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Delay-Power Tradeoff of Fixed-Rate Wireless Transmission With Arbitrarily Bursty Traffics

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ABSTRACT Wireless communication system is expected to provide service with low latency and high energy efficiency. To improve the energy efficiency, the transceiver prefers sending packets, when the channel states are good. However, such opportunistic transmission may induce undesirably large latency. Therefore, a fundamental tradeoff exists between the average transmission power and average queuing delay, and is studied in this paper via cross-layer probabilistic scheduling. In particular, we consider the delay-power tradeoff when the packet arrivals have arbitrary probabilistic distributions. A Markov reward model is adopted to model the queue of the backlogged packets. Based on that, we formulate a nonlinear optimization problem and convert it into a linear programming (LP) problem by using variable substitution. The optimal solution to the LP problem allows us to derive the optimal scheduling parameters. Based on the optimal solution, we can derive the optimal scheduling policy, which turns out to be threshold-based. Besides, we consider the source scheduling with the specific packet arrival distribution being unknown. Adaptive algorithms are proposed to achieve the corresponding delay-power tradeoff.

INDEX TERMS Cross-layer design, delay-power tradeoff, quality of service, probabilistic scheduling, controllable queuing system.

I. INTRODUCTION

Recently, the Internet of Things (IoT) is one of the most popular concepts since it provides us a vision, in which a number of intelligent devices and things will be connected to the Internet and share information [1]. The IoT such as sensor networks, wearable devices and vehicular Ad hoc network have been applied to our daily life to provide real-time services like tracking, monitoring, e-healthcare and home and industrial automation system. In such applications, low latency is a key Quality of Service (QoS) metric to measure the quality of serving delay-sensitive applications. On the other hand, energy efficiency is a performance metric which has been causing increasing attention because of the wide use of wireless mobile terminals in IoT scenarios to which energy resource is quite limited. To improve power efficiency, the transmitter always seeks to transmit in the good channel state since it spends less power. However, it may cause undesirably large queuing delay to wait for a good channel state, which is intolerable for serving delay sensitive traffics and vice versa. Thus, there exists a fundamental tradeoff between the average queueing delay and the transmission power. What's more, it turns out that analyzing and optimizing the system performance such as queueing latency and energy efficiency is not a trivial work due to the randomness of packet arrival and channel state. Thus, to deal with the uncertainties happen in different layers, cross-layer approach is considered and has been widely studied in the past decades.

There have already been some work on cross-layer design over energy efficient wireless transmission. Several topics which are related to communication are reviewed and analyzed in [2] from an information-theoretic perspective. The information-theoretic treatments usually ignore the bursty nature of real sources, therefore, the queueing delay is ignored. Thus, queueing theory can be adopted to study the QoS metric such as queueing delay. In [3], the authors considered a pure queueing model and developed a concept termed effective capacity (EC) to model the link-layer. To the best knowledge of us, Collins and Cruz firstly proposed the idea of cross-layer scheduling jointly based on the queue and channel states in [4] when minimizing the average power under the constraints of average delay and peak transmission power. Berry and Gallager aimed to regulate the average power consumption and queueing delay based on user's transmission rate and power under the framework of cross-layer in [5].

In [6], a scheduling policy, referred as Lazy scheduling, was proposed to minimize the transmission energy consumption given the deadline constraint for each packet. The existence of the optimal stationary scheduling strategy was shown in [7] where some structural results were also obtained. Then [8] studied on several cross-layer resource allocation problems for wireless fading channels with power and transmit rate adaptation. Ata aimed to minimize the consumed power under the constraint of packet drop rate in [9], where fixed channel, Poisson packet arrival and exponentially distributed packet size are considered.

Various optimization methods were used to achieve the optimal delay-power tradeoff. Two of the major methods are Dynamic Programming (DP) and Markov Decision Process (MDP) [10]. The delay-power tradeoff problem was investigated in the framework of MDP in [5], where DP was used to numerically compute the optimal solution. DP method was also used to obtain the optimal solution to the delay-power tradeoff problem in [11] and [12]. Besides, constrained Markov decision process (CMDP) was adopted to formulated the delay and power tradeoff in [13], where the authors obtained an optimal policy to achieve the power and delay tradeoff for the considered single-user system and multi-user system. Network calculus was used to model energy-efficient transmission with deadline constraint in [6] and [14]. Based on cumulative curves methodology, the optimal transmission policy for minimizing the transmission power under the QoS constraints was obtained in [14]. Fractional programming was used to solve the scheduling problem in [15] and [16]. The authors aimed to minimize the total consumed power under the constraints of rate, delay, contiguous allocation and maximum power in [17]. They proposed two energy-efficient iterative schedulers based on Binary Integer Programming (BIP) and performed a low-complexity greedy algorithm to solve the BIP problem.

Usually, it is not a trivial work to solve the optimization problem which is derived in the cross-layer framework and obtain its analytical solution [18]. Recently, we presented a joint queue-aware and channel-aware probabilistic scheduling to achieve the optimal delay-power tradeoff of fixed-rate wireless transmission in our previous work [19]. The probabilistic scheduling was applied to analyze the delay-power tradeoff in the scenarios of two-user multiple access system in [20] and cognitive multiple access network in [21] and [22]. In [19], we considered the time-slotted system, where data packets were assumed to obey Bernoulli distribution for simplicity and transmitted via a discrete-time blocking-fading channel. We proved that the optimal scheduling policy to achieve the optimal delay-power tradeoff under these system assumptions was the threshold-based policy. The threshold-based policy determines packet transmission based on the optimal thresholds imposed on the queue length, defined as the number of backlogged packets in the buffer. In [23], with same packet arrival model and channel model, we considered two different cases which are based on the relationship between the transmission time for a data packet and the length of a time slot. We studied the delay-power tradeoff for both the two cases and proved that the optimal scheduling policy is also threshold-based. Part of this work is shown in [24], where we studied the delay-power tradeoff with generalized packet arrival distribution. Considering the burstiness of traffic arrival in practical applications, it is necessary to consider the system with an arbitrarily random packet arrival distribution. In this work, we adopt an arbitrarily random packet arrival distribution to capture the burstiness of the traffic, namely, there is no limitation on the number or the distribution of the arriving packets during one time slot. We aim at analyzing the tradeoff between the average queueing delay and the average consumption power under this assumption and obtaining an optimal scheduling policy to achieve the optimal delay-power tradeoff. However, due to the general distribution, it becomes more complex when we build the Markov chain and its balanced equations. Besides, it is more complex to analytically describe the scheduling strategy because more probability parameters are imported. In this paper, by considering the sum of a series of transition probabilities instead of a single one as in [19], we describe the optimal delay-power tradeoff with an LP problem. By analyzing the structure of its optimal solution, we obtain the optimal scheduling policy as the threshold-based policy. Based on the special format of the threshold-based policy, we consider the delay-power tradeoff without the distribution of the packet arrival and propose efficient algorithms to achieve the minimum delay under average power constraint.

The remainder of this paper is organized as follows. In Section II, the system model for the problem is established. A probabilistic scheduling strategy is introduced in Section III, along with the formulation of the Markov chain model. The analytical expressions of the average queueing delay and transmission power are obtained in Section IV. We formulate a nonlinear optimization problem in Section V, and convert it into an LP problem. By deriving the optimal solution to the LP problem, we can obtain the optimal scheduling policy theoretically. In Section VI, we consider the delay-power tradeoff with the packet arrival distribution being unknown and propose an adaptive threshold algorithm to obtain the optimal scheduling parameters. Numerical results and concluding remarks are presented in Sections VII and VIII, respectively.

Through this paper, let $a \wedge b$ and $a \vee b$ denote $max\{a, b\}$ and $min\{a, b\}$, respectively.

II. SYSTEM MODEL

We study the scenario that a source node transmits packets to its destination via a wireless link as shown in Fig.1(a). In this section, we introduce our cross-layer system model, consisting of the random data arrival in the network layer, the queueing behaviour in the data link (DDL) layer, and power adaptation and data transmission in the physical (PHY) layer.

As shown in Fig.1(b), data packets arrive at the network layer from upper layers or the other nodes randomly. In the

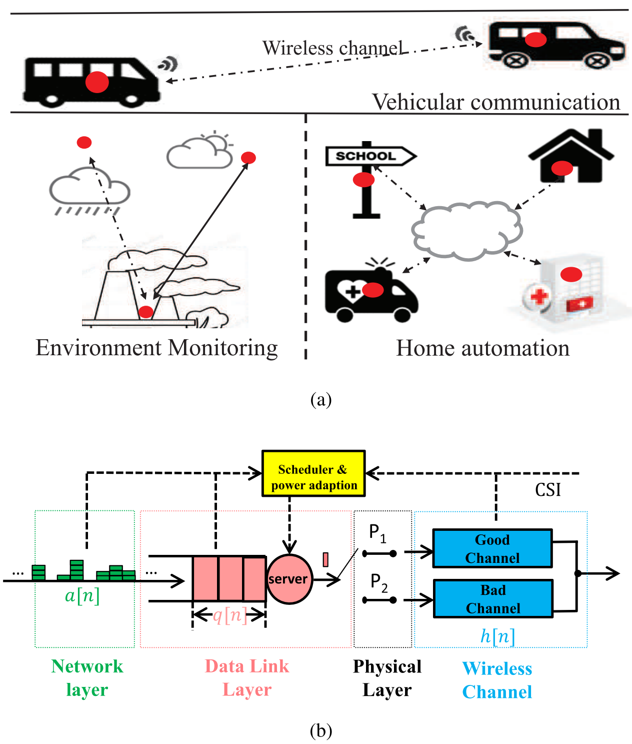

FIGURE 1. System Model. (a) Communication Scenarios. (b) Cross-layer System model.

time-slotted system, $a[n]$ denotes the number of the packets arriving at the source buffer in the nth time slot and is time-varying but independent and identically distributed ($i.i.d$) across time slots. Due to the bursty data arrival, $a[n]$ is supposed to be a random variable, which obeys an arbitrary distribution. Its mass probability function is given by

$$\Pr\{a[n] = m\} = p_m, \quad m = 0, 1, 2, \cdots, \tag{1}$$

where m is a nonnegative integer and p_m belongs to the interval [0, 1]. Due to the normalization constraint, we have

$$\sum_{m=0}^{\infty} p_m = 1. \tag{2}$$

We focus on the scenario with bounded data arrival, i.e., there exists $M \geq 0$, for all $m > M$, $p_m = 0$, which accounts for traffic shaping and admission control in wireless network. From Eq. (1), the average packet arrival rate is obtained as

$$\bar{a} = \lim_{N\to\infty} sup \frac{1}{N} \sum_{n=0}^{N} a[n] = \sum_{m=0}^{M} m \cdot p_m. \tag{3}$$

The transmitter employs a buffer to backlog the packets. Without loss of generality, the capacity of the buffer K is assumed to be sufficiently large, thus, the buffer overflow could be negligible.[1]

[1]Note that if the given average power is too small, packets will be sent only in the good channel and a few bad channel. Thus, the queue length will increase dramatically. For the finite buffer, packet drop will happen. This situation should be avoided in practice. Thus, in this work, we focus on the delay-power tradeoff under the assumption that the buffer capacity is sufficiently large.

Let $s[n]$ denote the number of packets transmitted in the nth time slot. The queueing state, defined as the number of packets stored in the buffer at the end of time slot n [25], is updated as

$$\begin{aligned} q[n] &= \left\{min\{q[n-1] + a[n], K\} - s[n]\right\}^{+} \\ &= \left\{q[n-1] + a[n] - s[n]\right\}^{+}, \end{aligned} \tag{4}$$

where the superscript ' + ' denotes nonnegative, i.e., $a^{+} = max\{a, 0\}$. The second equality holds because the buffer capacity is assumed to be sufficiently large. If $a[n]$ data packets arrive at the source buffer and $s[n]$ data packets are transmitted in the nth slot, the queue length is updated based on Eq. (4).

We consider discrete-time block-fading channel model, i.e., the channel states are assumed to be invariant during each time slot and time-varying but $i.i.d$ across time slots. In this paper, a two-state wireless channel model is adopted to differ the good channel states from the deep fading ones [4]. Let $h[n]$ denote the channel state. $h[n] = $ '$good$' means the channel state is good, i.e., the channel gain is quite large or the fading can be ignored in the nth time slot while $h[n] = $ 'bad' indicates that the wireless channel remains in deep fading. The probability mass function of $h[n]$ is given by

$$\begin{cases} \Pr\{h[n] = \text{'}good\text{'}\} = \beta, \\ \Pr\{h[n] = \text{'}bad\text{'}\} = 1 - \beta, \end{cases} \tag{5}$$

where β belongs to the interval [0, 1]. Two-state block-fading channel model is applicable for many IoT applications such as those shown in Fig.1(a). Taking environment monitoring for example, a '$good$' channel appears when the monitoring devices (denoted by the red dots) are able to perform line-of-sight transmission while a 'bad' channel appears when the bad weather happens.

In our model, we assume that the channel state information (CSI) is known to the transmitter through a feedback channel [26], [27], as shown in Fig.1(b). Intuitively, the transmitter can use power adaption to meet the targeted BER at the receiver side. Let P_1 denote the power needed to transmit one packet successfully in the good channel state and P_2 in the bad channel state. It is reasonable to assume that P_2 is larger than P_1. This is due to the fact that more power is required to combat wireless channel fading when the channel condition is bad.

For simplicity, we consider fixed-rate transmission schemes which have been widely applied in practice [28]. Without loss of generality, the transmission data rate is assumed to be one packet per slot. Hence, at most one data packet can be delivered in each slot, i.e., $s[n]$ takes value from set $\{0, 1\}$.

The scheduling policy on the transmitter side is described as follows: at the beginning of each time slot, the scheduler makes a probabilistic decision on whether or not to transmit a packet in the current time slot based on the collected information including the arrival status $a[n]$, the current channel state $h[n]$ and the data buffer state $q[n-1]$. At the end of each slot, the scheduler updates the buffer state $q[n]$ according to Eq. (4). In this paper, we attempt to find an optimal scheduling strategy to achieve the optimal delay-power tradeoff for the considered system model.

III. PROBABILISTIC SCHEDULING MODEL

In this section, we introduce a general description of probabilistic scheduling. Based on that, a discrete-time Markov chain is established to model the queueing system.

A. PROBABILISTIC SCHEDULING

To improve power efficiency, a scheduler always seeks to transmit in the good channel state since it spends less power. However, it may cause undesirably large queuing delay to wait for the channel to turn '*good*', which is intolerable for serving delay sensitive traffics. Thus, the scheduler should try to achieve a good balance between the average queueing delay and the average power consumption.

In this work, we propose a probabilistic scheduling policy as follows. When the channel state is '*good*', the source will transmit as long as the buffer is non-empty, i.e., $s[n] = 1$, when $h[n] =$ '*good*', $q[n-1] + a[n] > 0$. When the channel state is '*bad*', the scheduler determines to transmit with probability f_k^m or keep silent with probability $1 - f_k^m$, given the buffer state $q[n-1] = k$ and the data arrival state $a[n] = m$. In the sequel, we will discuss the service process of the queuing system in two cases based on the queue state at the end of the $(n-1)$ time slot.

Case 1: $q[n-1] = 0$. In this situation, if $a[n] = 0$, the source node has no packet to send. Data transmission could happen only when $a[n] > 0$. The service process can be described as

$$s[n] = \begin{cases} 1 \ w.p.\ 1, & a[n] = m, h[n] = \text{'good'}, \\ 1 \ w.p.\ f_k^m, & a[n] = m, h[n] = \text{'bad'}, \\ 0 \ w.p.\ 1 - f_k^m, & a[n] = m, h[n] = \text{'bad'}, \\ 0 \ w.p.\ 1, & a[n] = 0, \end{cases} \tag{6}$$

where $m \in \{1, 2, \cdots, M\}$ and the abbreviation '*w.p.*' represents '*with the probability of*'.

Case 2: $q[n-1] = k > 0$. In this situation, there must be packets waiting in the buffer. The source determines whether to transmit or not based on the data arrival state $a[n]$ and the current channel state $h[n]$. Thus, the service process can be described as

$$s[n] = \begin{cases} 1 \ w.p.\ 1, & h[n] = \text{'good'}, \\ 1 \ w.p.\ f_k^m, & a[n] = m,\ h[n] = \text{'bad'}, \\ 0 \ w.p.\ 1 - f_k^m, & a[n] = m,\ h[n] = \text{'bad'}. \end{cases} \tag{7}$$

where $m \in \{0, 1, \cdots, M\}$.

The proposed scheduling strategy depends on probabilistic parameters $\{f_k^m | 0 \leq k \leq K, 0 \leq m \leq M\}$. We aim to find the optimal scheduling strategy by deciding the optimal probabilistic parameters.

B. MARKOV CHAIN MODEL

Based on the mathematical description of the probabilistic scheduling strategy we developed in Eqs. (6)-(7), the queueing system can be formulated as a discrete-time Markov chain, where each state presents the buffer state $q[n]$. Due to the Markovian effect, the one-step transition probability from state $\{q[n-1] = k\}$ to state $\{q[n] = l\}$ can be denoted by

$$\begin{aligned} \tau_{k,l} &= Pr\{q[n] = l | q[n-1] = k, q[n-2] = k_1 \cdots\} \\ &= Pr\{q[n] = l | q[n-1] = k\}. \end{aligned} \tag{8}$$

We use $\lambda_{k,m}$ $(0 \leq k \leq K, 0 \leq m \leq M)$ and μ_k $(1 \leq k \leq K)$ to characterize the transition probabilities of the Markov chain. An example of the Markov chain of the buffer state with $M = 3$ is shown in Fig.2, where $\lambda_{k,m}$ is used to denote the transition probability $\tau_{k,k+m}$ while μ_k is used to denote the transition probability $\tau_{k,k-1}$. In each time slot, the queue length is at most increased by $M = 3$ due to a new data arrival, while decreased by one due to the transmission of one data packet. The transition probability $\lambda_{k0} = \tau_{k,k}$ is the probability that the queue length remains the same.

Theorem 1: The queue length $q[n]$ can be described by a $(K+1)$-state Markov chain, the transition probability $\tau_{k,l}$ of which satisfies $\tau_{k,l} = 0$ for $|k - l| > M$. The transition probabilities characterized by $\lambda_{k,m}$ are expressed as

$$\lambda_{k,m} = \beta p_{m+1} + (1-\beta)\Big[p_{m+1} f_k^{m+1} + p_m (1 - f_k^m)\Big], \tag{9}$$

where $0 \leq k \leq K$ and $1 \leq m \leq M$. And μ_k are given by

$$\mu_k = \beta p_0 + (1-\beta) p_0 f_k^0, \tag{10}$$

where $1 \leq k \leq K$. The probabilities that the queue states remain the same are given by

$$\lambda_{k,0} = \tau_{k,k} = \begin{cases} 1 - \sum_{m=1}^{M} \lambda_{k,m}, & k = 0, \\ 1 - \sum_{m=1}^{M} \lambda_{k,m} - \mu_k, & 1 \leq k \leq K. \end{cases} \tag{11}$$

Proof: From Eq. (4), we obtain the following inequality

$$\big|q[n] - q[n-1]\big| \leq \big|a[n] - s[n]\big|. \tag{12}$$

Since $a[n]$ and $s[n]$ are both nonnegative integers, we have

$$\begin{aligned} \big|q[n] - q[n-1]\big| &\leq |a[n] - s[n]| \\ &\leq max\{a[n], s[n]\} \\ &= M. \end{aligned} \tag{13}$$

Hence, the increase of the queue length is upper bounded by M in each slot, i.e., no transition takes place from state $\{q[n-1] = k\}$ to state $\{q[n] = k + l\}$ for any $l > M$.

We derive Eqs. (9) and (10) according to the probabilistic scheduling policy described in Section III-A. The queue state $\{q[n-1] = k\}$ transits to $\{q[n] = k + m\}$ with probability $\lambda_{k,m}$ if $a[n] - s[n] = m$. This event takes place in the following three cases. Case 1): one packet is delivered $(s[n] = 1)$ with probability 1 when there is new data arrival $(a[n] = m + 1)$

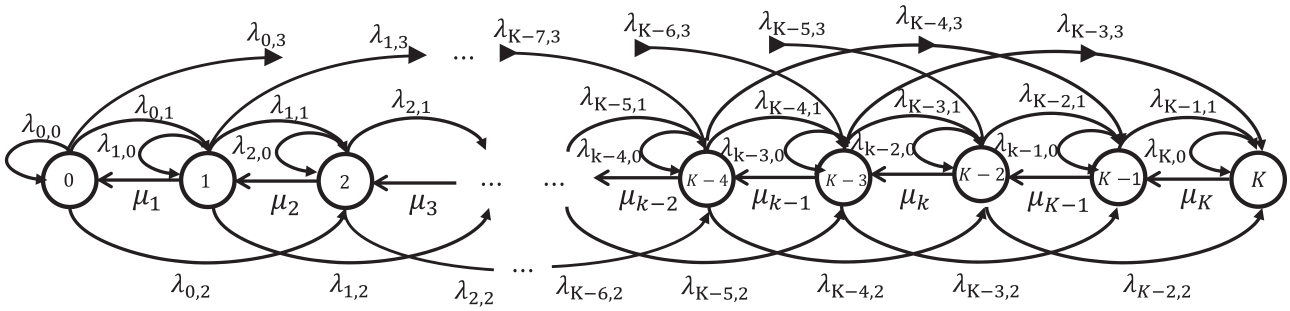

FIGURE 2. An example of Markov chain of the buffer state with $M = 3$.

and the current channel state is '*good*'. Accordingly, the transition probability is equal to βp_{m+1}. Case 2): one packet is delivered ($s[n] = 1$) with probability f_k^{m+1} when there is new data arrival ($a[n] = m + 1$) and the current channel state is '*bad*'. Thus, the probability in this case is $(1 - \beta)p_{m+1}f_k^{m+1}$. Case 3): no packet is delivered ($s[n] = 0$) with probability $1 - f_k^m$ when there is new data arrival ($a[n] = m$) and the current channel state is '*bad*'. The probability in this case is $(1 - \beta)p_m(1 - f_k^m)$. By summarizing the probabilities of above three cases, the expression of $\lambda_{k,m}$ is obtained and given in Eq. (9).

The queue state $\{q[n] = k\}$ transits to state $\{q[n] = k - 1\}$ with probability μ_k, when one packet is delivered over good channel state or over bad channel with probability f_k^0 while there is no data arrival ($a[n] = 0$). Hence, the transition probability μ_k can be obtained as $\beta p_0 + (1 - \beta)p_0 f_k^0$.

Eq. (11) holds because of the probability normalization. Since $\sum_{l=-1}^{M} \tau_{k,l} = 1$, we have

$$\begin{aligned}\lambda_{k,0} &= \tau_{k,k}\\ &= 1 - \tau_{k,k-1} - \sum\nolimits_{l=1}^{M} \tau_{k,k+l}\\ &= 1 - \mu_k - \sum\nolimits_{l=1}^{M} \lambda_{k,m}.\end{aligned}$$

Since no packets will be transmitted when the buffer is empty, $\lambda_{k,0}$ $(k = 0)$ is given specially. ∎

We use π_k to denote the steady state probability of $\{q[n] = k\}$ and vector $\boldsymbol{\pi}$ to denote $[\pi_0, \pi_1, \cdots, \pi_K]$. By exploiting the property of the Markov chain, we present the stationary distribution of the Markov chain in the following theorem.

Theorem 2: The steady-state probability π_k is given by

$$\pi_k = \frac{1}{\mu_k} \sum_{i=1}^{M \vee k} \pi_{k-i} \sum_{j=i}^{M} \lambda_{k-i,j}, \quad 1 \le k \le K. \tag{14}$$

Proof: The balance equations of the Markov chain can be expressed as

$$\pi_k = \pi_{k+1}\mu_{k+1} + \sum_{i=(k-M)\wedge 0}^{k} \pi_i \lambda_{i,k-i}, \quad 1 \le k \le K. \tag{15}$$

We prove the following equations instead of Eq. (14) for convenience.

$$\pi_k \mu_k = \sum_{i=1}^{M \vee k} \pi_{k-i} \sum_{j=i}^{M} \lambda_{k-i,j}, \quad 1 \le k \le K. \tag{16}$$

Eq. (16) is proved by mathematical induction.

In the first step, we show that Eq. (16) holds when $k = 1$. Specifically, by substituting $k = 1$ into Eq. (15), we obtain

$$\pi_0 = \pi_1 \mu_1 + \pi_0 \lambda_{0,0}. \tag{17}$$

By substituting $\lambda_{0,0}$ given by Eq. (11) into Eq. (17), we get

$$\pi_1 \mu_1 = \pi_0 \sum_{m=1}^{M} \lambda_{0,m}. \tag{18}$$

In the second step, we assume that Eq. (16) holds for $k = 2, 3, \cdots, s - 1$, where s is a positive integer greater than 2. In particular, when $k = s - 1$, the following equation

$$\pi_{s-1}\mu_{s-1} = \sum_{i=1}^{M \vee (s-1)} \pi_{s-1-i} \sum_{j=i}^{M} \lambda_{s-1-i,j} \tag{19}$$

is satisfied.

At last, we prove that Eq. (16) holds when $k = s$. According to balance equation Eq. (15),

$$\pi_{s-1} = \pi_s \mu_s + \pi_{s-1}\lambda_{s-1,0} + \sum_{i=1}^{M \vee (s-1)} \pi_{s-1-i}\lambda_{s-1-i,i}. \tag{20}$$

Recalling Eq. (11), we can obtain $\lambda_{s-1,0} = 1 - \sum_{j=1}^{M} \lambda_{s-1,j} - \mu_{s-1}$. By inserting $\lambda_{s-1,0}$ into Eq. (20) and extracting $\pi_s \mu_s$, we arrive at

$$\begin{aligned}\pi_s \mu_s &= \pi_{s-1} \sum_{j=1}^{M} \lambda_{s-1,j} + \pi_{s-1}\mu_{s-1}\\ &\quad - \sum_{i=1}^{M \vee (s-1)} \pi_{s-1-i}\lambda_{s-1-i,i}\\ &= \pi_{s-1} \sum_{j=1}^{M} \lambda_{s-1,j} + \sum_{i=1}^{M \vee (s-1)} \pi_{s-1-i} \sum_{j=i+1}^{M} \lambda_{s-1-i,j}\\ &= \sum_{i=1}^{M \vee s} \pi_{s-i} \sum_{j=i}^{M} \lambda_{s-i,j}.\end{aligned} \tag{21}$$

The second equation holds due to the assumption in Eq. (19). By far, Eq. (16) is verified. Dividing μ_k on both sides of Eq. (16), we obtain Eq. (14). ■

Remark 1: From Theorem 2 and its proof, one can see that the steady-state probability π_k $(1 \le k \le K)$ is a linear combination of π_l $\big(l = (k-M)\wedge 0, (k-M+1)\wedge 0, \cdots, k-1\big)$ with their coefficients relating to the transition probabilities $\tau_{l,k}$. More specifically, from Eq. (18)*, we can conclude that π_k is actually a linear function of π_0.*

Corollary 1: The steady probability π_k $(1 \le k \le K)$ can be described by π_0, i.e.

$$\pi_k = \mathcal{F}_k(\pi_0), \quad 1 \le k \le K. \tag{22}$$

Intuitively, we have the following normalization equation

$$\pi_0 + \sum_{k=1}^{K} \mathcal{F}_k(\pi_0) = 1. \tag{23}$$

IV. DELAY & POWER ANALYSIS

After obtaining the stationary distribution of the Markov chain, we will evaluate the interested performance metrics that are the average queueing delay and the average power consumption in this section.

We can express the average queue length with the steady-state probability distribution.

$$E\{q[n]\} = \sum_{k=0}^{K} k\pi_k \tag{24}$$

By applying the Little's Law [25], we derive the average queueing delay as

$$D = \frac{1}{\bar{a}} \sum_{k=0}^{K} k\pi_k. \tag{25}$$

The expression of average consumed power $\mathcal{P}^{aver}$ will be derived in the following part by extending the Markov chain model built in Section III-B into a Markov reward model. Specifically, we attach a transmit power to each state of the Markov chain as a reward. The reward may take a value as P_1, P_2 and 0, corresponding to the power consumption for one packet delivery over the good channel, one packet delivery over the bad channel, and no data transmission, respectively. Let random variable $c[n]$ denote the power consumption given the queue state $q[n-1] = k$ during time slot n. Let $P_0 = 0$. We can define the conditional probabilities that $c[n] = P_i$, $(i \in \{0, 1, 2\})$ as ψ_{ki}.

Lemma 1: The expression of ψ_{ki} is described as

$$\begin{aligned}
\psi_{k1} &= Pr\{c[n] = P_1 \big| q[n-1] = k\} \\
&= \begin{cases} \beta(1-p_0), & k = 0, \\ \beta, & k \ge 1, \end{cases}
\end{aligned} \tag{26}$$

$$\begin{aligned}
\psi_{k2} &= Pr\{c[n] = P_2 \big| q[n-1] = k\} \\
&= \begin{cases} (1-\beta)\sum\limits_{m=1}^{M} p_m f_0^m, & k = 0, \\ (1-\beta)\sum\limits_{m=0}^{M} p_m f_k^m, & k \ge 1, \end{cases}
\end{aligned} \tag{27}$$

$$\psi_{k0} = Pr\{c[n] = 0 \big| q[n-1] = k\} = 1 - \psi_{k1} - \psi_{k2}. \tag{28}$$

Proof: In Eq. (26), we give the probability that one packet delivery occurs over the good channel. This happens with probability 1 if and only if the channel state is good and the queue is not empty, i.e., $a[n] + q[n-1] > 0$. In Eq. (27), we give the probability that one packet delivery occurs over the bad channel. This happens with probability f_k^m if and only if the channel state is bad and the queue length is not empty, i.e., $a[n] + q[n-1] > 0$. Eq. (28) is obtained based on the normalization equation. ■

Given the current buffer state $\{q[n-1] = k\}$, the power consumption $c[n] \in \{P_1, P_2, 0\}$ is determined by the scheduling probabilities. The overall average power consumption is the weighted sum of the power consumed in all states. We give the following two lemmas in order to derive the expression of the average transmission power more clearly.

Lemma 2: The transition probabilities of the Markov chain can be expressed as

$$\begin{cases} \mu_k = \beta p_0 + (1-\beta)p_0 f_k^0, \\ \sum\limits_{i=m}^{M} \lambda_{k,i} = (1 - \sum\limits_{i=0}^{m} p_i) + (1 - f_k^m)(1-\beta)p_m, \end{cases} \tag{29}$$

where $1 \le m \le M$. The sending probabilities can be extracted from Eq. (29) *and shown as*

$$f_k^m = \begin{cases} \dfrac{\mu_k - \beta p_0}{(1-\beta)p_0}, & m = 0, \\ 1 - \dfrac{\sum\limits_{i=m}^{M} \lambda_{k,i} - (1 - \sum\limits_{i=0}^{m} p_i)}{(1-\beta)p_m}, & 1 \le m \le M. \end{cases} \tag{30}$$

Proof: In Eq. (9), we can get $\lambda_{k,M}$ as

$$\lambda_{k,M} = (1-\beta)p_M(1 - f_k^M) \tag{31}$$

and $\lambda_{k,M-1}$ as

$$\lambda_{k,M-1} = \beta p_M + (1-\beta)\big[p_M f_k^M + p_{M-1}(1 - f_k^{M-1})\big]. \tag{32}$$

Summarizing Eq. (31) and Eq. (32), we get

$$\lambda_{k,M} + \lambda_{k,M-1} = p_M + p_{M-1}(1-\beta)(1 - f_k^{M-1}). \tag{33}$$

Similarly, the following equality can be obtained

$$\begin{aligned}
\sum_{i=m}^{M} \lambda_{k,i} &= (1 - \sum_{i=0}^{m} p_i) \\
&\quad + (1 - f_k^m)(1-\beta)p_m, \quad 1 \le m \le M
\end{aligned} \tag{34}$$

The conclusion about μ_k is exactly the same as Eq. (10), we move it here for convenience.

We have arrived at Eq. (29) by far. By extracting f_k^m $(m = 0)$ and f_k^m $(1 \le m \le M)$ from Eq. (29), the conclusion in Eq. (30) can be derived, respectively. ■

Lemma 3: The weighted sum of steady-state $\boldsymbol{\pi}$ under probability ψ_{k2} is given by

$$\sum_{k=0}^{K} \pi_k \psi_{k2} = \bar{a} - \beta + \beta\pi_0 p_0. \tag{35}$$

Proof: From Eq. (27), we know that

$$\sum_{k=0}^{K}\pi_k\psi_{k2} = \pi_0(1-\beta)\sum_{m=1}^{M}p_m f_0^m + \sum_{k=1}^{K}\pi_k(1-\beta)\sum_{m=0}^{M}p_m f_k^m \quad (36)$$

Two terms on the right-hand side of Eq. (36) are shown respectively as follows. The first term is given in the following Eq. (37).

$$\begin{aligned}
&\pi_0(1-\beta)\sum_{m=1}^{M}p_m f_0^m\\
&= \pi_0\sum_{m=1}^{M}(1-\beta)p_m\left(1-\frac{\sum_{i=m}^{M}\lambda_{0,i}-(1-\sum_{i=0}^{m}p_i)}{(1-\beta)p_m}\right)\\
&= \pi_0\sum_{m=1}^{M}\left\{(1-\beta)p_m-\left[\sum_{i=m}^{M}\lambda_{0,i}-(1-\sum_{i=0}^{m}p_i)\right]\right\}\\
&= \pi_0(1-\beta)(1-p_0)-\pi_0\sum_{m=1}^{M}\left[\sum_{i=m}^{M}\lambda_{0,i}-(1-\sum_{i=0}^{m}p_i)\right]
\end{aligned} \quad (37)$$

In Eq. (37), the first equality is obtained by substituting f_0^m with f_k^m, $(k=0)$ from Eq. (30).

The second term in the right-hand side of Eq. (36) is given in the following Eq. (38).

$$\begin{aligned}
&\sum_{k=1}^{K}\pi_k(1-\beta)\sum_{m=0}^{M}p_m f_k^m\\
&= \sum_{k=1}^{K}\pi_k(1-\beta)p_0 f_k^0 + \sum_{k=1}^{K}\pi_k(1-\beta)\sum_{m=1}^{M}p_m f_k^m\\
&= \sum_{k=1}^{K}\pi_k(\mu_k-\beta p_0)\\
&\quad + \sum_{k=1}^{K}\pi_k\sum_{m=1}^{M}\{(1-\beta)p_m-[\sum_{i=m}^{M}\lambda_{k,i}-(1-\sum_{i=0}^{m}p_i)]\}\\
&= \sum_{k=1}^{K}\pi_k\mu_k-\beta p_0(1-\pi_0)+(1-\beta)(1-p_0)(1-\pi_0)\\
&\quad - \sum_{k=1}^{K}\pi_k\sum_{m=1}^{M}[\sum_{i=m}^{M}\lambda_{k,i}-(1-\sum_{i=0}^{m}p_i)]
\end{aligned} \quad (38)$$

The second equality holds because we substitute f_k^0 and f_k^m $(1\le m\le M)$ with f_k^m from Eq. (30), respectively.

Thus, by summarizing Eq. (37) and Eq. (38), we get

$$\begin{aligned}
&\sum_{k=0}^{K}\pi_k\psi_{k2}\\
&= \beta\pi_0p_0-\beta+1-p_0+\sum_{k=1}^{K}\pi_k\mu_k-\sum_{k=0}^{K}\pi_k\sum_{m=1}^{M}\sum_{i=m}^{M}\lambda_{k,i}\\
&\quad +\pi_0(1-\sum_{i=0}^{m}p_i)+\sum_{k=1}^{K}\pi_k(1-\sum_{i=0}^{m}p_i)\\
&= \beta\pi_0p_0-\beta+1-p_0+\pi_0\sum_{m=1}^{M}(1-\sum_{i=0}^{m}p_i)\\
&\quad +\sum_{k=1}^{K}\sum_{m=1}^{M}\pi_k(1-\sum_{i=0}^{m}p_i)\\
&= \beta\pi_0p_0-\beta+1-p_0+\sum_{m=1}^{M}(1-\sum_{i=0}^{m}p_i)\\
&= \beta\pi_0p_0-\beta+\bar{a}
\end{aligned} \quad (39)$$

The second equality holds due to Eq. (15), i.e., the equilibrium equations of the Markov chain. The third equality holds due to $\sum_{k=0}^{K}\pi_k=1$. The last equality holds due to the fact that $1-p_0+\sum_{m=1}^{M}(1-\sum_{i=0}^{m}p_i)=\bar{a}$. ■

Transmission powers P_1 and P_2 are given system parameters and usually optimized based on the network settings and users' quality of experiences, but beyond the scope of this paper. Let ΔP denote (P_2-P_1) and $\eta=\frac{\Delta P}{P_1}$, we normalize $\mathcal{P}^{aver}$ by P_1 as $\bar{\mathcal{P}}=\frac{\mathcal{P}^{aver}}{P_1}$.

Theorem 3: The average transmission power is

$$\mathcal{P}^{aver} = P_1\cdot\bar{a}+\Delta P(\bar{a}-\beta+\beta\pi_0p_0). \quad (40)$$

Hence, the normalized average transmission power can de described as

$$\bar{\mathcal{P}} = \bar{a}+\eta(\bar{a}-\beta+\beta\pi_0p_0). \quad (41)$$

Proof: By applying the law of total probability, the average transmission power is equal to

$$\begin{aligned}
\mathcal{P}^{aver} &= \sum_{k=0}^{K}\pi_k(\psi_{k0}\cdot 0+\psi_{k1}\cdot P_1+\psi_{k2}\cdot P_2) && (42)\\
&= \sum_{k=0}^{K}\pi_k(\psi_{k1}P_1+\psi_{k2}P_2) && (43)\\
&= P_1\beta(1-\pi_0p_0)+P_2\sum_{k=0}^{K}\pi_k\psi_{k2}, && (44)
\end{aligned}$$

where the last equality is obtained by substituting the expression of ψ_{k1} given by Eq. (26) into Eq. (43).

By substituting Eq. (35) from Lemma 3 into Eq. (44), we obtain the expression of the average transmission power as given by Eq. (40). Normalizing Eq. (40) with P_1, We arrive at Eq. (41). ■

The analytical expressions of the average queueing delay and the average transmission power are both determined by the steady-state probabilities. It provides us a way to achieve the optimal delay-power tradeoff by optimizing the steady-state probabilities, which is discussed in next section.

V. OPTIMAL DELAY-POWER TRADEOFF

In this section, a non-linear optimization problem is formulated to minimize the average queueing delay under average power constraint. It is converted to an LP problem in order to obtain its solution. Besides, an optimal transmission strategy named threshold-based policy can be obtained based on the optimal solution to the LP problem.

A. OPTIMIZATION PROBLEM

In this paper, the analytical expressions of the average queueing delay and average transmisson power allow us to optimize the overall performance via an LP method which is in contrast to the usual MDP method.

Notice that the average transmission power can be expressed by a linear combination of π_0 in Eq. (41) and the average queueing delay is a linear combination of the steady-state probabilities $\{\pi_k\}$ $(0 \le k \le K)$ in Eq. (25). Moreover, recall Corollary 1 and Remark 1, π_k $(1 \le k \le K)$ is a linear function of π_0 and the coefficients are related to the state transition probabilities. At the mean time, we have shown that the state transition probabilities can be expressed by the scheduling probabilities $\{f_k^m\}$ in Lemma 2. Let $\mathcal{P}_{th}$ denote the given normalization power constraint. We then formulate the following nonlinear optimization problem with π_0 and $\{f_k^m\}$ being optimization variables.

$$\min_{\{f_k^m,\pi_0\}} D = \frac{1}{\bar{a}}\sum_{k=0}^{K} k\pi_k$$
$$\text{s.t.} \begin{cases} \bar{a} + \eta(\bar{a} - \beta + \beta\pi_0 p_0) \le \mathcal{P}_{th} & \text{(a)} \\ \pi_k = \dfrac{1}{\mu_k}\displaystyle\sum_{m=1}^{M\vee k} \pi_{k-m}\sum_{i=m}^{M}\lambda_{k-m,i}, \quad 1 \le k \le K & \text{(b)} \\ \displaystyle\sum_{k=0}^{K}\pi_k = 1 & \text{(c)} \\ \pi_k \ge 0, \quad 0 \le k \le K & \text{(d)} \\ f_k^m \in [0,1], \quad 0 \le k \le K, 0 \le m \le M & \text{(e)} \end{cases} \tag{45}$$

Inequality (45.a) is the maximum average power constraint. Constraints (45.b) and (45.c) are derived directly from the property of the Markov chain. Constraint (45.d) describes the non-negativity of the steady-state probabilities. Constraint (45.e) shows that as a probability, $f_k^m \in [0, 1]$.

In problem (45), the optimization object and constraints $\big[45.\text{(a-d)}\big]$ are linear combination of steady-state probabilities $\boldsymbol{\pi}$. Based on this observation, we can convert optimization problem (45) to the following LP problem with steady-state probabilities $\boldsymbol{\pi}$ being optimization variable.

Theorem 4: The optimization problem (45) *is equivalent to the following LP problem*

$$min_{\{\pi_k\}}\ D = \frac{1}{\bar{a}}\sum_{k=0}^{K} k\pi_k$$
$$s.t. \begin{cases} \pi_0 \le 1 \vee \big[(\mathcal{P}_{th} - \bar{a})\eta^{-1} - \bar{a} + \beta\big](\beta p_0)^{-1} & (a) \\ \pi_k \le \beta^{-1} r_0 \displaystyle\sum_{m=1}^{M\vee k} \\ \qquad \times (r_{m1} + r_{m2})\pi_{k-m}, \quad 1 \le k \le K & (b) \\ \pi_k \ge r_0 \displaystyle\sum_{m=1}^{M\vee k} r_{m2}\cdot\pi_{k-m}, \quad 1 \le k \le K & (c) \\ \pi_k \ge 0, \quad 0 \le k \le K & (d) \\ \displaystyle\sum_{k=0}^{K}\pi_k = 1 & (e) \end{cases} \tag{46}$$

where $r_0 = 1/p_0$, $r_{m1} = (1-\beta)p_m$, $r_{m2} = 1 - \sum_{i=0}^{m} p_i$.

Proof: The average power constraint introduced in (45.a) also describes a constraint of π_0. The following inequality can be obtained by extracting π_0 from (45.a).

$$\pi_0 \le \frac{(\mathcal{P}_{th} - \bar{a})\eta^{-1} - \bar{a} + \beta}{\beta p_0} \tag{47}$$

Clearly, $\pi_0 \le 1$. Thus, we obtain constraint (46.a).

Since $f_k^m \in [0, 1]$, the state transition probabilities $\lambda_{k,j}$ $(0 \le k \le K)$ and μ_k $(1 \le k \le K)$ given by Eq. (29) should satisfy the following inequalities

$$\beta p_0 \le \mu_k \le p_0. \tag{48}$$

$$1 - \sum_{i=0}^{m} p_i \le \sum_{i=m}^{M}\lambda_{k,i} \le (1-\beta)p_m + 1 - \sum_{i=0}^{m} p_i, \tag{49}$$

where $1 \le m \le M$.

In Eq. (48), we get the minimum of μ_k referred as βp_0 when $f_k^0 = 0$ and the maximum referred as p_0 when $f_k^0 = 1$. In Eq. (49), we get the maximum of $\sum_{i=m}^{M}\lambda_{k-m,i}$ referred as $(1-\beta)p_m + 1 - \sum_{i=0}^{m} p_i$ when $f_{k-m}^m = 1$ and the minimum referred as $1 - \sum_{i=0}^{m} p_i$ when $f_{k-m}^m = 0$ $(m \in \mathbb{M}^+)$. Notice that the upper bound of $\sum_{i=m}^{M}\lambda_{k-m,m}$ and the lower bound of μ_k can be reached at the same time. Recalling the constraint (45.b), we then obtain the maximum of π_k

$$\pi_k \le \beta^{-1} r_0 \sum_{m=1}^{M\vee k}(r_{m1} + r_{m2})\pi_{k-m}. \tag{50}$$

Similarly, we can obtain the minimum of π_k

$$\pi_k \ge r_0 \sum_{m=1}^{M\vee k} r_{m2}\cdot\pi_{k-m}. \tag{51}$$

Replacing constraints (45.b) and (45.e) with Eq. (50) and Eq. (51), we arrive at optimization problem (46). ■

For a given average power constraint $\mathcal{P}_{th}$, we will solve optimization problem (46) in order to get the minimum queuing delay D^* and the optimal steady-state probability $\boldsymbol{\pi}^*$.

Remark 2: D^* is a monotonically decreasing function of $\mathcal{P}_{th}$, and is expressed as

$$D^* = d(\mathcal{P}_{th}). \tag{52}$$

Proof: Suppose $\boldsymbol{\pi} = [\pi_0, \pi_1, \cdots, \pi_K]$ is a set of steady-state probabilities which minimize the average delay D under constraints $\big(46.\text{(a-e)}\big)$. The corresponding transmission power $\bar{\mathcal{P}} = \bar{a} + \eta(\bar{a} - \beta + \beta\pi_0 p_0)$. We will show that if there exists another set of steady-state probabilities $\boldsymbol{\pi}' = [\pi_0', \pi_1', \cdots, \pi_K']$ which cost more power $\bar{\mathcal{P}}'$ $(\bar{\mathcal{P}}' > \bar{\mathcal{P}})$ to transmit, a smaller queueing delay D' will be induced.

Considering the normalization equation $\sum_{k=0}^{K}\pi_k = 1$ and the formula of the average delay, we should set steady-state probability π_k with a bigger value for smaller index k while set a smaller value for larger index k in order to achieve a smaller delay. Let integer $k_{th} > 0$. We add a non-negative value δ_{π_k} to π_k for $k \le k_{th}$ while subtract δ_{π_k} from π_k

for $k > k_{th}$. Thus, a new set of steady-state probabilities are obtained,

$$\pi'_k = \begin{cases} \pi_k + \delta_{\pi_k}, & k \le k_{th}, \\ \pi_k - \delta_{\pi_k}, & k > k_{th}, \end{cases} \tag{53}$$

where δ_{π_0} satisfies the constraint

$$\begin{aligned} \delta\mathcal{P} &= \mathcal{P}' - \mathcal{P} \\ &= \eta\beta(\pi'_0 - \pi_0)p_0 \\ &= \eta\beta\delta_{\pi_0}p_0 > 0, \end{aligned} \tag{54}$$

and $\{\delta_{\pi_k}\}$ satisfy constraints [46.(b-e)].

Since $\sum_{k=0}^{K}\pi_k = \sum_{k=0}^{K}\pi'_k = 1$, we have

$$\sum_{k=0}^{k_{th}}(\pi'_k - \pi_k) = \sum_{k=k_{th}+1}^{K}(\pi_k - \pi'_k). \tag{55}$$

Thus, we have

$$\begin{aligned} D' - D &= \frac{1}{\bar{a}}(\sum_{k=0}^{K}k\pi'_k - \sum_{k=0}^{K}k\pi_k) \\ &= \frac{1}{\bar{a}}\left[\sum_{k=0}^{k_{th}}k(\pi'_k - \pi_k) - \sum_{k=k_{th}+1}^{K}k(\pi_k - \pi'_k)\right] \\ &< \frac{1}{\bar{a}}\left[k_{th}\sum_{k=0}^{k_{th}}(\pi'_k - \pi_k) - (k_{th}+1)\sum_{k=k_{th}+1}^{K}(\pi_k - \pi'_k)\right] \\ &< 0. \end{aligned} \tag{56}$$

Thus, we can draw a conclusion that if $\mathcal{P} < \mathcal{P}'$, then $D^* = d(\mathcal{P}) > D' = d(\mathcal{P}') \ge D^{*\prime} = d(\mathcal{P}')$. Therefore, the minimum queueing delay $d(\cdot)$ is a decreasing function of average power $\mathcal{P}_{th}$. ■

B. OPTIMAL SOLUTION

In this subsection, we will present the optimal solution to optimization problem (46). Let $\mathcal{P}_{max}$ and $\mathcal{P}_{min}$ denote the consumed power when transmission always happen whatever the channel state is and transmission happens only in the good channel which refers to opportunistic communication [29], respectively. When $\mathcal{P}_{th} > \mathcal{P}_{max}$, the transmission will be not constrained by the average power. In this situation, one packet will always be sent out as long as the buffer is not empty. When $\mathcal{P}_{th} < \mathcal{P}_{min}$, the transmitter may not even afford to transmit one packets during every good channel. More packet will be backlogged in the buffer, and the queue is not stable in this situation. Thus, we focus on the situation $\mathcal{P}_{min} \le \mathcal{P}_{th} \le \mathcal{P}_{max}$.

In optimization problem (46), the objective function has the format that π_k with larger k has bigger weight. Thus, in order to minimize the objective function, π_k should be assigned its maximum for smaller index k and its minimum for larger index k. Due to constraint (46.e), there exists an optimal threshold k^* imposed on the queue length. According to the above analyses and constraints $\big(46.\text{(b-c)}\big)$, the optimal solution to problem (46) can be derived and shown in the following theorem.

Theorem 5: The optimal solution to optimization problem (46) can be described as

$$\begin{cases} \pi^*_k = 1 \vee \left[(\mathcal{P}_{th} - \bar{a})\eta^{-1} - \bar{a} + \beta\right] \\ \qquad \times (\beta p_0)^{-1}, & k = 0, \\ \pi^*_k = \beta^{-1}r_0\sum_{m=1}^{M\vee k}\pi^*_{k-m}(r_{m1} + r_{m2}), & 1 \le k < k^*, \\ \pi^*_k = \cdot r_0\sum_{m=1}^{M\vee k}\pi^*_{k-m}r_{m2}, & k > k^*, \end{cases} \tag{57}$$

where k^* and π_{k^*} can be exclusively determined by

$$\sum_{k=0}^{k^*-1}\pi^*_k + \pi^*_{k^*} + \sum_{k=k^*+1}^{K}\pi^*_k = 1. \tag{58}$$

Theorem 5 shows the optimal solution to the delay-power tradeoff. Based on the optimal steady-state probability, we can further derive the optimal scheduling probabilities.

C. THRESHOLD-BASED POLICY

According to Theorem 5, there exists a threshold k^* imposed on the queue length. Steady-state probability π^*_k will be assigned its maximum if $k < k^*$ and its minimum if $k > k^*$. Combining with the bounds of μ_k and $\sum_{i=m}^{M}\lambda_{k-m,i}$ in Eqs. (48) and (49), we know that $\sum_{i=m}^{M}\lambda^*_{k-m,i}$ achieves its upper bound while μ^*_k achieves its lower bound when $k < k^*$ and $\sum_{i=m}^{M}\lambda^*_{k-m,i}$ achieves its lower bound while μ^*_k achieves its upper bound when $k > k^*$, that is

$$\sum_{i=m}^{M}\lambda^*_{k-m,i} = \begin{cases} r_{m1} + r_{m2}, & k < k^*, \\ r_{m2}, & k > k^*, \end{cases} \tag{59}$$

$$\mu^*_k = \begin{cases} \beta p_0, & k < k^*, \\ p_0, & k > k^*, \end{cases} \tag{60}$$

where $m \in \{1, 2\cdots, M\}$. The case that $k = k^*$ can be derived by a determined $\boldsymbol{\pi}^*$ based on Theorem 2 and given as

$$\pi^*_{k^*} = \frac{1}{\mu^*_{k^*}}\sum_{i=1}^{M\vee k^*}\pi^*_{k^*-i}\sum_{j=i}^{M}\lambda^*_{k^*-i,j}. \tag{61}$$

We can derive many pairs of $\sum_{i=m}^{M}\lambda^*_{k^*-m,i}$ and $\mu^*_{k^*}$, each of them can derive the optimal steady-probability thus achieve the minimum queueing delay.

Due to this special structure, a threshold-based scheduling strategy can be presented. By inserting Eq. (59) and Eq. (60) into Eq. (30), the scheduling probability can be determined as:

$$f^{m\,*}_{k-m} = \begin{cases} 0, & k < k^*, \\ 1, & k > k^*. \end{cases} \tag{62}$$

In Eq. (62), if $k - m < 0$, we will ignore the situation or set f^m_{k-m} as 0 since the buffer state cannot be negative.

We calculate $f_{k^*-m}^{m\ *}$ by the following equation which is derived from Eq. (30).

$$f_{k^*-m}^{m*} = \begin{cases} \dfrac{\mu_{k^*-m}^* - \beta p_0}{r_{m1}}, & m = 0, \\ 1 - \dfrac{\sum\limits_{i=m}^{M} \lambda_{k^*-m,i}^* - r_{m2}}{r_{m1}}, & m > 0. \end{cases} \tag{63}$$

From Eqs. (62) and (63), the transmit probabilities are only determined by the queue length after a new packet arrival, i.e., the queue length at the end of last time slot $q[n-1]$ plus the new packet arrival $a[n]$. The optimal scheduling policy can be described as a threshold-based policy. On one hand, minimizing the average queueing delay requires the scheduler to conduct transmission frequently, therefore, the queue length can't be too large. On the other hand, the power resource is limited which restricts the frequency of transmission especially when the channel state is poor. Thus, there exists a threshold queue length to compromise the two above limitations. Specifically, no packet transmission happens if $q[n-1]+a[n] < k^*$, one packet will be transmitted if $q[n-1]+a[n] > k^*$, and one packet will be transmitted with the threshold transmit probability if $q[n-1]+a[n] = k^*$.

VI. DELAY-POWER TRADEOFF POLICY FOR UNKNOWN ARRIVAL DISTRIBUTION

In this section, we consider the delay-power tradeoff problem with the packet arrival distribution being unknown which is in contrast to the assumption of packet arrival in Section II. To achieve the minimum queueing delay, an intuitive method is using the historic transmission parameters for reference. However, the historic parameters is probably not optimal. Thus, adaptive algorithms are proposed to achieve the optimal delay-power tradeoff based on the threshold-based policy.

A. POWER CONSTRAINT AND QUEUE THRESHOLD ANALYSES

On one hand, a given power constraint $\mathcal{P}_{th}$ corresponds to an optimal queue threshold k^* and an optimal threshold transmit probability f_k^* based on the threshold-based policy. A sketch of this relationship is given in Fig.3. Particularly, for similar power constraints, same threshold may be derived but different threshold transmit probabilities will be assigned. On the other hand, this relationship provides us a way to approach the power constraint by adjusting the threshold k and the threshold transmit probability f_k. Specifically, if k increases which means less packets will be transmitted, the consumption power will decrease, and vice versa. As given by the dash lines with arrow in Fig.3, a definite k can determine an approximate scope of the consumption power $[\mathcal{P}_{kl}, \mathcal{P}_{ku}]$. If we further decide f_k, the real power consumption can be approached approximately. Base on the above analyses, if we need to approach the given power, the first step is to determine k^*, the next step is to find f_k^*.

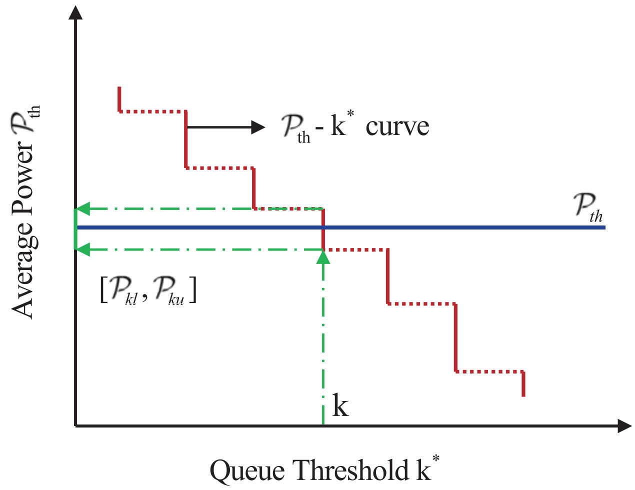

FIGURE 3. The relationship between $\mathcal{P}_{th}$ and k: A sketch.

B. ADAPTIVE THRESHOLD ALGORITHM

The optimal delay-power tradeoff can be achieved by the threshold-based policy, regardless of the specific arriving packets' distribution is known or not. With this guidance and analyses in Section VI-A, algorithms are proposed to determine the queue threshold k^* and the threshold transmit probability f_k^*.

We first elaborate the main idea on how to obtain the optimal queue threshold. The scheduler is assumed to be capable of collecting the historical data of the consumption power. An arbitrarily chosen threshold k^0 is given before the transmission starts. The scheduler transmits packets with k^0 being the queue threshold for a certain time window δ. Then, it collects the present consumption power $\mathcal{P}(n)$ and compares $\mathcal{P}(n)$ with the given power constraint $\mathcal{P}_{th}$. Based on the comparison results, a decision of how to adjust k will be made. Specifically, if $\mathcal{P}(n) > \mathcal{P}_{th}$, the threshold should be increased. Otherwise, the threshold should be decreased. The scheduler repeats the above operations till the threshold approaches its real value.

The effectiveness of Algorithm 1 is shown in Fig.3. Any given power constraint $\mathcal{P}_{th}$, which is described by the horizontal solid line, will have an intersection with the $\mathcal{P}_{th}$-k curve. Thus, for any given power constraint $\mathcal{P}_{th}$, there always exists a corresponding queue threshold k^*.

Given the power constraint $\mathcal{P}_{th}$, Algorithm 1 will output the exact optimal queue threshold k^*. To precisely achieve the optimal delay-power tradeoff, the threshold transmit probability f_k^*, ranged from 0 to 1, will be optimized by using searching method like dichotomy and so on.

There are three input parameters in Algorithm 1, namely, the given power constraint $\mathcal{P}_{th}$, the presupposed threshold k^0, and the adjustment step of threshold δ. The power constraint $\mathcal{P}_{th}$ is fixed and given by the system. The initialized k^0 can be chosen arbitrarily. Because the algorithm will limit to the the optimal threshold eventually. However, a rough estimation of the optimal value will decrease the convergence time. As for

Algorithm 1 Dynamic Programming for Searching the Optimal Queue Threshold: Algorithm 1

Input:

Given power constraint, $\mathcal{P}_{th}$;
Presupposed threshold, k^0;
Adjustment step of the threshold, δ.

Output:

Threshold imposed on the queue, k^*.

```
k = k^0, P(0) = 99, n = 1;
Transmit packets with threshold-based policy and with k
  being the queue threshold for finite time δ;
Collect consumed power information P(n);
Compare P(n) with the P_th.
   if P(n) < P_th & P(n − 1) > P_th
       exetute (12);
   elseif P(n) > P_th
       k = k + δ, n = n + 1, execute (2);
   else
       k = k − δ; n = n + 1, execute (2);
   endif
return k* = k
```

Algorithm 2 Dynamic Programming for Searching the Queue Threshold: Algorithm 2

Input:

Given power constraint, $\mathcal{P}_{th}$;

Output:

Threshold imposed on the queue, k^*.

```
k_now = 0, k_pre = −1, n = 0, i = 0, P(0) = 999;
Transmit packets with k_now as queue threshold for finite
  time δ, n = n + 1;
Collect consumed power information P(n);
Compare P(n) with the P_th.
   if P(n) < P_th & P(n−1) > P_th & |k_now − k_pre| == 1
       exetute (12);
   elseif P(n) > P_th
       k_pre = k_now, i = i + 1, k_now = 2^i, execute (2);
   else
       k_pre = k_now, k_now = k_now − 1,  execute (2);
   endif
return k* = k_now
```

the adjustment step δ, a fixed step is adopted in Algorithm 1, thus, the convergence is linear. Algorithm 2 is introduced as a different threshold adjustment method, where the threshold is initialized with a small value, increased exponentially to approach the optimal value quickly, and adjusted slightly such as in a linear way once approaching the real value. The convergence process of Algorithm 2 is shown in Fig.4.

VII. NUMERICAL RESULTS

In this section, we validate the threshold-based policy and the proposed adaptive threshold algorithm via Monte-Carlo simulation results. In the simulation, packets are generated

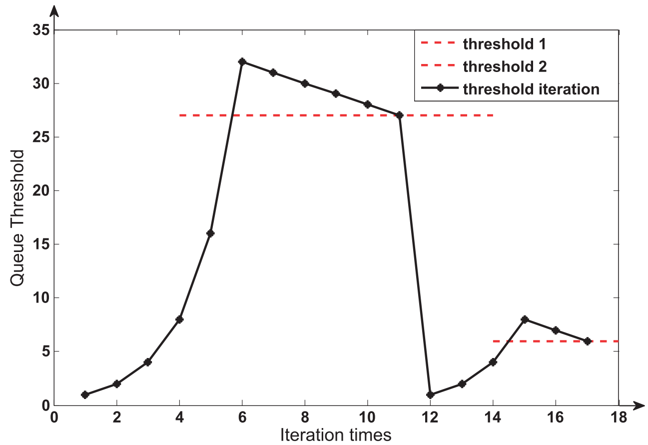

FIGURE 4. Dynamic programming: Algorithm 2.

TABLE 1. Simulation parameter settings.

Arrival Rate			Arrival Variances				BER Requirements		
$\bar{a}$	p_1	p_2	$\bar{a}$	Var	p_1	p_2	BER	P_1	P_2
0.55	0.30	0.125	0.5	0.53	0.18	0.16	10^{-4}	0.107	101.64
0.50	0.32	0.09	0.5	0.46	0.26	0.12	10^{-3}	0.103	10.14
0.45	0.35	0.05	0.5	0.39	0.34	0.08	10^{-2}	0.05	0.99

obeying a probabilistic distribution $\{p_m\}$. The maximum number of arrival packet is limited by $M = 2$. We adopt two-state block fading channel model. The probability distribution of the channel state β is set as 0.6. The transmission power P_1 and P_2 for different targeted BER and the distributions of the packet arrival $\{p_m\}$ with different average arrival rates and variances are presented in Table 1 for each simulation for convenience. The scheduler collects the above information and transmits packets based on the threshold-based policy. Each simulation runs 10^7 time slots.

In Fig.5(a), the targeted BER on the receiver side is set as 10^{-3}. Thus, P_1 and P_2, which denote the transmission power in the good channel and bad channel, are set to 0.103 and 10.14 respectively from Table 1. The delay-power tradeoff curves are given under different average packet arrival, i.e., $\bar{a} = 0.55$, 0.50 and 0.45, respectively (the unit of the queuing delay is timeslot.). Firstly, we validate the threshold-based policy. We draw the delay-power tradeoff curves in Fig.5(a) where the theoretical results are presented as the solid lines while the simulation results are marked by symbol ' + '. We show that the theoretical results are match well with the simulation results. The optimal delay-power tradeoff curve is piece-wise linearly. Each knee point denotes threshold changing. The points on the segment between two knee points have identity k^* but different f_k^*. Secondly, the average minimum queueing delay is a decreasing function with the average power as expected. What's more, as the available power decreases, the average queueing delay increases dramatically. At last, to achieve the same average queueing delay, more power will be consumed for a higher average packet arrival rate. Because more packets will be

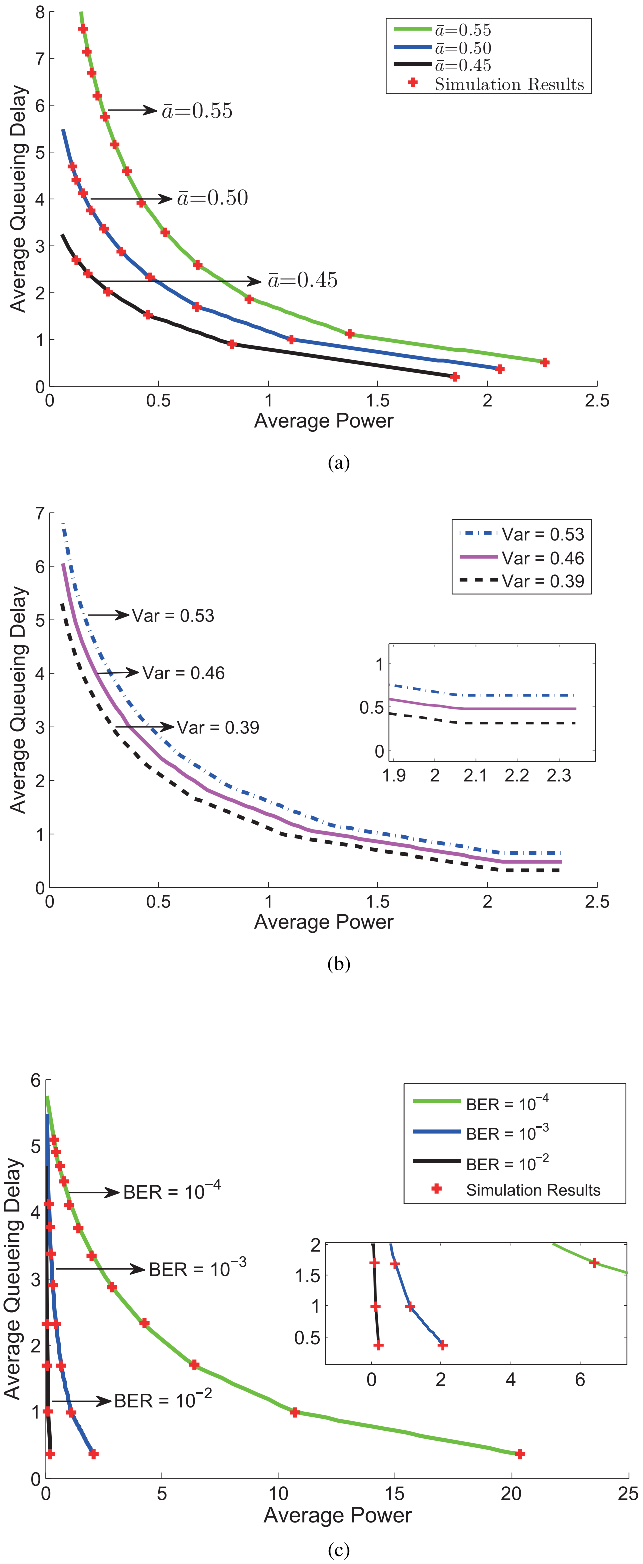

FIGURE 5. **Simulation Results. (a) Different arrival rates. (b) Different arrival variances. (c) Different targeted BERs.**

backlogged in the queue, the threshold will be reduced to increase the frequency of transmission to meet the identity queueing delay. As a result, this will increase the probability of suffering bad channel states and thus consume more power.

Fig.5(b) describes the optimal delay-power tradeoff curves under different packet arrival variances when the average packet arrival rate $\bar{a}$ is identical and set as 0.5. As given in Table 1, the variance *Var* is set as 0.53, 0.46, and 0.39, respectively. The targeted BER is 10^{-3}. In Fig.5(b), given the identical power constraint, a greater queueing delay will be induced for higher variance. This is due to the fact that higher variance indicates a more bursty packet arrival pattern. As a result, the threshold will increase if the available power remains the same. What's more, we draw and magnify the curves when available power is more than the maximum consumption power $\mathcal{P}_{max}$. The minimum queueing delay remains the same in this situation because packets are transmitted in every slot whatever the channel state is, i.e., the optimal threshold is zero.

In Fig.5(c), we present the delay-power tradeoff curves when different targeted BERs are considered on the receiver side, i.e., BER is set to 10^{-2}, 10^{-3}, and 10^{-4}, respectively. Let the average packet arrival rate $\bar{a} = 0.5$. A higher queueing delay will be for a more strict targeted BER requirement if the available consumption power is identity. To meet a more strict targeted BER, the transmitter has to improve the power to transmit one packet. If the power constraint is given, the scheduler will make a decision of increasing the threshold out of energy efficiency. Hence, the queueing delay will increase.

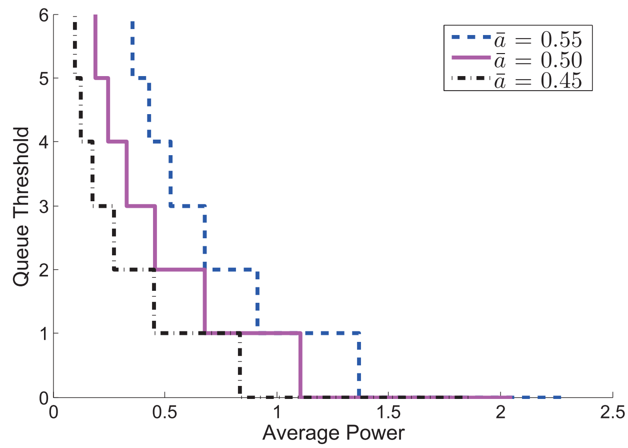

FIGURE 6. **Threshold-power Curves.**

In Fig.6, we describe the relationship between the optimal threshold k^* and the given power constraint $\mathcal{P}_{th}$. The targeted BER is 10^{-2}. The average packet arrival rate is set to 0.45, 0.50, and 0.55, respectively. The results validate our conclusion in Section VI-A. The k-$\mathcal{P}_{th}$ curves are stair-step. As the available power increases, the queue threshold decreases since the transmitter is afford to transmit more frequently in the bad channel. What's more, under the same power constraint, the optimal threshold k^* is an increasing function of the average arrival rate.

At last, we focus on the proposed adaptive threshold algorithm and present the performance of Algorithm 2. Let $p_1 = 0.32$ and $p_2 = 0.09$. The distribution is used to generate the arrival packets and will be an unknown

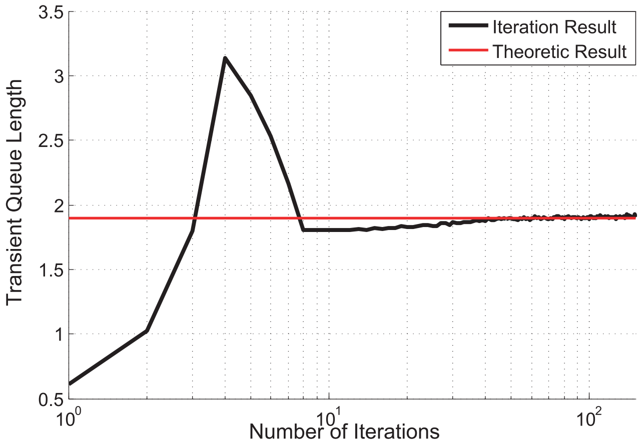

FIGURE 7. Iteration performance with Logarithmic coordinate axis.

parameter to our algorithm. In Fig.7, we present the iteration results of Algorithm 1and plot them in the logarithmic coordinate. Let zero be the start threshold. The threshold firstly increases as a power function of 2, then changes in a linear way with the adjustment step $\delta = 1$. The iteration results eventually approaches the theoretical result in finite steps.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we aimed to achieve the optimal delay-power tradeoff of fixed-rate wireless transmission with arbitrarily bursty traffics by presenting a joint channel-aware and queue-aware scheduling. We proposed a Markov chain model to model the queueing state and extended it to a Markov reward model to analyze the average delay and power consumption. A cross layer optimization problem was formulated to minimize the average queueing delay given a power constraint. The optimization problem was converted into a Linear Programming problem, the optimal solution of which gave a threshold-based probabilistic scheduling along with the optimal delay-power tradeoff. Furthermore, we presented a threshold adaptation policy to achieve the optimal delay-power tradeoff with unknown packet arrival distributions. An the end of this paper, simulation results were given to validate the threshold-based policy and the adaptive threshold algorithms. Interesting future works include the delay-power tradeoff in generalized system models.

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