# Throughput Maximization for the Wireless Powered Communication in Green Cities

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***Abstract*—Wireless power transfer (WPT) is a recently developed technique to perfectly address the energy problem for smart city sensors that do not have a readily wired power supply. In a radio-frequency-powered wireless communication system, sensors first harvest energy via the radio-frequency WPT, and then, transmit sensed data to the receiver. The "harvest-then-transmit" protocol is used to coordinate the two operations, in which we wish to optimally decide when to harvest energy, when to transmit data, and what transmission rate should be used such that the data are maximally transmitted. Unlike existing works, we assumed that the wireless transferred power is dynamically changing, instead of being constant, which is more realistic in green smart city applications, e.g., Industry 4.0 workshop, smart transportation, and smart buildings, where environments are continuously changing, so the wireless transferred power is affected dynamically. In this paper, we present an optimal scheduling algorithm for the offline case where the varying WPT is known in advance. Based on the optimal principles learned from the offline case, we have designed an efficient online algorithm. Finally, we report our simulation results that demonstrate that our online scheduling algorithm can adaptively and efficiently achieve high data throughput.**

***Index Terms*—Harvest-then-transmit, optimal offline algorithm design, time-varying wireless power, wireless power transfer (WPT), wireless powered communication.**

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## I. Introduction

IN SMART cities, a massive number of sensors and devices need to be deployed to conduct various monitoring to support smart city applications. However, not all deployed sensors have a readily wired power supply. Maintaining sufficient available energy becomes a major issue for these wireless devices, affecting their working lifetime, and thus, the functionality of related smart city applications. Recently, a wireless power transfer (WPT) technique is being developed to address this problem. A number of major achievements have been obtained and reported [1]–[8]. For example, the hardware for wireless power receivers have been built that are able to harvest energy from everyday radio-frequency (RF) signals such as TV broadcast signals [1], WiFi signals [2], and Bluetooth signals [3]. Meanwhile, hardware for wireless power chargers have also been built that can charge multiple devices concurrently [4], [5]. The wireless power charger placement problems have been recently investigated in [6]–[8].

The WPT has many potential applications in green smart cities. For example, in industry 4.0 workshops, wireless sensors deployed on moving parts of machines or on workers harvest energy wirelessly and transmit sensed data to Internet-of-Things gateways; in smart buildings, portable surveillance cameras, which can be rapidly deployed on demand, receive wireless power, and stream video to a wireless access point; and in smart transportations, speed radars are charged by the WPT and deliver traffic speed data to a long-term-evolution base station. These application scenarios are shown in Fig. 1.

In WPT-enabled wireless devices, the "harvest-then-transmit" (HTT) protocol is widely adopted [9], [10], [18]–[21], such that they first harvest energy, and then, use this energy to transmit data. The power transfer and data transmission are separated in the RF-powered wireless communication for many reasons, e.g., one antenna needs be shared by the two modules [14], [22], limited bandwidth needs be shared by the two operations [15], hybrid access points or cellular systems are designed to separate downlink from uplink [9], [16], [20], and a battery cannot be charged and discharged at the same time, e.g., battery half duplex [17].

This paper studies how to design an HTT protocol to transmit the maximum amount of data in a given time duration. More especially, we wish to optimally determine when we should do power transfer (charging), when should do data transmission (sending), and what transmission rate we should use such that

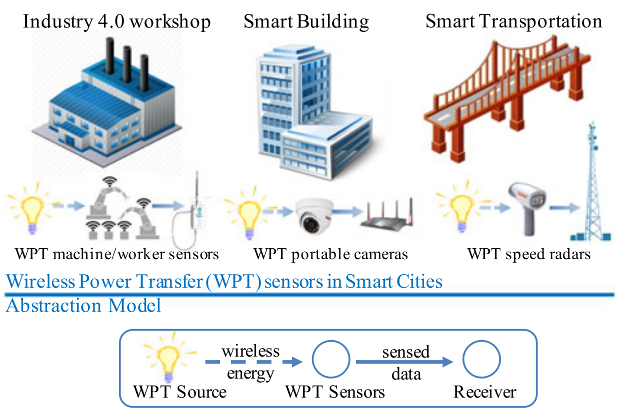


Fig. 1. WPT applications in smart cities.

the maximum amount of data can be transmitted with the limited harvested power.

Most existing research works on this problem assume that the WPT is static and stable [9], [10], [18], [19]. Ju *et al.* [9] are among the first group of researchers to investigate this problem. They have observed an important tradeoff that setting a longer charging time leads to a shorter transmission time but at a higher transmission rate since more energy would have been charged, while setting a shorter charging duration results in a lower transmission rate but a longer sending duration. They have proposed a way of finding the best time allocation to achieve the maximum data throughput. Zewde *et al.* [10] extend this result by further considering quality of service (QoS) constraints, while Liu *et al.* [18] extend this result by introducing the fairness for multiple users. Zhao *et al.* [19] have also studied the same throughput maximization problem and proposed a numerically searching technique to solve it.

As a related work, our previous study [20] on the WPT also assumed stable power transfer but studies a different optimization problem, in which we have analytically solved this problem and designed an HTT protocol to achieve the minimum delay for transmitting a given set of data packets.

As can be seen, most related research works [9], [10], [18]–[20] have assumed that the WPT is at a constant rate over time. However, in scenarios like Industry 4.0 workshops, smart transportations, and smart buildings, environments are continuously changing, hence, the WPT at a distance is affected dynamically. Two research papers [21] and [22] have considered such a time-varying wireless power supply. However, solutions/algorithms from both papers rely on known stochastic distribution information to ease theoretical analysis, which is usually unavailable in real-world scenarios.

Our contributions in this paper are summarized as follows.

1) We formulate an adaptive *HTT-scheduling* problem aiming at throughput maximization for the time-varying power transfer WPT channels.
2) As the first step, we have solved the simple case where the power transfer is stabe at a constant rate. A surprising discovery is that the optimal transmission rate is independent of the length of the transmission time, but solely depends on the power transfer rate.
3) Based on such a stepping-stone result, we present an optimal scheduling algorithm for the offline case where the varying WPT is known in advance.
4) Following the optimality principles learned from the offline case, we have designed an online heuristic algorithm that does not rely on stochastic distribution information. Simulations have demonstrated its superior performance.

The remainder of this paper is organized as follows. In Section II, we formally define the system model and the optimization problem. A set of optimality principles for the adaptive *HTT scheduling* is obtained and presented in Section III. An optimal scheduling algorithm for the offline problem is presented in Sections IV and V. Section VI proposes an online algorithm and introduces the simulation results. Sections VII concludes this paper.

## II. Problem Formulation

### A. System Model

We consider a simple communication channel consisting of a data receiver and a wireless powered data transmitter. The transmitter transmits data to the receiver over an additive white Gaussian noise (AWGN) wireless communication channel, which is widely adopted in the literature [9]–[13], [19], [20], [23]. A power source, such as TV/WiFi broadcasting signal, cellular signal, or power beacon, is assumed to provide the wireless power to the transmitter. The HTT protocol requires the transmitter to first receive energy, and then, transmit data. At any moment, the transmitter can either receive power or transmit data, but not at the same time [9], [14]–[17], [20], [22].

Time is equally slotted with each slot being one unit of time. Let $T$ be the total number of slots to be scheduled and slots are labeled in sequence, $1, 2, \ldots, T$. We assume the length of each slot is so small such that the power being transferred within each slot is at a constant rate. However, it may vary from slot to slot. Let vector $\mathbf{p} = \{p_1, p_2, \ldots, p_T\}$ denote the WPT rate, where $p_i$ is the rate in slot $i$, $i = 1, 2, \ldots, T$. It is also called the *supply power vector*. For simplicity, we assume all supply powers are distinct, e.g., $p_i \neq p_j \ \forall i \neq j$. Our results can be easily extended. Each Slot $i$ is divided into two phases, the *charging phase* $i$ and the *sending phase* $i$, with the corresponding lengths to be $1 - \beta_i$ and $\beta_i$ respectively, $i = 1, 2, \ldots, T$. Moreover, if $\beta_i = 0$, slot $i$ is called a *charging slot*. It is called a *sending slot* if $\beta_i = 1$. In *sending phase* $i$, the transmission power is denoted as $\rho_i$, which is subject to the *range constraint*, $0 \leq \rho_i \leq \rho_{\max} \ \forall i \in [0, T]$, where $\rho_{\max}$ is the maximum transmission power imposed by the hardware.

Fig. 2 shows a possible scenario to illustrate the notions of time slot, transmission power in each slot, charging phase, and sending phase.

### B. Problem Formulation

Let $H(t)$ be the total energy charged into the battery in the first $t$ time slots, which can be calculated as $H(t) = \sum_{i=1}^{t} p_i(1 - \beta_i)$, $\ t = 1, 2, \ldots, T$. Let $E(t)$ be the total energy consumed in the first $t$ time slots, which can be calculated as $E(t) =$

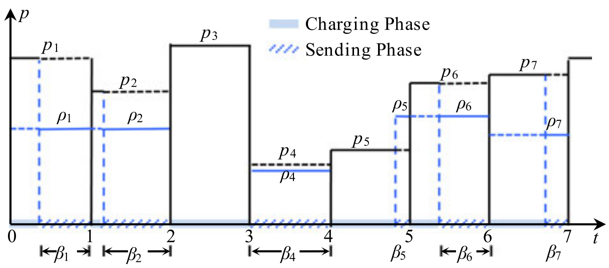


Fig. 2. Time is slotted and wireless supply power $p_i$ varies from slot to slot. Each time slot is divided into a charging phase and a sending phase. A phase can be of zero length. Lengths $\beta_i$ and transmission powers $\rho_i$, $1 \le i \le T$, are to be determined in order to maximize the throughput.

$\sum_{i=1}^{t} \rho_i \beta_i,\ \ t = 1, 2, \ldots, T$. Let $R(t)$ be the remaining energy in the battery at the end of slot $t$, which can be calculated as $R(t) = E_{\text{init}} + H(t) - E(t),\ \ t = 1, 2, \ldots, T$. For any $t$, $R(t)$ must be equal to or larger than 0, which is called the *energy causality constraint*, $R(t) \ge 0, t = 1, 2, \ldots, T$.

In sending phase $i$, the transmission power $\rho_i$ is related to the transmission rate $r_i$ through the *power-rate function* $r_i = \log(1 + \rho_i), i = 1, 2, \ldots, T$, as commonly assumed for a single-user point-to-point AWGN channel [9]–[13], [19], [20], [23]. As a result, the total amount of data transmitted during the time interval $[1, T]$, from the start of slot 1 to the end of slot $T$, can be calculated by $B = \sum_{i=1}^{T} r_i \beta_i = \sum_{i=1}^{T} \beta_i \log(1 + \rho_i)$. $B$ is also called the *data throughput*.

*Definition 1:* Given a WPT system as described previously, including $\mathbf{p}$ and $E_{\text{init}}$, the maximum throughput HTT-scheduling (maxT-HTTs) problem is to determine the lengths $\{\beta_i\}$ and its transmission powers $\{\rho_i\}$ for each sending phases $i$, such that the data throughput $B$ is maximized under the constraints *range constraint* $0 \le \rho_t \le \rho_{\max}$ and *energy causality constraint* $R(t) \ge 0, 1 \le t \le T$.

In the offline *maxT-HTTs* problem, $\mathbf{p}$ is completely known before scheduling. It is called online problem if the values of $\beta_t$ and $\rho_t$ are determined based on the first $t$ elements in $\mathbf{p}$, that is, $\{p_1, p_2, \ldots, p_t\}$.

## III. *sOPT* Power

In this section, we introduce the notion of *sOPT power* that will play a key role in designing an optimal scheduling. Let us first investigate the following basic problem, which is a simple version of the *maxT-HTTs* problem of Definition 1. There are following three assumptions: 1) the wireless supply power is at a constant rate $p$ for every slot; 2) the entire time span $(0, T)$ is treated as a single time slot and it will be divided into two phases; and 3) initial energy $E_{\text{init}}$ and power limitation $\rho_{\max}$ are ignored. Let $\beta$ be the ratio of the length of the sending phase over the total time $T$. Then, the problem is how to determine the optimal ratio $\beta$ and the transmission power $\rho$ in the sending phase in order to maximize the total throughput?

*Lemma 1:* For the basic problem, the maximum throughput can only be achieved if the transmission power is $\rho = \frac{p-1}{\mathcal{W}(\frac{p-1}{e})} - 1$, and the length of the sending phase $\beta = \frac{p}{\rho_s + p}$, where function $\mathcal{W}(z)$ is the Lambert W function [24].

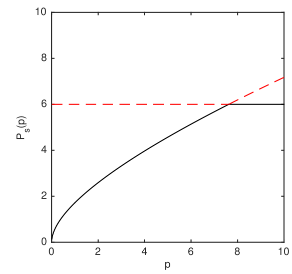


Fig. 3. Curve of function $\rho = P_s(p)$ when $\rho_{\max} = 6$.

*Proof:* See the Supplementary Material. ■

We further have the following important observation. *Although the optimal length of the sending/charging phase depends on both $T$ and $p$, the optimal transmission power $\rho_s$ is independent of $T$.* This observation is quite surprising and interesting. Some previous works in the literature [9], [10], [18], [19] also studied the same basic problem, but they failed to discover the observation, because they all focused on finding the phase length $\beta$, instead of the optimal transmission power $\rho$. This discovery reveals an essential property of the WPT and is a stepping stone toward the optimal solutions for the general scheduling problem. It is also expected to play important roles in solving other scheduling problems in the field of the WPT.

We now introduce one more notation in preparation for the general case, where the wireless power $p$ may change from slot to slot. It is called *sOPT power* function, and it is a function of the power rate $p$, For any given wireless supply power $p$, the *sOPT power* $P_s(p)$ is defined as $P_s(p) = \min\{\frac{p-1}{\mathcal{W}(\frac{p-1}{e})} - 1, \rho_{\max}\}$, where $\rho_{\max}$ is the maximum available transmission power, which is imposed by the hardware.

Function $P_s(p)$ is the most important notion throughout this paper. Fig. 3 shows the curve of this function for the range of $p \in (0, 10)$ to give the reader intuitive idea about this function. For any given *sOPT power* $\rho$, we can compute its inverse function according to the proof of Lemma 1, $p = P_s^{-1}(\rho) = (1 + \rho)(\ln 2 \log(1 + \rho) - 1) + 1$.

## IV. Optimal Offline Solution for a Special Case

In this section, we solve a simpler case of the *maxT-HTTs* problem where the sequence of power supplies in vector $\mathbf{p} = \{p_1, p_2, \ldots, p_T\}$ is assumed as a decreasing sequence. That is, $p_1 > p_2 > \cdots > p_T$. First, we make some useful observations, which are as follows.

1) In any optimal solution, there is no remaining energy in battery at the ending time $T$.
2) In any optimal solution, transmission power (in all sending phases) must be equal.
3) In the optimal solution, there is a dividing power, such that higher supply power slots receive energy, lower power slots transmit data.

Observation 2) is true because of the convexity of the *power-rate function*. Detailed proof can be found in [23]. Observation 3) is true because we can always swap two slots if the lower power slot receives energy and the higher power slot transmit data. After swapping, more energy is charged but the sending cost the same amount of energy.

From the aforementioned three observations, natural questions are, what is the dividing power that tells high supply power slots from low power slots, and what exactly is the single transmission power in all sending phases? The following theorem connects these questions to the sOPT power, $P_s(p)$.

*Theorem 1:* In the optimal solution, there must exist a variable $w_{\rm opt}$ such that any slot with power $p > w_{\rm opt}$ ($p < w_{\rm opt}$) must be a charging (sending) slot; the transmission power in all sending phases must equal $P_s(w_{\rm opt})$ and battery is empty at time $T$. Note, if in a slot, $p = w_{\rm opt}$, there must be another variable $b_{\rm opt} \in [0, 1]$ such that the sending phase length is $b_{\rm opt}$.

*Proof:* We prove by contradiction. Suppose there exists an optimal solution that violates this theorem, we want to find the contradiction. Such optimal solution must satisfy the aforementioned three observations. Since $\mathbf{p}$ decreases, the entire time is divided into two parts, the first part charging and the second part sending. Assume that in the sending part, the optimal transmission power is $\rho_{\rm opt}$ that empties the battery at $T$. Define $w_o = P_s^{-1}(\rho_{\rm opt})$. Because this theorem is violated, there is 1) at least one phase with power $p > w_o$ that is used for sending, or 2) at least one phase with power $p < w_o$ that is used for charging. We next show a contradiction for 2), and contradiction for 1) is similar and left to the readers.

Among all charging slots and phases with $p < w_o$, let slot $k$ be the last one, e.g., $p_k < w_o$. Then, phase $k$ is the last part of the charging part, after which starts the sending duration at power $\rho_{\rm opt}$. We want to show that such schedule can be further improved, which will be a contradiction. Such improvement can been seem more easily if we slightly modify the supply power but not change the actual sending. Assume the energy in battery is $E$ by the end of charging phase $k$, e.g., right before sending start. We replace the charging duration with a new charging duration in which the wireless power is $p_k$ and this duration lasts $E/p_k$. Note, such new duration may begin before time 0, we assume that is possible. For the sending duration, we modify the supply power to be $p_k$. This modification will not affect the actual sending and the throughput, because energy accumulated in battery is the same when sending starts, and supply power in sending duration does not play any role in the schedule and change it affect nothing. Now, the wireless supply power keeps the same, $p_k$, throughout the entire duration, moreover, supply power in phase $k$ right before sending starts is not changed, e.g., it keeps being $p_k$. However, we have $p_k < w_o = P_s^{-1}(\rho_{\rm opt})$.

Since function $P_s(p)$ is a monotone increasing function as shown in Fig. 3, we have $P_s(p_k) < \rho_{\rm opt}$. By starting sending earlier, the transmission power decreases, because the charging phase becomes shorter, hence, less power is charged while the sending phase becomes longer. Let $\rho'_{\rm opt}$ be the new transmission power, then $\rho'_{\rm opt} < \rho_{\rm opt}$. As long as $P_s(p_k) < \rho'_{\rm opt} < \rho_{\rm opt}$ holds, we have $B(\rho'_{\rm opt}) > B(\rho_{\rm opt})$, since $B(\rho)$ monotone decreases after $\rho = P_s(p_k)$ (see the proof of Lemma 1). Starting sending earlier increases the throughput, which contradicts the assumption $\rho_{\rm opt}$ is optimal.

The proof of the existence of $b_{\rm opt} \in [0, 1]$ is trivial, since it is defined that the charging phase length $b \in [0, 1]$. ■

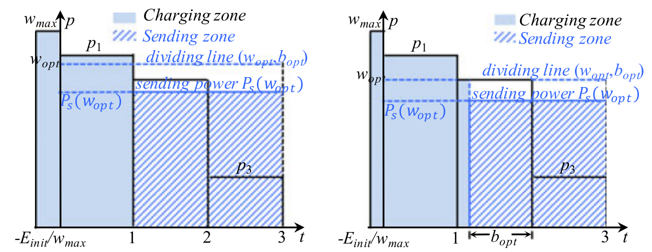


Fig. 4. Examples of the *d-line raising system*. The curve of $\mathbf{p}$ is drawn in a time–power diagram, where initial energy is treated as precharged during a virtual charging phase. A dividing line $(w, b)$ divides the curve into two parts. The area beneath the higher part of the curve is defined as the *charging zone*, whose area is the actual energy charged into battery. In the lower part, the area beneath the sending power line, which is of height $P_s(w)$, is defined as the *sending zone*. Its area is the actual energy consumed. Depending on $E_{\rm init}$, there are two slightly different types of optimal solutions, e.g., $w_{\rm opt} \neq p_i$, for $\forall i$, and $w_{\rm opt} = p_i$, for $\exists i$.

Once the two tuple $(w_{\rm opt}, b_{\rm opt})$ is determined, the optimal schedule is determined, e.g., not only when to charging and when to sending is determined, but also what the send power is determined. Now the only question is how to find $(w_{\rm opt}, b_{\rm opt})$. Define two tuple $(w, b)$ to be the *dividing line*, denoted as $\Omega = (w, b)$, where $0 \le w$ and $0 \le b \le 1$. Define $(w_1, b_1) > (w_2, b_2)$, if $w_1 > w_2$ or $w_1 = w_2$ but $b_1 > b_2$.

Given $E_{\rm init}$, $\mathbf{p}$ and a dividing line $\Omega = (w, b)$, the $P_s(w, b)$ schedule is as follows:

1) if $p_i > w$, we set $\beta_i = 0$, $\rho_i = 0$;
2) if $p_i < w$, we set $\beta_i = 1$, $\rho_i = P_s(w)$;
3) if $p_i = w$, we set $\beta_i = b$, $\rho_i = P_s(w)$.

Obviously, $P_s(w_{\rm opt}, b_{\rm opt})$ schedule is the optimal schedule that maximizes the throughput before $T$. We want to test different dividing line $\Omega = (w, b)$ to find the optimal one.

*Lemma 2:* In a $P_s(w, b)$ schedule, when dividing line $\Omega = (w, b)$ raises, the energy used in sending increases, while energy charged decreases, hence the remaining energy $R(T)$ reduces monotonically.

*Proof:* See the Supplementary Material. ■

When $R(T) = 0$, such dividing line $\Omega = (w, b)$ is optimal. We, hence, design the *d-line raising system* to find the optimal dividing line. Two examples of the system are presented in Fig. 4. We assume initial energy $E_{\rm init}$ is precharged into an empty battery during a virtual charging phase. Let the virtual wireless supply power be $w_{\max}$, where $w_{\max} = P_s^{-1}(\rho_{\max})$, and the virtual phase be with length $E_{\rm init}/w_{\max}$. Since the maximum transmission power is $\rho_{\max}$, hence the virtual phase is guaranteed to be a charging phase. We draw the curve of $\mathbf{p}$ together with this virtual charging phase in a time–power diagram; see Fig. 4. A dividing line $\Omega = (w, b)$ divides the curve into two parts, the higher part and the lower part. The areas representing the charged energy and consumed energy are defined as the *charging zone* and the *sending zone*. Hence, the difference between the two areas is the remaining energy $R(T)$.

The core idea of the *d-line raising system* is to raise the dividing line $\Omega = (w, b)$ slowly from its lowest position, e.g., $(0, 0)$, stop as soon as the two zone areas equal, then the optimal dividing line is found. When $(w, b) = (0, 0)$, the entire area is charging zone and no sending zone. When the *dividing line*

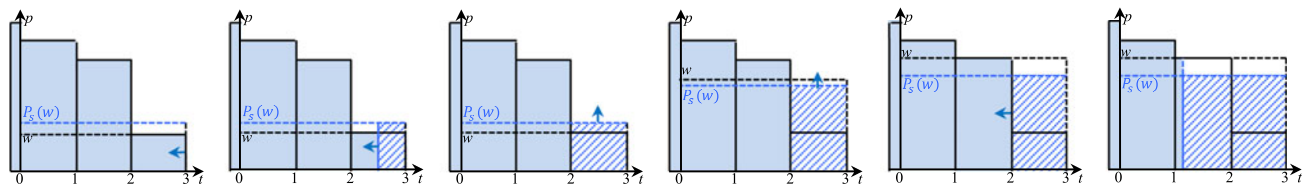


Fig. 5. In the *d-line raising system*, the *dividing line* $(w, b)$ raises slowly to find its optimal position. The initial position is $(0, 0)$, at which the entire area is charging zone. When $(w, b)$ arises, either $w$ grows or $b$ grows. If $w$ grows, $P_s(w)$ grows too, so the sending zone grows vertically. If $b$ grows, the sending zone grows horizontally, while the charging zone shrinks horizontally. In either case, the difference between the two zones decreases monotonically. The dividing line stops raising when the two zone areas equal.

**Algorithm 1:** `d-line_raising_schedule`.

set $p_0 = w_{\max} = P_s^{-1}(\rho_{\max})$ for loop purpose;
$E_c = E_{\text{init}} + \sum \mathbf{p}$, $E_s = 0$;
**for** $i = T$ **to** $1$ **do**
  $l = T - i + 1$;
  $\Delta c{=}p_i$, $\Delta s = P_s(p_i) + (P_s(p_{i-1}) - P_s(p_i)) * l$;
  **if** $E_c - \Delta c < E_s + \Delta s$ **then** break;
  $E_c -= \Delta c$, $E_s += \Delta s$;
**end**
$b = 1 - \frac{[(p_i + P_s(p_i)) - (E_c - E_s)]^+}{p_i + P_s(p_i)}$ [1];
$w = P_s^{-1}\left(P_s(p_i) + \frac{[(E_c - E_s) - (p_i + P_s(p_i))]^+}{l}\right)$;
return $(w, b)$.

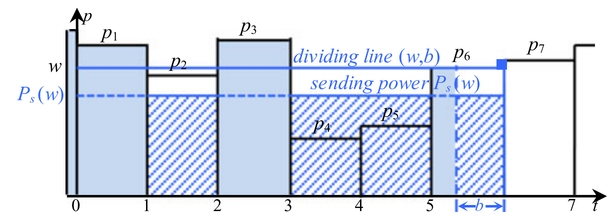


Fig. 6. Algorithm `d-line_raising_general` is illustrated. Its procedure is, starting from $(0, 0)$, the dividing line slowly arises, it stops when the charging zone area equals sending zone area. In this illustration, only the first six slots are considered. The rational is, if we sort these six slots, and then, apply `d-line_raising_schedule`, we got the same results, which is optimal.

arises, the sending zone grows, either vertically ($w$ and $P_s(w)$ grow) or horizontally ($b$ grows), while the charging zone shrinks horizontally. Therefore, there must exist a unique dividing line position at which the two zones equal. And we stop at such position. Fig. 5 is an illustration of the process of the *d-line raising system*.

In the formal algorithm, the process of dividing line raising can be efficiently speed up by testing only a handful positions, e.g., $(p_i, 0), i = T, T-1, \ldots, 1, 0$. If at position $(p_i, 0)$, charging zone is still larger than the sending zone, we go to test the next higher position $(p_{i-1}, 0)$. Eventually, we locate the optimal dividing line between two positions, and then, the final position can be computed directly. Algorithm `d-line_raising_schedule` provides formal details to find the optimal dividing line $\Omega = (w, b)$.

*Lemma 3:* Algorithm `d-line_raising_schedule` computes the optimal dividing line $(w_{\text{opt}}, b_{\text{opt}})$ in $O(T)$ steps.

*Proof:* See the Supplementary Material. ∎

## V. Optimal Offline Solution

Although Algorithm `d-line_raising_schedule` was previously introduced to handle the special case where $\mathbf{p}$ is a decreasing sequence, it can be easily adopted to the general $\mathbf{p}$ case. Recall that we slowly rise the dividing line and stop when the charging zone area and sending zone area are equal, we do exactly the same in the general case. The only difference is the charging zone no longer stays on the right of the sending zone. The dividing line will meet each $p_i$ in a sorted order when it raises. Lemma 2 still holds, e.g., when dividing line arise, the sending zone grow, while the charging zone shrinks. We stop when the two equal each other. We define such a revised algorithm `d-line_raising_general`. This algorithm is applied for the first six slots of Fig. 2, and the resulting schedule is shown in Fig. 6.

However, in the general $\mathbf{p}$ case, it may be impossible to make the two areas equal by a single dividing line. For example, in Fig. 6, when we further include slot 7 into consideration, problem arises. Since $p_7$ is greater than the current dividing line $\Omega = (w, b)$, it enlarges the area of charging zone. We hence have to rise $\Omega$ in order to make the two areas equal. However, we already have $R(6) = 0$, it is impossible to further rise $\Omega$. So there is no single dividing line for the entire duration $[0, 7]$ such that $R(7) = 0$.

Consequently, we conclude that the optimal dividing line does not necessarily keep constant throughout the entire duration $[0, T]$. Instead, it may change multiple times. Suppose it keeps constant at $\Omega_i = (w_i, b_i)$ in duration $[\tau_{i-1}, \tau_i)$, and changes at time $t = \tau_i$. Then, $\Omega_i = (w_i, b_i)$ is called the $i$th dividing line segment. The problem is to find all dividing line segments.

Before we go any further to the algorithm, we first investigate some optimality properties of the optimal dividing line.

1) Two adjacent dividing line segments, $\Omega_i$ and $\Omega_{i+1}$, can be equalized to be a single dividing line segment $\Omega_i'$ to transmit more data, as long as the new schedule is feasible.
2) The optimal dividing line increases only.
3) The optimal dividing line increases at battery empty points.

The proofs of these three optimality properties can be found in the Supplementary Material.

[1] $[a]^+ = a$ if $a \geq 0$, and $[a]^+ = 0$ if $a < 0$.

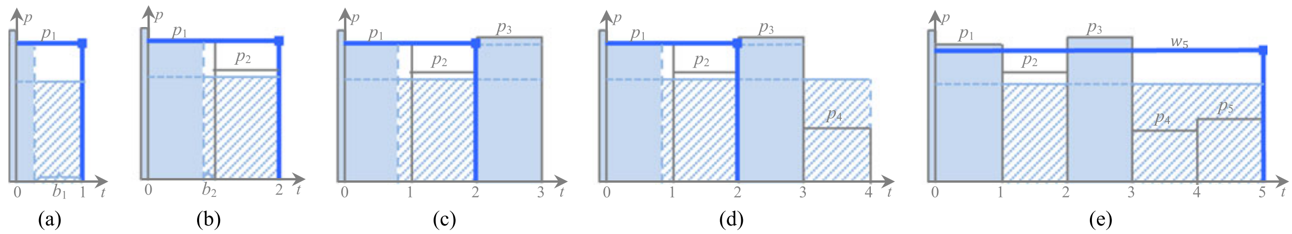


Fig. 7. Example of the execution of our algorithm. In (a), $\Omega^{(1)} = (p_1, b_1)$ equals the two zones, and battery is empty at $\tau^{(1)} = 1$. In (b), since $p_2 < p_1$, sending zone is enlarged in slot 2, hence, dividing line drops from $\Omega^{(1)}$ to $\Omega^{(2)} = (p_1, b_2)$ to equal the two zones and empty battery at $\tau^{(2)} = 2$. In (c), since $p_3 > p_1$, charging zone is enlarged, but battery at $t = 3$ cannot be emptied by any single dividing line. So, we set $\Omega^{(3)} = \Omega^{(2)}$, which empties the battery at $\tau^{(3)} = \tau^{(2)}$. In (d), although $p_4 < p_1$, which means the sending zone is enlarged, however the charging zone is still larger than the sending zone, so still no single dividing line can empty battery at $t = 4$, hence, $\Omega^{(4)} = \Omega^{(3)}$ and $\tau^{(4)} = \tau^{(3)}$. In (e), Slot 5 is a sending zone, the charging zone area is now smaller than the sending zone area. We, hence, lower the dividing line from $\Omega^{(4)} = (p_1, b_2)$ to $\Omega^{(5)} = (w_5, 0)$ that empties the battery $\tau^{(5)} = 5$.

**Algorithm 2:** $\mathtt{iECP}(t, (w, b), H, E, Q)$.

**Input :** Current time $t$, previous dividing line $(w, b)$, energy charged $H$ and energy consumed $E$ (both at $t-1$), and max-heap $Q$ that stores power lower than $w$.

**Output:** Updated dividing line $(w, b)$ and battery depletion point $\tau$, new remaining energy $R$, and new max-heap $Q$.

1: **if** $p_t > w$ **then**
2: $\quad E+ = p_t$;
3: **else**
4: $\quad H+ = P_s(w)$;
5: $\quad$ Insert-MaxHeap$(Q, p_t)$;
6: **end**
7: **if** $H > E$ **then return** $((w, b), 0, H, E, Q)$;
8: **while** *isEmpty-Heap(Q)==false* **do**
9: $\quad p_x$=Top-MaxHeap$(Q)$; //Do not extract
10: $\quad l$=size-Heap$(Q)$;
11: $\quad \Delta H = wb, \Delta E = P_s(w) * b + (P_s(p_x) - P_s(w)) * l$;
12: $\quad$ **if** $H + \Delta H \geq E - \Delta E$ **then** break;
13: $\quad$ Extract-MaxHeap$(Q)$;
14: $\quad H+ = \Delta H, E- = \Delta E, w = p_x, b = 1$;
15: **end**
16: $b_{\text{new}} = \frac{[(w+P_s(w))b-(E-H)]^+}{w+P_s(w)}$;
17: $w_{\text{new}} = P_s^{-1}\left(P_s(w) - \frac{[(E-H)-(w+P_s(w))b]^+}{l}\right)$;
18: **return** $((w_{\text{new}}, b_{\text{new}}), t, 0, 0, Q)$.

We are now ready to present the algorithm. The high level idea is quite simple, we want to find the first changing point for the optimal dividing line and after such a point the same problem repeats. According to previous lemmas: 1) at such a point, the battery is empty; 2) before such a point, there is a single dividing line; and 3) after such a point, the dividing line increases.

Since we do not know where the first changing point is, we check each and every time instance $t = 1, 2, \ldots, T$ by computing the single dividing line that empties the battery at that instance. Our algorithm works in iteration. In iteration $t$, it computes the dividing line for the first $t$ slots based on the previously computed dividing line for the first $t-1$ slots. The efficiency is built on the incremental style of work in each iteration. The core idea of the proposed algorithm is illustrated in Fig. 7. The detailed pseudocode for each iteration is presented in Algorithm iECP.

For the execution of iteration $t$, iECP is invoked. Obviously, we must have $H \geq E$ before the execution, where $H$ and $E$ is the energy charged and consumed before $t$. Whether slot $t$ is a charging slot or a sending slot is determined by comparing $w$ with $p_t$, so $E$ and $H$ are modified accordingly in Lines 1–6. After the modification, if $H > E$ holds, there is no feasible single constant dividing line that empties the battery at time $t$. This is because either $H = E$ holds at some earlier time before $t$ or $w = w_{\max}$, arise the dividing line is impossible for both cases. Hence, we directly go to the next iteration as in Line 7.

We must have $H \leq E$ if the **while** loop in Line 8 is executed, in which we lower down the dividing line, causing the charging zone shrinking while the sending zone growing. When the two areas equal, we stop. More especially, when the dividing line drops, it meets powers one by one in the order from high to low, we thus need an efficient data structure to manage power. We choose the maximum heap, because both extract the largest power and adding a power are with $O(\log(T))$ time complexity. In each of the **while** loop, the dividing line drops to the next large power. In Line 11, the extra energy $\Delta H$ charged and the less energy $\Delta H$ consumed are computed for the drop. We continue dropping until $H + \Delta H \geq E - \Delta E$ holds. Then, we use general formulas in Lines 14 and 15 to compute the optimal position of the dividing line.

Algorithm Varying_Source_WPT computes all the chan ging points and the dividing lines between them.

In Algorithm Varying_Source_WPT, $t_0$ is the new starting point, initialized to be 1. The **while** loop iterates to find the next changing point and update the $t_0$ to be right after the new changing point. Inside each **while** loop, algorithm iECP is invoked for each $t \in [t_0, T]$ by the **for** loop. Each invocation returns a new dividing line $(w, b)$ and the charged energy $H$ and consumed energy $E$. If the returned $H > E$, then no feasible single dividing line can equal the two areas, the **for** thus continues to the next invocation in Line 6. Only if the returned $H = E$, we keep the current dividing line and changing point

**Algorithm 3:** `Varying_Source_WPT`.

```
1:  t_0 = 1;
2:  while t_0 ≤ T do
3:      w=w_max, b = 1, H = 0, E = 0, init-maxHeap(Q);
4:      for t = t_0 to T do
5:          ((w, b), τ, H, E, Q)=iECP(t, (w, b), H, E, Q);
6:          if H > E then continue;
7:          Ω_min = (w, b), τ_min = τ;
8:      end
9:      Set dividing line Ω_min in [t_0, τ_min];
10:     t_0 = τ_min + 1;
11: end
```

in $\Omega_{\min}$ and $\tau_{\min}$, respectively. When **for** terminates at Line 8, $\Omega_{\min}$ and $\tau_{\min}$ store the dividing line and the changing point we want.

*Observation 1:* In every execution of the **for** loop, as the loop repeats, dividing line kept in $\Omega_{\min}$ (Line 6) decreases, while its corresponding changing point $\tau_{\min}$ increases.

The correctness is based on that an invocation of `iECP` either drops the dividing line or keeps it the same. Hence, when the **for** loop terminates, the lowest feasible dividing line and its corresponding changing point is kept in $\Omega_{\min}$.

*Theorem 2:* The algorithm `Varying_Source_WPT` computes the optimal schedule for the offline problem in $O(T^2 \log T)$ steps.

*Proof:* See the Supplementary Material. ■

Examples of the execution of Algorithm `Varying_Source_WPT` are illustrated in Figs. 6 and 7. The first five iteration results of the **for** loop are presented in five subfigures of Fig. 7, respectively. The sixth iteration result have been presented in Fig. 6. Obviously, $\Omega_1 > \Omega_2 = \Omega_3 = \Omega_4 > \Omega_5 > \Omega_6$, satisfies Observation 1.

## VI. Online Algorithm and Simulations

In this is section, we study the online *maxT-HTTs* problem, where no future information about the wireless supply power is known. We propose a heuristic algorithm, namely *d-line guided online algorithm*, which is based on optimal properties learned from the offline problem. We then evaluate the performance of our online heuristic algorithm by comparisons with the optimal offline solutions.

### A. Online Algorithm

The online algorithm makes scheduling decision for each slot, one by one, with only information from previous slots. We assume the online algorithm determines the phase length $\beta$ and transmission power $\rho$ for the current time slot at its beginning time, when the supply power for this slot is already known. The core idea of our proposed *d-line guided online algorithm* is to use average supply power to anticipate any unknown future supply power and apply the *d-line raising system* to compute the offline optimal schedule. Well-designed modifications are then made to guarantee the schedule performance in the online fashion. Keep in mind that once a time-slot lapsed, the schedule for it can no longer be changed, however, schedule for any upcoming slot can be recalculated according to new information.

Specifically, we assume that at the beginning of the current slot $t$, the remaining energy in battery is $E_r$, the supply power for the this slot is known to be $p$ and the history average wireless supply power for previous slots is $\bar{p}$. In order to use *d-line raising system*, we assume the power supply for future slots to be $\bar{p}$. That is, supply power in time slot $t+1, t+2, \ldots, T$ are assumed to be the same, $\bar{p}$.

Since supply power have only two values, $p$ and $\bar{p}$ in duration $[t, T+1)$, the execution of *d-line raising system* is quite simple and compute the optimal schedule is easy. However, if the current slot is a pure charging/sending slot by the *d-line raising system*, it must be carefully modified, because charging or sending for the entire slot is lack of flexibility, especially when we do not really know about the future information.

In the following, we discuss three cases.

1) $p < \bar{p}$ and the current slot is divided into two phases by the *d-line raising system*. It is easy to see that, the current slot consists of both types of phases only if the ending of the current slot is a battery empty point. We, hence, compute $\beta$ according to such depletion assumption, $E_r + p(1-\beta) = P_s(p)\beta$, so $\beta = \frac{E_r + p}{p + P_s(p)}$. With the requirement $0 \le \beta \le 1$, we have $E_r \le P_s(p)$ and meanwhile $\rho = P_s(p)$. The intuitive is that since the battery is empty at the ending of slot $t$, the initial battery energy $E_r$ cannot be too much, and $P_s(p)$ is the upper bound. In case, the current slot is the last time slot, namely $t = T$, we have the same calculation for computing $\rho$ and $\beta$.

2) $p \ge \bar{p}$ and the current slot is divided into two phases by the *d-line raising system*. It is easy to see that, the first battery empty point must be the ending of the last slot $T$. Thus, we establish the equation $E_r + p(1\beta) = (T - t + \beta)P_s(p)$ based on such depletion assumption. We, therefore, have $\beta = \frac{E_r - [(T-t+1)P_s(p) - (P_s p + p)]}{P_s p + p}$, and meanwhile, $\rho = P_s(p)$. With the requirement $0 \le \beta \le 1$, we have $(T-t+1)P_s(p) - (P_s(p) + p) \le E_r \le (T - t + 1)P_s(p)$. The intuitive explanation is, first, the initial energy cannot be too much, e.g., $E_r \le (T - t + 1)P_s(p)$, otherwise it is a pure sending phase; second, the initial energy cannot be too little, e.g., $E_r \ge (T - t + 1)P_s(p) - (P_s(p) + p)$, otherwise it is a pure charging phase.

3) The current slot is a sending/charging slot by the *d-line raising system*. It will result in lack of flexibility if we set a pure charging/sending slot in the online scenario, since we need to prepare for the unknown future. We, therefore, make modifications to the schedule, in which we set $\rho = P_s(\bar{p})$ and change the sending phase length to be $\beta$. Compare to a pure charging slot, such sending phase costs $(p + P_s(\bar{p}))\beta$ energy loss, including $p\beta$ energy less charged and $P_s(\bar{p})\beta$ energy consumed. In any slot, an average of $\bar{p}$ energy can be charged. We want them equal, e.g., $(p + P_s(\bar{p}))\beta = \bar{p}$, because, in a long run, the energy charged and energy consumed will equal. So,

**Algorithm 4:** `d-line_guided_online`$(E_r, t, p)$.

Compute the average receive power as $\bar{p}$;
**if** $p < \bar{p}$ **and** $E_r - P_s(p) \le 0$ **or** $t = T$ **then**
  $\beta = \min\left\{1, \frac{E_r + p}{p + P_s(p)}\right\}$;
  $\rho = P_s(p)$;
**else if** $p \ge \bar{p}$ **and** $(T - t + 1)P_s(p) - (P_s(p) + p) \le E_r$ **and** $E_r \le (T - t + 1)P_s(p)$ **then**
  $\beta = \frac{E_r - [(T-t+1)P_s(p) - (P_s p + p)]}{P_s p + p}$;
  $\rho = P_s(p)$;
**else**
  $\beta = \min\left\{1, \frac{\bar{p}}{p + P_s(\bar{p})}, \frac{E_r + p}{p + P_s(\bar{p})}\right\}$;
  $\rho = P_s(\bar{p})$;
**end**
$B = \rho\beta$;
$E_r \leftarrow E_r + p * (1 - \beta_t) - \rho * \beta$;

$\beta = \min\{1, \frac{\bar{p}}{p + P_s(\bar{p})}\}$. Meanwhile, to guarantee energy not depleted before $t$, we require $\beta \le \frac{E_r + p}{p + P_s(p)}$, hence, $\beta = \min\{1, \frac{\bar{p}}{p + P_s(\bar{p})}, \frac{E_r + p}{p + P_s(\bar{p})}\}$.

The following present the detailed algorithm.

In the well-designed modification in case (3), we can see that the larger $p$, the smaller $\beta$; the smaller $p$, the larger $\beta$. This is consistent with our intuition: the higher wireless supply power, the more time should be used to charge the battery, while the lower supply power, the more time should be used to send data.

## B. Simulation Settings

We use two real-world measurement-based wireless power models to evaluate the efficiency of the proposed `d-line_guided_online` algorithm.

1) A real-world industrial environment in Lund, Sweden. The factory hall has a floor area of 94 m × 70 m and a ceiling height of 10 m. This hall contains many metallic objects, e.g., pipes, pumps, and cylinders, which is a rich scattering environment. According to an on-site measurement report [25], the received power at a distance of $d$ from the power source is modeled in decibel following a random distribution, as

$$P_{\text{FACTORY}}(d) = P_0 - 10n\log_{10}\left(\frac{d}{d_0}\right) - L_\delta$$

where the path loss $P_0 = -48$ dB at a distance $d_0 = 1$ m, and log-normal fading $L_\delta \sim \text{Lognorm}(0, 1.1)$. We assume the distance $d = 4.2$ m, and the path loss exponent $n = 1$.

2) A real-world office building environment at Lund University, Lund, Sweden. Office floor sizes are between 10 and 30 m$^2$, where the outer walls of the building consist of brick and reinforced concrete, whereas gypsum wallboards separate different offices. According to an on-site measurement report [26], the distance-dependent received power is modeled, in decibel, as the following random distribution:

$$P_{\text{OFFICE}}(d) = P_0 - 10n\log_{10}\left(\frac{d}{d_0}\right) - L_e - L_b$$

where the path loss $P_0 = -43$ dB at a distance $d_0 = 1$ m, the environmental shadowing loss $L_e \sim \text{Lognorm}(0, 2.3)$, the body shadowing loss $L_b \sim \text{Lognorm}(0, 2.3)$, and the path loss exponent $n = 1.4$. We assume the distance $d = 4.2$ m.

These two wireless supply power distributions will be referred as $P_{\text{FACTORY}}$ and $P_{\text{OFFICE}}$, whose mean values are denoted as $p_{\text{fact}}$ and $p_{\text{offi}}$. As a conclusion, the factory distribution has a lower standard deviation because of the rich multipath in the factory hall. While the office distribution has a higher deviation because it involves human bodies.

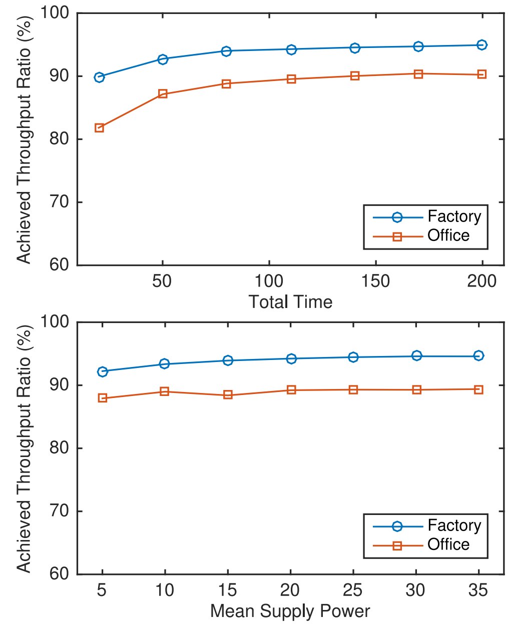


Fig. 8. Achieved throughput ratios toward the offline maximum by the online algorithm are used to evaluate the performance. Two real-world measurement-based wireless power models are used in the evaluation. The default setting is total time $T = 120$ and mean wireless supply power $p_{\text{fact}} = p_{\text{offi}} = 25$.

## C. Simulation Results

Since there is no other algorithms in the literature that studies the same throughput maximization problem, we compare our online algorithm to the offline optimal algorithm. The achieved throughput ratios toward the offline maximum by the online algorithm are used to evaluate the performance as in Fig. 8.

In simulations, a total of $T = 120$ time slots are considered. In each slot, the wireless supply power is generated following two distributions, respectively, e.g., $P_{\text{FACTORY}}$ or $P_{\text{OFFICE}}$. Their mean values are set $p_{\text{fact}} = p_{\text{offi}} = 25$. In this simulation, we change the total time slot $T$ and the mean supply power $p_{\text{fact}}(p_{\text{offi}})$, one at a time, to evaluate their impact on the algorithm performance. Each value shown in figures is the mean value from 60 random instances.

In Fig. 8(a), time $T$ varies from 20 to 200. We can see that, in both factory and office scenarios, the longer evaluation time, the better our online algorithm performance. This is because the performance of the online algorithm relies on the average power. The longer evalution time, the history average is more accurate. In the office scenario, power distribution has a higher deviation, so the averaging-based online algorithm performs worse than in the factory scenario. However, even when the total time is as short as 20, the achieved ratio is still more than 90% in the factory setting.

We can see from Fig. 8(b) that the efficiency of the proposed algorithm rises as the mean supply power increases in factory. This is because when the mean supply power goes lower, more time is needed to charge the same amount of energy, as a result, more difficulty for our online algorithm to achieve a good throughput, so its efficiency drops. Since in the office scenario, the distribution deviation is high, so its efficiency does not increase with the power increases. However, in all the tested cases, the achieved ratio stays higher than 80%.

## VII. Conclusion

In this paper, we first formulated the throughput maximization HTT-scheduling problem for the dynamic wireless supply power. Then, a basic property, namely $sOPT$ power, was presented. Based on this property, we introduced the concept of the *dividing line* and the *d-line raising system*. We then investigated a special case of the problem, e.g., the wireless supply power decreases in sequence. Some optimality properties were observed, and the optimal offline algorithm was designed based on the *dividing line* and the *d-line raising system*. These properties and the proposed algorithm were then extended to the most general scenario, where the supply power dynamically changes. Finally, an online heuristic algorithm was proposed and simulations were conducted to evaluate its efficiency.

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