ATHOME: Automatic Tunable Wireless Charging for Smart Home^{*}

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ABSTRACT

We present ATHOME, an Automatic Tunable wireless charging framework for smart low-power devices in current and future HOME. ATHOME automatically tunes the charging power of multiple stationary wireless chargers to provide enough energy that can continuously power up smart devices with varying working power profiles, while minimizing the total charging power to reduce energy cost. To reach this goal, ATHOME first solves a hard open problem of calculating the minimum required charging power for powering up a device with limited energy storage size and varying power profile. Based on the minimum charging power obtained for each device, ATHOME then provides an optimal solution with polynomial-time complexity that automatically tunes the charging power of all chargers in a real-time fashion, which enables all devices to work continuously while minimizing total charging power. We implement ATHOME on a WISP platform with 8 rechargeable nodes. Experiments demonstrate that ATHOME provides sufficient and tight charging power that enables devices to work continuously.

CCS CONCEPTS

•Computer systems organization →Embedded systems;

KEYWORDS

Internet-of-Things, wireless rechargeable sensor network

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1 INTRODUCTION

The Internet-of-Things (IoT) is one of the fastest-growing technology across all computing fields. A conservative estimate predicts

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that the number of smart devices connected to the IoT network will be nearly 40 billion by 2019, which is approximately 30 devices for every active user in the world. The maturity of IoT enables the realization of “Smart Home”, where all the home appliances and smart devices will be integrated, linking their intelligence to create an environment that no longer needs ongoing human intervention. A widely implemented example is that the motion sensor used in the security system is integrated with the home’s light and heating control system to automatically switch off the lights and heating when nobody is at home.

One tremendous challenge in realizing the Smart Home vision is the need for continuously powering a large number of low-power devices (e.g., sound and motion sensors) without the need of human intervention [7, 8]. Most of such devices will be battery-powered for reasons of cost, size, and convenience. Meanwhile, batteries introduce additional bulk, weight, cost, and require recharging or replacement that involves maintenance cost and is not feasible at large scales [29]. Due to the scale and installation locations of smart devices, using wired charging is clearly not a practical option. To resolve this critical charging issue, the recently emerged wireless charging technology [16] becomes a promising solution. Based on the revolutionary wireless charging technology, a number of research platforms and commercial products have been introduced such as Wireless Identification and Sensing Platform (WISP) [32], Moo [2], Powercast [6]. Even product-level wireless charging systems have been recently developed that can wirelessly charge multiple small embedded devices (from smoke detectors to cameras) from as far as 30 feet away [5].

A Fundamental Research Challenge. To enable efficient wireless charging, a fundamental challenge is to determine the minimum charging power of wireless chargers that are often stationarily installed in different physical locations, such that enough energy can be provided to enable all smart IoT devices to work continuously. Unfortunately, most of the existing solutions assume that devices either do not carry any energy storage or they carry energy storage of unlimited size [10] [13] [36]. This assumption makes the problem significantly simpler but is unfortunately invalid in practice. Most sensors or embedded devices nowadays are equipped with capacitors or rechargeable batteries of limited size as the energy storage. For example, WIPS [14] stores its harvested energy on a 100 μ F capacitor and Moo’s capacitor is 10 μ F [33]. Having an energy storage is effective because any unused power provided by the wireless charger can be stored for later use.

To identify why the fact that devices carrying energy storage of limited size may bring tremendous challenges to the charging problem, we have conducted experiments using a WISP 4.1 DL tag and a standard commercial RFID reader. Our measurements reveal a fundamental challenge under this setting, where the **energy overflow problem** may occur when the charging power exceeds a device's required charging power. When the device's energy storage becomes full, any redundant energy will overflow and be wasted. It is very challenging to explicitly calculate the amount of overflowed energy given a specific charging power, particularly when a device's working power profile changes over time in a complicated manner. This further causes hardness in determining whether a given charging power is sufficient to continuously power up the device. On the other hand, assuming an energy storage with unlimited capacity does not incur this energy overflow problem and thus makes the problem rather trivial to be solved (experimental data and further details are given in Sec. 2.2). Moreover, since multiple chargers can charge a device in range simultaneously, a critical problem is to determine how to automatically tune the charging power of each charger such that all devices can receive enough energy to work continuously while the total charging power is minimized. This problem is non-trivial because devices exhibit different working power profiles. Resolving these research challenges is the focus of this paper.

We present ATHOME, an Automatic Tunable wireless charging framework for smart embedded devices in current and future smart HOME. ATHOME automatically tunes the charging power of multiple stationary wireless chargers to provide enough energy that continuously powers up smart embedded devices with varying working power profiles, while minimizing the total charging power to reduce energy cost. To reach this goal, ATHOME first resolves a key open problem due to energy overflow: how to derive the optimal charging power required to power up a device with energy storage of limited capacity and a varying working power profile. A novel analytic geometry method is presented that precisely characterizes the overflowed energy and the energy actually received by a device given a specific charging power. A set of novel techniques are proposed to validate whether a given charging power is sufficient to enable a device to work continuously, and then a step further, whether it is the minimum charging power among all sufficient ones (Sec. 3). Then based on each device's minimum required charging power and the locations of all chargers and devices, ATHOME provides an optimal solution with polynomial-time complexity that tunes all chargers' charging power, such that all devices can be powered up continuously while the total charging power provided by chargers is minimized. ATHOME can automatically tune the chargers' charging power with dynamic device join/leave events in a real-time fashion.

We evaluate ATHOME by implementing the framework on a WISP platform with 8 rechargeable nodes and conducting extensive experiments under various settings. Experimental results show that ATHOME can correctly and efficiently provide enough energy to all devices to work continuously. The amount of energy provided by the charger under ATHOME is also very close to the amount of actual consumed energy that is measured at runtime. Moreover, to assess the performance of ATHOME if applied in an actual smart home with a large number of smart devices and chargers, we have

Figure 1: WISP node used in our lab.

performed extensive sets of simulations. The simulation results show that ATHOME can achieve good scalability, and the difference between the amount of supplied energy under ATHOME and the minimum amount of energy required to power up all devices is very small under almost all settings.

To the best of our knowledge, ATHOME represents the first solution that can be applied in smart homes to derive the optimal charging power for IoT devices with limited energy storage and varied power profiles. While ATHOME focuses on the home, connected IoT devices are being widely seen in many other domains, including airports, factories, and forests. For example, in a forest environment, thousands of sensors may be randomly deployed to measure the illuminance without human supervision [18]. Efficiently charging such large number of sensors using wireless chargers may be the only feasible solution for energy provision. We believe the design of ATHOME can be generally applied to automatically tune the charging power for connected smart devices in other domains as well.

2 MOTIVATION AND CHALLENGES

This section motivates ATHOME by describing key challenges of identifying the optimal charging power for devices with limited energy storage. As the charging power provided by a charger may fluctuate in practice, we first describe a set of measurements on characterizing such fluctuation and our approach to deal with it.

2.1 Charging Power Fluctuation

A critical factor impacting energy provisioning in smart home is the wireless charging model. In this section, we describe a widely studied wireless charging model [13]. We also adjust this model accordingly to better represent the charging behavior under our problem context, which is validated by the experiments we perform.

According to the empirical model of wireless recharging in WRSNs provided in [13], the receive power p_r of RF signal, d meters away from the source power p_0 , can be obtained by

$$p_r = \frac{G_s G_r \eta}{L_p} \left(\frac{\lambda}{4\pi(d + \beta)} \right)^2 p_0, \quad (1)$$

where G_s is the source antenna gain, G_r is the receive antenna gain, η is the wavelength, L_p is polarization loss, λ is rectifier efficiency, and β is a parameter to adjust the Friis' free space equation for short distance transmissions. Note that this wireless recharge model is additive for multiple concurrent chargers, which has been verified in indoor environments [13]. Under any specific charging power, the actual runtime charging power may fluctuate due to noise. To handle such fluctuation, this model uses curve fitting to approximate the charging power curve. However, in some cases, the actual charging power value may be smaller than the one obtained by using this curve fitting approach. Under our problem context, in order to guarantee sufficient charging power to power up devices continuously, we construct a lower bound curve that approximates the actual power curve using safe lower bound power

Figure 2: Charging Model

values instead. Our motivation and validation of this method is given by the following set of measurements we perform.

We perform indoor experiments to measure the charging power fluctuation induced by the instable experiment environment. We use the WISP4.1DL tag shown in Fig. 1. The reader is a standard commercial RFID reader, Impinj Octane3 Speedway, with circularly polarized antennas. It has a transmit gain of $G_s = 8 \text{ dBi}$. The transmit frequency of readers ranges between 920-925 MHz; thus, the average wavelength is about 0.33 m. The WISP tag has a linearly polarized dipole antenna and has a receive gain of $G_r = 2 \text{ dBi}$ according to [31]. We let the antenna of the reader be parallel with the antenna of the tag to lessen orientation effects. The tag is programmed to be in the quiescent state for all the experiments to maximize the received energy stored in the capacitor of capacitance $C = 100 \mu\text{F}$. We record the initial voltage V_i and final voltage V_f of the capacitor as well as the wireless recharge duration Δt . The wireless recharge power can be calculated by $\frac{C}{2\Delta t}(v_f^2 - v_i^2)$ [31]. The distance between the antennas of the reader and tag is 0.5 m and the charging experiment is performed 60 times.

The experiment results on charging power are plotted in Fig. 2a as denoted by “experiment”. We can see that the average charging power at the distance of 0.5 m is about 0.8 mW, which is depicted in Fig. 2a as denoted by “fitting”. We also plot the lower bound of the charging power (0.77 mW) in Fig. 2a as denoted by “lower-bound”. From Fig. 2a, we see that the curve fitting results closely approximate the measured power values, and the lower bound of the charging power curve is only 3.75% smaller than the fitting results. To further validate this approach, we perform experiments to construct the charging power lower bound curve when the distance between device and charger varies. The average charging power when the distance between the antennas of the reader and tag varies from 0.3 m to 1.5 m with an increment of 0.1 m is plotted in Fig. 2b. As seen in the figure, same conclusion can be drawn. Thus, in this paper, we use the power’s lower bound fitting curve to safely represent the actual charging power.

By adopting this charging model, we can calculate given a specific charging power supplied by the charger, the actual charging power that is received by a device with a certain distance to the charger. When a tag is far away from a reader, the tag’s antenna will receive negligible power of the reader’s RF signals, which is hard to be rectified to useful electrical energy. We denote this threshold of negligible power by $\bar{p}^{path}$ and the corresponding distance from the reader by r . When $d > r$, we assume that $p_r = 0$. Hence, for a charger located at (0, 0) with a supplied charging power of p_0 , the charging power received by a device at point (x, y) is given by

$$p_r(x, y) = \begin{cases} \frac{\alpha}{(d+\beta)^2} & \text{if } d \leq r \\ 0 & \text{if } d > r \end{cases} \quad (2)$$

$$\text{where } \alpha = \frac{G_s G_r \eta}{L_p} \left(\frac{\lambda}{4\pi} \right)^2 p_0.$$

2.2 Key Challenges: Energy Overflow due to Limited Energy Storage

The goal of wireless charging in smart home is to provide the lowest yet sufficient charging power to all smart devices for them to work continuously. As discussed in Sec. 2.1, Eq. 2 derives the charging power an embedded device can receive. In this section, we illustrate the key challenges in determining the minimum charging power a device requires to work continuously when given its working power profile through conducting a set of motivational case studies.

We again use the WISP 4.1DL platform, which integrates two classic sensors: an acceleration meter and a temperature sensor. Fig. 3a shows a sample measured working power profile of a WISP during a two-minute interval: during the first minute, the acceleration meter consumes 0.416 mJ/s energy and during the second minute, the temperature sensor consumes 0.716 mJ/s energy.

We performed three sets of experiments using three different energy buffer settings: (i) no energy buffer, (ii) sufficiently large energy buffer with a size of 100 mJ, and (iii) an energy buffer with a size of 5.215 mJ (i.e., the original WISP setting). We seek to find the lowest yet sufficient charging power that enables the WISP node to work continuously. For the rest of the paper, we use the term “optimal charging power” of a device, denoted by P_{opt} , to denote this lowest yet sufficient charging power for this device.

WISP with no energy buffer. When the device has no energy buffer, it is quite easy to determine the optimal charging power. Given a device’s working power profile, it is necessary for the charging power to be at least the device’s required working power at any point of time. We have performed experiments using WISP to validate this claim. Given the WISP’s working power profile shown in Fig. 3a, we set the charger to provide a charging power of 0.716 mJ/s during the two-minute interval. The WISP node is indeed able to work continuously in this case. However, as shown in Fig. 3b, a total amount of 18 mJ energy is wasted because the WISP has a working power of only 0.416 mJ/s during the first minute.

WISP with sufficiently large energy buffer. In this case, we assume that a device carries an energy buffer that is large enough to store any redundant energy received by the WISP in this experiment. To perform this experiment, we equip the WISP node with an energy buffer of 100 mJ that is sufficient to store any redundant energy during the two-minute charging period. As observed in Fig. 3c, the WISP node during the two-minute experiment only requires 67.92 mJ energy. Thus, if the energy buffer is sufficiently large, the charger should suffice to only provide a charging power of $67.92 \text{ mJ} / 120 \text{ s} = 0.566 \text{ mJ/s}$. The experiments validate this claim, where the WISP node can work continuously when provided a charge power of 0.566 mJ/s. Notice that roughly at time 120s, the supplied energy curve and the required energy curve actually intersect. This implies that at time 120s, the WISP node consumes up all the energy it has received within [61s, 120s]. It also indicates that in this case, a charging power of 0.566 mJ/s is the optimal charging power, i.e., any charging power less than 0.566 mJ/s may cause the WISP node to fail at a certain time point before 120s.

Figure 3: Case studies illustrating the energy overflow problem.

WISP with an energy buffer of size 5.215 mJ. In the third experiment, we let the charger again provide a charging power of 0.566 mJ/s to a WISP node that carries an energy buffer of size 5.215 mJ (i.e., the original WISP energy buffer setting). In this experiment, the WISP node actually stopped working roughly at time 95s, as shown in Fig. 3d. The key reason is that **due to the limited energy buffer size, the redundant energy received by the WISP cannot be all stored in the buffer, thus causing energy overflow**. Specifically, during [0, 60s], the accelerate meter requires a working power of 0.416 mJ/s and thus can work correctly. However, different from the second experiment discussed above, only 5.215 mJ redundant energy can be stored in the buffer within [0, 60s], causing an energy overflow of 3.785 mJ. Fig. 3d well illustrates this scenario, where the “Received Energy” curve denotes the actual amount of energy the WISP received (i.e., not including any overflowed energy). As seen in the figure, roughly at time 95s, the received energy curve intersects with the required energy curve. Another observation seen from this figure is that the amount of overflowed energy is represented by the gap area in between the supplied energy curve and the received energy curve. **A key challenge in determining the optimal charging power for a device**. As the above three experiments suggest, when a device carries no energy buffer or sufficiently large energy buffer, the problem of finding the optimal charging power is relatively easy. However, when a device carries an energy buffer of limited capacity (which is the common case in practice), it is hard to calculate the optimal charging power due to the *energy overflow problem*. It is very challenging to specifically calculate the amount of overflowed energy given a working power profile and a charging power. Particularly when the given power profile is complex (e.g., non-linear), the problem becomes more challenging and it may not be feasible to calculate the exact amount of overflowed energy.

Problem statement. We consider a smart home that contains a set $S = s_1, s_2, s_3, \dots, s_n$ of n stationary smart devices and m stationary chargers. Each device s_i has an energy storage with capacity of B_i . The working power of each device may vary over time due to different operations including sensing, communication, and computation. We assume that the working power profile of each device can be obtained (e.g., through profiling) since most devices have a fixed set of functionalities and a pre-defined operational schedule.¹ (For

Figure 4: Illustration of power- and energy-related concepts

example, a smart curtain is programmed to automatically open at 8 am everyday morning and closed at 6 pm every evening.) Without loss of generality, let $P_i(t)$ denote s_i 's required power over time according to its profile. Correspondingly, the integral of $P_i(t)$ defines s_i 's required energy $E_i(t)$, which is the amount of energy required by the device to work within $[0, t]$. The objective is to minimize the total charging power of all chargers while guaranteeing that all devices receive sufficient energy to work continuously.

Design overview of ATHOME. To solve this problem, we present ATHOME, which is a two-stage framework consisting of a charging calculus stage (Sec. 3) and a charging power tuning stage (Sec. 4). During the charging calculus stage, ATHOME explicitly identifies the optimal charging power required for each individual device given its working power profile and energy storage size; while during the charging power tuning stage, ATHOME attempts to tune each charger's charging power, so that all smart devices can receive sufficient energy to work continuously with minimized total charging power.

3 STAGE ONE: CHARGING CALCULUS

In this section, we develop a charging calculus theory to calculate P_{opt} for a device according to its working power profile and energy storage size in 2 steps. First, we present a set of novel methods that can validate (i) whether a given charging power is sufficient to support a device to work continuously, and (ii) if sufficient, then whether this charging power is P_{opt} (i.e., the minimum charging power among all sufficient ones). Second, we first identify a safe charging power range with a lower bound P_{min} and an upper bound P_{max} , and then present a binary search algorithm to identify P_{opt} by searching this range $[P_{min}, P_{max}]$.

Next, we first present several needed concepts and definitions, then present our approach in finding P_{opt} under three scenarios depending on three energy storage settings.

¹Note that ATHOME can also be applied to event-driven device operation scenarios, where smart devices may incur different functionalities triggered by multiple events. Whenever a functionality is triggered, ATHOME obtains the corresponding working power profile for that functionality (i.e., the required power from the beginning to the end of performing the functionality) and tune the charging power accordingly. Thus, under event-driven scenarios, whenever a new event occurs which triggers the power profile of a device to change, ATHOME will automatically tune the charging power provided by each charger accordingly. Such event-driven scenarios can be

supported by ATHOME because each device has a fixed number of functionalities and the working power profile for each functionality can be obtained through profiling.

In Sec. 2.2, we have illustrated the concept of supplied and required power and energy, as well as their corresponding geometrical representations in the graph (i.e., the corresponding power and energy curves) using a case study. We now formally define these concepts and the corresponding notations. From the geometrical perspective, the slope of a point on $E_i(t)$ represents the corresponding required power $P_i(t)$ at that time point. For example, in Fig. 4a, $P_i(t)$ reaches its maximum value at t_{max} , where $E_i(t)$ also reaches its maximum slope at t_{max} . The charging power supplied by the charger can be denoted as a straight line. For example, in Fig. 4a, the charging power for s_i , denoted P_c , is represented using a straight line. Correspondingly, in Fig. 4b, the supplied energy, denoted $E_c(t)$, is represented as a straight line with slope P_c .

3.1 Finding P_{opt} with No Energy Storage

Without any energy storage, in order to supply s_i with sufficient energy to work continuously, the charging power should be at least the maximum power required by s_i at any time point. Therefore, the optimal charging power for s_i without energy storage is $P_{opt} = P_c^{max} = \max_{t \in T} P_i(t)$, as shown in Fig. 4a.

3.2 Finding P_{opt} with Sufficient Storage

In this case, given sufficient energy storage, we know that a device can receive any amount of supplied energy (as any redundant energy can be stored in the storage). Thus, it suffices to find a charging power yielding a supplied energy that is at least the required energy $E_i(t)$ at any time point.

Geometrically speaking, the supplied energy curve yielded by this charging power must be above or tangent to the required energy curve at any time point. Among all such charging power values, P_{opt} is the smallest value that yields a supplied energy curve tangent to the required energy curve, as illustrated in Fig. 4a and Fig. 4b where P_c^{min} represents P_{opt} and E_c^{min} represent the corresponding supplied energy under P_c^{min} . This is because only when the supplied energy curve is tangent to the required energy curve, the slope of the supplied energy curve becomes the smallest, implying a minimum charging power P_{opt} that can support the device to work continuously. Finding the tangent line to a given curve is a classic analytic geometry problem. Thus, we can apply existing methods introduced in [28] to find P_c^{min} . After obtaining $E_c^{min}(t)$, we know that if the capacity of energy storage B_i is larger than $\max_{t \in T} \{E_c^{min}(t) - E_i(t)\}$, then B_i is large enough to store redundant supplied energy for s_i at any time. Let B^{max} denote $\max_{t \in T} \{E_c^{min}(t) - E_i(t)\}$. Therefore, when the energy storage is at least B^{max} , the optimal charging power can be calculated as $P_{opt} = P_c^{min}$.

3.3 Finding P_{opt} with Limited Energy Storage

In this case where $B_i < B^{max}$, P_c^{min} may not be sufficient. We first illustrate this claim using an example. Fig. 5a shows that from 0 to t_2 , the charging power P_c^{min} is larger than the required power $P_i(t)$, and the shaded area E_{st} denotes the amount of stored energy during this time period. Since $B_i < B^{max}$, we know that the energy storage must become full at some time t_1 , which implies $B_i = E_{st}$. During $[t_1, t_2]$, the charging power remains to be larger than the required power. Thus, the supplied energy starts overflowing within $[t_1, t_2]$. The area E_{of} denotes the amount of overflowed energy. During $[t_2, t_3]$, the charging power P_c^{min} becomes smaller than the required

Figure 5: Energy overflow and received energy.

power $P_i(t)$. The shaded area E_{sup} denotes the amount of energy that node s_i needs to consume from the energy storage in order to work continuously. If the area of E_{st} is smaller than the area of E_{sup} , then s_i will stop working at some time within $[t_2, t_3]$. As discussed in Sec. 3.2, P_c^{min} is sufficient for s_i if and only if the area of E_{of} is 0. However, if $B_i < B^{max}$, energy overflow will happen and the area of E_{of} must be greater than 0, which makes P_c^{min} infeasible.

By the above discussion, we know that P_c^{min} serves as a safe lower bound of any feasible charging power that is sufficient to support s_i , while P_c^{max} clearly serves as a safe upper bound of any feasible charging power according to the discussion in Sec. 3.1. Thus, we know that $P_{opt} \in [P_c^{min}, P_c^{max}]$. To find the value of P_{opt} , an intuitive approach is to perform a binary search. For each searched charging power value, we now present a set of methods that can validate whether this charging power is feasible (i.e., sufficient to power up a device continuously) and optimal; if not, we shall continue the search process using the updated lower and upper bounds on the charging power.

Before presenting the validation methods, we first define and analyze the “received energy” concept because understanding the properties associated with the received energy is critical to understand the validation methods. This concept is formally defined as follows.

Definition 3.1. The received energy of s_i under a given charging power, denoted as $E_i^{cs}(t)$, is the amount of energy actually received by s_i . Due to the limited energy storage, some supplied energy may overflow. Therefore, $E_i^{cs}(t)$ equals to the supplied energy minus the overflowed energy:

$$E_i^{cs}(t) = E_c(t) - E_i^{of}(t), \quad (3)$$

where $E_c(t)$ denotes the amount of supplied energy at t and $E_i^{of}(t)$ denotes the amount of overflowed energy at t . The amount of energy stored in the energy storage at any time t is thus $\max(0, E_i^{cs}(t) - E_i(t))$, where $E_i(t)$ denotes the amount of required energy at t .

As illustrated in Fig. 5b, the green curve $E_i^{CS}(t)$ represents the received energy under a charging power of P_c^{min} . As seen in this figure, the received energy curve becomes lower than the supplied energy curve E_c^{min} at time t_1 . This is because energy starts overflowing at t_1 . At a certain time point in $[t_2, t_3]$, s_i stops working when the received energy curve $E_i^{CS}(t)$ intersects the required energy curve $E_i(t)$ and becomes lower than $E_i(t)$ after t_1 .

In general, $E_i^{cs}(t)$ may experience three stages: storage charging stage, overflow stage, and storage discharging stage (note that these three stages may appear in different order for different scenarios).

Fig. 5a gives a general example illustrating these three stages when $B_i < B^{max}$ and the charging power is P_c^{min} .

Storage Charging Stage: During $[0, t_1]$, the charging power is larger than the required power and the redundant charging energy is stored in the energy storage. $E_i^{cs}(t)$ can thus be calculated as:

$$E_i^{cs}(t) = E_c^{min}(t), t \in [0, t_1]. \quad (4)$$

Overflow Stage: The energy storage becomes full at t_1 . During $[t_1, t_2]$, the charging power P_c^{min} is larger than the consumed power $P_i(t)$. Since the storage is full, the redundant charging energy overflows. Thus, $E_i^{cs}(t)$ can be calculated as:

$$E_i^{cs}(t) = E_i(t) + B_i, t \in [t_1, t_2]. \quad (5)$$

Storage Discharging Stage: During $[t_2, t_3]$, the charging power P_c^{min} is at most the required power $P_i(t)$. Then the amount of received energy during $[t_2, t_3]$ equals to the amount of charging energy. By t_2 , s_i has already received $E_i(t_2) + B_i$ amount of energy. Therefore, $E_i^{cs}(t)$ can be calculated as:

$$E_i^{cs}(t) = E_i(t_2) + B_i + P_c^{min} \times (t - t_2), t \in [t_2, t_3]. \quad (6)$$

By analyzing the above three stages and the geometrical meanings of various power and energy curves, we have the following three important observations.

OBSERVATION 1. An observation herein is that if the charging power cannot provide enough energy to the embedded device for it to work continuously, the device only stops during one of its storage discharging stages. Motivated by this observation, when we validate a charging power's feasibility, we only need to examine the device's energy status during its storage discharging stages.

OBSERVATION 2. Another observation herein is that the discharging stages of a device occur when the charging power just becomes smaller than the required power (e.g., in Fig. 5a, t_2 denotes such a transition time point). Correspondingly, on the energy figure, the discharging stages occur when the slope of the received energy curve just becomes smaller than the required energy curve (e.g., in Fig. 5b, t_2 denotes such a transition time point).

OBSERVATION 3. A third observation herein is that the received energy curves of a device during its storage discharging stages must be straight lines, and the slopes of these lines must be the same as the slope of the supplied energy curve. This is because during the storage discharging stages, all the supplied energy must be received and consumed by the device.

During a storage charging stage or a storage discharging stage, the energy clearly will not overflow. Therefore, if there are any consecutive storage charging and discharging stages, we can combine them into one non-overflow stage. Assume any such non-overflow stage starts at t_s and ends at t_e , the received energy $E_i^{cs}(t)$ within this period under any given charging power P_c can be calculated by considering two cases:

- case 1: a non-overflow stage begins with a charging stage, in which case $E_i^{cs}(t) = E_c(t)$, $t \in [t_s, t_e]$ because the received energy equals to the supplied energy if no energy overflow occurs. Geometrically, the curve representing $E_i^{cs}(t)$ is a straight line because the curve of $E_c(t)$ is a straight line.
- case 2: a non-overflow stage begins with a discharging stage, which implies that this discharging stage happens

Figure 6: (a) An example illustrating the received energy over time. (b) An example illustrating rays

after an overflow stage. In this case, $E_i^{cs}(t) = E_i(t_s) + B_i + P_c \times (t - t_s)$, $t \in [t_s, t_e]$, because s_i receives $E_i(t_s) + B_i$ amount of energy by t_s and receives $P_c \times (t - t_s)$ amount of energy within $[t_s, t]$. Geometrically, the curve representing $E_i^{cs}(t)$ in this case is also a straight line because the terms $E_i(t_s)$, B_i , and P_c are all constants.

On the other hand, during an overflow stage $[t_{s'}, t_{e'}]$, $E_i^{cs}(t)$ can be calculated as:

$$E_i^{cs}(t) = E_i(t) + B_i, t \in [t_{s'}, t_{e'}]. \quad (7)$$

Geometrically, the curve representing $E_i^{cs}(t)$ in an overflow stage has the same shape as $E_i(t)$, which can be in any shape according to s_i 's working power profile (e.g., a curve or a straight line). According to the above equation, specifically, the curve of $E_i^{cs}(t)$ within $[t_{s'}, t_{e'}]$ can be obtained by moving the corresponding $E_i(t)$ curve within $[t_{s'}, t_{e'}]$ towards the y axis (forward direction) for B_i units (see an example interval $[t_1, t_2]$ illustrated in Fig. 5b).

Thus, by considering the above two scenarios (i.e., non-overflow and overflow stages), the curve of the received energy $E_i^{cs}(t)$ is composed of two types of curves: one is the straight-line segments with the same slope as the supplied energy curve; the other type is the curves obtained by moving the required energy curve towards the y-axis (forward direction) for B_i time units. In Fig. 6a, we show another example illustrating the different stages $E_i^{cs}(t)$ may experience, when $B_i < B^{max}$ and $P_c \in (P_c^{min}, P_c^{max})$. As seen in the figure, $[t_0, t_1]$ is a non-overflow stage starting with a charging stage; $[t_1, t_2]$ and $[t_4, t_5]$ are overflow stages; $[t_2, t_4]$ and $[t_5, t_6]$ are non-overflow stages starting with a discharging stage. The curve of $E_i^{cs}(t)$ is clearly in the shape of straight lines with the same slope of the supplied energy curve during $[t_0, t_1]$, $[t_2, t_4]$ and $[t_5, t_6]$; while the curve $E_i^{cs}(t)$ has the same shape as the required energy curve during $[t_1, t_2]$ and $[t_3, t_4]$. Specifically, the curve of $E_i^{cs}(t)$ within $[t_1, t_2]$ and $[t_3, t_4]$ is obtained by moving the corresponding required energy curve within the same intervals towards the y axis (forward direction) for B_i units.

Based upon the above discussions on understanding the properties of $E_i^{cs}(t)$, we now develop a set of methods that validate whether a given P_c is feasible and optimal for a device, mostly arguing from the geometrical perspective of the curves of $E_i^{cs}(t)$ and $E_i(t)$. Thus, to avoid confusion, let $\overline{E_i(t)}$ denote the curve of $E_i(t)$, $\overline{E_i^{cs}(t)}$ denote the curve of $E_i^{cs}(t)$, and $\overline{E_c(t)}$ denote the curve of $E_c(t)$.

Validating whether a given P_c is feasible and optimal. To validate whether a given charging power P_c is feasible to support s_i to work continuously, it suffices to check whether the corresponding received energy $E_i^{cs}(t)$ is at least the required energy $E_i(t)$ at any

time t . From the geometric aspect, it suffices to verify whether $\overline{E_i^{cs}(t)}$ is always above or tangent to $\overline{E_i(t)}$ in order for P_c to be feasible; for otherwise, $\overline{E_i^{cs}(t)}$ intersecting and then being lower than $\overline{E_i(t)}$ implies the device stops working after the intersection point of time.

To examine the geometrical relationship between $\overline{E_i^{cs}(t)}$ and $\overline{E_i(t)}$ for a given P_c , we derive three methods in the next section (Lemmas 3.4-3.6), which validate whether $\overline{E_i^{cs}(t)}$ is above $\overline{E_i(t)}$ (Lemma 3.4), whether $\overline{E_i^{cs}(t)}$ tangents to $\overline{E_i(t)}$ (Lemma 3.5), and prove that P_c is optimal when $\overline{E_i^{cs}(t)}$ tangents to $\overline{E_i(t)}$ at any time point (Lemma 3.6). In order to examine the geometric relationship between $\overline{E_i^{cs}(t)}$ and $\overline{E_i(t)}$, the most straightforward approach is to derive the precise mathematical expression of $\overline{E_i^{cs}(t)}$. However, as we discussed earlier, during overflow stages, $\overline{E_i^{cs}(t)}$ mimics the shape of $\overline{E_i(t)}$. However, it may not be possible to mathematically derive $\overline{E_i(t)}$ if the corresponding working power profile cannot be mathematically expressed. Even if $\overline{E_i^{cs}(t)}$ can be mathematically expressed, it is significantly time consuming to validate whether $\overline{E_i^{cs}(t)} \geq \overline{E_i(t)}$ holds for every time instance t .

In the following, we introduce a set of novel techniques that define and utilize additional auxiliary curves to efficiently examine the relationship between $\overline{E_i^{cs}(t)}$ and $\overline{E_i(t)}$.

Definition 3.2. Let T^b denote the set of Storage Discharging Intervals (SDI), which represent the corresponding set of the storage discharging stages. Note that according to the definition of a storage discharging stage, the charging power is smaller than the required power. Let $T^b = \{[t_1^{b,s}, t_1^{b,e}], [t_2^{b,s}, t_2^{b,e}], \dots, [t_k^{b,s}, t_k^{b,e}]\}$ be composed of k intervals where $k \geq 1$.

For example, in Fig. 5a, the charging power is P_c^{min} , and during $[t_2, t_3]$, the charging power becomes smaller than the required power. Therefore, in this example, $T^b = \{[t_2, t_3]\}$.

Since it is challenging to compare $\overline{E_i^{cs}(t)}$ with $\overline{E_i(t)}$, we define the following auxiliary curves, called “rays”, to assist the comparison.

Definition 3.3. In order to compare $\overline{E_i^{cs}(t)}$ with $\overline{E_i(t)}$, we define an auxiliary ray set $R = \{R_1, R_2, \dots, R_k\}$ of k rays. Each ray corresponds to a SDI. The starting point of each R_k ($1 \leq k \leq q$) is $(t_k^{b,s}, E_i(t_k^{b,s}) + B_i)$, where $t_k^{b,s}$ is defined in Def. 3.2. All rays have the same slope, which equals P_c . Let P^r denote the set of starting points of rays in R .

According to the definition of a storage discharging stage, a SDI must occur after a storage charging stage or a storage overflow interval. During a storage charging stage or a storage overflow stage, the charging power is larger than the required power. But during a SDI, the supplied charging power is at most the required power. Thus, at the beginning of each SDI (i.e., $t_i^{b,s}$ ($1 \leq i \leq k$)), the charging power must be equal to the required power. We can find all the starting time instances of SDIs, i.e., $t_i^{b,s}$ ($1 \leq i \leq k$), in two steps: (i) find all the time instances when the slope of the required energy curve is equal to the slope of the supplied energy curve (which is a straight line), and (ii) remove all the time instances after which the slope of the required energy curve becomes at most the

slope of the supplied energy curve. The remaining time instances will be the set of $t_i^{b,s}$ ($1 \leq i \leq k$).

For example, in Fig. 6b, we find the starting time instance $t_i^{b,s}$ for each ray corresponding to a SDI as follows. In the first step, we can find three time instances, i.e. t_2 , t_3 and t_5 , when the slope of the required energy curve is equal to the slope of the supplied energy curve. In the second step, we find that only after t_3 , the slope of the required energy curve becomes smaller than the slope of the supplied energy curve. Thus, we remove t_3 from the set and we obtain t_2 and t_5 as the starting time instances of two rays, R_1 and R_2 , as shown in Fig. 6b. The start point of R_1 is thus $(t_2, E_i(t_2) + B_i)$ and the start point of R_2 is $(t_5, E_i(t_5) + B_i)$.

Intuitively, these rays denote the amount of received energy for s_i after $t_k^{b,s}$, assuming that the energy storage size is infinite and the energy storage stores B_i at $t_k^{b,s}$. In other words, R denotes the curves representing the maximum possible amount of received energy of s_i after $t_k^{b,s}$. Note that due to the limitation of the energy storage's capacity, the charging energy may overflow and the received energy curve may be partially under R . As an illustrating example, in Fig. 6b, the starting point of R_1 is $(t_2, E_i(t_2) + B_i)$ and the slope is P_c^{min} . R_1 overlaps with $\overline{E_i^{cs}(t)}$ during $[t_2, t_3]$.

Based on the definition of this ray set R , we can prove the following lemmas. Before presenting the lemmas, we first explain the intuition behind these lemmas.

The intuition behind Lemmas 3.4-3.6. The intuitions behind the lemmas are as follows. (i) Observation 1 implies that we only need to examine the geometrical relationship between the received energy curve $\overline{E_i^{cs}(t)}$ and the required energy curve $\overline{E_i(t)}$ during the device's discharging stages; (ii) Observation 3 implies that during the device's discharging stages, $\overline{E_i^{cs}(t)}$ must be straight lines and their slopes are equal to the supplied energy curve $\overline{E_c(t)}$; (iii) Observation 2 gives possible time points $T = \{t_1, t_2, \dots, t_q\}$ at which a discharging stage starts.

Since it is impossible to know whether the energy storage is full at the specific time instance t_i , $1 \leq i \leq q$, we instead assume that the energy storage is full at time t_i , $1 \leq i \leq q$ and the charging energy will not overflow after t_i . We can then draw q auxiliary curves that characterize the received energy under these assumptions, which are rays by Def. 3.3. According to Def. 3.3, there are two possible geometrical relationships between the original received energy curve and the rays: (i) if the energy storage is full at t_i , $1 \leq i \leq q$, the corresponding ray R_i is identical to the received energy curve during the corresponding SDI $[t_i^{b,s}, t_i^{b,e}]$. (ii) if the energy storage is not full at t_i , $1 \leq i \leq q$, ray R_i must be above the received energy curve during that SDI, and the received energy curve during that SDI must be covered by a ray, the start point of which is the end point of the previous storage overflow stage.

Because we assume a larger amount of energy in the energy storage than the amount of energy the device really stores at t_i , $1 \leq i \leq q$ and there is no energy overflowing after the previous overflow stage. Thus, we can compare the geometrical relationships between rays and $\overline{E_i(t)}$ instead to examine the geometrical relationship between $\overline{E_i^{cs}(t)}$ and $\overline{E_i(t)}$.

Since both rays and $\overline{E_i(t)}$ can be mathematically expressed, finding the spatial relationship between rays and $\overline{E_i(t)}$ thus becomes a

Algorithm 1 Binary Search Algorithm**Require:** $P_i(t), B_i$ **Ensure:** P_{opt}

```

1:  $P_c = \frac{P_c^{min} + P_c^{max}}{2}, P_{opt} = 0.$ 
2: set  $P_c$  as the charging power to be validated
3: while  $P_{opt} = 0$  do
4:   if  $\overline{E_i^{cs}(t)}$  is not below  $\overline{E_i(t)}$  at any time  $t$  (using Lemma 1 to validate) then
5:     if there exists at least one time instance  $t$  at which  $\overline{E_i^{cs}(t)}$  is tangent to  $\overline{E_i(t)}$  then
6:        $P_{opt} = P_c$  (according to Lemma 3)
7:     else
8:        $P_c^{max} = P_c$ 
9:     end if
10:  else
11:     $P_c^{min} = P_c$ 
12:  end if
13: end while

```

classic problem in analytic geometry. We can apply the method introduced by the book [28] to examine the geometrical relationship between R and $\overline{E_i(t)}$.

Fig. 6b shows an example illustrating this intuition. Due to space constraints, the detailed proof of these three lemmas are given in an online version [1].

LEMMA 3.4 (ABOVE VALIDATION). $\overline{E_i^{cs}(t)}$ is above $\overline{E_i(t)}$ if and only if $\forall j, R_j$ is not below $\overline{E_i(t)}$.

LEMMA 3.5 (TANGENT VALIDATION). $\overline{E_i^{cs}(t)}$ tangents to $\overline{E_i(t)}$ if and only if $\exists j, R_j$ is tangent to $\overline{E_i(t)}$ and other rays are above $\overline{E_i(t)}$.

LEMMA 3.6 (UNIQUE VALIDATION). Given $E_i(t)$ and B_i , there exists a unique charging power P_{opt} , under which the corresponding received energy curve $\overline{E_i^{cs}(t)}$ is tangent to $\overline{E_i(t)}$.

Finding P_{opt} through binary search. Given the required power profile $P_i(t)$ and the storage buffer size B_i , we adopt a binary search algorithm to find P_{opt} for s_i by using Lemmas 1-3 to validate the feasibility and optimality of each searched value P_c . The pseudo-code of the binary search algorithm is given below.

On Line 4, the algorithm checks whether under P_c , the corresponding $\overline{E_i^{cs}(t)}$ is not below $\overline{E_i(t)}$ according to Lemma 3.4. If not, then it implies that this P_c can be safely used as the lower bound for P_{opt} because P_c is too small to be feasible (Line 11). Otherwise, if true, then the algorithm checks on Line 5 whether $\overline{E_i^{cs}(t)}$ is ever tangent to $\overline{E_i(t)}$ according to Lemma 3.5. If not, then it implies that this P_c can be safely used as the upper bound for P_{opt} because the P_c is feasible but too large (Line 8). Otherwise, if true, then the algorithm sets $P_{opt} = P_c$ (Line 6) according to Lemma 3. This binary search algorithm will stop whenever finding the P_{opt} value.

4 STAGE TWO: CHARGING POWER TUNING

With the minimum required charging power derived for each device in Sec. 3, our objective in stage two is to tune each charger's charging power to enable all devices to work continuously while minimizing the total charging power. Note that a device may receive energy from multiple chargers simultaneously. To formulate this problem, let us first assume the stationary chargers are

Table 1: Energy consumption modules

Module	required power (mW)
LED/Accelerometer	0.4925 / 0.3120
MCU (Active)/MCU (LPM4)	0.3292 / 0.2029
Temperature sensor	0.2786

placed at several different locations and denote each location j as (j_x, j_y) . The location of a device s_i in the network can be identified using localization techniques [27] and represented as (L_x^i, L_y^i) . Consequently, the distance between a location j and s_i 's location is $d_{i,j} = \sqrt{(L_x^i - j_x)^2 + (L_y^i - j_y)^2}$, and the charging power to s_i by the corresponding charger, denoted as $P_{i,j}$, can be calculated by Eq. (2).

Formally, let P_i denote the minimum required charging power of s_i obtained using the charging calculus solution presented in Sec. 3. Let P^j denote the output charging power by the j^{th} charger. Given the locations of m stationary chargers in this area, we can mathematically formulate this problem as:

$$\min \sum_{j=1}^m P^j \quad (8)$$

$$\text{subject to : } \sum_{j=1}^m P_{i,j} \geq P_i, 1 \leq i \leq n \quad (9)$$

$$P_{i,j} = \frac{\alpha}{(d_{i,j} + \beta)^2} P^j, 1 \leq i \leq n, 1 \leq j \leq m \quad (10)$$

$$d_{i,j} = \sqrt{(L_x^i - j_x)^2 + (L_y^i - j_y)^2}, \quad (11)$$

where $\sum_{j=1}^m P^j$ denote the total output charging power of all chargers, and $P^j (1 \leq j \leq m)$ is the only variable in this formulation. Thus, this formulation is a classic linear programming and solving this formulation yields an optimal solution with polynomial-time complexity [24].

5 IMPLEMENTATION AND EXPERIMENTS

To assess the performance of our proposed techniques, we have conducted experiments based on real implementations.

5.1 Experiment setup and baseline

Fig. 8 shows our indoor experimental testbed. We utilize two chargers (Powercaster TX91501 [6]) and 8 rechargeable sensor nodes (WISP 4.1 [9]) which are deployed in a 1.2 m $\times$ 1.2 m square area. WISP integrates two onboard sensors (one 3-axis accelerometer and one temperature sensor), a machine control unit and a led. The required power of each module is listed in Table 1. By selectively turning on/off different modules, we can simulate the scheduling of different workloads on the sensor nodes over time. We use two energy storage settings in the experiments: energy storage size of 5 mJ and 2.5 mJ [14]. In addition, we apply ATHOME to tune chargers' power in this system to supply energy to the sensor nodes. Note that these two chargers are actually directional and can only transmit energy to the sensor nodes through one direction. Thus, we simulate an omnidirectional charger by putting two chargers back to back together, and experiment results show that this setup provides reasonable precision. We use a digital oscilloscope (R&S RTO Digital Oscilloscope[3]) to measure the voltage of the sensor

Figure 7: Experiment results and implementation testbed.

nodes' energy storage. Since the required energy can not be directly measured, we use the voltage drop to calculate the amount of required energy.

Figure 8: Our experimental testbed.

The evaluation goal is to investigate (i) correctness: whether the charging power provided by ATHOME is sufficient to support sensor nodes to work continuously in practice; if certain sensor nodes fail due to interference (e.g., unexpected charging or required power burstiness), then what is the frequency of such failure cases, and (ii) tightness: what is the gap between the supplied energy under ATHOME and the actual required energy measured at runtime, denoted as “Actual” in all result figures.

Correctness validation. Fig. 7 shows eight subfigures, each of which contains five curves representing the required energy by each corresponding sensor node, and the measured supplied energy and received energy yielded by ATHOME under two energy storage sizes: 2.5 mJ and 5 mJ. (Note that the names of the five corresponding legends in each subfigure are intuitive enough to describe these five curves.) In the experiments, all sensor nodes except for the first sensor node are able to work continuously during the whole experimental duration. As seen in Fig. 7, we can see the received energy on sensor node 2, 3, 4, 5, 6, 7 and 8 is no less than the required energy at any time (under both energy storage settings), which implies that these sensor nodes can continuously operate throughout the entire experiment period. By inspecting Fig. 7b more closely, we can discover that the two curves, “ATHOME Received 5 mJ” and “Required Energy”, have one point in

common. This is because the energy storage becomes empty at this time point. In several figures (e.g., Fig. 7c and Fig. 7e), it is seen that the curve representing “ATHOME Received 2.5 mJ” is not a straight line. This is because the energy storage becomes full at some time points and the charging energy partially overflows when the charging power is larger than the required power.

On the other hand, as seen in Fig. 7a, the received energy curve presenting ATHOME Received 5 mJ for the first sensor node is partially below the required energy curve roughly at and after time 4. In our power model, we assume the required power of each device is given and stable according to the profile. But in practice, the required power may fluctuate. Thus, when the actual required power becomes larger than the expected required power, the sensor nodes may run out of energy. For example, in Fig. 7a the storage becomes empty roughly at time 4 under “ATHOME Received 5 mJ”, the charging power equals the required power during [4, 6]. But since the required power fluctuates at time 4, the actual required power becomes larger than the charging power, thus causing the first sensor node to run out of energy. The experiment results also show that most of the sensor nodes (7/8) work correctly during our experiment period. However, generally speaking, the experiment results demonstrate that the charging power solution yielded under ATHOME is sufficient and can correctly power up devices for them to work continuously.

Tightness validation. As seen in all eight subfigures in Fig. 7, “ATHOME Received 5 mJ” yields a supplied energy that is quite close to the Required Energy. For example, as seen in Fig. 7a, the supplied energy under ATHOME for the first sensor node with an energy storage size of 5 mJ is at most 8% more than the required energy at any time instance. This implies that the charging power values yielded by ATHOME are reasonably tight. Moreover, the supplied energy curve is very close to the received energy curve for almost all sensor nodes under both energy storage settings. For example, as seen in Fig. 7b, Fig. 7d and Fig. 7e, the received energy curve almost overlaps with the supplied energy curve (for both energy storage settings). This indicates that there is very little energy that overflows. Another interesting observation is that on

Figure 9: Simulation results.

most of the sensor nodes, “ATHOME Received 2.5 mJ” yields larger supplied energy than “ATHOME Received 5 mJ”. This is because with a smaller energy storage, “ATHOME Received 2.5 mJ” can store less energy in the storage thus requires a larger amount of supplied energy.

Discussion. Our experiments reveal insights about why ATHOME can significantly reduce the amount of overflowed energy. Intuitively, under the same working power profile, a sensor node with larger energy storage (5 mJ) needs smaller amount of supplied energy than the sensor node with smaller energy storage (2.5 mJ). This is because with a smaller energy storage, the sensor node stores less energy in the storage during the time periods when the charging power is larger than the working power, thus requiring a larger amount of supplied energy to satisfy its energy requirement during the time periods when the charging power becomes less than the working power. This intuition is proved by the experimental results. As seen in all eight subfigures in Fig. 7, the gap between “ATHOME Supplied” and “Required Energy” is larger for “2.5 mJ” than the corresponding gap for “5 mJ”. This implies that there is less energy overflow for the “5 mJ” case. Another counter-intuitive observation from our experimental results is that in most cases, the supplied energy is greater than the received energy, which implies overflowed supplied energy. This is because the charging power is a constant value and the supplied energy should be no less than the required energy at any time instance for all sensor nodes. Thus, in order to supply enough energy to the sensor nodes at the “peak” of their working power, the supplied energy may be larger than the received energy after the “peak”. For example, in Fig. 7b, at time 5, “ATHOME supplied 5 mJ” equals to “ATHOME Received 5 mJ” and “Required Energy”. This implies that at the “peak”, the supplied energy equals to the required energy and the sensor node will fail at time 5 if the charger provides a smaller charging power. Thus, even the charging power is optimal for this sensor node, the supplied energy still overflows.

6 SIMULATION-BASED EVALUATION

To further assess ATHOME if applied in an actual smart home with a large number of smart devices and chargers, we have performed extensive sets of simulations. In this section, we present the obtained simulation results.

Simulation setup. We assume wireless rechargeable devices are randomly deployed over a 50 feet $\times$ 50 feet two-dimensional square area (the average home size in America [10]). The default number of embedded devices is 500 [4]. For the charging model (Eq. 2), we set $\alpha = 150$ and $\beta = 30$. These values are chosen because they fit our experiment curve well as mentioned in Sec. 2.1. For each device,

the average capacity of energy storage is 5J [14] and the average required power is 25 mw [26]. Each point in each figure is obtained by averaging 100 runs with different node deployments and system parameters.

Baseline setup. Currently there is no existing work that is designed to minimize the total charging power of all chargers for devices with limited energy storage. For comparison purposes, we introduce a baseline method that charges devices continuously assuming no energy storage, denoted by “NSC”. Thus, NSC treats P_c^{max} as the required charging power for each device.

In addition to the baseline method, we also compare with the required energy calculated according to the working power profile, denoted by “Required Energy”. It is used to demonstrate the tightness of the solution yielded by ATHOME, i.e., the performance gap between ATHOME and the (analytically) minimum energy required by devices.

Simulation Results. Impact of the number of devices. We first examine the impact of the number of devices on the total supplied energy under ATHOME, NSC and Required Energy. Results are shown in Fig. 9a. As seen in Fig. 9a, ATHOME has output much less supplied energy than NSC under all cases. For example, when the number of devices is 500, 25 J is the total supplied energy yielded by ATHOME while NSC needs to provide 35 J, which is about 40% larger than the amount of energy provided by ATHOME. We can also see that ATHOME yields a supplied energy that is quite close to the Required Energy baseline, which indicates a tight performance.

Impact of the average buffer size. We also study the impact of the average energy storage size on the total supplied energy by all deployed chargers for under ATHOME, NSC and Required Energy. In Fig. 9b, we can see that the performance curve of NSC is a horizontal line. This is because NSC operates assuming no buffer. Clearly, ATHOME outperforms NSC by a large margin in all cases. Also, ATHOME again performs quite closely to the Required Energy baseline in all cases.

Impact of the standard deviation of the required power. We also study the impact of standard deviation of nodes’ required power. As seen in Fig. 9c, ATHOME still outperforms NSC by a large margin and performs very closely to the Required Energy baseline. Another observation is that when the standard deviation increases, the supplied energy under all three methods also increases. This is because a large deviation indicates that the sensor nodes may consume a larger amount of energy in a shorter period of time. To satisfy the energy requirement, more supplied energy will be required.

Impact of the average required power. To investigate the impact of the average required power on the total supplied energy under ATHOME, NSC and Required Energy, we perform simulations with average required power varying from 1 *mw* to 200 *mw*, and the results are shown in Fig. 9d. We can see that as the average required power increases, the total supplied energy increases. That is because when the average required power increases, more energy is required to support the nodes. Again, ATHOME achieves a quite close performance to the Required Energy baseline and outperforms NSC. For example, when the average required power is 25 *mw*, ATHOME supplies 16 *J* energy to support all sensor nodes while Oracle supplies 15 *J*, which is only 6.25% less than the amount of energy supplied by ATHOME.

7 RELATED WORK

Rechargeable sensor networks research has received much attention recently due to its wide application domains [11, 15, 17, 19–23, 25, 30, 32]. Based on the types of chargers deployed in the network, rechargeable sensor networks can be divided into two categories: mobile charger-based networks and stationary charger-based networks. Several mobile charger scheduling algorithms were studied to sustain the lifetime of wireless sensor networks [12, 20, 30]. Xie *et al.* [30] adopted a mobile charger traveling policy within the network for charging sensor nodes continuously. While traveling within the network, the charger makes a number of stops and charge sensor nodes near those stops. By satisfying certain constraints, none of the sensor nodes in the network will ever run out of energy. In [20], the authors make an assumption that the charging time for each sensor node is much longer than the mobile charger's traveling time, and thus the spatial aspects of the problem is ignored by the scheduling algorithms. In [12], He *et al.* divide the sensor nodes into different groups, and apply TSP algorithms to recharge nodes within each group. Fu *et al.* [11] solved this problem by planning the optimal movement strategy of the RFID reader, such that the time to charge all nodes in the network above their energy threshold is minimized. Their study provides reasonable performance with the assumption that sensor nodes do not operate during charging period. Therefore, they are not suitable for practical usage of sensor nodes because nodes can be charged while operating.

8 CONCLUSION

In this paper, we present ATHOME, which automatically tunes the charging power of multiple stationary wireless chargers to provide enough energy that continuously power up smart devices with varying working power profiles, while minimizing the total charging power. We implement ATHOME on a WISP platform with 8 rechargeable nodes. Evaluation results based on both experiments and simulations demonstrate that ATHOME provides sufficient, tight, and adaptive charging power enables nodes to work continuously.

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