Analysis and Power Scheduling Algorithm in Wireless Powered Communication Networks

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***Abstract*—Wireless powered communication networks (WPCN) which allow an energy source (ES) to wirelessly transfer its power to a wireless device (WD) is becoming a promising technology in modern wireless networks. Besides extending network longevity, WPCN eliminates the need for frequent manual battery replacement or recharging.**

Even WPCN is a potential solution, how to optimize network lifetime to guarantee network substantiality and reliability is challenging. This problem has not yet been considered carefully in literature. In addition, existing related works do not consider both uplink and downlink traffic which directly impact device lifetime as well as network lifetime. This paper, therefore, deals with the problem of optimizing network lifetime by appropriately scheduling transmitted power from an ES to each WD. To this end, the paper first proposes models for device lifetime and network lifetime. Based on the models, the strategy to optimize network lifetime is derived. The paper then proposes a power scheduling algorithm performed at an ES to maximize network lifetime under several network conditions. The proposed algorithm takes into account bi-directional traffic at each WD. The proposed models and the performance of power scheduling algorithm are verified by simulations. The paper is an useful guideline to assess reliability duration of the network and provides several directions to ensure network reliability and substantiality.

***Index Terms*—WPCN, power scheduling, optimal network lifetime.**

I. Introduction

A wireless powered communication networks (WPCN) in which a radio signal enables wireless energy transfer is a promising technology to prolong network lifetime without operation interruptions. Compared to conventional battery-powered wireless networks, WPCN eliminates the need for manual battery replacement or recharging. Compared to opportunistic energy harvesting (EH) approaches in which end devices harvests energy from nature such as solar, wind power, vibration, WPCN is more stable due to the possibility of full control over transmitting power, waveforms, and occupied time or frequencies dimensions [1].

A typical WPCN consists of a data center (DC), an energy source (ES), and a number of wireless end-device (WD). DC and ES can be co-allocated in a hybrid architecture or be separated. The hybrid architecture helps to reduce deployment cost by sharing communication and signal processing modules but it may bring co-channel interference and doubly-near-far problems [1]. In addition, as a device cannot involve in both data transmission and power transfer simultaneously due to the restriction on the circuits [2], co-ordination for channel assess is required to avoid collision between data transmission and energy transmission. On the other hand, separated architecture can tackle this problem by pursuing a flexible balance between data and energy transmission [3], [4], [5]. In addition, due to the independence of energy and information sources, this architecture requires less complicated co-ordination compared to hybrid architecture. Therefore, this paper considers WPCN with separated DC and ES architecture.

Scheduling to improve energy efficiency in WPCN networks has been widely studied in literature. Several existing works on scheduling have focused on how to schedule power for data transmission. Online scheduling algorithms were proposed in [6] to decide how energy resource is used to transmit data packets. Jang et al. [7] adaptively changed transmission rate according to the traffic load and available energy to minimize the packet transmission time. However, network scenario in this study is too simple with only one user. Charing control scheme was studied in [3], [8] to allocate power over subchannel for maximizing network lifetime. In addition to power allocation, other scheduling studies focused on time and duration for information and energy transmission periods to maximize system energy efficiency or network sum-rates [2], [6]. In other studies, the authors scheduled time to charge energy for nodes [9], [10] which performed specific tasks such as information gathering or sensing.

Besides power scheduled for data transmission, other existing scheduling works with deal with different network purposes. In [11], the authors proposed a scheduling scheme to maximize the sum ergodic throughput of a power-beacon (PB)-assisted wireless powered communication network. In their study, the PB located between several sensors and a base station (BS) first performed wireless energy transfer to the sensors and then assisted forwarding the information of each sensor to the BS based on TDMA protocol. A distributed scheduling protocol for energy and information transmissions in WPCN was proposed in [12]. In particular, the authors proposed an energy queueing model based on an energy decoupling property to derive the throughput performance. A scheduling wireless power transfer and data transmission was formulated as Markov chain in [13] to reduce packet loss rate and to increases network goodput. As the authors are aware, non of existing works deal with scheduling power for WD to maximize overall network lifetime.

In a WPCN, ES is shared among WDs in the network. Therefore, transmitting power from ES to each WD strongly affects how much energy that a device can harvest and consequently how long the lifetimes of device and network are. In addition to power scheduling, most of existing works do not consider the impact of downlink (DL) traffic to each WD even many applications are two-way communications [1]–[4], [6]–[13]. These research assume that the WD uses harvested energy only for its uplink (UL) transmission. This assumption, however, underestimates the impacts of DL traffic to network energy consumption because when a device receives a packet, it also consumes certain energy. In some platform chips such as CC2420 [19], the energy consumed to receive a packet is more than that to transmit a packet. Furthermore, even in some wireless sensor networks (WSN) where UL traffic is more often than DL traffic, the DL data transmission rate is still frequent. For example, beacon frame is broadcasted from coordinator to all sensors at every superframe in beacon-enabled IEEE 802.15.4 networks [14] or at every Target Beacon Transmission Time (TBTT) in WiFi networks [15]. Therefore, the impacts of DL transmission rate to network performance have to be taken into consideration. This limitation is solved in this paper.

This paper deals with power scheduling from an ES to each WD in a WPCN to enhance the network longevity. The main contributions of the paper are summarized as follows:

1) The paper first proposes a model for the lifetime of a WD. Then the upper-bound and lower-bound of the device lifetime are derived. Based on the models and these bounds, network operators are able to asses when some WDs in the network are running out so that appropriate interventions can be done.
2) The paper proposes a model for network lifetime and then provides numerical analysis for its possible optimization. This analysis brings some directions for the lifetime optimizations based on several influence factors such as load allocation, power scheduling, and time sharing among WDs in the networks.
3) The paper proposes a power scheduling algorithm, performed at an ES, to maximize network lifetime in some network circumstances. This objective is done by allocating appropriate power transmitted from the ES to each WD while considering their UL and DL transmission rates. All proposed models and the performance of algorithm are verified by extensive simulations.

II. System Model

We consider a WPCN consisting of one DC, one ES and N distributed WD$_i$ ($1 \leq i \leq N$) belonging to set $\mathbb{S} = \{\text{WD}_i;\ i = 1,..., N\}$, as shown in Fig.1. DC and ES are connected to stable power sources. We assume that DC and ES are performed on separate frequencies without interfering with each other. ES broadcasts power to WDs by radio in the DL direction. We assume that the power is transferred in one frequency to save network resource and to simplify implementation. ES can transmit power to all or several WDs simultaneously depending on its antenna. If the antenna is $directional$ which radiates RF energy to only one intended sector at a time, only WDs in the sector can harvest energy. On the other hand, if the antenna is $omni-directional$, RF energy can be radiated to all directions and all WDs can harvest the energy simultaneously. Data transmission between DC and WDs is performed in one or several frequencies. As current circuit technologies do not support both energy harvesting and information decoding at the same time [2], while WD$_i$ is harvesting energy, it does not transmit or receive data.

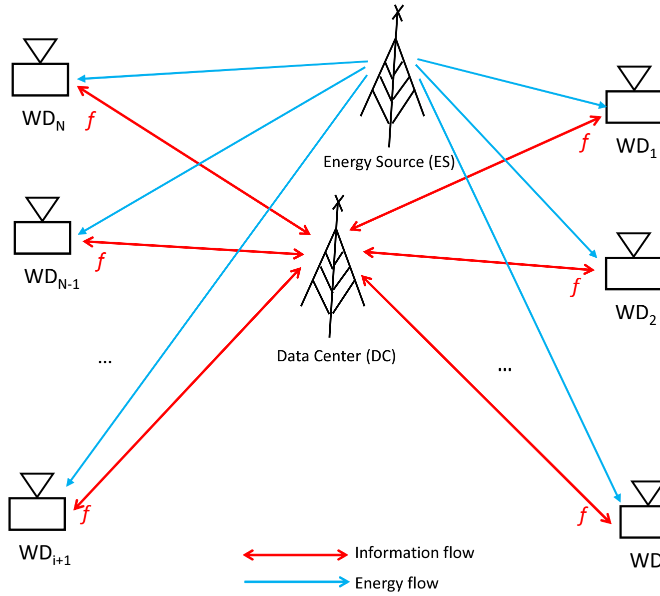

Fig. 1. WPCN network architecture

The structure of a WD consists of three main blocks: communication block, RF energy harvesting block and rechargeable battery block as shown in Fig.2. Control unit controls switching between communication block and RF energy harvesting block. The main component of the RF energy harvesting block is an energy harvester which harvests energy emitted by ES, stores the energy in rechargeable battery, and discards the energy when battery is full. One example of energy harvester is powercast P1110 [17] or P2100B [18] chips whose actual performance numbers will be given in the evaluation section Commonly used rechargeable battery can be a super-capacitor (e.g., NiCd, SLA battery type). The main component of communication block is a sensor chip, for example CC2420 [19] performing two-way data transmission between WD and DC. Because a node cannot perform both data transmission and power transfer simultaneously, the data transmission and energy harvesting periods have to alternate based on time division fashion. The operation time of WD is therefore divided into cycles each of which consists of an energy harvesting period with duration T_1 (seconds) and a data transmission period with duration T_2 (seconds) as shown in Fig.3. The duration of a cycle, T, is denoted as $T = T_1 + T_2$ (seconds).

III. Analytical Models

This section derives an analytical model for the lifetime of a WD and consequently the upper and lower limits of the lifetime. Then, the model for network lifetime is inferred.

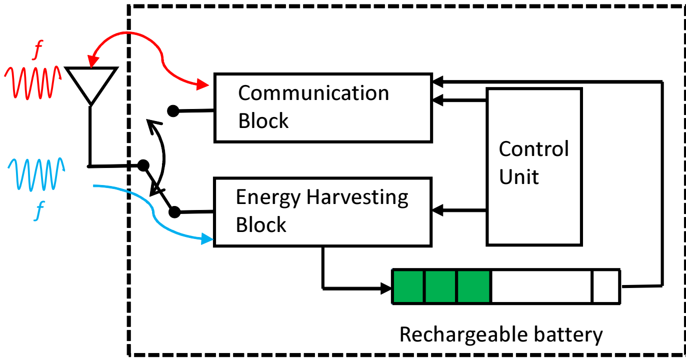

Fig. 2. Wireless end-device architecture

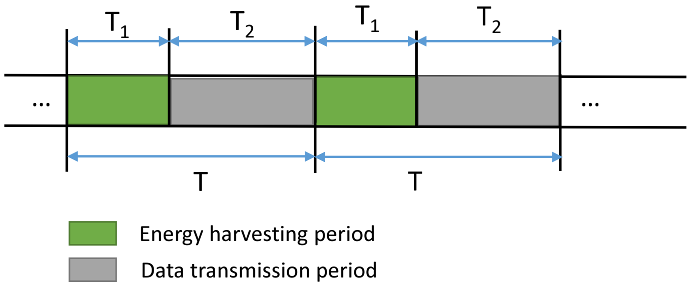

Fig. 3. Time operation of a WD.

Based on these models and upper and lower limits, this section presents an analysis based on which the maximum lifetime of the network in some situations can be achieved.

A. Device lifetime and its upper and lower bounds

We consider the case that the antenna of an ES is $omni-directional$ i.e., all WDs can receive energy from the ES. Let P_0^i be the power that ES transmits to WD$_i$ with $1 \leq i \leq N$. Assume that the transmit power satisfies power constraints (i.e, the total transmitted power is bounded by $\sum_{i=1}^{N} P_0^i \leq P_0$ where P_0 is the maximum transmitted power at the ES). Let h_i and η be the channel power gain between ES and WD$_i$ and energy harvesting efficiency, respectively. Then the amount of energy that WD$_i$ harvests during t seconds is $\eta P_i^0 h_i t$. Suppose that channel access is scheduled so that at least one frequency is available when WD$_i$ needs to send or receive a packet. (Channel access scheduling is another problem for network resource management but this is beyond the scope of this paper). With this assumption, WD$_i$ can transmit or receive a packet as long as it has enough energy.

Let E_R^i (Joules) and E_T^i(Joules) be the energy that WD$_i$ consumes to receive and to transmit one packet, respectively. In addition, let λ_i and δ_i (number of packets per second) be the average DL and UL rates to and from WD$_i$, respectively. These parameters can be measured by hardware support or software monitoring. During t, WD$_i$ requires the amount of $t(\lambda_i E_R^i + \delta_i E_T^i)$ (Joules) to process its data. The $harvested$ energy during time interval (0, t) is approximated by

$$Q_i(t) = \eta P_i^0 h_i \frac{T_1}{T} t. \tag{1}$$

Let E_0^i and $E(t)$ be the initial energy and the residual energy at time t, respectively. In addition, let B (Joules) denote the capacity of rechargeable battery. Then, $E(t)$ is defined such that:

$$E(t) = min\{E_0^i + Q_i(t) - t(\lambda_i E_R^i + \delta_i E_T^i), B\}. \tag{2}$$

If $E_0^i + Q_i(t) - t(\lambda_i E_R^i + \delta_i E_T^i) \leq 0$, the system is in a $failure$ $state$ at time t. Otherwise, $E(t)$ is approximately calculated as:

$$E(t) = E_0^i + \frac{T_1}{T} \eta P_i^0 h_i t - t(\lambda_i E_R^i + \delta_i E_T^i) \tag{3}$$

A WD$_i$ is said to be $energy$ $depleted$ if its remaining energy is less than a certain threshold ν such that normal operation cannot be maintained. Without loss of generality, we assume that ν = 0. If the RF harvested energy is always greater than the consumed energy, the device will never be $energy$ $depleted$ and $E(t)$ continues increasing. When the rechargeable battery is full, i.e $E(t)$ = B, the device stops charging. If this is not the case, we let L_i be lifetime of WD$_i$, then L_i has to satisfy $E(L_i)$ = 0. Therefore, L_i is calculated as follows:

$$L_i = \frac{E_0^i}{\lambda_i E_R^i + \delta_i E_T^i - \frac{\eta P_i^0 T_1 h_i}{T}}. \tag{4}$$

We can infer from (4) that

$$\frac{E_0^i}{\lambda_i E_R^i + \delta_i E_T^i} \leq L_i \leq \frac{E_0^i}{\lambda_i E_R^i + \delta_i E_T^i - \frac{\eta P_i^0 T_1 h_i}{T}}. \tag{5}$$

Let

$$L_{i_{min}} = \frac{E_0^i}{\lambda_i E_R^i + \delta_i E_T^i}. \tag{6}$$

and

$$L_{i_{max}} = \frac{E_0^i}{\lambda_i E_R^i + \delta_i E_T^i - \frac{\eta P_0 T_1 h_i}{T}}. \tag{7}$$

then we infer from (5) that

$$L_{i_{min}} \leq L_i \leq L_{i_{max}}. \tag{8}$$

L = $L_{i_{min}}$ when WD_i does not receive any energy from ES and L = $L_{i_{max}}$ when WD_i receives all energy transmitted by the ES.

B. Network lifetime

Network lifetime can be defined as the death of the first node in the network [16]. This assumption is reasonable because the network may be unstable or unreliable when a node goes down. Let L (seconds) be the network lifetime then L is determined such that:

$$L = min\{L_i\}. \tag{9}$$

where L_i is calculated by (4). This means that the network lifetime is determined by the shortest device lifetime. Therefore, if there exists WD_i and WD_j with $1 \leq i, j \leq N$ such that

$$L_{i_{max}} \leq L_{j_{min}}. \tag{10}$$

then, WD_j has no impacts to network lifetime. Then, it is useless to schedule power to WD_j for network lifetime optimization. This can happen in heterogeneous networks with very different applications. For example, devices which regularly send sensing information and ones which send streaming video to the DC. In this case, all energy should be dedicated to devices running the streaming video application. Therefore, to maximize the network lifetime, we should ignore all devices whose minimum lifetimes, calculated by (6), are grater than the maximum lifetime of any other devices, calculated by (7).

Let $\mathbb{S}^*$ be a subset of $\mathbb{S}$ where there are no WD_i, WD_j satisfying (10). Without loss of generality, assume that $\mathbb{S}$ = $\{\mathrm{WD}_i;\ i$ = 1,..., $M\}$ where $1 \leq M \leq N$. From (4), we have

$$\frac{1}{L_i} = \frac{\lambda_i E_R^i + \delta_i E_T^i}{E_0^i} - \frac{\eta T_1 h_i}{T E_0^i} P_i^0. \tag{11}$$

Assuming that η, h_i and E_0^i are the same for all WD_i, then

$$\sum_{i=1}^{M} \frac{1}{L_i} = \sum_{i=1}^{M} \frac{\lambda_i E_R^i + \delta_i E_T^i}{E_0^i} - \frac{\eta T_1 h_i}{T E_0^i} P_0. \tag{12}$$

In (12), $\lambda_i, \delta_i, T_1, T$ are network parameters, E_R^i, E_T^i are device dependent and η, h_i depends on environment. Eq.(12) gives us some directions for the network lifetime optimization. For example, the optimal solution can be achieved by allocating traffic load at each WD, by scheduling transmit power to each WD, or by adjusting energy harvesting time during each cycle. In this paper, we assume that traffic at each WD is given and we have to schedule transmit power to each WD such that the network lifetime is the maximum. Under these conditions, the right side of (12) is constant. For simplicity, let

$$K = \sum_{i=1}^{M} \frac{\lambda_i E_R^i + \delta_i E_T^i}{E_0^i} - \frac{\eta T_1 h_i}{T E_0^i} P_0. \tag{13}$$

Then, (12) can be rewritten as

$$\sum_{i=1}^{M} \frac{1}{L_i} = K \tag{14}$$

Because of (9), we have

$$\sum_{i=1}^{M} \frac{1}{L_i} = K \leq \frac{M}{L} \tag{15}$$

or

$$L \leq \frac{M}{K}. \tag{16}$$

where K is determined by (13). The maximum network lifetime, $maxL$, can be obtained as

$$maxL = \frac{M}{K}. \tag{17}$$

This happens when the transmit power to WD_i satisfies

$$\frac{\lambda_i E_R^i + \delta_i E_T^i}{E_0^i} - \frac{\eta T_1 h_i}{T E_0^i} P_i^0 = \frac{K}{M}. \tag{18}$$

or

$$P_i^0 = \frac{T E_0^i}{\eta T_1 h_i} \left(\frac{K}{M} - \frac{\lambda_i E_R^i + \delta_i E_T^i}{E_0^i} \right). \tag{19}$$

where K is determined by (13). In the network where traffic load at each device makes the right hand-side of (19) greater than zero, there exits a solution for scheduling the transmit power P_i^0 such that the overall network lifetime is the maximum. In this case, the solution is the optimal.

IV. Power Scheduling Algorithm

Based on the analysis in Section III, this section presents a power scheduling algorithm which allocates the transmit power P_i^0 from ES to device WD_i. The proposed algorithm is performed by the ES to maximize network lifetime in some situations.

Algorithm 1 Power Scheduling Algorithm

```
1: Input: λ_i, δ_i, E_i^0, T_1, T
2: Output: P_i^0
3: for i ← 1 to N do
4:     Calculate L_i, L_{i_max}, L_{i_min} by (4), (6), (7), respectively
5: end for
6: for i ← 1 to N do
7:     for j ← 1 to N do
8:         if L_{i_max} ≤ L_{j_min} then
9:             P_j^0 = 0;
10:            S* = S - j;
11:        end if
12:    end for
13: end for
14: Calculate M as the number of elements in S*
15: Calculate K by (13)
16: Calculate P_i^0 by (19)
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The pseudo code of our proposed power scheduling algorithm is described in Algorithm 1. Lines 3-5 are to calculate WD's lifetime and its upper and lower limits. Lines 6-12 are to find devices whose lifetimes are long enough so that they do not have impact on overall network lifetime. Lines 13-15 are for calculating P_i^0 based on (19), K, and M. The proposed algorithm converges when all i in subset $\mathbb{S}^* \subset \mathbb{S}$. This is a current limitation of this paper. Finding P_i^0 for all network conditions is left for our future works.

V. Performance Evaluation

This section first evaluates the accuracy of the proposed models for device lifetime and network lifetime under different network scenarios. The section then evaluates the performance of the proposed power scheduling algorithm. We use some parameters of Powercast transmitter and recivers [17], [18]. The network operates on 915Mhz frequency band. In all simulations, Powercast TA81501-1W is used in ES to transmit RF energy. In WD sides, P2110 Powerharvester with energy harvesting efficiency η = 0.51 is used as a harvester to receive energy from ES. Rechargeable battery has capacity of C=1000mAh and battery voltage is 1V [8]. Platform chip

CC2420 is used in communication board for data exchange between a WD and the DC. Packet size is 139 bytes which can be used in Zigbee/IEEE 802.15.4 networks [14]. According to CC2420 data sheet [19], the current consumption in its receiving state is 18.8 mA; therefore, with the voltage of 3V, the power consumption to receive one packet is $18.8 \times 3 = 56.4\, mW$. As the time needed to transmit this packet is 8.11ms [14], the energy to receive one packet is $56.4(mW) \times 8.11(ms) = 0.46mJ$. Similarly, suppose that level 0 is used for transmitting state, then power consumption in transmit state is $17.4mA$, consequently, the energy consumption is $17.4(mA) \times 3(V) \times 8.11(ms) = 0.42mJ$. We implemented simulations in C programming with different network scenarios. One simulation result is obtained from 1000 simulation runs with 1000 different seed values.

A. Proposed Models Validation

We validate the accuracy of our proposed models with different traffic distributions of UL and DL traffic at WDs. The traffic follows Poisson distribution which has been widely used for evaluation. (The proposed models also accurate for deterministic distribution which usually happens in wireless sensor networks). Fig. 4 presents the lifetime L_i of WD$_i$ with respect to different UL and DL traffic rates. Here, the initial battery is $0.75C$ which results in the initial energy E_0^i = $0.75Wh$ or $0.75\times3600J$. λ_i equals δ_i and varies from 1 to 6 (packets/s). The frame duration T=$500ms$, h_i=0.5, P_0^1 = $1mW$. It can be seen from the figure that as λ_i and δ_i increase, L_i decreases. The reason is that as the traffic rate increases, more packets arrive and leave at WD$_i$. Therefore, the WD$_i$ consumes more energy to receive and transmit those packets, thus its lifetime is shorten. The figure also presents device lifetime with different charging time T_1 (which are 0.1s and 0.4s in Fig.4) per frame. Curves with "no charge" caption are equivalent to conventional battery wireless network with no energy harvesting. The figure shows that the device lifetime increases with charging time as more energy is harvested during a frame. EH time can significantly improves device lifetime; however, the charging scheme is more effective when traffic rate is low and less effective when traffic increases. That is because the amount of energy harvested during one frame is small compared to the energy needed to process traffic. Fig.4 also compares numerical results i.e, (4), with the simulation results. It can be observed from the figure that numerical results are very close to the simulations results which validate our proposed models.

Fig.5 shows how L_i varies with respect to different charging duration T_1 per frame. The parameters on this scenarios are as the followings: E_0^i=$0.25Wh$ (initial capacity of $0.25C$), λ_i=0.5 (packets/s), T=$0.5s$, P_0^i=$1mW$ and δ_i varies. The figure presents that a higher T_1 results in a longer L_i and vice versa because if WD$_i$ harvests energy for a longer time, it obtains higher energy. In addition, the impact of T_1 on L_i is strong when δ_i is small and becomes less as δ_i increases. This is because when δ_i is small, the energy harvested in one frame is significant compared to the amount energy that WD$_i$ consumes to process traffic. The figure also illustrates the close match between simulation and numerical results.

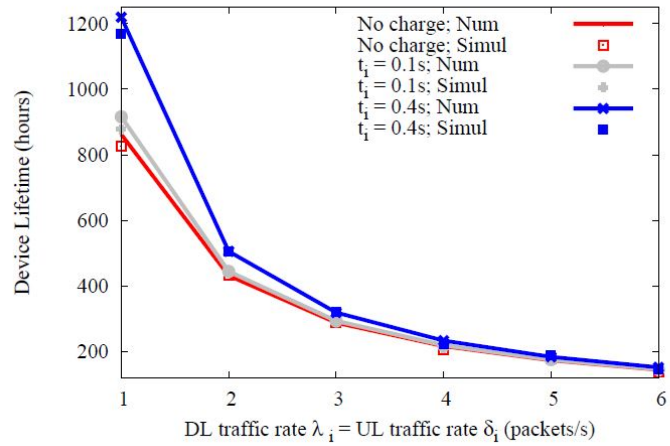

Fig. 4. Device lifetime vs. traffic rates.

Assume that there are four WDs in the network with equal UL traffic δ_i=δ. The frame duration is T=$0.5s$ and each WD harvests energy for a duration of $0.125s$ per frame. Furthermore, assume that channel power gain of the WD are equal to 0.5, then the network lifetime is determined by the one with highest DL traffic rate, called λ_{max}, as this device will be the first to be energy depleted. Fig. 6 illustrates the network lifetime with respect to δ under three cases of minimum DL traffic rate equal to 1,2, and 5, respectively. In this scenario, L decreases with δ as WD has to spend more energy to transmit packets. It can be observed from the figure that numerical results are very close to the simulations results which validate our proposed models.

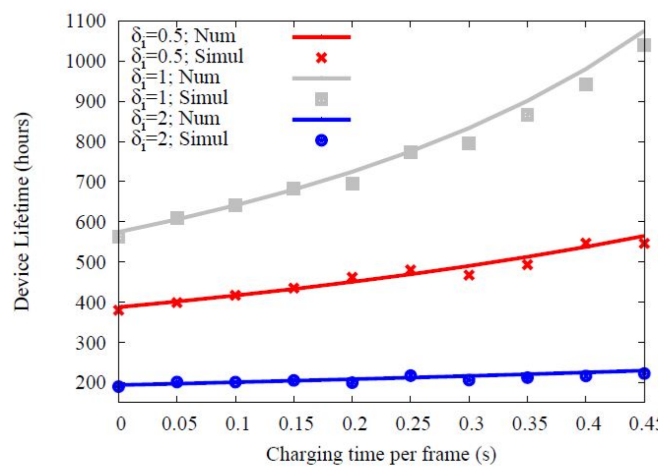

Fig. 5. Device lifetime vs. charging time under Poisson distribution of uplink/downlink traffic.

B. Power Scheduling Algorithm

In our network scenarios, there are 20 WDs each with initial battery of 0.75C. The (λ_i,δ_i,h_i) for WDs are as follows: (100,200,0.3), (10,20,0.5), (1,2,0.7), (2,4,0.9), (1,5,0.5), (1,7,0.4), (2,6,0.3), (1,2,0.6), (1,8,0.3), (1,3,0.5), (2,5,0.7), (10,10,0.9), (3,6,0.5), (20,40,0.4), (1,7,0.3), (8,16,0.6), (1,2,0.3), (2,4,0.5), (1,10,0.7), (2,10,0.9). Fig.7 shows how

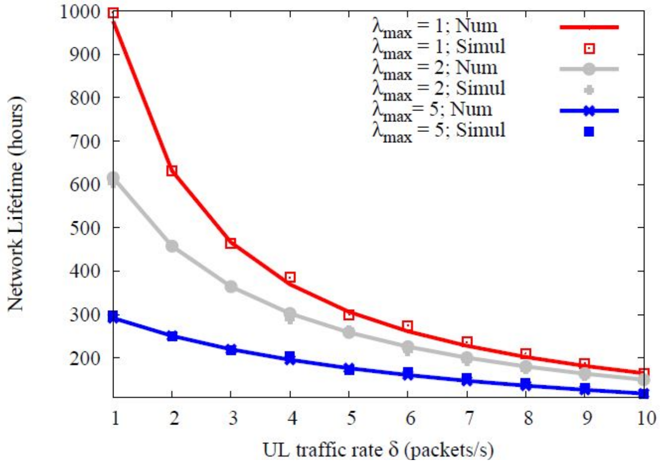

Fig. 6. Network lifetime vs. uplink traffic.

network lifetime varies with respect to charging time ratio defined as $\rho = \frac{T_1}{T_1+T_2}$. The figure shows that as ρ increases, network lifetime increases as well. With the above data set, traffic rates WDs are very different, which can be happened in homogeneous networks, the network lifetime is determined by WD with dominant traffic rate. The proposed algorithm will schedule all power to the WD_1 and other devices do not affect network lifetime.

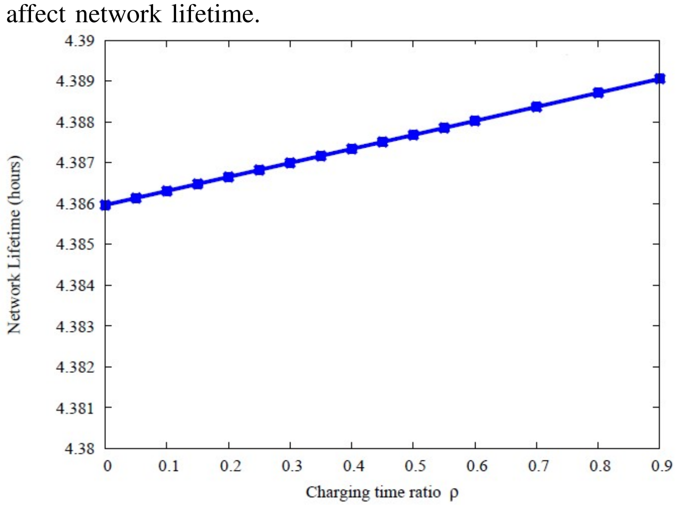

Fig. 7. Power scheduling algorithm performance.

VI. Conclusion

This paper dealt with the problem of scheduling transmit power from an energy source, capable of transmitting RF energy, to a wireless end device, capable of harvesting RF energy, in a WPCN to optimize the network lifetime. To this end, the paper proposed models for devices lifetime together with its upper and lower limitations based on which the analysis for optimization is derived. The analysis also provided some directions which can be looked into for lifetime optimization such as traffic load scheduling and time scheduling. The paper then proposed a power scheduling algorithm to allocate transmit power to each end device for the network optimization. Unlike most of existing works. the paper carefully considers the effects of DL and UL traffic rates on network lifetime. In addition, the impacts of other network parameters on network lifetime are also examined. The paper, therefore, provides an useful guideline for design of energy harvesting networks.

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