \leftarrow p_{10}$
    else
      $b_i^0(t+1) \leftarrow (p_{00}, p_{10})$

probabilities of the channels in steady-state. Consequently, the CR users' strategy is expected to be static over time slots. In the WS case, the expected reward is modified as

$$R(n) = \frac{T_s - \tau^w}{T_s} \sum_{i=n}^{n+M-1} p_i^0 \tag{3.5}$$

where p_i^0 represents the steady-state idle probability of the ith channel. The remaining problem-solving steps are similar to the ones in the SMCS protocols. However, the updating process of the belief states is not required for the CR users since the decision-making process in the SMCS-L protocols is on the long-term basis.

On the other hand, the problem in the NS case can also be solved based on the reward function as

$$R(L) = \frac{T_s - L\tau^n}{T_s} \sum_{i=1}^{L} p_i^n \tag{3.6}$$

where p_1^n denotes the idle probability of the channel that is the highest among the channels after the sorting. Then, the candidate channels for multiple channel sensing over time slots are the first L^* channels in $\vec{p}^n$ and the policy for channel sensing is static over time slots until the long-term statistics has been changed. Considering the special case that the occupancies of the PUs on each channel have the same statistics, i.e. $p_1^n = ... = p_i^n = ... = p_N^n = k$, (3.6) can be simplified as $R(L) = \frac{T_s - L\tau^n}{T_s} Lk$. Then, L^* can be derived as $\min(M, \frac{T_s}{2\tau^n})$ by taking the first order derivative of $R(L)$ with respect to L. For instance, if there are 10 channels with the same statistics and the ratio of the slot duration T_s to the sensing time τ^n is 10 to 1, L^* will be 5. In such case, the CR users are recommended to consistently choose 5 out of 10 channels to sense in each time slot.

Consequently, the implementation complexity of the SMCS-L protocol for both the WS and NS cases is reduced due to static strategy. Intuitively, the performance of the SMCS-L protocol is expected to degrade compared with that of the SMCS protocol, especially in the case that the PUs' occupancies change frequently. The reason is that the steady-state statistics may fail to reveal the transient behaviors of the realistic environment. The performance comparison between the proposed SMCS and SMCS-L protocols will be shown in the next section.

3.2 TSMCS Protocol under the Imperfect Sensing Scenario

3.2.1 Protocol Overview

The proposed SMCS protocols for imperfect sensing scenario follow the similar framework compared with the ones for perfect sensing scenario. However, due to the uncertainties of the sensing outcomes, the CR users may fail to access the expected spectrum access when mis-detections occur, which is illustrated in Fig. 3.2. Therefore, the selections for sensing time are taken into consideration in the proposed protocols. Furthermore, the updating

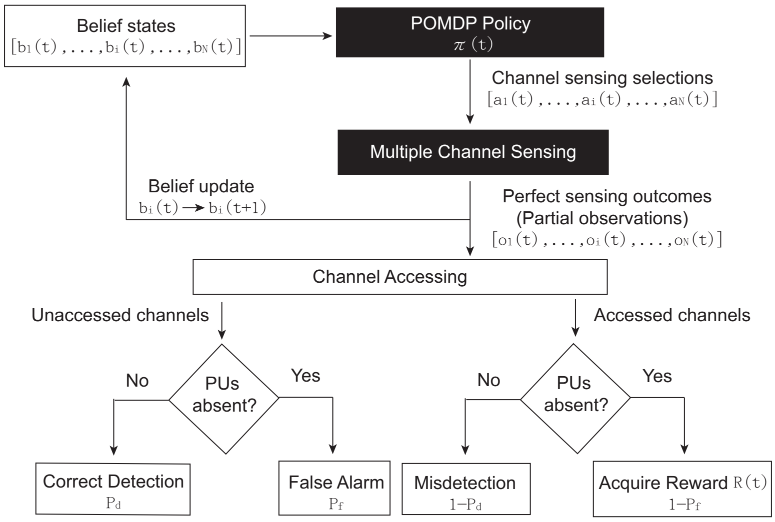


Figure 3.2: The flow chart of the proposed TSMCS protocol under the imperfect sensing scenario.

process of the belief states and calculation of the expected reward are designed based on the information about mis-detection and false alarm probabilities. Both the cases with wideband and narrowband sensing techniques will be studies as follows.

3.2.2 Wideband Sensing

Considering the imperfect wideband sensing scenario, the CR users' actions are to select the target channels and sensing time for wideband sensing, which can be considered as a joint optimization problem. In order to provide the CR users with a feasible solution to the problem, the two-step problem-solving algorithm is proposed. Specifically, the problem is divided into two subproblems as 1. Determine the optimal channel selection and 2. Find the optimal sensing time for the selected channels. It can be shown that the global optimum can be achieved by adopting the proposed algorithm without the loss of optimality, which is based on the convex property of the problem with respect to the sensing time. Therefore, it becomes feasible to efficiently solve the problem by exploiting existing methods. The detailed proof is given as follows.

Proposition 1. *The optimal solution to **Problem 2** in the wideband sensing case can be obtained by exploiting the proposed two-phase approach, where*

- *Phase 1. Find the all possible combinations for channel selection*
- *Phase 2. Find the optimal sensing time for each combination*

Proof. The proof of **Proposition 1** is built on the lemma as below.

Lemma 1. *The subproblem of maximizing the aggregated throughput given a given channel selection is a convex optimization problem with respect to wideband sensing time τ^w for all $0 < \tau^w < T_s$.*

Proof. For a given channel selection, (2.17) can be rewritten as $\sum_{i=1}^{N} f_i(\tau^w, t)$, where

$$f_i(\tau^w,t) = \begin{cases} \frac{T_s-\tau^w}{T_s} b_i^0(t)(1-P_i^f(\gamma, P_i^d, \tau^w, fs)) & \text{, if } a_i(t) = 1 \\ 0 & \text{, if } a_i(t) = 0 \end{cases} \tag{3.7}$$

$$P_i^f(\gamma, P_i^d, \tau^w, fs) = Q(\sqrt{2\gamma+1}\, Q^{-1}(P_i^d) + \sqrt{\tau^w f_s}\gamma) \tag{3.8}$$

The secondary derivative of (3.7) with respect to τ^w can be derived as

$$\frac{d^2 f_i(\tau^w,t)}{d(\tau^w)^2} = \begin{cases} -c\, b_i^0(t)\left((1-\frac{\tau^w}{T_s})\frac{1}{2\tau^w}(1+u_i\sqrt{\tau^w f_s}\gamma)+\frac{2}{T_s}\right)\frac{e^{-\frac{u_i^2}{2}}}{\sqrt{\tau^w}} & \text{, if } a_i(t) = 1 \\ 0 & \text{, if } a_i(t) = 0 \end{cases} \tag{3.9}$$

where

$$c = \frac{\gamma}{2}\sqrt{\frac{f_s}{2\pi}} \tag{3.10}$$

$$u_i = \sqrt{2\gamma+1}\, Q^{-1}(P_i^d) + \sqrt{\tau^w f_s}\gamma \tag{3.11}$$

It can be observed that the conditions $u_i > 0$ and $1 - \frac{\tau^w}{T_s} > 0$ can be satisfied when $\gamma, \tau^w, f_s > 0$ and $\tau^w < T_s$ respectively, which are considered feasible in the practical scenario. Noted that for $0 < \tau^w < T_s$,

$$\frac{d^2 f_i(\tau^w, t)}{d(\tau^w)^2} \leq 0, \ \forall i \tag{3.12}$$

Then, $f_i(\tau^w, t)$ is a concave function due to the fact that the secondary derivative of it is negative semidefinite. Therefore, according to the theory of convex optimization, $\sum_{i=1}^{N} f_i(\tau^w, t)$ is also a concave function since $f_i(\tau^w, t)$ is concave for all i.

As for the constraints in (2.18), given that M channels have been selected for wideband sensing, the constraints are reduced to $\tau^w > 0$ and $\tau^w < T_s$ which are obviously convex sets due to the fact that the line set must be convex.

Based on the convexity of the objective function and constraints, given the selected channels, the subproblem is a convex optimization problem with respective to τ^w for all $0 < \tau^w < T_s$. $\square$

According to **Lemma 1**, the optimal sensing time for a given channel selection is unique and can be obtained by existing approaches. As mentioned before, since there exist $N - M + 1$ combinations of channel selection in the wideband sensing case, the optimal solution can be obtained by exhaustively solving the optimization problems given $N - M + 1$ possible channel selections and choosing the solution that can achieve the maximum of expected rewards, which completes the proof of **Proposition 1**. Noted that the computational complexity of the proposed approach is linear time $O(n)$. $\square$

Among existing methods for solving convex optimization problems, the Lagrangian algorithm is applied in the second phase of the proposed approach. Let μ_1 and μ_2 be the Lagrangian multipliers for two inequality constraints, the Lagrangian function $L(\tau^w, \mu_1, \mu_2)$

can be written as

$$L(\tau^w, \mu_1, \mu_2) = \frac{T_s - \tau^w}{T_s} \sum_{i=1}^{N} a_i(t) \left(1 - P_i^f(\gamma, P_i^d, \tau^w, fs)\right) b_i^0(t) + \mu_1 \tau^w - \mu_2(\tau^w - T_s) \tag{3.13}$$

Furthermore, the necessary conditions for obtaining the solution are

$$\frac{dL(\tau^w, \mu_1, \mu_2)}{d\tau^w} = \begin{cases} \leqslant 0 & , \text{if } \tau^w = 0 \\ = 0 & , \text{if } \tau^w > 0 \end{cases} \tag{3.14}$$

(3.14) can further be expressed as

$$\frac{\partial L(\tau^w, \mu_1, \mu_2)}{\partial \tau^w} = \frac{1}{T_s} \sum_{i=1}^{N} a_i(t) \left(c\ (T_s - \tau^w) \frac{1}{\sqrt{\tau^w}}\ e^{-\frac{u_i^2}{2}} - (1 - Q(u_i)) \right) b_i^0(t) + \mu_1 - \mu_2 \tag{3.15}$$

In order to obtain the optimal solution, the values of the Lagrangian multipliers are required to be obtained. An iterative approach that exploits the gradient is utilized to update the values of the Lagrangian multipliers. Let $\mu_i^{(k)}$ be the value of μ_i after k iterations, where $i = 1, 2$. Then the updating process for $\tau^{w(k)}$ and $\mu_i^{(k)}$ can be expressed as follows.

$$\tau^{w(k+1)} = \tau^{w(k)} + \alpha^k \left(\frac{\partial L(\tau^{w(k)}, \mu_1^{(k)}, \mu_2^{(k)})}{\partial \tau^w}\right) \tag{3.16}$$

$$\begin{bmatrix} \mu_1^{(k+1)} \\ \mu_2^{(k+1)} \end{bmatrix} = \begin{bmatrix} \mu_1^{(k)} - \beta^k \tau^w \\ \mu_2^{(k)} + \beta^k (\tau^w - T_s) \end{bmatrix}^+ \tag{3.17}$$

where $[\cdot]^+ = \max\{\cdot, 0\}$. In order to guarantee the convergence of the Lagrangian algorithm, the diminishing step size $\alpha^k = c/\sqrt{k}$ and $\beta^k = c/\sqrt{k}$ are chosen for updating τ^w

and μ in the kth iteration respectively, where c is a tunable constant. Consequently, the optimal sensing time for all the combinations of channel selection in wideband sensing can be obtained by exploiting the Lagrangian algorithm. Finally, the channel selection with corresponding sensing time that achieves the maximum of the expected reward is chosen as the optimal solution to the joint optimization problem.

Based on the obtained optimal policy to the constrained POMDP problem, the CR users conduct the channel sensing and then access the expected idle channels. After that, the reward can be calculated based on the acquired throughput over the current time slot. However, noted that the CR users acquire zero reward if there exist packet collisions between the PUs and CR users, i.e. mis-detections occur. Furthermore, since the obtained observations are not fully reliable in the imperfect sensing scenario, the uncertainties of the sensing outcomes should be taken into consideration in the belief update. For ease of representation, $s_i = s_i(t)$, $s_i' = s_i(t+1)$, $b_i^0 = b_i^0(t)$, and $o_i = o_i(t)$. Then, based on the conditional observation probabilities, the estimations of the channel states in the next time slot are derived as

$$\begin{aligned} P(s_i' = 0 | o_i(t) = 0, b_i^0) &= \frac{P(s_i' = 0, o_i = 0, b_i^0)}{P(o_i = 0, b_i^0)} \\ &= \frac{P(s_i = 0, s_i' = 0, o_i = 0, b_i^0) + P(s_i = 1, s_i' = 0, o_i = 0, b_i^0)}{P(o_i = 0, b_i^0)} \\ &= \frac{b_i^0(1 - P_i^f)p_{00,i} + (1 - b_i^0)(1 - P_i^d)p_{10,i}}{b_i^0(1 - P_i^f) + (1 - b_i^0)(1 - P_i^d)} \qquad (3.18) \\ P(s_i' = 0 | o_i(t) = 1, b_i^0) &= \frac{P(s_i' = 0, o_i = 1, b_i^0)}{P(o_i = 1, b_i^0)} \\ &= \frac{P(s_i = 0, s_i' = 0, o_i = 1, b_i^0) + P(s_i = 1, s_i' = 0, o_i = 1, b_i^0)}{P(o_i = 1, b_i^0)} \\ &= \frac{b_i^0 P_i^f p_{00,i} + (1 - b_i^0)P_i^d p_{10,i}}{b_i^0 P_i^f + (1 - b_i^0)P_i^d} \qquad (3.19) \end{aligned}$$

Consequently, the the updating process of the belief states is summarized as

$$b_i^0(t+1) = \begin{cases} \dfrac{b_i^0(1-P_i^f)p_{00,i} + (1-b_i^0)(1-P_i^d)p_{10,i}}{b_i^0(1-P_i^f) + (1-b_i^0)(1-P_i^d)} & \text{, if } a_i(t) = 1 \text{ and } o_i(t) = 0 \\ \dfrac{b_i^0 P_i^f p_{00,i} + (1-b_i^0)P_i^d p_{10,i}}{b_i^0 P_i^f + (1-b_i^0)P_i^d} & \text{, if } a_i(t) = 1 \text{ and } o_i(t) = 1 \\ b_i^0(t)p_{00,i} + (1-b_i^0(t))p_{10,i} & \text{, if } a_i(t) = 0 \end{cases} \tag{3.20}$$

Noted that the updating process in (3.20) can be reduced to (3.2) by setting $P_i^d = 1$ and $P_i^f = 0$ for the perfect sensing scenario.

3.2.3 Narrowband Sensing

In the narrowband sensing case, the CR users can choose any combinations of the discontiguous channels for multiple channel sensing. Moreover, the sensing time for channels can be distinct from each other, i.e. $\tau_1^n \neq ... \neq \tau_i^n \neq \tau_N^n$. However, the decisions on sensing time are statistically dependent on each other due to the fact that the sensing time overhead is accumulated as $\sigma = \sum_{i=1}^N \tau_i^n$ in (2.19). As a result, the problem of finding the optimal sensing time for each channel can be regarded as a joint design for $\vec{\tau^n} = [\tau_1^n, ..., \tau_N^n]$. In general, solving the problem with multiple variables can be difficult and complicated, especially the case that N is large. Fortunately, it can be proved that the problem can still be solved by applying the proposed two-phase approach as similar to **Proposition 1**.

Proposition 2. *The optimal solution to* ***Problem 2*** *in the narrowband sensing case can be obtained by exploiting the proposed two-phase approach, where*

- *Phase 1. Find the all possible combinations for channel selection*
- *Phase 2. Find the optimal sensing time for each combination*

Proof. The proof of **Proposition 2** is built on the lemma as below.

Lemma 2. *The subproblem of maximizing the aggregated throughput given a channel selection is a convex optimization problem with respect to the narrowband sensing time* τ_i^n *for all* $0 \leq \tau_i^n \leq T_s$ *and* $\sum_{x=1}^{N} \tau_x^n < T_s,\ i = 1, ...N.$

Proof. Given a channel selection, (2.17) can be written as $\sum_{i=1}^{N} f_i(\vec{\tau^n}, t)$, where

$$f_i(\vec{\tau^n}, t) = \frac{T_s - \sum_{x=1}^{N} \tau_x^n}{T_s}(1 - P_i^f(\gamma, P_i^d, \tau_i^n, fs))b_i^0(t) \tag{3.21}$$

Taking the second-order partial derivatives of (3.21) with respect to (τ_j^n, τ_k^n) can be derived as

$$\frac{\partial^2 f_i(\vec{\tau^n}, t)}{\partial \tau_k^n \partial \tau_j^n} = \begin{cases} -\, c\left((1 - \frac{\sum_{x=1}^{N} \tau_x^n}{T_s})\frac{b_k^0(t)}{2\tau_k^n}(1 + u_k\sqrt{\tau_k^n f_s}\gamma) + \frac{2}{T_s}\frac{e^{-\frac{u_k^2}{2}}}{\sqrt{\tau_k^n}}\right) & \text{, if } i = j \text{ and } j = k \\ -\, c\frac{1}{T_s\sqrt{\tau_k^n}}e^{-\frac{u_k^2}{2}} & \text{, if } i = j \text{ and } j \neq k \\ 0 & \text{, if } i \neq j \end{cases} \tag{3.22}$$

where

$$c = \frac{\gamma}{2}\sqrt{\frac{f_s}{2\pi}} \tag{3.23}$$

$$u_k = \sqrt{2\gamma + 1}\, Q^{-1}(P_k^d) + \sqrt{\tau_k^n f_s}\gamma \tag{3.24}$$

Noted that $u_k > 0$ if $\gamma, \tau_k^n, f_s > 0$. Then, the Hessian matrix of $f_i(\vec{\tau^n}, t)$ can be obtained as

$$H(f_i) = \begin{bmatrix} \frac{\partial^2 f_i}{\partial(\tau_1^n)^2} & \cdots & \frac{\partial^2 f_i}{\partial\tau_1^n\partial\tau_j^n} & \cdots & \frac{\partial^2 f_i}{\partial\tau_1^n\partial\tau_N^n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f_i}{\partial\tau_k^n\partial\tau_1^n} & \cdots & \frac{\partial^2 f_i}{\partial\tau_k^n\partial\tau_j^n} & \cdots & \frac{\partial^2 f_i}{\partial\tau_k^n\partial\tau_N^n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f_i}{\partial\tau_N^n\partial\tau_1^n} & \cdots & \frac{\partial^2 f_i}{\partial\tau_N^n\partial\tau_j^n} & \cdots & \frac{\partial^2 f_i}{\partial(\tau_N^n)^2} \end{bmatrix}_{N\times N} = \begin{bmatrix} 0 & \cdots & d_1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & d_n & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & d_N & \cdots & 0 \end{bmatrix}_{N\times N} \tag{3.25}$$

where the conditions $d_n < 0$ for $n = 1, ...N$ can be satisfied according to (3.22) with $i = j$. To check the definiteness of $H(f_i)$,

$$\vec{\tau}^s H(f_i)\vec{\tau}^{s\top} = \vec{\tau}^s \frac{(H(f_i) + H^\top(f_i))}{2}\vec{\tau}^{s\top} \tag{3.26}$$

$$= \begin{bmatrix} \tau_1^s & \cdots & \tau_i^s & \cdots & \tau_N^s \end{bmatrix} \begin{bmatrix} 0 & \cdots & d_1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ d_1 & \cdots & d_i & \cdots & d_N \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & d_N & \cdots & 0 \end{bmatrix} \begin{bmatrix} \tau_1^s \\ \vdots \\ \tau_i^s \\ \vdots \\ \tau_N^s \end{bmatrix} \tag{3.27}$$

$$= \tau_i^s (d_i + \sum_{n=1}^{N} \tau_n^s d_n) \leq 0 \tag{3.28}$$

The last inequality in (3.26) is attributed to the fact that the sensing time for each channel τ_i^n should be non-negative. Then, $H(f_i)$ is said to be negative semidefinite, and $f_i(\vec{\tau}^n, t)$ is a concave function with respect to $\tau_i^s \geq 0$, , where $i = 1, ..., N$. Consequently, the $\sum_{i=1}^{N} f_i(\vec{\tau}^n, t)$ is also a concave function since $f_i(\vec{\tau}^n, t)$ is concave for all i.

Furthermore, since the constraints in (2.19) lie on the linear set, they are said to be convex sets as similar to the case in the imperfect wideband sensing. Based on the convexity of the objective function and constraints, given the selected channels, the sub-problem is a convex optimization problem with respec to τ_i^n for all $0 < \tau_i^n < T_s$ as well as $\sum_{x=1}^{N} \tau_x^n$. □

According to **Lemma 2**, the optimal solution to the problem can be obtained by exploiting the proposed two-phase approach as similar to **Proposition 1** except that the number of the combinations increases to $\sum_{i=0}^{M} \binom{N}{i}$. Noted that the required time complexity in the proposed approach for the narrowband sensing is $O(2^n)$ by exhaustive search, but the complexity can further be reduced to $O(n)$ when exploiting dynamic programming. □

Similarly, the Lagrangian approach is applied to find the optimal solution to the constrained POMDP problem. Let $\vec{\mu} = [\mu_1, ..., \mu_{N+1}]$ be the Lagrangian multipliers, the Lagrangian function $L(\vec{\tau}^s, \vec{\mu})$ is written as

$$\begin{aligned} L(\vec{\tau}^n, \vec{\mu}) = \quad & \frac{T_s - \sum_{x=1}^{N} \tau_x^n}{T_s} \sum_{x=1}^{N} \left(1 - P_x^f(\gamma, P_x^d, \tau_x^n, fs)\right) b_x^0(t) \\ & + \sum_{x=1}^{N} \mu_x \tau_x^n - \mu_{N+1} \left(\sum_{x=0}^{N} \tau_x^n - T_s \right) \end{aligned} \tag{3.29}$$

Furthermore, the necessary conditions for obtaining the solution are

$$\frac{\partial L(\vec{\tau}^n, \vec{\mu})}{\partial \tau_i^n} = \begin{cases} \leqslant 0, & \text{if } \tau_i^n = 0 \\ = 0, & \text{if } \tau_i^n > 0 \end{cases} \tag{3.30}$$

(3.30) can further be expressed as

$$\frac{\partial L(\vec{\tau}^n, \vec{\mu})}{\partial \tau_i^n} = \sum_{x=1}^{N} b_x^0(t) \left(c(1 - \frac{\sum_{y=1}^{N} \tau_y^n}{T_s}) \frac{1}{\sqrt{\tau_x^n}} e^{-\frac{u_x^2}{2}} - \frac{(1 - Q(u_x))}{T_s}) \right) + \mu_i - \mu_{N+1} \tag{3.31}$$

Let $\mu_i^{(k)}$ be the kth iteration of μ_i, where $i = 1, ..., N+1$. Then, $\vec{\tau}^{n(k)}$ and $\vec{\mu}^{(k)}$ can be updated as

$$\begin{aligned} \vec{\tau}^{n(k+1)} &= \vec{\tau}^{n(k)} + \alpha^k \begin{bmatrix} \frac{\partial L(\vec{\tau}^{n(k)}, \vec{\mu})}{\partial \tau_1^n} & \cdots & \frac{\partial L(\vec{\tau}^{n(k)}, \vec{\mu})}{\partial \tau_i^n} & \cdots & \frac{\partial L(\vec{\tau}^{n(k)}, \vec{\mu})}{\partial \tau_N^n} \end{bmatrix}^\top \\ &= \vec{\tau}^{n(k)} + \alpha^k \left(\bigtriangledown f(\vec{\tau}^{n(k)}, t) - Dg(\vec{\tau}^{n(k)}) \vec{\mu}^{(k)} \right) \\ &= \begin{bmatrix} \tau_1^{n(k)} \\ \vdots \\ \tau_i^{n(k)} \\ \vdots \\ \tau_N^{n(k)} \end{bmatrix} + \alpha^k \left(\begin{bmatrix} \frac{\partial f(\tau_1^{n(k)})}{\partial \tau_1^n} \\ \vdots \\ \frac{\partial f(\tau_i^{n(k)})}{\partial \tau_i^n} \\ \vdots \\ \frac{\partial f(\tau_N^{n(k)})}{\partial \tau_N^n} \end{bmatrix} - \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 & -1 \\ 0 & \ddots & \ddots & \ddots & \vdots & -1 \\ \vdots & \ddots & 1 & \ddots & \vdots & -1 \\ \vdots & \ddots & \ddots & \ddots & 0 & -1 \\ 0 & \cdots & \cdots & 0 & 1 & -1 \end{bmatrix} \begin{bmatrix} \mu_1^{(k)} \\ \vdots \\ \mu_i^{(k)} \\ \vdots \\ \mu_{N+1}^{(k)} \end{bmatrix} \right) \end{aligned} \tag{3.32}$$

where

$$\frac{\partial f}{\tau_i^s}(\tau_i^{n(k)}) = \sum_{x=1}^{N} b_x^0(t)\left(c(1-\frac{\sum_{y=1}^{N}\tau_y^{n(k)}}{T_s})\frac{1}{\sqrt{\tau_i^{n(k)}}}\,e^{-\frac{u_x^2}{2}} - \frac{(1-Q(u_x^{(k)})}{T_s})\right) \tag{3.33}$$

$$u_x^{(k)} = \sqrt{2\gamma+1}\,Q^{-1}(P_x^d) + \sqrt{\tau_x^{n(k)} f_s}\gamma \tag{3.34}$$

$$\begin{bmatrix} \mu_1^{(k+1)} \\ \vdots \\ \mu_i^{(k+1)} \\ \vdots \\ \mu_N^{(k+1)} \\ \mu_{N+1}^{(k+1)} \end{bmatrix} = \left[\begin{bmatrix} \mu_1^{(k)} \\ \vdots \\ \mu_i^{(k)} \\ \vdots \\ \mu_N^{(k)} \\ \mu_{N+1}^{(k)} \end{bmatrix} + \beta^k \begin{bmatrix} -\tau_1^{n(k)} \\ \vdots \\ -\tau_i^{n(k)} \\ \vdots \\ -\tau_N^{n(k)} \\ \sum_{x=1}^{N}\tau_x^{n(k)} - T_s \end{bmatrix}\right]^+ \tag{3.35}$$

where $\alpha^k = c/\sqrt{k}$ and $\beta^k = c/\sqrt{k}$ denote the diminishing step size in the kth iteration that can guarantee the convergence of the iterative approach. Consequently, the optimal channel selection with the corresponding sensing time for narrowband sensing can be obtained by exploiting the proposed TSMCS protocol. The remaining process including accessing and belief update for imperfect narrowband sensing is as similar to the one for wideband sensing.

3.2.4 Complexity Reduction

Although it is feasible to solve **Problem 2** by exploiting the proposed SMCS scheme, the computational complexity of problem-solving may be high as N increases due to the increased combinations of all possible channel selection. In order to solve it, the suboptimal scheme for SMCS (SCMS-S) is proposed, which applies heuristic algorithm instead of exhaustive search. The detailed steps of the SMCS-S scheme are shown as below.

- Step 1. Calculate the expected reward for each channel $R_i(t)$ with initialized sensing time

$$R_i(t) = (1 - P_i^f(\gamma, P_i^d, \tau, f_s))b_i^0(t) \tag{3.36}$$

- Step 2. Determine the priority of channel sensing by sorting $R_i(t)$ in descending order.

- Step 3. Select the channels with the first M highest priorities as the candidate channels

- Step 4. Find the optimal sensing time associated with the candidate channels by the subgradient method

Noted that the sensing time is initialized according to the standard IEEE 802.22 [4] in the first step and will be optimized once the candidate channels are determined. Consequently, **Problem 2** in the narrowband sensing case can be efficiently solved by exploiting the TSMCS-S protocol with the reduced computational complexity from exponential time $O(2^n)$ to linear time $O(n)$, as compared with the TSMCS protocol. However, the solution is considered sub-optimal since the channel selection is determined via heuristic search.

3.2.5 Stationary Strategy

In order to reduce the implementation complexity of the selection for multiple channel sensing, the TSMCS protocol with long-term statistics (TSMCS-L) for the imperfect sensing scenario is proposed to provide the CR users with simplified decision-making process. As similar to the perfect sensing scenario, the CR users' channel selections are based on the long-term statistics about the idle probabilities of N channels. However, noted that in consideration of the protection of the PUs, the selection for sensing time is required in the imperfect sensing scenario in order to meet the requirements of the PUs' detection probabilities over N channels. Therefore, the Lagrangian approaches are applied for finding the optimal sensing time once the channel selection has been determined. Furthermore, since the TSMCS-L protocol exploits the static strategy from a long-term perspective, the CR users are not required to update their information about the environment over time slots until the statistics of the channels has been changed.

Chapter 4

Performance Evaluation

In this section, simulations will be presented to demonstrate the performance of the proposed SMCS and SMCS-L protocols under the perfect sensing scenario in terms of aggregated throughput for the current time slot. On the other hand, TSMCS, TSMCS-S, and TSMCS-L protocols will be evaluated under the imperfect sensing scenario. Moreover, the performance of the proposed protocols will be presented in both the single and multiple channel operations. The simulation parameters are referred to the standard IEEE 802.22 [4] for WRAN using spectrum holes on TV bands as shown in **Table 1**.

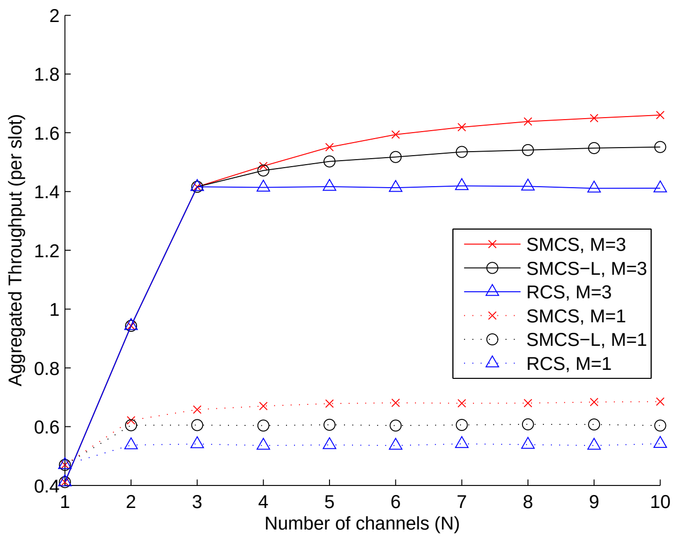
Table 4.1: Simulation parameters

Parameters	Values
Slot duration T_s	10ms
No. of subcarriers/channel N_f	32
Length of cyclic prefix	$MN_f/4$
Wideband sensing time τ^w	$100(MN_f)1.25/f_s$ms
Narrowband sensing time τ^n	1ms
Bandwidth B	6MHz
SNR γ	-15dB
Over-sampling rate f_s	$8B/7$ MHz

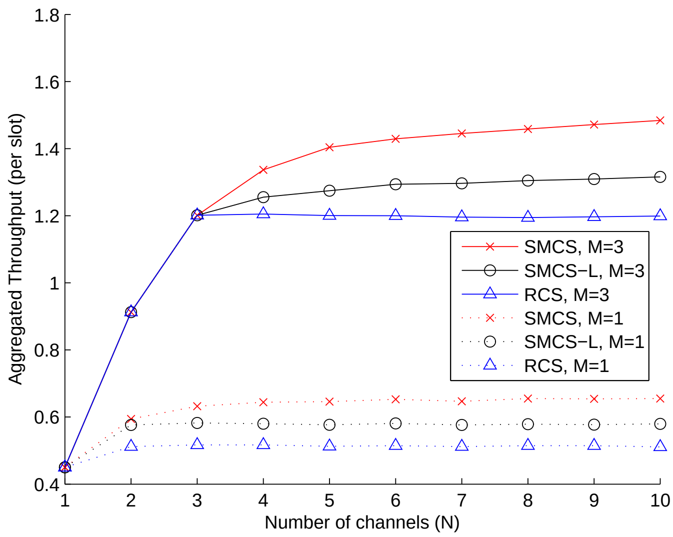
4.1 Performance Comparison under the perfect Sensing Scenario

First of all, the random channel sensing (RCS) protocol is implemented for the purpose of performance comparison. In the RCS protocol, the CR users randomly choose their target channels to sense without the need for decision-making process. The transition probabilities of N channels from idle state to idle state p_{00} are set from 0.7 to 0.9 with the constant difference between any two successive channels. On the other hand, the transition probabilities from busy state to idle state p_{10} are set from 0.5 to 0.7. For instance, in the case that there are 5 channels in the primary network, i.e. $N = 5$, p_{00} and p_{10} are set as $[0.7, 0.75, 0.8, 0.85, 0.9]$ and $[0.5, 0.55, 0.6, 0.65, 0.7]$ respectively. Fig. 4.1(a) illustrates the influence of the number of the channels on the system performance in the WS case, where the CR users' capability for maximum number of channel operations M is set as $M = 1$ and $M = 3$ for single and multiple channel operations, respectively. In the case of single channel operations, the CR users have no capability of sensing and accessing multiple channels and can only choose one channel within one time slot. Considering that the OFDM technique is exploited for simultaneous WS, for a OFDM system with 32 subcarriers per channel and cyclic prefix length of 8, the required sensing time for WS is $100(32 + 8)M/f_s$ if the CR users observe 100 OFDM symbols during sensing period [26]. As can be seen in the figure, the CR user' throughput is significantly improved by adopting the proposed SMCS protocol with both the single and multiple channel operations, i.e. without and with the assistance of channel aggregation. In addition, the aggregated throughput tends to saturate even as the number of the channels increases, which is due to the limitations on the CR users' maximum sensing range.

On the other hand, in the NS case, the required sensing time for each channel is set as 1ms according to the IEEE 802.22 [4] and the sensing time is the same among N



(a) Wideband sensing



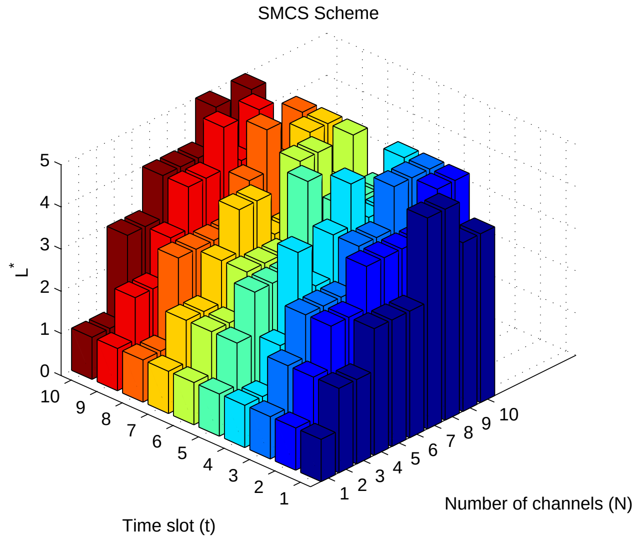
(b) Narrowband sensing

Figure 4.1: Performance comparison of CR users' aggregated throughput versus numbers of channels N under the perfect sensing scenario.

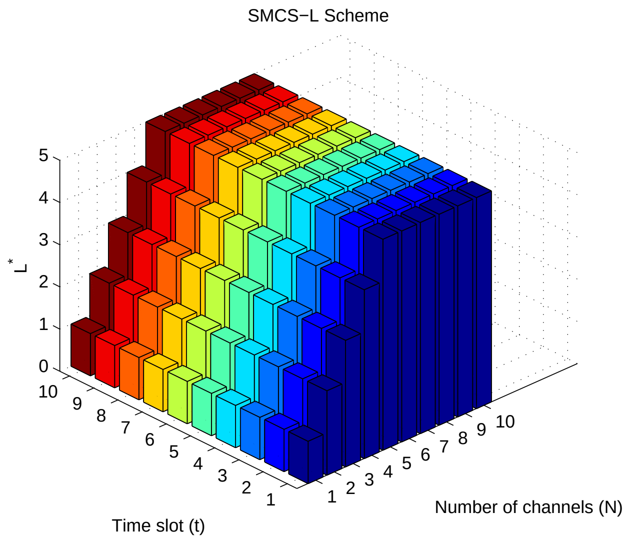
channels due to the identical bandwidth. As can be seen in Fig. 4.1(b), the proposed protocols outperform than the RCS protocol. Noted that different from the WS case, in order to prevent from resulting in excessive sensing overhead, the CR users may decide not to utilize the full capability of channel sensing, i.e. sense M channels, which is attributed to the tradeoff between spectrum opportunity exploration and sensing time overhead. Comparing the proposed SMCS and SMCS-L protocols, the performance of the SMCS-L tends to be degraded since the decision-making process in the SMCS-L is on the long-term basis without updating the information about the transient states of the environment. Therefore, the two proposed protocols can be regarded as performance-oriented and complexity-oriented approaches, respectively. Furthermore, the decision-making processes in the SMCS and SMCS-L protocols in the NS case are compared with respect to the time slots and the number of the channels. As can be seen in Fig. 4.2(a), the variations in the decisions on the numbers of the channels to be sensed L^* in the SMCS protocol reveal its adaptation to the dynamic-changing network environment. In other words, L^* is varying over time slots under the dynamic strategy. On the other hand, in the SMCS-L protocol, the CR users adopt the static strategy with the fixed number of the channels to be sensed L^* over time slots, which can be observed to be time-invariant in the figure.

4.2 Performance Comparison under the imperfect Sensing Scenario

The sensing errors are taken into consideration when conducting spectrum sensing under the imperfect sensing scenario. Considering that the PUs have QoS requirements for the detection probabilities P^d from 0.85 to 0.95 with equal difference between any consecutive channels, the CR users are required to meet the PUs' requirements when opportunistic

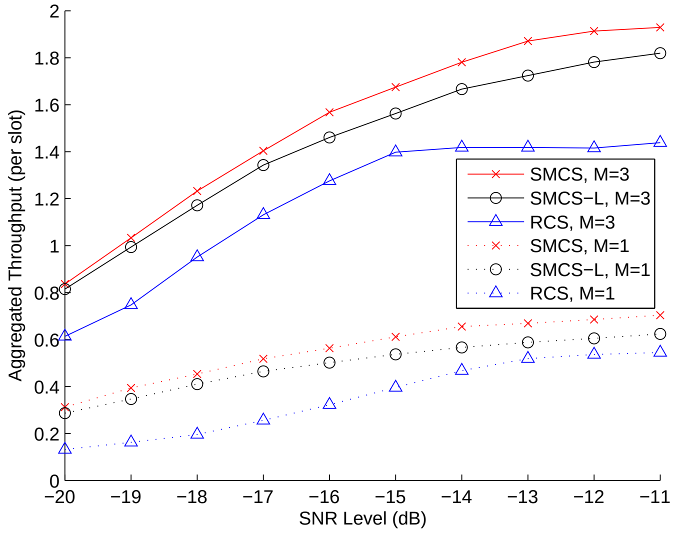


(a) SMCS

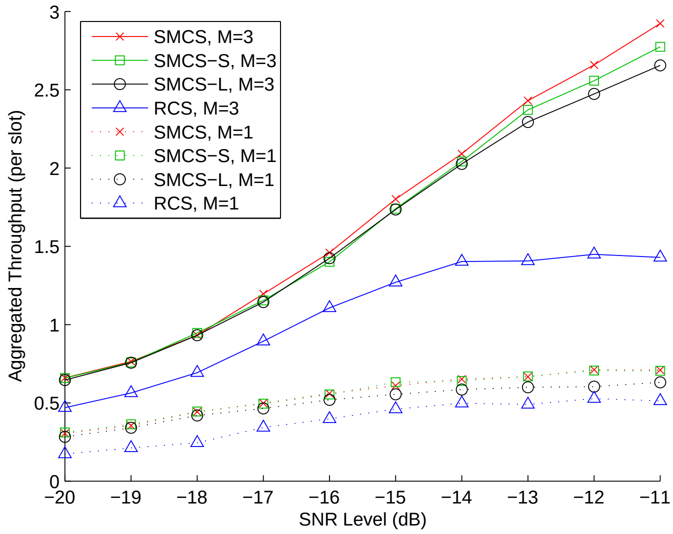


(b) SMCS-L

Figure 4.2: Dynamic characteristic of L^* in the SMCS and the SMCS-L protocols under the perfect narrowband sensing scenario.



(a) Wideband sensing



(b) Narrowband sensing

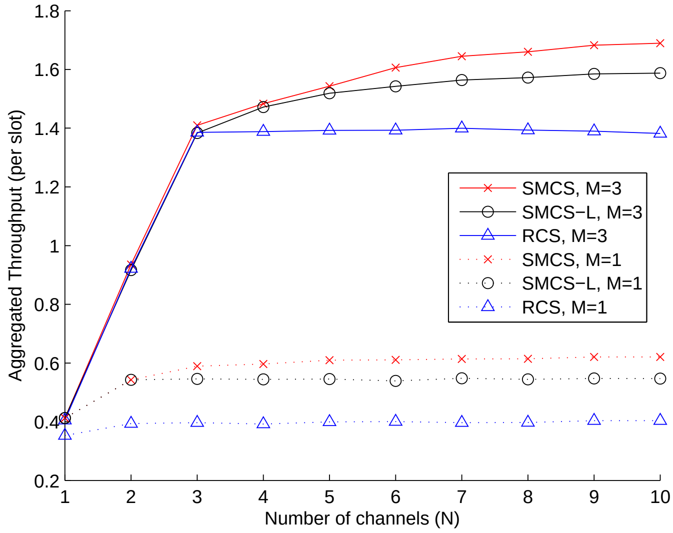
Figure 4.3: Performance comparison of CR users' aggregated throughput versus SNR. γ under the imperfect sensing scenario.

spectrum access. The performance is evaluated in terms of aggregated throughput while the false alarm is taken into consideration in the CR users' obtained reward. First of all, the proposed TSMCS, TSMCS-S, and TSMCS-L protocols are compared with the RCS protocol in the WS case, where the sensing time in the RCS protocol is similarly set as $100(32+8)M/f_s$. By varying the SNR of the received signals from the PUs, the performance comparison is shown in Fig. 4.3(a).

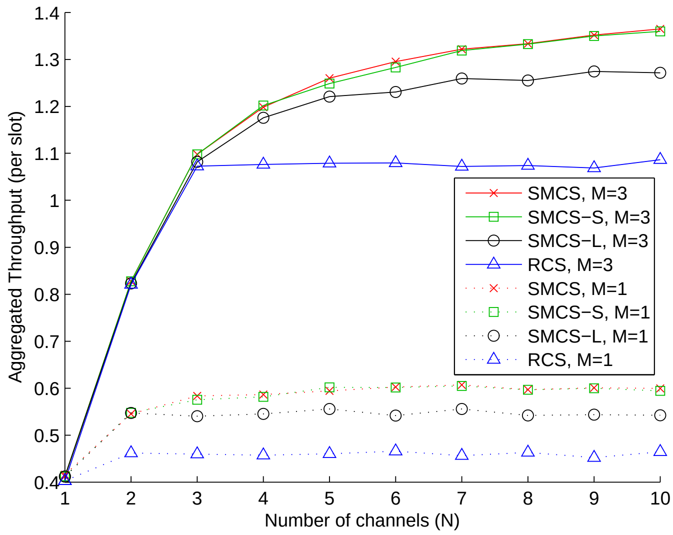
As can be seen in the figure, the proposed protocols have the better performance compared with the RCS protocol in the cases of both single and multiple channel operations. Noted that the aggregated throughput increases when the received signals have high SNR. It is due to the fact that the CR users can obtain accurate sensing outcomes without the need for excessive sensing time. In other words, the remaining time for data transmission is increased in such circumstance. In addition, the throughput tends to saturate by adopting the RCS protocol due to the improper channel selection during the sensing period. On the other hand, in the NS case, the performance gain provided by the proposed protocols can be clearly seen in Fig. 4.3(b). Noted that the proposed TSMCS-S protocol with the sub-optimal approach can be highly close to the maximum throughput while reducing its computational complexity, where the optimum is achieved by the TSMCS protocol with the exhaustive search over all the possible combinations of channel selection.

Moreover, considering the number of the channels in the primary network, the performance comparison in the WS and NS cases are shown in Fig. 4.4(a) and Fig. 4.4(b), respectively.

Obviously, the proposed protocols outperform than the RCS protocol in both cases and facilitate the CR users' optimal decision-making processes while keeping the protection of the PUs without introducing severe interference. Lastly, considering that the PUs vary their QoS requirements in terms of detection probabilities, the impacts on the CR user' performance in the WS and NS cases are shown in Fig. 4.5(a) and Fig. 4.5(b),



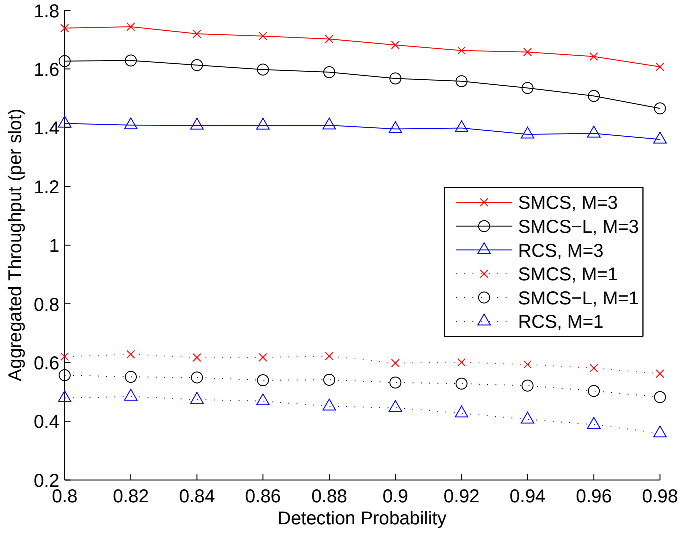
(a) Wideband sensing



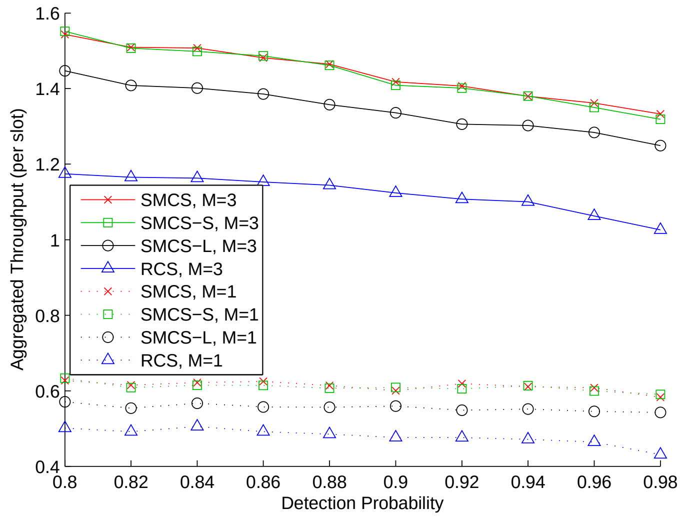
(b) Narrowband sensing

Figure 4.4: Performance comparison of CR users' aggregated throughput versus numbers of channels N under the imperfect sensing scenario.

respectively. As can be seen in the figure, the proposed protocols provide the CR users with the better approaches for achieving their objective. Noted that the performance is degraded as P_d increases, i.e. the PUs have more stringent constraints on the likelihood of mis-detection. It is due to the fact that the CR users intend to increase their sensing time for channel sensing in order to guarantee that the PUs will not be inferred with the outage probability. Consequently, the remaining time for data transmission is reduced and the probability of false alarm is also increased under such policy. Furthermore, noted that the performance in the NS case is more sensitive to the variations in the detection requirements, which is due to the fact that the allocated sensing time for each channel can be different from each other and is highly correlated with the corresponding probability of detection.



(a) Wideband sensing



(b) Narrowband sensing

Figure 4.5: Performance comparison of CR users' aggregated throughput versus detection probability P_d under the imperfect sensing scenario.

Chapter 5

Conclusions

In this thesis, in consideration of the sensing overhead in a partially observable network, the stochastic multiple channel sensing (SMCS) protocol is proposed. With only partial information, the optimal decision on channel sensing can be conducted, which is expected to achieve the maximum aggregated throughput for the current time slot. Consequently, not only the spectrum efficiency of primary network but also the system performance of CR network can be improved by exploiting the technique of channel aggregation. Furthermore, the two-phase SMCS (TSMCS) protocol is also proposed to address the problem of performance degradation due to sensing errors. Simulation results show that both the proposed the SMCS and TSMCS protocols can effectively enhance the CR users' aggregated throughput by conducting the optimal decision-making in the partially observable CR network with the protection of the PUs.

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