A STACKELBERG GAME-BASED ENERGY TRADING SCHEME FOR POWER BEACON-ASSISTED WIRELESS-POWERED COMMUNICATION

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ABSTRACT

This paper studies a power beacon-assisted wireless-powered communication network, consisting of one hybrid access point (AP), one information source, and multiple power beacons (PBs). The source has no embedded power supply, and thus, has to harvest RF energy from the AP in the downlink before transmitting its information to the AP in the uplink. The PBs are deployed to help the AP charge the source in the downlink. However, in practice, the AP and PBs may belong to different operators. Thus, incentives are needed for the PBs to assist the AP during DL energy transfer phase, which is referred to as "energy trading". We formulate this energy trading process as a Stackelberg game, in which the AP is a leader and the PBs are the followers. We then derive the Stackelberg equilibrium of the formulated game. Numerical results show that the proposed scheme can achieve better performance as either the number of the PBs or the value of the gain per unit throughput increase, and as the distance between source and PBs decreases.

Index Terms— Wireless energy transfer, RF energy harvesting, energy trading, Stackelberg game.

1. INTRODUCTION

Radio frequency (RF) energy harvesting and transfer techniques, have recently been regarded as a promising solution to power energy-constrained wireless networks [1–5]. The feasibility of this technique has been experimentally demonstrated by prototypes, as shown in [6, 7]. As an important and typical application of the RF energy harvesting and transfer techniques, a new type of networks, referred to as wireless-powered communication networks (WPCN-s), have recently attracted much attention (see [4] and the references therein). In a WPCN, wireless devices are only powered by the energy harvested from RF signals. A "harvest-then-transmit" protocol was developed for WPCNs in [8]. In this protocol, the users first collect energy from the signals broadcast by a hybrid access-point (AP) in the downlink (DL) and then use the harvested energy to send information to the AP in the uplink (UL). Very recently, several co-operative protocols were developed for WPCNs with different setups in [9–11].

In typical WPCNs, the hybrid AP is normally the only energy source of the whole network [4]. Very recently, Huang *et al.* proposed a novel idea of deploying a dedicated wireless energy network, consisting of multiple power transmitters, referred to as power beacons (PBs), that can provide wireless charging services to terminals via the RF energy transfer technique [5, 12]. The deployment of dedicated PBs in an existing cellular network was designed in [12] such that the updated network can provide both wireless access and wireless charging services. It is assumed in [12] that the PBs are deployed by the *same operator* of the existing network. However, in general, PBs can be deployed by *different authorities*. In such situations, incentives (e.g., monetary payments) are needed for the PBs to provide wireless charging services to their users. Here, we call the subscription and provision of wireless charging services as *energy trading* between PBs and their users. To the best of our knowledge, there are no published references that modeled and investigated this hierarchical interactions between the PBs and their users for the W-PCNs. This gap motivates this paper.

In this paper, we consider a WPCN consisting of one hybrid AP, one information source and multiple PBs that are deployed by different operators. We develop an energy trading framework for the considered PB-assisted WPCN using game theory. Specifically, we take the strategic behaviors of the AP and PBs into consideration and formulate the energy trading process between them as a Stackelberg game [13, 14]. In the formulated game, the AP acts a leader who buys energy from the PBs to charge the source by offering an energy price on per unit of harvested energy from the signals radiated by the PBs. The AP optimizes its energy price and DL energy transfer time to maximize its utility function defined as the difference between the benefits obtained from the achievable throughput and its total payment to the PBs. On the other hand, the PBs are the followers of the formulated game, and determine their optimal transmit powers based on the released energy price from the AP to maximize their own profits. The profit of each PB is defined as the payment received from the AP minus its energy cost. We then derive the Stackelberg equilibrium (SE) for the formulated game. Finally, numerical simulations are performed to investigate the impacts of various system parameters, such as the gain per unit throughput for the AP, the number of PBs, and the distance between the source and PBs, on the performance of the proposed scheme.

2. SYSTEM MODEL AND GAME FORMULATION

In this section, we first describe the system model and derive the expression of the achievable system throughput with the help of the PBs. Then, we formulate the Stackelberg game to model the energy trading process between the AP and PBs.

2.1. System Model

In this paper, we consider a PB-assisted WPCN consisting of one hybrid AP, one information source, and N deployed PBs, as shown in Fig. 1. We denote the set of these PBs as $\mathcal{N} = \{1, \ldots, N\}$. It is assumed that each node in the considered network is equipped with a single antenna and works in a half-duplex mode. The AP collects the information from the source. In addition, we assume that the AP and PBs are connected to constant power supplies. In contrast, the source has no embedded energy supplies, and thus needs to replenish

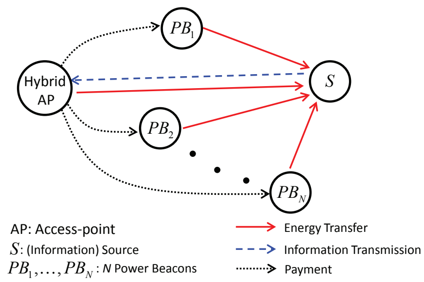


Fig. 1. System model for a PB-assisted WPCN.

energy from the RF signal sent by the AP and PBs. The "harvest-then-transmit" protocol proposed in [8] is implemented in this paper. In particular, during the first τT $(0 < \tau < 1)$ amount time of each transmission block, the source harvests wireless energy broadcast by the AP and the PBs in the DL. In the remaining $(1-\tau)\,T$ amount of time, the source uses the harvested energy to transmit its information to the AP in the UL. For convenience, but without loss of generality, we assume $T = 1$ and refer to the value of τ as the DL energy transfer time in the rest of this paper.

Let p_a and p_m denote the transmit powers of the AP and the mth PB during the DL energy transfer phase, respectively. It is assumed that the energy-carrying signals sent by the AP and PBs are independent and identically distributed (i.i.d.) random variables (RVs) with a zero mean and unit variance[1]. In addition, we assume that all channels experience independent slow and frequency flat fading, where the channel gains remain constant during each transmission block but change independently from one block to another. For simplicity, we consider a reciprocal channel model in this paper. That is, the channel gains between two nodes for the DL and UL phases are the same in each transmission block. We use $G_{a,s}$ and $G_{m,s}$ to denote the channel power gains between the AP and source, and that between the mth PB and the source, respectively.

The energy harvesting receiver at the source rectifies the RF signals received from the AP and PBs, and obtains a direct current to charge up its battery. The details of such an energy harvesting receiver can be found in [15]. The amount of energy harvested by the source can be expressed as

$$E_s = \eta\tau\left(p_a G_{a,s} + \sum\nolimits_{m=1}^{N} p_m G_{m,s}\right), \tag{1}$$

where $0 < \eta < 1$ is the energy harvesting efficiency. Note that the receiver noise at the source is ignored in (1) since it is in practice negligible for the energy receiver.

After the source replenishes its energy during the DL phase, it will transmit its information to the AP in the subsequent UL phase. It is assumed that the harvested energy is exhausted by the source for information transmission. The transmission power of the source is thus given by

$$p_s = \frac{E_s}{1-\tau} = \frac{\eta\tau\left(p_a G_{a,s} + \sum_{m=1}^{N} p_m G_{m,s}\right)}{1-\tau}. \tag{2}$$

Then, the signal-to-noise ratio (SNR) of the received signal at the hybrid AP during the UL phase can be expressed by

$$\gamma_a = p_s G_{a,s}/N_0, \tag{3}$$

[1] It is worth noting that phase synchronization between the AP and PBs is not required for the DL energy transfer since they transmit independent energy signals.

where N_0 is the power of the AWGN at the hybrid AP. Hence, the achievable throughput (bps) at the AP can be written as

$$R_{sa} = (1-\tau)\,W\log_2(1+\gamma_a), \tag{4}$$

where W is the bandwidth.

2.2. Stackelberg Game Formulation

In general, the PBs in the considered WPCN may belong to different authorities and act strategically. Incentives need to be provided by the AP to the PBs for their wireless charging services, i.e., assisting the energy replenishment of the source in the DL. Consequently, the AP needs to choose the most beneficial PBs. We model the strategic interactions between the AP and PBs as a Stackelberg game. A Stackelberg game is a strategic game that consists of a leader and several followers competing with each other for certain resources [13, 14]. The leader acts first and the followers respond to the actions of leader subsequently. In this paper, we formulate the AP as the leader, and the PBs as the followers. The AP (leader) imposes a price on per unit of energy harvested from the RF signals radiated by the PBs, referred as to the *energy price* in the following. Then, the PBs (followers) optimize their transmit powers based on the released energy price to maximize their individual profits.

Let λ denotes the energy price released by the AP. Mathematically, the total payment of the AP to the PBs can be expressed as

$$\Gamma(\tau,\lambda,\boldsymbol{p}) = \sum\nolimits_{m=1}^{N} \lambda\,(\tau p_m G_{m,s}), \tag{5}$$

where $\boldsymbol{p} = [p_1,\ldots,p_N]^T$ is the vector of the PBs' transmit powers, with $p_m \geq 0$ denoting the transmit power of the mth PB. Then, we define the utility function of the AP as

$$\mathcal{U}_a(\tau,\lambda,\boldsymbol{p}) = \mu R_{sa} - \Gamma(\tau,\lambda,\boldsymbol{p}), \tag{6}$$

where R_{sa} is defined in (4) and $\mu > 0$ is the gain per unit throughput for the AP. Therefore, the optimization problem for the AP or the *leader-level* game can be formulated as

$$(\text{P2.1}): \quad \begin{array}{l} \max\limits_{\tau,\lambda} \ \mathcal{U}_a(\tau,\lambda,\boldsymbol{p}) \\ \ \text{s.t. } \tau\in(0,1),\ \lambda\geq 0. \end{array} \tag{7}$$

Note that the optimal value of τ can be neither 0 nor 1 since both cases lead to zero throughput.

Each PB in the considered network can be modelled as a follower that wants to maximize its individual earning, which is defined as follows:

$$\mathcal{U}_m(p_m,\lambda,\tau) = \lambda\tau p_m G_{m,s} - \tau\mathcal{C}_m(p_m), \tag{8}$$

where the function $\mathcal{C}_m(\cdot)$ is used to model the cost of the mth PB per unit time for wirelessly charging the source with the transmit power p_m. In this paper, we consider the following quadratic model for the cost function of the PBs:

$$\mathcal{C}_m(x) = a_m x^2 + b_m x, \tag{9}$$

where $a_m > 0$ and $b_m \geq 0$ are pre-determined parameters that may be different for the PBs. Note that the quadratic function given in (9) has been widely adopted in the power market to model the energy cost [16].

Thus, the optimization problem for the mth PB or the *follower-level* game is given by

$$(\text{P2.2}): \ \max_{p_m} \ \mathcal{U}_m(p_m,\lambda,\tau),\ \text{s.t. } p_m\geq 0. \tag{10}$$

The Stackelberg game for the considered PB-assisted WPCN has been formulated by combining problems (P2.1) and (P2.2).

3. ANALYSIS OF THE PROPOSED GAME

In this section, we derive the SE of the formulated game by analyzing the optimal strategies for the AP and PBs to maximize their own utility functions.

It can be observed from (10) that for given values of τ and λ, the utility function of the mth PB is a quadratic function of its transmit power p_m and the constraint is affine, which indicate that the problem (P2.2) is a convex optimization problem. Thus, it is straightforward to obtain its optimal solution given in the following lemma:

Lemma 1 *For given values of τ and λ, the optimal solution for problem (P2.2) is given by*

$$p_m^* = \left(\frac{\lambda G_{m,s} - b_m}{2a_m}\right)^+, \tag{11}$$

where $(\cdot)^+ = \max(\cdot, 0)$.

Proof: The proof of this lemma follows by noting that the objective function of problem (P2.2) given in (8) is a concave function in terms of p_m.

Subsequently, we need to solve problem (P2.1) by replacing p_m with p_m^* given in (11). However, it is extremely hard to find the optimal expressions for λ and τ at the same time due to the complexity of the objective function of problem (P2.1) after the substitution of (11). To tackle this, we solve this problem optimally by two steps. *Specifically, we first find the closed-form expression for the optimal λ with a fixed value of τ. Then, the optimal value for τ is achieved in the second step via one-dimension exhaustive search.* After substituting (11) into (7), the optimization problem at the AP side *for a given value of τ* can be expressed as

$$(\text{P3.1}): \quad \begin{array}{l} \max\limits_{\boldsymbol{\kappa},\lambda} \ \mathcal{U}_a'(\tau, \boldsymbol{\kappa}, \lambda) \\ \text{s.t. } \kappa_m \in \{0,1\}, \forall m \in \mathcal{N}, \ \lambda \geq 0, \end{array} \tag{12}$$

where $\boldsymbol{\kappa} = [\kappa_1, \ldots, \kappa_N]^T$ is the indicator vector with the mth indicator defined as

$$\kappa_m = \begin{cases} 1, & \text{if } \lambda > \frac{b_m}{G_{m,s}}, \\ 0, & \text{if } \lambda \leq \frac{b_m}{G_{m,s}}, \end{cases} \tag{13}$$

and

$$\begin{aligned} \mathcal{U}_a'(\tau, \boldsymbol{\kappa}, \lambda) =& W' \ln C - \sum_{m=1}^{N} \kappa_m \lambda \tau \frac{\lambda G_{m,s} - b_m}{2a_m} G_{m,s} + \\ & W' \ln \left(1 + \frac{D}{C} \sum_{m=1}^{N} \kappa_m \frac{\lambda G_{m,s} - b_m}{2a_m} G_{m,s}\right), \end{aligned} \tag{14}$$

in which, $W' = \mu(1-\tau)W/\ln 2$, $C = 1 + \frac{\eta\tau G_{a,s} p_a G_{a,s}}{(1-\tau)N_0}$, and $D = \frac{\eta\tau G_{a,s}}{(1-\tau)N_0}$ are defined for notation simplification.

Unfortunately, problem (P3.1) is still not convex due to the indicator vector $\boldsymbol{\kappa}$, even if we regard the parameter τ as a constant. To address this issue, *we first consider a special case of problem (P3.1) by assuming that the gain per unit throughput (i.e., the parameter μ) is sufficiently large such that all PBs are involved during the DL energy transfer phase*. Thus, each indicator $\kappa_m = 1$ for any $m \in \mathcal{N}$. That is, $\lambda > \frac{b_m}{G_{m,s}}$, $\forall m$ holds. In this case, problem (P3.1) can be simplified to the following one:

$$(\text{P3.2}): \ \max_{\lambda} \ \mathcal{U}_a''(\tau, \lambda), \text{ s.t. } \lambda \geq 0, \tag{15}$$

where

$$\begin{aligned} \mathcal{U}_a''(\tau, \lambda) =& W' \ln C - \lambda^2 \tau X_N + 2\lambda\tau Y_N + \\ & W' \ln\left(1 + \frac{D}{C}(\lambda X_N - 2Y_N)\right), \end{aligned} \tag{16}$$

with $X_N = \sum_{n=1}^{N} \frac{G_{n,s}^2}{2a_n}$ and $Y_N = \sum_{n=1}^{N} \frac{b_n G_{n,s}}{4a_n}$.

We solve problem (P3.2) and have the following proposition:

Proposition 1 *The optimal solution to problem (P3.2) is given by*

$$\lambda^\star = \frac{-\left(\frac{C}{D} - 3Y_N\right) + \sqrt{\left(\frac{C}{D} - Y_N\right)^2 + \frac{2X_N W'}{\tau}}}{2X_N}. \tag{17}$$

Proof: Omitted due to space limitation. Please refer to [17].

Now, a natural question that arises is "*under what conditions, the optimal solution to the simplified problem in Proposition 1 is also that to the original problem (i.e., problem (P3.1))?*" To answer this question, we formulate the following proposition,

Proposition 2 *The optimal energy price given in (17) is also the optimal solution to the problem (P3.1)* if and only if *the following condition holds*

$$\begin{aligned} \mu >& \frac{2\tau(\ln 2)\left(X_N \max_{m\in\mathcal{N}} Z_m - 2Y_N + \frac{C}{D}\right)}{X_N(1-\tau)W} \times \\ & (X_N \max_{m\in\mathcal{N}} Z_m - Y_N), \end{aligned} \tag{18}$$

where $Z_m = \frac{b_m}{G_{m,s}}$.

Proof: Omitted due to space limitation. Please refer to [17].

Based on the above analysis, we are now ready to derive the optimal solution to problem (P3.1) given in the following proposition,

Proposition 3 *Let us assume that all PBs are sorted in the order $Z_1 < \ldots < Z_{N-1} < Z_N$. Then the optimal solution to problem (P3.1) is given by*

$$\lambda^* = \begin{cases} \tilde{\lambda}_N, & \text{if } \mu > Q_N, \\ \tilde{\lambda}_{N-1}, & \text{if } Q_{N-1} < \mu \leq Q_N, \\ \vdots & \quad \vdots \\ \tilde{\lambda}_1, & \text{if } Q_1 < \mu \leq Q_2, \end{cases} \tag{19}$$

where

$$\tilde{\lambda}_K = \frac{-\left(\frac{C}{D} - 3Y_K\right) + \sqrt{\left(\frac{C}{D} - Y_K\right)^2 + \frac{2X_K W'}{\tau}}}{2X_K}, \tag{20}$$

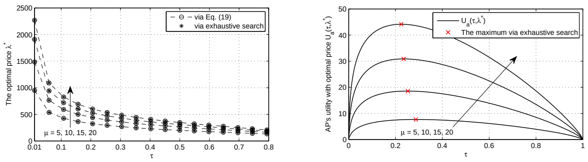
$$Q_K = \frac{2\tau(\ln 2)\left(X_K Z_K - 2Y_K + \frac{C}{D}\right)(X_K Z_K - Y_K)}{X_K(1-\tau)W}, \tag{21}$$

with $X_K = \sum_{n=1}^{K} \frac{G_{n,s}^2}{2a_n}$ *and* $Y_K = \sum_{n=1}^{K} \frac{b_n G_{n,s}}{4a_n}$, $\forall K \in \mathcal{N}$.

Proof: Omitted due to space limitation. Please refer to [17].

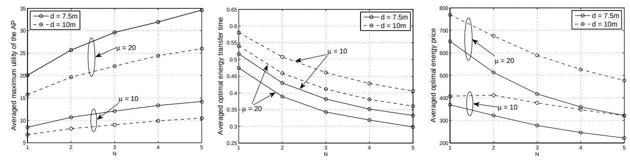
We have already obtained the optimal energy price of the AP for a fixed τ. Substituting the appropriate expression of λ^* given in (19) base on the value of μ into problem (P3.1), we have the following optimization problem regarding parameter τ:

$$(\text{P3.3}): \ \max_{\tau} \ \mathcal{U}_a'(\tau, \lambda^*), \ \text{ s.t. } 0 < \tau < 1. \tag{22}$$



(a) λ^* (b) $\mathcal{U}_a(\tau, \lambda^*)$

Fig. 2. The impact of the energy transfer time τ on (a) the optimal energy price λ^* and (b) the AP's utility $\mathcal{U}_a(\tau, \lambda^*)$ with the optimal energy price.



(a) $\mathbb{E}[\mathcal{U}_a(\tau^*, \lambda^*)]$ (b) $\mathbb{E}[\tau^*]$ (c) $\mathbb{E}[\lambda^*]$

Fig. 3. The curves of (a) averaged maximum utility of the AP $\mathbb{E}[\mathcal{U}_a(\tau^*, \lambda^*)]$, (b) averaged optimal energy transfer time $\mathbb{E}[\tau^*]$ and (c) averaged optimal energy price $\mathbb{E}[\lambda^*]$ versus the number of PBs with different values of μ and d.

Note that problem (P3.3) can be efficiently solved via one-dimension exhaustive search. We denote the optimal solution to problem (P3.3) by

$$\tau^* = \arg \max_{\tau \in (0,1)} \mathcal{U}'_a(\tau, \lambda^*). \tag{23}$$

This has completed the derivation of the SE for the formulated Stackelberg game, which is summarized in the following corollary,

Corollary 1 *The triple $(\tau^*, \lambda^*, \boldsymbol{p}^*)$ is the SE of the formulated Stackelberg game, where τ^*, λ^*, and $\boldsymbol{p}^*$ are given in (23), (19), and (11), respectively.*

4. NUMERICAL RESULTS

In this section, we present some numerical results to demonstrate the performance of the proposed game-theoretical scheme. To capture the effect of path-loss on the network performance, we use the channel model that $\mathbb{E}[G_{x,y}] = 10^{-3}(d_{x,y})^{-\alpha}$, where $\mathbb{E}[\cdot]$ denotes the expectation operation, $d_{x,y}$ is the distance between nodes x and y, and $\alpha \in [2, 5]$ is the path-loss factor [18]. Note that a 30dB average signal power attenuation is assumed at a reference distance of 1m in the above channel model [8]. In all following simulations, the gain per unit throughput (i.e, μ) is measured in per Mbps and the transmit powers of PBs (i.e., p_m's) are measured in milliWatt (mW). Accordingly, the units of the energy price λ released by the AP, and the cost parameters a_m's and b_m's of the PBs are per mW, per mW^2, and per mW. In addition, we set the AP transmit power $p_a = 1000$mW, the distance between the AP and source $d_{a,s} = 15$m, the path-loss exponent $\alpha = 2$, the noise power $N_0 = 10^{-8}$mW, the energy harvesting efficiency $\eta = 0.5$ and the bandwidth $W = 1$MHz. For simplicity, we choose the same values $a_m = 2 \times 10^{-6}$ and $b_m = 2 \times 10^{-3}$ for all PBs. To evaluate the impact of the number of PBs on the system performance, we assume that the distances from the PBs to the source are the same, i.e., $d_{m,s} = d, \forall m$.

We first validate our theoretical analysis presented in Sec. 3. To this end, we consider a four-PB network with one randomly generated channel realization given by $G_{a,s} = 8.0846 \times 10^{-6}$ and $[G_{m,s}]_{m=1,2,3,4} = [0.0470, 0.0787, 0.1798, 0.1824] \times 10^{-4}$. With this network setup, Fig. 2 illustrates the impact of the DL energy transfer time τ on both the optimal energy price λ^* and the AP's utility with the optimal energy price. It can be observed from Fig. 2 (a) that the values of the optimal energy price obtained via (19) and exhaustive search coincide with each other for all simulated cases, which validates our analytical results presented in Sec. 3. In addition, we can see from this subfigure that the optimal energy price decreases monotonically when the value of τ increases. The reason is that with a longer DL energy transfer time τ, the source can harvest more energy from its associated AP and less energy is required from the PBs, which renders the decrease of the optimal energy price. From Fig. 2 (b), we can see that there always exists a utility-optimal energy transfer time τ when the energy price is set to the optimal one. Furthermore, we can observe from this subfigure that the optimal value of τ slightly shifts to the left as the parameter μ increases.

Next, we investigate the averaged performance of the proposed game-theoretical scheme in the remaining figures, in which each curve is obtained by averaging over 10000 randomly generated channel realizations. Fig. 3 (a) illustrates the averaged maximum utility of the AP, denoted by $\mathbb{E}[\mathcal{U}_a(\tau^*, \lambda^*)]$. We can see that the averaged maximum utility of the AP is improved with the increasing of the number of PBs and the value of μ. But, it is reduced when the distance between the source and PBs is increased from 7.5m to 10m. This is because the nearer the PBs to the source, the higher the efficiency of DL energy transfer from the PBs to the source, which can reduce the AP's payments to the PBs for their wireless charging services. Moreover, as depicted in Fig. 3 (b), the averaged optimal energy transfer time $\mathbb{E}[\tau^*]$ is reduced as either the numbers of the PBs or the value of the gain per unit throughput increase, and as the distance between the source and PBs decreases. In Fig. 3 (c), we demonstrate the influences of the aforementioned parameters on the averaged optimal energy price, denoted by $\mathbb{E}[\lambda^*]$. We can see from Fig. 3 (c) that the value of $\mathbb{E}[\lambda^*]$ decreases as the number of PBs increases. Besides, the larger the parameter μ, the higher the averaged optimal energy price. It can also be observed from this subfigure that the reduction of the distance between the source and PBs can also diminish the optimal energy price. This is because the shorter the distance between the source and PBs, the more energy the source can harvest on average for the same transmit powers of the PBs, which leads to a lower energy price.

5. CONCLUSIONS

In this paper, we developed an energy trading framework for the power beacon-assisted wireless-powered communication networks. Considering the strategic behaviors of the hybrid access point (AP) and power beacons (PBs), we formulated a Stackelberg game for the considered network, in which the AP is the leader and the PBs are the followers. The Stackelberg equilibrium of the formulated game was subsequently derived. Numerical results showed that the proposed scheme can achieve better performance as either the numbers of the PBs or the value of the gain per unit throughput increase, and as the distance between the source and PBs decreases. At the same time, these changes also lead to a shorter downlink energy transfer time.

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