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Asymptotically Throughput Optimal Scheduling for Energy Harvesting Wireless Sensor Networks

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ABSTRACT In this paper, we investigate a single-hop wireless sensor network in which a fusion center (FC) collects data packets from M energy harvesting (EH) sensor nodes. Energy harvested by each node is stored without battery overflow and leakage at that node. The FC schedules K nodes over its mutually orthogonal channels to receive data from them in each time slot. The FC knows neither the statistics of EH processes nor the battery states of nodes. The FC solely has information on consequences of previous transmission attempts. We aim for obtaining an efficient and simple policy achieving maximum throughput in this network. The nodes are data backlogged and the data transmission only depends on the harvested energy of the scheduled nodes. A node can transmit data whenever it is scheduled, provided that it has sufficient energy. We propose a simple policy, *uniforming random ordered policy (UROP)*, for the problem. We exhibit that the UROP is nearly throughput-optimal over finite time horizons for a broad class of EH processes. We also prove that for *general* EH processes, UROP achieves *asymptotically optimal throughput* over the infinite time horizon under infinite capacity battery assumption. Numerical results indicate that even with finite-capacity batteries, UROP achieves near-optimal throughput over finite time horizons. We believe that UROP is applicable to much wider area than EH wireless sensor networks.

INDEX TERMS Energy harvesting (EH), scheduling algorithms, resource allocation, decision making, wireless sensor network.

I. INTRODUCTION

A. MOTIVATION

Internet of Things (IoT) is a smart sizable communication infrastructure of uniquely attributable wireless equipments which are able to communicate with each other via Internet [1]–[3]. IoT has been considered as one of the most promising networking paradigms that fill the gap between the physical and cyber world. In the IoT structures, the devices are generally equipped with wireless sensors [4] which enable efficient data transmission and collection anywhere [5]. Consequently, wireless sensor networks (WSNs) have numerous applications, such as smart cities [6], structural health monitoring [7], agriculture [8], frost monitoring [9] and ambient air monitoring [10]. Being prudent in energy consumption is very crucial for many WSN deployments. Energy harvesting (EH) [11] especially eases WSN applications in which it is impractical to replace battery. The sensor nodes can harvest energy in various ways [12]. Since energy is generally harvested in low amount from uncontrollable energy resources (solar, kinetic, etc.) [12], WSNs require energy efficient and robust policies [13], [14].

In this work, we consider a WSN in which a fusion center (FC) schedules EH wireless nodes in order to collect data. At each time slot (TS), the FC, which has no information on the battery states of the nodes, schedules K nodes for transmission. Channel imperfections such as fading, interference are ignored. The nodes are data backlogged but the data tranmission is limited within available energy. Each node stores the harvested energy without battery overflow and leakage. Provided that a node is scheduled and has sufficient energy to send data to the FC, it sends one data packet. Transmitting one data packet takes up one TS. FC aims for maximizing average throughput (reward) over a time horizon.

It is conceivable that the FC can access the battery states via some extra cost (i.e. feedback, extra time and energy) and computational complexity in some WSNs. For example, in [15] and [16], a central scheduler collects data from the sensor nodes by learning the instantaneous states of their batteries (energy remained in their batteries) via extra cost in random channel access periods. Li *et al.* [15] model their problem as a typical 0-1 Multiple Knapsack problem and propose a novel scheduling algorithm, κ-Fair Scheduling

Optimization Model (κ-FSOM), for a mobile WSN by considering residual energy levels, radio link quality of sensor nodes while satisfying fairness of at least κ for each node. The paper [16] extends the work in [15]. However, in many WSNs, wireless sensors may not have full observability because of environment dynamics, hardware limitations, or external noise [17]. Beside this, how often the FC should learn the battery states of nodes arises as another question. Learning the battery states less frequently may cause the FC to miss important knowledge about the battery states in some TSs. On the other hand, learning the battery states in each TS (via overheads) causes much more time and energy consumption. Therefore, from a practical perspective, it is more relevant that *the FC schedule the nodes with no information on the statistics of their EH processes or the instantaneous battery states*. We will show that this lack of information has a subtle impact on the throughput. This paper demonstrates a simple online policy through which, the FC can schedule the wireless nodes almost optimally with sole information on consequences of previous transmission attempts.

To define our scheduling problem precisely, we need a model for energy generation and utilization. The nodes access their own battery states solely at the beginning of TSs when they are selected to send data. Consequently, while physical energy harvesting, battery charging, and energy retrieval processes may be continuous in time, in our model, the battery state will be a discrete time process.[1] Furthermore, the battery of each node can store the harvested energy without any loss. This assumption is consistent with the many kinds of currently used batteries of which leakage is negligible for durations of numerous minutes because from the results in [18], the leakage results in little decrease in the stored energy (5% decrease for Lithium-ion batteries and 10% decrease for Nickel-based batteries within 24 hours). Based on these reasonable assumptions on the energy harvesting and storage processes, the average throughput (reward) criteria is a more appropriate performance measure than discounted throughput (reward) criteria for our problem [19].

The number of practical applications relying on vibrational or kinetic energy harvesting is increasing. The resulting EH processes, in contrast to solar EH processes, are typically not predictable [11], [13]. This is one of the motivations for our search for an optimal scheduler that does not have statistical knowledge about the underlying EH processes. Hence, a simple policy, *Uniforming Random Ordered Policy (UROP)*, is proposed for the problem at hand with a deterministic approach.[2] *Our algorithm, UROP, exploits missed transmission opportunities, which indirectly convey information about battery states of the scheduled nodes: according to our model, a node only misses its allocated time slot when it does not have sufficient energy to perform data transmission. Hence, the time slots in which some of the channels remain idle implicitly inform the scheduler of the energy states of the nodes which are scheduled over those channels.* While UROP is developed under infinite-capacity battery (i.e. no battery overflow) assumption, it will be evident that as long as the nodes have reasonable finite-capacity batteries, efficiency of UROP will not be affected significantly.

This paper extends our previous study [20] in several dimensions. In [20], a simple policy, UROP, is proposed for the problem. Then, upper and lower bounds for throughput performance of UROP are obtained for *general* EH processes under average throughput criteria. In this paper, we show that UROP is *asymptotically average throughput-optimal* over infinite time horizon for general admissible EH processes. Additionally, we investigate average throughput performance of UROP over finite time horizons. Under infinite capacity battery (no battery overflow) assumption, we show that UROP achieves *near-optimal* expected average throughput over a finite time horizon for a broad class of EH processes. Moreover, *inadmissible* EH processes are also introduced in this paper. Beside this, we investigate the throughput of UROP for inadmissible EH processes firstly in this paper and exhibit that UROP achieves the same throughput performance for inadmissible EH processes, too.

B. RELATED WORK

Although we do not limit the EH processes in this work to be Markovian processes, we can define our problem as a partially observable Markov decision process (POMDP) under Markovian assumption [21], [22]. Under this assumption, we can propose dynamic programming (DP) [23] as an optimal solution for the problem. Nevertheless, DP has exponential computational complexity in terms of state space of the related POMDPs, and this restricts the scalability of DP [24].

A second possible approach, also under Markovian assumptions, can be reinforcement learning approach if the problem is considered as a POMDP problem [25]. Q-learning [26], a very efficient model-free reinforcement learning algorithm, guarantees convergence to optimality in this problem. On the other hand, especially when the discount factor is very close to 1, the very slow convergence of Q-learning [27] makes it non-ideal for the scheduling problems with large state spaces. R-learning [28] maximizing the average reward can be considered as a solution; however, it does not guarantee to converge to optimality. As a result, reinforcement learning do not seem to provide a practical and efficient solution for this problem, particularly if the problem has sizeable state space (large number of nodes and channels of the FC). There are other approaches that can guarantee convergence to optimality in the long term [29]. Nevertheless, in practical aspects, a policy achieving near optimality rapidly is generally preferred to the policy converging to exactly optimal solution so slowly [17], [27].

[1] In this paper, we consider battery state of each node as a discrete time process because the node which is scheduled in a TS t measures the energy at its battery at the beginning of the TS t in order to decide whether it can transmit data or not.

[2] Except Section IV-C we do not make any stochastic assumption related to statistics of EH processes at nodes and consider the scheduling problem for general EH processes.

Another possible approach can be defining this problem as a restless multi-armed bandit (RMAB) which was extended from classical multi-armed bandit (MAB) problem [30] solved by Gittins [31]. For the RMAB problem, an optimal index policy was proposed by Whittle under certain assumptions [32]. The work in [33] proves that obtaining an optimal solution for general RMAB problem is PSPACE-hard. In search of a low-complexity scheduling algorithm, myopic policy (MP) has been suggested to numerous RMAB problems. Although it cannot achieve optimality in general because of focusing solely on the present state [34], it is exhibited that the MP achieves optimality under specific cases for the opportunistic spectrum access (OSA) problems in [35]–[42]. The references [43], [44], for example, studied a channel probing problem showed the suboptimality of MP. An important difference of the present problem from the OSA problems tackled in [35]–[44] is that here the scheduling decisions affect the transition probabilities as the resource is flexible.

The resource in [35]–[44], spectrum, is inflexible; that is, it cannot be stored and must be used at the instant when it is available, and at each TS, the channels evolve independently. Therefore, the scheduling decisions do not affect the transition probabilities. In contrast to spectrum, energy is a flexible resource which is able to be stored, and used later in time. In this respect, the policies proposed in [35]–[44] cannot applied to the problem at hand directly.

The nearest problems to our problem are the problems tackled in the papers [45]–[47]. We investigate almost the same problem in [45] and [46] except that we assume unlimited energy storage and no battery leakage at the nodes, in contrast to [45] and [46] which assume either unit capacity batteries with leakage or no battery (no storage capability). Both [45] and [46] define the scheduling problems as POMDP problems. As the work [45] and [46] have myopic approach to the scheduling problem, they take into account the immediate rewards more than future rewards. In [46], a single-hop WSN consisting of a multichannel central scheduler node and EH nodes with unit-capacity batteries (capable of storing energy which is only sufficient for sending one packet) is treated as a RMAB problem. Under specific assumptions, a MP which is based on a round-robin (RR) scheme is shown to be optimal. Then, [46] exhibits that for a specific case, this policy matches up with Whittle index policy, not optimal for RMAB problems in general [48]. The work [45] formulates this problem as a POMDP and prove that RR-based MP achieves optimal throughput for two cases: 1) nodes cannot send data and harvest energy at the same time, and the scheduling decisions have influence on transition probabilities of the EH processes, and 2) no node has storage capability (no battery). Unlike [45] and [46], the work in [47] considers the problem for much more general class of EH processes and investigates throughput performance of the RR based MP under infinite capacity battery assumption and average reward criteria. It is worth noting that, as the MPs in [45]–[47] are based on a RR scheme, [45]–[47] assumes that $\frac{M}{K}$ is an integer.

C. MAIN CONTRIBUTIONS

Our contributions are summarized as follows:

- As this paper assumes that battery capacity of the node is larger than unit capacity for the EH WSN problem, in Section III, we introduce two new notions for this problem: scheduling capacity of the FC and admissible EH process.
- In Section IV-A, we propose a simple policy, UROP, for the problem. In Section IV-B, we obtain upper and lower bounds for throughput performance of UROP for *general* EH processes under average throughput criteria. In Section IV-C, under infinite capacity battery (no battery overflow) assumption, we show that UROP achieves *near-optimal* expected average throughput over a finite time horizon for a broad class of EH processes. In Section IV-D, we show that UROP achieves *asymptotically optimal* average throughput over infinite time horizon for general admissible EH processes.
- As this work is the first work which considers *admissibility* for EH processes, in Section IV-E, *inadmissible* EH processes are also introduced. We study throughput of UROP for inadmissible EH processes and exhibit that UROP shows the same throughput performance for these processes, too.
- In Section V, we show that even if $\frac{M}{K}$ is not an integer, UROP still guarantees the same throughput performance whereas the MPs in [45]–[47] are not applicable. Moreover, we show that with reasonable finite-capacity batteries, UROP achieves almost the same performance as it does under infinite capacity battery assumption.

D. ORGANIZATION

The rest of this paper is organized as follows. In Section II, we give the system model and problem definition. In Section III, we study the conditions when scheduling capacity of FC is exceeded. In Section IV, under infinite capacity battery assumption, we propose a simple policy, UROP, for this scheduling problem. Next, we obtain bounds on throughput performance of UROP for general (uniform, non-uniform, Markovian, i.i.d., etc.) EH processes. Then, it is shown that UROP is *near-optimal* over finite time horizons for a broad class of EH processes and *asymptotically optimal* for general EH processes under average reward criteria. Furthermore, it is exhibited that UROP is also nearly optimal over a finite time horizon and asymptotically optimal for general EH processes even if the scheduling capacity of FC is exceeded. In Section V, we compare UROP with the MP in [45]–[47] in terms of throughput. In Section VI, we conclude our work and provide the future directions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this work, we consider a single-hop wireless sensor network (WSN) where a fusion center (FC) schedules M energy

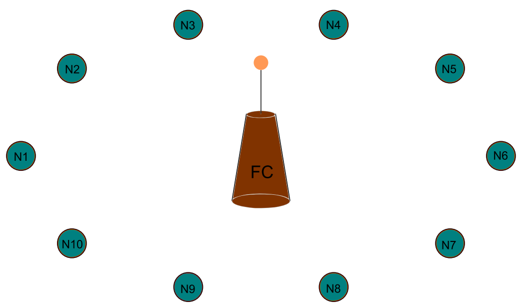

FIGURE 1. **A single-hop WSN where FC collects data packets from EH wireless sensors surrounding it.**

harvesting (EH) sensors in each time slot (TS) in order to collect data (please see Fig. 1). S denotes index set of the nodes, i. e., $S = \{1, 2, \ldots, M\}$. The system operates in a time-slotted fashion indexed as $t = 1, 2, \ldots, T$. In each TS, FC schedules K nodes to receive data packets from them. Error-free communication is assumed in the network. It is assumed that the nodes always have data packets to send (each nodes has *data backlog* as in [45]–[47]) over a time horizon of T TSs. All data packets have the same size and transmitting one data packet takes one TS. *Unit energy* is defined as the amount of energy which one node needs for transmitting one packet in one TS (including all overheads). $E_i(t)$ and $E_i^h(t)$ denote the energy harvested by node i in TSs 1 thru t and energy harvested by node i in TS t, respectively; i.e.,

$$E_i^h(t) = E_i(t) - E_i(t-1). \tag{1}$$

Under a policy π, *activation set* is defined as set of the nodes scheduled in TS t and denoted by $\pi(t)$ ($|\pi(t)| = K, \forall \pi, t$ in our problem). When a node is scheduled and has sufficient energy in TS t, that node sends one packet. The number of packets sent by node i in TS t under a policy π is found by $\mathbb{I}_{\{i \in \pi(t)\}} \mathbb{I}_{\{B_i^\pi(t) \geq 1\}} \in \{0, 1\}$ where $\mathbb{I}_{\{.\}}$ is the indicator function and $B_i^\pi(t)$ is the energy stored in battery of node i in TS t if the FC use the policy π. It can be written as

$$B_i^\pi(t+1) = B_i^\pi(t) + E_i^h(t) - \mathbb{I}_{\{i \in \pi(t)\}} \mathbb{I}_{\{B_i^\pi(t) \geq 1\}} \quad \forall i, t. \tag{2}$$

The number of packets collected by the FC in TSs 1 through t under a policy π is

$$V^\pi(t) = \sum_{i=1}^{M} V_i^\pi(t) = \sum_{i=1}^{M} \sum_{\tau=1}^{t} \mathbb{I}_{\{i \in \pi(\tau)\}} \mathbb{I}_{\{B_i^\pi(\tau) \geq 1\}}, \tag{3}$$

where $V_i^\pi(t)$ is the number of packets sent by node i within the first t TSs under a policy π.

The work in [45] and [46] aim to obtain an algorithm achieving maximum throughput over the time horizon under expected discounted throughput (reward) criteria, where the discount factor, β, account for battery leakage that happens as data transmission is withheld. The stored energy in typical batteries decreases less than 10% within 24 hours due to battery leakage [18][3] so the battery leakage is neglected in our problem formulation. As the scheduling problem is tackled under no battery leakage assumption from [18] and infinite data backlog, the problem is delay insensitive by nature. Thus, in our objective function, the discount factor is eliminated, i.e. $\beta = 1$ and from [18] and [19], the throughput maximization problem at hand can be formulated over finite and infinite time horizons under average throughput (reward) criteria as follows.

Problem 1: Expected average reward (throughput) maximization over a finite time horizon

$$\max_{\{\pi(t)\}_{t=1}^{T}} \frac{1}{\mathrm{T}} \mathbb{E}\left[\mathrm{V}^\pi(\mathrm{T})\right]$$
$$s.t.\ (2)$$

Problem 2: Expected average reward (throughput) maximization over infinite time horizon

$$\lim_{T \to \infty} \max_{\{\pi(t)\}_{t=1}^{T}} \frac{1}{\mathrm{T}} \mathbb{E}\left[\mathrm{V}^\pi(\mathrm{T})\right]$$
$$s.t.\ (2)$$

Problem 3: Sample path average reward (throughput) maximization over infinite time horizon

$$\lim_{T \to \infty} \max_{\{\pi(t)\}_{t=1}^{T}} \frac{1}{\mathrm{T}} \mathrm{V}^\pi(\mathrm{T})$$
$$s.t.\ (2)$$

In Problem 1 and Problem 2, expectation is taken over the statistics of EH processes. We introduce several notions which are useful in the remainder of the paper.

Definition 1: An ***optimal policy*** *maximizes total throughput of all nodes up to KT over time horizon, T, i.e.:*

$$\pi^* \triangleq \arg\max_{\pi \in G} \frac{V^\pi(T)}{T},^4 \tag{4}$$

where G denotes the set of all feasible scheduling policies.

Definition 2: A policy π is called ***asymptotically optimal*** *if*

$$\lim_{T \to \infty} \frac{V^\pi(T)}{V^*(T)} = 1 \quad w.p.\ 1.^5 \tag{5}$$

Definition 3: Under a ***fully (100%) efficient policy***, π^{FE}, *the nodes consume their harvested energy over the time horizon such that $B_i^{\pi^{FE}}(T) < 1, \forall i \in S$ which yields*

$$V^{FE}(T) = \sum_{i=1}^{M} V_i^{FE}(T) = \sum_{i=1}^{M} \lfloor E_i(T) \rfloor. \tag{6}$$

As it is explained in Section III, an optimal policy cannot achieve fully efficiency for some EH processes.

[3]This decrease less than 10% yields that $0.9999999988 \leq \beta < 1$ if length of a TS is less than 1 msec. Practically, β can be taken as 1.

[4]For some EH processes, the number of throughput optimal policies may be more than one.

[5]Although $V^\pi(t)$ denotes the total throughput achieved in first t TSs under a policy π, the total throughput achieved in first t TSs under a policy π^{FE} is denoted by $V^{FE}(T)$ instead of $V^{\pi^{FE}}(T)$ for simplicity. In addition, $V^*(T)$, $V^{RR}(T)$, and $V^{UROP}(T)$ are used instead of $V^{\pi^*}(T)$, $V^{\pi^{RR}}(T)$ and $V^{\pi^{UROP}}(T)$, respectively. Similarly, $V_i^{FE}(T)$, $V_i^*(T)$, $V_i^{RR}(T)$, and $V_i^{UROP}(T)$ are used instead of $V_i^{\pi^{FE}}(T)$, $V_i^{\pi^*}(T)$, $V_i^{\pi^{RR}}(T)$ and $V_i^{\pi^{UROP}}(T)$, respectively.

Definition 4: ***Efficiency of a policy*** π, $\eta(\pi)$, *is the ratio of throughput of a policy* π *over that of a fully efficient policy,* π^{FE}, *over the time horizon,* T, *i. e.,*

$$\eta(\pi) \triangleq \frac{V^{\pi}(T)}{V^{FE}(T)} \tag{7}$$

Notice that $\eta(\pi^{FE}) = 1$ by definition.

Definition 5: ***Intensity,*** ρ, *is the sum of integer parts of the harvested energy by all nodes (over the time horizon,* T*) which is divided by* KT*,i.e.,*

$$\rho \triangleq \frac{\sum_{i=1}^{M} \lfloor E_i(T) \rfloor}{KT} = \frac{V^{FE}(T)}{KT}. \tag{8}$$

Definition 6: ***Intensity of node*** i, ρ_i, *is the integer part of the harvested energy by node* i *(over the time horizon,* T*) which is divided by* $\frac{KT}{M}$, *i.e.,*

$$\rho_i \triangleq \frac{M \lfloor E_i(T) \rfloor}{KT} = \frac{M V_i^{FE}(T)}{KT}. \tag{9}$$

Note that intensity is average of intensities of all nodes, i.e.,

$$\rho = \frac{\sum_{i=1}^{M} \rho_i}{M}. \tag{10}$$

The number of data packets which can be sent by all nodes from TS $t+1$ to T is denoted by $Y(t)$ and it is defined as

$$Y(t) \triangleq V^{FE}(T) - V^{*}(t). \tag{11}$$

The number of data packets which can be sent by node i from TS $t+1$ to T is denoted by $Y_i(t)$, and it is defined as

$$Y_i(t) \triangleq V_i^{FE}(T) - \max_{\pi^* \in G^*} V_i^{*}(t), \tag{12}$$

where G^* denotes the set of all throughput-optimal policies.

Table 1 provides the notation commonly used in this paper for ease of reference.

TABLE 1. Summary of symbols and notation.

Symbol	Definition
M	Number of energy harvesting sensor nodes
K	Number of mutually orthogonal channels of FC
S	Index set of all sensor nodes
T	Time horizon
$E_i(t)$	Total energy harvested by node i until TS t
$E_i^h(t)$	Energy harvested by node i in TS t
$B_i^{\pi}(t)$	Stored energy in battery of node i in TS t under policy π
$\pi(t)$	Set of scheduled nodes in TS t under a policy π
$V^{\pi}(t)$	Throughput of all nodes in TSs 1 through t under policy π
$V_i^{\pi}(t)$	Throughput of node i in TSs 1 through t under policy π
$V^{*}(T)$	Throughput over time horizon T under π^* (Definition 1)
$V^{FE}(T)$	Throughput over time horizon T under π^{FE} (Definition 3)
$\eta(\pi)$	Efficiency of a policy π (Definition 4)
ρ	Intensity (Definition 5)
ρ_i	Intensity of node i (Definition 6)
$Y(t)$	Number of packets which can be sent by all nodes in $(t, T]$
$Y_i(t)$	Number of packets which can be sent by node i in $(t, T]$

III. SCHEDULING CAPACITY

To obtain an efficient policy, we should consider *scheduling capacity* of FC. It accounts for maximum number of nodes which can be scheduled by the FC in one TS. As FC has K mutually orthogonal channels, it schedules K nodes in each TS. If the energy harvesting rate is high such that the scheduling capacity of the FC is exceeded, no fully (100%) efficient policy exists.

In Theorem 1, we look for the conditions on the EH processes at nodes under which a fully efficient policy exists.

Theorem 1: For $0 \leq t < T$,

i) *If* $Y(t) > K(T-t)$ *for some* t *or* $Y_i(t) > (T-t)$ *for some* t *and some node* $i \in S$, *none of feasible policies (including optimal policies) will have fully (100%) efficiency.*

ii) *If* $Y(t) \leq K(T-t)$ $\forall t$ *and* $Y_i(t) \leq (T-t)$ $\forall t$, $\forall i \in S$, *fully efficient policies exist (optimal policies become fully efficient).*

Proof: Please see Appendix A. □

Theorem 1 gives us motivation to introduce admissible EH processes which are useful in the remainder of this paper.

Definition 7: If $Y(t) < K(T-t)$ $\forall t$ *and* $Y_i(t) \leq (T-t)$ $\forall i \in S$, $\forall t$, *the EH process becomes* ***admissible EH process****.*

We consider both *admissible and inadmissible EH process* to investigate efficiency of UROP in Section IV.

IV. EFFICIENCY OF UNIFORMING RANDOM ORDERED POLICY

A. UNIFORMING RANDOM ORDERED POLICY (UROP)

In this subsection, we propose a simple and efficient policy *Uniforming Random Ordered Policy (UROP)* for general EH processes.[6] Then, we investigate efficiency of UROP under admissible EH processes in Section IV-B, IV-C and IV-D. After then, we show that UROP demonstrates the same performance under inadmissible EH processes in Section IV-E. Notice that by Definition 7, admissible EH processes imply that some channels remain idle in some TSs even if an optimal policy is applied. The following proposition gives us motivation to propose UROP for the problem at hand.

Proposition 1 (Optimality for a Node): If $B_i^{\pi}(t) < 1$ *for a node i, then the throughput achieved by node i until TS t under the policy* π *is maximal.*

Proof: $\lfloor B_i^{\pi}(t) \rfloor$ denotes the number of packets which can be sent by node i with the stored energy in TS t. If node i has sent all packets which could be sent with $E_i(t)$ until TS t under the policy π, $\lfloor B_i^{\pi}(t) \rfloor = 0$ (or equivalently $B_i^{\pi}(t) < 1$), and the node i achieves maximum throughput (via total energy harvested) by TS t under the policy π. □

Proposition 1 indicates that a scheduling policy maximizing the throughput of the node until TS t has been applied to the node until TS t unless a scheduled node can send a packet at TS t. Considering this fact, we propose UROP for the problem (please see Algorithm 1). To schedule nodes efficiently, UROP benefits from the TSs in which some of channels remains idle in order to make inference about battery state of the nodes scheduled over those channels (whether these nodes have energy sufficient for sending at least one

[6] In [49], UROP is firstly proposed to solve the scheduling problem for certain class of EH processes. In [49] and [50], the scheduling problem is investigated for narrower class of EH processes.

Algorithm 1 Uniforming Random Ordered Policy (UROP)

Initialization:

1) For TS t, *activation vector,* $\mathbf{\Pi}$, is a $1 \times K$ vector such that its j^{th} element, denoted by $\mathbf{\Pi}(j)$, represents index of the node which is scheduled via j^{th} channel of the FC.

2) Before starting to scheduling, order the nodes randomly. Initialize $\mathbf{\Pi}$ by selecting the first K nodes w.r.t. the initial random order $(1, 2, \ldots, M)$, i. e., $\mathbf{\Pi} = [1 \quad 2 \quad \ldots \quad K]$.

3) Introduce a variable, $Next$. Initially, $Next = K + 1$.

Algorithm:

for $t = 1$ to T **do**

  for $j = 1$ to K **do**

    # Comment: Battery states are updated as in Equation (2). If a node $\mathbf{\Pi}(j)$ has enough energy for transmission, it transmits one packet.

    if $B^{\pi^{UROP}}_{\mathbf{\Pi}(j)}(t) \geq 1$ **then**

      $B^{\pi^{UROP}}_{\mathbf{\Pi}(j)}(t) \leftarrow B^{\pi^{UROP}}_{\mathbf{\Pi}(j)}(t) - 1;$

    # Comment: If a node $\mathbf{\Pi}(j)$ does not have enough energy for transmission, then FC looks for the node which is next in the line of waiting nodes (Being a waiting node i means that $i \notin \pi^{UROP}(t)$). If Next represents the index of the node which is next in the line of waiting nodes, then schedule the node Next over channel j in TS $t + 1$.

    else if $Next \notin \pi^{UROP}(t)$ **then**

      $\mathbf{\Pi}(j) \leftarrow Next;$

      #Comment: With equation $Next \leftarrow mod_M Next$, we assign "Next modulo M" to "Next" according to modular arithmetic rules to keep the cyclic order.

      $Next \leftarrow Next + 1; Next \leftarrow mod_M Next;$

      # Comment: If Next is not the index of the node which is next in the line of waiting nodes, then increase Next until $Next \notin \pi^{UROP}(t)$. When such a node Next is found, schedule node Next over channel j in TS $t + 1$.

    else

      while $Next \in \pi^{UROP}(t)$ **do**

        $Next \leftarrow Next + 1; Next \leftarrow mod_M Next;$

      end while

      $\mathbf{\Pi}(j) \leftarrow Next;$

      $Next \leftarrow Next + 1; Next \leftarrow mod_M Next;$

    end if

  end if

  end for

end for

packet or not when they are scheduled). According to UROP, if a scheduled node is not able to send data to the FC in TS t, then in TS $t + 1$, the FC schedules the node which is next in the waiting line instead of the (previously scheduled) node which does not have sufficient energy for transmission.

According to UROP, the FC orders the nodes arbitrarily and keep this order throughout the time horizon. Then, it chooses the activation set of the first K nodes in the ordering in the first TS. In the sequel, it assigns a channel to each node in the activation set. If any node in the activation set did not transmit data (which implies that they were out of energy at the beginning of the TS), the FC replaces this node with a node from the activation vector, respecting the initial ordering. Thus, forming a new activation vector with K nodes. The scheduling continues according to the cyclic order.

Notice that, it may be hard to estimate which sensors will harvest the most amount of energy especially when the environmental conditions change fast. Therefore, we investigate the average throughput performance of Algorithm 1, Uniforming Random Ordered Policy (UROP), by considering the worst case. Hence, we obtained lower bounds for the efficiency performance of UROP for the most general class of energy harvesting processes in Section IV-B. As a result, we do not assume any specific ordering and mention it as randomly ordering to emphasize that our algorithm guarantees an asymptotically optimal throughput independent from the initial ordering.

B. EFFICIENCY BOUNDS OF UROP

In this subsection, we investigate the bounds on efficiency of UROP for *general* admissible EH processes.

If a node i which is scheduled over a channel j does not transmit data to the FC in a TS t due to energy shortage in its battery, then an *idleness* occurs in the channel j in the TS t and it is denoted by pair $\left(j, \gamma_l^j\right)$ where γ_l^j is the l^{th} one of idle TSs which occur in the j^{th} channel. Figure 2 represents idlenesses in an example scheduling table. To illustrate, $\gamma_2^1 = 3$ means that channel 1 is idle for the second time in TS 3. Similarly, $\gamma_3^2 = 7$ means that channel 2 is idle for the third time in TS 7. In TS γ_l^j, the FC drops an energy-depleted node which uses j^{th} channel for data transmission and it schedules another node over the same channel.

The set of all idlenesses is denoted by $I = \left\{\left(j, \gamma_l^j\right), 1 \leq j \leq K\right\}$.

Let's denote by f_i and f_i' the TSs next to when the FC starts scheduling node i for the last time (in TS $f_i + 1$) and for the second last time (in TS $f_i' + 1$), respectively. To illustrate, $f_1 = 13, f_3 = 15, f_8 = 12$ and $f_1' = 5, f_3' = 8, f_8' = 4$ in the example scheduling table given in Figure 2. Let F_1 and F_2 be the set of all idlenesses $\left(j, \gamma_l^j\right)$ such that $\gamma_l^j = f_i$ for some node $i \in S$ and the set of all idlenesses $\left(j, \gamma_l^j\right)$ such that $\gamma_l^j = f_i'$ for some node $i \in S$, respectively. As the network consists of M EH nodes, $|F_1| = |F_2| = M$ for a sufficiently large time horizon.

*Definition 8: **Last leaving TS of node** i, denoted by ζ_i, is the last TS in which the FC leaves (stops scheduling) the node i over a time horizon T.*

The set of last leaving TSs of all nodes is denoted by $L = \{\zeta_1, \zeta_2, \ldots, \zeta_M\}$. To illustrate, $\zeta_1 = 16$, $\zeta_4 = 11$ and $\zeta_8 = 15$ in the example scheduling table given in Figure 2.

Lemma 1: $L \subset (F_1 \cup F_2)$.

Proof: The FC starts scheduling a new node if and only if it drops another node. For each node i, $(F_1 \cup F_2)$ contains two consecutive time slots (the last time, f_i, and second last

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Channel 1	1	4	4	7	7	1	1	1	3	3	3	6	6	1	1	1	4
Channel 2	2	5	5	5	8	8	8	2	2	2	5	5	8	8	8	3	3
Channel 3	3	6	6	6	6	6	6	6	4	4	4	7	7	7	2	2	5

FIGURE 2. An example table kept by the FC for scheduling $M = 8$ nodes over $K = 3$ channels over a finite time horizon, $T = 17$. Dark colored slots show busy slots (the TS in which FC can collect one data packet from the node scheduled by it) and white colored slots show idle slots, idlenesses, (TS in which the FC cannot collect a data packet from the node scheduled by it).

time, f_i') next to when the FC starts scheduling the node i. If the FC has not stopped scheduling a node i, it cannot *start* to serving (scheduling) that node i again. Consequently, $(F_1 \cup F_2)$ includes at least one last leaving TS for each node i, i.e., $\zeta_i \in (F_1 \cup F_2)\ \forall i \in S$. Hence, $L \subset (F_1 \cup F_2)$. □

In Lemma 1, we prove that all nodes leave (separate from) the activation set (a departure occurs when a scheduled node cannot transmit data) at least once in $F_1 \cup F_2$. From Proposition 1 and Lemma 1, UROP achieves optimality at least once for each node in $F_1 \cup F_2$. Therefore, Proposition 1 and Lemma 1 give us a handle on the efficiency of UROP, which is investigated in Theorem 2, Theorem 3, Theorem 4 and Proposition 2.

Let S_{last} be the index set of nodes which are scheduled and transmit data in the last TS T (the deadline), i.e.,

$$\mathbb{I}_{\{i \in S_{last}\}} = \mathbb{I}_{\{i \in \pi^{UROP}(T)\}} \mathbb{I}_{\left\{B_i^{\pi^{UROP}}(T) \geq 1\right\}}. \tag{13}$$

Remark 1: Each node $i \in S_{last}$ transmits $T - f_i$ data packets to the FC in TSs $f_i + 1$ through T.

Remark 2: $\rho = 0$ means that no node has sufficient energy to send even one data packet in TSs 1 through T, which makes this case trivial. $\rho \geq 1$ means that there is no idleness (inadmissible EH processes) if a 100% efficient policy is used by the FC. However, UROP makes inference from the idlenesses in order to schedule the nodes efficiently. Therefore, $0 < \rho < 1$ is considered in Theorem 2, Theorem 3 and Theorem 4.

By Theorem 2, we investigate efficiency bounds of UROP.

*Theorem 2: For general admissible EH processes, **efficiency bounds of UROP** are given as*

$$1 - \frac{K(T - \zeta_{min})}{V^*(T)} \leq \eta(\pi^{UROP}) \leq 1, \tag{14}$$

where $\zeta_{min} = \min_{i \in S} \zeta_i$ and $V^*(T) = V^{FE}(T)$.

Proof: Please see Appendix B. □

C. EFFICIENCY OF UROP OVER FINITE TIME HORIZON

In Theorem 2, we have found the efficiency bounds of UROP for general admissible EH processes. However, ζ_{min} cannot be found if all details of the scheduling and the statistics of EH processes, $\{\pi(t)\}_{t=1}^T$ and $\left\{E_i^h(t)\right\}_{t=1}^T$ $\forall i$, over the finite time horizon are not known. As ζ_{min} is random (not known), Theorem 2 does not provide enough information on the expected efficiency of UROP over the finite time horizon. In this subsection, we investigate bounds of expected efficiency of UROP over a finite time horizon under expected average throughput criteria (Problem 1) under two assumptions (Assumption 1 and Assumption 2). Now, we introduce a new notion *elephant node* which help us obtain the expected efficiency bounds of UROP over a finite time horizon.

*Definition 9: If the node which is next in the line (initial random order) to be scheduled by the FC under UROP has already been sending data permanently because its last selection (scheduling), then this node become **elephant node** between the previous selection and the current selection times.*

In case of an elephant node, the FC start to schedule the next node in the waiting line (the node which comes after the elephant node according to the initial randomly order) over an available channel; however, the elephant node continues sending data to the FC. Figure 3 shows a case in which an elephant node exists. We first assume no elephant node in Theorem 3 for easiness. Then, the assumption is lifted in Remark 4.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Channel 1	1	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	8
Channel 2	2	5	5	5	5	7	7	7	1	1	1	3	3	6	6	6	1
Channel 3	3	6	6	6	6	6	6	8	8	8	2	2	5	5	5	7	7

FIGURE 3. The scheduling table kept by FC for $M = 8$ nodes and $K = 3$ channels over a finite time horizon, $T = 17$. Light colored slots show idle slots labeled by node ID (assigned to nodes with respect to the initial random order), whereas dark colored slots shows busy slots. *Node 4 becomes elephant node* because Node 4 gives no idleness in a round and continues to send data in TSs 2 thru 15. Notice that node 4 has already transmitted data in TS 11 and instead of it, node 5 is started to be scheduled via channel 3 in TS 13.

Remark 3: From Proposition 1, if a node gives idle slot (is not able to transmit data in that slot), then that node achieves "Optimality for a node". This makes easier to analyze the efficiency of UROP and obtain lower bounds for its performance over the finite time horizons. After that, we consider the case when at least one node behaves as elephant node. Moreover, to find expected length of arrival rounds in Lemma 2, we need to make no elephant node assumption where Lemma 2 is critical for Theorem 3 in which we investigate efficiency of UROP over the finite time horizons.

*Definition 10: Assume that 0^{th} selection (arrival) time of each node i is 0. **The l^{th} arrival round of node** i, denoted by $\tau_{ar,i}^l$, is defined as the time interval between the $(l-1)^{th}$ and l^{th} selection times of node i. The length of the l^{th} arrival round of node i is denoted by $\left|\tau_{ar,i}^l\right|$.*

Notice that if a node i is started to be scheduled l^{th} time by the FC in TS t, then the l^{th} selection time is TS $t - 1$.

To illustrate by Figure 3, 1^{st} selection times of node 2, 5 and 7 are 0, 1 and 5, respectively (Notice that $\left|\tau^0_{ar,i}\right| = 0\ \forall i$). Therefore, $\left|\tau^1_{ar,2}\right| = 0$, $\left|\tau^1_{ar,5}\right| = 1$, $\left|\tau^1_{ar,7}\right| = 5$ in the example scheduling table given in Figure 3. Similarly, 2^{nd} selection times of node 2, 5 and 7 are 10, 12 and 15, respectively. Therefore, $\left|\tau^2_{ar,2}\right| = 10$, $\left|\tau^2_{ar,5}\right| = 11$, $\left|\tau^2_{ar,7}\right| = 10$.

We state the precise assumptions on the EH processes under which we investigate efficiency of UROP over a finite time horizon under expected average throughput criteria.

Assumption 1: EH processes at all nodes are ergodic in mean [51], i. e., $\lim_{T\to\infty} \rho_i = \mathbb{E}[\rho_i]\ \ \forall i$,[7] *where by Definition 6,* $\lim_{T\to\infty} \rho_i = \lim_{T\to\infty} \frac{M\sum_{t=1}^{T} E_i^h(t)}{KT}$.

Assumption 2: Lengths of arrival rounds of all nodes are ergodic in mean [51], i. e., $\lim_{n\to\infty} \frac{1}{n}\sum_{l=1}^{n} \left|\tau^l_{ar,i}\right| = \mathbb{E}\left[\left|\tau^l_{ar,i}\right|\right]\ \ \forall i, l$.

Under the assumptions above, we obtain the bounds of expected efficiency of UROP in Theorem 3 by the following lemma.

Lemma 2: Under Assumption 1, Assumption 2 and no elephant node assumption, for $0 < \rho < 1$,

$$\mathbb{E}\left[\left|\tau^l_{ar,i}\right|\right] = \frac{M}{K(1-\mathbb{E}[\rho])}. \tag{15}$$

Proof: Please see Appendix C. □

Theorem 3: Under Assumption 1, Assumption 2 and no elephant node assumption, for $0 < \rho < 1$, ***expected efficiency bounds of UROP*** *are given as*

$$1 - \frac{2M}{(1-\mathbb{E}[\rho])\rho TK} < \mathbb{E}\left[\eta(\pi^{UROP})\right] \leq 1. \tag{16}$$

Proof: Please see Appendix D. □

Corollary 1: If EH processes of all nodes are i.i.d. and mean ergodic, then $\rho \approx \mathbb{E}[\rho]$ *for sufficiently large time horizons from Hoeffding inequality [52], which implies that the lower bound on expected efficiency of UROP in Theorem 3 is approximately* $1 - \frac{2M}{(1-\rho)\rho TK}$.

By the following remark, it is explained that the bounds in Theorem 3 is valid for elephant node case, too.

Remark 4 (When Elephant Nodes Are Present): When a regular node (which does not become an elephant node) is scheduled by UROP, it gives rise to one idleness in a round. However, during the interval when a node become elephant node, it do not give idleness by definition. If some nodes become elephant node in a round, these do not leave any TS idle in that round. Accordingly, UROP is not able to give up any TS (idleness) to make inference about the battery states of these nodes while they become elephant node. Therefore, instead of giving an idleness, each elephant node i transmit one more data packet if it becomes an elephant node over a round. This shows that efficiency bounds of UROP in Theorem 3 are also valid for elephant node case.[8]

[7]This assumption also implies that $\lim_{T\to\infty} \rho = \mathbb{E}[\rho]$ from (10).

[8]In fact, we expect that lower bound of expected efficiency of UROP in elephant node case becomes larger than lower bound obtained in Theorem 3.

Hence, from Theorem 3, Corollary 1 and Remark 4, UROP is a *near-optimal* solution of *Problem 1* (over finite time horizon under expected average throughput criteria) for a broad class of EH processes under Assumption 1 and Assumption 2.

D. EFFICIENCY OF UROP OVER INFINITE TIME HORIZON

From Theorem 2 and Corollary 1 in [47], efficiency of the MP in [45]–[47] depend on not only intensity, ρ, but also intensity of some node i, ρ_i, (for these nodes, $\rho_i > 1$) and it cannot improve as the time horizon goes to infinity. Moreover, if the MP is applied, the batteries of nodes for which $\rho_i > 1$ overflow over infinite time horizon from Theorem 2 and Corollary 1 in [47]. On the other hand, under general admissible EH processes, efficiency of UROP goes to 1 as $T \to \infty$, which is proved by Theorem 4.

Theorem 4: UROP achieves asymptotically optimal throughput for Problem 2 and Problem 3 under general admissible EH processes.

Proof: Firstly, assume that no node become elephant node over the infinite time horizon and $\zeta_{min} = \min_{1\leq i\leq M} \zeta_i$. We observe that under admissible EH processes, $T - \zeta_{min} < \infty$ as $T \to \infty$. Otherwise, $\rho \geq 1$ since there are a finite number of idlenesses over the infinite time horizon. If $0 < \rho < 1$, then $V^*(T) = V^{FE}(T) = \rho TK$ ($\rho = 0$ is a trivial case). Hence, efficiency bounds of UROP in Theorem 2 can be written as

$$1 - \frac{K(T-\zeta_{min})}{\rho TK} \leq \eta(\pi^{UROP}) \leq 1$$
$$\lim_{T\to\infty}\left(1 - \frac{K(T-\zeta_{min})}{\rho TK}\right) \leq \lim_{T\to\infty} \eta(\pi^{UROP}) \leq 1 \tag{17}$$

As $\lim_{T\to\infty} \frac{(T-\zeta_{min})}{\rho T} = 0$ for $0 < \rho < 1$, then $\lim_{T\to\infty} \eta(\pi^{UROP}) = 1$, which yields that $\lim_{T\to\infty} \frac{V^{UROP}(T)}{V^*(T)} = 1$, since $\eta(\pi^*) = \eta(\pi^{FE}) = 1$ for admissible EH processes. From Definition 2, UROP achieves *asymptotical throughput-optimality* under admissible EH processes.

If some nodes become elephant node in some rounds, these nodes do not give any idleness in those rounds. Therefore, instead of giving idleness in a round, each elephant node transmits more data packets during the round in which it becomes an elephant node. Hence, efficiency bounds of UROP in (17) are also valid for elephant node case under admissible EH processes. Consequently, for these nodes, UROP becomes an optimal policy (and fully efficient policy under admissible EH processes), which means that UROP achieves 100% throughput. Thus, UROP is *asymptotically optimal* in case of elephant nodes, too.

Hence, UROP achieves *asymptotical throughput-optimality* for *Problem 3* under *general* admissible EH processes, which yields that UROP also achieves *asymptotical throughput-optimality* for *Problem 2* under *general* admissible EH processes. □

E. EXTENSION TO INADMISSIBLE ENERGY HARVESTING PROCESSES

In Section IV-C and IV-D, for admissible EH processes, efficiency of UROP is investigated over both finite and infinite time horizons. By following proposition, efficiency of UROP is investigated under inadmissible EH processes.

Proposition 2: Under general inadmissible EH processes,

i) *UROP is nearly throughput-optimal over a finite time horizon for a broad class of inadmissible EH processes (Problem 1).*

ii) *UROP achieves asymptotical-optimal throughput for general inadmissible EH processes (Problem 2, Problem 3).*

Proof: Please see Appendix E. □

V. NUMERICAL RESULTS

In this section, we firstly evaluate efficiencies of UROP and the MP in [45]–[47], for the time horizons varying from 0 TS to 2000 TSs in Section V-A where we consider efficiency of UROP for both $\frac{M}{K} \in \mathbb{Z}$ and $\frac{M}{K} \notin \mathbb{Z}$ cases. Then, we compare efficiencies of OP (optimum policy according to Definition 1), UROP and the MP in [45]–[47], for the intensities varying from 0.2 to 2.0 in Section V-B where we consider efficiency of UROP for five different battery capacities, i.e., $B = 20, 30, 50, 100, \infty$.

A. EFFICIENCY VS. TIME

In this section, efficiencies of two scheduling policies, namely UROP and the MP in [45]–[47], are evaluated for the varying time horizons ($0 \leq T \leq 2000$). Firstly, efficiencies of UROP and the MP are evaluated for i.i.d. and Markovian EH processes under admissible low intensity ($\rho = 0.2$) and admissible high intensity ($\rho = 0.975$) traffic. Secondly, efficiencies of UROP and the MP are compared for i.i.d. and Markov EH processes under inadmissible ($\rho = 1.38$) traffic. In these comparisons, we consider both cases of infinite-capacity and finite-capacity battery. We investigate efficiencies of both policies under nonuniform EH processes.[9]

For the comparisons, $M = 100$ and $K = 10$ is taken for both UROP and the MP to handle a case that $\frac{M}{K}$ is integer. Beside this, by taking $M = 103$ and $K = 10$, efficiency of UROP is also investigated for case that $\frac{M}{K}$ is noninteger. The nonuniform, admissible, low intensity traffic ($\rho = 0.2$) is formed by taking $\rho_i = 2.1$ for 5 nodes and $\rho_i = 0.1$ for remaining nodes. Moreover, nonuniform admissible high intensity traffic ($\rho = 0.975$) is formed by taking $\rho_i = 3$ for 25 nodes and $\rho_i = 0.3$ for remaining ones. In addition, nonuniform inadmissible ($\rho = 1.38$) EH processes is formed by taking $\rho_i = 3$ for 40 nodes and $\rho_i = 0.3$ for remaining ones. I.i.d. EH processes are modelled as Poisson. For each node i, Markovian EH process is formed by a state space $\{0, 1, 2\}$ and a 3×3 transition matrix P_i s.t.

$$P_i = \begin{bmatrix} 0.90 & 0.05 & 0.05 \\ 0.05 & 0.90 & 0.05 \\ 0.05 & 0.05 & 0.90 \end{bmatrix}, \quad \forall i \in S. \tag{18}$$

The energy harvested by node i in TS t, $E_i^h(t)$, is equal to $\rho_i \times M_i(t)$ where the EH state of node i in TS t is denoted by $M_i(t) \in \{0, 1, 2\}$ (recall that each transmission needs unit energy).

In Figure 4 *(admissible, low intensity, i.i.d. EH process)*, efficiency of UROP is 0.997 whereas efficiency of the MP is 0.688 for $T = 2000$. In Figure 5 *(admissible, high intensity, i.i.d. EH process)*, UROP continues to attain 0.945 efficiency whereas the efficiency of the MP is 0.464 for $T = 2000$. The drastic difference between efficiencies of MP in these two cases is expected because Theorem 2 and Corollary 1 in [47] indicates that efficiency achived by MP decreases as the nodes with $\rho_i > 1$ increase in number. From Theorem 2 and Corollary 1 in [47], $\eta(\pi^{MP}) \leq 0.725$ and $\eta(\pi^{MP}) \leq 0.487$ for $T = 2000$ under the low intensity ($\rho = 0.2$) and high intensity ($\rho = 0.975$) admissible EH processes, respectively.

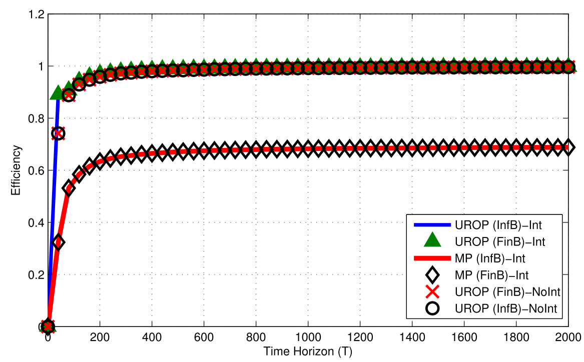

FIGURE 4. Efficiencies of UROP and MP under infinite capacity and finite capacity ($B_i = 50$) battery assumptions for an i.i.d., low intensity ($\rho = 0.2$) EH processes if $\frac{M}{K} \in \mathbb{Z}$ (Int case). Efficiency of UROP is also evaluated for $\frac{M}{K} \notin \mathbb{Z}$ (NoInt case).

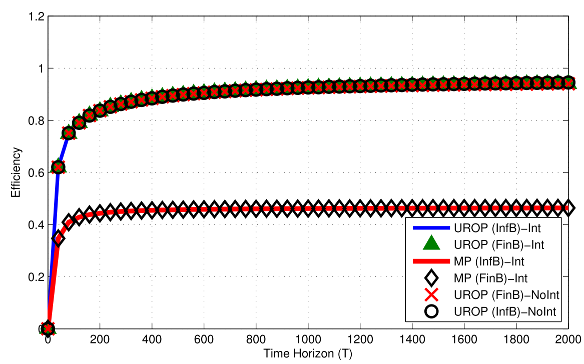

FIGURE 5. Efficiencies, of UROP and MP under infinite capacity and finite capacity ($B_i = 50$) battery assumptions for an i.i.d., high intensity ($\rho = 0.975$) EH processes if $\frac{M}{K} \in \mathbb{Z}$ (Int case). Efficiency of UROP is also evaluated for $\frac{M}{K} \notin \mathbb{Z}$ (NoInt case).

In Figure 6 *(admissible, low intensity, Markov EH processes)*, efficiency of UROP is 0.997 whereas efficiency of

[9] Both policies can achieve efficiencies very close to 1 (100%) over a finite horizon for uniform EH processes. Therefore, the results are not given for this trivial case.

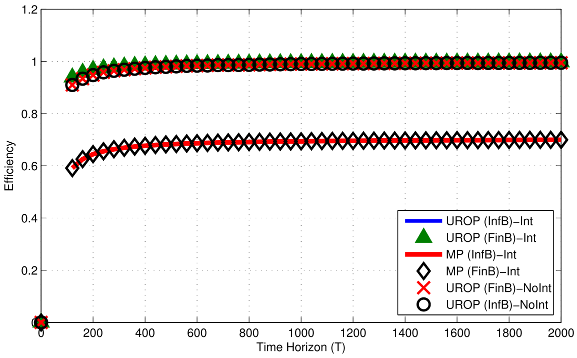

FIGURE 6. Efficiencies of UROP and MP under infinite capacity and finite capacity ($B_i = 50$) battery assumptions for a Markov low intensity ($\rho = 0.2$) EH processes if $\frac{M}{K} \in \mathbb{Z}$ (Int case). Efficiency of UROP is also evaluated for $\frac{M}{K} \notin \mathbb{Z}$ (NoInt case).

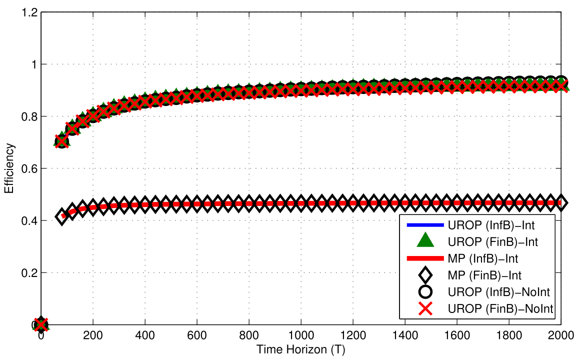

FIGURE 7. Efficiencies of UROP and MP under infinite capacity and finite capacity ($B_i = 50$) battery assumptions for a Markov high intensity ($\rho = 0.975$) EH processes if $\frac{M}{K} \in \mathbb{Z}$ (Int case). Efficiency of UROP is also evaluated for $\frac{M}{K} \notin \mathbb{Z}$ (NoInt case).

the MP is 0.700 for $T = 2000$. In Figure 7 *(admissible, high intensity, Markov EH process)*, UROP achieves efficiency of 0.931 whereas efficiency of the MP is 0.469 for $T = 2000$. The decrease in efficiency of the MP is expected from Theorem 2 and Corollary 1 in [47] as mentioned in previous paragraph. When the admissible EH process has memory (Markov EH processes), we observe quite similar results to those in admissible memoriless (i.i.d.) EH processes.

In Figure 8 *(inadmissible, i.i.d. EH process)*, efficiency of UROP is 0.719 whereas efficiency of the MP is 0.394 for $T = 2000$. From Theorem 2 and Corollary 1 in [47], efficiency of the MP is expected to be $\eta(\pi^{MP}) \leq 0.420$ for $T = 2000$ under the inadmissible ($\rho = 1.38$) EH processes. For inadmissible EH processes, from Definition 1 and Definition 3,

$$\eta(\pi^*) = \frac{V^*(T)}{V^{FE}(T)} \leq \frac{1}{\rho}. \tag{19}$$

From (19), $\eta(\pi^*) \leq 0.725$ so UROP is near-optimal for $T = 2000$ under inadmissible i.i.d. EH processes.[10] In Figure 9 *(inadmissible, Markov EH process)*, efficiency of UROP is 0.710 whereas efficiency of the MP is 0.394 for $T = 2000$.

[10] Notice that efficiency of UROP is closer to that of an optimal scheduling policy for the inadmissible EH process than that for admissible EH processes.

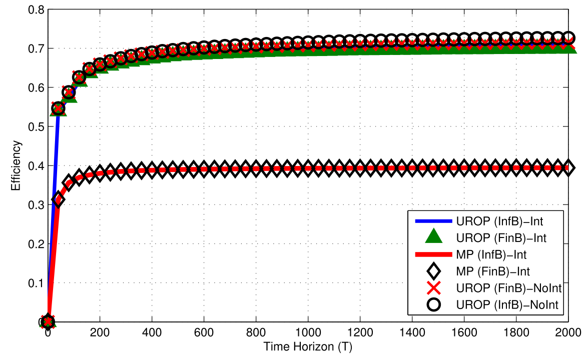

FIGURE 8. Efficiencies of UROP and MP under infinite capacity and finite capacity ($B_i = 50$) battery assumptions for an i.i.d., inadmissible ($\rho = 1.38$) EH processes if $\frac{M}{K} \in \mathbb{Z}$ (Int case). Efficiency of UROP is also evaluated for $\frac{M}{K} \notin \mathbb{Z}$ (NoInt case).

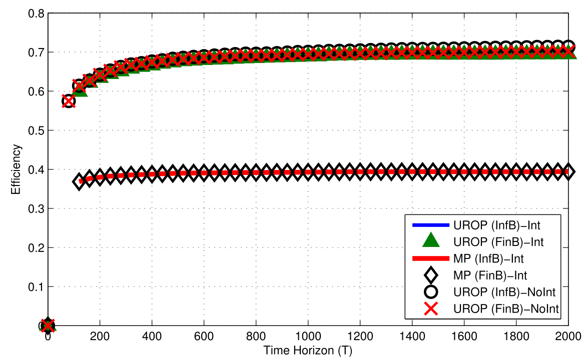

FIGURE 9. Efficiencies of UROP and MP under infinite capacity and finite capacity ($B_i = 50$) battery assumptions for a Markov, inadmissible ($\rho = 1.38$) EH processes if $\frac{M}{K} \in \mathbb{Z}$ (Int case). Efficiency of UROP is also evaluated for $\frac{M}{K} \notin \mathbb{Z}$ (NoInt case).

Considering the figures in this section (Figure 4-9), we wish to make three additional remarks. Firstly, UROP converges to an optimal policy as $T \to \infty$ (it is *asymptotically throughput optimal*), as proved in Section IV-D. Secondly, efficiency of UROP with infinite-capacity battery is very close to those with reasonable finite-capacity batteries (The efficiency difference between the two cases is less than 0.015). Finally, UROP can achieve near optimality for both $\frac{M}{K} \in \mathbb{Z}$ and $\frac{M}{K} \notin \mathbb{Z}$ cases, whereas the MPs in [45]–[47] need $\frac{M}{K} \in \mathbb{Z}$ assumption even for applicability. Hence, we can observe that UROP is much more efficient and self-adaptive (to the stochastic EH processes) than the MPs in [45]–[47].

B. EFFICIENCY VS. INTENSITY

In this subsection, $M = 100, K = 10$ and $T = 2000$ are taken to compare efficiencies of OP (optimal policy according to Definition 1), UROP and the MP for the intensities varying from 0.2 to 2.0. I.i.d. EH processes are modelled as Poisson.[11] For each node i, Markovian EH process is formed by a state

[11] $\rho = 0.2$ is formed by 100 nodes with $\rho_i = 0.2$ and 0 node with $\rho_i = 2.0$. If we increase the intensity of 5 nodes with $\rho_i = 0.2$ to 2.0, then the intensity ρ increase by 0.09. For example, 95 nodes with $\rho_i = 0.2$ and 5 nodes with $\rho_i = 2.0$ forms $\rho = 0.29$.

space {0, 1, 2} and a 3 × 3 transition matrix P_i such that the Equation (18) holds. The energy harvested by node i in TS t, $E_i^h(t)$, is equal to $\rho_i \times M_i(t)$ where the EH state of node i in TS t is denoted by $M_i(t) \in \{0, 1, 2\}$.

Figure 10 represents the efficiencies of UROP, MP and OP versus the intensity[12] when $T = 2000$ and for different values of battery capacity $B = 20, 30, 50, 100, \infty$.[13] under i.i.d. EH processes. Recall that the upper bound of efficiency of OP is 1, i. e., $\eta(\pi^*) \leq 1$ for $\rho \leq 1$ from Definition 1 and Theorem 1. From this figure, we can firstly observe that efficiencies of UROP and MP decrease as intensity gets larger than 1 since $\eta(\pi^*) = \frac{1}{\rho} < 1$ for $\rho > 1$. Moreover, efficiency of UROP is very close to efficiency of OP for $B = 20, 30, 50, 100, \infty$. As intensity increases and become between 0.92 and 1.19, the number of idlenesses decreases which makes UROP give more idle TSs than required for optimal scheduling. Furthermore, for all battery capacities $B = 20, 30, 50, 100, \infty$, efficiency of UROP is generally much greater than efficiency of the MP. Finally, the increase in intensity implies the increase in average energy harvesting rates of nodes and thus the difference between optimal policy and the others decreases due to the energy redundancy at nodes.

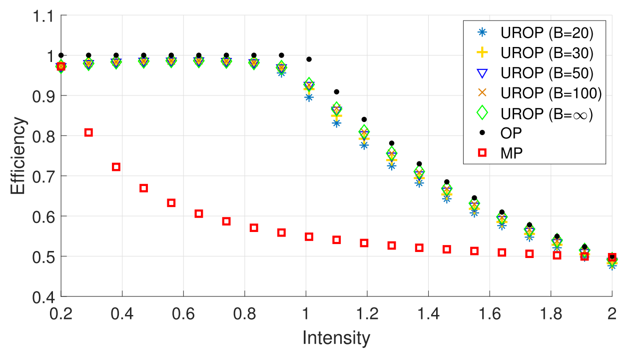

FIGURE 10. **Efficiencies of UROP, MP and OP (optimum policy) vs. intensity for i.i.d. EH processes in $T = 2000$ TSs. Efficiency of UROP is investigated for $B = 20, 30, 50, 100, \infty$ while efficiencies of MP and OP are investigated only for $B = \infty$ because efficiencies of MP and OP do not depend on battery capacity.**

Figure 11 shows the efficiencies of UROP, MP and OP vs. the intensity for Markov EH processes. When the EH processes have memory (Markov EH processes), we observe quite similar results to those in memoriless (i.i.d.) EH processes.

In the following two subsubsections, we will investigate the efficiencies of UROP, MP and OP more precisely by the help of two tables which are obtained for admissible and inadmissible i.i.d. EH processes.[14]

[12]Notice that intensity can also be considered approximate average of total energy harvesting rate normalized by K.

[13]As efficiency of OP and MP do not affect from battery capacity, we add one curve for each of MP and OP whereas we add all five curves of UROP for $B = 20, 30, 50, 100, \infty$.

[14]As the results for Markov EH processes are quite similar to those for i.i.d. EH processes, tables for Markov EH processes are not reported in this paper.

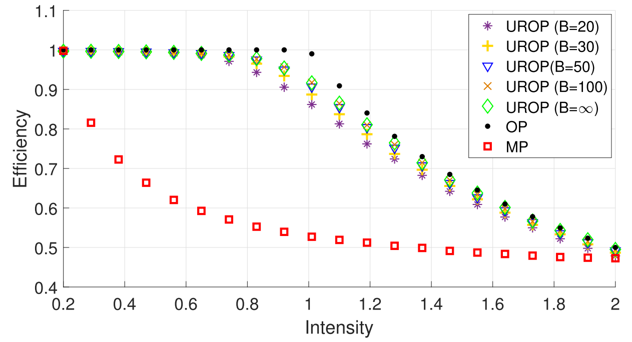

FIGURE 11. **Efficiencies of UROP, MP and OP (optimum policy) vs. intensity Markov EH processes in $T = 2000$ TSs. Efficiency of UROP is investigated for $B = 20, 30, 50, 100, \infty$ while efficiencies of MP and OP are investigated only for $B = \infty$ because efficiencies of MP and OP do not depend on battery capacity.**

1) ADMISSIBLE EH PROCESSES

From Table 2, we can firstly observe that efficiency of UROP is exactly the same under all different battery capacities for the same intensity up to $\rho = 0.83$ ($\rho \leq 0.83$). It is known that UROP benefits from the idle TSs to schedule the nodes efficiently and $\rho \leq 0.83$ means that more than one sixth of all KT slots (K channels during the time horizon T TSs) become idle. Beside this, the M nodes are not waiting too much for intensities $\rho \leq 0.83$ because Lemma 2 states that for $0 < \rho < 1$, the expected value of the l^{th} arrival round of node i, denoted by $\tau_{ar,i}^l$, is $\mathbb{E}\left[\left|\tau_{ar,i}^l\right|\right] = \frac{100}{10(1-0.83)} \approx 58.82$, with $M = 100$ nodes and the FC with $K = 10$ channels for $\rho = 0.83$[15]. Thus, expected value of energy harvested by node i in an arrival round can be calculated as $\rho_i \frac{K}{M} \mathbb{E}\left[\left|\tau_{ar,i}^l\right|\right] \approx \frac{\rho_i}{(1-\rho)}$ where $\rho_i \frac{K}{M}$ is the ratio of TSs when FC schedules node i to time horizon T. As ρ_i takes 2 at most in the simulations, the maximum expected value of energy harvested by a node in an arrival round becomes 11.76 units of energy which is less than minimum battery capacity in the simulations, $B = 20$. Therefore, UROP schedules the nodes with efficiency greater than 0.97 and its efficiency does not change for different battery capacities for intensities up to $\rho = 0.83$. On the other hand, efficiency of MP decreases from 0.972 to 0.571 as ρ increases from 0.20 to 0.83. Notice that if only 5 of 100 nodes have intensity of 2.0 (greater than 1), efficiency of MP decreases to 0.808, which is expected to be less than 0.828 from Theorem 2 and Corollary 1 in [47].

Secondly, for $\rho = 0.92$, the expected value of the l^{th} arrival round of node i is $\mathbb{E}\left[\left|\tau_{ar,i}^l\right|\right] = \frac{100}{10(1-0.92)} \approx 125$, with $M = 100$ nodes and the FC with $K = 10$ channels. For $\rho = 0.92$, the maximum expected value of energy harvested by a node in an arrival round is 25 units of energy which is greater than only $B = 20$, not greater than the other battery capacities. Therefore, efficiency of UROP does not change for $\rho = 0.92$ under different battery capacities except $B = 20$ and it outperforms MP efficiency of which is 0.559. Efficiencies of

[15] If EH processes of all nodes are i.i.d. and mean ergodic, then $\rho \approx \mathbb{E}[\rho]$ for sufficiently large time horizons from Hoeffding inequality [52].

TABLE 2. Efficiency of OP (Optimal policy), MP and UROP for i. i. d. admissible EH processes under both infinite and finite capacity battery assumptions. Maximum efficiency difference represents the efficiency (of UROP) difference between $B = \infty$ and $B = 20$ cases for the same intensity. Notice that although EH processes with $\rho = 1.01$ are inadmissible, we add the efficiency values for $\rho = 1.01$ to this table. Thus, we can observe efficiency difference between admissible EH processes and the EH processes with intensities slightly more than 1 (Remind that scheduling capacity of the FC is exceeded if $\rho > 1$ from Theorem 1).

Number of nodes with $\rho_i = 2.0$	0	5	10	15	20	25	30	35	40	45
Number of nodes with $\rho_i = 0.2$	100	95	90	85	80	75	70	65	60	55
Intensity (ρ)	0.20	0.29	0.38	0.47	0.56	0.65	0.74	0.83	0.92	1.01
$\eta(\pi^{OP})$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.990
$\eta(\pi^{MP})$	0.972	0.808	0.722	0.670	0.633	0.606	0.587	0.571	0.559	0.549
$\eta(\pi^{UROP})$ for $B = \infty$	0.972	0.980	0.983	0.986	0.987	0.987	0.985	0.982	0.970	0.927
$\eta(\pi^{UROP})$ for $B = 100$	0.972	0.980	0.983	0.986	0.986	0.987	0.985	0.982	0.969	0.926
$\eta(\pi^{UROP})$ for $B = 50$	0.972	0.980	0.983	0.986	0.986	0.987	0.985	0.982	0.969	0.926
$\eta(\pi^{UROP})$ for $B = 30$	0.972	0.980	0.983	0.986	0.986	0.987	0.985	0.982	0.969	0.916
$\eta(\pi^{UROP})$ for $B = 20$	0.972	0.980	0.983	0.986	0.986	0.987	0.985	0.982	0.956	0.897
Maximum efficiency difference	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.030

TABLE 3. Efficiency of UROP, MP and OP for inadmissible EH processes under both infinite and finite capacity battery assumptions. Maximum efficiency difference represents the efficiency (of UROP) difference between $B = \infty$ and $B = 20$ cases for the same intensity. Maximum efficiency deviance represents the relative efficiency difference between $B = \infty$ and $B = 20$ cases for the same intensity.

Number of nodes with $\rho_i = 2.0$	50	55	60	65	70	75	80	85	90	95	100
Number of nodes with $\rho_i = 0.2$	50	45	40	35	30	25	20	15	10	5	0
Intensity (ρ)	1.10	1.19	1.28	1.37	1.46	1.55	1.64	1.73	1.82	1.91	2.00
$\eta(\pi^{OP})$	0.909	0.840	0.781	0.730	0.685	0.645	0.610	0.578	0.549	0.524	0.500
$\eta(\pi^{MP})$	0.541	0.533	0.527	0.521	0.517	0.513	0.509	0.506	0.502	0.498	0.497
$\eta(\pi^{UROP})$ for $B = \infty$	0.867	0.810	0.756	0.711	0.669	0.632	0.598	0.567	0.539	0.515	0.492
$\eta(\pi^{UROP})$ for $B = 100$	0.867	0.810	0.756	0.708	0.668	0.630	0.596	0.566	0.538	0.513	0.491
$\eta(\pi^{UROP})$ for $B = 50$	0.864	0.803	0.750	0.703	0.662	0.625	0.592	0.562	0.534	0.510	0.488
$\eta(\pi^{UROP})$ for $B = 30$	0.850	0.792	0.740	0.694	0.654	0.618	0.585	0.555	0.529	0.505	0.483
$\eta(\pi^{UROP})$ for $B = 20$	0.831	0.776	0.725	0.682	0.643	0.608	0.576	0.547	0.521	0.499	0.477
Maximum efficiency difference	0.036	0.034	0.031	0.029	0.026	0.024	0.022	0.020	0.018	0.016	0.015
$\eta^*(\pi^{MP})$	0.595	0.634	0.675	0.714	0.755	0.795	0.835	0.875	0.914	0.951	0.994
$\eta^*(\pi^{UROP})$ for $B = \infty$	0.954	0.964	0.968	0.974	0.977	0.980	0.981	0.981	0.981	0.984	0.984
$\eta^*(\pi^{UROP})$ for $B = 100$	0.954	0.964	0.968	0.970	0.975	0.977	0.977	0.979	0.979	0.980	0.982
$\eta^*(\pi^{UROP})$ for $B = 50$	0.950	0.956	0.960	0.963	0.967	0.969	0.971	0.972	0.972	0.974	0.976
$\eta^*(\pi^{UROP})$ for $B = 30$	0.935	0.942	0.947	0.951	0.955	0.958	0.959	0.960	0.963	0.965	0.968
$\eta^*(\pi^{UROP})$ for $B = 20$	0.914	0.923	0.928	0.934	0.939	0.942	0.945	0.946	0.948	0.953	0.954
Maximum efficiency deviance	0.040	0.041	0.040	0.040	0.038	0.038	0.036	0.035	0.033	0.031	0.030

UROP are 0.969 and 0.970 for $B = 30, 50, 100$ and $B = \infty$, respectively whereas its efficiency is 0.956 for $B = 20$. On the other hand, efficiency of MP becomes 0.559 as expected from Theorem 2 and Corollary 1 in [47] which presents the upper bound of MP as 0.565.

Thirdly, for $\rho = 1.01$, we cannot find the maximum expected value of energy harvested by a node in an arrival round from Lemma 2. However, we observe that efficiency of UROP for $B = 30$ (like $B = 20$) differs from the efficiencies of UROP for $B = 50, 100, \infty$. Efficiency of UROP are 0.897, 0.916, 0.926, 0.926 and 0.927 for $B = 20, 30, 50, 100$ and $B = \infty$, respectively. On the other hand, efficiency of MP decreases to 0.549 as expected from Theorem 2 and Corollary 1 in [47] which gives efficiency upper bound of MP as 0.554.

To sum up, UROP outperforms the MP for $B = 20, 30, 50, 100$ and $B = \infty$ under all admissible EH processes. UROP achieves such efficiency greater than 0.95 for admissible EH processes with the intensities $\rho \leq 0.92$. Efficiency of MP decreases below 0.81 even if a small portion (like 5%) of the nodes have intensity of $\rho_i = 2.0$ (greater than 1). MP achieves efficiency of 0.972 only for a trivial case of $\rho = 0.2$ (uniform case, $\rho_i = 0.2\ \forall i$). Hence, UROP is much more robust and efficient solution than MP for all battery capacities (as evaluated for $B = 20, 30, 50, 100$ and $B = \infty$) under admissible EH processes.

2) INADMISSIBLE EH PROCESSES

From Table 3, we make the following observations. Firstly, efficiency of all policies decreases because increase in intensity means increase in average EH rate. As EH rate increases more, the amount of energy remained in the batteries of nodes increase, which cause decrease in efficiency of all policies including optimal policy (Recall that fully efficient policy is not feasible, cannot be found, for inadmissible EH processes).

Secondly, so as to evaluate efficiencies of UROP and MP relative to efficiency of OP for inadmissible EH processes, we define a new notion, relative efficiency of a policy π, which is the ratio of efficiency of a policy π to that of a policy π^*, i.e.,

$$\eta^*(\pi) \triangleq \frac{\eta(\pi)}{\eta(\pi^*)}. \tag{20}$$

As the intensity, and so, average EH rate increases, the difference in efficiency of UROP between $B = 20$ and $B = \infty$ decreases. Moreover, relative efficiency of UROP between $B = 20$ and $B = \infty$ decreases, too. Beside this, as the intensity increases, relative efficiency of UROP increases. This means that UROP achieves closer efficiency to optimal efficiency for inadmissible EH processes with higher intensities.

Thirdly, UROP shows a superior performance compared with MP such that $\eta(\pi^{UROP}) > \eta(\pi^{MP})$ for all intensities except the intensity $\rho = 2.0$, which is formed when all nodes have the same intensity of 2.0. Except $\rho = 2.0$, all inadmissible EH processes with the intensities up to 1.91 are formed by both the nodes with $\rho_i = 0.2$ and nodes with $\rho_i = 2.0$. From these results, it can be observed that UROP is much more adaptive in nonuniform EH processes than MP. On the other hand, $\rho = 2.0$ implies that all nodes harvests two times more energy than KT, the scheduling capacity of the FC, over the time horizon T. Due to the energy redundancy in batteries of all nodes when $\rho = 2$, this is a trivial case for the problem which considers energy-efficient data collection in low-power WSNs. In this trivial case, MP which is a Round-Robin (RR) policy with quantum=1 TS [47] achieves relative efficiency of 0.996 by allocating nearly $\frac{KT}{M}$ TSs to each node which harvests nearly $\frac{2KT}{M}$ units of energy.

As a result, MP is a smart solution only for the uniform inadmissible EH processes (where all nodes have same intensity greater than 1.0) whereas UROP is a much more smart and efficient solution than the MP for the nonuniform inadmissible EH processes.

VI. CONCLUSION AND FUTURE WORK

In this work, we tackle a problem occurring in a single-hop wireless sensor network where a fusion center schedules a group of energy harvesting sensors for data collection. It has no information on the statistics of energy harvesting processes at nodes or instantaneous battery states of nodes. The communication in the wireless network is error-free and each sensor node has data backlog. Statistics of energy harvesting processes cannot be accessed by fusion center and the infinite-capacity batteries does not have leakage.

The problem is defined as average throughput (reward) maximization problems (Problem 1, Problem 2, Problem 3). A simple algorithm, *Uniforming Random Ordered Policy (UROP)*, is proposed for these problems. It is proved that UROP achieves *asymptotical-optimal throughput* without considering statistics of their energy harvesting processes (Markovian, i.i.d., uniform, nonuniform, etc.) and battery states of nodes over infinite time horizon (Problem 2, Problem 3). Even over a finite time horizon, UROP achieves *near-optimal throughput* with no feedback about battery states and energy harvesting statistics of nodes for a broad class of energy harvesting processes (Problem 1). Furthermore, numerical results show that even with reasonable finite-capacity batteries, UROP achieves *near-optimal throughput* over finite time horizons.

As future work, we search for extending the problem in the single-hop case to the multi-hop case. We also plan to consider fairness as a performance criteria for the problem in the future. For this purpose, we will also consider the problem for such extreme cases that K of M nodes harvests so much energy that they do not leave the channels of fusion center (FC). In this extreme case, the other $M - K$ nodes get stuck on the waiting list, which causes unfairness among the nodes. We plan to tackle this problem by considering the channel dynamics in the system. As similar problems may occur in several areas other than energy harvesting wireless sensor networks, we believe that novel concepts and approaches in this work can help the researchers investigating similar problems and UROP is applicable to a wider area including robotic networks, economics, etc.

APPENDIX A
PROOF OF THEOREM 1

i) As each scheduled node is assigned to only one channel by FC in each TS, it can transmit at most $T - t$ data packets to FC from TS $t + 1$ to TS T. If $Y_i(t) > T - t$ for some node i, then the node i will have an excessive energy which is enough to send $Y_i(t) - (T - t)$ packets at the time horizon, T. Therefore, no fully efficient policy exists.

Even if $Y_i(t) \le T - t \ \forall i \in S$ and $\forall t$, no fully efficient policy exists when $Y(t) > K(T - t)$, for some $t < T$ since the total available uplink rate is K data packets per TS.

ii) As part (i) states, a node can send $T - t$ packets to FC in TSs $t + 1$ thru T. If $Y_i(t) \le T - t \ \forall i \in S$ and $\forall t$, a sensor node i can use up its harvested energy for data transmission under some optimal policies such that $B_i^{\pi^*}(t) < 1 \ \forall i$ if a channel is available for node i.

$Y_i(t) \le T - t \ \forall i \in S$ and $\forall t$ is necessary but insufficient for fully efficient policies to exist. A fully efficient policy exists (optimal policy become 100% efficient) if $Y(t) \le K(T - t), \quad \forall t$ also holds. Notice that by using an optimal policy, the FC can collect data over all channels in all TSs provided that at least K of the nodes have enough energy for data transmission in each TS.

APPENDIX B
PROOF OF THEOREM 2

For admissible EH processes, from (12), the throughput of node i under an optimal scheduling policy can be written as

$$V_i^*(T) = V_i^{FE}(T) = V_i^{UROP}(\zeta_i) + Y_i(\zeta_i), \tag{21}$$

since $V_i^{UROP}(\zeta_i) = \max_{\pi^* \in G^*} V_i^*(\zeta_i) \quad \forall i \in S$ from (12) and Definition 8. To investigate efficiency of UROP over a time horizon T, we focus on the total throughput loss by UROP which is denoted by $V_{loss}^{UROP}(T)$ and defined as

$$\begin{aligned} V_{loss}^{UROP}(T) &\triangleq V^*(T) - V^{UROP}(T) \\ &= \sum_{i=1}^{M} Y_i(\zeta_i) - \sum_{i \in S_{last}} (T - f_i), \end{aligned} \tag{22}$$

where $\mathbb{I}_{\{i \in S_{last}\}} \triangleq \mathbb{I}_{\{i \in \pi^{UROP}(T)\}} \mathbb{I}_{\left\{B_i^{\pi^{UROP}}(T) \geq 1\right\}}$ and $V^{UROP}(T) = \left[V_i^{UROP}(\zeta_i) + \sum_{i \in S_{last}} (T - f_i)\right]$.

From (21) and (22), efficiency of UROP is

$$\eta(\pi^{UROP}) = \frac{V^{UROP}(T)}{V^*(T)} = 1 - \frac{V_{loss}^{UROP}(T)}{V^*(T)}. \tag{23}$$

From (23), upper and lower bounds of efficiency of UROP are obtained as follows.

Upper bound for efficiency of UROP: From (23), $\eta(\pi^{UROP}) = 1$ iff

$$\sum_{i \in S_{last}} (T - f_i) = \sum_{i=1}^{M} Y_i(\zeta_i). \tag{24}$$

The equality (24) occurs iff

$$Y_i(\zeta_i) = (T - f_i)\, \mathbb{I}_{\{i \in S_{last}\}} \quad \forall i, \tag{25}$$

from (13). If sensor nodes harvest energy such that the equation (25) holds, then $\eta(\pi^{UROP}) = 1$. Hence, UROP can achieve efficiency up to 100%, i.e., $\eta(\pi^{UROP}) \leq 1$.

Lower bound for efficiency of UROP: Firstly, the lower bound is obtained for the single channel case, $K = 1$. Then, the results for $K = 1$ are extended to the multichannel case.

In case of single channel, without loss of generality, the last scheduled node is assumed to be node 1 (Please see Figure 12). If node 1 is not dropped at TS T, we have

$$\zeta_{min} = \zeta_1 < \zeta_2 < \ldots < \zeta_M \leq T. \tag{26}$$

	T-16	T-15	T-14	T-13	T-12	T-11	T-10	T-9	T-8	T-7	T-6	T-5	T-4	T-3	T-2	T-1	T
Chn 1	1	1	1	2	2	3	3	3	4	4	4	5	5	6	6	6	1

FIGURE 12. An example scheduling table for single channel case with 6 nodes where T is the time horizon. The dark TSs represents data transmission and white ones shows the idlenesses. Note that $(\zeta_1, \zeta_2, \zeta_3, \zeta_4, \zeta_5, \zeta_6) = (T-14, T-12, T-9, T-6, T-4, T-1)$.

From (22), $V_{loss}^{UROP}(T)$ is written as

$$\begin{aligned} V_{loss}^{UROP}(T) &= \sum_{i=1}^{M} Y_i(\zeta_i) - \sum_{i \in S_{last}} (T - f_i) \\ &\leq \sum_{i=1}^{M} Y_i(\zeta_i). \end{aligned} \tag{27}$$

From (26) and Theorem 1, (27) yields

$$V_{loss}^{UROP}(T) \leq T - \zeta_{min}. \tag{28}$$

In K-channel (multi-channel) case, without loss of generality, we assume that $\zeta_{min} = \min_{1 \leq i \leq M} \zeta_i$ and it occurs in channel 1. As a next step, we construct lists of scheduled nodes for each channel in order to convert the multichannel case into K single channel cases. The j^{th} list, L_j, includes the index set of the nodes whose last leaving TS occurs over the j^{th} channel. Note that from the construction scheme of the lists, it is clear that $L_g \cap L_j = \emptyset\ \forall g \neq j$ and $\bigcup_{j=1}^{K} L_j = S$. Let the number of nodes in the j^{th} list be M_j. For the ease of notation, *renumber* the nodes at each list starting from 1 so that the index set of nodes that are in L_j becomes $\{1, \ldots, M_j\}$. $\zeta_{i,j}^f$ denotes the last leaving TS for node $i \in L_j$ where i is the new index given with regard to the renumeration (Please see Figure 13).

	T-16	T-15	T-14	T-13	T-12	T-11	T-10	T-9	T-8	T-7	T-6	T-5	T-4	T-3	T-2	T-1	T
Chn 1	1	1	1	5	5	5	2	2	2	5	5	1	1	3	3	3	6
Chn 2	2	2	2	2	6	6	6	3	3	6	6	6	6	4	4	4	1
Chn 3	3	3	4	4	4	1	1	1	4	4	4	4	2	2	2	5	5

FIGURE 13. An example scheduling table for a multichannel case ($K = 3$) with 6 nodes where T is the time horizon. The dark TSs represents data transmission and white ones shows the idlenesses. Note that the set of all nodes can be written as partition of the following three sets, $L_1 = \{1, 3\}$, $L_2 = \{6, 4\}$ and $L_3 = \{2, 5\}$. $(\zeta_1, \zeta_2, \zeta_3, \zeta_4, \zeta_5, \zeta_6) = \left(\zeta_{1,1}^f, \zeta_{1,3}^f, \zeta_{2,1}^f, \zeta_{2,2}^f, \zeta_{2,3}^f, \zeta_{1,2}^f\right) = (T-4, T-2, T-1, T-1, T, T-4)$.

The number of packets which can be sent by node $i \in L_j$ in TSs $\zeta_{i,j}^f + 1$ through TS T under a fully efficient policy is denoted by $Y_{i,j}\left(\zeta_{i,j}^f\right)$. From (26), $V_{loss}^{UROP}(T)$ is written as

$$\begin{aligned} V_{loss}^{UROP}(T) &= V^*(T) - V^{UROP}(T) \\ &= \sum_{j=1}^{K} \sum_{i=1}^{M_j} Y_{i,j}\left(\zeta_{i,j}^f\right) - \sum_{i \in S_{last}} (T - f_i) \\ &\leq \sum_{j=1}^{K} \sum_{i=1}^{M_j} Y_{i,j}\left(\zeta_{i,j}^f\right). \end{aligned} \tag{29}$$

From Theorem 1, (29) yields

$$\begin{aligned} V_{loss}^{UROP}(T) &\leq \sum_{j=1}^{K} \left(T - \zeta_{1,j}^f\right) \\ &\leq K\left(T - \zeta_{min}\right), \end{aligned} \tag{30}$$

where $\zeta_{min} = \min_{1 \leq j \leq K} \zeta_{1,j}^f$ and the equality holds in (30) if $\zeta_{1,1}^f = \zeta_{1,j}^f \quad \forall j \in \{2, \ldots, K\}$.

From (23), (28) and (30),

$$1 - \frac{K(T - \zeta_{min})}{V^*(T)} \leq \eta(\pi^{UROP}).$$

Hence, Theorem 2 is proved.

APPENDIX C
PROOF OF LEMMA 2

Assume that no node becomes elephant node over the time horizon (no elephant node assumption). For $0 < \rho < 1$,

$$\rho = 1 - \frac{\sum_{i=1}^{M} l_i(T)}{\sum_{i \in \pi^{UROP}(T)} f_i + \sum_{i \in \pi^{UROP}(T)} (T - f_i)} \tag{31}$$

where $l_i(T)$ denotes the number of idlenesses in which node i is separated, i.e., stopped to be scheduled by the FC over the time horizon, T. By the definition of arrival round, $f_i = \sum_{l=1}^{l_i(T)+1} \left|\tau_{ar,i}^{l}\right|$, from which the equation (31) yields

$$\rho = 1 - \frac{\sum_{i=1}^{M} l_i(T)}{\sum_{i\in\pi^{UROP}(T)} \sum_{l=1}^{l_i(T)+1} \left|\tau_{ar,i}^{l}\right| + \sum_{i\in\pi^{UROP}(T)} (T-f_i)}. \tag{32}$$

As $T \to \infty$, $T - f_i < \infty\ \forall i$ and $l_i(T) \to \infty\ \forall i$ since $\rho < 1$. Under Assumption 1, expected value of intensity is

$$\begin{aligned}
&\mathbb{E}[\rho]\\
&= \lim_{T\to\infty} \rho\\
&= 1 - \frac{\lim_{T\to\infty} \sum_{i=1}^{M} l_i(T)}{\lim_{T\to\infty} \sum_{i\in\pi^{UROP}(T)} \sum_{l=1}^{l_i(T)+1} \left|\tau_{ar,i}^{l}\right| + \lim_{T\to\infty} \sum_{i\in\pi^{UROP}(T)} (T-f_i)}\\
&= 1 - \frac{\sum_{i=1}^{M} \lim_{T\to\infty} \frac{l_i(T)}{C(T)}}{\sum_{i\in\pi^{UROP}(T)} \lim_{T\to\infty} \frac{\sum_{l=1}^{l_i(T)+1} \left|\tau_{ar,i}^{l}\right|}{C(T)} + \sum_{i\in\pi^{UROP}(T)} \lim_{T\to\infty} \frac{(T-f_i)}{C(T)}}\\
&= 1 - \frac{\sum_{i=1}^{M} \lim_{T\to\infty} \frac{l_i(T)}{C(T)}}{\sum_{i\in\pi^{UROP}(T)} \lim_{T\to\infty} \frac{\sum_{l=1}^{l_i(T)+1} \left|\tau_{ar,i}^{l}\right|}{l_i(T)+1} \lim_{T\to\infty} \frac{l_i(T)+1}{C(T)}}.
\end{aligned} \tag{33}$$

where $C(T) = \max_{i\in S} l_i(T)$. As a node i can be scheduled only once more than another node under no elephant node assumption, the number of arrival rounds between two nodes cannot be differed more than one, i.e.,

$$\max_{i\in S} l_i(T) - \min_{i\in S} l_i(T) \leq 1. \tag{34}$$

Under Assumption 1, Assumption 2 and no elephant node assumption, from (34), the equation (33) yields

$$\mathbb{E}[\rho] = 1 - \frac{M}{\sum_{i\in\pi^{UROP}(T)} \mathbb{E}\left[\left|\tau_{ar,i}^{l}\right|\right]}. \tag{35}$$

Under Assumption 2, $\mathbb{E}\left[\left|\tau_{ar,i}^{l}\right|\right] = \mathbb{E}\left[\left|\tau_{ar,m}^{j}\right|\right]\ \forall i, m, l, j$ since each node waits the other $M-1$ nodes to be scheduled in order to be scheduled again. Therefore, (35) yields

$$\mathbb{E}[\rho] = 1 - \frac{M}{K\mathbb{E}\left[\left|\tau_{ar,i}^{l}\right|\right]}.$$

Hence, expected value of the length of arrival rounds is $\mathbb{E}\left[\left|\tau_{ar,i}^{l}\right|\right] = \frac{M}{K(1-\mathbb{E}[\rho])}$ under Assumption 1, Assumption 2 and no elephant node assumption.

APPENDIX D
PROOF OF THEOREM 3

Under Assumption 2 and no elephant node assumption (no node becomes elephant node in any time interval), $\mathbb{E}\left[\left|\tau_{ar,i}^{l}\right|\right] = \mathbb{E}\left[\left|\tau_{ar,m}^{j}\right|\right]\ \forall i, m, l, j$ since each node waits the other $M-1$ nodes to be scheduled in order to be scheduled again. From Theorem 2, the efficiency of UROP is

$$1 - \frac{K(T-\zeta_{min})}{V^*(T)} \leq \eta(\pi^{UROP}) \leq 1. \tag{36}$$

where $\zeta_{min} = \min_{1\leq i\leq M} \zeta_i$.

The efficiency of UROP is investigated for admissible EH processes which satisfy $V^*(T) = \rho TK$.

As ρ, T and K are known, $V^*(T)$ is also deterministic. (37) takes expectation over $T - \zeta_{min}$ that depends on statistics of EH processes.

$$\begin{aligned}
\mathbb{E}\left[\eta(\pi^{UROP})\right] &\geq 1 - \mathbb{E}\left[\frac{K(T-\zeta_{min})}{V^*(T)}\right]\\
&= 1 - \frac{\mathbb{E}[T-\zeta_{min}]}{\rho T}.
\end{aligned} \tag{37}$$

From Lemma 1, no node $i \in S - S_{last}$ can be chosen (started being scheduled) more than twice by FC in TSs ζ_{min} through T under no elephant node assumption. As $\zeta_{min} \geq \min_{m\in S} f'_m$ from Lemma 1,

$$\mathbb{E}[T-\zeta_{min}] \leq \mathbb{E}\left[T - \min_{m\in S} f'_m\right]. \tag{38}$$

Under Assumption 2 and no elephant node assumption,

$$\mathbb{E}\left[T - \min_{m\in S} f'_m\right] < 2\mathbb{E}\left[\left|\tau_{ar,i}^{l}\right|\right]. \tag{39}$$

From (38) and (39), (37) yields

$$1 - \frac{2\mathbb{E}\left[\left|\tau_{ar,i}^{l}\right|\right]}{\rho T} < \mathbb{E}\left[\eta(\pi^{UROP})\right]. \tag{40}$$

From (40) and Lemma 2, expected efficiency bounds of UROP can be obtained as

$$1 - \frac{2M}{(1-\mathbb{E}[\rho])\,\rho TK} < \mathbb{E}\left[\eta(\pi^{UROP})\right] \leq 1,$$

under Assumption 1, Assumption 2 and no elephant node assumption.

APPENDIX E
PROOF OF PROPOSITION 2

From Definition 7, inadmissible EH processes satisfy

$$(T-t) < Y_i(t), \quad \forall i \in S \tag{41}$$

or

$$K(T-t) \leq Y(t), \quad \forall t. \tag{42}$$

First, assume that (41) holds but (42) does not occur. Some node i transmits data in TSs t thru T without leaving the channel (without giving any idleness) if the FC schedules them in TSs t thru T under UROP. This implies that UROP is *near-optimal* over a finite time horizon for a broad class of EH processes (*Problem 1*). As $T \to \infty$, UROP starts to schedule each node i which satisfies (41) within a finite time. After being scheduled by UROP, these nodes continue to send data without giving any idleness from TS t to TS T. This implies that for general EH processes, UROP is *asymptotically optimal* over infinite time horizon (*Problem 2* and *3*).

For inadmissible EH processes satisfying (42), the performance of UROP is investigated over finite (part (i)) and infinite (part (ii)) time horizons, separately.

i) First, consider a case in which M idlenesses occurs over a finite time horizon, T. For this admissible EH process, the FC collects $KT - M$ data packets by an optimal policy. For this case, UROP is near-optimal, which means that UROP achieves such a throughput, $V^{UROP}(T)$, close to $KT - M$.

Further increase of the intensity such that $\rho \geq 1$ (inadmissible EH process) requires some nodes to have larger intensities and average EH rates, which implies that $E_i(T)$ increases for some node i such that $\lfloor E_i(T) \rfloor$ increase for those nodes. Therefore, for $\rho \geq 1$, average number of data packets transmitted by all nodes during a round increases under UROP. Since each node gives 1 idleness in a round as it does under admissible EH processes, the ratio of the number of idlenesses over KT decreases under UROP. This implies that throughput of UROP is near to that of optimal scheduling policies for inadmissible EH processes as for admissible EH processes. As an extreme case, if some node can harvest too much energy such that those nodes can transmit data in each TS when scheduled, then no idleness occurs under UROP. Therefore, it can be said that as intensity increases, UROP can achieve more throughput up to the scheduling capacity of the FC ($KT \geq V^*(T) \geq V^{UROP}(T)$). Hence, UROP is *near-optimal* over a finite time horizon for a broad class of inadmissible EH processes (*Problem 1*).

ii) For inadmissible EH processes, even if an optimal policy is applied by the FC, the harvested energy accumulates in infinite-capacity batteries of all nodes since scheduling capacity of the FC is exceeded. As the whole accumulated energy over the time horizon T, $(\rho - 1)KT$, the average accumulated energy is $(\rho - 1)K$.

From Theorem 4, we know that UROP is asymptotically optimal for $\rho < 1$. For $\rho \geq 1$, the average EH rates become more than those for $\rho < 1$. Therefore, the average number of packets sent by node i in one round becomes more for $\rho \geq 1$ than those for $\rho < 1$, which yields that the ratio of the number of idlenesses over KT becomes less for $\rho \geq 1$. This implies that UROP approaches to optimality faster for $\rho \geq 1$ than it does for $\rho < 1$. Hence, UROP is *asymptotically optimal* for *general* inadmissible EH processes (*Problem 2*, *3*).

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