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協力式感知無線網路之電量管理及高吞吐量協定設計
期末報告

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摘要

由於現存的無線網路系統採用固定頻寬分配的方式，而使得頻譜使用效率不佳，根據研究指出，有 62%的已分配頻帶在任意的時間、地點、頻帶是沒有被使用的。利用感知網路(cognitive radio)動態偵測和使用有認證頻帶(licensed band)的技術，可增加頻譜的使用效率，然而不可避免地，感知網路使用者(secondary user)會對主要使用者(primary user)產生干擾，所以干擾和功率的控制是感知網路須解決的問題。在這篇報告中，考慮通道增益(channel gain)和主要使用者資訊流(primary traffic)下，利用賽局理論(game theory)的限制隨機賽局(constrained stochastic game)求得最佳的策略。在管理功率方面，底層波型(underlay waveform)和重疊波型(overlay waveform)的網路環境皆有考慮。另外，為了確保感知網路使用者的干擾不會影響主要使用者，利用可允須干擾(allowable interference)當作行為限制。根據限制隨機賽局的表示法，可以證明奈許平衡解(Nash equilibrium)存在於此功率管理的問題。而模擬的驗證也可確認和推導的結果一致。

另一方面，基於跳頻選擇機制的資源擷取控制通訊協定 (channel-hopping based medium access control (MAC) protocols)被提出來增進分散式多頻帶無線感知網路下的通道容量而不需使用額外的控制通道，在其中，每個感知使用者必須隨機去跟隨初始的跳頻序列(channel-hopping sequence)去進行通道的偵測以及資料傳輸。在本報告中，無線隨意感知網路基於跳頻選擇機制的資源擷取控制通訊協定在配對傳輸以及廣義傳輸的模式底下，考慮現實感知網路中的不完美通道檢測以及同步，利用排隊理論模型(queueing theory)提出感知網路下的通

道吞吐量分析以及主要使用網路(primary networks)所能提供的通道空閒資源和其所受感知使用者影響所產生的封包延遲。接著，根據此分析模型，基於動態規畫(dynamic programming)的技巧，在主要使用者的封包延遲限制之下提出最佳的跳頻選擇機制 (OCS)，藉著開發最佳的資源分配機制去平衡通道空閒資源和通道使用率，此方法可以找出此網路底下最佳的通道吞吐量，同時降低對主要使用者的干擾。從模擬的結果中可以看出所提出的最佳的跳頻選擇機制的確和其它傳統的跳頻機制相比可以大幅提升網路的吞吐量，並且確保主要使用網路的封包延遲限制。

Abstract

Recent studies have been conducted to indicate the ineffective usage of licensed bands due to the static spectrum allocation. In order to improve the spectrum utilization, the cognitive radio (CR) is therefore suggested to dynamically exploit the opportunistic primary frequency spectrums. The interference from the secondary users (SUs) to the primary user (PU) consequently draws the attention to the spectrum and power management for the cognitive radio networks. In this report, the constrained stochastic games are utilized to exploit the optimal policies for power management by considering the variations from both the channel gain and the primary traffic. Both the underlay and overlay waveforms are considered within the network scenarios for the proposed power management scheme. Constraints for allowable interferences will be applied in order to preserve the communication quality among the primary and the secondary users. According to the formulation of the constrained stochastic games, the existence of the constrained Nash equilibrium will be validated with rigorous proofs, which will be acquired as the optimal policies for the power management problem. Simulation results further validate the correctness of the theoretically derived policies for dynamic power management.

On the other hand, channel-hopping based medium access control (MAC) protocols are proposed to improve the capacity in a decentralized multi-channel CR networks without extra usage of a control channel. Each CR user has to stochastically follow a default channel-hopping sequence in order to sense a channel and to conduct its frame transmission. In this report, based on the channel-hopping protocol, an analysis is conducted on both the probability of channel availability and the average frame delay for the primary queueing networks. The analytical model is proposed by

considering the impact caused by imperfect sensing of the CR users and the imperfect synchronization between the primary and CR networks. According to the proposed model with more realistic considerations, an optimal channel-hopping sequence (OCS) approach is designed for the CR users based on dynamic programming technique. It is designed by exploiting the optimal load balance between both the channel availability and channel utilization within the delay constraints of PUs. By adopting the OCS approach, the maximum aggregate throughput of CR users and the quality of service (QoS) requirement of PUs can both be achieved. Numerical results illustrate that the proposed OCS scheme can effectively maximize the aggregate throughput compared to conventional channel-hopping sequences, and as well guarantee the QoS requirement of the PUs.

Publication:

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[7] Chia-Wei Wang, Yu-Pin Hsu, and **Kai-Ten Feng**, "Dynamic Power Management in Cognitive Radio Networks based on Constrained Stochastic Games," in Proceedings of *IEEE Globe Telecommunications Conference (Globecom)*, Honolulu, HI, Nov. 2009.

Dynamic Power Management in Cognitive Radio Networks based on Constrained Stochastic Games

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***Abstract*—Recent studies have been conducted to indicate the ineffective usage of licensed bands due to the static spectrum allocation. In order to improve the spectrum utilization, the cognitive radio is therefore suggested to dynamically exploit the opportunistic primary frequency spectrums. The interference from the secondary users to the primary user consequently draws the attention to the spectrum and power management for the cognitive radio networks. In this paper, the constrained stochastic games are utilized to exploit the optimal policies for power management by considering the variations from both the channel gain and the primary traffic. Both the underlay and overlay waveforms are considered within the network scenarios for the proposed power management scheme. Constraints for allowable interferences will be applied in order to preserve the communication quality among the primary and the secondary users. According to the formulation of the constrained stochastic games, the existence of the constrained Nash equilibrium will be validated with rigorous proofs, which will be acquired as the optimal policies for the power management problem. Simulation results further validate the correctness of the theoretically-derived policies for dynamic power management.**

Keywords: Cognitive radio, dynamic power management, constrained stochastic games, constrained Nash equilibrium.

I. Introduction

Due to rapid development of wireless systems, the demand for wireless spectrums has resulted in spectrum scarcity based on the conventional fixed allocation schemes. Even with the intensive usage of frequency spectrums, it has been studied by extensive measurements [1] that 62% of spectrum still remains unoccupied by the licensed primary user (PU). Cognitive radio (CR) is an intelligent wireless communication system that is perceptible to its surroundings. It is advanced as an emerging technology to effectively exploit the under-utilized spectrum in order to overcome the overcrowded spectrum problem.

There are two types of spectrum sharing that are defined for the CR networks (CRNs), including the underlay and the overlay waveforms. The underlay waveform represents that the unlicensed secondary users (SUs) are allowed to simultaneously share the primary frequency spectrum with the PUs. The transmission power of the SUs are in general limited in order not to cause excessive interferences to the PUs. On the other hand, an overlay waveform allows the SUs to perform packet transmission under the existence of a spectrum hole. The spectrum hole is defined as a frequency band authorized to PUs, however, it is vacant at a particular time and geographic location. With the overlay waveform, the SUs can sense and identify the existence of spectrum hole for data communications. Therefore, spectrum utilization can be enhanced with these frequency-agile features. The research work in the CRNs has been investigated from various aspects. The work proposed in [2; 3] presents the techniques for spectrum sensing and detection; while [4; 5] investigate the spectrum allocation problem for the CR. There are also research [6; 7] focusing on the medium access control design for the CRNs.

Game theory [8] has been considered a feasible mathematical tool for solving the resource allocation problems in CRNs. The fundamental concept of game theory is to resolve the conflict and cooperation between intelligent rational decision-makers (DMs). Instead of reaching a globally optimized solution based on identical objective, the DMs within the gaming formulation are seeking for solutions selfishly without the knowledge of other DMs' decisions. The primary reason is due to the inherent conflicts between the objectives that are assigned among the DMs, which can be adopted to model the behaviors of both PUs and SUs within the CRNs. After reaching the optimized solution (i.e. Nash equilibrium (NE) [8]) based on the game theory, each individual DM will not benefit from any action to deviate from the NE. In other words, by considering the conflicted interests between the DMs, the solutions obtained at the NE will provide every DM to possess the optimal resource allocation.

In general, two different types of games are categorized for the game theory, i.e. the strategic games and the extensive games. With the objective of reaching the NE, all DMs simultaneously select their strategies only for one-time by adopting the strategic games [8], which have been exploited to resolve the power control problem for the CRNs in recent research work [9; 10]. The work in [9] proposed an algorithm for distributed multi-channel power allocation based on the strategic gaming model; while the pricing-based games are utilized in [10] to achieve a higher signal-to-noise ratio with the guarantee of reliable data transmissions.

On the other hand, the extensive games [8; 11; 12] represent a class of gaming models where the DMs repeatedly conduct decision-making numerous times for resource allocation,

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where the scheme proposed in [12] utilized the repeated game to solve NE point under underlay waveform. Unlike the strategic games that each DM considers his strategy only at the beginning of the game, the extensive games is implemented whenever a decision has to be made in order to increases the spectrum efficiency by the multi-stage gaming model. Furthermore, constrained stochastic games [13; 14] are formulated by extending the extensive games for dynamically-changing environments with the consideration of certain constraints for optimization. It can be considered as an extension of the Markov decision process from a single DM to multiple DMs. The power allocation algorithm proposed in [15] imposes both the power and the buffer length constraints under the environments with varying channel states. It is noticed that only independent states between the DMs are considered in [15], i.e. the states of power and buffer length for each DM is independent to those from other DMs. However, constrained stochastic games can also be applied to the resource management problems for CRNs.

In this paper, the constrained stochastic games are adopted and extended to study the dynamic power management problem in CRNs. The dynamic environments occurred from the channel variations and the uncertain spectrum holes will be modeled as the ergodic Markov decision process. It is noticed that the spectrum holes are considered the dependent states for each SU since the SUs are sharing to utilize the spectrum holes while the original licensed PU is temporarily releasing the frequency band. Moreover, each SU can perceive its own current state but is unaware of the states and strategies from the other SUs. As the licensed spectrum is occupied by the PUs, the underlay waveform is executed by the SUs with the introduction of reasonable interferences to the PUs. On the other hand, the SUs will share the spectrum hole with the overlay waveform as the primary traffic is absent. Constraints for allowable interferences will also be imposed to preserve the communication quality among the SUs under the existence of spectrum holes. With the satisfaction of the defined constraints, the constrained NE [14] suggests an optimal solution to the dynamic power assignment according to the SUs' current state within the CRNs.

The rest of this paper is organized as follows. Section II presents the system model. The corresponding proofs for the existence of constrained Nash equilibrium are provided in Section III. Numerical evaluation is performed in Section IV; while Section V draws the conclusions.

II. System Model for Dynamic Power Management with Constrained Stochastic Games

The schematic diagram of the CRN is illustrated in Fig. 1, where a synchronous slotted time structure is considered. A PU is communicating with its primary base station; while there exists $N = 2$ SU pairs where SU(Tx) is intending to transmit its data packets to the respective SU(Rx) within the same frequency spectrum as the PU. The overlay waveform is shown at the time slot 2 where a spectrum hole happens for the SUs to share the licensed band without the existence of the PU. At both time slots 1 and 3, with tolerable interferences to the PU, the SUs coexist with the PU to conducts their transmissions under the execution of the underlay waveform.

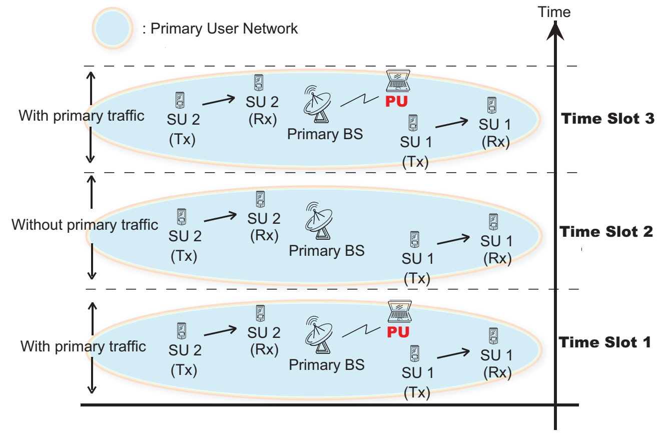

Fig. 1. The schematic diagram of the cognitive radio network for dynamic power management. (Tx : transmitter , Rx : receiver)

At each time slot t, each SU(Tx) i forwards its data packets with a specific power level $p_i^t \in \boldsymbol{p}_i \triangleq \{p_{i,0}, p_{i,1}, \cdots, p_{i,\max}\}$, which is referred as the action set in the game theory. The global set of the power level for the entire CRN is denoted as $\mathbf{P} = \prod_{i=1}^{N} \boldsymbol{p}_i$. The dynamic environment in CRN is modeled as an ergodic Markov chain [16], where feedback information is considered available for each SU pair, i.e. from SU(Rx) to SU(Tx). In other words, each SU(Tx) will possess the information about all the current states that are detected by its corresponding SU(Rx). The compound state s_i^t of each SU i at the time slot t is constructed by two elements ϕ_i^t and g_i^t, i.e. $s_i^t = (\phi_i^t, g_i^t)$. The parameter $\phi_i^t \in \boldsymbol{\phi}_i \triangleq \{0, 1\}$ is utilized to denoted the status of the PU, where $\phi_i^t = 0$ indicates the absence of the primary traffic, and $\phi_i^t = 1$ represents the existence of the PU within the CRN. It is noted that, at each time slot t, the indication of the primary traffic ϕ_i^t is considered equal for all the SUs i that share the licensed spectrum. Therefore, the global space can be obtained as $\mathbf{\Phi} = \prod_i^N \boldsymbol{\phi}_i = \{\alpha, \cdots, \alpha\}$, where $\mathbf{\Phi}$ has N elements with $\alpha \in \{0, 1\}$. Moreover, the state of the channel gain for each SU i at time slot t is denoted by the index $g_i^t \in \boldsymbol{g}_i \triangleq \{0, \cdots, L_i - 1\}$. The compound state s_i^t will therefore belong to the set $\boldsymbol{s}_i = \boldsymbol{\phi}_i \times \boldsymbol{g}_i$ with the length of state vector equal to $2L_i$. The global state space of s_i^t considering all the N SUs can also be represented as $\mathbf{S} = \prod_{i=1}^{N} \boldsymbol{s}_i$. Furthermore, $P_{xy}^i = \mathcal{M}(s_i^{t+1} = y | s_i^t = x)$ is utilized to express the state transition probability, where $\mathcal{M}(\varepsilon)$ is the probability measure over an event ε.

A history at time epoch t of SU i is a time sequence of its current state as well as its previous states and actions, which is denoted as $\boldsymbol{h}_i^t = (s_i^0, p_i^0, s_i^1, p_i^1, \cdots, s_i^{t-1}, p_i^{t-1}, s_i^t)$ with $s_i^k \in \boldsymbol{s}_i$ and $p_i^k \in \boldsymbol{p}_i$. Let $\mathbf{H}_i^t$ be the collection of all possible histories of length t for SU i. A policy employed by SU i can be denoted as a sequence $\boldsymbol{u}_i = (u_i^0, u_i^1, \cdots, u_i^t)$, where $u_i^t : \mathbf{H}_i^t \rightarrow \mathcal{M}(\boldsymbol{p}_i)$ is a function mapping from the histories to the probability measure over the action sets of SU i. The elements within the policy u_i^t indicate the occurring probabilities for their corresponding power level $p_{i,j}$ for $j = 0$ to $\max$. It is noted that the decision of the policy u_i^t for each SU is independent to that for the other SUs. The set of all reasonable policies for SU i is in the policy space $\mathbf{U}_i$, i.e. $\boldsymbol{u}_i \in \mathbf{U}_i$. Therefore, with the consideration of all the N SUs, the global policy space $\mathbf{U} = \prod_{i=1}^N \mathbf{U}_i$ is called the class of multi-policies. In addition, the multi-policy except SU i is defined as $\boldsymbol{u}_{-i} = (\boldsymbol{u}_1, \boldsymbol{u}_2, \cdots, \boldsymbol{u}_{i-1}, \boldsymbol{u}_{i+1}, \cdots, \boldsymbol{u}_N) \in \boldsymbol{U}_{-i}$. Moreover, the stationary policies are characterized as the policy that is independent of the histories, i.e. $u_i^t : \boldsymbol{s}_i \to \mathcal{M}(\boldsymbol{p}_i)$ as a function mapping only from the current state $\boldsymbol{s}_i$. The union of all possible stationary policies is denoted as $\mathbf{U}_i^S \in \mathbf{U}_i$, and $\mathbf{U}^S = \prod_{i=1}^N \mathbf{U}_i^S \in \mathbf{U}$ represents the class of stationary multi-policies.

In this paper, the immediate utility of SU i is defined as r_i which is a function of $(\boldsymbol{s}^t, \boldsymbol{p}^t)$. For example, the achievable transmission data rate of SU i can be applied to the immediate utility as follows

$$r_i(\boldsymbol{s}^t, \boldsymbol{p}^t) = B \cdot \log_2 \left(1 + \frac{p_i^t \, \nu_{ii}(s_i^t)}{\sum_{j \neq i} p_j^t \, \nu_{ji}(s_j^t) + \sigma_i^2 + \varepsilon_i \phi_i^t} \right) \quad (1)$$

where $\boldsymbol{s}^t = (s_1^t, s_2^t, \cdots, s_N^t) \in \mathbf{S}$ and $\boldsymbol{p}^t = (p_1^t, p_2^t, \cdots, p_N^t) \in \mathbf{P}$. The parameter B denotes the bandwidth of the licensed spectrum with unit in Hz. The function $\nu_{ji}(s_j^t)$ represents the corresponding channel gain from SU j(Tx) to SU i(Rx) in state s_j^t, and σ_i^2 is the power of the noise under the assumption of additive, white, and Gaussian distribution. ε_i denotes the interference from the primary traffic that imposes on SU i. The expected utility of SU i with the policy $\boldsymbol{u} = (\boldsymbol{u}_1, \boldsymbol{u}_2, \cdots, \boldsymbol{u}_N) \in \mathbf{U}$ and the initial state $\boldsymbol{s}^0 = (s_1^0, s_2^0, \cdots, s_N^0) \in \mathbf{S}$ can be obtained as

$$R_i(\boldsymbol{s}^0, \boldsymbol{u}) = \limsup_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} E_{\boldsymbol{s}^0}^{\boldsymbol{u}} \left[r_i(\boldsymbol{s}^t, \boldsymbol{p}^t) \right] \quad (2)$$

where $E_{\boldsymbol{s}^0}^{\boldsymbol{u}}$ is the operator for the computation of expectation value. Furthermore, the allowable interferences between the SUs and the PU are considered in order to guarantee the quality of service (QoS) of the CRN. The supreme expected allowable interference at the SU i(Rx) is obtained as

$$I_{i,j}(\boldsymbol{s}^0, \boldsymbol{u}) = \limsup_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{k=1}^{N} E_{\boldsymbol{s}^0}^{\boldsymbol{u}} \left[p_k^t \cdot \nu_{ki}(s_k^t) \cdot \delta_j(\phi_k^t) \right] \quad (3)$$

where δ is the Kronecker delta function. In (3), $I_{i,0}(\boldsymbol{s}^0, \boldsymbol{u})$ indicates the case with the absence of primary traffic, i.e. $\delta_0(\phi_i^t = 0) = 1$; while $I_{i,1}(\boldsymbol{s}^0, \boldsymbol{u})$ denotes the case with primary traffic, i.e. $\delta_1(\phi_i^t = 1) = 1$. Under the usage of licensed band from PU, the influence occurred from the SUs is confined by $I_{i,1}(\boldsymbol{s}^0, \boldsymbol{u}) \leq C_1$ to assure the QoS of the PU, where C_1 denotes the the PU's tolerable interference. Considering the case without the primary traffic, the allowable interference between the SUs are constrained by $I_{i,0}(\boldsymbol{s}^0, \boldsymbol{u}) \leq C_0$, where C_0 indicates the QoS constraint among the SUs that share the common spectrum band. Therefore, the set of feasible policies can be defined as $\boldsymbol{u} \in \mathbf{U}$ in order to satisfy the condition $I_{i,j}(\boldsymbol{s}^0, \boldsymbol{u}) \leq C_j$ for $j \in \{0, 1\}, \forall i$.

It is considered that the SUs are rational [8] such that all SUs are intending to maximize their corresponding utilities in (2). Furthermore, the decision for each SU i to transmit packets with the power level p_i^t at the beginning of time slot t is determined without additional knowledge about the states and actions from the other SUs. As a result, the constrained Nash equilibrium (CNE) [14] will be utilized to facilitate the power management problem from the perspective of game theory, which is defined as follows.

Definition 1. A multi-policy $\boldsymbol{u}^* = (\boldsymbol{u}_1^*, \boldsymbol{u}_2^*, \cdots, \boldsymbol{u}_N^*) \in \mathbf{U}$ is a constrained Nash equilibrium (CNE) if it is a feasible policy such that for all SUs i

$$R_i(\boldsymbol{s}^0, \boldsymbol{u}^*) \geq R_i(\boldsymbol{s}^0, [\boldsymbol{u}_{-i}^* | \boldsymbol{v}_i]) \quad (4)$$

for any feasible policies $[\boldsymbol{u}_{-i}^* | \boldsymbol{v}_i]$, where the policy $[\boldsymbol{u}_{-i}^* | \boldsymbol{v}_i]$ means that SU i uses the policy $\boldsymbol{v}_i$ while other SUs $k \neq i$ takes the policy $\boldsymbol{u}_k^*$.

The purpose of this paper is to provide the mechanism for dynamic power management based on the optimal polices that are derived from the CNE. The existence of CNE for the considered problem will be acquired in the next section.

III. Existence of CNE for Dynamic Power Management

In this section, the constrained optimization problem for dynamic power management considering a single SU will first be introduced in Problem 1. The linear programming methodology as formulated in Problem 2 will be associated with Problem 1 based on the proofs in Lemmas 1 to 3. Consequently, the dynamic power management problem as defined in Definition 1 will be proved in Theorem 1 for the entire N SUs in the CRN. Consider fixed policies for the other SUs, a constrained optimization problem for a single SU can be formulated to obtain the best response [8] as follows.

Problem 1 (Constrained Optimization Problem (COP))**.** Given a fixed set of policies $\boldsymbol{u}_{-i} \in \mathbf{U}_{-i}$, find an optimal policy $\boldsymbol{v}_i^*$ for SU i in order to maximize the expected utility

$$R_i(\boldsymbol{s}^0, [\boldsymbol{u}_{-i} | \boldsymbol{v}_i]) \quad (5)$$

subject to

$$I_{i,j}(\boldsymbol{s}^0, [\boldsymbol{u}_{-i} | \boldsymbol{v}_i]) \leq C_j \quad \forall j \in \{0, 1\} \quad (6)$$

Therefore, a CNE multi-policy $\boldsymbol{u}^* \in \mathbf{U}$ in Definition 1 can be verified while $\boldsymbol{u}_i^*$ represents the optimal policy in Problem 1 for all SU i providing other SUs take the policies $\boldsymbol{u}_{-i}^*$. In order to resolve Problem 1, the defined COP can be correlated with a linear programming problem by extending from the previous studies [14; 17; 18]. A linear programming problem is defined as follows.

Problem 2 (Linear Programming (LP) problem)**.** Consider a set of state-action pairs for SU i characterized by $\mathbf{K}_i = \{(s_i, p_i) : s_i \in \mathbf{S}_i, p_i \in \mathbf{P}_i\}$ as well as $\mathbf{K} = \prod_i^N \mathbf{K}_i$ and $\mathbf{K}_{-i} = \prod_{j\neq i}^N \mathbf{K}_i$. Given a set of stationary policies $\boldsymbol{u}_{-i} \in \mathbf{U}_{-i}^S$, find $\boldsymbol{z}^*_{i,\boldsymbol{u}_{-i}} = \{z^*_{i,\boldsymbol{u}_{-i}}(s_i, p_i) : (s_i, p_i) \in \mathbf{K}_i\}$ which maximizes

$$\mathscr{R}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}) = \sum_{(s_i,p_i)\in\mathbf{K}_i} \mathcal{R}_{i,\boldsymbol{u}_{-i}}(s_i, p_i) \cdot z_{i,\boldsymbol{u}_{-i}}(s_i, p_i) \quad (7)$$

subject to

$$\mathscr{I}_{i,j}(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}) = \sum_{\substack{(s_i,p_i)\in\mathbf{K}_i \\ \phi_i=j}} \mathcal{I}_{i,\boldsymbol{u}_{-i}}(s_i, p_i) \frac{z_{i,\boldsymbol{u}_{-i}}(s_i, p_i)}{\boldsymbol{Z}_{i,j}} \leq C_j \ \forall j \in \{0, 1\} \quad (8)$$

$$\sum_{(s_i,p_i)\in\mathbf{K}_i} z_{i,\boldsymbol{u}_{-i}}(s_i, p_i) \left[\delta_{r_i}(s_i) - P^i_{s_i r_i}\right] = 0 \quad \forall r_i \in \mathbf{S}_i \quad (9)$$

$$\sum_{(s_i,p_i)\in\mathbf{K}_i} z_{i,\boldsymbol{u}_{-i}}(s_i, p_i) = 1 \quad (10)$$

$$z_{i,\boldsymbol{u}_{-i}}(s_i, p_i) \geq 0 \quad \forall (s_i, p_i) \in \mathbf{K}_i \quad (11)$$

where $P^i_{s_i r_i}$ in (9) is the transition probability from state s_i to r_i for SU i. The value of $\delta_{r_i}(s_i)$ in (9) is equal to 1 as the state $s_i = r_i$, otherwise $\delta_{r_i}(s_i) = 0$. The denominator $\boldsymbol{Z}_{i,j}$ in (8) is utilized for normalization purpose as

$$\boldsymbol{Z}_{i,j} = \sum_{\substack{(s_k,p_k)\in\mathbf{K}_i \\ \phi_k=j}} z_{i,\boldsymbol{u}_{-i}}(s_k, p_k) \quad (12)$$

The functions $\mathcal{R}_{i,\boldsymbol{u}_{-i}}(s_i, p_i)$ in (7) and $\mathcal{I}_{i,\boldsymbol{u}_{-i}}(s_i, p_i)$ in (8) are the expected immediate utility and the allowable interference while SU i executes the power level p_i at the state s_i under the case that the other SUs are adopting the policy $\boldsymbol{u}_{-i}$. Both functions can be expressed as

$$\mathcal{R}_{i,\boldsymbol{u}_{-i}}(s_i, p_i) = \sum_{\substack{(\boldsymbol{s},\boldsymbol{p})_{-i}\in\mathbf{K}_{-i}, \\ \phi_k=\phi_i,\forall k\neq i}} \prod_{m\neq i} \Omega_{i,m} \cdot r_i(\boldsymbol{s}, \boldsymbol{p}) \quad (13)$$

$$\mathcal{I}_{i,\boldsymbol{u}_{-i}}(s_i, p_i) = \sum_{\substack{(\boldsymbol{s},\boldsymbol{p})_{-i}\in\mathbf{K}_{-i}, \\ \phi_k=\phi_i,\forall k\neq i}} \prod_{m\neq i} \Omega_{i,m} \left(\sum_{k=1}^N p_k\, \nu_{ki}(s_k)\right) \quad (14)$$

where $\Omega_{i,m}$ corresponds to the probability of the state-action pair (s_m, p_m) for SU m. Let the stationary distribution of the state s_m for SU m be $\pi_m(s_m)$, $\Omega_{i,m}$ can be computed as

$$\Omega_{i,m} = \frac{u_m(p_m|s_m)\pi_m(s_m)}{\sum_{\substack{(s_k,p_k)\in\mathbf{K}_m, \\ \phi_k=\phi_i}} u_m(p_k|s_k)\pi_m(s_k)} \quad (15)$$

where $u_m(p_m|s_m)$ denotes the probability measure for SU m to conduct action p_m based on the state s_m. The normalized term in the denominator of (15) is utilized to indicate that common spectrum among all the SUs will result in the correlation among the states of each SU, i.e. $\phi_m = \phi_i$ for all $m \neq i$.

A set of nonnegative real numbers is defined as $\boldsymbol{\omega}_i = \{\omega_i(s_i, p_i) : (s_i, p_i) \in \mathbf{K}_i\}$. The probability $\boldsymbol{\gamma}_i(\boldsymbol{\omega}_i) = \{\gamma^{p_i}_{s_i}(\boldsymbol{\omega}_i) : (s_i, p_i) \in \mathbf{K}_i\}$ can be define as $\gamma^{p_i}_{s_i}(\boldsymbol{\omega}_i) = \omega_i(s_i, p_i)/\sum_{p_k} \omega_k(s_k, p_k)$ in the case that $\sum_{p_k} \omega_k(s_k, p_k) \neq 0$. Otherwise, an arbitrary value is assigned to $\gamma^{p_i}_{s_i}(\boldsymbol{\omega}_i)$ such that $\sum_{p_k} \gamma^{p_i}_{s_i}(\boldsymbol{\omega}_i) = 1$. The parameter $\boldsymbol{\lambda}_i(\boldsymbol{\omega}_i)$ represents a set of stationary policies for SU i that selects its power level p_i at the state s_i with the probability $\gamma^{p_i}_{s_i}(\boldsymbol{\omega}_i)$. Furthermore, $f_i(s^0_i, \boldsymbol{u}_i; s_i, p_i)$ is denoted as the limiting point of the time sequence $\{f^t_i(s^0_i, \boldsymbol{u}_i; s_i, p_i)\}_t$. The expected state-action frequency $f^t_i(s^0_i, \boldsymbol{u}_i; s_i, p_i)$ [18] for SU i at time t can be obtained as

$$f^t_i(s^0_i, \boldsymbol{u}_i; s_i, p_i) = \frac{1}{t} \sum_{k=0}^{t-1} P^{\boldsymbol{u}_i}_{s^0_i}(s^k_i = s_i, p^k_i = p_i) \quad (16)$$

where $P^{\boldsymbol{u}_i}_{s^0_i}(\varepsilon)$ is the the probability measure over the event ε with the policy $\boldsymbol{u}_i$ and the initial state s^0_i. Based on the definition of the state-action frequency, the relationship between the COP and the LP problem can be constructed as follows.

Lemma 1. *Given a set of stationary policies $\boldsymbol{u}_{-i} \in \mathbf{U}^S_{-i}$, for any $\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}$ that satisfies (9) to (11) will result in $\mathscr{R}_{i,j}(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}) = R_i(\boldsymbol{s}^0, [\boldsymbol{u}_{-i}|\boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})])$ for SU i.*

Proof: Based on the definition of $R_i(\boldsymbol{s}^0, \boldsymbol{u})$ in (2), the following equation can be obtained:

$$R_i(\boldsymbol{s}^0, \boldsymbol{u}) = \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} E^{\boldsymbol{u}}_{\boldsymbol{s}^0}\left[r_i(\boldsymbol{s}^t, \boldsymbol{p}^t)\right] \quad (17)$$

$$= \limsup_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{(s_i,p_i)\in\mathbf{K}_i} \sum_{\substack{(\boldsymbol{s},\boldsymbol{p})_{-i}\in\mathbf{K}_{-i} \\ \phi_l=\phi_i,\forall l\neq i}} r_i(\boldsymbol{s}, \boldsymbol{p}) \cdot$$

$$P^{\boldsymbol{u}_i}_{s^0_i}(s^t_i = s_i, p^t_i = p_i) \prod_{j\neq i} \frac{P^{\boldsymbol{u}_j}_{s^0_j}(s^t_j = s_j, p^t_j = p_j)}{\sum_{\substack{(s_k,p_k)\in\mathbf{K}_j \\ \phi_k=\phi_i}} P^{\boldsymbol{u}_j}_{s^0_j}(s^t_j = s_k, p^t_j = p_k)} \quad (18)$$

$$= \sum_{(s_i,p_i)\in\mathbf{K}_i} f_i(s^0_i, \boldsymbol{u}_i; s_i, p_i) \cdot$$

$$\left[\sum_{\substack{(\boldsymbol{s},\boldsymbol{p})_{-i}\in\mathbf{K}_{-i} \\ \phi_l=\phi_i,\forall l\neq i}} r_i(\boldsymbol{s}, \boldsymbol{p}) \prod_{j\neq i} \frac{f_j(s^0_j, \boldsymbol{u}_j; s_j, p_j)}{\sum_{\substack{(s_k,p_k)\in\mathbf{K}_j \\ \phi_k=\phi_i}} f_j(s^0_j, \boldsymbol{u}_j; s_k, p_k)}\right] \quad (19)$$

$$= \sum_{(s_i,p_i)\in\mathbf{K}_i} f_i(s^0_i, \boldsymbol{u}_i; s_i, p_i) \cdot \mathcal{R}_{i,\boldsymbol{u}_{-i}}(s_i, p_i) \quad (20)$$

It is noted that the equality from (18) to (19) is mainly due to the assumption of stationary multi-policy. By substituting $\boldsymbol{u}_i$ in (20) with $\boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})$, it can be obtained that $f_i(s^0_i, \boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}); s_i, p_i) = z_{i,\boldsymbol{u}_{-i}}(s_i, p_i)$. The relationship between (5) and (7) can therefore be established, which completes the proof. □

Lemma 2. *Given a set of stationary policies $\boldsymbol{u}_{-i} \in \mathbf{U}^S_{-i}$. By choosing $\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}$ based on (9) to (11), the* *following relationship can be obtained: $\mathscr{I}_{i,j}(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}) = I_{i,j}(\boldsymbol{s}^0, [\boldsymbol{u}_{-i}|\boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})])$. Moreover, $\boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})$ is considered a feasible policy for the COP if $\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}$ additionally satisfies (8).*

Proof: The allowable interference in (3) can be expressed via the state-action frequency as

$$I_{i,j}(\boldsymbol{s}^0, \boldsymbol{u}) = \sum_{\substack{(\boldsymbol{s},\boldsymbol{p})\in\mathbf{K}\\ \phi_m=j,\forall m}} \left(\sum_{k=1}^{N} p_k\, \nu_{ki}(s_k)\right) \cdot \prod_{l=1}^{N} \frac{f_l(s_l^0, \boldsymbol{u}_l; s_l, p_l)}{\sum_{\substack{(s_k,p_k)\in\mathbf{K}_l\\ \phi_k=j}} f_l(s_l^0, \boldsymbol{u}_l; s_k, p_k)} \quad (21)$$

By adopting similar procedures as that from the proof of Lemma 1, the relationship that $\mathscr{I}_{i,j}(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}) = I_{i,j}(\boldsymbol{s}^0, [\boldsymbol{u}_{-i}|\boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})])$ can be easily acquired. Furthermore, since $I_{i,j}(\boldsymbol{s}^0, [\boldsymbol{u}_{-i}|\boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})]) = \mathscr{I}_{i,j}(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}) \le C_j$ for all j, it can be found that $\boldsymbol{\lambda}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})$ will be a feasible policy for the COP. This completes the proof. □

Lemma 3. *Given the set of policies $\boldsymbol{u}_{-i} \in \mathbf{U}_{-i}^S$ and $\boldsymbol{z}^*_{i,\boldsymbol{u}_{-i}}$ as an optimal solution for the LP problem. It is discovered that $\boldsymbol{\lambda}_i(\boldsymbol{z}^*_{i,\boldsymbol{u}_{-i}})$ will be the best response for the COP.*

Proof: Based on Lemmas 1 and 2 associated with Theorem 3.6 in [17], the proof of this lemma can be achieved. □

In order to extend the results to N SUs, the following parameters are defined. Given the set $\boldsymbol{z} = (\boldsymbol{z}_1, \boldsymbol{z}_2, \cdots, \boldsymbol{z}_N)$ such that $\boldsymbol{z}_i = \{z_i(s,p) : (s,p) \in \mathbf{K}_i\}$ will satisfy (8) to (11), where $\boldsymbol{u} = (\boldsymbol{u}_1, \boldsymbol{u}_2, \cdots, \boldsymbol{u}_N)$ with $\boldsymbol{u}_i = \boldsymbol{\lambda}_i(\boldsymbol{z}_i)$. The set $\mathbf{Z}_i$ is composed by the elements $\boldsymbol{z}_i$ as stated above, and the global space $\mathbf{Z} = \prod_{i=1}^N \mathbf{Z}_i$. By considering the mapping function $\Psi_i(\boldsymbol{z}) : \mathbf{Z} \to \mathbf{Z}_i$, the set of optimal solutions for the LP problem in Problem 2 for each SU i can be denoted as $\Psi_i(\boldsymbol{z}) = \{z^*_{i,\boldsymbol{u}_{-i}}(s,p) : (s,p) \in \mathbf{K}_i\}$. Moreover, its product space can also be defined as $\Psi(\boldsymbol{z}) : \mathbf{Z} \to \mathbf{Z}$ where

$$\Psi(\boldsymbol{z}) = \prod_{i=1}^{N} \Psi_i(\boldsymbol{z}) \quad (22)$$

Theorem 1. *There exists a stationary multi-policy $\boldsymbol{u} \in \mathbf{U}^S$ as the CNE for dynamic power management problem of the considered CRN.*

Proof: According to the association of both the COP and the LP problem as described in Lemma 3, it remains to show if there exists a fixed point (i.e. $\boldsymbol{z} \in \Psi(\boldsymbol{z})$) to the vector-valued function as in (22). The domain of $\Psi_i(\boldsymbol{z})$ (i.e. $\mathbf{Z}_i$) is considered a compact and convex set by investigating (8) to (11), and so is its product space $\mathbf{Z}$. It is noted that $\Psi_i(\boldsymbol{z})$ is defined as

$$\Psi_i(\boldsymbol{z}) = \arg\max_{\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}\in\mathbf{Z}_i} \mathscr{R}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}) \quad (23)$$

where $\mathscr{R}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})$ is observed to be a continuous function in terms of $\boldsymbol{z}_{i,\boldsymbol{u}_{-i}}$. Therefore, both $\Psi_i(\boldsymbol{z})$ and its product space $\Psi(\boldsymbol{z})$ are considered non-empty based on the extreme value theorem [19]. Furthermore, $\Psi(\boldsymbol{z})$ is a convex set for all $\boldsymbol{z} \in \mathbf{Z}$ due to the linearity of $\mathscr{R}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})$. The continuity of $\mathscr{R}_i(\boldsymbol{z}_{i,\boldsymbol{u}_{-i}})$ results in the closed graph of $\Psi(\boldsymbol{z})$. The proof can consequently be completed by adopting the Kahutain's fixed point theorem [8]. □

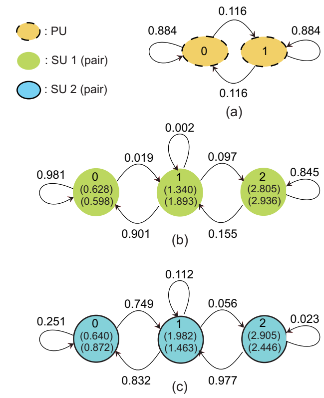

Fig. 2. Simulation parameters: (a) transition probabilities of primary traffic states (0: without primary traffic, 1 : with primary traffic); (b) transition probabilities of channel gain states for SU 1; (c) transition probabilities of channel gain states for SU 2. Thereinto, the value within the parenthesis for the channel gain state indicate the channel gain in that state.

Remark 1. *Given $\boldsymbol{z}^* \in \Psi(\boldsymbol{z}^*)$, the set of stationary multi-policies $\{\boldsymbol{\lambda}_1(\boldsymbol{z}_1^*), \boldsymbol{\lambda}_2(\boldsymbol{z}_2^*) \cdots, \boldsymbol{\lambda}_N(\boldsymbol{z}_N^*)\}$ is a CNE to the dynamic power management problem for the considered CRN.*

IV. Numerical Evaluation

In this section, simulations are conducted to verify the results attained from the derivation of the optimal policy. The computation of CNE can be obtained by [8; 20]. It is noted that the immediate utility function r_i as described in (1) is utilized as the objective to be achieved for the power management problem. With the bandwidth of $B = 10$ MHz for the considered licensed spectrum, one PU and two SU pairs are considered in the CRN with the period of $T = 1000$ time slots for power management. The power constraints without and with the primary traffic are defined as $C_0 = 1000$ and $C_1 = 100$ in the unit of watt respectively, i.e. the allowable interferences among the SUs and from the SUs to the PU. The action set $\boldsymbol{p}_i = \{0, 100, 200, 300, 400\}$, interference from primary traffic $\varepsilon_i = 5$, and the noise power $\sigma_i^2 = 1$ are assumed for both SUs.

Fig. 2 illustrates the transition probabilities for both the primary traffic states and channel gain states. As in Fig. 2 (a), the value of the primary traffic state with 0 denotes the absence of primary traffic; while value with 1 stands for the existence of primary traffic. The transition probabilities of channel gain states for SU 1 and 2 are depicted in Fig. 2 (b) and (c) respectively where the the channel gains are also denoted for each state. In each state, the first value is the channel gain of self-traffic and the second value denotes that from other SU. For example, for channel gain state 2 of SU 1, the channel gain from SU 1(Tx) to SU 1(Rx) is 2.805 and that

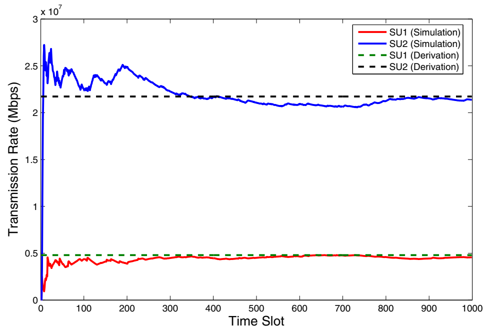

Fig. 3. Performance comparison: the transmission rates by adopting the optimal policies for SU 1 and 2 (solid lines: simulations, dashed lines: theoretical derivation).

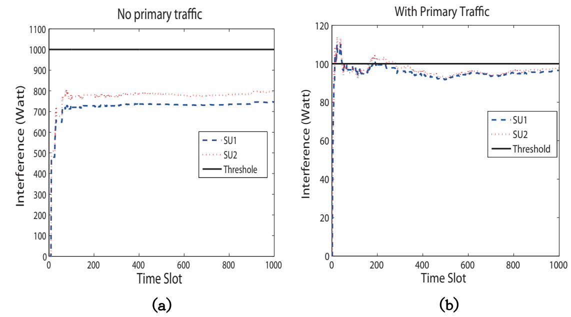

Fig. 4. Performance comparison: the allowable interference by adopting the optimal policies under case (a) without and case (b) with the primary traffic (solid lines: allowable threshold, dashed lines: simulation).

from SU 1(Tx) to SU 2(Rx) is 2.936. Based on the parameters as above, the optimal policies $\boldsymbol{u}_1$ and $\boldsymbol{u}_2$ for SU 1 and 2 that are acquired from the derivation in previous sections can be obtained as

$$\boldsymbol{u}_1(g_1,\phi_1) = \begin{bmatrix} \{0,0,1,0,0\} & \{1,0,0,0,0\} \\ \{0,1,0,0,0\} & \{1,0,0,0,0\} \\ \{0.108,0.892,0,0,0\} & \{1,0,0,0,0\} \end{bmatrix}$$

$$\boldsymbol{u}_2(g_2,\phi_2) = \begin{bmatrix} \{0,0,0,0,1\} & \{0,1,0,0,0\} \\ \{0,0,0,0,1\} & \{0,1,0,0,0\} \\ \{0,0,0,0,1\} & \{0.776,0.224,0,0,0\} \end{bmatrix}$$

where the columns indicate the state for the existence of primary traffic, i.e. column 1 without PU and column 2 with PU. The rows represent the channel gain states as denoted in Fig. 2 (b) and (c), i.e. row 1 for channel state 0, row 2 for channel state 1, and row 3 for channel state 2. The elements within the policy matrices $\boldsymbol{u}_1$ and $\boldsymbol{u}_2$ represent the probability measures on the action set. For example, $\boldsymbol{u}_1(0,0) = \{0,0,1,0,0\}$ denotes that SU 1 will take action on the power level $p_{1,2} = 200$ with probability of 1; while other power levels will not be executed.

Simulations are conduct to compare the performance with that derived from the formulations in the previous sections. Fig. 3 shows the transmission rates by adopting the optimal policies for SU 1 and 2; while Fig. 4 illustrates the allowable interferences under the cases with and without the primary traffic. It can be observed that the simulations results are consistent with that obtained from the theoretical derivations. For example, the optimal policy adopted by SU 1 results in the transmission rate of around $4.9 \times 10^6 (bps)$ after $T = 250$; while the theoretical value is computed as $4.802 \times 10^6 (bps)$. The transmission rate for SU 2 is around $2.1 \times 10^7 (bps)$ after $T = 450$, which is consistent with the derived value of $2.173 \times 10^7 (bps)$. As a result, it can be seen that the optimal policies based on the derivation of the constrained stochastic games is achievable for dynamic power management of the CRN.

V. Conclusion

This paper proposes a dynamic power management scheme for maximizing the transmission rate in the cognitive radio networks (CRN). The variations from both the spectrum holes and the channel gains are considered in the network scenarios for the CRN. Associated with the constraints of allowable interferences, the constrained stochastic games are utilized to acquired the optimal policies based on the objective of maximized data transmission rate. The existence of the constrained Nash equilibrium can be proved and is served as the optimal policies for the power management problem. Simulations are performed to validate the correctness of the optimal policies that are proposed for the dynamic power management in CRN.

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Design and Analysis of Optimal Channel-Hopping Sequence for Cognitive Radio Networks

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Abstract*—In recent years, channel-hopping based medium access control (MAC) protocols are proposed to improve the capacity in a decentralized multi-channel cognitive radio (CR) networks without extra usage of a control channel. Each CR user has to stochastically follow a default channel-hopping sequence in order to sense a channel and to conduct its frame transmission. In this paper, based on the channel-hopping protocol, an analysis is conducted on both the probability of channel availability and the average frame delay for the primary queueing networks. The analytical model is proposed by considering the impact caused by imperfect sensing of the CR users and the imperfect synchronization between the primary and CR networks. According to the proposed model with more realistic considerations, an optimal channel-hopping sequence (OCS) approach is designed for the CR users based on dynamic programming technique. It is designed by exploiting the optimal load balance between both the channel availability and channel utilization within the delay constraints of primary users (PUs). By adopting the OCS approach, the maximum aggregate throughput of CR users and the quality of service (QoS) requirement of PUs can both be achieved. Numerical results illustrate that the proposed OCS scheme can effectively maximize the aggregate throughput compared to conventional channel-hopping sequences, and as well guarantee the QoS requirement of the PUs.

Keywords: Cognitive radio, queueing networks, channel-hopping sequence, dynamic programming, quality of service.

I. Introduction

The increasing demand for spectrum resource lately has caused the so-called spectrum scarcity problem primarily due to the conventional approaches of static spectrum allocation. In fact, according to the regulations from FCC [1], a large portion of the priced frequency spectrum is underutilized in most of the time and location, i.e., known as spectrum holes. Consequently, cognitive radio (CR) for dynamic spectrum access (DSA) has been prevailing exploited for more efficient spectrum utilization over the licensed bands [2] such as the IEEE 802.22 [3; 4] standard. It is an emerging standard that allocates spectrums for TV broadcast services via a license-exempt basis. The CR user (CRU), i.e., unlicensed user, is capable of sensing the channel condition and can adapt its internal parameters to access the licensed channels while these channels are not being utilized by the primary users (PUs), i.e, licensed users. In addition to the IEEE 802.22 standard which focused on specification for a centralized CR network, there are also a great number of research interested in decentralized DSA in multi-channel TDMA-based (i.e., time slotted-based) primary networks. The main focus is on how to design a medium access control (MAC) protocol to effectively exploit the channel availability under the overlay paradigm considering that both the PUs and CRUs cannot transmit simultaneously.

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These MAC protocols can be categorized into two different types of schemes according to their access strategies, including the sensing-based and the probability-based methods. The sensing-based scheme indicates that the CRUs have to sense part of the channels before deciding which channel to access. In general, it will lead to higher channel utilization. However, it is considered impractical for each CRU to equip multiple transceivers to conduct spectrum sensing or inefficient for a CRU to sense and switch among the entire frequency spectrums within a slot time in order to obtain the required knowledge of spectrum map. On the other hand, the probability-based scheme indicates that the CRUs have to decide which channel to sense according to certain statistical information from the PUs and consequently transmit their data. This type of scheme is implemented to amend the problem arising from sensing-based protocols by considering each CRU can only possess a single transceiver for channel sensing. Therefore, it becomes important for the CRUs to accurately acquire the opportunities for accessing an idle channel in an efficient manner.

In [5], an opportunistic spectrum access MAC protocol was proposed based on a common control channel approach for the CRUs to both negotiate the channel reservation and determine which channel to sense based on the stationary idle probability of the PU in each channel. However, the usage of an additional common control channel is still in controversy. The partially observable Markov decision process framework in [6] provides an optimal sensing strategy for a CRU to select and sense a channel which has the highest potential in maximizing throughput. However, the proposed framework is computationally complex and is not considered suitable for networks with multiple CRUs. For a more realistic scenario, the channel-hopping based protocols are proposed in

[7; 8], in which the CRUs switch among the licensed channels with their distinct default channel-hopping sequences. When a CR transmitter wants to communicate with its intend CR receiver, the CR transmitter changes its hopping schedule and follows the channel-hopping sequence of the intended receiver to conduct the negotiation and consequently transmit the data if the channel is not currently used by the PU.

Furthermore, it is assumed in most of the existing sensing-based and probability-based protocols that CRUs are required to be synchronized with the PUs and to exactly sense either the idle or busy state of the PUs. However, these two assumptions are considered impractical in realistic circumstances due to the reasons as follows: (a) there is no communication recognized between the primary and the CR networks which makes global synchronization difficult; and (b) the long sensing time for perfect spectrum sensing will degrade the channel utilization especially for shorter slot time.

In this paper, based on the channel-hopping schemes, analytical models are studied for both the probability of channel availability for the CRUs and average frame delay of the PUs. The proposed models consider the possible collision events with imperfect synchronization and sensing under a primary network containing multiple channels, and each channel is modeled as a Geo/G/1 queueing system. By exploiting this realistic coexisting system, the optimal channel-hopping sequence (OCS) based on dynamic programming (DP) is derived in order to achieve maximum aggregate throughput for the CRUs and average frame delay of the PUs with quality of service (QoS) guaranteed. Based on the proposed OCS scheme, optimal load balance can be achieved between the probability of channel availability and channel utilization within the CR network under the knowledge of frame arrival probabilities of PUs. Numerical results are also presented to illustrate that the prosed OCS approach is feasible to capture the rapidly varying opportunities of spectrum holes for the CRUs.

The rest of this paper is organized as follows. Section II presents the system model and the analysis for the coexisting system between primary queueing network and CR network. Based on the analysis, the proposed OCS scheme is modeled and derived by dynamic programming in Section III. Section IV illustrates the performance evaluation for the proposed OCS mechanism; while the conclusions are drawn in Section V.

II. System Model and Analysis

Both the primary and the CR networks are slotted systems with the same slot duration T_s, in which the CR network is depicted as the dotted vertical lines in Fig. 1. Due to imperfect synchronization, the time difference between these two networks can be observed at the starting epoches, i.e., in Fig. 1, at the beginning of each slot as $\Delta t = t_2 - t_1$. For the primary network with M identical bandwidth channels, each of them is occupied by a PU independently with Bernoulli arrival process [9] with the probability λ_i of one frame arrival and the probability $1 - \lambda_i$ of no frame arrival at the starting epochs for $i = 1, 2, ..., M$. It is noted that infinite

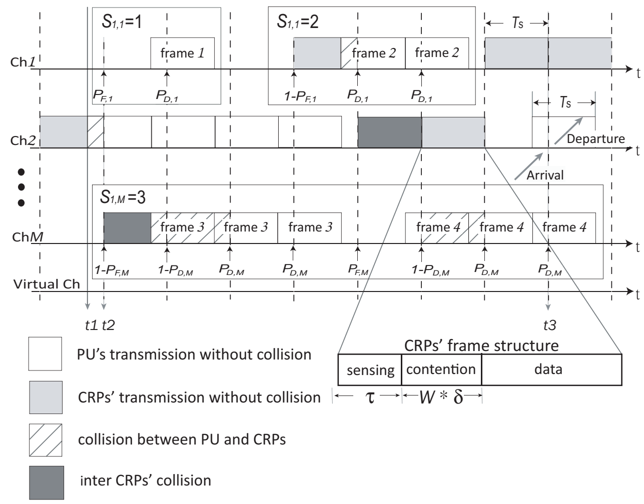

Fig. 1. Schematic diagram for the coexistence of both the primary and the CR networks.

queue capacity is assumed for each channel, where the frame duration is equal to a slot length. Given that the PUs will retransmit until success, i.e., no collisions happened to a frame, the service length can be determined as will be presented in Subsection II-B.

Furthermore, the CR network contains N pairs of CRUs (CRPs) with saturation traffic where each pair is consisted of two CRUs, including a transmitter and a receiver. It is assumed that data communication only happens within a CRP and all CRPs are affected by the same set of PUs. Based on the channel-hopping protocol as in [7], each CRP has to follow a default channel-hopping sequence generated by the delivery of a pseudo random generator in the same discrete probability distribution $\mathbf{P}$, which is defined as $\mathbf{P} = [p_1, ..., p_M, p_{virtual}]$ with p_i denoting the channel hopping probability for $i = 1, 2, ..., M$. It is utilized to stochastically determine which channel to hop to, and to carry out sensing and contending for data transmission in a reasonably fair manner. The frame structure including sensing, contending, and data transmission phases is illustrated in Fig. 1. Moreover, the virtual channel accounts for the relinquishment in transmissions of certain CRPs, which is represented as $p_{virtual} = 1 - \sum_{i=1}^{M} p_i$.

A. Imperfect Sensing

In realistic situation, sensing decisions of the CRPs is considered imperfect. Two probabilities are considered as follows: (a) the detection probability p_d for detecting the PU when the PU does exist, and (b) the probability of false alarm p_{fa} for detecting the PU while the PU does not exist. The relationship between p_d and p_{fa} has been studied in [10] for an energy detector, which can be assumed for each individual CRP as

$$p_{fa} = Q(\sqrt{2\gamma + 1}\, Q^{-1}(p_d) + \sqrt{\tau f_s}\, \gamma), \tag{1}$$

where τ is the sensing time, γ is the signal-to-noise ratio (SNR) of the PU at the CRP's receiver, and f_s denotes the

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channel sampling rate of the CRP. The $Q(\cdot)$ function represents the complementary distribution function of a standard Gaussian variable. Noted that p_d is also called the sensing threshold which can be adjusted by the CRP, and p_{fa} is an increasing function of p_d under fixed values of τ, γ, and f_s.

According to (1), it can be found that significant amount of sensing time τ is required for achieving perfect sensing, i.e., exactly sense the state of PU to be either busy ($p_d = 1$) or idle ($p_{fa} = 0$). The sensing time τ is considered much larger than the 10 ms slot size as specified in IEEE 802.22 standard [3] owing to the limitation in hardware and sensing algorithms. Therefore, perfect sensing is considered impractical and will severely degrade the channel utilization. Furthermore, by assuming all the CRPs with the same sensing threshold p_d, the average probability of detection $P_{D,i}$ for all CRPs hopping to channel i with correct detection, and the average probability of false alarm $P_{F,i}$ for all CRPs hopping to channel i with false alarm can be respectively written as

$$P_{D,i} = \sum_{n=0}^{N} H_{N,n,i}\, p_d^n = [1 - p_i(1 - p_d)]^N, \tag{2a}$$

$$P_{F,i} = \sum_{n=0}^{N} H_{N,n,i}\, p_{fa}^n = [1 - p_i(1 - p_{fa})]^N, \tag{2b}$$

where $H_{N,n,i}$ represents the probability of n out of the N CRPs hopping to channel i with probability p_i as

$$H_{N,n,i} = \binom{N}{n} p_i^n (1 - p_i)^{N-n}. \tag{3}$$

B. Probability of Channel Availability and Average Frame Delay

In this subsection, the impacts caused by imperfect synchronization and sensing of CRPs are analyzed in the probability of channel availability and average frame delay of the primary queueing network. The primary network in each channel is a Geo/G/1 discrete-time queueing system with retransmitting capability if its frames are collided by the CRPs. Noted that the arrivals and departures, i.e., service completions, of the primary network occur at the starting epochs simultaneously. Moreover, in order to ensure the analysis tractable, the Arrival First (AF) scheme [11] is introduced as the scheduling policy for the queue. In other words, the frame arrivals takes precedence over departures during the starting epochs as shown in Fig. 1 at t_3 in channel 2. The distribution of system size, i.e., queue plus the channel, observed at the departure points is then identical to that of the original Geo/G/1 system proven in [11]. Therefore, the probability of channel availability for the CRPs and average frame delay of the PU can be analyzed by the derivation of system size distribution at the departure points as in [12].

Considering channel i for $i = 1, 2, ..., M$, let $X_{m,i}$ be defined as the discrete random variables (RVs) of the number of system size observed in the mth departure point. $S_{1,i}$ and $S_{2,i}$ are denoted as RVs of service time in condition that $X_{m,i} = 0$ and $X_{m,i} > 0$ respectively. $A_{1,i}$ and $A_{2,i}$ are defined as RVs of the number of arrival frames in condition that service time is equal to $S_{1,i}$ and $S_{2,i}$, respectively. Therefore, the relationship between $X_{m,i}$, $A_{1,i}$, and $A_{2,i}$ can be derived as

$$X_{m+1,i} = \begin{cases} A_{1,i} & X_{m,i} = 0, \\ X_{m,i} + A_{2,i} - 1 & X_{m,i} \geq 1. \end{cases} \tag{4}$$

Let probability mass function (PMF) $a_{r,k,i} = Pr(A_{r,i} = k)$ for $r = 1$ and 2, both of them can be formulated as

$$\begin{aligned} a_{r,k,i} &= \sum_{l=k}^{\infty} Pr(S_{r,i} = l) Pr(A_{r,i} = k | S_{r,i} = l) \\ &= \sum_{l=k}^{\infty} \binom{l}{k} Pr(S_{r,i} = l) \lambda_i^k (1 - \lambda_i)^{l-k}. \end{aligned} \tag{5}$$

Fig. 1 depicts the relationship between $S_{1,i}$ and CRPs' sensing actions, i.e., $P_{D,i}$ and $P_{F,i}$, by considering cases for $S_{1,i} = 1$, 2, and 3. Noted that $S_{1,i}$ also means the service time condition on no PU's frame in the previous slot according to PU's clock. Therefore, it can be observed that the sensing action made by the CRPs in the previous slot becomes either $P_{F,i}$ or $1 - P_{F,i}$, instead of either $P_{D,i}$ or $1 - P_{D,i}$. As in Fig. 1, it can be seen that the successful frame transmitted by PU requires two CRPs' successive $P_{D,i}$ except for $S_{1,i} = 1$. Consequently, both cases $S_{1,i} = 1$ and $S_{1,i} > 1$ should be considered respectively. Moreover, the first sensing probability of either $P_{F,i}$ or $1-P_{F,i}$ condition on $S_{1,i} > 1$ should also be studied since the second sensing action should be $1 - P_{D,i}$ if the first sensing action is $P_{F,i}$. It is noted that $S_{1,i} = 1$ represents the first sensing action as $P_{F,i}$ and the second sensing action to be $P_{D,i}$.

It is assumed that the PUs do not exist in the sensing period τ of CRPs since τ is much shorter compared to the slot time T_s. The carrier sensing in the contention phase cannot detect the existence of the PU due to the difference of natures from the detector in spectrum sensing [13]. Let $c_{1,i}(z)$ and $q_i(z)$ be respectively defined as the z-transform of the PMF of $S_{1,i}$ and the PMF of transmitting until the existence of two successive $P_{D,i}$. According to (2a) and (2b), $c_{1,i}(z)$ can be written as

$$c_{1,i}(z) = P_{F,i}[P_{D,i}z + (1-P_{D,i})q_i(z)z] + (1-P_{F,i})q_i(z), \tag{6}$$

and $q_i(z)$ is derived by recursive method as follows

$$q_i(z) = f_i(z)[P_{D,i}z + (1 - P_{D,i})q_i(z)z],$$

which can be simplified as

$$q_i(z) = \frac{P_{D,i} f_i(z) z}{1 - (1 - P_{D,i}) f_i(z) z}, \tag{7}$$

where $f_i(z)$ represents the z-transform of geometric distribution with parameter $P_{D,i}$. It can be written as

$$f_i(z) = \frac{P_{D,i} z}{1 - (1 - P_{D,i}) z}. \tag{8}$$

Furthermore, $S_{2,i}$ denotes the service time for a new frame, i.e., not a retransmitting frame, served right after the previous frame. It indicates that the sensing action of CRPs in the last slot must be $P_{D,i}$ such that the previous frame can leave the queue. The z-transform of the PMF of $S_{2,i}$ can be derived similar to $S_{1,i}$ as

$$c_{2,i}(z) = P_{D,i}z + (1 - P_{D,i})q_i(z)z. \quad (9)$$

Let $h_{r,i}(z)$ be defined as the z-transform of $a_{r,k,i}$ in (5) for $r = 1, 2$, which can be derived as

$$h_{r,i}(z) = \sum_{k=0}^{\infty} a_{r,k,i}z^k = \sum_{l=0}^{\infty} Pr(S_{r,i} = l)(1 - \lambda_i + \lambda_i z)^l \quad (10)$$
$$= c_{r,i}(1 - \lambda_i + \lambda_i z).$$

Moreover, let $\pi_{j,i}$ be defined as the steady state probability of $X_{m,i} = j$, i.e., with $m \to \infty$. Based on the relationship in system size observed at the departure points as in (4), it can be obtained that

$$\pi_{j,i} = \pi_{0,i}\, a_{1,j,i} + \sum_{k=1}^{j+1} \pi_{k,i}\, a_{2,j-k+1,i}. \quad (11)$$

The z-transform of $\pi_{j,i}$, denoted as $g_i(z)$, can be derived as

$$g_i(z) = \frac{\pi_{0,i}[h_{1,i}(z)z - h_{2,i}(z)]}{z - h_{2,i}(z)}. \quad (12)$$

Therefore, according to the boundary conditions $g_i(1) = 1$, $h_{1,i}(1) = 1$, and $h_{2,i}(1) = 1$, the probability of channel availability for the CRPs can be obtained by using L'Hopital's rule as

$$\pi_{0,i} = \left.\frac{1 - h'_{2,i}(z)}{h'_{1,i}(z)z + h_{1,i}(z) - h'_{2,i}(z)}\right|_{z=1}, \quad (13)$$

where $h'_{r,i}$ denotes the derivative of $h_{r,i}$. The average frame delay of the PU can be derived by the Little's Theorem as

$$D_i(p_i) = L_i(p_i)/\lambda_i, \quad (14)$$

where the average system size $L_i(p_i)$ is acquired by taking the derivative of (12) at $z = 1$ using L'Hopital's rule as

$$L_i(p_i) = \sum_{j=0}^{\infty} j\pi_{j,i} = g'_i(z)|_{z=1}. \quad (15)$$

C. Aggregate Throughput

Based on the analysis in the primary network under certain channel-hopping sequence of the CRPs, the aggregate throughput of CRPs can consequently be obtained according to the CRP's frame structure as shown in Fig. 1. Assuming that the CRPs are transmitting in a single-hop wireless network, there are n out of N CRPs hopping to the ith channel with the probability $H_{N,n,i}$ as defined in (3). Due to imperfect sensing, there are probability of α out of n CRPs with correct sensing while channel i is idle which can be represented as

$$F_{n,\alpha} = \binom{n}{\alpha}(1 - p_{fa})^{\alpha} p_{fa}^{n-\alpha}. \quad (16)$$

After sensing the channel availability, the contention-based scheme as defined in IEEE 802.11 DCF mode will be adopted. There exists α CRPs contending for the data transmission which will choose a backoff value randomly in the interval of $[0, W - 1]$, where W is the fixed window size. The CRPs can transmit data only when their backoff values count down to zero. Therefore, the average successful transmission time C_α with no inter-collision between α CRPs can be obtained as

$$C_\alpha = \frac{\alpha}{W}\sum_{\beta=1}^{W}(1 - \frac{\beta}{W})^{\alpha-1}(T_s - \beta\delta - \tau), \quad (17)$$

with δ denotes the mini-slot for carrier-sensing. The throughput of the CRPs with normalization factor $1/T_s$ in the ith channel can be represented with the probability of channel availability in (13) and the probability of $(1 - \lambda_i)$ indicating that no PU occurs to transmit while a CRP is successfully transmitting, i.e.

$$\eta_i(p_i) = \frac{1}{T_s}\pi_{0,i}(1 - \lambda_i)\sum_{n=1}^{N}\sum_{\alpha=1}^{n} H_{N,n,i}F_{n,\alpha}C_\alpha, \quad (18)$$

where the unit of the throughput is in time slots. As a result, the aggregate throughput under the probability distribution $\mathbf{P}$ can be acquired as

$$\eta(\mathbf{P}) = \sum_{i=1}^{M}\eta_i(p_i) = \frac{1}{T_s}\sum_{i=1}^{M}\pi_{0,i}(1 - \lambda_i)\left[\frac{Np_i(1 - p_{fa})}{W}\right] \cdot \sum_{\beta=1}^{W}(T_s - \beta\delta - \tau)\left[1 - \frac{\beta p_i(1 - p_{fa})}{W}\right]^{N-1}. \quad (19)$$

III. PROPOSED OPTIMAL CHANNEL-HOPPING SEQUENCE (OCS) APPROACH

In previous section, the throughput analysis is conducted in the realistic circumstance with the coexistence of both the PUs and the CRPs. In this section, an approach for obtaining OCS will be developed which not only can maximize the aggregate throughput of the CRPs in (19) but also ensure the QoS requirements of the PUs under the knowledge of PUs' frame arrival probability. The optimization problem can be formulated as

$$\begin{aligned} &\mathbf{P}^* = \arg\max_{\mathbf{P}}\ \eta(\mathbf{P}) \\ \text{s. t.}\quad & D_{min} \le D_i(p_i) \le D_{c,i}, \quad i = 1, 2, ..., M \\ & 0 \le p_i \le 1, \quad i = 1, 2, ..., M \\ & \sum_{i=1}^{M} p_i \le 1, \end{aligned} \quad (20)$$

where $\mathbf{P}^*$ is the OCS. $D_{c,i}$ represents the delay constraint for the QoS requirement of PU in channel i, and D_{min} is equal to one slot under no collision in PU's transmissions. In other words, the emphasis of this paper is to obtain OCS in N CRPs for optimal load balance under the consideration of PU's QoS requirements. Interestingly, the optimization problem in (20) can be viewed as a sequential optimal decision problem from channel 1 to M. However, due to the nonlinearity in the throughput (18) w.r.t. p_i, each decision (i.e., the hopping

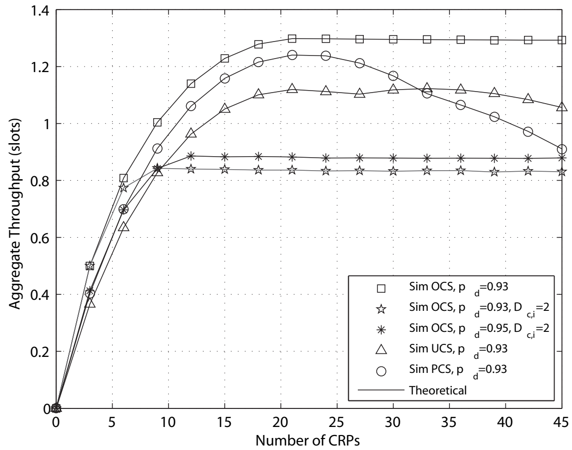

Fig. 2. Aggregate throughput of CRPs under different channel-hopping sequences with number of channels $M = 4$ (each channel has arrival rate $\lambda_i = 0.05, 0.05, 0.4, 0.4$ for $i = 1, 2, 3, 4$).

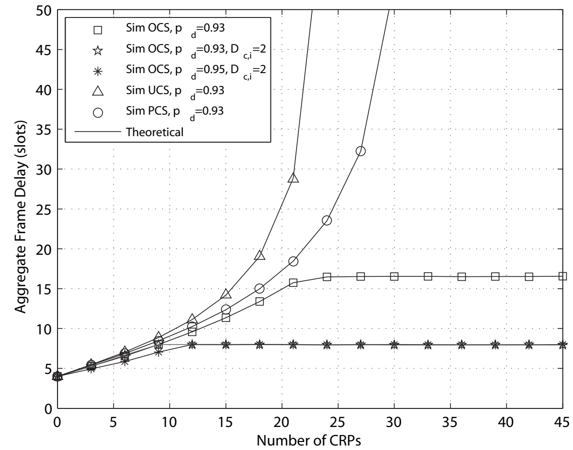

Fig. 3. Aggregate frame delay of PUs under different channel-hopping sequence with number of channels $M = 4$ (each channel has arrival rate $\lambda_i = 0.05, 0.05, 0.4, 0.4$ for $i = 1, 2, 3, 4$).

probability p_i) cannot be independently determined since the throughput can also be incurred in the rest of the undecided channels. In other words, it is not possible to directly allocate all the hopping probability into a channel with the lowest frame arrival probability since potential throughput may exist in the rest of channels unassigned with hopping probabilities. In order to resolve this problem, the DP-based approach in [14] is introduced for obtaining the OCS.

A. Dynamic Programming Formulation for OCS

In this subsection, the optimization problem in (20) for multiple channels can be formulated into a DP problem as in [14]. A reward function $\phi_i(\epsilon_i)$ at channel i denotes the maximum value of throughput summed from channel i to channel M with the channel available probability ϵ_i, which is the probability to be allocated from channel i to channel M. Moreover, an instant reward function $\eta_i(p_i)$ as in (18) plus the constraint $p_{c,i}$ which is the replacement of delay constraint $D_{c,i}$ since the average frame delay in (14) is a strictly increasing function (i.e. one-to-one mapping) of p_i. The DP recursive form can therefore be written as

$$\phi_i(\epsilon_i) = \max_{0 \le p_i \le \min\{p_{c,i},\, \epsilon_i\}} \{\eta_i(p_i) + \phi_{i+1}(\epsilon_i - p_i)\}, \quad (21)$$

where $\epsilon_1 = 1$ and $\epsilon_{i+1} = \epsilon_i - p_i$. The maximum aggregate throughput in OCS can be obtained as

$$\eta(\mathbf{P}^*) = \phi_1(\epsilon_1), \quad (22)$$

where $\mathbf{P}^*$ from the OCS approach is the combination of channel-hopping probability obtained by the DP recursion in each channel. The allowable channel-hopping probabilities p_i for each channel is quantized from 0 to 1 with quantized level Δ_p, which will relate to the accuracy of the proposed OCS. After off-line solving the OCS for different numbers of CRPs with linear complexity $O(M \cdot (1/\Delta_p)^2)$ proportioned to the number of channels M, the proposed OCS scheme can consequently be recorded into a look-up table for CRPs in order to acquire the OCS corresponding to N for real time implementation.

IV. Performance Evaluation

In this section, performance of the proposed OCS approach will be evaluated and compared to the other conventional channel-hopping sequences. The system parameters are adopted from IEEE 802.22 standard in [3; 4] for the CR network operating on TV bands as bandwidth $B = 6$ MHz, slot duration $T_s = 11.28$ ms, the SNR for spectrum sensing $\gamma = -20$ dB, and over-sampling rate in spectrum sensing of the CRPs $f_s = 8B/7$. Moreover, the parameters in the CRP's frame structure are set as sensing time $\tau = 1$ ms, contention window $W = 64$, and mini-slot $\delta = 20$ μs. Fig. 2 shows the aggregate throughput of the CRPs simulated with the combination of four channels with PUs' frame arrival rates $\lambda_i = 0.05, 0.05, 0.4, 0.4$ for $i = 1, 2, 3, 4$. The corresponding aggregate frame delay of the PUs are provided in Fig. 3. The aggregate frame delay is the summation of average frame delay in each channel, which can be utilized as a measurement for the QoS requirement in the primary system, i.e., the system will break down if the queue of a channel becomes unstable. The quantized level Δ_p for searching OCS is set as 0.001, which is accurate enough to obtain the proposed OCS in the simulation settings. Moreover, two conventional channel-hopping sequences are also simulated for comparison purpose as follows: (a) uniform channel-hopping sequence (UCS) with the probability $p_i = 1/M$ for $i = 1, 2, ..., M$, and (b) proportional channel-hopping sequence (PCS) with channel hopping probabilities proportioning to the complement of λ_i. It is designed according to the situation that smaller frame arrival probability is assumed to result in larger channel availability, which can be written as

$$p_i = \frac{1-\lambda_i}{\sum_{i=1}^{M}(1-\lambda_i)}, \quad i = 1, 2, ..., M. \tag{23}$$

Fig. 2 shows that the proposed OCS can provide higher aggregate throughput compared to the other channel-hopping sequences since it can exactly exploit the potential throughput in multiple channels. It is interesting to note that the aggregate throughput in OCS will saturate after exceeding a certain number of CRPs while the number of the CRPs is large enough to utilize each channel with optimal throughput. In general, the design concept arises from assigning additional CRPs into the virtual channel in order to reduce collision with the PU.

On the other hand, as show in Fig. 3, the aggregate frame delay of primary network can also be guaranteed by adopting the proposed OCS approach. As a result, even though the delay constraints is not taken into consideration, the OCS still can ensure the QoS requirement of the PUs to a certain level. In order to provide tighter QoS requirement for the PUs, the case with constraints $D_{c,i} = 2$ for $i = 1, 2, 3, 4$ are also shown in both Figs. 2 and 3. The effect with delay constraint $D_{c,i} = 2$ can be observed with lowered aggregate frame delay of PUs and consequently lowered aggregated throughput of CRPs. With different sensing thresholds p_d, the large p_d will have enhanced aggregate throughput than the small p_d case since the number of CRPs is large enough to exploit channel availability. On the other hand, smaller p_d results in smaller p_{fa} which can provide the CRP to quickly discover the idle slots and consequently increase the channel utilization over the large p_d which blocks the CRPs' access into the channel which makes the channel utilization in (17) down when the number of CRPs is small.

Furthermore, in Fig. 2, the aggregate throughput of PCS is better than UCS first, which can be explained that PCS puts more CRs into good channels (i.e., with lower arrival probabilities) than UCS, but when too many CRs are in the good channels, the aggregate throughput will degrade more quickly than UCS due to too much collision in the good channels. On the other hand, in Fig. 3, UCS will make the primary system unstable quickly due to too much CRs allocated to the bad channels (i.e., with large arrival probabilities) at first. As a result, the merits of adopting the OCS approach can be observed.

V. CONCLUSION

In this paper, under the considerations of imperfect spectrum sensing and imperfect synchronization, analytical models are developed for the probability of channel availability and average frame delay of the multi-channel primary network with the existence of cognitive radio (CR) users. Based on the analysis, an approach for obtaining the optimal channel-hopping sequence (OCS) is designed based on dynamic programming technique. The proposed OCS approach can both achieve maximum aggregate throughput of the CR users and ensure feasible average frame delay of primary users (PUs) under their quality of service (QoS) requirements. Both the analytical and simulation results show that the proposed OCS approach can effectively enhance the aggregate throughput of the CR users and also guarantee the QoS requirements of the PUs.

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