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Throughput Analysis of an Energy Harvesting Multichannel System under Delay and Energy Storage Constraints

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***Abstract*—High power to guarantee strict performance requirement and low power to avoid energy depletion results in an inevitable conflict for a renewable energy harvesting communication system (REHCS) with finite energy storage. This paper proposes a generic approach to study the per-flow performance in such a multichannel system multiplexed by multiple flows. The queueing delay constraint and energy storage constraint are constructed to express the probabilistic bound of queuing delay and that of energy depletion respectively. We study these constraints with the statistical information of the processes including traffic arrivals and service, energy harvesting and consumption. The lower bound of the long term maximum per-flow throughput is then derived to meet the constraints under a specific system. The accuracy of the proposed approach is validated by simulation experiments. The analysis reveals how the sustained throughput is affected by various factors, such as the queueing delay and energy storage constraints, the packet size, the energy block size, the traffic scheduling schemes, the bandwidth allocation schemes as well as the interdependence among the channel service processes. Particularly, the analysis also provides valuable insight into traffic admission control from the viewpoint of small queueing delay and finite energy storage.**

***Index Terms*—Energy harvesting multichannel system, queueing delay constraint, energy storage constraint, per-flow throughput, stochastic network calculus.**

I. INTRODUCTION

GREEN communications has recently drawn significant attention due to the growing concern about the cost in using fossil fuel to power traditional communication infrastructures [1, 2]. Renewable energy has been considered as an option to power various sorts of wireless communication systems, such as wireless sensors [3], mobile phones [4] and base stations [5]. In some of these systems, information is forwarded in parallel by multiple channels. One noteworthy example is the orthogonal frequency division multiplexing (OFDM) system where the available spectrum is divided into multiple orthogonal subcarriers [5, 6]. Unlike fossil fuel energy, renewable energy is usually harvested randomly and finitely. For instance, the amount of harvested solar energy is time-varying and jointly depends on the time of one day, the weather and the season [7]. Since the energy being harvested may either be sufficient or insufficient to the current energy demand, it is necessary to deploy energy storage equipments in order to store the surplus energy or compensate the energy depicts. Besides, energy storage capacity is always finite for a practical system. Thus, it should be taken seriously to allocate transmission power properly in order to avoid energy depletion. On the other hand, real-time services such as multimedia video and live broadcast are often bursty in nature and require strict delay guarantees, which needs high service rate and implicitly high transmission power. As a result, high power to ensure strict delay guarantee and low power to avoid energy depletion come into conflict. Therefore, it is worth studying the delay and energy storage constraints in a REHCS [8]. Furthermore, a more valuable question arises as how much throughput (i.e., the data rate) can be sustained for a flow by such a multichannel system under these performance constraints, especially when there are already other flows being served in the system.

Some efforts have been devoted to studying the energy efficiency in energy harvesting multichannel systems [5, 6]. In [5], Derrick *et al.* studied a practical close-to-optimal online resource allocation algorithm with causal system knowledge to maximize the energy efficiency for an energy harvesting base station. In [6], Xu *et al.* studied the optimal offline solution to an AWGN multichannel scenario subject to a total energy harvesting power constraint. Since these works are based on the traditional information theory, delay constraint as well as traffic characteristics are not taken into account. In [9], the problem was studied in a single-flow-two-way-channel system and the short term throughput was obtained. However, to the best of our knowledge, the problem about the long term per-flow throughput under the queueing delay and energy storage constraints is still open.

To address this issue, we propose a generic approach to study the per-flow performance in an energy harvesting multichannel system. The system is assumed to have finite energy storage and serve multiple flows simultaneously. We use the complementary cumulative distribution function (CCDF) of the packet queueing delay and that of the energy depletion to

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characterize the queueing delay constraint of a designated flow and the energy storage constraint of the system respectively. These constraints are subsequently derived with the statistical information of multiple traffic arrivals, system service, energy harvesting and energy consumption. Thereafter, we formulate a per-flow throughput problem relevant to various impact factors including traffic characteristics (i.e., traffic type and packet size), energy characteristics, flow scheduling scheme, bandwidth allocation scheme and interdependency among the channel service processes. The solution of the throughput problem is presented under a specific system with multiple Rayleigh fading channels. Moreover, the accuracy of the proposed approach is validated by simulation experiments. Specifically, the derived energy depletion probability is a tight upper bound of the corresponding simulation result. Additionally, the derived per-flow throughput result is close to the simulation result, especially while loosening performance constraints or transmitting smaller packets.

In the literature, related studies on traffic transmission with energy harvesting which consider both delay and energy storage are summarized as follows. Ozel *et al.* proposed a water-filling algorithm to maximize the traffic throughput under a given delay deadline in an offline scenario [10]. Mao *et al.* studied an optimal energy harvesting algorithm to maximize the throughput under a buffer constraint [11]. Note that the buffer constraint is equivalent to the queueing delay constraint. References [10, 11] are based on an underlying assumption that the traffic rate is constant. In other words, traffic characteristics which have great impacts on system performance were absent. In [12, 13], the authors considered the system which harvested energy from both renewable energy source and grid energy source. The minimum grid energy consumption to meet the average delay requirement was studied with Bernoulli [12] and independent identical distribution [13] processes including traffic and energy arrivals respectively. However, works [10–13] are based on the single-flow-single-channel scenarios.

The proposed approach to deal with the considered problem is based on the stochastic network calculus theory [14, 15]. It is an effective tool for performance analysis of complex queueing problems which may otherwise only rely on the classical queueing theory (see the discussions in [15]). Recently, the stochastic network calculus theory has been applied to deal with the energy consumption problems. Energy harvesting and energy demand processes were modeled by Wu *et al.* [16], Wang *et al.* [17] and Ghiassi-Farrokhfal *et al.* [7], respectively. Researchers thereof revealed the relationship between energy harvesting and energy consumption. However, the impact factors of energy demand such as traffic arrival process and system service process were not taken into account. Works comprehensively considering traffic characteristics and energy consumptions are conducted in [18, 19]. The minimum energy consumption needed to sustain traffic transmission was firstly studied by Zafer with deterministic traffic arrival [18]. In our early work [19], we generalized Zafer's work by taking stochastic traffic arrival process into account. However, the energy harvesting process and energy storage constraint were still absent. In [20], we constructed an energy harvesting system model with consideration of stochastic traffic arrival process and energy harvesting process as well as finite energy storage, and ascertained the minimum energy harvesting rate needed to sustain the given traffic throughput under the delay and energy storage constraints. Nevertheless, limitation still exists due to the reason that the analysis in [18–20] were also based on the single-flow-single-channel scenarios with deterministic service processes.

Compared with the existing works, the contributions of this paper are as follows:

- This paper proposes a generic approach to study the queueing delay, energy depletion and per-flow throughput in a REHCS. The proposed approach is tractable to be applied since it is appropriate to any stochastic processes of traffic arrivals, system service, energy harvesting and energy consumption.
- This paper first studies the multi-flow-multichannel s-cenario in a REHCS and reveals the impacts of flow scheduling scheme and bandwidth allocation scheme on the per-flow throughput. It is highlighted that the considered scenario can be simplified into the existing scenarios [10–13, 18–20] through setting the number of flows and that of channels both to 1.
- This paper takes the interdependence among the channel service processes into account. It not only provides analysis for the case of independent channel services as assumed in the existing works [5, 6, 9], but also derives the worst case performance for the case that the channel service processes are not independent.
- Unlike the existing works which mostly focus on power allocation schemes to ascertain the fluid traffic throughput (i.e., average channel capacity) [9–13], this paper studies the queueing delay and energy storage constrained per-flow throughput for a packet flow with stochastic traffic arrivals. It is able to provide valuable insight into per-flow admission control to a REHCS.

The remainder of this paper is organized as follows. In Section II, the system model is presented and the performance constraints are constructed. In the end of this section, an generic problem about maximizing the per-flow throughput is formulated. In Section III, the performance constraints are derived under a general scenario. Additionally, the stochastic service curve for the overall system is derived. In Section IV, we solve the formulated problem under a specific scenario. In Section V, numerical results are presented and discussed. Finally, we give further discussion in Section VI and conclude the paper in Section VII.

II. Modeling and Formulating

A. Notations

This paper employs a discrete time model. The following mathematical notations are useful for the subsequent analysis.

We use Ψ to denote the set of non-negative, non-decreasing functions, i.e., $\Psi = \{f(\cdot) : \forall\ 0 \le x_1 \le x_2, 0 \le f(x_1) \le f(x_2)\}$, and $\overline{\Psi}$ to denote the set of non-negative, non-increasing functions, i.e., $\overline{\Psi} = \{f(\cdot) : \forall\ 0 \le x_1 \le x_2, 0 \le f(x_2) \le f(x_1)\}$.

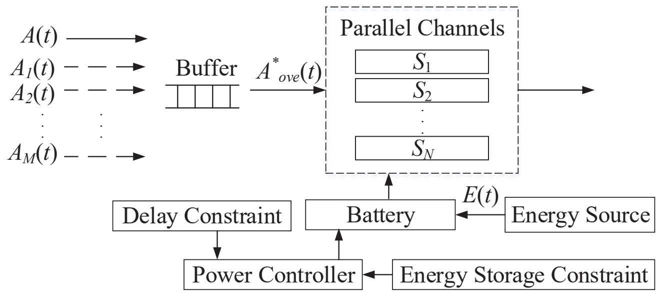

Fig. 1. System model

For a stochastic process $X(t)$, $\mathbb{E}[e^{\theta X(t)}]$ is called the *moment generating function* of $X(t)$, where $\mathbb{E}(\cdot)$ denotes the expectation of its argument.

For two functions $f(x)$ and $g(x)$, the *min-plus convolution* is defined as

$$f \otimes g(x) = \inf_{0 \le y \le x} \{f(y) + g(x-y)\}.$$

And the *min-plus deconvolution* is defined as

$$f \oslash g(x) = \sup_{y \ge 0} \{f(x+y) - g(y)\}.$$

The min-plus convolution and its deconvolution can be used to transform the non-linear queueing system to the 'somewhat looking' linear system (see detail in [21]).

For a variable x, we let $[x]_1$ denote $\min\{x, 1\}$ and $[x]_+$ denote $\max\{x, 0\}$.

We use $X(s,t)$ to denote the bivariate extension of the cumulative process $X(t)$, i.e., $X(s,t) := X(t) - X(s)$ which means the cumulative amount of X within time interval (s,t]. In this paper, the cumulative processes, such as A, α, A^*, S, β, E, e, P, and p, all conform this definition.

B. System Model

Fig. 1 depicts a REHCS consisting of N orthogonal channels, a power controller, a battery and a buffer. The energy is assumed to be harvested from the ambient energy source and be used to transmit traffic only. In addition, the system is causal, i.e., traffic cannot be served before arriving at the system and energy cannot be consumed before being harvested.

We define the energy harvested at some point as an *energy block*. Note that the energy block size is random since the amount of harvested energy is time-varying. If the energy being harvested is sufficient to satisfy the current energy consumption, the leftover energy will be stored in a battery with finite storage capacity until it is fully charged. In contrast, whenever there have deficiencies in the current energy harvesting, the battery will be discharged to compensate these energy deficits until the stored energy is depleted. At that time, there will be system outage and all the packets in the buffer will be discarded.

There are $M+1$ $(M \ge 0)$ packet flows multiplexing the transmission channels through a unified scheduling scheme. The scheduling scheme can be first-in-first-out (FIFO) or strict priority (SP), or etc. At any time, a channel can only serve one packet and a packet can be served by only one channel. When all the channels are busy, the packets are temporarily stored in a buffer with infinite capacity. In contrast, whenever there have available channels and meanwhile any packet needing to be served, the system will randomly choose an available channel to serve the head-of-line packet in the buffer. Besides, a power controller is configured to allocate appropriate power for the traffic transmission under some requirements.

Without loss of generality, we focus on any one of the $M+1$ flows and denote it by A. The other flows are regarded as cross flows and denoted by $\{A_i : 1 \le i \le M\}$. We use $A(t)$ to denote the cumulative amount of flow A input to the system up to time t. The cumulative traffic amount of flow A departing the buffer is denoted by $A^*(t)$. Similar definitions of flows $\{A_i : 1 \le i \le M\}$ are represented by $\{A_i(t) : 1 \le i \le M\}$ and $\{A_i^*(t) : 1 \le i \le M\}$ respectively. In addition, the cumulative system capacity is denoted by $S(t)$. Likewise, the cumulative amount of the harvested energy and that of the consumed energy up to time t are denoted by $E(t)$ and $P(t)$ respectively. Furthermore, we assume all the cumulative processes in this paper are equal to 0 but the battery is fully charged at time 0.

The stochastic network calculus characterizes a stochastic process via a probabilistic envelop. Concretely, we use an upper bound with the corresponding violation function, which is called as a stochastic arrival curve, to describe the cumulative amount of traffic arrival. The cumulative amount of traffic departure is similarly described by a lower bound with the corresponding violation function which is called as a stochastic service curve. The mathematical definitions of the stochastic arrival curve and stochastic service curve are shown as follows.

Definition 1. ***(Stochastic Arrival Curve)*** **[15]** *A flow A is said to have a stochastic arrival curve $\alpha \in \Psi$ with the violation function $f_\alpha \in \overline{\Psi}$, denoted by $A \sim< f_\alpha, \alpha >$, if for all $0 \le s \le t$ and all $x \ge 0$, there holds*

$$Pr\{\sup_{0 \le s \le t} \{A(s,t) - \alpha(s,t)\} > x\} \le f_\alpha(x).$$

Definition 2. ***(Stochastic Service Curve)*** **[15]** *A system S is said to provide a stochastic service curve $\beta \in \Psi$ with the violation function $f_\beta \in \overline{\Psi}$, denoted by $S \sim< f_\beta, \beta >$, if for all $t \ge 0$ and all $x \ge 0$, there holds*

$$Pr\{A \otimes \beta(t) - A^*(t) > x\} \le f_\beta(x),$$

where $A \otimes \beta(t)$ means the cumulative amount of service guaranteed by the service curve $\beta(t)$.

Note that if the amount of the traffic or that of the service is deterministically bounded, the corresponding violation function will be equal to 0.

Learning the idea of characterizing arrival process and service process from the stochastic network calculus, we construct the stochastic energy harvesting curve and stochastic energy consumption curve to characterize the energy harvesting process and energy consumption process respectively. Similar definitions can also be found in [7, 16, 17].

Definition 3. ***(Stochastic Energy Harvesting Curve)*** *An energy harvesting process E is said to have a stochastic energy* *harvesting curve $e \in \Psi$ with the violation function $f_e \in \overline{\Psi}$, denoted by $E \sim< f_e, e >$, if for all $0 \le s \le t$ and all $x \ge 0$, there holds*

$$Pr\{\sup_{0\le s\le t}\{e(s,t) - E(s,t) > x\}\} \le f_e(x).$$

Definition 4. ***(Stochastic Energy Consumption Curve)*** *An energy consumption process P is said to have a stochastic energy consumption curve $p \in \Psi$ with the violation function $f_p \in \overline{\Psi}$, denoted by $P \sim< f_p, p >$, if for all $0 \le s \le t$ and all $x \ge 0$, there holds*

$$Pr\{\sup_{0\le s\le t}\{P(s,t) - p(s,t)\} > x\} \le f_p(x).$$

For flow A, the virtual queueing delay $D(t)$ is defined as

$$D(t) = \inf\{d : A(t) \le A^*(t+d)\},$$

where $D(t)$ refers to the queueing delay of the last bit arriving at time t. The virtual delay $D(t)$ upper-bounds the real delay $D_r(t)$ within a maximum gap t_r which represents the maximum transmission time of a packet [22]. Since the gap between real delay and virtual delay is small, using virtual delay has advantage in simplifying the analysis without losing accuracy [15, 19, 20, 23, 24].

Due to the randomness, the energy being harvested may be insufficient to the energy being consumed, which brings energy deficits. Let $B(t)$ denote the cumulative amount of energy deficits up to time t, then there holds for

$$B(t) = \max\{0, B(t_l) + P(t_l, t) - E(t_l, t)\}, \quad (1)$$

where t_l represents the last period before time t when energy consumption or energy harvesting occurs.

C. Performance Constraints and Problem Formulation

The system performance and reliability are assessed in terms of the following two constraints:

1) The *queueing delay constraint*, denoted by (ϵ_d, d), is defined as

$$Pr\{D(t) > d\} \le \epsilon_d. \quad (2)$$

It means that the queueing delay $D(t)$ exceeding threshold d is controlled within probability ϵ_d.

2) The *energy storage constraint*, denoted by (ϵ_b, b), is defined as

$$Pr\{B(t) > b\} \le \epsilon_b. \quad (3)$$

It means the probability that the cumulative energy deficits $B(t)$ exceeds the battery storage capacity b (i.e., the stored energy is depleted) is controlled within ϵ_b.

Since the multiple traffic arrival processes and energy harvesting process are all stochastic, it is significant to investigate what affects and how to guarantee the stochastic performance constraints. Furthermore, if these constraints are regarded as the QoS requirements to the system, the maximum throughput (i.e. traffic arrival rate) of flow A sustained by the system is worth studying. Specifically, we formulate a generic per-flow throughput problem as follows

$$\begin{aligned} \textbf{max} \quad & r_a((\epsilon_d, d), (\epsilon_b, b), E, P, \{A_i : 1 \le i \le M\}, A, S) \\ \textbf{subject to} \quad & Pr\{D(t) > d\} \le \epsilon_d \\ & Pr\{B(t) > b\} \le \epsilon_b \end{aligned}, \quad (4)$$

where r_a denotes the average throughput of flow A. Different from the existing works which just consider average channel capacity as throughput without any performance constraints [10, 11] or assume static channel transmission [19, 20], the per-flow throughput here is jointly dominated by processes A, $\{A_i : 1 \le i \le M\}$, P, E, S, the traffic scheduling scheme, and the queueing delay and energy storage constraints. Therefore, the per-flow throughput formulated in this paper explains the traffic admission of a REHCS more comprehensively.

III. Performance Analysis for General Case

A. Assumptions

The following reasonable assumptions can make the problem specific.

The system is work-conserving, which means no channels can be idle as long as the system has packets to transmit. In this case, the busy periods of the channels are all coincident.

The battery is assumed to be ideal, i.e., the discharging rate and charging rate are infinite, the storage efficient and depth of discharge are 1, and the self-discharging rate is 0 [25].

In addition to traditional system stability condition that average traffic arrival rate cannot be greater than average service rate and energy consumption rate cannot be greater than energy harvesting rate, two stronger stability conditions are employed as follows:

$$\lim_{t\to\infty} \frac{1}{t}[\alpha(t) - \beta(t)] \le 0, \quad (5)$$

$$\lim_{t\to\infty} \frac{1}{t}[p(t) - e(t)] \le 0. \quad (6)$$

Note that these two stability conditions are both sufficient conditions for system stability. The former one has been proved to be reasonable and widely applied in the stochastic network calculus framework (see e.g. [15, 16, 19, 23]). Although $\alpha(t)$ is not the actual arrival rate and $\beta(t)$ is also not the actual service rate, the analysis can be accurate through properly choosing their values to yield tight performance bounds. The latter condition is justified because the stochastic process on the traffic plane and that on the energy plane are similarly modeled.

B. Performance Analysis

In this subsection, the queueing delay and energy storage constraints are investigated with the statistical information of $\{A_i : 1 \le i \le M\}$, A, S, P and E. Firstly, the energy storage constraint is summarized as the following theorem.

Theorem 1. *For a stable system with battery storage capacity b, if the energy harvesting process E and the energy consumption process P are characterized by $E \sim< f_e, e >$ and*

$P \sim< f_p, p >$ respectively, the energy depletion probability is bounded by

$$Pr\{B(t) > b\} \le [f_p \otimes f_e(b - p \oslash e(0))]_1.$$

Proof. The proof of Theorem 1 is presented in Appendix B. □

Theorem 1 implies the energy storage constraint is dominated by the energy harvesting process E and energy consumption process P, and it can be easily analyzed with the help of the stochastic energy harvesting curve and stochastic energy consumption curve. Moreover, Section IV will present how to the obtain these curves.

The following theorem summaries the queueing delay constraint.

Theorem 2. *Consider a stable energy harvesting multichannel system S as depicted in Fig. 1. Suppose the designated flow A is characterized as $A \sim< f_\alpha, \alpha >$ and the cross flows $\{A_i : 1 \le i \le M\}$ are characterized as $\{A_i \sim< f_{\alpha_i}, \alpha_i >: 1 \le i \le M\}$. The system S provides service with an overall stochastic service curve as $S \sim< f_{\beta_{ove}}, \beta_{ove} >$. Additionally, the energy storage constraint is given as (ϵ_b, b), i.e., $Pr\{B(t) > b\} \le \epsilon_b$. Then for queueing delay threshold $d \ge 0$, the delay violation probability is bounded by*

$$\begin{aligned} &Pr\{D(t) > d\} \\ \le&[f_\alpha \otimes f_{\alpha_1} \otimes \cdots \otimes f_{\alpha_M} \otimes f_{\beta_{ove}}(\inf_{0\le s\le t}\{[\beta_{ove}(s, t+d) \\ &- \sum_{i=1}^{M} \alpha_i(s, t+d-\tau)]_+ I_{\{t+d-s>\tau\}} - \alpha(s,t)\}) + \epsilon_b]_1 \end{aligned}$$

where $I_{\{k\}}$ is the indicator function where $I_{\{k\}} = 1$ if event k is true, and $I_{\{k\}} = 0$ otherwise. The nonnegative free parameter τ which is independent of s and t dominates the traffic scheduling scheme.

Proof. The proof of Theorem 2 is presented in Appendix C. □

Note that the queueing delay constraint not only depends on the traffic arrival and system service processes, but also on the energy storage constraint. Besides, in Theorem 1 and Theorem 2, the energy storage constraint and queueing delay constraint have been derived for the general case where processes A, $\{A_i : 1 \le i \le M\}$, S, E, P do not require to be independent of each other. In fact, the traffic arrival process and the service process are usually correlated in packet-switching networks, especially in multi-hop networks [26]. The energy consumption process depends on the energy harvesting process due to the energy storage constraint.

On the other hand, from Theorem 2, the overall stochastic service curve of a multichannel system is critical for achieving the queueing delay constraint. However, this service curve has not yet been achieved before, even though the stochastic service curve for a single server has been adequately studied [27]. The following theorem demonstrates how to obtain the overall stochastic service curve with the service process of each channel.

Theorem 3. *Consider a multichannel system with N orthogonal channels. For any channel i, the corresponding service process is denoted by S_i and is suppose to has stationary increments.*

If $\{S_i : 1 \le i \le N\}$ are all independent of each other, the whole system guarantees a stochastic service curve $S \sim< f_{\beta_{ove}}, \beta_{ove} >$ with

$$\begin{aligned} &\beta_{ove}(t) = \sum_{i=1}^{N} \beta_i(t) \le \sum_{i=1}^{N}(-\frac{1}{\theta_a}\log \mathbb{E}[e^{-\theta_a S_i(t)}]) \\ &f_{\beta_{ove}}(x) = e^{-\theta_a x} \end{aligned} . \quad (7)$$

Here, $\beta_i(t) \le -\frac{1}{\theta_a}\log \mathbb{E}[e^{-\theta_a S_i(t)}]$, denotes the stochastic service curve of S_i, and θ_a is a nonnegative optimization parameter.

However, if processes $\{S_i(t) : 1 \le i \le N\}$ are not independent, a looser violation function still holds as

$$f_{\beta_{ove}}(x) = [Ne^{-\frac{\theta_a x}{N}}]_1. \quad (8)$$

Proof. The proof of Theorem 3 is given in Appendix D. □

Note that the channel service processes are usually independent when the channels are orthogonal. However, they may not be independent sometimes due to special system setting. In Theorem 3, we derive both two cases for the overall system service process to make the analysis complete.

Also note that if $-\frac{1}{\theta_a}\log \mathbb{E}[e^{-\theta_a S_i(t)}]$ can be exactly calculated, it can then be directly employed as the stochastic service curve of S_i. Such processes include Poisson process, Gaussian process, Bernoulli process, and etc [15, 28]. On the other hand, for some service processes such as exponential on-off process, Markov modulated process, and etc., $-\frac{1}{\theta_a}\log \mathbb{E}[e^{-\theta_a S_i(t)}]$ cannot be easily calculated but still has a tight lower bound. We can employ this lower bound as the stochastic service curve of S_i [15, 28].

IV. Performance Analysis for Specific Case

In the following, we show how to apply the proposed theorems to ascertain the queueing delay and energy storage constraints under a specific scenario. Thereafter, the solution of problem (4) is also presented.

A. Specific Scenario Description

The packet size is assumed to be constant as L_a (in unit of bits), while the energy block size is assumed to be exponentially distributed with average value L_e (in unit of J). The traffic arrival process of flow A and energy harvesting process of the system are both Poisson distributed with average rate r_a (in unit of bits/s) and r_e (in unit of W) respectively. Besides, we assume a periodical flow A_1 with arrival rate r_{a_1} multiplexes the system resources with flow A .

The stochastic arrival curve of a traffic flow defined as Definition 1 can be expressed as the effective bandwidth of the flow [28]. Specifically, the stochastic arrival curve of flow A holds as

$$\begin{aligned} &\alpha(t) = \frac{1}{\theta_a}\log \mathbb{E}[e^{\theta_a A(t)}] = \frac{r_a t}{\theta_a L_a}(e^{\theta_a L_a} - 1) \\ &f_a(x) = e^{-\theta_a x} \end{aligned} , \quad (9)$$

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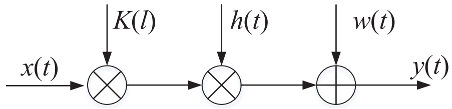

Fig. 2. Wireless channel model

where θ_a is a nonnegative optimization parameter. The stochastic arrival curve of flow A_1 holds as

$$\begin{aligned} &\alpha_1(t) = \frac{1}{\theta_a}\log\mathbb{E}[e^{\theta_a A_1(t)}] = r_{a_1}t \\ &f_{a_1}(x) = 0 \end{aligned}, \tag{10}$$

The stochastic energy harvesting curve is proved to hold as follows (see Appendix E).

$$\begin{aligned} &e(t) = -\frac{1}{\theta_e}\log\mathbb{E}[e^{-\theta_e E(t)}] = \frac{r_e t}{1+\theta_e L_e} \\ &f_e(x) = e^{-\theta_e x} \end{aligned}, \tag{11}$$

where θ_e is a nonnegative optimization parameter.

We allocate a fixed total power for the traffic transmission, such that the energy storage constraint is easily ensured even though energy is harvested randomly. Alike the stochastic arrival curve, $\frac{1}{\theta_e}\log\mathbb{E}[e^{\theta_e P_t t}]$ can represent the stochastic energy consumption curve due to their similar definition. The stochastic energy consumption curve of P holds as

$$\begin{aligned} &p(t) = \frac{1}{\theta_e}\log\mathbb{E}[e^{\theta_e P_t t}] = P_t t \\ &f_p(x) = 0 \end{aligned}. \tag{12}$$

Here, $f_p(x) = 0$ since the transmission power is constant.

The total bandwidth of the system is fixed as W_t and the bandwidth allocated to channel i is denoted by $W_i (1 \le i \le N)$, i.e., $W_t = \sum_{i=1}^{N} W_i$. The transmission power allocated to channel i is denoted by P_i, i.e., $P_t = \sum_{i=1}^{N} P_i$. Additionally, P_i is in direct proportion to W_i, i.e., for all $1 \le i \le N$, there holds $\frac{P_i}{W_i} = \frac{P_t}{W_t}$.

The service process is modeled in terms of the approach in [29]. All the channels are assumed to be additive white Gaussian noise (AWGN) flat-fading Rayleigh channels. Each one of them can be modeled as Fig. 2, there holds

$$y(t) = x(t)K(l)h(t) + w(t).$$

Here, $x(t)$ and $y(t)$ are the input signal and output signal of a channel respectively. $K(l)$ is the path loss function with distance parameter l, $h(t)$ represents a complex channel gain of small scale fading. In particular, the envelope process $|h(t)|$ and the phase process are independent, with $|h(t)|$ being Rayleigh distributed and the phase being uniform distributed over $[0, 2\pi)$. Additionally, the additive Gaussian noise term $w(t)$ has the power spectral density of $N_0/2$.

Without loss of generality, we choose channel i $(1 \le i \le N)$ as an example to characterize the channel model. According to the Shannon theorem, the instantaneous capacity of channel S_i holds as

$$C_i(t) = W_i\log_2\Big(1 + \frac{P_i K(l)|h_i(t)|^2}{N_0 W_i}\Big). \tag{13}$$

Apparently, the packets are reliably transmitted when $R_i \le C_i(t)$, otherwise they cannot be transmitted correctly and have to be retransmitted at once. Suppose the instantaneous channel state information is unavailable to the transmitter and the service rate R_i on channel i is fixed. Since $C_i(t)$ depends on $|h_i(t)|$, there exits a threshold η_i for $|h_i(t)|$ above which $R_i \le C_i(t)$ holds. Solving the inequality $R_i \le W_i\log_2(1 + \frac{P_i K(l)|h_i(t)|^2}{N_0 W_i})$, we have

$$|h_i(t)| \ge \sqrt{\frac{N_0 W_i}{P_i K(l)}(2^{\frac{R_i}{W_i}} - 1)} = \eta_i. \tag{14}$$

Therefore, the channel model is transformed into a Gilbert-Elliott channel model with two Markov states ON and OFF. In ON state, packets are transmitted at a rate R, while in OFF state, no packets can be transmitted. For channel i, we denote by μ_i^{ON} the state transition rate from OFF to ON, and by μ_i^{OFF} the one from ON to OFF. It is easily verified that the stability probability for the ON state is $\mu_i^{ON}/(\mu_i^{ON} + \mu_i^{OFF})$, while the one for the OFF state is $\mu_i^{OFF}/(\mu_i^{ON} + \mu_i^{OFF})$. In terms of the channel model, we establish the relationship between the state transition rates and the transmission threshold η_i, as shown in the following

$$\begin{aligned} &\frac{\mu_i^{ON}}{\mu_i^{ON} + \mu_i^{OFF}} = Pr\{|h_i(t)| \ge \eta_i\} = \int_{\eta_i}^{\infty} x e^{-\frac{x^2}{2}}\mathrm{d}x = e^{-\frac{\eta_i^2}{2}} \\ &\frac{\mu_i^{OFF}}{\mu_i^{ON} + \mu_i^{OFF}} = Pr\{|h_i(t)| < \eta_i\} = 1 - e^{-\frac{\eta_i^2}{2}} \end{aligned}$$

where $f_{h_i}(x) = x e^{-\frac{x^2}{2}}$ with $x > 0$ is the marginal distribution of the envelop process $|h_i(t)|$. Additionally, $\mu_i^{ON} + \mu_i^{OFF}$, denoted by κ_i, can be considered as the mean decaying rate of the channel memory. Thus, the state transition rates are linked to the physical layer parameters,

$$\begin{aligned} &\mu_i^{ON} = \kappa_i e^{-\frac{\eta_i^2}{2}} \\ &\mu_i^{OFF} = \kappa_i - \kappa_i e^{-\frac{\eta_i^2}{2}} \end{aligned}. \tag{15}$$

In order to maximize the average system capacity, what we can control are the transmission power and transmission rate. On the one hand, higher transmission power implies larger transmission capacity, therefore we should choose the maximum transmission power under the energy storage constraint. On the other hand, a higher transmission rate R_i allows more traffic to be transmitted when channel i is in ON state, however, it also implies that the event of ON state is less often due to higher threshold η_i. Therefore, the optimal R_i, denoted by R_i^{opt}, exits to maximize the average capacity of channel i, i.e.,

$$R_i^{opt} e^{-\frac{\eta_i^2}{2}} = \frac{R_i^{opt}\mu_i^{ON}}{\mu_i^{ON} + \mu_i^{OFF}} \ge \frac{R_i \mu_i^{ON}}{\mu_i^{ON} + \mu_i^{OFF}}. \tag{16}$$

As a result, the optimal average capacity of the overall system is obtained as follows,

$$R_{ove}^{ave} = \sum_{i=1}^{N}\frac{R_i^{opt}\mu_i^{ON}}{\mu_i^{ON} + \mu_i^{OFF}}. \tag{17}$$

For the expression $-\frac{1}{\theta_a}\log\mathbb{E}[e^{-\theta_a S_i(t)}]$ discussed after Theorem 3, a celebrated lower bound for two state Markov process has been ascertained in [30], there holds

$$\frac{t}{2\theta_a}(R_i^{opt}\theta_a+\mu_i^{ON}+\mu_i^{OFF} - \sqrt{(R_i^{opt}\theta_a-\mu_i^{ON}+\mu_i^{OFF})^2+4\mu_i^{ON}\mu_i^{OFF}}).$$

For the overall system, according to the interdependence information of the channel service processes, we carry forward the analysis for both two cases where: 1) the channel service processes of are all independent (ind. for short), 2) the service processes are not independent (cor. for short). According to Theorem 3, we finally achieve the optimal overall stochastic service curve of the multichannel system as follows

$$\begin{aligned}\beta_{ove}(t)&=\sum_{i=1}^{N}\frac{t}{2\theta_a}(R_i^{opt}\theta_a+\mu_i^{ON}+\mu_i^{OFF}\\&\quad-\sqrt{(R_i^{opt}\theta_a-\mu_i^{ON}+\mu_i^{OFF})^2+4\mu_i^{ON}\mu_i^{OFF}})\\&=\sum_{i=1}^{N}\frac{t}{2\theta_a}(R_i^{opt}\theta_a+\kappa_i\\&\quad-\sqrt{(R_i^{opt}\theta_a+\kappa_i)^2-4R_i^{opt}\theta_a\kappa_i e^{-\frac{\eta_i^2}{2}}})\\f_{\beta_{ove}}(x)&=\begin{cases}e^{-\theta_a x} & \text{ind.}\\ [Ne^{-\frac{\theta_a x}{N}}]_1 & \text{cor.}\end{cases}\end{aligned} \tag{18}$$

B. Performance Constraints

We first calculate the energy storage constraint. According to the stability condition (6), we have

$$P_t\le\frac{r_e}{1+\theta_e L_e}.$$

Solving the inequality, there holds $\theta_e\le\frac{r_e-P_t}{P_tL_e}$. If battery storage capacity is given as b, the tightest probabilistic bound of energy depletion can be obtained directly by using Theorem 1. There holds

$$Pr\{B(t)>b\}\le e^{-\frac{(r_e-P_t)b}{P_tL_e}}. \tag{19}$$

In order to achieve the queueing delay constraint, we need to calculate the maximum value of θ_a which is denoted by θ_a^{opt} through solving the following inequality according to the stability condition (5).

$$\frac{r_a}{\theta_a L_a}(e^{\theta_a L_a}-1)+r_{a_1}\le\sum_{i=1}^{N}\frac{1}{2\theta_a}(R_i^{opt}\theta_a+\kappa_i - \sqrt{(R_i^{opt}\theta_a+\kappa_i)^2-4R_i^{opt}\theta_a\kappa_i e^{-\frac{\eta_i^2}{2}}}). \tag{20}$$

Thereafter, the delay constraint is achieved by using Theorem 2. There holds

$$\begin{aligned}&Pr\{D(t)>d\}\\&\le[f_\alpha\otimes f_{\alpha_1}\otimes f_{\beta_{ove}}(\inf_{0\le s\le t}\{[\beta_{ove}(s,t+d)\\&\quad-\alpha_1(s,t+d-\tau)]_+I_{\{t+d-s>\tau\}}-\alpha(s,t)\})+\epsilon_b]_1\\&\le\begin{cases}[2e^{-\frac{\theta_a^{opt}(\beta_{ove}(d)-r_{\alpha_1}(d-\tau))}{2}}+e^{-\frac{(r_e-P_t)b}{P_tL_e}}]_1 & \text{ind.}\\ [(N+1)e^{-\frac{\theta_a^{opt}(\beta_{ove}(d)-r_{\alpha_1}(d-\tau))}{N+1}}+e^{-\frac{(r_e-P_t)b}{P_tL_e}}]_1 & \text{cor.}\end{cases}\end{aligned} \tag{21}$$

In the second line, we employed the stability condition (5) and expression (18). Note that for any $0\le s\le t$, $t+d-s\ge\tau$ implies $0\le\tau\le d$. And $Pr\{D(t)>d\}$ is monotonically decreasing as τ increases since $Pr\{D(t)>d\}\in\overline{\Psi}$. If flow A is scheduled with FIFO scheme, choosing $\tau=d$ minimizes the upper bound of $Pr\{D(t)>d\}$.

C. Maximum Sustained Per-flow Throughput

In what follows, we are going to solve the throughput problem (4) with the information of the energy harvesting process, the cross traffic arrival process as well as the queueing delay and energy storage constraints.

Let the righthand side term of (19) equal to ϵ_b, the maximum total transmission power which the system can provide holds as

$$P_t^{\max}=\frac{r_eb}{b-L_e\ln\epsilon_b}. \tag{22}$$

Therefore, the maximum transmission power allocated to channel i $(1\le i\le N)$ holds as

$$P_i^{\max}=\frac{r_eb}{b-L_e\ln\epsilon_b}\frac{W_i}{W_t}.$$

Thereafter, the optimal transmission rate R_i^{opt} of channel i can be determined according to (14) and (16). And then the optimal overall stochastic service curve $\beta_{ove}(t)$ can be calculated according to (18).

Let the last line term of (21) equal to ϵ_d and replacing θ_a^{opt} with θ_a, we have

$$\beta_{ove}(d)=\begin{cases}\frac{2}{\theta_a}\ln\frac{2}{\epsilon_d-\epsilon_b}+r_{\alpha_1}(d-\tau) & \text{ind.}\\ \frac{(N+1)}{\theta_a}\ln\frac{N+1}{\epsilon_d-\epsilon_b}+r_{\alpha_1}(d-\tau) & \text{cor.}\end{cases}. \tag{23}$$

The parameter θ_a can be calculated by invoking (23) into the second line term of (18). Note that θ_a depends on the energy harvesting rate r_e, the arrival rate of flow A_1, the optimal transmission rate $\{R_i^{opt}|1\le i\le N\}$, the channel memory decaying rate $\{\kappa_i|1\le i\le N\}$, the energy storage constraint (ϵ_b,b), and the delay constraint (ϵ_d,d). It can be easily calculated with the help of MATLAB.

After that, combining (23) with (20), we have

$$\begin{aligned}\frac{r_a}{\theta_a L_a}(e^{\theta_a L_a}-1)+r_{a_1}&\le\sum_{i=1}^{N}\frac{1}{2\theta_a}(R_i^{opt}\theta_a+\kappa_i\\&\quad-\sqrt{(R_i^{opt}\theta_a+\kappa_i)^2-4R_i^{opt}\theta_a\kappa_i e^{-\frac{\eta_i^2}{2}}}).\\&=\frac{\beta_{ove}(d)}{d}\end{aligned}$$

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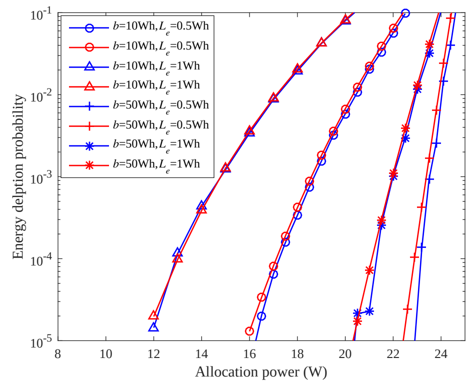
In the end, we ascertain the maximum sustained throughput $r_a^{\max}$ according to (23). There holds

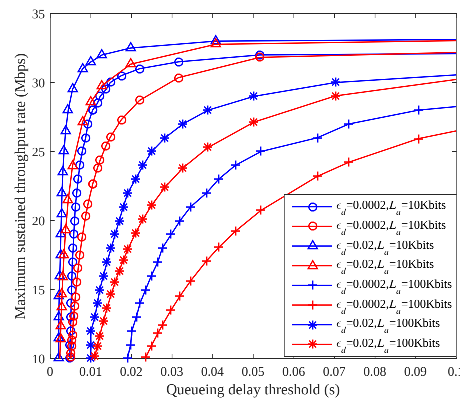
$$r_a^{\max} = \begin{cases} (2\ln\frac{2}{\epsilon_d-\epsilon_b} - r_{a_1}\tau\theta_a)\frac{L_a}{(e^{\theta_a L_a}-1)d} & \text{ind.} \\ ((N+1)\ln\frac{N+1}{\epsilon_d-\epsilon_b} - r_{a_1}\tau\theta_a)\frac{L_a}{(e^{\theta_a L_a}-1)d} & \text{cor.} \end{cases} \quad (24)$$

V. Numerical Results

In this section, we are going to discuss the impact factors on the per-flow throughput under the scenario of Section IV. For all the numerical and simulation experiments, we set the total bandwidth of the system W_t=20MHz. We assume the power spectral density of the background noise N_0=10^{-18}W/Hz and constant path loss $K(l) = -110$dB [31]. The mean decaying rate of each channel memory $\kappa_i (1 \le i \le N)$ is assumed to be 1000s^{-1} [29]. Except special statement, the packets from different flows are scheduled under FIFO scheme (i.e., $\tau = d$), the bandwidth is equally allocated to 10 independent channels, the queueing delay constraint (ϵ_d, d) and the energy storage constraint (ϵ_b, b) are set to (0.0002, 0.05s) and (0.0001, 50Wh) (where 1Wh=3600J) respectively, the packet size L_a is set to 10Kbits and the average energy block size L_e is set to 1Wh, The cross traffic rate r_{α_1} is set to 10Mbps. Furthermore, we assume a wind turbine harvesting energy to support the transmission. The average harvesting rate can be expressed as $r_e = 0.5\rho\pi r^2 v^3 \Delta(\lambda_1, \lambda_2) \approx 25$W [32], where ρ is the air density (about 1.22kg/m^3), r is the blade radius (1m), v is the average wind speed (3.1m/s), and Δ is the average power coefficient (0.44) which is a function of tip speed ratio λ_1 and blade pitch angle λ_2.



(a) energy depletion probability



(b) per-flow throughput

Fig. 3. Simulation results (blue) v.s. analytical results (red)

A. Comparison with simulation results

We first check the accuracy of the analysis with the help of simulation experiments. The simulation results of the energy depletion probability and per-flow throughput are depicted in Fig. 3(a) and Fig. 3(b) respectively. The time slot length is set to 1ms. In Fig. 3(a), we simulate each allocation power for 10 times with time length 10^8s and recorded the number of energy depletion time slots. The energy depletion probability is calculated by averaging the proportion of the number of energy depletion time slots for each allocation power. Fig. 3(a) validates that the derived energy depletion probability tightly upper-bounds the corresponding simulation result. Moreover, modeling the harvested energy with smaller energy block size enables higher allocation power when energy depletion probability requirement is invariant. That means a fluid model is able to maximize the allocation power. In Fig. 3(b), the overall transmission power and the transmission rate per channel are set to 21.11W and 6.47Mbps respectively according to expressions (22) and (16). The simulation times for a given traffic rate is set to 10, during which the queueing delays of 2×10^5 packets are recorded. We obtain the delay violation probability through calculating the average proportion of the packets whose delays exceed the given delay threshold. As depicted in Fig. 3(b), the analytical results are confirmed to be reasonable lower bounds of the corresponding simulation results since the maximum gap is lower than 5Mbps even though the delay constraint is quite strict. Moreover, loosening the delay constraint or transmitting smaller packets not only guarantees higher per-flow throughput, but also improves the accuracy of the analysis.

B. Impact of flow scheduling scheme

Fig. 4 illustrates the impact of flow scheduling scheme through FIFO scheme ($\tau = d$) and SP scheme ($\tau = 0$). The designated flow is served in the same priority with the cross flow under FIFO scheme while it is served in the lowest priority under SP scheme. Therefore, FIFO scheme outperforms SP scheme in both per-flow throughput and system throughput. Moreover, under FIFO scheme, the system throughput increases with cross traffic rate though the per-flow throughput decreases. This phenomenon implies that the multiplexing gain of FIFO scheme increases with the cross traffic rate. However, opposite trend is found under SP scheme.

C. Impact of Queueing Delay and Energy Storage Constraints

Fig. 5(a) and Fig. 5(b) indicate how much per-flow throughput can be sustained under various queueing delay constraints and energy storage constraints. In Fig. 5(b), the queueing delay constraint (ϵ_d, d) is set to (ϵ_b+0.0001, 0.05s), meaning that the delay violation probability is fixed as 0.0001 when energy is

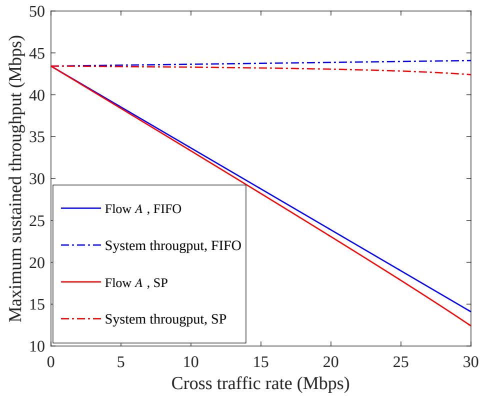
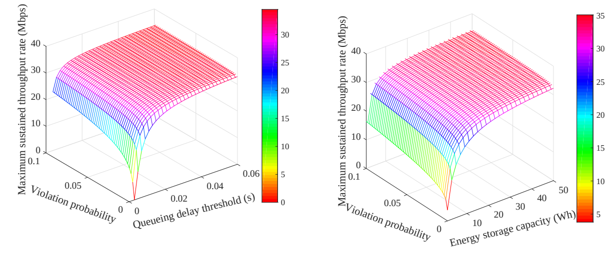


Fig. 4. Throughput v.s. cross traffic rate



(a) queueing delay constraint (b) energy storage constraint

Fig. 5. Traffic throughput v.s. performance constraint

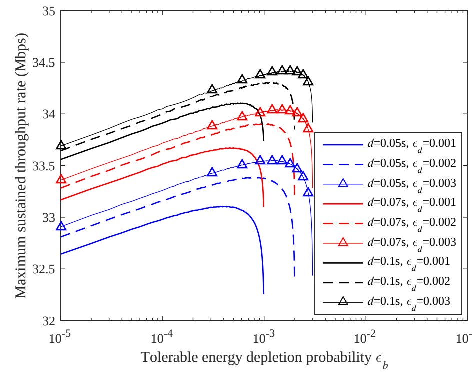


Fig. 6. Traffic throughput v.s. tolerable probability of energy depletion for different cases of delay constraints

sufficient. It is obvious that system with looser performance constraints can sustained higher per-flow throughput. However, if the transmission power and transmission rate are fixed, overly loosening performance constraints will not achieve remarkable throughput gain. For instance, Fig. 5(a) shows that the per-flow throughput increases quite slowly with the delay threshold after which is larger than 0.05s. This is because the system throughput has approached to the average system capacity in such case.

Note that the queueing delay constraint herein is not only dominated by the traffic and service characteristics as usual [19] when energy is sufficient, but also by the energy storage constraint. Fig. 6 illustrates the maximum sustained throughput $r_a^{\max}$ as a function of energy depletion probability ϵ_b when queueing delay constraint is fixed. It is shown that each case has optimal ϵ_b corresponding to unique maximum $r_a^{\max}$. That means higher traffic arrival rate can be accessed under the same queueing delay constraint if the tolerable energy depletion probability can be reasonably loosened, i.e., the transmission power can be reasonably raised. However, the sustained $r_a^{\max}$ decreases sharply as ϵ_b increases when ϵ_b is larger than the optimal point. In addition, a counterintuitive phenomenon is shown that a larger tolerable queueing deadline may lead to a lower sustained throughput even though the delay violation probability ϵ_d is fixed. For instance, fixing $\epsilon_d = 0.003$, the $r_a^{\max}$ under a larger delay deadline (e.g. $d = 0.07s$) is lower than the one under a smaller deadline (e.g. $d = 0.05s$) when the former corresponding $\epsilon_b = 0.0025$ and the latter $\epsilon_b = 0.002$. Therefore, excessively loosening the energy depletion probability would reduce $r_a^{\max}$. The reason addresses that the delay constraint of energy sufficient case is too strict to be guaranteed for high traffic arrival rate. In summary, traffic throughput can be improved by dealing well with the tradeoff between the queueing delay constraint and energy storage constraint.

D. Impact of Bandwidth Allocation Schemes

In a practical communication system, the available radio spectrum may not always be consecutive. The inconsecutive radio spectrums can be considered as different orthogonal channels. We consider 4 bandwidth allocation schemes in Table I. Scheme 1 is regarded as the reference case where bandwidth is equally allocated to all channels. It has been validated by simulation experiments in Fig. 3 that the throughput evaluation under Scheme 1 is accurate enough when the channel service processes are all independent. In schemes 2-4, different amounts of bandwidth are allocated to different channels in terms of different geometric distances from scheme 1. The geometry distance is used to check the deviation between the accurate result (i.e., Scheme 1 with independent channel service processes) and the throughput evaluation under other schemes with different interdependencies among the channel service processes. Fig. 7 shown that the throughput evaluation of schemes 2-4 is accurate and irrelevant to the geometric distance while channel service processes are all independent. However, when channel service processes are not independent, the scheme with larger geometry distance achieves more conservative throughput evaluation.

Secondly, we are interested in the relationship between the sustained throughput and the number of channels. Fig. 8 depicts the variation tendency of $r_a^{\max}$ based on scheme 1. There is no doubt that the analytical result of the independent

TABLE I
BANDWIDTH ALLOCATION

Scheme	Bandwidth allocation (MHz)	Geometric distance
Scheme 1	(2 2 2 2 2 2 2 2 2 2)	0
Scheme 2	(0.5 0.5 1 3 5 5 3 1 0.5 0.5)	$\sqrt{31} \cdot 10^6$
Scheme 3	(0.5 0.5 0.5 4 6 6 1 0.5 0.5 0.5)	$\sqrt{50.5} \cdot 10^6$
Scheme 4	(0.5 0.5 0.5 0.5 8 8 0.5 0.5 0.5 0.5)	$\sqrt{90} \cdot 10^6$

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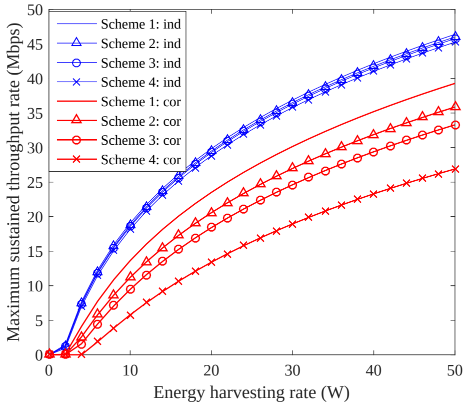

Fig. 7. Traffic throughput v.s. energy harvesting rate for different cases of bandwidth allocation

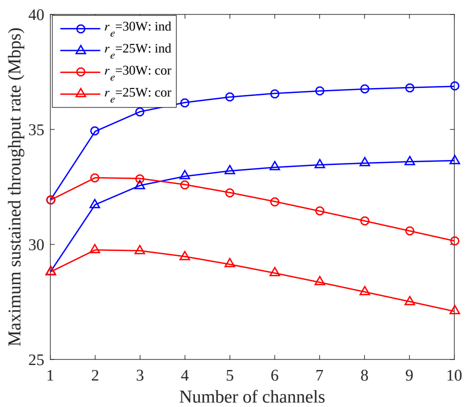

Fig. 8. Traffic throughput v.s. number of channels for different cases of energy harvesting rate

case agrees with that of the correlated case under the single-channel scenario (i.e., $N = 1$). However, as N increases, the throughput variation trend becomes different. With independence assumption on service processes, $r_a^{\max}$ increases with N. This tendency coincides with that of the M/M/K systems based on the traditional queueing theory [33]. It can be explained that the system with more channels has higher probability to avoid the buffer backlogs. Differently, with correlation assumption on service processes, there exits optimal N to maximize $r_a^{\max}$. This is because the min-plus convolution makes the analytical result conservative and meanwhile the times of using the min-plus convolution to derive $r_a^{\max}$ is correlated with N. When N is less than the optimal point, the gain of increasing N outperforms the degradation of using min-plus convolution, the sustained throughput still increases with N. However, the phenomenon is reversed when N is larger than the optimal point.

Note that the result of correlated case is derived in the worst case where all the service processes of the channels are not independent. It has reference value in suggesting how much per-flow throughput can be sustained at least if we cannot ascertain any correlation information among the channel service processes.

VI. Discussion

This paper focuses on the generic approach of analyzing the per-flow performance including the queueing delay constraint, energy storage constraint and throughput. For ease of understanding the analysis procedure, we characterized the stochastic processes with classic queueing models and analyzed the performance quantitatively. However, we highlight that the approach is also applicable to the practical scenarios. The reason is as follows. On the one hand, the stochastic arrival curve and stochastic energy consumption curve can be achieved by retracting the statistical information from the practical sample data. For example, self-similar and heavy tailed traffic was characterized by the stochastic arrival curve as $\alpha(t) = (r_a + a)t, f_a(x) = Kx^{-b(1-H)}$, where a, b, K, H are all free parameters [24]. The solar energy harvesting process was characterized by the stochastic energy harvesting curve as $e(t) = (r_e + a)t, f_e = (b_1 + b_2)(\frac{c_2}{b_1})^{\frac{b_1}{b_1+b_2}}(\frac{c_1}{b_2})^{\frac{b_2}{b_1+b_2}} e^{-\frac{b_1 b_2}{b_1+b_2}}$, where a, b_1, b_2, c_1, c_2 are all fitting parameters [7]. On the other hand, the energy consumption process is constrained by the energy storage constraint and energy harvesting process, such that the stochastic energy consumption curve always exits in the form of (12). For example, if the overall power allocation is based on the greedy police, i.e., the the system always uses the whole power stored in the battery at time t to transmit data at time $t + \tau$, where τ is the power allocation interval and we assume the energy harvesting during τ cannot exceeding the energy storage capacity b. In this case, the stochastic energy consumption curve holds as $p(t) = \frac{(t-\tau)_+}{\theta_e} \log \mathbb{E}[e^{\theta_e E(1)}] + \max\{t, \tau\}\frac{b}{\tau}, f_p(x) = f_e(x)$. Furthermore, the stochastic service curve for single channel has been extensively studied not only in stochastic network calculus framework [23], but also in effective capacity framework [34]. For example, with the perfect channel state information, the SNR is partitioned into different levels corresponding to different transmission rates. Therefore, the service process of each channel is generalized as finite state Markov channel (FSMC) model. Moreover, the FSMC model can also be characterized by the the stochastic service as defined in this paper (detail see in [23]). Thereafter, the overall service curve of the system can be derived by using Theorem 3 and per-flow performance can be derived according to Theorem 2. Since the practical model is complex in calculation due to large amounts of free parameters, the future work addresses how to simplify the practical model without sacrificing analysis accuracy.

VII. Conclusion

This paper proposed a stochastic network calculus based approach to study the per-flow performance in an renewable energy harvesting multichannel system with finite energy storage. We completed a general derivation for the distribution of queueing delay of a designated flow and that of energy depletion of the considered system. Furthermore, we shown how to jointly use the statistical information of traffic arrivals, system service, energy harvesting and energy consumption, the energy storage and queueing delay constraints to determine the traffic access rate for the considered system, which provided analytical insight into the traffic admission control.

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APPENDIX A

Lemma 1. *For the sum of a collection of random variables $Z = \sum_{i=1}^{N} X_i$, no matter whether X_i is independent of X_j $(i \neq j)$ or not, the CCDF of Z holds as*

$$\begin{aligned} F_Z(z) &\leq [F_{X_1} \otimes F_{X_2} \otimes \cdots \otimes F_{X_N}(z)]_1 \\ &= [\inf_{z_1,\cdots,z_N \geq 0, \sum_{i=1}^{N} z_i = z} \{\sum_{i=1}^{N} F_{X_i}(z_i)\}]_1, \end{aligned}$$

where F_{X_i} $(1 \leq i \leq N)$ represent the CCDF of X_i.

Proof. The proof of Lemma 1 can be found in [15] (see Lemma 1.5 of [15]). Here, we improve the bound by adding function $[\cdot]_1$. This is because if $\inf_{z_1,\cdots,z_N \geq 0, \sum_{i=1}^{N} z_i = z}\{\sum_{i=1}^{N} F_{X_i}(z_i)\} > 1$, the probabilistic bound will be meaningless. □

APPENDIX B
PROOF OF THEOREM 1

According to the definition of $B(t)$ in (1), we have

$$\begin{aligned} B(t) &= \max\{0, B(t_l) + P(t_l, t) - E(t_l, t)\} \\ &= \sup_{0 \leq s \leq t} \{P(s,t) - E(s,t)\} \end{aligned}.$$

In the second line we recursively calculated the first line from time 0 to time t. Consequently, for $\forall\ t, b \geq 0$, there holds

$$\begin{aligned} &Pr\{B(t) > b\} \\ =&Pr\{\sup_{0 \leq s \leq t} \{P(s,t) - E(s,t)\} > b\} \\ =&Pr\{\sup_{0 \leq s \leq t} \{P(s,t) - p(s,t) + e(s,t) \\ &\quad - E(s,t) + p(s,t) - e(s,t)\} > b\} \\ \leq&Pr\{\sup_{0 \leq s \leq t} \{P(s,t) - p(s,t)\} + \sup_{0 \leq s \leq t} \{e(s,t) - E(s,t)\} \\ &\quad > b - \sup_{0 \leq s \leq t} \{p(s,t) - e(s,t)\}\} \\ \overset{(a)}{\leq}& Pr\{\sup_{0 \leq s \leq t} \{P(s,t) - p(s,t)\} + \sup_{0 \leq s \leq t} \{e(s,t) - E(s,t)\} \\ &\quad > b - p \oslash e(0)\} \\ \overset{(b)}{\leq}&[f_p \otimes f_e(b - p \oslash e(0))]_1 \end{aligned}.$$

In step (a), we employed the definition of min-plus deconvolution. In step (b), we used Lemma 1 in Appendix A. Thus, the proof is completed.

APPENDIX C
PROOF OF THEOREM 2

As mentioned earlier, energy depletion means no energy is left to sustain the traffic transmission. In this case, the queueing delay constraint cannot be satisfied definitely, i.e., for all $t, d \geq 0$, there holds

$$Pr\{D(t) > d\} = 1.$$

Even though the harvested energy is sufficient for the current energy consumption, the traffic may violate the queueing threshold since the traffic arrival process and service process are both stochastic. In this case, the violation probability of the queueing threshold d is bounded by

$$\begin{aligned} &Pr\{D(t) > d\} \\ \overset{(a)}{\leq}& Pr\{A(t) - A^*(t+d) > 0\} \\ \leq& Pr\{\sup_{0 \leq s \leq t} \{A(s,t) - \alpha(s,t) + \alpha(s,t) - \beta(s,t+d)\} \\ &\quad + A \otimes \beta(t+d) - A^*(t+d) > 0\} \\ \leq& Pr\{\sup_{0 \leq s \leq t} \{A(s,t) - \alpha(s,t)\} + A \otimes \beta(t+d) - A^*(t+d) \\ &\qquad > \inf_{0 \leq s \leq t} \{\beta(s,t+d) - \alpha(s,t)\}\} \\ \overset{(b)}{\leq}& [f_\alpha \otimes f_\beta(\inf_{0 \leq s \leq t} \{\beta(s,t+d) - \alpha(s,t)\})]_1 \end{aligned}$$

Here, step (a) holds because event $\{D(t) > d\}$ implies event $\{A(t) > A^*(t+d)\}$. In step (b), we applied Lemma 1 in Appendix A. Furthermore, $< f_\beta, \beta >$ is the stochastic service curve for flow A, which has been derived in the Theorem 1 of [35]. There holds

$$\begin{aligned} \beta(s,t) &= [\beta_{ove}(s,t) - \sum_{i=1}^{M} \alpha_i(s, t-\tau)]_+ I_{\{t-s>\tau\}} \\ f_\beta(x) &= f_{\alpha_1} \otimes \cdots \otimes f_{\alpha_M} \otimes f_{\beta_{ove}}(x) \end{aligned}. \quad (25)$$

Here, $\tau = 0$ means flow A is scheduled in the lowest priority among all the flows while $0 < \tau \leq t - s$ means all the flows are scheduled with FIFO principle.

Therefore, for the energy sufficiency case, we have

$$\begin{aligned} &Pr\{D(t) > d\} \\ \leq& [f_\alpha \otimes f_{\alpha_1} \otimes \cdots \otimes f_{\alpha_M} \otimes f_{\beta_{ove}}(\inf_{0 \leq s \leq t}\{[\beta_{ove}(s,t+d) \\ &- \sum_{i=1}^{M} \alpha_i(s, t+d-\tau)]_+ I_{\{t+d-s>\tau\}} - \alpha(s,t)\})]_1 \end{aligned}$$

In the end, the overall violation probability of the queueing threshold is bounded by

$$\begin{aligned} &Pr\{D(t) > d\} \\ =&[Pr\{D(t) > d | B(t) \leq b\} + Pr\{B(t) > b\}]_1 \\ \overset{(a)}{\leq}& [[f_\alpha \otimes f_\beta(\inf_{0 \leq s \leq t} \{\beta(s,t+d) - \alpha(s,t)\})]_1 \epsilon_m + \epsilon_b]_1 \\ \overset{(b)}{\leq}& [[f_\alpha \otimes f_\beta(\inf_{0 \leq s \leq t} \{\beta(s,t+d) - \alpha(s,t)\})]_1 + \epsilon_b]_1 \\ \leq& [f_\alpha \otimes f_{\alpha_1} \otimes \cdots \otimes f_{\alpha_M} \otimes f_{\beta_{ove}}(\inf_{0 \leq s \leq t}\{[\beta_{ove}(s,t+d) \\ &- \sum_{i=1}^{M} \alpha_i(s, t+d-\tau)]_+ I_{\{t+d-s>\tau\}} - \alpha(s,t)\}) + \epsilon_b]_1 \end{aligned}$$

In step (a), ϵ_m $(1 - \epsilon_b \leq \epsilon_m \leq 1)$ denotes the maximum probability that the battery has energy. In step (b), we loosened ϵ_m to 1, which is reasonable because ϵ_m must be quite close to 1 for a reliable communication system.

APPENDIX D
PROOF OF THEOREM 3

From the perspective of the system, the aggregated traffic flow is denoted by A_{ove}, and the corresponding departure of the buffer is denoted by A^*_{ove}. There holds $A_{ove}(s,t) = A(s,t) + \sum_{i=1}^{M} A_i(s,t)$ and $A^*_{ove}(s,t) = A^*(s,t) + \sum_{i=1}^{M} A^*_i(s,t)$.

Let us consider any time $t \geq 0$. Since the system is work-conserving, the proof can be classified into two cases.

Case 1: t is not in any backlogged period. In this case all the packets arrived up to time t have left the buffer before time t. Hence, $A_{ove}(t) = A^*_{ove}(t)$, and

$$\begin{aligned}&A_{ove} \otimes \beta_{ove}(t) - A^*_{ove}(t)\\ \leq &A_{ove}(0,t) + \beta_{ove}(t,t) - A^*_{ove}(t).\\ = &\beta_{ove}(t,t) - S(t,t)\end{aligned}$$

Case 2: t is within a backlogged period. Suppose t_0 is the start time of the last backlogged period and $t_0 \leq t$. That means $A^*_{ove}(t_0) = A_{ove}(t_0)$, and $A^*_{ove}(t_0,t) = S(t_0,t)$. Thus, we have

$$\begin{aligned}&A \otimes \beta_{ove}(t) - A^*_{ove}(t) \leq A_{ove}(t_0) + \beta_{ove}(t_0,t) - A^*_{ove}(t)\\ = &\beta_{ove}(t_0,t) - A^*_{ove}(t_0,t) = \beta_{ove}(t_0,t) - S(t_0,t)\end{aligned}.$$

Thus, for boht two cases and all $x > 0$, there exits $t_0 \leq t$ to hold as

$$\begin{aligned}&Pr\{A_{ove} \otimes \beta_{ove}(t) - A^*_{ove}(t) > x\}\\ \leq &Pr\{\beta_{ove}(t_0,t) - S(t_0,t)) > x\}\end{aligned},$$

where for the first case we let $t_0 = t$. Besides, for the service processes of all the channels $\{S_i(t) : 1 \leq i \leq N\}$, we have

$$S(t) = \sum_{i=1}^{N} S_i(t).$$

Since the service processes all have stationary increments, if $\{S_i(t) : 1 \leq i \leq N\}$ are all independent of each other, according to the Definition 2, there holds

$$\begin{aligned}&Pr\{A_{ove} \otimes \beta_{ove}(t) - A^*_{ove}(t) > x\}\\ \leq &Pr\{\beta_{ove}(t_0,t) - S(t_0,t) > x\}\\ \overset{(a)}{\leq} &e^{-\theta_a x}\mathbb{E}[e^{\theta_a(\beta_{ove}(t_0,t) - S(t_0,t))}]\\ = &e^{-\theta_a x}\mathbb{E}[e^{\theta_a(\sum_{i=1}^{N}(\beta_i(t_0,t) - S_i(t_0,t)))}]\\ \leq &e^{-\theta_a x}\prod_{i=1}^{N}\mathbb{E}[e^{\theta_a(\beta_i(t_0,t) - S_i(t_0,t))}]\\ \overset{(b)}{=} &e^{-\theta_a x}\end{aligned}.$$

Here, in step (a) we applied the Chernoff bound, and in step (b) we chosen the value $\beta_i(t) \leq -\frac{1}{\theta_a}\log\mathbb{E}[e^{-\theta_a S_i(t)}]$ $(1 \leq i \leq N)$.

On the other hand, if $\{S_i(t) : 1 \leq i \leq N\}$ are not independent, there holds

$$\begin{aligned}&Pr\{A_{ove} \otimes \beta_{ove}(t) - A^*_{ove}(t) > x\}\\ \leq &Pr\{\sum_{i=1}^{N}(\beta_i(t_0,t) - S_i(t_0,t)) > x\}\\ \overset{(a)}{\leq} &[\inf_{x_1+\ldots+x_N=x}\{\sum_{i=1}^{N}(Pr\{\beta_i(t_0,t) - S_i(t_0,t) > x_i\})\}]_1\\ \overset{(b)}{\leq} &[\inf_{x_1+\ldots+x_N=x}\{\sum_{i=1}^{N}(e^{-\theta_a x_i}\mathbb{E}[e^{(\theta_a(\beta_i(t_0,t) - S_i(t_0,t))}])\}]_1\\ \overset{(c)}{=} &[\inf_{x_1+\ldots+x_N=x}\{\sum_{i=1}^{N} e^{-\theta_a x_i}\}]_1\\ = &[Ne^{-\frac{\theta_a x}{N}}]_1\end{aligned}.$$

In step (a), we applied Lemma 1 in Appendix A. In step (b), we used the Chernoff bound. In step (c), we chosen the value $\beta_i(t) \leq -\frac{1}{\theta_a}\log\mathbb{E}[e^{-\theta_a S_i(t)}]$ $(1 \leq i \leq N)$. Hence, Theorem 3 is proved.

Appendix E
Proof of Stochastic Energy Harvesting Curve

According to Definition 3, we should prove the following expression

$$Pr\{\sup_{0 \leq s \leq t}\{-\frac{1}{\theta_e}\log\mathbb{E}[e^{-\theta_e E(s,t)}] - E(s,t) > x\}\} \leq e^{-\theta_e}.$$

We first introduce the definition of martingale.

Definition 5. ***(Martingale)*** [22, 36, 37] *Consider a stochastic process* $\boldsymbol{U} = \{U(t) : t \geq 0\}$ *such that* $U(t)$ *is integrable for all* t*. Let also a family* $\boldsymbol{F} = \{F_t : t \geq 0\}$ *of sub-*σ*-algebras of* F *satisfying two properties: (1)* $F_s \subseteq F_t$ *for all* $s \leq t$*, and (2)* $U(t)$ *is* F_t*-measurable for all* $t \geq 0$*.* $U(t)$ *is said to be a martingale iff for all* $0 \leq s \leq t$*, there holds*

$$\mathbb{E}[U(t)|F_s] = U(s).$$

Since $E(t)$ is compound Poisson process, it has independent and stationary increments. Consider a sequence of non-negative random variables $\{U(s) : 0 \leq s \leq t\}$, formed by

$$U_s = e^{\theta_e(-\frac{1}{\theta_e}\log\mathbb{E}[e^{-\theta_e E(s)}] - E(s))}.$$

Consider also the filtration of σ-algebras

$$F_s = \sigma\{E(i) : 0 \leq i \leq s\},$$

i.e., $F_s \subseteq F_t$ for all $s \leq t$. It is obvious that $U(s)$ is F_s-measurable for all $s \geq 0$ and $u \geq 0$, we consequently have

$$\begin{aligned}&\mathbb{E}[U(s+u)|F_s]\\ \overset{(a)}{=} &\mathbb{E}[U(s)e^{\theta_e(-\frac{1}{\theta_e}\log\mathbb{E}[e^{-\theta_e E(u)}] - E(s,s+u))}|F_s]\\ \overset{(b)}{=} &U(s)\mathbb{E}[e^{\theta_e(-\frac{1}{\theta_e}\log\mathbb{E}[e^{-\theta_e E(u)}] - E(s,s+u))}]\\ \overset{(c)}{=} &U(s)\frac{1}{\mathbb{E}[e^{-\theta_e E(u)}]}\mathbb{E}[e^{-\theta_e E(u)}]\\ = &U(s)\end{aligned}$$

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Here, step (a) and (b) hold since $E(t)$ has independent increments and $U(s)$ is F_s-measurable. Step (c) holds since $E(t)$ has stationary increments. Let $u = t - s$, we prove $U(t) = e^{\theta_e(-\frac{1}{\theta_e}\log \mathbb{E}[e^{-\theta_e E(t)}] - E(t))}$ is a martingale. We have

$$
\begin{aligned}
&Pr\{\sup_{0\le s\le t}\{-\frac{1}{\theta_e}\log \mathbb{E}[e^{-\theta_e E(s,t)}] - E(s,t) > x\}\} \\
=&Pr\{\sup_{0\le s\le t}\{e^{\theta_e(-\frac{1}{\theta_e}\log \mathbb{E}[e^{-\theta_e E(s,t)}] - E(s,t))}\} > e^{\theta_e x}\} \\
=&Pr\{\sup_{0\le s\le t}\{U(t-s)\} > e^{\theta_e x}\} \\
=&Pr\{U(1) > e^{\theta_e x}\} \\
=&Pr\{e^{\theta_e(-\frac{1}{\theta_e}\log \mathbb{E}[e^{-\theta_e E(1)}] - E(1))} > e^{\theta_e x}\} \\
\overset{(a)}{\le}& e^{-\theta_e x}\mathbb{E}[e^{\theta_e(-\frac{1}{\theta_e}\log \mathbb{E}[e^{-\theta_e E(1)}] - E(1))}] \\
=&e^{-\theta_e x}
\end{aligned}
.
$$

In step (a), we used the Chernoff bound. Therefore, $-\frac{1}{\theta_e}\mathbb{E}[e^{-\theta_e E(t)}]$ is a stochastic energy harvesting curve of $E(t)$ with violation probability $e^{-\theta_e x}$. According to the statistical information of $E(t)$, there holds

$$
-\frac{1}{\theta_e}\mathbb{E}[e^{-\theta_e E(t)}] = \frac{r_e t}{1+\theta_e L_e}.
$$

Thus, the stochastic energy harvesting curve of $E(t)$ is proved.

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