Towards Optimal Operation State Scheduling in RF-Powered Internet of Things

Abstract—RF power transfer is becoming a reliable solution to energy supplement of Internet of Things (IoT) in recent years, thanks to the emerging off-the-shelf wireless charging and sensing platforms. However, as a core component of IoT, sensor nodes mounted with these platforms can not work and harvest energy simultaneously, due to the low-manufacture-cost requirement. This leads to a new design challenge of optimally scheduling sensor nodes' operation states: working or recharging, to achieve a desirable network utility. The operation state scheduling problem is quite challenging, since the time-varying network topology leads to spatiotemporal coupling of scheduling strategies. In our design, we first consider a single-hop special case of small-scale networks. We employ geometric programming to transfer it into a convex optimization problem, and obtain an optimal analytical solution. Then a general case of large-scale multi-hop networks is investigated. Based on Lyapunov optimization technique, we design a State Scheduling Algorithm (SSA) with a proved performance guarantee. Our algorithm decouples the primal problem by defining a dynamic energy threshold vector, which successfully schedules each sensor node to the desirable state according to its energy level. To verify our design, the SSA is implemented on a Powercast wireless charging and sensing testbed, achieving about 85% of the theoretical optimal with quite low time complexity. Furthermore, numerous simulation results demonstrate that the SSA outperforms the baseline algorithms and achieves good performance under different network settings.

Index Terms—Computer Society, IEEE, IEEEtran, journal, LaTeX, paper, template.

1 Introduction

The Internet of Things (IoT) has grown from concept to reality in the pase few decades. It is estimated that the IoT industry will consist of about 30 billion objects by 2020 [1]. The maturity of IoT has brought great convenience to our day-to-day life. However, the energy constraint has hindered IoT to realize its full potential. Most of the existing IoT sensor nodes are powered by batteries. The limited battery capacity leads to insufficient sensor node lifetime and high network operation cost. With the recent breakthrough in wireless charging technology, radio frequency (RF) power transfer is becoming a convenient, safe, and reliable solution to providing sustainable energy for low-power electronic devices. RF power transfer enables IoT to achieve a flexible and low-cost deployment, which gives rise to RF-powered IoT. Due to its great potential, RF-powered IoT has been applied to various scenarios, such as smart tracking [2], structural health monitoring [4], wearable devices [3], etc.

Wireless rechargeable sensor networks (WRSNs) is the key front-end component of RF-powered IoT. WRSNs collect information of the physical world via sensor nodes and upload data to servers for further fusion and decision. To achieve high operation efficiency, many works have focused on improving the network utility of WRSNs. Network utility is usually defined as a specific performance required by applications, such as minimizing network deployment cost [4], charging latency [5] [6], communication delay [7], etc.

In most of the previous works, data collection and energy transfer were assumed to run simultaneously, the same way as in the battery-powered sensor networks. This assumption does not hold for most of the commercial wireless charging and sensing platforms. For instance, Powercast [8] and WISP [9] are two pioneering platforms for battery-free wireless applications, which have been extensively investigated [4] [6] [10]. To reduce the manufacture cost, these two platforms use a super capacitor as an energy buffer. Such a design deprives sensor nodes of working (discharging) and harvesting energy (recharging) simultaneously. This makes the utility optimization problem quite different from the battery-powered sensor networks, which can be illustrated by Fig. 1. Since sensor nodes can not work while being recharged, we need to schedule them to proper operation states (i.e., working or recharging) in different slots.

The operation state scheduling problem is quite challenging since both the state scheduling and routing control are coupling. Specifically, because of the battery capacity constraint, sensor nodes should switch their states according to the energy level. This makes the network topology dynamic, which leads to a temporal coupling of optimization strategies among different time slots. Moreover, in every time slot, we should jointly optimize each sensor node's sensing rate and routing path, which results in a spatial coupling of strategies. Therefore, we find that the network utility optimization problem in WRSNs has a strong spatiotemporal coupling, which makes it impossible to directly apply the existing solutions. Our paper tackles this issue and makes the following contributions.

1.1 Contributions

In this paper, we provide both theoretical analysis and practical evaluation on operation state scheduling in WRSNs. The main contributions can be summarized as follows:

1) To the best of our knowledge, this is the first attempt to take the hardware design constraint into consideration. We formulate a working-recharging operation state scheduling problem to maximize the network utility (In this work, we

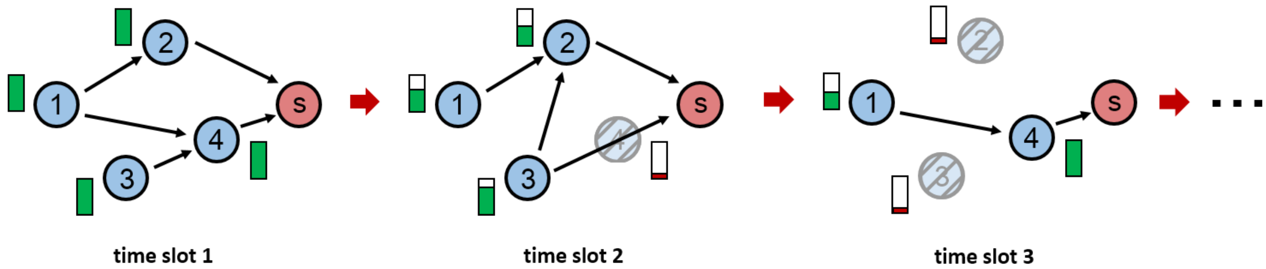

Fig. 1. State scheduling and time-varying topology in a wireless rechargeable sensor network

focus on maximizing the time-average network throughput). This is pressingly needed in most of the commercial wireless charging and sensing systems for a wide range of scenarios, such as intruder detection, environment monitoring, warehouse monitoring, etc.

2) We investigate two cases of the problem: a single-hop communication case and a general multi-hop communication case. In the first case, sensor nodes transmit data directly to the sink stations. It can be applicable in small-scale working areas. We find that, the problem can be reduced to a typical *Local Time Allocation Problem*. We then introduce geometric programming to convert it into a convex optimization problem, and obtain the optimal analytical solution.

In the second case, sensor nodes relay data for neighbor nodes when the network size is large. We notice that such an operation state scheduling problem is quite difficult to solve, since the multi-hop communication leads to a time-varying network topology, which introduces strong spatiotemporal coupling to the problem.

To tackle this challenge, we design an algorithm named State Scheduling Algorithm (SSA), which decouples the problem by defining a dynamic energy threshold vector. This mechanism successfully schedules each sensor node to the feasible state according to its energy level. Then, we can optimize the network utility by applying the max-flow model with fixed topology. The SSA provides a near-optimal solution with a theoretically proved worst-case bound.

3) To verify our design, we first conduct practical experiments based on the Powercast wireless charging and sensing platform. Experimental results demonstrate that the SSA algorithm performs at least 85% of the optimal while guaranteeing fairness among different sensor nodes. Moreover, the experiments verify that the SSA algorithm has quite low time complexity. Then, we conduct extensive simulations with rational coefficient settings to further evaluate the performance of the SSA. It is shown that our design outperforms the baseline methods with high energy efficiency, and is quite robust to different network settings.

1.2 Related Work

The scheduling problems in RF-powered IoT can be categorized into two different perspectives: power supplement scheduling and data collection scheduling.

1.2.1 Power Supplement Scheduling

There are many researchers making contributions to maximizing the harvested power or decreasing the charging delay [11] [12] [13]. Angelopoulos et al. studied the impact of the charging process on the network lifetime, and proposed a charging protocol to optimize a mobile charger's trajectory and energy provision for sensor nodes in the WSNs [14]. Wang et al. designed an optimal recharging scheme to improve the amount of replenished energy, while reducing the movement of mobile chargers [15]. He et al. designed an energy-synchronizing charging protocol to significantly reduce the mobile chargers' travel distance and sensor nodes' charging delay [6]. Guo et al. noticed the non-linear superposition charging effect caused by radio interference among different wireless chargers. They formulated a concurrent charging scheduling problem and provided efficient solution [16]. Dai et al. took the potential risk of electromagnetic radiation (EMR) into consideration. A joint optimization scheme of charging utility of devices and EMR intensity was proposed [17]. However, these works rarely considered the influence of data transmission process in practical system implementation.

1.2.2 Data Collection Scheduling

There are some works investigating the data collection scheduling problems [18] [19] [20]. A transmission power allocation problem was investigated by Xu et al., and both off-line and on-line solutions were provided [21]. Wang et al. developed efficient algorithms to compute the optimal transmission scheduling schemes [22]. Taking dense deployments of sensor nodes and wireless channel interference into consideration, Fateh et al. solved the joint scheduling of tasks and messages problem to minimize the consumed energy [23]. Mehrabi et al. considered the problem of data collection in mobile sink networks, designing an optimization model to incorporate the effective and heterogeneous duration of sensor nodes' transmission in each time slot [24]. Considering both of the battery-free and battery-deployed cases, - Che et al. designed a harvest-then-transmit protocol by partitioning time frames into a downlink phase for energy replenishment, and an uplink phase for data transfer. A joint optimization problem of frame partition between the two phases and the wireless nodes' transmit power was solved to maximize sensor nodes' spatial throughput subject to a successful information transmission probability constraint [25]. Li et al. noticed the packet loss problem due to energy insufficiency and data buffer overflow. They investigated a novel optimal scheduling strategy based on a centralized MDP model, to minimize data packet loss from a WRSN in terms of the nodesąŕ energy consumption and data queue state information [26]. Further, Zhang et al. jointly considered data sensing and data transmission, designed a balanced energy allocation scheme and proposed a distributed sensing rate and routing control algorithm [27]. Few of these works were done under RF-powered scenarios, thus the results can not be applied to the working-recharging operation state scheduling problem directly.

The existing works have either contributed to optimization of power supply or data collection. However, few works noticed the coupling issue when the two processes exist simultaneously in practical scenarios, which makes the sensor node working-charging state scheduling problem quite challenging. Thus, we intend to reveal the insights of power supply and data collection process and investigate optimal operation state scheduling strategy in RF-Powered Internet of Things in this paper.

1.3 Paper Organization

The rest of the paper is organized as follows: We present the system model in Section II. Then we provide an optimal solution to single-hop case in Section III. In Section IV, an approximation algorithm for multi-hop case is proposed. We evaluate our design via both practical experiments and numerous simulations in Section V. Finally, the conclusion is made in Section VI.

2 System Model

We consider a wireless rechargeable sensor network with a set $\mathcal{N} \overset{def}{=} \{1...N\}$ of sensor nodes. They are deployed to sense data of interest and upload them to sink stations. There is also a set of $\mathcal{M}_c$ chargers and $\mathcal{M}_s$ sink stations, which have sufficient energy, deployed beforehand for energy provisioning and data collection, respectively. The network is supposed to operate in a finite-horizon period consisting of discrete time slots $\mathcal{T} \overset{def}{=} \{1...T\}$.

As aforementioned, each sensor node has two operation states: in $State\ R$, sensor nodes replenish energy from chargers and store it in the energy buffer; in $State\ W$, sensor nodes conduct sensing and communication tasks to upload the sensing data to sink stations. In every time slot, each sensor node can only select one of the two states. Before presenting the detailed problem formulation below, some important notations are summarized in TABLE 1.

TABLE 1
Summary of Notations

Symbol	Definiton
$\mathcal{N}_w^{(t)}$	set of sensor nodes in $State\ W$ in time slot t
$r_i^{(t)}$	data sensing rate of sensor node i in time slot t
$f_{ij}^{(t)}$	data flow rate from sensor node i to j in time slot t
$f_{in}^{(t)}$	data flow rate from sensor node i to sink n in time slot t
$c_{ij}^{(t)}$	time-varying link capacity
$e_i^{(t)}$	remaining energy of sensor node i after time slot t
d_{ij}	Euclidean distance between sensor node i and j
B_0	battery capacity of each sensor node
R_0	upper sensing rate for each sensor node
$U(.)$	utility function
α_i	proportion of time for communication
$\theta_i^{(t)}$	time-varying virtual energy threshold
$E_i(t)$	energy queue of sensor node i
V	parameter for penalty function

2.1 Energy Recharging and Consumption Model

2.1.1 Energy Recharging Model

Our design is based on the Powercast wireless charging and sensing platform. We utilize the Friis' space equation, which has been experimentally proved to be a good approximation of energy recharging [4] and commonly applied, to represent the energy recharging model in Equation 1. We claim that our design can work on any energy recharging models, whose charging power is monotone increasing with the distance between chargers and sensor nodes.

$$P_r = \frac{G_s G_r \eta}{L_p}\left(\frac{\lambda}{4\pi(d+\beta)}\right)^2 P_0, \quad (1)$$

where d is the Euclidean distance between the sensor node and the charger, P_0 is the source power, G_s is the source antenna gain, G_r is the receive antenna gain, L_p is the polarization loss, λ is the wavelength, η is a parameter to adjust the model for short distance transmission. Since these coefficients are all constant, for easy presentation, we simplify the energy charging model as $P_r = \frac{a}{(d+b)^2}$.

2.1.2 Energy Consumption Model

In our design, we select the radio model proposed by Heinzelman et al. [28]:

$$P_{T_x}(k,d) = (p_t + \epsilon \times d^4) \times k, \quad (2)$$

$$P_{R_x}(k) = p_r \times k, \quad (3)$$

which describes the relationship between energy consumption and data transmission. Eq. (2) is the power consumption for data transmission. Eq. (3) shows the power consumption of data reception. In this model, d is the Euclidean distance between transmitter and receiver, k is the number of transmitted data bits, and p_t, p_r, ϵ are constant parameters associated with the communication environment.

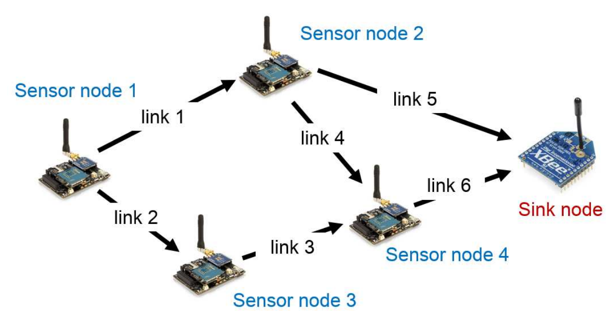

Fig. 2. Dynamic routing

2.2 Data Flow Constraint

Without loss of generality, we assume a dynamic routing scheme. That is, sensor nodes can forward data to their next hops via a different route according to current conditions, such as sensor nodes' energy levels, channel capacity, etc.

As shown in Fig. 2, sensor node 1 divides its data into two parts and sends them to sensor node 2 and sensor node 3 separately, whereas sensor node 3 only selects sensor node 4 as its data's next hop, etc. Finally, all the data is able to be uploaded to the sink node. Dynamic routing fully utilizes the network energy, since the energy-sufficient sensor nodes can take more relay tasks, and the energy-insufficient ones can rely on other sensor nodes' relay. Under such a condition, each sensor node should satisfy the data flow balance. As shown in Equation 4, the aggregate incoming data flow equals to the aggregate outgoing data flow plus its generating data flow.

$$r_i^{(t)} + \sum_{j=1}^{\mathcal{N}_w^{(t)}} f_{ji}^{(t)} = \sum_{j=1}^{\mathcal{N}_w^{(t)}} f_{ij}^{(t)} + \sum_{k=1}^{M_s} f_{in}^{(t)}. \tag{4}$$

Moreover, we consider the link capacity. Let $0 \leq c_{ij}^{(t)} < +\infty$ be the time-varying capacity of wireless link (x, y) at time slot t, which depends on actual wireless channel conditions. Then, we have the following constraint for each link:

$$0 \leq f_{ij}^{(t)} \leq c_{ij}^{(t)}. \tag{5}$$

2.3 Battery Capacity Constraint

In each time slot, sensor node's consumed energy should never exceed the sum of the accumulated energy and the received energy; and the remaining energy should never exceed the battery capacity. Let $e_i^{(t)}$, $\phi_i^{(t)}$ and $\psi_i^{(t)}$ denote sensor node i's remaining energy, consumed energy and received energy in time slot t, respectively. Then, we have the following formulations. For each sensor node in $State\ W$, the total consumed energy is defined by

$$\begin{aligned}\phi_i^{(t)} =& p_0 r_i^{(t)} + p_r \sum_{j=1}^{\mathcal{N}_w^{(t)}} f_{ji}^{(t)} + \sum_{j=1}^{\mathcal{N}_w^{(t)}} (p_t + \epsilon d_{ij}^4) f_{ij}^{(t)} + \\ & \sum_{k=1}^{M_s} (p_t + \epsilon d_{in}^4) f_{in}^{(t)},\end{aligned} \tag{6}$$

where p_0 is the unit energy of sensing, and $0 \leq \phi_i^{(t)} \leq \phi_{max}$.

For each sensor node in $State\ R$, the total received energy can be expressed by

$$\psi_i^{(t)} = \sum_{m=1}^{M_c} \frac{a}{(d_{im} + b)^2}, \tag{7}$$

where $0 \leq \psi_i^{(t)} \leq \psi_{max}$.

The remaining energy after time slot t can be calculated as

$$e_i^{(t)} = e_i^{(t-1)} - \phi_i^{(t)} + \psi_i^{(t)}. \tag{8}$$

Thus, the battery capacity constraint is obtained:

$$0 \leq e_i^{(t)} \leq B_0. \tag{9}$$

2.4 Optimization Objective

Our objective is to maximize the network utility. The utility can be defined as a specific performance required by applications, such as quality of monitoring, network throughput, etc. For sensor node i, it obtains utility $U(r_i^{(t)})$ when it senses $r_i^{(t)}$ bytes of data in time slot t and uploads them to the sink station. The utility function is commonly assumed to be increasing and strictly concave [29]. In this paper, the utility function is set as $U(r_i^{(t)}) \overset{def}{=} log(r_i^{(t)})$, since it can guarantee the data transmission fairness among each sensor node, while maximizing the time-average network throughput. We claim that the results can easily be extended to other utility settings. Then we have the time-average utility maximization problem as follows:

Primal Problem:

$$\begin{aligned} & max \quad \frac{1}{\mathcal{T}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}_w^{(t)}} U(r_i^{(t)}) \\ & s.t. \quad \begin{cases} (5) - (10) \\ 0 \leq r_i^{(t)} \leq R_0 \end{cases} \quad \forall i, j \in \mathcal{N}, \forall t \in \mathcal{T}, \end{aligned} \tag{10}$$

where $\frac{1}{\mathcal{T}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}_w^{(t)}} U(r_i^{(t)})$ is the time-average utility of the network over time period $\mathcal{T}$.

2.5 Problem Hardness and Insights

In this subsection, we show that the primal problem is NP-hard, which makes it difficult to address. Then, the insights is discussed to show its spatiotemporal coupling.

Theorem 1. *The primal problem is NP-hard.*

Proof. We first prove that the primal problem is an NP problem. Given a specific sensor node operation state scheduling strategy and the time average utility of the whole network, we need to prove whether it is a feasible solution in polynomial time. That is, we should check whether the maximum average network utility obtained under the given sensor node operation state scheduling strategy can cover the given one. Thus, the proof is transformed to a traditional sensor network utility maximization problem. According to [4], it can be formulated as a linear programming and solved in polynomial time. Therefore, the primal problem is an NP problem.

To further prove that the primal problem is NP-hard, we reduce the maximum set cover (MSC) problem [30], which is known to be NP-hard, to our primal problem.

Definition of the Maximum Set Cover Problem: Given a collection $C = \{S_i\}$ of subsets of a finite set R, find a family of set covers $S_1, ..., S_p \in C$ with weights $\lambda_1, ..., \lambda_p \in [0, 1]$, so that $\sum_{i=1}^{p} \lambda_i$ is maximized and for each element s in C, s appears in $S_1, ..., S_p$ with a total weight of at most 1.

In our primal problem, let the sensor node operation state scheduling strategy be S_i, thus the collection of different strategies form C. In every time slot, we should select one strategy from C, and it contributes to the total network utility. Let's consider a special case of this problem, that we suppose the contribution to network utility of each sensor node operation state scheduling strategy is known as λ_i. Then, this problem is equal to the MSC problem. So far, we have reduced the MSC problem to a special case of our primal problem. And the set cover problem is known to be NP-hard. Consequently, our primal problem is an NP-hard probelm. □

Moreover, we present the insights of the primal problem to explain why it is difficult to solve. As the example shown in Fig. 1, at the beginning of the time series, every sensor node's energy buffer is full. Thus, they all switch to $State\ W$. In time slot 1, four sensor nodes construct the most energy efficient routes to transmit as much data as possible. Then in the second time slot, since the energy level of Sensor node 4 is low, it turns to $State\ R$ to replenish energy. The other three sensor nodes and the sink station form a new topology for energy-efficient sensing and routing. This process continues to the end of the time series.

In every time slot, we should jointly optimize each sensor node's sensing rate and routing path. Thus, the spatial coupling exists. On the other hand, the network topology in every slot is dynamic, since sensor nodes' operation states are changing. This leads to a temporal coupling among different time slots. Therefore, such problem is a spatiotemporal coupled one, which is quite difficult to tackle.

In this work, we consider to solve the primal problem in two different scenarios: the single-hop communication case for small-scale network and the multi-hop communication case for large-scale network.

3 State Scheduling in Small-Scale Networks

In this section, we propose an optimal analytical solution for the single-hop case, where sensor nodes transmit data directly to sink stations without relay. This case can be broadly applied to small-scale network scenarios.

In RF-powered IoT, sensor nodes are very "energy-sensitive" because of the strict energy limitation. Therefore, in the single-hop case, a sensor node trends to select the nearest sink station greedily. Constraint (4) can be simplified as

$$r_i^{(t)} = f_{in^*}^{(t)}, \tag{11}$$

where n^* represents the specific sink station that sensor node i transmit data to. And we can sum Constraint (6) in different time slots together:

$$\phi_i^{'} = p_0 r_i + \sum_{k=1}^{M_s} (p_t + \epsilon d_{in^*}^4) f_{in^*}. \tag{12}$$

Notice that under the single-hop setting, each sensor node does not relay data for others. Thus, the network topology is fixed, that is, there is no spatial coupling in this case. The primal problem can be separated to each sensor node's local sensing rate optimization problem.

For each sensor node, the objective is to allocate its operation time to recharging and communication, so that its average sensing rate in a period of time $\mathcal{T}$ is maximized. Thereby, we can sum Constraint (8) in different time slots together and reduce the local sensing rate optimization to a time allocation problem. We define another symbol α_i to represent the proportion of time that sensor node i allocates to communication. Intuitively, $(1-\alpha_i)$ is the proportion of time that sensor node i allocate to recharge energy. Then we obtain the local time allocation problem formulation:

Local Time Allocation Problem:

$$\begin{aligned} & max \quad r_i \alpha_i \\ & s.t. \quad \begin{cases} \phi_i^{'} \le \psi_i \\ 0 \le r_i \le R_0, \\ 0 \le \alpha_i \le \dfrac{1}{\mathcal{T}} \end{cases} \end{aligned} \tag{13}$$

where ψ_i is the total harvested energy in the whole time series. Since the locations of chargers are supposed to be known, it is easy to obtain the received energy, thus ψ_i can be regarded as constant in the following calculation. By solving this problem, we can obtain the optimal time allocation scheme for each sensor node. Then according to the sensor node's energy buffer size, it is easy to calculate the sensing rate.

This problem is not convex, since $r_i \alpha_i$ is not a concave function. Thus, it is difficult to obtain the analytical solution. To tackle this problem, we introduce geometric programming to convert it to a convex one.

Theorem 2. *The time allocation problem can be converted to a convex optimization problem by geometric programming.*

Proof. We introduce two variables x and y to replace r_i and α_i, where $x = log r_i$ and $y = log \alpha_i$. Thus, we have the following new formulation:

$$\begin{aligned} & max \quad e^{x+y} \\ & s.t. \quad \begin{cases} (p_0 + p_t + \epsilon d_{in^*}^4) e^{x+y} + \psi_i e^y - \psi_i \le 0 \\ x \le log R_0. \\ y \le log \dfrac{1}{\mathcal{T}} \end{cases} \end{aligned} \tag{14}$$

Notice that the new objective function is the maximization of a concave function, which is equivalent to the minimization of a convex function. Hence, all the inequality constraints are affine. Therefore, the new formulation is a convex optimization problem. □

Since the new problem is convex, we can apply Karush-Kuhn-Tucker (KKT) conditions to calculate the optimal analytical solution [32]:

$$\begin{cases} x = log R_0 \\ y = log \dfrac{\psi_i}{R_0(p_0 + p_t + \epsilon d_{in^*}^4) + \psi_i} \\ opt = \dfrac{\psi_i R_0}{R_0(p_0 + p_t + \epsilon d_{in^*}^4) + \psi_i} \end{cases}. \tag{15}$$

4 State Scheduling in Large-Scale Networks

In larger-scale networks, with the assistance of relay from neighbors, sensor nodes can transmit data to sink stations over a long distance via multi-hop routing. However, the introduction of multi-hop communication makes it impossible to decouple the primal problem directly. Thus, the optimization problem is quite different from the previous one. To address such a problem, we propose a State Scheduling Algorithm (SSA) based on Lyapunov optimization technique. Furthermore, some important performances are also discussed extensively.

4.1 The SSA Algorithm

This subsection presents the State Scheduling Algorithm (SSA), a near-optimal solution to the operation state scheduling problem with performance guarantee. The key idea of this design is to construct a sensor node's operation state scheduling algorithm based on Lyapunov optimization. Lyapunov optimization is a modern theory of analysis, control and optimization for dynamic networks, which is applicable to problem of energy-efficient and profit-maximizing decision. In this work, we show that by selecting an appropriate energy threshold vector, we ensure that (1) each sensor node's energy level never exceeds its buffer size; (2) the time-average utility is quite close to the optimal.

We define a virtual energy threshold vector $\boldsymbol{\theta} \overset{def}{=} (\theta_i^{(t)}, i \in \mathcal{N}, t \in \mathcal{T})$, and $\boldsymbol{E}(t) \overset{def}{=} e_i^{(t)} - \theta_i^{(t)}$ as the vector of all sensor nodes' energy queues. To simplify the proof, the initial backlogs are assumed to be $\boldsymbol{E}(0) = 0$. The intuition of the definitions is that to keep the value of Lyapunov function small enough, we should "push" $e_i^{(t)}$ to $\theta_i^{(t)}$. By further optimize the value of $\theta_i^{(t)}$, we ensure that the energy queue is bounded and the algorithm achieves a near optimal solution. Here, we have the following Lyapunov function:

$$L(t) = \frac{1}{2}\sum_{i\in\mathcal{N}} E_i^2(t) = \frac{1}{2}\sum_{i\in\mathcal{N}} (e_i^{(t)} - \theta_i^{(t)})^2. \tag{16}$$

In addition to stabilize the queues defined in Lyapunov function, we also have an associated stochastic "penalty" process, i. e. the utility function incurred by control actions. Thus, we define 1-slot Lyapunov drift plus penalty as

$$\Delta_1 L(t) - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)}) = L(t+1) - L(t) - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)}), \tag{17}$$

where V is a positive constant parameter in the theorem, and is included for further analysis.

We have the theorem below for the drift:

Theorem 3. *If sensor nodes' state scheduling and data transmission satisfy the data flow balance and battery capacity constraint proposed in Section III, our 1-slot Lyapunov drift plus penalty:*

$$\begin{aligned}\Delta_1 L(t) - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)}) \le \frac{1}{2}MN \\ + \sum_{i\in\mathcal{N}} (e_i^{(t)} - \theta_i^{(t)})(\psi_i^{(t)} - \phi_i^{(t)}) - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)}),\end{aligned} \tag{18}$$

where $M = \psi_{max}^2 + \phi_{max}^2$.

Proof. The detailed proof is provided in Appendix A. □

Now we propose the SSA algorithm based on the Lyapunov drift. The key idea is to minimize the right-hand side of (18) subject to the data flow balance and energy capacity constraint in Equation (4) and Equation (8). The SSA algorithm operates as follows:

1. Virtual Energy Threshold. At the beginning of every time slot, we first calculate each sensor node's specific energy threshold for further operation state scheduling. We design an recursive formula as follows:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + \frac{\psi_{max} - \phi_{max}}{2}. \tag{19}$$

Algorithm 1: The SSA Algorithm

Input: Parameters $a, b, p_0, p_t, p_r, B_0, R_0, V$
Inatialize: $\theta_i^{(0)}, e_i^{(0)}$;
for $t \in \mathcal{T}$ **do**
  update $\theta_i^{(t)}$ as (19);
  set each sensor node's state according to (20);
  set up the network topology with sensor nodes in $State\ W$;
  calculate utility $U(r_i^{(t)})$ by solving (21);
end
Output: $\frac{1}{\mathcal{T}}\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)})$

2. Operation State Scheduling. Then each sensor node selects its operation state according to the following mechanism:

$$\begin{cases} State\ W, & if\ e_i^{(t)} \ge \theta_i^{(t)} \\ State\ R, & otherwise, \end{cases} \tag{20}$$

which indicates that sensor nodes determine their operation states according to their current energy level. If one sensor node's energy level is higher than its energy threshold, it turns to $State\ W$ to sense and forward data, otherwise it turns to $State\ R$ to replenish energy from chargers.

3. Sensing Rate Control and Routing. After the operation state scheduling, the primal problem is divided into subproblems in every time slot. Thus, the network topology is fixed. Then we can obtain each sensor node's optimal sensing rate and the optimal routing path by solving the following problem:

$$\begin{aligned} max \quad & \sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)}) \\ s.t. \quad & \begin{cases} (5)-(7) \\ \phi_i^{(t)} \le e_i^{(t)} \qquad \forall i,j \in \mathcal{N}_w^{(t)}. \\ 0 \le r_i^{(t)} \le R_0 \end{cases} \end{aligned} \tag{21}$$

We notice that this problem is a typical max-flow model [31], which is a convex optimization problem, since the objective function is concave and all the constraints are linear. Thereby, we can solve it by applying existing methods [32] in polynomial time.

4.2 Performance Analysis

We now provide the detailed theoretical analysis of the SSA algorithm. In the following parts, we first present that with the recursive formula for $\theta_i^{(t)}$ proposed in Equation (19), the energy queue $E_i(t)$ is deterministic bounded. Then we show that by applying the SSA algorithm, we can minimize the Lyapunov drift and the time-average throughput is quite close to the optimal with a proved worst-case bound.

4.2.1 Deterministic Bounded Energy Queue

Theorem 4. *With the recursive formula for for $\theta_i^{(t)}$ in Equation (19), the data queue is bounded by*

$$|e_i^{(t)} - \theta_i^{(t)}| \le \frac{\psi_{max} + \phi_{max}}{4}. \tag{22}$$

Proof. See Appendix B. □

4.2.2 Performance Guarantee

To simplify the proof, we suppose the whole time series $\mathcal{T}$ is divided into K time slots with slot size of T_0 (i.e. $\mathcal{T} = KT_0$). Assume that there is an optimal solution of Problem (10) which is defined as $\frac{1}{KT_0}\sum_{t=1}^{KT_0}\sum_{i=1}^{N} U^*(r_i^{(t)})$, we have the following theorem for performance guarantee:

Theorem 5. *If we apply the SSA algorithm, the Lyapunov drift in (18) can be minimized and the obtained time-average utility satisfies:*

$$\frac{1}{KT_0}\sum_{t=1}^{KT_0}\sum_{i=1}^{N} U(r_i^{(t)}) \geq \frac{1}{KT_0}\sum_{t=1}^{KT_0}\sum_{i=1}^{N} U^*(r_i^{(t)}) - \frac{1}{2}\frac{MN}{V}. \tag{23}$$

Proof. See Appendix C. □

4.2.3 Impact of parameter V

As mentioned above, V is a positive constant parameter that associates the energy queues and utility function. We show in this section that, in practical solutions of the primal problem, V plays an important role in both networks utility and energy queue performance. Therefore, select a proper value for V is critical.

1. Network Performance. As presented in (23), the gap between the SSA solution and the optimal solution is $\frac{1}{2}\frac{MN}{V}$. Thus, the larger V is, the small the gap is.

2. Energy Queue. Energy queue is another significant factor in our design. We intend to keep it as stable as possible. Here we obtain the following theorem of the relationship between average energy queue length and the value of V:

Theorem 6. *If we apply the SSA algorithm, the average energy queue length can be bounded as follows:*

$$\frac{1}{TN}\sum_{t=1}^{T}\sum_{i=1}^{N} E_i(t) \leq \frac{M + 2V(U_{max} - U_{min})}{2\lambda}, \tag{24}$$

where

$$M = \psi_{max}^2 + \phi_{max}^2,$$

and λ is a positive constant that satisfies

$$\lambda \geq \phi_i^{(t)} - \psi_i^{(t)} + \theta_i^{(t+1)} - \theta_i^{(t)}.$$

Proof. See Appendix D. □

As shown in (24), it is clear that parameter V has an impact on the average energy queue length. When the value of V is getting larger, the energy queue bound is getting loose.

Consequently, in application of the SSA algorithm, the users can change the value of V according to their preference. That is if a tight network performance is required, the value of V should be set larger. Otherwise, if the energy queue bound is preferred, the value of V should be set smaller.

5 Evaluation

In this section, we conduct practical testbed experiments and numerous simulations with rational coefficient settings to verify our design.

5.1 Testbed Experiments

In this section, we conduct field experiments to further verify the performance of the SSA algorithm.

Fig. 3. Testbed based on Powercast

5.1.1 Testbed

We test the SSA algorithm on our Powercast testbed (Fig. 3). The system is deployed in a $250cm \times 250cm$ square area, with 7 wireless rechargeable sensor nodes, 6 $TX91501$ power transmitters and 2 sink stations connecting to 2 laptops, respectively. Chargers provide wireless power for sensor nodes with $3W$ transmission power. Sensor nodes communicate with each other via $Zigbee$ protocol. We run the SSA algorithm on the testbed for 60 time slots with $1s$ for each, and adopt the time-average network throughput as the utility. Fig. 4 shows the network topology and an example of a time slot: in current slot, Sensor node 2, 4, 6 are in $State\ R$ to recharge energy, and Sensor node 1, 3, 5, 7 are in $State\ W$ to sense data and upload them to sink stations.

5.1.2 Experimental Results

The experiment results are shown in Fig. 5, we compare the performance of SSA with the theoretically optimal solution proposed in Section III. We can see that the time-average network throughput tends to be stable over time. The SSA performs at least 85% of the optimal, which verifies that the SSA provides near-optimal solution. We also record each sensor node's total sensing rate in Fig. 6. The results show that there is little difference among sensor nodes' total sensing rates. This indicates that our design of objective function successfully guarantees the utility fairness. Moreover, in the practical experiments, we set the duration of one time slot as $1s$. This demonstrates that the SSA should terminate in quite short time intervals. Thereby, the experimental result also shows that the SSA has very low time complexity.

5.2 Simulations

We consider a $600m \times 600m$ network with 200 wireless rechargeable sensor nodes randomly deployed in the target area. There are also 20 sink stations and 200 chargers, to collect data and provide RF energy for sensor nodes, respectively. Without loss of generality, we set their locations randomly. We adopt the throughput as the network utility and test a $120s$ time period with time slot size of $6s$ in our simulations. According to our pre-experiments, the power

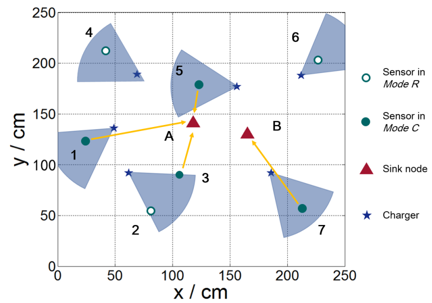

Fig. 4. Network topology

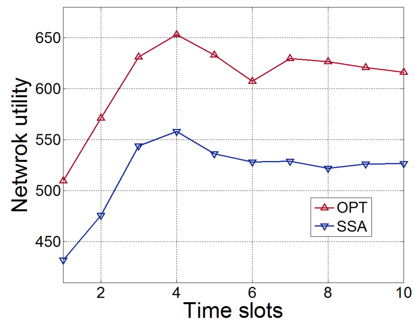

Fig. 5. Experimental results

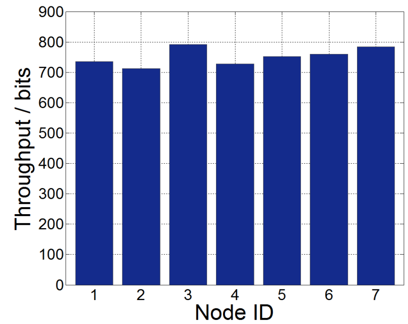

Fig. 6. Utility of each sensor node

consumption of sensing tasks is $p_0 = 0.00024mW/bit$. As for the energy recharging model and consumption model proposed in Section II, we set $a = 7.593mW/m^2$, $b = 0.3154m$, $pt = pr = 558nJ/bit$ and $\epsilon = 44.66pJ/bit/m^2$. Based on our practical experiment platform, the battery capacity is set to $0.0045J$. Moreover, each sensor node's initial energy is decided randomly.

Then we obtain the following simulation results by running our algorithms multiple times with different network topologies, network sizes, coefficient settings, etc.

5.2.1 Baseline Setup

In small-scale networks with single-hop communication, we set the optimal solution proposed in Section III as baseline. In large-scale networks, to the best of our knowledge, there is no existing work that considered the operation state scheduling problem with multi-hop communication. We compare the performance of SSA with two heuristic mechanisms: *a)* We define a fixed energy threshold θ in SSA to decide sensor node's operation state, hereby we set $\theta = 0.5 \times B_0$ and name this mechanism as 0.5-thr. *b)* We schedule all the sensor nodes alternately, that all the sensor nodes turn to $State\ R$ in odd time slots, and turn to $State\ W$ in even time slots. We name this mechanism as Alt.

5.2.2 System Performance

First, we compare the performance of SSA with 0.5-thr and Alt in multi-hop case. We test the algorithms under different sensor node deployment settings. The result is shown in Fig. 7. We can see that the network utility increases as the number of sensor nodes grows, which conforms with intuition. SSA improves about 10% and 20% of network utility compared with 0.5-thr and Alt, respectively.

We also present the performance of SSA in small-scale networks. As proposed in Fig. 8, our design still outperforms the two baseline algorithms and achieves about 85% of the optimal. Notice that, in our simulation settings, sensor nodes, sink stations and chargers are assumed to be randomly deployed. However, in practical settings, the network should be deployed more energy-efficiently according to the practical demands. Energy-efficient network deployment results in high utility. Thus, our algorithm can perform much better.

5.2.3 Impact of Network Size

As the scale of IoTs is increasing rapidly, the robustness of our algorithm under different network sizes is also of great interest. We present the simulation results in Fig. 9. Although the network size is changing, our design still outperforms other mechanisms. As the network size increases, the communication distances between sensor nodes are becoming larger, thus network utility decreases faster. This indicates that the wireless charging power and energy consumption of wireless communication are very "energy-sensitive", since they are both inversely proportiona1 to the $2nd - 4th$ power of the transmission distance.

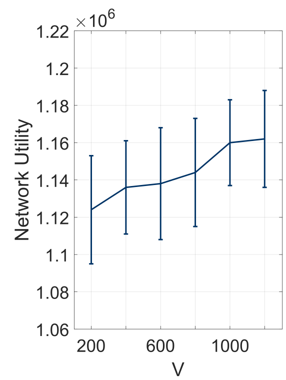

Fig. 10. Impact of V on network utility

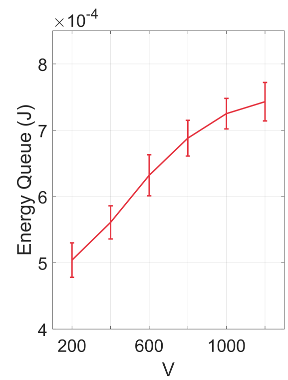

Fig. 11. Impact of V on energy queue

5.2.4 Impact of Parameter V

It is clear that parameter V plays an important role in our SSA algorithm. As shown in Section 4, both the network utility and energy queue are bound by V. Thus, we test the impact of parameter V via massive simulations. Fig. 10 presents that network utility increases with the value of V, which demonstrates the analysis of (23), i.e. a larger V can improve the network utility. Fig. 11 demonstrates that the increasing of V results in a longer energy queue length, which has been analyzed in (24). Therefore, our SSA algorithm provides a tradeoff for users, that users can adjust the value of V according to their demands on network utility and energy queue length.

5.2.5 System Insights

In this part, we try to explain why the SSA performs much better than the other mechanisms. The key factor that affects the network utility of RF-powered IoT is the power efficiency. The sensor nodes should fully utilize the recharged energy, in order to maximize the network utility.

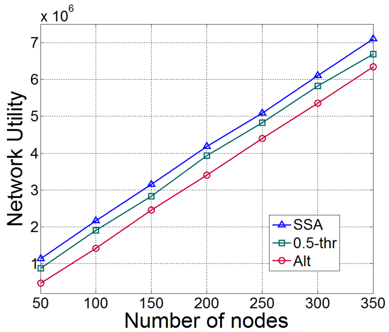

Fig. 7. Throughput comparison in large-scale networks

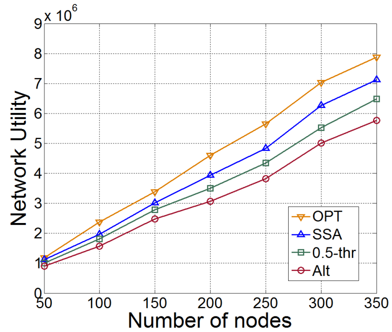

Fig. 8. Throughput comparison in small-scale networks

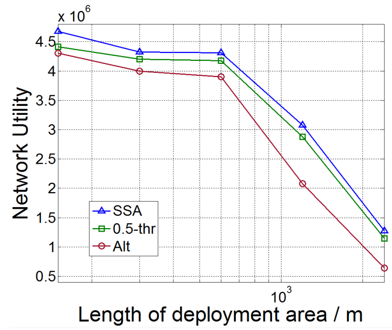

Fig. 9. Throughput vs. length of deployment area

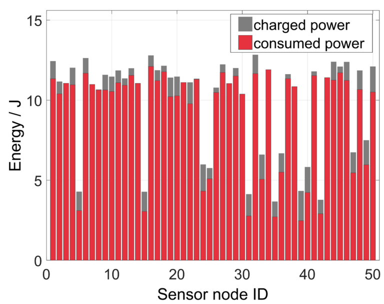

Fig. 12. Energy efficiency of SSA

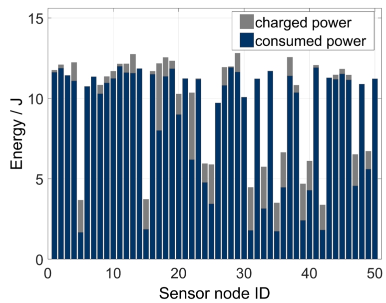

Fig. 13. Energy efficiency of 0.5-thr

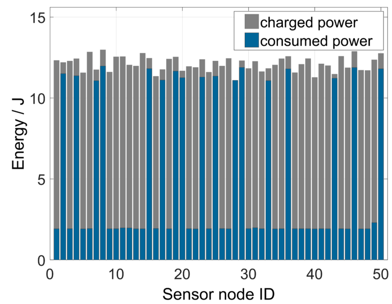

Fig. 14. Energy efficiency of Alt

To verify our assumption, we record each sensor node's charged power and consumed power of SSA, 0.5-thr and Alt. The result is shown in Fig. 12, 13, 14, respectively.

We proceed to check the energy efficiency. SSA achieves 89.9%, 0.5-thr's is 85.8% and Alt's is only 42.7%. Clearly, the energy efficiency of SSA is much higher than the others.

This is because the state scheduling optimization makes the network operate under dynamic topology. Dynamic topology enables sensor nodes with sufficient energy to undertake more relay tasks for the energy insufficient sensor nodes nearby. Thus, all the sensor nodes can fully utilize their recharged energy. This leads the network to a better balance between collecting energy flow and uploading data flow. Moreover, the global optimization of energy threshold further provides near-optimal network topology in every slot. Thereby, our design can achieve high overall energy efficiency, and this improvement finally results in a higher network utility.

6 Conclusion

In this paper, we took the first attempt to consider the working-recharging state scheduling problem in RF-powered IoT. We studied two cases of this problem: the single-hop case and the multi-hop case. For the first case, we introduced geometric programming to transfer it into a convex optimization problem, and obtained the optimal analytical solution. For the second one, we found it quite difficult to address, since the multi-hop communication introduced strong spatiotemporal coupling. We designed an S-SA algorithm based on Lyapunov optimization. Our design decoupled the primal problem temporally by introducing a dynamic energy threshold vector, which scheduled sensor nodes to appropriate operation states in every time slot. Then, in every slot, the network utility was optimized by applying the max-flow model. Finally, we conducted field experiments based on our Powercast testbed and numerous simulations to verify the design, and further discussed the system insight from the aspect of energy efficiency.

Appendix A
Proof of Theorem 3

Here we prove Theorem 2.

$$
\begin{aligned}
&\Delta_1 L(t) - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)})\\
&= L(t+1) - L(t) - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)})\\
&\le \frac{1}{2}\sum_{i\in\mathcal{N}}({\psi_i^{(t)}}^2 + {\phi_i^{(t)}}^2) + \sum_{i\in\mathcal{N}}(e_i^{(t)} - \theta_i^{(t)})(\psi_i^{(t)} - \phi_i^{(t)})\\
&\quad - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)})\\
&\le \frac{1}{2}MN + \sum_{i\in\mathcal{N}}(e_i^{(t)} - \theta_i^{(t)})(\psi_i^{(t)} - \phi_i^{(t)}) - V\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)}),
\end{aligned}
\tag{25}
$$

where $M = \psi_{max}^2 + \phi_{max}^2$.

Appendix B
Proof of Theorem 4

It is easy to see that Inequality (23) holds for $t = 0$, since $E_i(0) = 0$ for all $i \in \mathcal{N}$. Now we assume that

$|e_i^{(t)} - \theta_i^{(t)}| \leq \frac{\psi_{max}+\phi_{max}}{4}$ holds for all i in slot t. We show that this inequality also holds for slot $(t+1)$.

Case 1: $e_i^{(t)} \geq \theta_i^{(t)}$.

We have

$$e_i^{(t)} - \theta_i^{(t)} \leq \frac{\psi_{max} + \phi_{max}}{4}$$

and

$$e_i^{(t+1)} = e_i^{(t)} - \phi_i^{(t)}.$$

Then

$$\begin{aligned}|e_i^{(t+1)} - \theta_i^{(t+1)}| &\leq \phi_{max} - \frac{\psi_{max} + \phi_{max}}{4} + \frac{\psi_{max} - \phi_{max}}{2} \\ &= \frac{\psi_{max} + \phi_{max}}{4}.\end{aligned}$$

Case 2: $e_i^{(t)} < \theta_i^{(t)}$.

We have

$$\theta_i^{(t)} - e_i^{(t)} \leq \frac{\psi_{max} + \phi_{max}}{4}$$

and

$$e_i^{(t+1)} = e_i^{(t)} + \psi_i^{(t)}.$$

Then

$$\begin{aligned}|e_i^{(t+1)} - \theta_i^{(t+1)}| &\leq \psi_{max} - \frac{\psi_{max} + \phi_{max}}{4} - \frac{\psi_{max} - \phi_{max}}{2} \\ &= \frac{\psi_{max} + \phi_{max}}{4}.\end{aligned}$$

So far, Inequality (23) has been proved.

Appendix C
Proof of Theorem 5

C.1 Minimize Lyapunov Drift

Consider the Lyapunov drift in Inequality (24), we should minimize the right-hand side of the inequality. The first term is constant, thus it can be neglected.

For the second term $\sum_{i\in\mathcal{N}}(e_i^{(t)} - \theta_i^{(t)})(\psi_i^{(t)} - \phi_i^{(t)})$, we should set it as negative to minimize the right-hand side. Notice that for $\psi_i^{(t)}$ and $\phi_i^{(t)}$, there is only one of them can exist in one time slot because of the state scheduling. Thereby, for each sensor node we schedule the second term as:

$$\begin{cases} -\phi_i^{(t)}(e_i^{(t)} - \theta_i^{(t)}), & if\ e_i^{(t)} \geq \theta_i^{(t)} \\ \psi_i^{(t)}(e_i^{(t)} - \theta_i^{(t)}), & otherwise, \end{cases} \tag{26}$$

which indicates that if Sensor node i's energy level is higher than its energy threshold, it is scheduled to consume energy, i. e. turns to $State\ W$; otherwise it is scheduled to harvest energy, i. e. turns to $State\ R$. This result is in accord with the intuition. Notice that so far the primal problem has been decoupled to subproblems in every time slots.

For the third term in Inequality (24), it is obvious that we should maximize $\sum_{i\in\mathcal{N}_w^{(t)}} U(r_i^{(t)})$, while subject to the constraints mentioned in previous sections. Thus, by applying the SSA algorithm, the Lyapunov drift is minimized.

C.2 Approximate Optimality

Now we define the T-slot Lyapunov drift with penalty for $1 \leq k \leq K$:

$$\begin{aligned}&\Delta_T L(kT) - V\sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N} U(r_i^{(t)}) \\ &= \sum_{t=kT-T+1}^{kT}(\Delta L(t) - \sum_{i=1}^{N} U(r_i^{(t)})) \\ &\leq \frac{1}{2}\sum_{i=1}^{N}({\psi_i^{(t)}}^2 + {\phi_i^{(t)}}^2) - V\sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N} U^*(r_i^{(t)}) \\ &+ \sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N}(e_i^{(t)} - \theta_i^{(t)})(\psi_i^{(t)} - \phi_i^{(t)}) \\ &\leq \frac{1}{2}MNT + \sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N}(e_i^{(t)} - \theta_i^{(t)})(\psi_i^{(t)} - \phi_i^{(t)}) \\ &- V\sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N} U(r_i^{(t)}) \\ &\leq \frac{1}{2}MNT + \sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N}(e_i^{*(t)} - \theta_i^{*(t)})(\psi_i^{*(t)} - \phi_i^{*(t)}) \\ &- V\sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N} U^*(r_i^{(t)}).\end{aligned} \tag{27}$$

Taking a telescopic sum of the inequality above over $k \in \{1...K\}$ and dividing both sides by VKT, we have

$$\begin{aligned}&\frac{1}{V}L(KT+T) - \frac{1}{V}L(1) \\ &\leq \frac{1}{KT}\sum_{t=1}^{KT}\sum_{i=1}^{N} U(r_i^{(t)}) + \frac{1}{2}\frac{MN}{V} - \frac{1}{KT}\sum_{t=1}^{KT}\sum_{i=1}^{N} U^*(r_i^{(t)}) \\ &+ \frac{1}{VKT}\sum_{t=kT-T+1}^{kT}\sum_{i=1}^{N}(e_i^{(t)} - \theta_i^{(t)})(\psi_i^{(t)} - \phi_i^{(t)}).\end{aligned} \tag{28}$$

It is obvious that $L(KT+T) \geq 0$, and we consider $L(1) = 0$, we have

$$\frac{1}{KT}\sum_{t=1}^{KT}\sum_{i=1}^{N} U(r_i^{(t)}) \geq \frac{1}{KT}\sum_{t=1}^{KT}\sum_{i=1}^{N} U^*(r_i^{(t)}) - \frac{MN}{2V}.$$

So far, we have obtained the worst-case bound for network utility.

Appendix D
Proof of Theorem 6

First, we have the 1-slot Lyapunov drift plus penalty that satisfies

$$\begin{aligned}
&\Delta_1 L(t) - V\sum_{i=1}^{N} U(r_i^{(t)}) \\
&= L(t+1) - L(t) - V\sum_{i=1}^{N} U(r_i^{(t)}) \\
&\leq \frac{1}{2}\sum_{i=1}^{N}({\psi_i^{(t)}}^2 + {\phi_i^{(t)}}^2) - V\sum_{i=1}^{N} U(r_i^{(t)}) \\
&+ \sum_{i=1}^{N}(e_i^{(t)} - \phi_i^{(t)})(-\phi_i^{(t)} + \psi_i^{(t)} - \theta_i^{(t+1)} + \theta_i^{(t)}) \\
&\leq \frac{1}{2}MN - V\sum_{i=1}^{N} U(r_i^{(t)}) - \lambda\sum_{i=1}^{N} E_i^{(t)},
\end{aligned} \tag{29}$$

where

$$M = \psi_{max}^2 + \phi_{max}^2,$$

and λ is a positive constant that satisfies

$$\lambda \geq \phi_i^{(t)} - \psi_i^{(t)} + \theta_i^{(t+1)} - \theta_i^{(t)}.$$

Rearrange the items and take a telescopic sum of the inequality above over time T, we finally obtain

$$\frac{1}{TN}\sum_{t=1}^{T}\sum_{i=1}^{N} E_i(t) \leq \frac{M + 2V(U_{max} - U_{min})}{2\lambda}.$$

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