# Energy Efficiency and Delay Tradeoff in Wireless Powered Communication Networks

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***Abstract*—Energy efficiency (EE) and delay are two crucial metrics in WPCN. In general, the transmitter always transmits the information in a good channel state to improve EE while it may lead to delay due to waiting for a good channel state. Thus, there exists a tradeoff between EE and delay. In this paper, we investigate the EE and delay tradeoff with considering the time-varying channel and stochastic traffic arrivals. We formulate this problem as a stochastic optimization model, which optimizes the EE subject to both the data queue stability and the harvested energy availability. To solve the formulation, a general and effective algorithm, referred to as EE and delay tradeoff algorithm (EEDTA), is developed by employing the fractional programming method and Lyapunov optimization theory, which does not require any a prior distribution knowledge of channel states and data arrivals. Moreover, the theoretical analysis and simulation results show that the EEDTA achieves an EE-delay tradeoff, which mathematically depicted by [*O*(1/V),*O*(V)] with V as a control parameter, and can flexibly strike the tradeoff by simply tuning V. Simulation results verify the theoretical analysis.**

***Index Terms*—WPCN, EE, delay, time allocation, power control.**

## I. Introduction

The explosive growth of wireless communication services has triggered a dramatic increase in the energy consumption, which leads to a surge of carbon footprints and economic expenditures [1]. Facing the challenges from both ecology and economy, wireless powered communication network (WPCN), a newly emerging green wireless communication technology, has attracted considerable attention both in academia and industry. In typical WPCN systems, where the harvested radio frequency (RF) energy is attenuated by signal propagation, EE is particularly important from the aspect of the practical implementations. Additionally, quality of service (QoS) in terms of delay is another crucial metric in WPCN [2]. In general, to improve EE, the transmitter always transmits information when there is a good channel state. Unfortunately, undesirably high delay may emerge on account of waiting for a good channel state [3]. Thus, how to study the tradeoff between EE and delay is an interesting but challenging subject in WPCN.

The optimization of EE in WPCN was discussed in [4]–[6]. The author in [4] studied the resource allocation for EE optimization while guaranteeing the user's QoS in terms of the minimum rate requirement. In [5], joint time and power allocation problem was addressed to optimize EE for time division mode switching (TDMS) system. With considering both time allocation and energy beam-forming, an iterative algorithm was proposed in [6] to optimize EE in distributed massive multi-input multi-output (DM-MIMO) systems. However, the proposed algorithms in [4]–[6] are based on the assumptions of stationary channel conditions and infinite backlog, which is impracticable in realistic network, wherein channel conditions are time-varying and traffic arrivals are stochastic. Besides, the delay is neglected in [4]–[6], which is an important metric to measure the QoS of traffic. Literature [7] exhibited that there existed a banlance between EE and delay in other scenarios. To our best knowledge, the tradeoff between EE and delay in WPCN has not yet been investigated in the literature.

In this paper, we study the inherent EE and delay tradeoff by jointly considering time allocation and power control for the newly emerging WPCN systems.The problem is formulated as a stochastic optimization model to optimize the time-averaged EE under the constraints of the data queue stability and the harvested energy availability. With the aid of fractional programming method and Lyapunov optimization theory, we propose an EE and delay tradeoff algorithm (EEDTA) to tackle the formulated tough non-convex problem. The theoretical analysis proved that the developed EEDTA can flexibly tune the EE-delay performance and can achieve an EE-delay tradeoff of [***O***(1/V),***O***(V)], where V is a control parameter.

## II. System Model and Preliminaries

### A. System Model

We consider a WPCN consisting of a power station (PS), $K$ wireless powered devices (WPDs) and a information receiving station (IRS). Denote the PS with $k = 0$ and these $K$ WPDs with $k = 1, \cdots, K$. A system model is shown in Figure 1. Assuming all of the nodes in our system are operating in the time division multiplexing access (TDMA) mode over the same frequency band. In the WET stage, the PS transfers RF signal to WPDs and the IRS receives the information from WPDs in the WIT stage. Both the PS and IRS have a fixed power supply. Each WPD is equipped with two buffers, i.e., data buffer and energy buffer. These $K$ WPDs have to store the harvested energy from PS into the energy buffer first and utilize it to communicate with IRS later.

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To simplify the analysis, we adopt a time frame structure, which is illustrated in Figure 2. We divide the time horizon into time slots indexed by $t$ and assume a normalized unit time slot for convenience. Let $\tau_0(t), \tau_1(t), \tau_2(t), \cdots, \tau_K(t)$ be the time portions allocated to the PS and WPD $1, 2, \cdots, K$, respectively. At the beginning of the time-slot $t$, i.e., $\tau_0(t)$, the PS transfers the RF signal to WPDs. And during the remanent time portion $1-\tau_0(t)$, the $K$ WPDs send messages to the IRS. Note that the user WPD $k$ can only transmit the information to the IRS during its allocated time portion $\tau_k(t)$ in time-slot $t$.

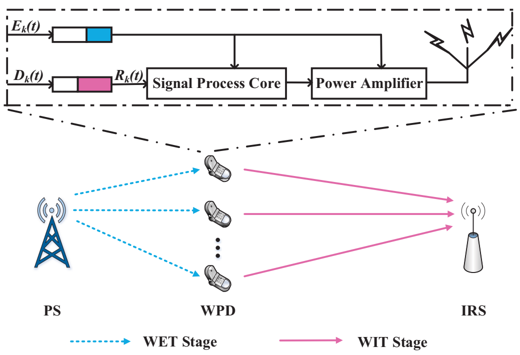


Figure 1. Network structure

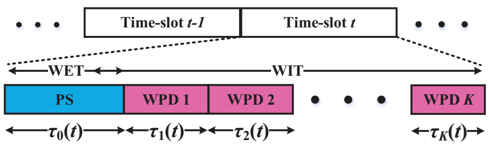


Figure 2. Frame structure

### B. Power Consumption Model

For the considered WPCN system, the total energy consumption consists of two parts: the energy consumed during WET stage and WIT stage. Assume the energy consumption of a transmitter includes two parts, the over-the-air transmit energy consumption and the circuit energy consumption. And the circuit energy consumption is neglected when no transmission happens [2].

Denote the downlink and the uplink channel gains in time-slot $t$ by $h_k(t)$ and $g_k(t)$, respectively. During the WET stage, the PS broadcasts the RF signal to WPDs with the power $P_0^{tr}(t)$. Then the energy harvested at WPD $k$ in time-slot $t$ is

$$W_k(t) = \eta_k \tau_0(t) P_0^{tr}(t) H_k(t), \forall k \neq 0, \tag{1}$$

where $\eta_k \in (0, 1]$ represents for the energy conversion efficiency of WPD $k$ and $H_k(t) \triangleq |h_k(t)|^2$. Let $Q_k^W(t)$ denote the energy queue at time-slot $t$ and we obtain the dynamics of the energy queue

$$Q_k^W(t+1) = [Q_k^W(t) - (P_k^{tr}(t) + P_k^{ci}(t))\tau_k(t)]^+ + W_k(t), \tag{2}$$

where $[x]^+ = \{x, 0\}$. During the WET stage, the overall energy cost $W_{\mathrm{WET}}(t)$ is

$$W_{\mathrm{WET}}(t) = P_0^{tr}(t)\tau_0(t) - \sum_{k=1}^{K} W_k(t) + P_0^{ci}(t)\tau_0(t), \tag{3}$$

where $P_0^{ci}(t)$ is the constant circuit power consumption of the PS, and $P_0^{tr}(t)\tau_0(t) - \sum_{k=1}^{K} W_k(t)$ is the energy loss due to wireless channel propagation. During the WIT stage, the energy consumption, i.e., $W_{\mathrm{WIT}}(t)$, is

$$W_{\mathrm{WIT}}(t) = \sum_{k=1}^{K} \left(P_k^{tr}(t)\tau_k(t) + P_k^{ci}(t)\tau_k(t)\right), \tag{4}$$

where $P_k^{ci}(t)$ is the constant circuit power consumption of the WPD $k$. Thus, we obtain the total energy consumption of the system in time-slot $t$, denoted by $W_{\mathrm{A}}(t)$

$$W_{\mathrm{A}}(t) = W_{\mathrm{WET}}(t) + W_{\mathrm{WIT}}(t). \tag{5}$$

### C. Energy Efficiency

For the WPD $k$, given the transmit power $P_k^{tr}(t)$ and allocated time $\tau_k(t)$, we attain the achievable data rate

$$R_k(t) = \tau_k(t)\log_2\left(1 + \frac{P_k^{tr}(t)G_k(t)}{B\sigma^2}\right), \tag{6}$$

where $\sigma^2$ is the noise power spectral density, $B$ is the system bandwidth, and $G_k(t) = |g_k(t)|^2$. Then, the total transmission rate of the system at time-slot $t$ is

$$R_A(t) = \sum_{k=1}^{K} R_k(t). \tag{7}$$

Let $Q_k^D(t)$ denote the data queue. The dynamics of the data queue is

$$Q_k^D(t+1) = [Q_k^D(t) - R_k(t)]^+ + D_k(t), \tag{8}$$

where $D_k(t)$ is the arrival data rate at time-slot $t$. In practical system, the achievable rate $R_k(t)$ and the arrival data rate $D_k(t)$ always have upper bounds, i.e., $R_k^{max}$ and $D_k^{max}$. Note that the average delay is proportional to the average queue length for a given traffic arrival rate according to Little's Theorem [8]. And the data queue is stable if it has a finite time-averaged queueing delay. Thus, we can depict the time-averaged queueing delay through data queue length.

Define the EE of the considered WPCN system as the ratio of the long-term total energy consumption to the corresponding time-averaged aggregate data delivered. Then the EE is

$$\begin{aligned}\rho_{ee} &= \lim_{t\to\infty} \frac{\sum_{v=1}^{t} \mathbb{E}\{W_A(\boldsymbol{\tau}(v), \boldsymbol{P^{tr}}(v))\}}{\sum_{v=1}^{t} \mathbb{E}\{R_A(\boldsymbol{\tau}(v), \boldsymbol{P^{tr}}(v))\}} \\ &= \frac{\lim_{t\to\infty} \frac{1}{t}\sum_{v=1}^{t} \mathbb{E}\{W_A(\boldsymbol{\tau}(v), \boldsymbol{P^{tr}}(v))\}}{\lim_{t\to\infty} \frac{1}{t}\sum_{v=1}^{t} \mathbb{E}\{R_A(\boldsymbol{\tau}(v), \boldsymbol{P^{tr}}(v))\}} = \frac{\overline{W}_A}{\overline{R}_A}, \end{aligned} \tag{9}$$

where $\boldsymbol{P^{tr}}(v) = \{(P_k^{tr}(v)), k = 0, 1, 2, \cdots\}$, $\boldsymbol{\tau}(v) = \{\tau_k(v), k = 0, 1, 2, \cdots\}$, $\overline{W}_A$ and $\overline{R}_A$ are defined as the time-averaged energy consumption and the time-averaged transmission rate, respectively. Without loss of generality, we assume both $\overline{W}_A$ and $\overline{R}_A$ are positive. The definition of EE in our paper is different from [2], where EE is defined in a static perspective.

### *D. Problem Formulation*

We minimize the time-averaged EE subject to both the data queue stability and the harvested energy availability constraints to reveal the fundamental tradeoff between EE and delay. Hence, we formulate the problem as follows

$$
\begin{aligned}
\mathcal{P}1: &\min_{\tau_k(t), P_k^{tr}(t)} \quad \rho_{ee} = \frac{\overline{W}_A}{\overline{R}_A} \\
\text{s.t.}\ \ & \text{C1}: \sum_{k=0}^{K} \tau_k(t) \le 1, \forall t \\
& \text{C2}: P_0^{tr} \le P_0^{max} \\
& \text{C3}: (P_k^{tr}(t) + P_k^{ci}(t))\tau_k(t) \le Q_k^W(t) + W_k(t), \forall k \ne 0 \\
& \text{C4}: \lim_{v\to\infty} \frac{1}{v} \sum_{t=1}^{v} Q_k^D(t) < \infty.
\end{aligned} \tag{10}
$$

In (10), $P_0^{max}$ is the maximum transmit power of the PS. C1 means the sum of the allocated time to the PS and the WPDs is not larger than 1 account for each time-slot is normalized to be unit. C2 is the peak transmit power constraint of the PS. C3 ensures that the energy consumed for WIT does not exceed the total available energy in the energy buffer at the present moment. C4 ensures that the data queue is stable.

It is obvious that problem $\mathcal{P}1$ is a stochastic optimization problem, which is non-convex, and the resource allocation $P_k^{tr}$ and $\tau_k$ are coupled. Such a problem can be solved by using techniques such as dynamic programming [9], which may lead to the curse of dimensionality and is of high computational complexity. To avoid this challenge, we propose an effective algorithm, which is described in detail in the next section.

## III. EE and Delay Tradeoff

In this section, with the aid of fractional programming, we change the non-convexity $\mathcal{P}1$ into $\mathcal{P}2$, which is a linear programming. We transform $\mathcal{P}4$ into a series of successive optimization problem by employing Lyapunov optimization theory and then obtain a convex problem. By solving this problem, we reveal the tradeoff between the EE and delay.

### *A. Equivalent Problem Transformation*

Problem $\mathcal{P}1$ is a nonconvex optimization problem, while we find it belongs to nonlinear fractional programming. By utilizing the Dinkelbach's method [10] we transform $\mathcal{P}1$ into the following optimization problem

$$
\begin{aligned}
\mathcal{P}2: \quad &\min_{\tau_k(t), P_k^{tr}(t)} \quad \overline{W}_A(\boldsymbol{\tau}, \boldsymbol{P^{tr}}) - \rho_{ee}^{*}\overline{R}_A(\boldsymbol{\tau}, \boldsymbol{P^{tr}}) \\
&\text{s.t.}\ \ \text{C1}, \text{C2}, \text{C3}, \text{C4}.
\end{aligned} \tag{11}
$$

However, it is also difficult to solve $\mathcal{P}2$ because we cannot identify the value of $\rho_{ee}^{*}$ which is the objective of $\mathcal{P}1$. We propose $\rho_{ee}(t)$ for $t \in \{1, 2, 3, \cdots\}$ with $\rho_{ee}(0) = 0$ as

$$
\rho_{ee}(t) = \frac{\sum_{v=1}^{t-1} \mathbb{E}\{W_A(\boldsymbol{\tau}(v), \boldsymbol{P^{tr}}(v))\}}{\sum_{v=1}^{t-1} \mathbb{E}\{R_A(\boldsymbol{\tau}(v), \boldsymbol{P^{tr}}(v))\}}. \tag{12}
$$

Replace $\rho_{ee}^{*}$ by $\rho_{ee}(t)$, then $\mathcal{P}2$ is casted as $\mathcal{P}3$:

$$
\begin{aligned}
\mathcal{P}3: \quad &\min_{\tau_k(t), P_k^{tr}(t)} \quad \overline{W}_A(\boldsymbol{\tau}, \boldsymbol{P^{tr}}) - \rho_{ee}(t)\overline{R}_A(\boldsymbol{\tau}, \boldsymbol{P^{tr}}) \\
&\text{s.t.}\ \ \text{C1}, \text{C2}, \text{C3}, \text{C4}.
\end{aligned} \tag{13}
$$

For simplicity, we use term $\overline{W}_A(t)$ to refer to $\overline{W}_A(\boldsymbol{\tau}, \boldsymbol{P^{tr}})$, and $\overline{R}_A(t)$ to refer to $\overline{R}_A(\boldsymbol{\tau}, \boldsymbol{P^{tr}})$ in the following discussion.

### *B. PS Transmit Power*

*Theorem 1:* In order to obtain the optimal EE, the PS should transmit the energy at the maximum power, i.e. , $P_0^{tr*} = P_0^{max}$.

*Proof*: We prove the *Theorem 1* through contradiciton. We propose two solutions to $\mathcal{P}3$. The first one is supposing the optimal solution to $\mathcal{P}3$ in time-slot $t$ is $\Phi^* = \{P_0^{tr*}(t), P_k^{tr*}(t), \tau_0^*(t), \tau_k^*(t)\}, \forall k \ne 0$, and supposing the PS transmit power satisfies $P_0^{tr*}(t) < P_0^{max}(t)$. Under such an assumption we obtain the optimal solution $\Phi^*$ denoted by $\rho^*$. The other one solution is $\Phi' = \{P_0^{tr\prime}(t), P_k^{tr\prime}(t), \tau_0'(t), \tau_k'(t)\}, \forall k \ne 0$, and suppose the PS transmit power satisfies $P_0^{tr\prime}(t) = P_0^{max}(t)$. The corresponding optimal value is $\rho'$. Furthermore, we assume the difference between the two solutions only exists in the WET stage, i.e., the condition in WIT stage between two solutions is same. Then we have $\forall k \ne 0, P_0^{tr*}(t)\tau_0^*(t) = P_0^{tr\prime}(t)\tau_0'(t), \tau_k^*(t) = \tau_k'(t), P_k^{tr*}(t) = P_k^{tr\prime}(t), W_k^*(v) = W_k'(v), R_k^*(v) = R_k'(v)$, and thus we obtain $\rho^* > \rho'$ which contradicts the assumption that $\rho^*$ is the optimal solution. *Theorem 1* is thus proved. □

### *C. Lyapunov Optimization Theory*

Observing $\mathcal{P}3$, we find it is a nonconvex problem which couples with both static constraints C1-C3 and time-averaged constraint C4. Lyapunov optimization is a method which considers the joint problem of stability queue and optimizing performance. Utilize the property of Lyapunov optimization theory, we can solve $\mathcal{P}3$. Define the Lyapunov function as

$$
L(Z(t)) = \frac{1}{2}\sum_{k=1}^{K}(Q_k^D(t))^2, \tag{14}
$$

where $Z(t) = \{Q_k^D(t) : k = 1, 2, \cdots, K\}$. Then we describe the one-step conditional Lyapunov drift according to the update equation of $Q_k^D(t)$ as

$$
\triangle\{Z(t)\} = \mathbb{E}\{L(Z(t+1)) - L(Z(t))|Z(t)\}, \tag{15}
$$

where $\mathbb{E}\{\cdot\}$ denotes the expectation operator. According to the dynamic data queue equation (8), we have the following Lyapunov drift

$$
\triangle\{Z(t)\} \le C^{max} - \sum_{k=1}^{K} E\{Q_k^D(t)R_k(t)|Z(t)\}, \tag{16}
$$

$$C^{max} = \frac{1}{2}\sum_{k=1}^{K}\left((R_k^{max})^2 + (D_k^{max})^2 + 2Q_k^D(t)D_k(t)\right). \quad (17)$$

The Lyapunov drift-plus-penalty approach is

$$\triangle\{Z(t)\} + VE\{W_A(t) - \rho_{ee}(t)R_A(t)|Z(t)\} \le C^{max} +$$
$$E\{V(W_A(t) - \rho_{ee}(t)R_A(t)) - \sum_{k=1}^{K} Q_k^D(t)R_k(t)|Z(t)\}, \quad (18)$$

where $V(V > 0)$ is an arbitrary system control parameter, and it is regraded as the "importance weight" on how much we emphasize on the EE or delay. By controlling $V$, we can adjust the EE and delay tradeoff.

Based on the analysis above, to minimize the righthand of (18) we can jointly consider the time and power allocation with the data queue being stable. According to Lyapunov optimization theory, we can solve $\mathcal{P}3$ by solving the following optimization problem

$$\mathcal{P}4: \max_{\tau_k(t), P_k^{tr}(t)} \sum_{k=1}^{K} Q_k^D(t)R_k(t) - V(W_A(t) - \rho_{ee}(t)R_A(t))$$
$$\text{s.t.} \quad \text{C1, C2, C3}. \quad (19)$$

According to *Theorem 1* we attain the equivalent problem $\mathcal{P}5$ in next page, where $Y_k(t) \triangleq \eta_k P_0^{max} H_k(t), \forall k \neq 0$ and $e_k(t) \triangleq \tau_k(t)P_k^{tr}, \forall k \neq 0$. It is easy to prove that $\mathcal{P}5$ is a convex optimization problem. The detail of the proof is omitted to avoid redundancy.

Now, we transfer the original stochastic optimization problem $\mathcal{P}1$ into a static deterministic optimization problem $\mathcal{P}5$, which is convex and can be solved by standard convex optimization techniques, e.g., the interior point method.

Based on the analysis in the last subsection, we propose an EE and delay tradeoff algorithm, referred to as EEDTA, as following

**Algorithm 1** EEDTA

1: **Input**: $P_0^{max}, \{P_k^{ci} : k = 0, 1, ..., K\}, K, \sigma^2, B, V$, the maximum tolerance $\epsilon$;
2: At the beginning of each time-slot $t$, observe the current queue states $Q_k^D(t), Q_k^E(t), \forall k \neq 0$ and the channel gains $h_k(t), g_k(t), \forall k \neq 0$.
3: Update $Q_k^D(t), Q_k^W(t)$ and $\rho_{ee}(t)$ according to (2), (8) and (12), respectively.
4: Repeat step 2-3 in each time-slot.

### D. Performance Analysis

In order to evaluate the performance of the proposed algorithm and analyze the fundamental tradeoff between EE and delay, we introduce a Lemma first and make some assumptions.

*Lemma 1:* Suppose that $\boldsymbol{\lambda}$ is strictly interior to the capacity region $\Psi$, and that $\boldsymbol{\lambda} + \varepsilon$ is still in $\Psi$ for a positive $\varepsilon$. Suppose that $\mathcal{P}1$ is feasible, i.e., given average arrival data rate $\lambda_k, \forall k \neq 0$, that there exists at least a power and time allocation solution to satisfy all of the constraints in $\mathcal{P}1$, and that is, given average arrival data rate $\lambda_k + \varepsilon, \forall k \neq 0$, $\mathcal{P}1$ is also feasible. Then, for any $\delta > 0$, there exists an i.i.d. algorithm that satisfies

$$E\{W_A^\omega(t)\} \le E\{R_A^\omega(t)\}(\rho_{ee}^{opt} + \delta), \quad (21)$$

$$E\{R_k^\omega(t)|Z(t)\} \le E\{R_k^\omega(t)\} \ge \lambda_k + \varepsilon, \quad (22)$$

where $W_A^\omega(t)$, $R_A^\omega(t)$ and $R_k^\omega(t)$ are the resulting values under i.i.d. algorithm $\Theta^\omega(t)$.

*Proof:* The proof of *Lemma 1* can be found in [11]. □

*Assumption 1:* Notice that the transmit power of the PS is bounded by $P_0^{max}$ in reality and the circuit power consumption is constant, hence we assume that the time-averaged power consumption is bounded by the $P_{max}$.

By exploiting *Lemma 1* and the assumption above, we are now ready to answer how the performance of the EEDTA is. And we have the following two bounds

$$\rho_{ee} \le \rho_{ee}^{opt} + \frac{c^{max}/R_{min}}{V}, \quad (23)$$

$$\overline{Q} \le \frac{c^{max} + V(\rho_{ee}^{opt}R_{max} + P_{max})}{\varepsilon}, \quad (24)$$

where $\rho_{ee}$ denotes for the solution obtained by our proposed algorithm and $\rho_{ee}^{opt}$ represents for the optimal value obtained by solving $\mathcal{P}1$. $\overline{Q}$ is the time-averaged data queue length. $R_{max}$ ($R_{min}$) is the maximum (minimum) transmission rate.

*Proof:*The proof of (23) and (24) is similar to [7] thus we omit it for space-saving.

## IV. Simulation Results

In this section, simulations are provided to validate our theoretical results and analyze the EE and delay tradeoff. We set four WPDs randomly and uniformly distributed on the right hand side of PS with the reference distance of 2 meters and the maximum service distance is 15 meters. The IRS is located 150 meters far away from the PS. We jointly consider the path loss and small-scale Rayleigh fading. The simulation parameters are shown in Table I. For simplicity, we assume the energy conversion efficiencies are equal for all WPDs, i.e., $\eta_k = \eta$. Similarly, we set $\lambda_k = \lambda, \forall k \neq 0$, and $P_k^{ci} = P_k, \forall k \neq 0$.

Table I
List of Simulation Parameters.

| | |
|---|---|
| Path loss exponent $\varrho$ | 3 |
| System bandwidth $B$ | 1MHz |
| Power spectral density of noise $\sigma^2$ | -174 dBm/Hz |
| Maximum transmit power of the PS $P_0^{max}$ | 10 Watt |
| WPD's energy conversion efficiencies $\eta$ | 0.9 |
| Data buffer size $B^D$ | 1000 bit/Hz |
| Energy buffer size $B^W$ | 10 Joule |
| Circuit power of PS $P_0^{ci}$ | 0.05 Watt |
| Circuit power of PS $P_k^{ci}$ | 0.001 Joule |

Figure 3 displays the resulting EE against control parameter $V$. As $V$ increases, $\rho_{ee}$ converges, and according to (23), $\rho_{ee}$ can be arbitrarily approach to $\rho_{ee}^{opt}$ for large enough $V$. Besides, $\rho_{ee}$ decreases to the optimal at the speed of $\boldsymbol{O}(1/V)$ as $V$

$$
\begin{aligned}
\mathcal{P}5: \qquad & \max \quad \sum_{k=1}^{K} \left(Q_k^D(t) + V\rho_{ee}(t)\right)\tau_k(t)\log_2\left(1 + \frac{e_k(t)\gamma_k(t)}{\tau_k(t)}\right) - V\sum_{k=1}^{K}\left(e_k(t) + p_k^{ci}\tau_k(t)\right) \\
& \qquad -V\left(P_0^{max}(t) + P_0^{ci} - \sum_{k=1}^{K} Y_k(t)\right)\tau_0(t) \\
& \text{s.t.} \quad \begin{cases} \sum_{k=0}^{K}\tau_k(t) \le 1, \\ e_k(t) + P_k^{ci}\tau_k(t) \le Q_k^E(t) + Y_k(t)\tau_0(t), \forall k \ne 0. \end{cases}
\end{aligned} \tag{20}
$$

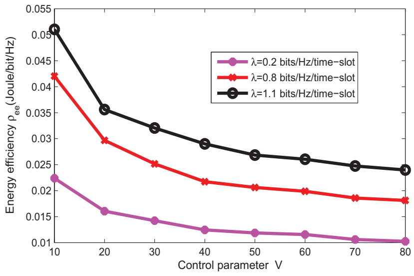


Figure 4. EE against V

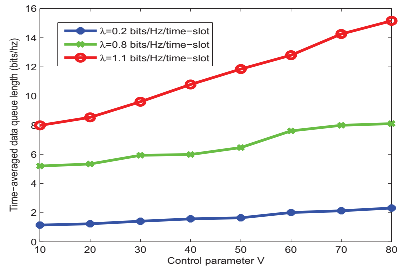


Figure 5. Time-averaged queue length against V

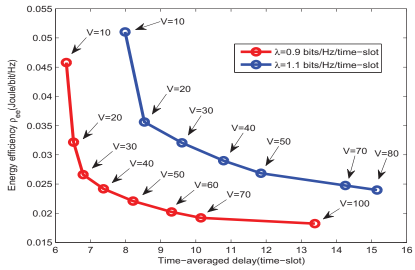


Figure 6. EE and delay tradeoff

increases for any given $\lambda$. As shown in Figure 4, the time-averaged queue length is bounded which verifies the correctness of the (24). As expected, $\overline{Q}$ increases at the speed of $\boldsymbol{O}(V)$ as $V$ increases. And $\overline{Q}$ is larger with a larger $\lambda$, which is following from Little's theorem. Jointly considering Figure 3 and Figure 4, it is obviously that there exists a tradeoff between EE and delay, which is verified in Figure 5.

Figure 5 shows the EE and delay tradeoff with different $\lambda$ for the considered WPCN. It is shown that with larger the time-averaged delay, the less EE is obtained. And with the analysis above, it is easy to find that the tradeoff is quantitatively characterized by $[\boldsymbol{O}(1/V), \boldsymbol{O}(V)]$. Moreover, we can adjust the tradeoff by controlling the parameter $V$. That is, if we pay more attention to EE but not the delay, we can increase $V$, and vice versa.

## V. Conclusions

In this paper, we jointly considered time allocation and power control to investigate the tradeoff between EE and delay for WPCN. We formulated a stochastic optimization problem subject to both the data queue stability and the harvested energy availability and solved the problem through the exploitation of fractional programming and Lyapunov optimization theory to reveal the tradeoff. Correspondingly, an EE and delay tradeoff algorithm (EEDTA) was proposed, which can push the EE arbitrarily close to the optimal without any a prior distribution knowledge of CSI and traffic arrivals.

## VI. Acknowledgement

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