Optimal Frequency-Temporal Opportunity Exploitation for Multichannel Ad Hoc Networks

Bowen Li, *Student Member, IEEE*, Panlong Yang, *Member, IEEE*, Jinlong Wang, *Member, IEEE*, Qihui Wu, *Member, IEEE*, Shao-Jie Tang, *Student Member, IEEE*, Xiang-Yang Li, *Senior Member, IEEE*, and Yunhao Liu, *Senior Member, IEEE*

Abstract—In multichannel system, user could keep transmitting over an instantaneous "on peak" channel by opportunistically accessing and switching among channels. Previous studies rely on constant transmission duration, which would fail to leverage more opportunities in time and frequency domain. In this paper, we consider opportunistic channel accessing/releasing scheme in multichannel system with Rayleigh fading channels. Our main goal is to derive a throughput-optimal strategy for determining when and which channel to access and when to release it. We formulate this real-time decision-making process as a two-dimensional optimal stopping problem. We prove that the two-dimensional optimal stopping rule can be reduced to a simple threshold-based policy. Leveraging the absorbing Markov chain theory, we obtain the optimal threshold as well as the maximum achievable throughput with computational efficiency. Numerical and simulation results show that our proposed channel utilization scheme achieves up to 140 percent throughput gain over opportunistic transmission with a single channel and up to 60 percent throughput gain over opportunistic channel access with constant transmission duration.

Index Terms—Opportunistic channel access/release, optimal stopping, time-frequency diversity, finite-state Markov channel

1 Introduction

Improving transmission efficiency over wireless channels is a well studied but still hot research topic in wireless communication area. A key research issue is dealing with the time-varying nature of wireless channels, which is caused by multipath propagation in mobile environments. Conventional signal processing approaches such as equalization, coding, etc., [1], [2] in physical layer are not enough, as many studies [3], [4], [5] have shown more potential to further improve system throughput by exploiting the opportunities in channel dynamics. Specifically, as the qualities of different channels may differ significantly at the same time, user could sequentially probe channels and then opportunistically access an instantaneous good channel for data transmission. Recent studies such as [6], [7], [8] have made considerable progress in devising opportunistic access strategies for exploiting such kind of link-layer diversity.

However, all these investigations are built upon a constant transmission duration model, which results in inefficient opportunity exploitation. Commonly, the transmission duration is set to be channel coherence time, and they construct opportunistic access strategies with the assumption that channel quality would remain unchanged during a coherence time and change independently across coherence times. Since coherence time is a statistical measure of the time duration over which channel quality is highly correlated [1], the actual channel may either keep in a good state for much longer than coherence time or go bad quickly during the coherence time. Thus, holding on a constant transmission duration may lead to opportunity loss in either time domain (as the channel is still in good state, but should be released due to the end of transmission slot) or frequency domain (as the channel quality becomes poor, but should still transmit over it due to transmission duration constraints).

Motivated by the above observations, we aim to devise a more flexible channel utilization scheme, exploiting instantaneous opportunities in both time and frequency domain. Unlike previous work assuming time-independent block fading, we characterize the time dependence of Rayleigh fading channel by introducing finite-state Markov channel (FSMC) model. In our scheme, the decisions on which channel to access as well as how long to use it are made according to the instantaneous channel quality. Our main goal is to devise the throughput-optimal channel access and release strategy for such dynamic multichannel system. There are mainly two challenges.

First, two-dimensional opportunity exploitation problem is more complex than previous studies. User should make

- *B. Li, J. Wang, and Q. Wu are with the Institute of Communications Engineering, PLA University of Science and Technology, Po Box 105, No. 2, Biao-Ying, Yu-Dao Street, Nanjing, Jiangsu 210007, China. E-mail: lbw1225@gmail.com, wjl543@sina.com, wqhqhw@163.com.*
- *P. Yang is with the Institute of Communications Engineering, PLA University of Science and Technology, Po Box 110, No. 2, Biao-Ying, Yu-Dao Street, Nanjing, Jiangsu 210007, China. E-mail: panlongyang@gmail.com.*
- *S.-J. Tang is with the CS Department, Illinois Institute of Technology, 10 West 31st Street, Chicago, IL 60616. E-mail: tangshaojie@gmail.com.*
- *X.-Y. Li is with the CS Department, Illinois Institute of Technology, 10 West 31st Street, Chicago, IL 60616, and TNLIST, Tsinghua University. E-mail: xli@cs.iit.edu.*
- *Y. Liu is with the MOE Key Lab, School of Software, TNLIST, Tsinghua University, Hai-Dian, Beijing 100084, China, and the Hong Kong University of Science and Technology. E-mail: yunhao@greenorbs.com.*

Manuscript received 31 Aug. 2011; revised 22 Dec. 2011; accepted 5 Feb. 2012; published online 2 Mar. 2012.
Recommended for acceptance by X. Cheng.
For information on obtaining reprints of this article, please send e-mail to: tpds@computer.org, and reference IEEECS Log Number TPDS-2011-08-0585.
Digital Object Identifier no. 10.1109/TPDS.2012.84.

decisions in time and frequency domain, purely depending on the instantaneous quality of the operating channel and the statistical information of candidate channels. Switching among channels in frequency scale and probing channel quality in time scale will lead to the increased computation complexity and extra communication overhead.

Second, we consider both channel accessing and releasing processes in one theoretical framework. These two processes are continuous to each other and highly correlated. After an optimal stopping point is achieved, we also need to provide an optimal restart point for continuous channel utilization process. Obviously, conventional optimal stopping theory cannot be applied to this issue directly.

In this work, we first decompose the joint two-dimensional optimization problem into a two stage, one-dimensional optimization problem. And then prove that the optimal channel release strategy has a threshold structure under the Rayleigh fading channel. Based on the threshold-based channel release strategy in time domain, we further prove that the optimal channel access strategy in frequency domain also shows threshold property. Further analysis shows that the two-dimensional optimal stopping rule can be reduced to a simple one-threshold policy. Finally, we obtain the optimal threshold as well as corresponding achievable throughput by constructing an absorbing Markov analytical model, where an absorbing state is a state that cannot be left away once entered in.

Our main contributions of the paper can be summarized as follows:

- A novel opportunistic channel utilization scheme for flexibly exploiting link-layer time-frequency diversity is proposed. We devise a throughput-optimal strategy for determining when and which channel to access and when to release it. We show that our proposed scheme achieves throughput gains over traditional approaches (up to 140 percent over opportunistic transmission (OT) with a single channel and up to 60 percent over opportunistic channel access (OCA) with constant transmission duration).
- A two-dimensional optimal stopping analytical framework for characterizing the continuous decision-making process in both time and frequency domain is established. We prove that the throughput-optimal channel access and release strategy has a simple one-threshold structure, which shows relatively high practicability for real time decision making based on current hardware capability.
- An analytical model based on absorbing Markov chain theory is proposed for analyzing the dynamic data transmission process over Rayleigh fading channel. Closed-form expression for the expected throughput under the threshold-based strategy is deduced. We further propose an efficient algorithm whose time complexity is at most $O(\mathbf{k})$ to attain the optimal threshold, where $\mathbf{k}$ is the number of channel states whose achievable rate is higher than the expected rate of single channel.

The rest of the paper is organized as follows: Section 2 lists the related work. Section 3 presents system model. In Section 4, we investigate in depth the problem of joint opportunistic channel accessing and releasing control, and derive the structural property of the optimal strategy. Section 5 constructs an analytical model for accurately analyzing system performance and proposes an efficient algorithm for acquiring the optimal strategy. In Section 6, we provide numerical results. Finally, Section 7 concludes our paper.

2 Related Work

There have been several literatures on investigating optimal channel access strategies for exploiting frequency diversity in multichannel networks [6], [7], [8], [9], [10]. The gains from opportunistic band selection is first analyzed by Sabharwal et al. [6]. To balance the tradeoff between channel exploration and exploitation, a finite-horizon optimal stopping analytical model is proposed and the corresponding optimal channel skipping policy is presented. Later, Guha et al. [7] and Chang and Liu [8] consider such sequential channel probing and accessing scheme in more general scenarios (e.g., with arbitrary number of channels, statistically nonidentical channels, and possibly different probing costs), and derive corresponding optimal strategies with strong proofs. Most recently, Shu and Krunz [9] consider a homogeneous channel utilization scenario and focus on deriving the throughput-optimal strategy in cognitive radio networks under sensing errors, while Jiang et al. [10] focus on investigating computation-efficient algorithm for acquiring the optimal order in sequential channel sensing/probing and accessing process under optimal stopping rule.

Along a different avenue, opportunistic scheduling [11], [12] investigate multiuser diversity exploitation in single channel networks. Chaporkar and Proutiére [11] consider the broadcast fading channel, where a single transmitter sends data to several receivers. Using stochastic control formulation, they derived the optimal scheduling strategy. Zheng et al. [12] consider distributed opportunistic scheduling in an ad hoc network, where many links contend for the same channel using random access. The optimal scheme turns out to be a pure threshold policy by using optimal stopping formulation.

All existing studies on optimizing link-layer diversity exploitation consider constant transmission duration model, with the assumption that channel state holds unchange during the transmission duration and changes independently across durations. In contrast, we consider a more realistic scenario, where the time dependence of Rayleigh fading channel is characterized by FSMC model. Furthermore, the problem we considered in this study is not deriving the optimal channel accessing policy only, but a joint strategy for determining when to access medium as well as when to release it with instantaneous channel state. In such case, the traditional single-dimension stochastic optimization approaches as used in [6], [7], [8], [9], [10], [11], [12] are no longer applicable in solving our two-dimensional decision-making problem.

Apart from the above-mentioned work that investigates optimal control on diversity exploitation using stochastic optimization framework, there are also many studies on protocol design for achieving diversity gain. Auto Rate Fallback (ARF) [13] is the first commercial implementation system with multirate capability. Motivated by the fact that channel quality is highly correlated during a coherence time, Opportunistic Auto Rate (OAR) [14] grants the user a constant access time that allows multiple packet transmissions back to back. Using the channel skipping policy

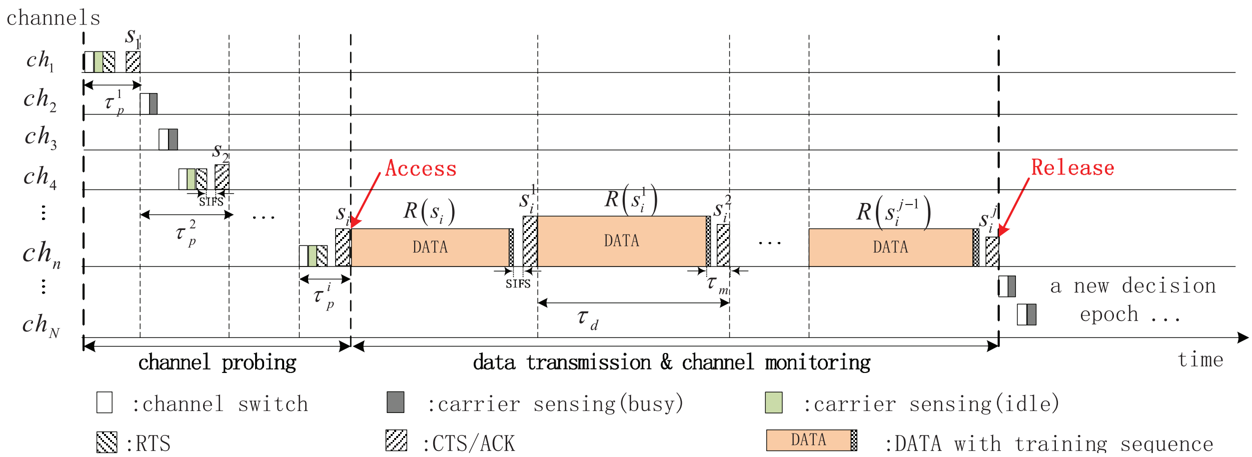

Fig. 1. Measurement-based frequency-temporal opportunity exploitation scheme.

derived in [6], Multichannel Opportunistic Auto Rate (MOAR) is proposed to exploit the channel variation across multiple channels [3]. We believe that our proposed policy can be applied to these protocols for further improving the system throughput.

To the best of our knowledge, ours is the first work jointly optimizing the time and frequency opportunities exploitation using stochastic control theory.

3 System Model

We consider a one-hop ad hoc system consisting of M users and N channels. Users in the networks are equipped with software-defined radio (SDR)-based transceiver, thus could opportunistically access arbitrary channel with flexible transmission parameters. In such opportunistic spectrum utilization system, there are usually more available channels than the concurrent communication pairs could use. For example, there are about 50 channels in TV band and more than 20 TV channels are available for white-space communication at a time with half of the US population [15]; meanwhile, the number of concurrent communication pairs in one hop is commonly less than 20. Considering these factors, we assume $M < N$ throughout this paper.

3.1 Measurement-Based Opportunistic Channel Utilization Mechanism

The procedure of the proposed opportunistic channel utilization scheme can be described as follows. When a user wants to send data, it transmit a RTS packet in the control channel.[1] If the receiver is in the control channel and is ready to receive data, it sends back a CTS. We assume that a channel probing sequence (e.g., based on random-number generator) is shared via such handshake. Then, the transmitter and receiver skip to the first channel of the shared probing sequence simultaneously and carry out the measurement-based channel utilization process as depicted in Fig. 1.

There exist two kinds of channel measurements in our scheme: probing channel in frequency domain and monitoring channel in time domain.

For probing channels in frequency domain, user needs to switch among channels. Each channel switching needs t_{switch} for radio parameters (e.g., frequency, modulation, and power level) adjustment. With the advanced development hardware [16], the channel switching time is commonly lower than 100 microseconds. Then, a $DIFS$ time is consumed for carrier sensing, so as to make sure that user would not conflict with an ongoing transmission. If the channel is found to be occupied by data transmission, user skips to another channel immediately. Otherwise, user contends for channel probing by the transmitter sending a training sequence embedded RTS. The receiver should respond with a CTS if it successfully receives the RTS, feeding back the estimated channel quality information. Based on the observed channel state, user makes decision on whether to access current channel or to skip to continue channel probing process.

For transceiver synchronization in case of probing collisions, both the transmitter and the receiver would stay in current channel[2] excepting that: 1) some other user probes the channel successfully and accesses the channel for data transmission; *or* 2) user wins the probing contention and finds that the channel state is poor for himself to use.

When the user decides to access a channel after observing that the channel is in good state, it transmits data packet sequentially with a packet duration τ_d, using the corresponding maximum achievable rate. By embedding training sequence into the tail of the DATA packet and the channel quality information into ACK, the user monitors channel quality variations periodically. Since the channel monitoring needs neither channel switching nor additional measurement packets, it costs only tens of microseconds [17], which is much more time saving than channel probing. Similarly, after receiving each ACK, user makes real-time decision on whether to continue transmitting over current channel or to release it for a new round of channel searching process.

Clearly, under the same decision rule, the transmitter and receiver will always probe, access, and switch to the same channel synchronously, since they shared the same channel skipping sequence and observed the same channel condition.

3.2 Wireless Channel Model

Wireless channels are assumed to experience independent Rayleigh fading (i.e., channels are separated by more than a coherent bandwidth). A Rayleigh fading channel can be

1. The control channel may be a dedicated one or rendezvous channel set with a pseudorandom channel switching design [6].

2. Meanwhile, the transmitter would retransmit the RTS packet with a random back off time when no CTS feedback is received.

accurately modeled as a finite-state Markov channel in a slow fading environment [18], [19], [20]. Each state corresponds to one transmission mode for adaptive modulation and coding. With a K state FSMC: $\{0, 1, \ldots, K-1\}$, the signal-to-noise ratio (SNR) γ at the receiver can be partitioned into multiple nonoverlapping intervals by SNR thresholds Γ_k $(k \in \{0, 1, \ldots K\})$, where $0 = \Gamma_0 < \Gamma_1 < \Gamma_2 < \cdots < \Gamma_K = \infty$. The channel is in state k if $\Gamma_k \leq \gamma < \Gamma_{k+1}$ and user can achieve the data rate $R(k) = B\log_2(1 + \Gamma_k)$ bps. Without loss of generality, we denote the gap on transmission rate between adjacent channel states as η. Thus, $\Gamma_k = 2^{\frac{k\eta}{B}} - 1$, where $k \in \{0, 1, \ldots K-1\}$.

As in a typical multipath propagation environment, the received instantaneous SNR γ is distributed exponentially with p.d.f. [19], [20]

$$p(\gamma) = \frac{1}{\gamma_0}\exp\left(-\frac{\gamma}{\gamma_0}\right), \quad \gamma \geq 0. \tag{1}$$

Here, γ_0 is the average received SNR, and the steady-state probability π_k $(k = 0, 1, \ldots, K-1)$ is given by

$$\pi_k = \int_{\Gamma_k}^{\Gamma_{k+1}} p(\gamma)d\gamma = e^{-\frac{\Gamma_k}{\gamma_0}} - e^{-\frac{\Gamma_{k+1}}{\gamma_0}}. \tag{2}$$

It is assumed that state transitions can occur only between adjacent channel states [19], [20]. The state transition probability $q_{s,s'}$ can be obtained as follows:

$$\begin{aligned}
&q_{k,k-1} = \frac{\Lambda(\Gamma_k)}{\pi_k}\tau_d, && k = 1, 2, \ldots, K-1\\
&q_{k,k+1} = \frac{\Lambda(\Gamma_{k+1})}{\pi_k}\tau_d, && k = 0, 1, \ldots, K-2\\
&q_{k,k} = 1 - q_{k,k+1} - q_{k,k-1}, && k = 1, 2, \ldots, K-2\\
&q_{0,0} = 1 - q_{0,1},\ q_{K-1,K-1} = 1 - q_{K-1,K-2}, &&
\end{aligned} \tag{3}$$

where τ_d is the length of packet duration time and $\Lambda(\cdot)$ is the level crossing rate function given by [19], [20]

$$\Lambda(\Gamma) = \sqrt{\frac{2\pi\Gamma}{\gamma_0}} f_d e^{-\frac{\Gamma}{\gamma_0}}. \tag{4}$$

Here, f_d denotes the maximum Doppler frequency shift due to mobility. According to (3) and (4), it is clear that the channel state transition rate is proportional to the node's mobile speed.

4 Properties of the Optimal Channel Access/Release Strategy

In this section, we formulate the decision-making process as a two-dimensional optimal stopping problem and derive the properties of the optimal stopping rule which maximizes the system throughput.

4.1 Problem Formulation

We consider the couple of continuous *sequential channel probing process* and *data transmission and channel monitoring process* as one decision epoch (as shown in Fig. 1).

Each channel probing process consists of several channel probing steps, where one probing step is defined as the procedure of successfully observing an channel (i.e., finding an idle channel and successfully probing it). Let τ_S be the time cost for taking one channel switching plus carrier sensing, and τ_R be the time consumed for one round of measurement packets exchanging. Then, the time cost for the ℓth channel probing step is given by $\tau_p^\ell = \kappa_\ell\tau_S + \tau_R$, where $\kappa_\ell \in \{1, 2, \ldots\}$ is the number of channels user skipped before successfully probing a channel. Denote s_ℓ as the corresponding observed channel state. The frequency domain channel quality observations $\{s_1, s_2, \ldots\}$ satisfy the channel steady-state distribution π_k, which can be derived from (2).

When the user decides to access a channel after observing channel state s_i, the channel quality of currently operating channel is monitored packet by packet, where the monitoring cost for each duration τ_d is τ_m. The time domain observations $\{s_i^1, s_i^2, \ldots\}$ can be characterized by conditional probability $q_{k,l} = \Pr\{s_i^{\ell+1} = l \big| s_i^\ell = k\}$, which are given by (3).

Suppose that user decides to access a channel with state s_i after the ith channel probing step, and then release the channel when the channel state turns to s_i^j in the jth channel monitoring step, then, the observed channel state sequence is $\{s_1, s_2, \ldots, s_i; s_i^1, s_i^2, \ldots, s_i^j\}$, and the throughput reward is given by

$$\phi(i,j) = \frac{b(i,j)}{t(i,j)} = \frac{(\tau_d - \tau_m)\sum_{\ell=0}^{j-1} R(s_i^\ell)}{\sum_{\ell=1}^{i} \tau_p^\ell + j\tau_d}, \tag{5}$$

where $b(i,j)$ and $t(i,j)$ are, respectively, the number of transmitted bits and consumed time in the decision epoch consisting of i probing steps and j monitoring steps. $R(s_i^\ell)$ denotes the maximum achievable rate of channel in channel state s_i^ℓ, and $s_i^0 = s_i$.

Define $\Psi \doteq \{\psi = (I, J) : 0 \leq I \leq \infty, 0 \leq J \leq \infty\}$ as the set of all possible two-dimensional stopping rules, where I and J are the stopping rule for channel probing process and data transmission process, respectively. Our objective is to maximize the expected throughput, i.e.,

$$\max_{\psi\in\Psi} E[\Phi(\psi)] = \max_{\psi\in\Psi} E\left[\frac{B(\psi)}{T(\psi)}\right]. \tag{6}$$

Here, $B(\psi)$ and $T(\psi)$ are, respectively, denoted to be the number of transmitted bits and consumed time in one decision epoch under rule ψ.

As for each decision epoch, the channel states are approximately independent between epochs (except the channel current in using); thus, the decision process can be regarded as an independent iterative process. Maximizing the true expected throughput $E[B(\psi)/T(\psi)]$ is then equivalent to maximizing the ratio $E[B(\psi)]/E[T(\psi)]$ [21]. Consequently, our goal is simplified to derive the optimal joint rule $\psi^* \in \Psi$, which is given by

$$\psi^* = \arg\max_{\psi\in\Psi} \frac{E[B(\psi)]}{E[T(\psi)]}. \tag{7}$$

The major notations we use in this paper are listed in Table 1.

TABLE 1
Summary of Notations

Notation	Description
i	Index of channel probing step in frequency domain
j	Index of channel monitoring step in time domain
$R(k)$	The achievable rate of channel in state k
π_k	Channel steady-state probability
$q_{k,l}$	Transition probability of channel from state k to state l
τ_p^i	Time cost for the i^{th} channel probing step
τ_d	Packet duration
τ_m	Time cost for channel monitoring in each packet
s_i	The exact quality of the i^{th} probed channel
s_i^j	The exact quality of the i^{th} probed channel after user transmitting the j^{th} packet over it
$b(i,j)$	Number of transmitted bits in the epoch consisting of i probing steps and j monitoring steps
$t(i,j)$	The time consumed in the epoch consisting of i probing steps and j monitoring steps
k_λ^r	Channel releasing threshold for a given λ
k_λ^a	Channel accessing threshold for a given λ
$b'(k,k_\lambda^r)$	Number of transmitted bits in the process accessing channel with state k and releasing it once the quality goes worse than k_λ^r
$t'_d(k,k_\lambda^r)$	Data transmission time in the process accessing channel with state k and releasing it once the quality goes worse than k_λ^r
I	Stopping rule in freq. domain, i.e. access strategy
J	Stopping rule in time domain, i.e. release strategy
ψ	Joint channel access/release strategy, $\psi = (I,J)$
$\Phi(\psi)$	Expected throughput under strategy ψ

4.2 Structural Property of the Optimal Stopping Rule

Since the optimal stopping rule I^* and J^* are interactive, it is difficult to solve this joint stopping problem directly. To decompose the multiplicative two-dimensional stopping problem, we introduce the following lemma:

Lemma 1. *If* $\sup_{\psi\in\Psi} E[B(\psi) - \lambda T(\psi)] = 0$ *can be satisfied, then* $\sup_{\psi\in\Psi} E[B(\psi)]/E[T(\psi)] = \lambda$. *Moreover, if* $\sup_{\psi\in\Psi} E[B(\psi) - \lambda T(\psi)] = 0$ *is attained at* $\psi^* \in \Psi$, *then* ψ^* *is optimal for maximizing* $\sup_{\psi\in\Psi} E[B(\psi)]/E[T(\psi)]$.

The result of Lemma 1 is evident. Strict proof can be found in [21].

Leveraging this lemma, we construct a new optimization problem, where the reward is given by

$$\begin{aligned} w_{(i,j,\lambda)} &= b(i,j) - \lambda t(i,j) \\ &= (\tau_d - \tau_m)\sum_{t=0}^{j-1} R\big(s_i^t\big) - \sum_{\ell=1}^{i} \lambda\tau_p^\ell - j\lambda\tau_d. \end{aligned} \tag{8}$$

The corresponding objective function is given by

$$V(\lambda) = \max_{\psi\in\Psi} E[B(\psi) - \lambda T(\psi)]. \tag{9}$$

Then, according to Lemma 1, to derive the optimal rule to the original rate of return problem is equivalent to find the optimal strategy that maximizes $V(\lambda)$ with a proper λ. Specifically, the parameter λ can be considered as the supposed expected system throughput. For a given λ, there exists an optimal strategy ψ_λ^* (consists of I_λ^*, J_λ^*) to the transformed problem that achieves the maximum expected reward $V(\lambda)$. $V(\lambda) > 0$ means that one could increase λ by applying a better strategy and $V(\lambda) < 0$ means that there is not any strategy could achieve the supposed throughput. By tuning λ that makes $V(\lambda) = 0$ (denote as λ^*), we then obtain the optimal strategy $\psi_{\lambda^*}^*$, which is also the optimal solution to the original problem. Correspondingly, λ^* is the maximum achievable system throughput (i.e., answer for (6)).

Before diving into the detailed investigation of the optimal rule, we first discuss the value scope of λ^* as follows:

Theorem 1. $\lambda^* \geq \frac{(\tau_d-\tau_m)}{\tau_d}\bar{R}$, *where* $\bar{R} = \sum_{k=0}^{K-1}\pi_k R(k)$.

Proof. Consider $\psi^1 = \{(I,J) : I = 1, J = \infty\}$, which means that user would access the first idle channel it sensed for data transmission and never switch channel. In such case, user could achieve the expected throughput $E[\Phi(\psi^1)] = \frac{(\tau_d-\tau_m)}{\tau_d}\sum_{k=0}^{K-1}\pi_k R(k)$. Recalling that λ^* is the expected throughput under the optimal strategy ψ^*, we have

$$\lambda^* = E[\Phi(\psi^*)] \geq E\big[\Phi(\psi^1)\big] = \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}. \tag{10}$$

This completes the proof. □

Based on Theorem 1, we now focus on exploring the optimal strategy in $\lambda > \frac{(\tau_d-\tau_m)}{\tau_d}\bar{R}$.

For a given λ and frequency domain stopping rule I, the reward of releasing current channel after monitoring s_I^j can be derived from (8)

$$\begin{aligned} w_{(I,j,\lambda)} &= (\tau_d - \tau_m)\sum_{t=0}^{j-1} R\big(s_I^t\big) - j\lambda\tau_d - \sum_{\ell=1}^{I}\lambda\tau_p^\ell \\ &= \sum_{t=0}^{j-1}\big[R\big(s_I^t\big)(\tau_d - \tau_m) - \lambda\tau_d\big] - \sum_{\ell=1}^{I}\lambda\tau_p^\ell. \end{aligned}$$

Then, the optimal temporal stopping rule $J_{(\lambda,I)}^*$ is given by

$$\begin{aligned} J_{(\lambda,I)}^* &= \arg\max_J E\left[\sum_{t=0}^{j-1}\big[R\big(s_I^t\big)(\tau_d - \tau_m) - \lambda\tau_d\big] - \sum_{\ell=1}^{I}\lambda\tau_p^\ell\right] \\ &= \arg\max_J E\left[\sum_{t=0}^{j-1}\big[R\big(s_I^t\big)(\tau_d - \tau_m) - \lambda\tau_d\big]\right]. \end{aligned} \tag{11}$$

As stated before, the mutual dependence between the two-dimensional rules makes the optimal decision-making problem involved. However, (11) shows that the impact of frequency-domain stopping rule on the time domain strategy can be fully represented by parameter λ. Hence, we can derive the structure of the optimal temporal stopping rule under a given λ first.

For this part, we have the following theorem:

Theorem 2. *Denote* $k_\lambda^r = \max\{k : R(k) < \frac{\tau_d\lambda}{(\tau_d-\tau_m)}\}$. *For a given* $\lambda > \frac{(\tau_d-\tau_m)}{\tau_d}\bar{R}$, *the optimal temporal stopping rule is given by*

$$J_\lambda^* = \min\big\{j : s_I^j \leq k_\lambda^r\big\}. \tag{12}$$

Proof. We prove the theorem using two supporting lemmas.

Denote $\chi_{\ell_1}^{\ell_2} = \sum_{\ell=\ell_1}^{\ell_2} [R(s_I^\ell)(\tau_d - \tau_m) - \lambda\tau_d]$ as the summation of reward user obtained from ℓ_1 to ℓ_2. For the problem defined in (11), we have the following lemma:

Lemma 2. *For a given λ and channel state s_I^j:*

1. *If there exists $\ell \geq 0$ making $E[\chi_j^{j+\ell} | s_I^j] \geq 0$, then the optimal strategy is to continue transmitting packet over current channel;*
2. *If $E[\chi_j^{j+\ell} | s_I^j] < 0$ come into existence for all $\ell \geq 0$, then the optimal strategy is to stop.*

Proof. Let U_j denote the expected reward one could attain in the jth step under the optimal strategy, then we have

$$U_j = \max\{\chi_0^{j-1}, \chi_0^{j-1} + \max_\ell E[\chi_j^{j+\ell} | s_I^j]\}.$$

If there exists an integer $\ell \geq 0$ making $E[\chi_j^{j+\ell} | s_I^j] \geq 0$, then, $\chi_0^{j-1} + \max_\ell E[\chi_j^{j+\ell} | s_I^j] \geq \chi_0^{j-1}$. From the principle of optimality, it is optimal to continue transmitting over current channel. Otherwise, if for all $\ell \geq 0$, $E[\chi_j^{j+\ell} | s_I^j] < 0$, the best choice is to stop. □

Define function $f(\ell, k) = E[R(s^{(\ell)}) | s^0 = k]$, where $\ell = 0, 1, 2, \ldots$ is the time index and $k \in \{0, 1, \ldots, K-1\}$ is the channel state. Then, we have

Lemma 3. *$f(\ell, k)$ is a decreasing function of ℓ when $k \in \{k : R(k) \geq \bar{R}\}$ and a increasing function of ℓ when $k \in \{k: R(k) < \bar{R}\}$.*

Proof. From (3), we obtain the one step expected rate difference as

$$f(1,k) - f(0,k) = \frac{\tau_d \eta}{\pi_k}[\Lambda(\Gamma_{k+1}) - \Lambda(\Gamma_k)].$$

According to (4), there exists a SNR threshold γ^* (corresponding to the data rate R^*), satisfying that $\frac{\partial\Lambda(\Gamma)}{\partial\Gamma} \geq 0$ in $\Gamma \leq \gamma^*$ and $\frac{\partial\Lambda(\Gamma)}{\partial\Gamma} \leq 0$ in $\Gamma \geq \gamma^*$, which means that $f(1,k) > f(0,k)$ in $R(k) < R^*$ and $f(1,k) < f(0,k)$ in $R(k) > R^*$.

Recalling that the transitions would only occur between adjacent states, thus for arbitrary channel state k_1, k_2, where $R(k_1) > R^* > R(k_2)$, we have $R(k_1) = f(0,k_1) > f(1,k_1) > R^* > f(1,k_2) > f(0,k_2) = R(k_2)$. By further recursive deductions, we have: $R(k_1) > f(1,k_1) > \cdots > f(\infty,k_1) \geq R^* \geq f(\infty,k_2) > \cdots > f(1,k_2) > R(k_2)$. Since for all k, $f(\infty,k) = \bar{R}$ (property of the FSMC), we conclude $R^* = \bar{R}$. □

Next we prove Theorem 2.

On one hand, since $k_\lambda^r = \max\{k : R(k) < \frac{\tau_d}{(\tau_d - \tau_m)}\lambda\}$, if $s_I^j > k_\lambda^r$, we have $R(s_I^j) \geq \lambda\frac{\tau_d}{(\tau_d - \tau_m)}$. Then, $E[\chi_j^{j+0} | s_I^j] = R(s_I^j)(\tau_d - \tau_m) - \lambda\tau_d > 0$. According to Lemma 2, the optimal strategy in this case is to continue transmitting packet over current channel.

On the other hand, if $s_I^j \leq k_\lambda^r$, $R(s_I^j) < \lambda\frac{\tau_d}{(\tau_d - \tau_m)}$. As $\lambda > \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$, we have $E[R(s_I^\infty) | s_I^j] = \bar{R} < \lambda\frac{\tau_d}{(\tau_d - \tau_m)}$. According to Lemma 3, for all $\ell \geq 0$, we have □

$$\begin{aligned} E[R(s_I^{j+\ell}) | s_I^j] &= f(\ell, s_I^j) \\ &\leq \max\{f(0, s_I^j), f(\infty, s_I^j)\} \\ &= \max\{R(s_I^j), E[R(s_I^\infty) | s_I^j]\} \\ &< \max\left\{\lambda\frac{\tau_d}{\tau_d - \tau_m}, \bar{R}\right\} = \frac{\lambda\tau_d}{\tau_d - \tau_m}. \end{aligned}$$

Thus, we have $E[R(s_I^{j+\ell})(\tau_d - \tau_m) - \lambda\tau_d] < 0$, $\forall \ell \geq 0$. Consequently, for all $\ell \geq 0$, $E[\chi_j^{j+\ell} | s_I^j] < 0$. Based on Lemma 2, we conclude that the optimal strategy here is to stop transmitting packet over current channel.

Theorem 2 guarantees that there exists an optimal temporal stopping rule leading to maximum expected reward for the problem defined in (9). Moreover, the optimal rule shows a simple threshold structural property: continuing transmitting over current channel when the observed channel state is better than k_λ^r and switching to another channel otherwise.

Based on the obtained optimal release threshold J_λ^*, we then derive the structure of joint optimal rule for a given λ as follows: for a given λ with corresponding optimal temporal stopping rule J_λ^*, the reward of accessing a channel after observing channel state s_i is

$$w_{(i, J_\lambda^*, \lambda)} = b'(s_i, k_\lambda^r) - \lambda t'_d(s_i, k_\lambda^r) - \lambda\sum_{\ell=1}^{i}\tau_p^\ell, \tag{13}$$

where $b'(s_i, k_\lambda^r)$ and $t'_d(s_i, k_\lambda^r)$ denote, respectively, the number of transmitted bits and data transmission time, during the process that user accesses a channel with state s_i and releases it when the channel state is no better than k_λ^r. Accordingly, the optimal stopping rule in frequency domain is given by

$$\begin{aligned} I^*_{(\lambda, J_{\lambda^*})} &= \arg\max_I E[w_{(i, J_\lambda^*, \lambda)}] \\ &= \arg\max_I \Bigg\{ E[b(s_i, k_\lambda^r)] - \lambda E[t_d(s_i, k_\lambda^r)] \\ &\quad - \lambda E\left[\sum_{\ell=1}^{I}\tau_p^\ell\right]\Bigg\}. \end{aligned} \tag{14}$$

For the convenience of description, we introduce a function $h_\lambda(k_1, k_2)$, which is defined by $h_\lambda(k_1, k_2) \doteq E[b'(k_1, k_2)] - \lambda E[t'_d(k_1, k_2)]$. The optimal frequency domain stopping rule for a given λ is given by following theorem:

Theorem 3. *Denote $k_\lambda^a = \min\{k : h_\lambda(k, k_\lambda^r) \geq V(\lambda)\}$, where $k_\lambda^a > k_\lambda^r$. For a given $\lambda > \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$, the optimal frequency-domain stopping rule is given by*

$$I_\lambda^* = \min\{i : s_i \geq k_\lambda^a\}. \tag{15}$$

Proof. As stated before, our model is an infinite-horizon problem without recall. Suppose user pays τ_p^1 and observes s_1. If user continues from this point, the s_1 is skipped and the cost τ_p^1 has already been paid. Since the expectation $E[\tau_p]$ is constant, which means that the expected cost for a further observation is constant. Thus, the decision-making process at arbitrary decision point is totally the same as that at the very beginning, which means the rule that leads maximum reward is invariant in time.

Let $V^*(\lambda)$ denote the expected return from an optimal frequency domain stopping rule $I^*_{(\lambda,J^*_\lambda)}$. From the principle of optimality, if $h_\lambda(s_1, k^r_\lambda) < V^*(\lambda)$ (after paying τ_p^1 and observing s_1) user should continue, and if $h_\lambda(s_1, s^r_\lambda) \geq V^*(\lambda)$ user should stop. This argument can be made at any decision point, since the decision-making process is invariant in time. Hence, the rule given by the principle of optimality is

$$I^*_\lambda = \min\{i \geq 1 : h_\lambda(s_i, k^r_\lambda) \geq V(\lambda)\}. \tag{16}$$

Since channel transition probability $q_{k,l} = 0$ when $|k - l| > 1$ and the data rate $R(k)$ is strictly increasing with k, $h_\lambda(s_i, k^r_\lambda)$ is a strictly increasing function of s_i. Thus, the optimal accessing rule can be rewritten as

$$I^*_\lambda = \min\{i \geq 1 : s_i \geq k^a_\lambda\},$$

where $k^a_\lambda = \min\{k : h_\lambda(k, k^r_\lambda) \geq V(\lambda)\}$.

This completes the proof. □

According to Theorem 3, the optimal frequency-domain stopping rule is also exhibiting a simple threshold structure, despite the exact value of $V(\lambda)$ is not known yet.

Now, according to Theorems 2 and 3, we conclude that the optimal joint rule ψ^*_λ defined in (9) shows threshold structural property for $\lambda > \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$. Thus, for the case that the supposed maximum throughput $\lambda^* > \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$, the optimal strategy $\psi^*_{\lambda^*}$ must also be threshold based. As stated before, λ^* is then the maximum achievable system throughput and $\psi^*_{\lambda^*}$ is exactly the solution to the original problem (described by (7)).

To simplify the description, $I^*_{\lambda^*}$, $J^*_{\lambda*}$, and $\psi^*_{\lambda^*}$ are denoted as I^*, J^*, and ψ^*, respectively, in the following description. Then, we have

Theorem 4. *The joint optimal stopping rule can be described as*

$$\psi^* = \left\{(I, J) : \begin{array}{c} I = \min\{i : s_i \geq k^*\} \\ J = \min\{j : s_i^j < k^*\} \end{array}\right\}. \tag{17}$$

And following properties holds for the optimal threshold k^*:

1. *if $\lambda^* > \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$, then $k^* \in \{k : R(k) > \bar{R}\}$;*
2. *if $\lambda^* = \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$, then $k^* = 0$.*

Proof. Case 1: $\lambda^* > \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$.

If the supposed system throughput $\lambda^* > \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$, as stated in Theorems 2 and 3, there exists a threshold $k^r_{\lambda^*}$ for optimal channel release decision and a threshold $k^a_{\lambda^*} > k^r_{\lambda^*}$ for optimal channel access decision. Denote $k^* = k^r_{\lambda^*} + 1$. As $k^r_{\lambda^*} = \max\{k : R(k) < \frac{\tau_d}{(\tau_d - \tau_m)}\lambda^*\}$, we have

$$R(k^*) \geq \frac{\tau_d}{\tau_d - \tau_m}\lambda^*. \tag{18}$$

Note that under the channel release rule J^*_λ, user would transmit over the channel with state s only when $R(s) \geq \frac{\tau_d}{\tau_d - \tau_m}\lambda^*$. Thus, we have

$$h(k^*, k^r_{\lambda^*}) = E[b'(k^*, k^r_{\lambda^*})] - \lambda^* E[t'_d(k^*, k^r_{\lambda^*})] \geq 0.$$

Then, k^* can be described as

$$k^* = \min\{k : k > k^r_{\lambda^*}; h(k, k^r_{\lambda^*}) \geq 0\}. \tag{19}$$

Recalling that $V(\lambda^*) = 0$, according to Theorem 3, we have

$$\begin{aligned} k^a_{\lambda^*} &= \min\{k : h(k, k^r_{\lambda^*}) \geq V(\lambda^*)\} \\ &\equiv \min\{k : h(k, k^r_{\lambda^*}) \geq 0\}. \end{aligned} \tag{20}$$

Then, from (19) and (20), we have $k^* = k^a_{\lambda^*} = k^r_{\lambda^*} + 1$. By integrating Theorems 2 and 3, we get the form of joint optimal rule as in (17).

Furthermore, according to (18), we have $R(k^*) \geq \frac{\tau_d}{\tau_d - \tau_m}\lambda^* > \bar{R}$. Then, the first part of this theorem is proved.

Case 2: $\lambda^* = \frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$.

In this case, the maximum expected throughput is $\frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$. As mentioned before, strategy $\psi^1 = \{(I, J) : I = 1, J = \infty\}$ leads to expected throughput $\frac{(\tau_d - \tau_m)}{\tau_d}\bar{R}$. Thus, ψ^1 is optimal strategy here. Note that $I = \min\{i : s_i \geq 0\} = 1$ and $J = \min\{j : s_i^j < 0\} = \infty$. Thus, ψ^1 is equivalent to ψ^* with $k^* = 0$. Then, we get the second part of this theorem. □

This theorem simplifies the joint two-dimensional optimal stopping rule to a simple one-threshold policy, which means that one can achieve maximum throughput by the following simple strategy:

1. Probing channels sequentially in frequency domain and accessing medium once the observed channel state is better than or equal to k^*;
2. Monitoring current in use channel packet by packet and releasing it once the observed channel state is worse than k^*.

5 Acquisition of the Optimal Strategy

In this section, we first analyze the channel access delay as well as system throughput of the threshold-based channel access/release approach. And then, we propose an efficient algorithm for acquiring the optimal threshold.

5.1 Performance Analysis of Threshold-Based Strategy

We first consider the sequential channel probing process under the threshold-based opportunistic channel access policy.

With the proposed collision-free channel utilization scheme, the probability that an arbitrary probed channel is occupied by some other user can be approximately treated as $\theta_B = \frac{M-1}{N}$, where $M - 1$ is the number of users currently in the network and N is the number of available channels. The corresponding probability that the probed channel is idle is approximated to be $\theta_I = 1 - \frac{M-1}{N}$. Then, the expected time consumed for probing an idle channel (i.e., expected channel probing cost) $E[\tau_p]$ is given by

$$\begin{aligned} E[\tau_p] &= \sum_{\kappa=1}^{\infty} \theta_B^{\kappa-1}\theta_I(\kappa\tau_S + \tau_R) \\ &= \theta_I\tau_S\sum_{\kappa=1}^{\infty}\kappa\theta_B^{\kappa-1} + \theta_I\tau_R\sum_{\kappa=1}^{\infty}\theta_B^{\kappa-1} \\ &= \frac{\tau_S}{\theta_I} + \tau_R. \end{aligned} \tag{21}$$

Under threshold-based policy $\psi_{k'}$ with access threshold k', user will access channel once the observed channel state is better than or equal to k'. Thus, the expected time consumed in sequential channel probing process of one decision epoch is given by

$$\begin{aligned} E[T_a(\psi_{k'})] &= E[\tau_p] \sum_{\ell=1}^{\infty} \left\{ \ell [\Pr(s_\ell < k')]^{(\ell-1)} \Pr(s_\ell \geq k') \right\} \\ &= E[\tau_p] \Pr(s_\ell \geq k') \sum_{\ell=1}^{\infty} \left\{ \ell [\Pr(s_\ell < k')]^{(\ell-1)} \right\} \\ &= \frac{1}{1 - P_{k'}} \left(\frac{\tau_S}{\theta_I} + \tau_R \right), \end{aligned} \tag{22}$$

where $P_{k'} \doteq \Pr(s_\ell < k') = \sum_{k=0}^{k'-1} \pi_k$ and π_k is the channel steady-state probability defined in (2).

We now analyze the dynamic data transmission process under threshold-based policy. For this part, we first introduce the absorbing Markov chain model from [22].

Definition 1. *A state k of a Markov chain is called absorbing if it is impossible to leave it (i.e., $q_{k,k} = 1$). A Markov chain is absorbing if it has at least one absorbing state, and if from every state it is possible to go to an absorbing state (not necessarily in one step).*

By setting the states $k < k'$ as absorbing states, we construct an absorbing Markov chain from the FSMC model presented in Section 3.2. Then, the dynamic data transmission process under threshold policy $\psi_{k'}$ is fully described by the constructed absorbing Markov chain. The corresponding transition matrix of the transient states is

$$\mathbf{Q}_{k'} = \left\{ \begin{array}{cccc} q_{k',k'} & q_{k',k'+1} & \cdots & 0 \\ q_{k'+1,k'} & q_{k'+1,k'+1} & q_{k'+1,k'+2} & \vdots \\ 0 & \ddots & \ddots & 0 \\ \vdots & q_{K-2,K-3} & q_{K-2,K-2} & q_{K-2,K-1} \\ 0 & \cdots & q_{K-1,K-2} & q_{K-1,K-1} \end{array} \right\},$$

where $q_{k,l}$ is defined in (3). Then, we have the following statements from [22].

Lemma 4. *For an absorbing Markov chain, the matrix $\mathbf{I} - \mathbf{Q}_{k'}$ has an inverse $\mathbf{U}$ and $\mathbf{U} = \mathbf{I} + \mathbf{Q}_{k'} + \mathbf{Q}_{k'}^2 + \cdots$ The kl-entry $u_{k,l}$ of the matrix $\mathbf{U}$ is the expected number of times the chain is in state l, given that it starts in state k.*

The strict proof of Lemma 4 can be found in [22, Theorem 11.4 of chapter 11.2].

In the following expressions, we denote (k, k') as the condition that user accesses a channel with state k and releases it when the channel state is worse than k' (where $k \geq k'$). Then, according to Lemma 4, the expected time of a data transmission phase under the condition (k, k') is

$$\begin{aligned} E\left[t_d'(k,k')\right] &= \sum_{\ell=0}^{\infty} \tau_d \mathbf{e}_{k+1-k'}^T \mathbf{Q}_{k'}^{(\ell)} \mathbf{z}_{k'}^{K-1} \\ &= \tau_d \mathbf{e}_{k+1-k'}^T (\mathbf{I} - \mathbf{Q}_{k'})^{-1} \mathbf{z}_{k'}^{K-1}, \end{aligned} \tag{23}$$

where $\mathbf{e}_{k+1-k'}$ is the $(k+1-k')$th column of the identity matrix $\mathbf{I}_{K-k'}$, and $z_{k'}^{K-1}$ is $(K-k') \times 1$ vector that all entries are 1.

Then, the expected time of data transmission process in one decision epoch under the policy $\psi_{k'}$ can be calculated as

Initialize $\bar{k} = \min\left\{k : R(k) > \bar{R}\right\}$, $k^* = 0$;
for $k = K - 1 : \bar{R}$ **do**
  attain $E\left[\Phi\left(\psi_k\right)\right]$ using Equ. (27);
  if $E\left[\Phi\left(\psi_k\right)\right] > \frac{(\tau_d - \tau_m)}{\tau_d} R(k-1)$ **then**
    $k^* = k$;
    break;
  end if
end for

Fig. 2. Algorithm for optimal threshold acquisition.

$$\begin{aligned} E[T_d(\psi_{k'})] &= E\left[E\left[t_d'(k,k')\right] | k \geq k'\right] \\ &= \frac{\tau_d \left(\sum_{k=k'}^{K-1} p_k \mathbf{e}_{k+1-k'}^T\right) (\mathbf{I} - \mathbf{Q}_{k'})^{-1} \mathbf{z}_{k'}^{K-1}}{1 - P_{k'}} \\ &= \frac{\tau_d \mathbf{p}_{\mathbf{k'}}^{\mathbf{K-1}} (\mathbf{I} - \mathbf{Q}_{\mathbf{k'}})^{-\mathbf{1}} \mathbf{z}_{\mathbf{k'}}^{\mathbf{K-1}}}{1 - P_{k'}}. \end{aligned} \tag{24}$$

Here, $\mathbf{p}_{k'}^{K-1} \doteq [\pi_{k'}, \pi_{k'+1}, \ldots, \pi_{K-1}]$.

Similarly, we get the expected number of transmitted bits in one decision epoch under the condition (k, k') as follows:

$$\begin{aligned} E[b'(k,k')] &= \sum_{\ell=0}^{\infty} (\tau_d - \tau_m) \mathbf{e}_{k+1-k'}^T \mathbf{Q}_{k'}^{(\ell)} \mathbf{r}_{k'}^{K-1} \\ &= (\tau_d - \tau_m) \mathbf{e}_{k+1-k'}^T (\mathbf{I} - \mathbf{Q}_{k'})^{-1} \mathbf{r}_{k'}^{K-1}, \end{aligned} \tag{25}$$

where $\mathbf{r}_{k'}^{K-1} \doteq [R(k'), R(k'+1), \ldots, R(K-1)]$.

Then, the expected number of transmitted bits in one decision epoch under the policy $\psi_{k'}$ is

$$\begin{aligned} E[B(\psi_{k'})] &= E[E[b'(s_k, s_{k'})] | k \geq k'] \\ &= \frac{(\tau_d - \tau_m) \sum_{k=k'}^{K-1} p_k \mathbf{e}_{k+1-k'}^T (\mathbf{I} - \mathbf{Q}_{k'})^{-1} \mathbf{r}_{k'}^{K-1}}{1 - P_{k'}} \\ &= \frac{(\tau_d - \tau_m) \mathbf{p}_{k'}^{K-1} (\mathbf{I} - \mathbf{Q}_{k'})^{-1} \mathbf{r}_{k'}^{K-1}}{1 - P_{k'}}. \end{aligned} \tag{26}$$

Consequently, according to (22), (24), and (26), we get the expected throughput of threshold strategy $\psi_{k'}$ as follows:

$$\begin{aligned} E[\Phi(\psi_{k'})] &= \frac{E[B(\psi_{k'})]}{E[T_a(\psi_{k'})] + E[T_d(\psi_{k'})]} \\ &= \frac{(\tau_d - \tau_m) \mathbf{p}_{k'}^{K-1} (\mathbf{I} - \mathbf{Q}_{k'})^{-1} \mathbf{r}_{k'}^{K-1}}{\tau_d \mathbf{p}_{k'}^{K-1} (\mathbf{I} - \mathbf{Q}_{k'})^{-1} \mathbf{z}_{k'}^{K-1} + \frac{\tau_S}{\theta_I} + \tau_R}. \end{aligned} \tag{27}$$

5.2 Optimal Threshold Acquisition

In this section, we propose an efficient algorithm for acquiring the optimal threshold as well as the optimal strategy. The proposed algorithm is presented in Fig. 2.

We explain the validity of this algorithm as follows. Denote k^* as the optimal threshold. Then, $\lambda^* = E[\Phi(\psi_{k^*})]$. On one hand, if $E[\Phi(\psi_{k^*})] > \frac{(\tau_d - \tau_m)}{\tau_d} \bar{R}$, then $k_{\lambda^*}^r = \max\{k : R(k) < \frac{\tau_d}{(\tau_d - \tau_m)} \lambda^*\}$ (refer to Theorem 2). Thus, $\frac{(\tau_d - \tau_m)}{\tau_d} R(k_{\lambda^*}^r) < E[\Phi(\psi_{k^*})] \leq \frac{(\tau_d - \tau_m)}{\tau_d} R(k_{\lambda^*}^r + 1)$. Recalling that $k_{\lambda^*}^r = k^* - 1$, we get

$$\frac{(\tau_d - \tau_m)}{\tau_d} R(k^* - 1) < E[\Phi(\psi_{k^*})] \leq \frac{(\tau_d - \tau_m)}{\tau_d} R(k^*). \tag{28}$$

Clearly, (28) is a necessary condition of the optimal threshold. Define threshold $k' = \max\{k : \frac{(\tau_d - \tau_m)}{\tau_d} R(k-1) < E[\Phi(\psi_k)]\}$. Then, since all $k > k'$ cannot satisfy (28), we assert $k^* \leq k'$. Furthermore, if some $k < k'$ is the optimal threshold, then according to (28), $E[\Phi(\psi_k)] \leq \frac{(\tau_d - \tau_m)}{\tau_d} R(k) \leq \frac{(\tau_d - \tau_m)}{\tau_d} R(k'-1) < E[\Phi(\psi_{k'})]$. It is inconsistent with the assumption that ψ_k is the optimal strategy. As a consequence of the above, the optimal threshold $k^* = k'$.

On the other hand, if for all $k \geq \bar{k}$, $E[\Phi(\psi_k)] \leq \frac{(\tau_d - \tau_m)}{\tau_d} R(k-1)$, then the maximum expected system throughput $\lambda^* \leq \frac{(\tau_d - \tau_m)}{\tau_d} R(\bar{k}-1) \leq \frac{(\tau_d - \tau_m)}{\tau_d} \bar{R}$. In this case, the optimal threshold $k^* = 0$ (refer to Theorem 4), and the maximum expected throughput $\lambda^* = \frac{(\tau_d - \tau_m)}{\tau_d} \bar{R}$ is achieved by ψ_{k^*}.

As a result, using this algorithm, the optimal strategy is acquired in at most $O(\mathbf{k})$, where $\mathbf{k} = K - \bar{k}$ is the number of the channel states where the achievable rate is higher than the expected rate of single channel.

6 Numerical and Simulation Results

In this section, we use simulations to evaluate the performance of our proposed optimal channel access/release scheme. Our simulations are developed using Matlab-based discrete-event simulation system. The simulation results presented below are based on the average of 10 independent runs, each lasting for 10 seconds of simulation time.

6.1 Scenarios and Strategies

Without loss of generality, we consider a typical wireless band with center frequency $f_c = 500$ MHz, where channels are with equally bandwidth $B = 2$ MHz. We consider typical scenarios where mobile speed v ranges from 1 to 15 m/s. Correspondingly, the maximum Doppler frequency shift f_d ranges from 1 to 25 Hz. The average received SNR γ_0 is considered ranging from 1 to 15 dB, so as to cover most communication scenarios. The wireless characteristic of each scenario is then completely represented by a (γ_0, v) pair. For each pair of (γ_0, v), we generate multiple independent channels, each with a series of time-varying channel states. Such FSMC channel is built using the method described in Section 3.2, where the rate interval $\eta = 1$ Mbps, packet duration $\tau_d = 1$ ms.

We consider three channel utilization strategies for performance comparison. The first one is *Opportunistic Transmission*. In such scheme, user could fully exploit the time diversity of a single channel by adapting transmit rate packet by packet perfectly. The theoretic average system throughput and medium access delay can be easily described, respectively, as $\Phi^{OT} = \frac{(\tau_d - \tau_m)}{\tau_d} \sum_{k=0}^{K-1} \pi_k R(k)$ and $D^{OT} = 0$.

The second one is *Opportunistic Channel Access with constant transmission duration* scheme. In such scheme, user sequentially probes channels and opportunistically accesses a good channel for data transmission. User would utilize the channel for a constant duration T_c (commonly set as channel coherence time) once accessing it. For this part, we apply the results of Shu and Krunz [9] to derive the corresponding optimal OCA strategy for a given T_c, which is built on the assumption that channel state is unchanged during T_c and changes independently across T_cs. Actually, the value of T_c

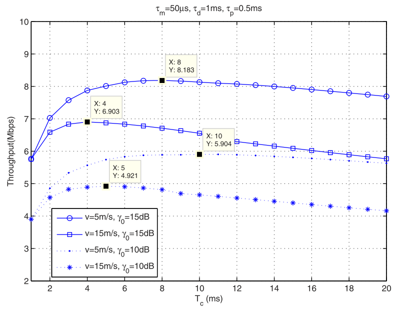

Fig. 3. Throughput of OCA versus T_c duration.

influences the system throughput heavily in practical scenarios with time-varying channels; however, little attention is paid on the acquisition of optimal T_c for a given wireless environment in [9]. To eliminate the influence of inappropriate value of T_c on the performance of OCA, we find an optimal T_c for each (v, γ_0) pair using exhaust algorithm. Specifically, we derive the maximum achievable system throughput under the optimal access strategy (derived with different value of T_c using the method proposed in [9]) in different scenarios. Then, for each simulation scenario (represented by a (v, γ_0) pair), we adopt the T_c that leads to the maximum achievable throughput as the exact transmission duration in the following simulations. As in Fig. 3, we consider single user case, and thus channel probing cost $\tau_p = \tau_S + \tau_R$ is 250 μs. Each curve presents a given wireless scenario. Then, e.g., in the case that $(v = 5\ \mathrm{m/s}, \gamma_0 = 15\ \mathrm{dB})$, we would adopt $T_c = 8$ ms and the corresponding optimal OCA strategy for performance comparison.

The third one is our proposed *Opportunistic Channel Access and Release* scheme (denoted as OCAR). The optimal strategies for OCAR in different scenarios are obtained using the algorithm described in Section 5.2.

6.2 Performance in Different Environments

In this section, we study system performance as a function of environmental parameters such as mobile speed v and average received SNR γ_0. As mentioned before, mobile speed affects the channel changing rate directly. Thus, a higher mobile speed indicates a more dynamic scenario while a lower one leads to a more stable environment. Averaged SNR γ_0 is another important factor relating to the expected channel quality. A bigger γ_0 means a better channel condition. Throughout this section, we consider that there is only one user in the network, so as to focus on the impacts of environmental factors. In such case, the channel probing cost $\tau_p = \tau_S + \tau_R$ is a constant. We fix $\tau_m = 50$ μs and $\tau_p = 500$ μs in this part.

To give an overall impression about the throughput of the three channel utilization schemes in different environments, we depict the expected system throughput as a function of γ_0 and v in Fig. 4. It is clear that the system throughput of all these three schemes are increasing with γ_0. However, the throughput gain of OCA and OCAR over OT (i.e., throughput ratio: $\frac{\Phi^{OCA}}{\Phi^{OT}}$ and $\frac{\Phi^{OCAR}}{\Phi^{OT}}$) are decreasing with γ_0, which indicates that frequency diversity exploitation is more beneficial in poor channel condition. On the other hand,

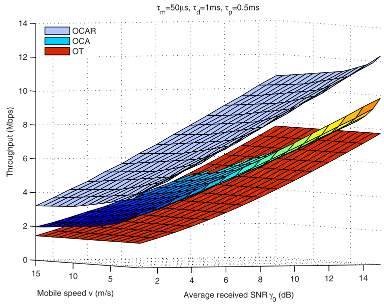

Fig. 4. Throughput versus environmental factors γ_0 and v.

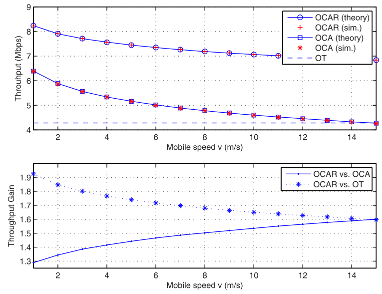

Fig. 6. Throughput and throughput gain versus mobile speed v.

such throughput gain is decreasing with v (as the system throughput of OCA and OCAR schemes are decreasing with v, while that of OT is independent with v). The reason is that, as channel changing rate increases, the decreasing transmission time in each epoch of OCA or OCAR boils the system throughput gain down. Moreover, the scheme purely exploiting the channel diversity in frequency domain (as OCA) performs worse than the one exploiting time domain diversity in single channel (as OT) when channel condition is good and fast changing (i.e., γ_0 and v are high). Meanwhile, our proposed OCAR scheme outperforms the other two schemes in all cases by jointly exploiting channel diversity in both time and frequency domain.

To learn more about the system performance of such joint time-frequency diversity exploitation scheme, we draw several performance metrics as a function of γ_0 and v, respectively, in Figs. 5, 6, 7, and 8. We are interested in the following performance metrics: 1) the average throughput, denoted as the average number of bits transmitted by user in each second; 2) the average medium access delay, denoted as the average time user spends until it finds a good channel and starts transmitting over it; and 3) the average data transmission time in each decision epoch. To verify the accuracy of our analysis, the throughput calculated according to the analytical model and the one obtained from the simulations are compared in these figures. For each scenario, we build 50 independent FSMC channels with the corresponding (γ_0, v) pair for simulating the wireless environment, and run 10 independent simulations with each lasting 10 seconds of simulation time. As a result, we obtain a group of performance outcome for each (γ_0, v) pair, where $\gamma_0 = (1, 2, \ldots, 15)$ dB and $v = (1, 2, \ldots, 15)$ m/s.

In Figs. 5 and 6, we depict the expected system throughput as a function of γ_0 and v, respectively. Note that both the theoretical and simulation values here are averaged results over either γ_0 or v. That is, as an example, the throughput of a given γ_0 (denoted by $\Phi(\gamma_0)$) is an averaged result of $\Phi(\gamma_0, v)$ over variable v, i.e., $\Phi(\gamma_0) = \frac{1}{15}\sum_{v=1}^{15} \Phi(\gamma_0, v)$. Similarly, $\Phi(v) = \frac{1}{15}\sum_{\gamma_0=1}^{15} \Phi(\gamma_0, v)$. The upper subfigure of each figure is the throughput curve, and the lower one is the throughput gain of OCAR over either OCA or OT, i.e., $\frac{\Phi^{OCAR}}{\Phi^{OCA}}$ and $\frac{\Phi^{OCAR}}{\Phi^{OT}}$.

Fig. 5 shows the rising trend of the three channel utilization schemes over γ_0. From the lower subfigure of Fig. 5, we find that OCAR scheme achieves 45-55 percent increment in average system throughput over OCA scheme and 50-140 percent increment over OT. What is more important, such joint time-frequency diversity exploitation gain increases as γ_0 decreases. It indicates that our OCAR scheme performs better in poor channel condition, where throughput improvement is most needed. On the other hand, Fig. 6 reveals the relationship between system throughput and mobile speed. It is clearly shown that the system throughput of OCA and OCAR schemes are decreasing with v, while that of OT is independent with v. Nevertheless, OCAR achieves substantial throughput improvement over OT as shown in the lower subfigure of Fig. 6 (60 percent increment even when $v = 15$ m/s). Moreover, comparing with OCA scheme, our OCAR outperforms 30 to 60 percent. And as channel changing rate increases, the throughput gain of OCAR over OCA increases. It means that our scheme is more insensitive to the channel fluctuations than OCA.

We now study the average channel access delay of OCAR and OCA schemes in different environments. The results are presented in Figs. 7 and 8. Similar to Figs. 5 and 6, the upper part of each figure is derived from following way: we first derive the access delay for each (γ_0, v) pair under corresponding optimal strategy, then average the results over either γ_0 or v, i.e., $D(\gamma_0) = \frac{1}{15}\sum_{v=1}^{15} D(\gamma_0, v)$ and

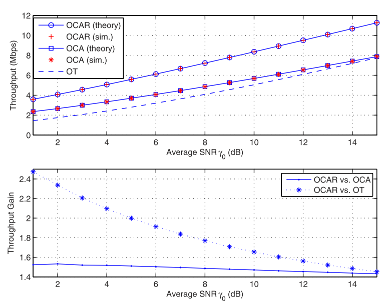

Fig. 5. Throughput and throughput gain versus average received SNR γ_0.

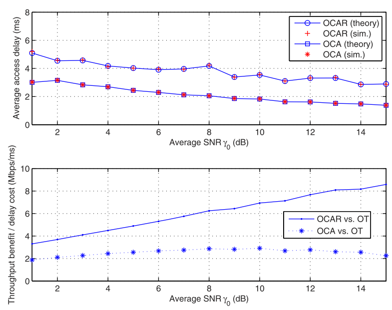

Fig. 7. Access delay analysis versus average received SNR γ_0.

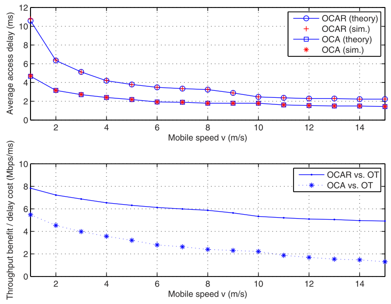

Fig. 8. Access delay analysis versus mobile speed v.

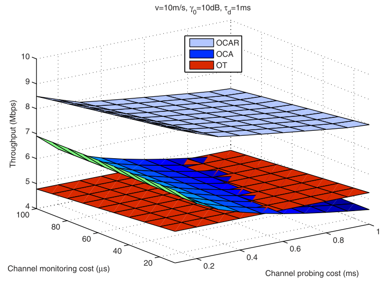

Fig. 10. Throughput versus observing cost τ_m and τ_p.

$D(v) = \frac{1}{15}\sum_{\gamma_0=1}^{15} D(\gamma_0, v)$. These curves reveal the relationships between average access delay and environmental factors. It is clear that the throughput gain of multichannel diversity exploitation is obtained at the cost of increasing channel access delay, and OCAR achieves more throughput gain than OCA with higher access delay. It seems that the throughput gain is proportional to incremental access delay for both OCAR and OCA. To further explore the exact relations between throughput gain and access delay, we calculated the ratio between throughput benefit and access delay cost of OCAR over OT as well as that of OCA over OT, i.e., $\frac{\Phi^{OCAR}-\Phi^{OT}}{D^{OCAR}}$ and $\frac{\Phi^{OCA}-\Phi^{OT}}{D^{OCA}}$ (since $D^{OT} = 0$). Then, the outcome can be treated as the throughput improvement per unit of access delay time. The results are presented in lower parts of Figs. 7 and 8. What inspire us is that, though the channel access delay of OCAR is higher than OCA, the efficiency on improving throughput with delay cost of OCAR is approximately twice greater than that of OCA.

In Fig. 9, we investigate the data transmission duration of OCAR and OCA in each epoch. The solid line represents the data transmission duration per epoch of OCA, while the dashed line represents that of OCAR. Recalling that for OCAR scheme, the data transmission time in each epoch is random, we depict both the averaged value and the (10, 90) percentiles value of data transmission time under OCAR. We can find that in both subfigures, the trends of curves are much alike: holds nearly constant when γ_0 varies and decreases as v increases. This result tells us that the channel occupying time per epoch is determined mainly by channel changing rate. In addition, the curves show two important characteristics: 1) the fluctuations of OCAR data transmission time are quite wide, and 2) the average data transmission time of OCAR is much longer than that of OCA. As the channel occupying time in each epoch is determined by the instantaneous channel quality in OCAR scheme, the first characteristic reveals the truth that the real channel quality may either keep high for a considerable long time or become poor in a wink. Thus, using a constant transmission time (as OCA does) leads poor system performance. Moreover, in order to guarantee that the channel quality is highly correlated (unchanging with high probability) during one transmission duration, the transmission time of OCA is obviously much more conservative than the average channel holding time, which results in the second characteristic of the curves.

6.3 Impact of Measure Parameters

In this section, we further study the system performance as a function of measure parameters such as channel monitoring and probing cost. The practical channel measure cost depends on the application system and corresponding hardware configuration. Throughout this section, we consider a typical scenario where ($\gamma_0 = 10$ dB, $v = 10$ m/s).

We first present the expected system throughput as a function of both channel monitoring cost τ_m and channel probing cost τ_p in Fig. 10. Here, τ_m ranges from 10 to 100 μs and channel probing time τ_p ranges from 0.1 to 1 ms (such value is reasonable for current hardware performance as discussed in Section 3.1). A direct observation is that, the variation of τ_m affects the performance of OCAR and OT only, while the channel probing cost τ_p only influences the results of OCAR and OCA. This is reasonable since τ_m is paid for time-domain diversity exploitation and τ_p is paid for frequency-domain diversity exploitation. Moreover, the system throughput of OCAR and OT are linearly deceasing with τ_m, while the variation of throughput of OCAR and OCA with τ_p is more complicated.

In Fig. 11, we depict both theoretical and simulation results of system throughput as a function of τ_p. Meanwhile, the throughput gain of OCAR over OCA is also presented

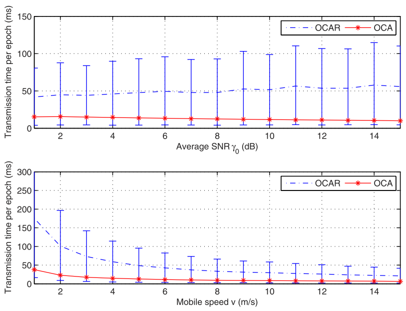

Fig. 9. Duration of transmission time in each epoch versus γ_0 and v.

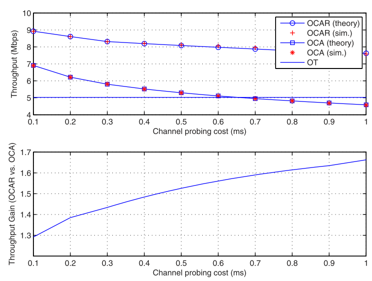

Fig. 11. Throughput and throughput gain versus probing cost τ_p.

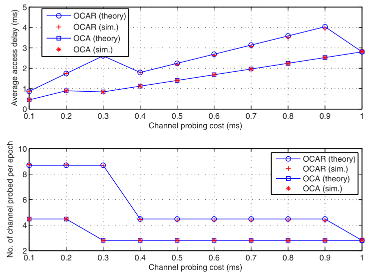

Fig. 12. Access delay analysis versus probing cost τ_p.

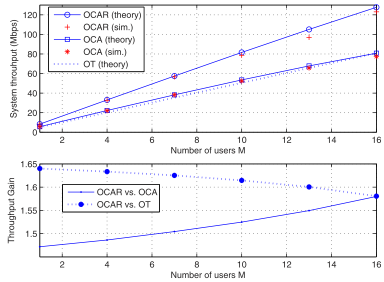

Fig. 14. Total throughput and throughput gain versus M.

in the lower part of this figure. There is no doubt that both the throughput of OCAR and OCA are decreasing with τ_p, since higher τ_p makes the channel exploration process more expensive. As shown in the figure, the throughput of OCA decreases as τ_p increases, and even performs worse than OT when $\tau_p > 0.6$ ms. In contrast, our proposed OCAR scheme outperforms OT 50 percent even when $\tau_p = 1$ ms. From the lower subfigure, we find that throughput gain of OCAR over OCA is increasing with τ_p, which means our OCAR scheme is much more bearable on the increasing of channel probing cost τ_p.

Fig. 12 shows the relationship between channel access delay and channel probing cost. The upper part depicts the channel access delay as a function of τ_p. It shows that: 1) the access delay of both OCAR and OCA are increasing with τ_p; 2) OCAR leads higher access delay than OCA; however, the delay gap between these two schemes (defined as $\frac{D^{OCAR}}{D^{OCA}}$) is gradually decreasing with τ_p. In addition, a interesting observation is that the increase of access delay is not strictly monotonic. To find out the root cause, we derive the expected number of probed channel in each epoch as a function of τ_p and present the result in lower part of Fig. 12. From the curves, we find that the number of probed channel decreases as the probing cost increases. It provides an explanation to the nonlinear increasing property of access delay curve: the increasing probing cost boiled down the system throughput and user has to lower down the access threshold so as to mitigate such loss.

As stated before, the value of channel monitoring time τ_m also influences the system performance. However, we skipped the simulation results about the impact of τ_m for that: 1) the impact of τ_m is straightforward, i.e., simple linear; and 2) it is also less severe than other parameters, since τ_m is commonly less than 10 microseconds while other parameters are in the level of milliseconds.

6.4 Multiuser Networks

In this section, we study the system performance in multiuser scenarios. When there are multiple users in the network, the time cost for each channel probing step is a random value consisting of several τ_Ss and one τ_R, since channels may be occupied by other users. In this section, we consider that there are totally 30 independent channels (i.e, N = 30). Each channel is generated using the FSMC transition probability derived with ($\gamma_0 = 10$ dB, $v = 10$ m/s). The τ_R is fixed at 100 μs. We consider τ_S ranging from 50 to 500 μs and M ranging from 1 to 20.

The expected system throughput of all the mentioned channel utilization schemes with different (τ_S, M) pairs are presented in Fig. 13, where the throughput is normalized by user number. It is shown that the normalized throughput of OT is a constant, while that of OCA and OCAR are decreasing with both τ_S and M. This is reasonable since the increase of M and τ_S raises the time cost for a successful channel probing.

We further evaluate the system performance by simulations. The overall system throughput and access delay are presented as functions of M in Figs. 14 and 15, respectively, where τ_S is fixed to be 250 μs. It shows that the simulation results match the analysis results well in both figures. In upper part of Fig. 14, the system throughput of both OCA and OCAR are increasing sublinear with M. Moreover, it shows that our proposed OCAR scheme outperforms the other two schemes a lot and the throughput benefit of OCA over OT in multiuser scenario is very limited (when M up to 16, such benefit is near zero). To further explore the benefit of OCAR scheme, we depict the throughput gain of OCAR over OCA and OT, respectively, in the lower part of Fig. 14. Clearly, it is shown that the throughput gain over OT is decreasing with M and that over OCA is increasing with M. This is reasonable since that: 1) the increasing number of users raises the cost for channel probing and

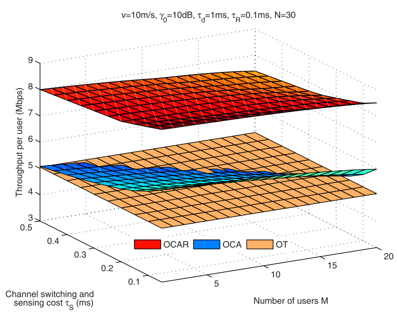

Fig. 13. Throughput versus τ_S and M.

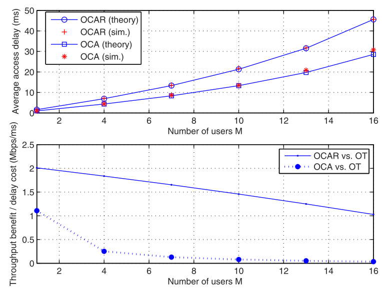

Fig. 15. Access delay analysis versus number of users M.

thus brings down the benefits of frequency diversity exploitation; and 2) OCAR is less susceptible to the increase of probing cost comparing with OCA.

The upper part of Fig. 15 shows the rising trend of channel access delay in respect of M. We further depict the ratio between the incremental throughput and additional access delay of OCAR and OCA in the lower part of Fig. 15, i.e., $\frac{\Phi^{OCAR}-\Phi^{OT}}{D^{OCAR}}$ and $\frac{\Phi^{OCA}-\Phi^{OT}}{D^{OCA}}$. It clearly shows that, although OCAR results in bigger channel access delay as M increases, it leads to a much higher efficiency on improving throughput with delay.

7 Conclusions and Future Work

In this study, we propose a time-frequency opportunistic channel utilization scheme, to exploit link-layer diversity in multichannel system under Rayleigh fading environment. We find that the throughput-optimal channel access/release strategy has a threshold structure, which indicates that user could easily make the right decisions on when and which channel to access and when to release the channel simply by comparing current channel quality with the threshold. Simulation results show that our proposed channel utilization scheme yields substantial throughput gain over conventional approaches. Moreover, note that the problem of *exploiting multiuser diversity in single-channel networks* is essentially equivalent to that of *exploiting multichannel diversity in single-user' perspective*, we can easily extend our framework to single-channel multiuser system for joint time and space diversity exploitation.

Although the proposed scheme in this paper could be applied in multiuser networks with slight constrain, it still stays in a link perspective, ignoring competition and collision between users as well as space diversity across users. It is of great interest to generalize this study to multiuser multichannel networks, investigating distributed scheme to jointly exploit time-frequency-space opportunities. We are currently working along this avenue.

Acknowledgments

This research is partially supported by NSF China under Grants No. 60932002, 61003277, 61232018, 61272487, 61170216, 61172062, NSF CNS-0832120, NSF CNS-1035894, China 973 Program under Grants No. 2009CB320400, 2010CB328100, 2010CB334707, 2011CB302705, program for Zhejiang Provincial Key Innovative Research Team, and program for Zhejiang Provincial Overseas High-Level Talents.

References

[1] T.S. Rappaport, *Wireless Communications: Principles and Practice,* second ed. Prentice Hall, Jan. 2002.

[2] M.-S. Alouini and A.J. Goldsmith, “Adaptive Modulation over Nakagami Fading Channels,” *Wireless Personal Comm.*, vol. 13, pp. 119-143, May 2000.

[3] V. Kanodia, A. Sabharwal, and E. Knightly, “MOAR: A Multi-Channel Opportunistic Auto-Rate Media Access Protocol for Ad Hoc Networks,” *Proc. First Int'l Conf. Broadband Network (BroadNets '04)*, pp. 600-610, 2004.

[4] Q. Zhang, Q. Chen, F. Yang, X. Shen, and Z. Niu, “Cooperative and Opportunistic Transmission for Wireless Ad Hoc Networks,” *IEEE Network,* vol. 21, no. 1, pp. 14-20, Jan./Feb. 2007.

[5] Y.P. Chen, J. Zhang, and I. Marsic, “Link-Layer-and-above Diversity in Multihop Wireless Networks,” *IEEE Comm. Magazine,* vol. 47, no. 2, pp. 118-124, Feb. 2009.

[6] A. Sabharwal, A. Khoshnevis, and E. Knightly, “Opportunistic Spectral Usage: Bounds and a Multi-Band CSMA/CA Protocol,” *IEEE/ACM Trans. Networking,* vol. 15, no. 3, pp. 533-545, June 2007.

[7] S. Guha, K. Munagala, and S. Sarkar, “Information Acquisition and Exploitation in Multichannel Wireless Systems,” *IEEE Trans. Information Theory*, 2007.

[8] N.B. Chang and M. Liu, “Optimal Channel Probing and Transmission Scheduling for Opportunistic Spectrum Access,” *IEEE/ACM Trans. Networking,* vol. 17, no. 6, pp. 1805-1818, Dec. 2009.

[9] T. Shu and M. Krunz, “Throughput-Efficient Sequential Channel Sensing and Probing in Cognitive Radio Networks under Sensing Errors,” *Proc. MobiCom '09,* pp. 37-48, 2009.

[10] H. Jiang, L. Lai, R. Fan, and H.V. Poor, “Optimal Selection of Channel Sensing Order in Cognitive Radio,” *IEEE Trans. Wireless Comm.,* vol. 8, no. 1, pp. 297-307, Jan. 2009.

[11] P. Chaporkar and A. Proutiére, “Optimal Joint Probing and Transmission Strategy for Maximizing Throughput in Wireless Systems,” *IEEE J. Selected Areas in Comm.,* vol. 26, no. 8, pp. 1546-1555, 2008.

[12] D. Zheng, W. Ge, and J. Zhang, “Distributed Opportunistic Scheduling for Ad Hoc Networks with Random Access: An Optimal Stopping Approach,” *IEEE Trans. Information Theory,* vol. 55, no. 1, pp. 205-222, Jan. 2009.

[13] A. Kamerman and L. Monteban, “WaveLAN-II: A High-Performance Wireless LAN for the Unlicensed Band,” *Bell Labs Technical J.,* vol. 2, no. 3, pp. 118-133, Aug. 1997.

[14] B. Sadeghi, V. Kanodia, A. Sabharwal, and E. Knightly, “OAR: An Opportunistic Auto-Rate Media Access Protocol for Ad Hoc Networks,” *Wireless Networks,* vol. 11, pp. 39-53, Jan. 2005.

[15] M. Mishra and A. Sahai, “How Much White Space Is There?” Technical Report UCB/EECS-2009-3, EECS Dept., Univ. of California, Berkeley, Jan. 2009.

[16] Y. Yuan, P. Bahl, R. Ch, P.A. Chou, J.I. Ferrell, T. Moscibroda, S. Narlanka, and Y. Wu, “KNOWS: Kognitiv Networking over White Spaces,” *Proc. IEEE Int'l Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN '07)*, 2007.

[17] K. Balach, S.R. Kadaba, and S. Nanda, “Channel Quality Estimation and Rate Adaptation for Cellular Mobile Radio,” *IEEE J. Selected Areas in Comm.,* vol. 17, no. 7, pp. 1244-1256, July 1999.

[18] P. Sadeghi, R. Kennedy, P. Rapajic, and R. Shams, “Finite-State Markov Modeling of Fading Channels - A Survey of Principles and Applications,” *IEEE Signal Processing Magazine,* vol. 25, no. 5, pp. 57-80, Sept. 2008.

[19] Q. Zhang and S.A. Kassam, “Finite-State Markov Model for Rayleigh Fading Channels,” *IEEE Trans. Comm.,* vol. 47, no. 11, pp. 1688-1692, Nov. 1999.

[20] R.K. Guha and S. Sarkar, “Characterizing Temporal SNR Variation in 802.11 Networks,” *Proc. IEEE Wireless Comm. and Networking Conf. (WCNC '06),* vol. 3, pp. 1408-1413, 2006.

[21] T. Ferguson, “Optimal Stopping and Applications,” http://www.math.ucla.edu/tom/stopping/content.html, 2012.

[22] C.M. Grinstead and J.L. Snell, “Introduction to Probability,” http://onlinebooks.library.upenn.edu/webbin/book/lookupid?key=olbp18382, 2012.

Bowen Li (S'11) received the BS degree in wireless communication from the Institute of Communication Engineering at the PLA University of Science and Technology, China, in 2007. He is currently working toward the PhD degree from PLA University of Science and Technology. His current research interests include stochastic optimization in cognitive radio networks, and energy efficient algorithm design for wireless sensor networks. He is a student member of the IEEE.

Panlong Yang (M'02) received the BS, MS, and PhD degrees in communication and information system from Nanjing Institute of Communication Engineering, China, in 1999, 2002, and 2005, respectively. During September 2010 to September 2011, he was a visiting scholar in HKUST. He is now an associate professor in the Nanjing Institute of Communication Engineering, PLA University of Science and Technology. His research interests include wireless mesh networks, wireless sensor networks and cognitive radio networks. He has published more than 50 papers in peer-reviewed journals and refereed conference proceedings in the areas of mobile ad hoc networks, wireless mesh networks and wireless sensor networks. He has also served as a member of program committees for several international conferences. He is a member of the IEEE, IEEE Computer Society, and ACM SIGMOBILE Society.

Jinlong Wang (M'05) received the BS degree in wireless communications, the MS and PhD degrees in communications and electronic system from the Institute of Communications Engineering, Nanjing, China, in 1983, 1986, and 1992, respectively. He is currently a professor at the PLA University of Science and Technology, China. He is also the co-chairman of IEEE Nanjing Section. He has published widely in the areas of signal processing for communications, information theory, and wireless networks. His current research interests include wireless communication, cognitive radio, soft-defined radio and ultrawide bandwidth (UWB) systems. He is a member of the IEEE.

Qihui Wu (M'08) received the BS degree in communications engineering, the MS and PhD degrees in communications and information system from the Institute of Communications Engineering, Nanjing, China, in 1994, 1997, and 2000, respectively. He is currently a professor at the PLA University of Science and Technology, China. His current research interests are algorithms and optimization for cognitive wireless networks, soft-defined radio and wireless communication systems. He is a member of the IEEE.

Shao-Jie Tang (S'09) received the BS degree in radio engineering from the Southeast University, China, in 2006. Since 2006, he has been working toward the PhD degree from the Computer Science Department, Illinois Institute of Technology. His current research interests include algorithm design and analysis for wireless ad hoc network and online social network. He is a student member of the IEEE.

Xiang-Yang Li (SM'08) received the bachelor's degree from the Department of Computer Science and the bachelor's degree from the Department of Business Management, Tsinghua University, P.R. China, both in 1995. He received the MS degree in 2000 and the PhD degree in 2001 from the Department of Computer Science, University of Illinois at Urbana-Champaign. He has been an associate professor since 2006 and an assistant professor from 2000 to 2006 of computer science at Illinois Institute of Technology. He published a monograph *Wireless Ad Hoc and Sensor Networks: Theory and Applications* and coedited the book *Encyclopedia of Algorithms*. His research interests include the cyber-physical systems, wireless sensor networks, game theory, and algorithms. He is a senior member of the IEEE.

Yunhao Liu (SM'06) received the BS degree in automation from Tsinghua University, Beijing, China, in 1995, and the MS and PhD degrees in computer science and engineering from Michigan State University, in 2003 and 2004, respectively. Being a member of Tsinghua National Lab for Information Science and Technology, he holds Tsinghua EMC Chair Professorship. He is the director of the Key Laboratory for Information System Security, Ministry of Education, and a professor at the School of Software, Tsinghua University. He is also a faculty member at the Department of Computer Science and Engineering, Hong Kong University of Science and Technology. His research interests include pervasive computing, peer-to-peer computing, and sensor networks. He is a senior member of the IEEE.