A LOW-COMPLEXITY, NEAR-OPTIMAL SCHEDULING POLICY FOR SOLVING A RESTLESS MULTI-ARMED BANDIT PROBLEM OCCURRING IN A SINGLE-HOP WIRELESS NETWORK

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

ÖMER MELIH GÜL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
ELECTRICAL AND ELECTRONICS ENG.

JUNE 2014

Approval of the thesis:

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ABSTRACT

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June 2014, 84 pages

Power resources and battery lifetime are important issues for wireless networks such as wireless sensor networks (WSNs). To extend the battery lifetime, the recent advances in energy harvesting (EH) techniques propose an effective solution. EH nodes can harvest energy from environmental sources (e.g. solar, wind, vibrational, thermal) to power their sensing, computing and communication functions. In this thesis, we develop a solution to a scheduling problem under three scheduling scenarios. Firstly, we consider a single-hop wireless network where the fusion center (FC) collects data from a set of m EH nodes (e.g. nodes of a WSN). In each time slot, k of m nodes can be scheduled by the FC for transmission over k orthogonal channels. FC has no direct knowledge of battery states of nodes, or EH processes; it only has causal information of the outcomes of transmission attempts. The objective is to find a low complexity scheduling policy whereby the fusion center can collect the maximum amount of throughput in this data backlogged system, where transmission is limited by harvested energy. Energy is assumed to be stored losslessly in the batteries of nodes, up to a storage capacity (infinite capacity case is also considered). The problem is treated in finite and infinite problem horizons. Secondly, we consider the case where the infinite data backlog assumption is lifted. Thirdly, we consider a dual problem of the first scheduling problem. A low-complexity policy, UROP (*Uniformizing Random Ordered Policy*) is proposed, whose near optimality is shown under general energy harvesting and data arrival processes (uniform, non-uniform, independent, Markovian). Numerical examples indicate that under a reasonable-sized battery and buffer capacity, UROP uses the arriving energy and data with almost perfect efficiency. As the problem is a restless multi-armed bandit (RMAB) problem with an average reward criterion, UROP may have a wider application area than communication network.

Keywords: communication networks, decision theory, energy harvesting, scheduling algorithms, wireless sensor networks, wireless networks, restless multi-armed bandit

ÖZ

TEK ATLAMALI BİR KABLOSUZ AĞDA OLUŞAN BİR HUZURSUZ ÇOK KOLLU HAYDUT PROBLEMİNİ ÇÖZEN DÜŞÜK KARMAŞIKLIKTA BİR ÇİZELGELEME POLİTİKASI

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Güç kaynakları ve pil yaşam ömürleri, Kablosuz Algılayıcı Ağları (KAA) için önemli konulardır. Pil yaşam ömrünü uzatmak için enerji hasatlama (EH) tekniklerindeki son gelişmeler etkili bir çözüm önermektedir. EH düğümler, düğümün algılama, hesaplama ve haberleşme işlevlerine güç sağlamak için çevresel (örneğin, güneş, rüzgar, titreşimsel, ısısal) kaynaklardan enerji hasatlarlar. Bu tezde çizelgeleme problemine üç çizelgeleme senaryosu altında çözüm geliştirilmektedir. İlk olarak, füzyon merkezinin (FM) enerji hasatlayan düğüm kümesinden veri topladığı tek atlamalı bir kablosuz ağ (örneğin KAA düğümleri) ele alınmakta ve her zaman dilimindeki m düğümün k tanesi FM tarafından k ortogonal kanal üzerinden iletim için çizelgelenmektedir. FM, EH süreçleri ve anlık pil durumları hakkında hiçbir bilgiye sahip değildir fakat önceki iletim sonuçlarını bilmektedir. Amaç, iletimin hasatlanan enerji ile sınırlı olduğu veri birikmiş sistemlerde füzyon merkezinin en yüksek miktarda veri hacmi toplamasını sağlayan düşük karmaşıklıkta bir çizelgeleme politikası bulmaktır. Enerjinin düğüm pillerinde belirli bir depolama kapasitesine kadar kayıpsız depolandığı kabul edilmektedir (sonsuz kapasite durumu da göz önünde bulundurulmuştur). Problem, sonlu ve sonsuz problem ufukları için incelenmektedir. İkinci olarak, sonsuz veri birikmesi kabulünün kaldırıldığı durum ele alınmaktadır. Üçüncü olarak, ilk çizelgeleme probleminin eşlek bir problemi ele alınmaktadır. Genel EH ve veri geliş süreçleri (düzgün,

düzgün olmayan, bağımsız, Markov) için eniyiye yakınlığı gösterilen ve düşük karmaşıklıkta bir politika, DRSP (*Düzgünleştiren Rastgele Sıralayan Politika*) önerilmektedir. Sayısal sonuçlar makul ölçüde pil ve arabellek kapasitesi varsayımıyla DRSP'nin gelen enerjiyi mükemmele yakın verimlilikle kullandığını göstermektedir. Bu problem ortalama ödül kriterli bir huzursuz çok kollu haydut (HÇKH) problemi olduğu için DRSP haberleşme ağları dışında daha geniş bir uygulama alanına sahiptir.

Anahtar Kelimeler: haberleşme ağları, karar kuramı, enerji hasatlama, çizelgeleme politikaları, kablosuz algılayıcı ağları, kablosuz ağlar, huzursuz çok kollu haydut

To my family

Halis Gül, Aynur Gül, Zehra Merve Gül

ACKNOWLEDGMENTS

There is a sentence on a billboard in New York which I totally agree with:"Advisor is important". Therefore, I would like to thank firstly my supervisor Professor Elif Uysal-Bıyıkoğlu for her support, guidance and friendship. It was a great honor and experience to work with her for the last two years and our cooperation influenced my academical and world view highly. I also would like to thank Professor Mübeccel Demirekler for her valueable feedback on this work. I also would like to thank Professor Yalçın Tanık and Head of Department Professor Gönül Turhan Sayan for their support which motivate me very much.

I thank my friends with whom I made projects, shared knowledge and spent time together at METU. Being an outstanding and a modest person, Tuğcan Aktaş has been a role model for me. I am quite lucky to be a colleague and friend of him at the same time. He has been interested and helpful in the success of my work. I cannot forget his friendly attitude and help. I owe him a lot. In addition to Tuğcan, my colleagues Pınar Şen, Özlem Tuğfe Demir, Mekki Uludağ, Hasan Ihsan Turhan and Çağrı Batıhan were close friends, either in the department or in the dormitory. I appreciate their earnest friendship. I am thankful to my friends and colleagues in our research group, Communication Networks Research Group, whose assistance and friendship I really appreciate, including Baran Tan Bacınoğlu, Sajjad Baghaee, Göksel Uçtu, Mahdi Shakiba Herfeh, Fatih Mehmet Özçelik, Elif Tuğçe Ceran and Tuğçe Erkılıç. I am also thankful to Ali Bulut Üçüncü, Gökhan Muzaffer Güvensen, Kemal Muslubaş, Gökhan Koray Gültekin, Hasan Uluşan, Samet Gelincik, Alptekin Yılmaz, Seçil Özdemir and Ömer Çayır.

This work is also supported by Turkcell Graduate Scholarship for Technology Leaders of Future, and TÜBİTAK-ARDEB Scientific and Technological Research Project Program (Project No: #110E252).

Lastly but not the least, I would like to express my gratitude to my family for their love and care which has been an essential motivation to complete this study. This thesis is dedicated to my family and all students in the department.

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FC	Fusion Center
WSN	Wireless Sensor Network
EH	Energy harvesting
POMDP	partially observable Markov Decision Process
DP	Dynamic Programming
RMAB	restless multi-armed bandit
MAB	multi-armed bandit
MP	myopic policy
RR	Round-Robin
DA	data arrival
TS	time slot
MSM	Maximum Size Matching
MWM	Maximum Weight Matching
HOL	head-of-line
UP	Uniformizing Policy
UROP	Uniformizing Random Ordered Policy

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Power resource and battery lifetime are important issues for networks such as Wireless Sensor Networks (WSNs). Energy harvesting (EH) [1] can enable WSN operation in environments where maintenance is impractical or too costly. Energy harvesting (EH) extends reliable operation lifetime [2, 3]. Energy may be harvested from the environment in many different ways (solar, kinetic, etc.) [4]. Since energy harvesters generally depend on uncontrollable energy resources and the amount of harvested energy is generally low [4, 5], WSNs need robust, environmentally adaptive, energy efficient policies for their operations.

As power (or energy) management is an important issue for networks, there is growing literature on scheduling in energy efficient communication systems in the recent years. Prabhakar, Uysal-Bıyıkoğlu and El Gamal [6, 7] have presented the pioneer works, which study an energy efficient transmission scheduling problem and propose the "lazy scheduling" technique as a solution based on the fact that data transmission rate is a concave function of transmission power. By the following years, there are many works which investigate similar problems ([8]-[18]). Also, [19] studies a problem of energy harvesting transmitter broadcasting individual data to two receivers. In [20], a similar scheduling problem is studied for energy harvesting transmitter with a discrete set of transmission rates over static as well as fading channels. The works [21, 22] investigated an extended version of the scheduling problem in [6, 7]. These works [21, 22] considers the scheduling problem with fading channels and energy harvesting transmitters and proposes near-optimal heuristics to the problem. In [23, 24] represent several experimental results which are derived by implementing the scheduling policies introduced in [20, 21] on a software defined radio. Moreover, several duty cycle optimization methods in energy harvesting WSNs are investigated in [25] for the application to low energy Bluetooth devices. Furthermore, [26, 27] studies optimization methods for the feedback system in a MISO downlink communication by considering the case where users are capable to harvest energy from the environment. [28] studies the minimum energy unicast routing problem in the presence of idealistic rateless codes. Likewise, [29, 30, 31] investigate several variations of a scheduling problem in a communication system in which a mobile Internet service provider, a flying platform in the lower stratosphere empowered by the renewable energy, is envisioned to provide Internet access to the users as it moves over an area. The problem is considered as dynamic knapsack problem. In [29, 30] study optimal decision strategies for mobile Internet service providers to provide Internet access to the users under a deterministic model. One of the notable contributions of this study is to use genetic algorithm and rule based optimization beside competitive online heuristics developed for the problem under deterministic model. In [31], the problem is modelled as a 0/1 knapsack problem under a stochastic model. Several online heuristics are proposed using threshold policies obtained through various methods applied to the decision problem, including rule-based heuristics.

In this thesis, three variations of a scheduling problem are considered. Firstly, we consider a WSN where a fusion center (FC) collects data from m EH sensor nodes by assigning the nodes to k orthogonal communication channels in each time slot. It is assumed that each node always has data to transmit (i.e., nodes are data backlogged). Each node has a battery (of a certain capacity, and without leakage) to store harvested energy. It is also assumed that the multi-access communication is error-free and there is no fading. If a node is scheduled, it will be assigned one of the channels. When a node is scheduled to transmit, it can transmit data to the FC if it has sufficient energy to send a packet. The transmission of each packet lasts an entire time slot. The objective of the FC is to maximize the total throughput over a finite or infinite problem horizon. This problem is studied in [32] and the work is extended to a more general case in [33]. The thesis presents a more detailed version of the contents of [32, 33].

In practice, battery states of nodes could be made available to the FC through some additional cost (i.e. additional time and energy loss due to additional feedback) and complexity. However, it is interesting from a practical perspective to consider the case where the FC makes scheduling decisions without knowledge of the instantaneous battery states at nodes, or their statistics. Fortunately, it turns out that this lack of knowledge has little effect on performance. We will observe that by knowing only the outcomes of previous transmission attempts, the FC can schedule almost as efficiently as an omniscient scheduler.

Assuming EH processes as Markovian processes, this problem may be formulated as a partially observable Markov Decision Process (POMDP), and Dynamic Programming (DP) [34] can be employed for optimal solution. However, the state space of DP should be very large to get a good approximation to the problems with continuous state variables like energy. Furthermore, DP has exponential complexity with respect to number of nodes m [34]. Therefore, complexity of DP may become excessively high for the EH scheduling problem with large number (hundreds) of nodes and large state space.

A second approach for solving this scheduling problem is reinforcement learning by considering the problem as a POMDP. Q-learning [35] is the easiest to implement and the most effective model-free algorithm among reinforcement learning algorithms. Q-learning guarantees convergence to optimal for a generic model. However, Q-learning is not applicable for problems with large-state space, because its convergence is slow [36]. In fact, many algorithms can guarantee the convergence to optimal behavior [37]. However, in many practical applications, a policy which achieves near optimality quickly is preferable to the policy which converges slowly to exact optimality [36]. As the discount factor gets closer to 1 (i.e. the undiscounted case), the convergence rate of Q-learning decreases more. There are approaches such as R-learning [38], which maximize average reward; however, the convergence of R-learning has not been proven. Also, reinforcement learning has a very important problem: *the trade-off between exploration and exploitation* [39]. Therefore, Q-learning and generally reinforcement learning do not seem to be suitable for obtaining an efficient and practical solution to this scheduling problem, especially when a large number of sensors and a continuous state variable, energy, is considered.

Another approach for this scheduling problem is to consider it as a restless multi-armed bandit problem (RMAB), which is a special version of POMDP. RMAB is an extension to classical multi-armed bandit (MAB) problem, which is solved optimally by Gittins [40] and an optimal solution is proposed under certain assumptions by Whittle [41]. Papadimitriou and Tsitsiklis show that finding optimal solution to a general RMAB is PSPACE-hard and it has a very high computational complexity [42]. Considering memory limits of sensors, a much more applicable policy is required. Therefore, a simpler approach called a myopic policy (MP) is suggested for RMAB problems and proven to be optimal in limited cases for the sensor management problems in [43, 44, 45]. However, a myopic policy is not generally optimal since MP concentrates only on the present and not consider the future [46, 47]. A channel probing problem is studied in [48] and it is shown that MP is not always optimal. The assumption that the scheduling decision does not affect transition probabilities was an appropriate one for the problems addressed in [43, 44, 45, 48]. However, this assumption does not apply to the EH scheduling problem at hand, this is not a reasonable assumption, as energy is a flexible resource that can be stored (without any discount, ignoring battery leakage which is very minor in practice [2]) and can be used whenever desired. On the other hand, spectrum is an inflexible resource that cannot be stored and that must be used at the instant when it is available. Therefore, the solutions presented in [43, 44, 45, 48] papers are not directly applicable to our problem.

The closest works in the literature to the problem at hand are the scheduling problems studied in [47, 49]. We have posed essentially the same problem, with the exception that no battery and unit sized batteries at nodes are assumed in [47] and [49], respectively. In both [47] and [49], the scheduling problem is formulated as a POMDP, where the focus is on immediate reward instead of future rewards. In [49], a single-hop wireless sensor network which consists of EH transmitter nodes with a unit sized battery and a central receiver node with multi server is considered as a restless multi-armed bandit problem (RMAB). Optimality of Whittle index policy which is generally suboptimal for RMAB [50] is proven for a certain case under certain assumptions on the EH process. In [49], the optimality of a Round-Robin based myopic policy is proved under the assumption that each node has only unit sized battery and the ratio between the number of transmitter nodes and the number of communication channels of the central node is an integer (m/k is an integer). In [47], the problem is formulated as POMDP and the optimality of MP is proven for two cases: 1) the nodes are not able to harvest and transmit simultaneously, and the EH process transition probabilities are affected by the scheduling decisions, and 2) the nodes have no battery. Since myopic policies proposed in [47, 49] are based on Round-Robin (RR) scheme, assuming that "m/k is an integer" is important (m/k is also the period of RR Policy). These assumptions are somewhat restrictive for real life implementation.

To set up the problem, a model about the generation and usage of energy is needed. First, energy in a node's battery decreases if the node sends a data packet. Second, energy in a battery increases in a continuous fashion by harvested energy. Third, battery leakage is neglected. This assumption follows from examining typical batteries in use today for which leakage is negligibly small for over durations of several minutes. Based on these mild assumptions about energy, a suitable performance measure for a policy can be average reward over the finite and the infinite horizon rather than expected total discounted reward for this scheduling problem which is a delay-insensitive communication problem [51]. In communication network problems, delay is investigated as average delay; and not as discount. In applications, EH sources may use vibrational or kinetic energy, the behavior of which is typically not predictable [1], [3]. Optimal scheduling for this continuous, independent EH process becomes a hard problem, and the problem requires good near-optimal solutions.

By taking a deterministic approach, a near-optimal transmission scheduling policy, Uniforming Random Ordered Policy (UROP) [32], is developed and proven to be near optimal by assuming that each sensor has an infinite capacity battery (It will be shown that if the sensors have a reasonable-sized finite battery, UROP has almost the same efficiency as its efficiency under a reasonable-sized finite battery assumption). It is also guaranteed that UROP is *asymptotically optimal* for a general case of energy arrival process under the infinite battery assumption (larger than unit battery) as the horizon length increases. In comparison with the myopic policies in [47, 49], UROP can still guarantee near-optimal performance when m/k is not an integer.

As a variation of the problem at hand, we consider a single hop network where a fusion center (FC) collects data from m EH nodes, according to a time-slotted operation. When a node is scheduled for transmission in a time slot, it transmits a packet if it has data to transmit, and sufficient energy to perform a transmission. The FC does not have direct knowledge of the state of the system (i.e. numbers of data packets or energy stored at nodes), or statistics of the energy harvesting and data arrival processes. We assume that k of the nodes (any subset of k distinct nodes) can be scheduled at any time. The objective of the FC is to maximize total throughput over a finite or infinite horizon. In fact, this problem is the extended version of the problem studied in [32]. This scheduling problem is studied in [52] and the work is extended to a more general case in [33]. The more detailed version of these works is presented here. The thesis presents a more detailed version of the contents of [32, 33, 52].

This problem may be also formulated as Restless Multi-Armed Bandit (RMAB) problem (proposed by Whittle [41]), and when energy and data arrivals are modeled as Markov processes, a partially observable Markov Decision Process (POMDP). Dynamic programming (DP) and reinforcement learning (RL) [36] are possible approaches for solution, however, these approaches do not provide practical solutions that scale well with the number of nodes and states of EH and DA processes. As the optimal solution of a general RMAB is PSPACE-hard [42], a simpler approach *myopic policy (MP)* is proposed for some RMAB problems. However, MP is generally suboptimal [46].

The problem was posed and studied, for a limited capacity battery for storing energy harvests, and infinite data backlog in [47, 49, 53]. The optimality of Round Robin (RR) based myopic policies are exhibited in the mentioned studies under certain conditions on energy harvesting processes. In [32], relaxing the battery constraint (allowing unlimited storage), the optimality of a simple randomized policy, *UROP* was shown. It was also argued that practically the same performance is obtained under finite storage capacity with this algorithm.

As a second variation of the scheduling problem, the first variation of the problem is extended to the unbacklogged case; i.e., when stability of data buffers is considered together with the efficient consumption of harvested energy. In particular, near-optimality of the UROP (redefined below for convenience) is exhibited under quite general energy harvest (EH) and data arrival (DA) processes under infinite battery and buffer assumptions. We also show through simulations that efficiency of UROP under a reasonable sized finite battery and buffer assumption deviates little from that under an unlimited buffer assumption. It is worth noting that unlike many RR based algorithms, UROP is completely flexible with respect to the number of users that can be scheduled at a time (k) in relation to the size of the user pool (m).

Thirdly, a dual version of the first problem is considered. In this problem, we consider a single hop communication network where a centralized controller (CC) collects data from m nodes, according to a discrete time fashion. When a node is scheduled in a time slot, it transmits a data packet if it has data to transmit. The CC does not have direct knowledge of the state of the system (i.e. numbers of data packets stored at nodes), or statistics of data arrival processes. We assume that k of the nodes (any subset of k distinct nodes) can be scheduled at any time. The objective of the FC is to maximize total throughput over a finite or infinite horizon.

The rest of this thesis is organized as follows. In Chapter II, first of the scheduling problems is considered. Then, the second scheduling problem is studied in Chapter III. In Chapter IV, a dual version of first scheduling problem is studied. Finally, Chapter V concludes the thesis.

CHAPTER 2

UROP: A SIMPLE, NEAR-OPTIMAL SCHEDULING POLICY FOR ENERGY HARVESTING WIRELESS NETWORKS

In this chapter, a network scheduling problem for a single-hop wireless network is investigated with the following assumptions. In the network, a fusion center (FC) schedules a set of energy harvesting nodes to collect data from them. Fusion center does not know the instantaneous battery states of nodes or the statistics of random energy harvesting processes. FC only knows the history of previous transmission attempts. The batteries of the nodes have infinite battery capacity and there is no leakage from the batteries.

The chapter is organized as follows. The system model and problem formulation are described in Section 2.1. In Section 2.2, we study the scheduling capacity. In Section 2.3, we show that Round-Robin based policies cannot guarantee 100% throughput under many non-uniform energy harvesting process for nodes. We show the optimal omniscient solution for this problem in section 2.4. In Section 2.5, we suggest a novel, low-complexity scheduling policy which is nearly throughput optimal for quite general energy harvesting processes (uniform, non-uniform, independent, correlated) in a finite horizon problem under an infinite battery assumption. Next, efficiency bounds on UROP are obtained. Section 2.6 extends the results from finite horizon to infinite horizon. In Section 2.7, we compare the performance of UROP with that of a Round-Robin policy and the Myopic Policies in [47, 49] through simulations. Computational complexities of the scheduling policies proposed in this chapter and Myopic Policies in [47, 49] are discussed in Section 2.8.

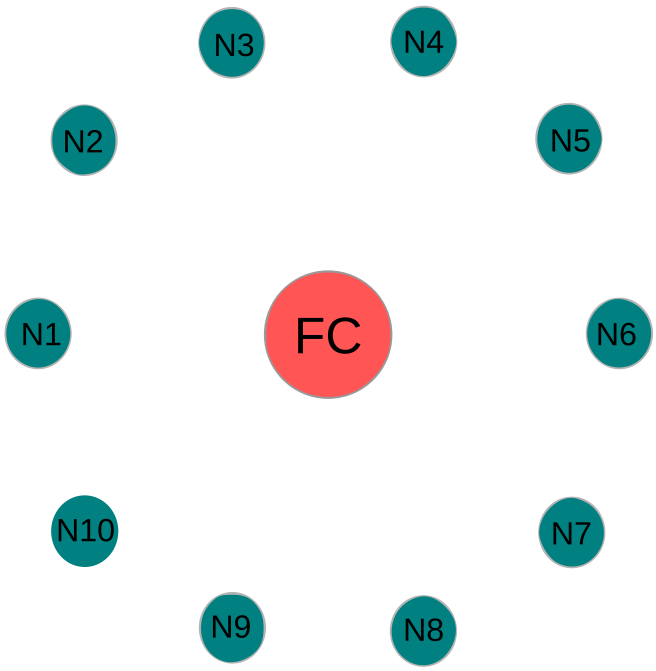

Figure 2.1: A single hop wireless network where a fusion center (FC) collects data from energy harvesting (EH) nodes located in a star topology around it.

2.1 System Model and Problem Formulation

We consider a single-hop wireless network in which m energy harvesting (EH)-capable nodes have circularly symmetric distribution around a Fusion Center (FC) and send data packets to FC (See Figure 2.1). The WSN operates in a time-slotted fashion over time slots (TSs) of equal duration. In each TS, FC schedules k out of m sensors for data transmission by assigning these to the k orthogonal channels. We assume that each node always has data to transmit (i.e. data is backlogged as in [47, 49]) during the problem horizon of T TSs. Data packets have *equal size* and require *unit energy* for transmission.

The EH processes are assumed to be independent for each node. The total energy harvested by node s_i upto TS t is denoted by $E_i(t)$, and the increment of this energy harvested during the TS t is denoted as $E_i^h(t)$. The energy present in the battery at t (stored minus used) is $B_i(t)$. Note that the performance of the communication system is investigated under infinite battery assumption. Then, the finite battery case with $B_i(t) = 50 \; \forall s_i$ is also considered in numerical results.

We denote by $S = \{s_1, s_2, .., s_m\}$ the set of all nodes. The amount of data sent by node s_i in TS t is $I(s_i \in S_{sc}(t))I(B_i(t) \geq 1) \in \{0, 1\}$ where $I(X)$ is the indicator function of event X, and $S_{sc}(t) \subset S$ is the set of k nodes scheduled at TS t. The set $S_{sc}(t)$ is determined by a scheduling policy π.

Two definitions are in order: A *fully efficient policy* (alternatively, a 100% *efficient policy*) ensures that the nodes use up all of the harvested energy by the end of the problem horizon, more precisely, $B_i(T) < 1 \; \forall s_i \in S$. An *optimal policy* is one that maximizes data throughput for the given sequence of energy harvests. For certain energy harvest processes, an optimal policy may not be fully efficient, as it will be clear in the next section.

In the communication network, $V(t)$ is the total number of data packets which FC received from the surrounding nodes from the beginning (first TS) to TS t. Consistently with previous literature ([47, 49]), the general objective is to maximize the total throughput (considering RMAB literature, the expected discounted reward) over the problem horizon

$$\max_{S_{sc}(t),t=1,..,T} V(T) = \max_{S_{sc}(t),t=1,..,T} \left[\sum_{t=1}^{T} \beta^{t-1} \sum_{s_i \in S} I(s_i \in S_{sc}(t))I(B_i(t) \geq 1) \right], \quad (2.1)$$

where $0 < \beta \leq 1$ is the discount factor, which reduces the value of data sent later. The discount factor corresponds to placing lower value on data that is delayed. However, note that the problem at hand assumes infinite backlog and is therefore delay insensitive by nature. The discount could also be considered to model battery leakage that happens as transmission is withheld. Therefore, average reward criterion is more suitable measure for delay-insensitive communication problems like this scheduling problem than a discounted reward criterion [51].

Consistently with our assumptions about infinite data buffers, infinite batteries, and no battery leakage, we shall set $\beta = 1$ and convert the objective function in (2.1) to that in (2.2), which is an average reward criterion, namely time average throughput

$$\max_{S_{sc}(t),t=1,..,T} \frac{V(T)}{T} = \max_{S_{sc}(t),t=1,..,T} E \left[\frac{1}{T} \sum_{t=1}^{T} \sum_{s_i \in S} I(s_i \in S_{sc}(t))I(B_i(t) \geq 1) \right]. \quad (2.2)$$

Note that the average throughput $\leq k$ by definition. We propose an algorithm, UROP, which achieves *nearly 100% throughput* (and 100% efficiency whenever a fully efficient schedule is feasible) in a broad class of energy harvesting (arrival) process under infinite battery assumption. In this chapter, η, efficiency of a policy π is defined as the ratio of the total throughput by policy π to the total throughput by fully efficient policy π^{fe} on the problem horizon ($\eta_{fe} = 1$). In Section 2.3, it is proven that efficiency of an arbitrary Round Robin Policy with quantum=1 TS π^{RR} is very close to that of myopic policy π^{MP} (η_{MP}) proposed in [47, 49]. Therefore, the efficiency of UROP π^{UROP} (η_{UROP}) will be compared with that of an arbitrary Round Robin Policy with quantum=1 TS π^{RR} (η_{RR}) in Section 2.7 for simplicity. Note that a Round Robin Policy with quantum=1 TS is a policy which allocates each node 1 TS during a round (cycle). A RR Policy with quantum=2 TSs allocates each node 2 TSs during a round, so on.

An arrival process is called *admissible* if a fully efficient schedule is possible. By the analogy with admissible processes in these problems, we introduce four new terms which we use for the EH scheduling problem in the rest of paper. *Partial Density of sensor* s_i, $D_i^{(t)}$, is the total number of packets sent by the sensor s_i with π^{fe} normalized by $\frac{k(T-t)}{m}$ in the interval $(t, T]$. *Partial Density* ($D^{(t)}$) is the average of partial densities of all sensors in the interval $(t, T]$,

$$D^{(t)} = \frac{\sum_{s_i \in S} D_i^{(t)}}{m}. \tag{2.3}$$

Density of sensor i, D_i, is the total number of packets sent by the node s_i with π^{fe} normalized by $\frac{kT}{m}$ during problem horizon T. *Density* (D) is the average of densities of all sensors during problem horizon T,

$$D = \frac{\sum_{s_i \in S} D_i}{m}. \tag{2.4}$$

In fact, D_i and D are used instead of $D^{(0)}$, $D_i^{(0)}$, respectively, for simplicity.

In the rest of paper, we consider the region $D, D^{(t)} \leq 1$ for analysing efficiency of UROP and comparing it with the RR-based myopic policies proposed in [47, 49].

Figure 2.2 and Figure 2.3 show two examples for both $D^{(0)} \leq 1$ and $D_i^{(0)} > 1$, respectively.

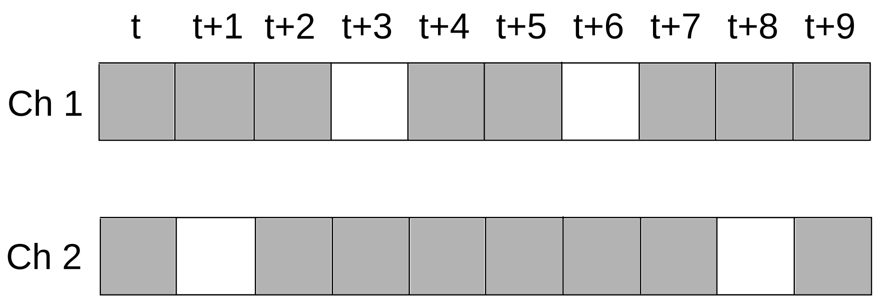

Figure 2.2: An example scheduling table kept by the fusion center (FC) for $m = 4$, $k = 2$ during the interval $[t, t + 9]$. Dark colored TSs represent busy slots, and the white ones represent idle ones. 4 of 20 slots are idle even under an optimum policy ($D^{(t)} = \frac{16}{20} = 0.8$).

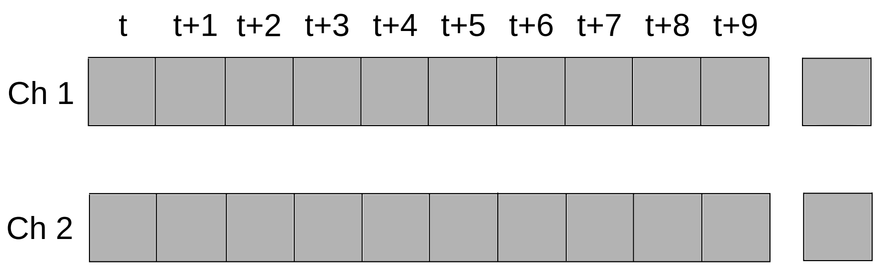

Figure 2.3: An example scheduling table kept by the fusion center (FC) for $m = 4$, $k = 2$ during the interval $[t, t + 9]$. Dark colored TSs represent busy slots. None of 20 slots are idle and two packets cannot be sent even the communication system have enough energy for transmission ($D^{(t)} = \frac{20+2}{20} = 1.1$).

2.2 Scheduling Capacity

To find a robust, efficient scheduling policy, we need to consider scheduling capacity of the FC. Scheduling capacity corresponds to the maximum number of nodes which can be scheduled by the FC in one TS. Since FC has k orthogonal channels, the scheduling capacity of the FC is k. If the amount of average harvested energy is so high that the scheduling capacity is exceeded, no 100% efficient policy exists and energy will keep accumulating (there is an energy surplus). Considering finite batteries, this will cause overflow in the batteries of nodes. Theorem 1 explores the region of energy harvest rates such that a 100% efficient policy is feasible.

We shall now make some definitions that will be used in the rest of this section and the paper. We denote by $V_i^{(t)}$ and $V^{(t)}$, the number of packets which could be sent by only node s_i and by all nodes, respectively in the interval $(t, T]$. $V_i^{(t)}$ and $V^{(t)}$ can be represented as

$$V_i^{(t)} = \left\lfloor B_i(t) + \sum_{j=t+1}^{T} E_i^h(j) \right\rfloor \tag{2.5}$$

$$V^{(t)} = \sum_{s_i \in S} V_i^{(t)}. \tag{2.6}$$

In the following theorem, we record the condition on the value of the total amount of harvested energy so that a 100% efficient policy is feasible (We look for the region that optimal policy is equivalent to 100% efficient policy). Note that according to the restriction in the system model, each node is assigned to at most one channel per time slot (i.e. send at most one packet per time slot).

Theorem 1. (Scheduling Capacity Theorem) *Assuming that one node can transmit one packet per time slot as mentioned in system model, for* $0 \leq t < T$*,*

(i) If $V_i^{(t)} > (T - t)$ *for some* $s_i \in S$ *and some* t *or* $V^{(t)} > k(T - t)$ *for some* t*, all possible policies will have efficiency below 100% and battery levels of some nodes grow unboundedly (in practice, considering finite batteries, they will overflow).*

(ii) If $V_i^{(t)} \leq (T - t)\ \forall s_i \in S \& \forall t$ *and* $V^{(t)} \leq k(T - t)\ \forall t$*, a 100% efficient policy that maximizes throughput while keeping battery levels of all nodes finite, exists.*

Proof. (i) As a node s_i can transmit one packet per time slot, a node can transmit $(T - t)$ data packets in the interval $(t, T]$. If $V_i^{(t)} > (T - t)$ for some $s_i \in S$, then each of these nodes cannot transmit $V_i^{(t)} - (T - t)$ data packets although it has enough energy to transmit them. Therefore, a 100% efficient policy does not exist and battery levels of these nodes grow unboundedly.

Even, $V_i^{(t)} \leq (T - t)\ \forall s_i \in S \& \forall t$, a 100% efficient policy does not exist if

$$V^{(t)} > k(T - t) \tag{2.7}$$

is satisfied.

As the total uplink rate available is k data packets per time slot, FC can accumulate at most $k(T - t)$ packets from the nodes in the interval $(t, T]$. Suppose that there is an optimum policy π^* which can achieve up to scheduling capacity. Then, efficiency of π^* equals to the maximum efficiency in the conditions (2.7), and it is represented as

$$\begin{aligned}\eta_* &= \frac{min\left\{k(T-t), V^{(t)}\right\}}{V^{(t)}} \\ &= \frac{k(T-t)}{V^{(t)}}.\end{aligned} \tag{2.8}$$

If (2.7) is satisfied, the scheduling capacity is exceeded in the interval $(t, T]$. By (2.7), $\eta_* < 1$. Hence, there is no 100% efficient policy which lets FC receive $V^{(t)}$ packets from the nodes.

(ii) As mentioned in part (i), a node can transmit $(T-t)$ data packets in the interval $(t, T]$. If $V_i^{(t)} \leq (T-t)\ \forall s_i \in S\&\forall t$, then a node s_i can transmit all of its data packets with its future energy harvests in the interval $(t, T]$.

$V_i^{(t)} \leq (T-t)\ \forall s_i \in S\&\forall t$ is required but not unique condition for the existence of a 100% efficient policy. If (2.9) is also satisfied, then a 100% efficient policy exists.

$$V^{(t)} \leq k(T-t) \tag{2.9}$$

FC can receive maximum $k(T-t)$ data packets from the nodes in the interval $(t, T]$. An omniscient policy could fill up all channels in all time slots as long as there is a sensor with available energy. Trivially, this achieves 100% efficiency if $D^{(t)} \leq 1$ (equivalent to (2.9)). It is summarized as

$$\begin{aligned}\eta_* &= \frac{min\left\{k(T-t), V^{(t)}\right\}}{V^{(t)}} \\ &= \frac{V^{(t)}}{V^{(t)}} \\ &= 1.\end{aligned} \tag{2.10}$$

By (2.10), $\eta_* = 1$. Hence, there is a fully efficient (100% efficient) policy which makes FC receive $V^{(t)}$ packets. Battery levels of all nodes are kept finite. Hence when $D^{(t)} \leq 1$, there is an optimal policy which is 100% efficient. □

Remark 1. *By definition of $D^{(t)}$, (2.7) is equivalent to $D^{(t)} > 1$. Define excess energy as $B_{ex}(t) = \sum_{i=1}^{m} \lfloor B_i(t) \rfloor = max\left\{0, V^{(t)} - k(T-t)\right\}$ by assuming that*

$V_i^{(t)} \leq (T-t)\ \forall s_i \in S \& \forall t$. By definition of $D^{(t)}$, $B_{ex}(t) = k(T-t)(D^{(t)}-1)$. As $D^{(t)} > 1$ and $T \rightarrow \infty$, battery levels of some nodes grow unboundedly.

2.3 Efficiency of RR-based Policies

The scheduling problem in this paper are also studied in [47, 49] for certain specific cases. Both papers propose RR-based policies with quantum=1 TS which are myopic policies. Then, they prove the optimality of these policies under certain specific cases.

First, we will investigate the efficiency of RR-based policies by Theorem 2. Then, we will prove by Theorem 3 that there is only a slight difference between the efficiencies of any two RR-based policies in long problem horizon $T(\frac{m}{k} \ll T)$. Hence, the efficiency of RR-based myopic policies in [47, 49] are investigated. It is shown that the policies in [47, 49] are generally suboptimal.

For the cases that each node has a battery larger than unit size, there is no known myopic policy in the literature. Therefore, we will compare UROP only with the policies in [47, 49], and the optimal policy in this paper.

Theorem 2. *Suppose that $T \gg \frac{m}{k} \in Z$ and the scheduling capacity of the FC is not exceeded by Theorem 1 ($V_i^{(t)} \leq (T-t)\ \forall s_i \in S, \forall t$ and $V^{(t)} \leq k(T-t)\ \forall t$). If there are some sensors $s_i \in S$ such that $V_i^{(t)} > \frac{k(T-t)}{m}$, all RR-based policies with quantum=1 TS will have efficiency below 100% although a fully efficient policy (π^{fe}) exists. Moreover, batteries of some sensors will overflow.*

Proof. Assume that there are some nodes $s_i \in S$ such that $V_i^{(t)} > \frac{k(T-t)}{m}$. We denote by H the set of these sensors. By definition $D_i^{(t)} > 1$ for nodes $s_i \in H$.

In this proof, what is implied by RR policy is RR-based policies with quantum=1 TS. We investigate efficiency of RR in the two possible cases:

i. If $\sigma = \frac{kT}{m} \in Z$, RR allocates each node σ TSs for transmission.

ii. If $\sigma = \frac{kT}{m} \notin Z$, RR allocates some nodes $\lfloor \sigma \rfloor + 1$ TSs and other nodes $\lfloor \sigma \rfloor$ TSs.

Case i: If the FC schedules m nodes by RR policy in the problem horizon T, RR policy allocates each node $\sigma = \frac{kT}{m} = \frac{T}{p}$ TSs equally. Although $V^{(t)} \leq k(T-t)$, each node $s_i \in H$ can transmit maximum σ data but cannot transmit $V_i^{(t)} - \sigma$ data due to RR policy. On the other hand, each of other nodes $s_i \in S - H$ can transmit all $V_i^{(t)}$ packets. By analogy with scheduling capacity, the efficiency of a RR policy can be represented as

$$\begin{aligned}
\eta_{RR} &= \frac{\sum\limits_{s_i \in S} min\left\{V_i^{(t)}, \sigma\right\}}{\sum\limits_{s_i \in S} V_i^{(t)}} \\
&= \frac{\sum\limits_{s_i \in H} min\left\{V_i^{(t)}, \sigma\right\} + \sum\limits_{s_i \in S-H} min\left\{V_i^{(t)}, \sigma\right\}}{\sum\limits_{s_i \in S} V_i^{(t)}} \\
&= \frac{\sum\limits_{s_i \in H} \sigma + \sum\limits_{s_i \in S-H} V_i^{(t)}}{\sum\limits_{s_i \in S} V_i^{(t)}} \\
&= 1 - \frac{\sum\limits_{s_i \in H} (V_i^{(t)} - \sigma)}{\sum\limits_{s_i \in S} V_i^{(t)}}
\end{aligned} \tag{2.11}$$

As $V_i^{(t)} > \sigma \; \forall s_i \in H$, $\eta_{RR} < 1$. Hence, suboptimality of RR policy is proven for the first case although there exists an 100% efficient policy by Theorem 1.

Case ii: If the FC schedules m nodes by RR policy in the problem horizon T, RR policy allocates some nodes $\lfloor \sigma \rfloor + 1$ TSs and other nodes $\lfloor \sigma \rfloor$ TSs for transmission where $\sigma = \frac{kT}{m} \notin Z$ and $\{\sigma\} \triangleq \sigma - \lfloor \sigma \rfloor$. To maximize efficiency of RR policy, we assume that each node $s_i \in H$ can transmit maximum $\lfloor \sigma \rfloor + 1$ data packets. However, each of these nodes cannot transmit $V_i^{(t)} - \lfloor \sigma \rfloor - 1$ data due to RR policy although $V^{(t)} \leq k(T-t)$. On the other hand, each of other nodes $s_i \in S - H$ can transmit all $V_i^{(t)}$ data packets. By the analogy with scheduling capacity, the efficiency of RR policy can be represented as

$$\begin{aligned}
\eta_{RR} &= \frac{\sum_{s_i \in S} min\left\{V_i^{(t)}, \sigma\right\}}{\sum_{s_i \in S} V_i^{(t)}} \\
&= \frac{\sum_{s_i \in H} min\left\{V_i^{(t)}, \sigma\right\} + \sum_{s_i \in S-H} min\left\{V_i^{(t)}, \sigma\right\}}{\sum_{s_i \in S} V_i^{(t)}} \\
&= \frac{\sum_{s_i \in H} (\lfloor \sigma \rfloor + 1) + \sum_{s_i \in S-H} V_i^{(t)}}{\sum_{s_i \in S} V_i^{(t)}} \\
&= 1 - \frac{\sum_{s_i \in H} (V_i^{(t)} - \lfloor \sigma \rfloor - 1)}{\sum_{s_i \in S} V_i^{(t)}}
\end{aligned} \tag{2.12}$$

As $V_i^{(t)} > \lfloor \sigma \rfloor + 1 \; \forall s_i \in H$, $\eta_{RR} < 1$. Hence, suboptimality of RR policy is also proven for the second case although there exists an 100% efficient policy by Theorem 1. □

By Theorem 2, efficiency of RR policies is investigated; however, to obtain the efficiency from (2.11) and (2.12) may be a bit complicated. To calculate efficiency of RR policies in a simpler way, efficiency of RR policies can be expressed with the following remark, alternatively. We use this remark to calculate efficiency of RR in Section 2.7.

Remark 2. ***Case i:*** *Considering the definition of $D_i^{(t)}$, η_{RR} can also be represented as*

$$\eta_{RR} = 1 - \frac{\sum_{s_i \in H} (D_i^{(t)} - 1)}{\sum_{s_i \in S} D_i^{(t)}}. \tag{2.13}$$

Since $D_i^{(t)} > 1 \; \forall s_i \in H$, $\eta_{RR} < 1$.

Case ii: *Considering the definition of* $D_i^{(t)}$, η_{RR} *can also be represented as*

$$\begin{aligned}\eta_{RR} &= 1 - \frac{\sum\limits_{s_i \in H} (D_i^{(t)}\sigma - \lfloor \sigma \rfloor - 1)}{\sum\limits_{s_i \in S} D_i^{(t)}\sigma} \\ &= 1 - \frac{\sum\limits_{s_i \in H} (D_i^{(t)} - 1)\sigma - (1 - \{\sigma\}))}{\sum\limits_{s_i \in S} D_i^{(t)}\sigma} \end{aligned} \quad (2.14)$$

It is known that $D_i^{(t)} > 1\ \forall s_i \in H$ *and* $(1 - \{\sigma\}) < (D_i^{(t)} - 1)\sigma$ *since* $\sigma \gg 1 > 1 - \{\sigma\}$. *Therefore,* $\eta_{RR} < 1$.

From Remark 2 and Theorem 1, efficiency of RR be as low as $\frac{k}{m}$. This worst case efficiency of $\frac{k}{m}$ occurs when k of the nodes always have sufficient energy to transmit a data packet in each TS and the remaining ones have no energy.

For a sufficiently long problem horizons, these results can be extended to RR-based policies with larger quanta. The following remark, used in the rest of the paper, is a consequence of the assumption there is no battery leakage.

Remark 3. (No battery leakage) *Let* $T_1, T_2 \in (0, T]$ *and* $T_1 < T_2$. *If* s_i *is not scheduled (selected) in interval* $(T_1, T_2]$, $B_i(T_1) \leq B_i(T_2)$ *where* $B_i(t)$ *is the energy remaining in battery of sensor* s_i *at the end of TS* t. *That is,* $B_i(t)$ *does not decrease unless* s_i *transmits data.*

Theorem 2 states that RR-based policies become suboptimal when $D_i^{(t)} > 1$ even for one node. In the following theorem (Theorem 3), it is shown that an arbitrary RR policy with quantum=1 TS has almost the same efficiency as any other RR policy with quantum=1 TS.

Theorem 3. (Upper and lower bounds on RR throughput) *Assume that* $\frac{m}{k} \in Z$. *In problem horizon* T,

$$max\left\{V^{RR}(T)\right\} - min\left\{V^{RR}(T)\right\} \leq m - k \quad (2.15)$$

where $min\left\{V^{RR}(T)\right\}$ *and* $max\left\{V^{RR}(T)\right\}$ *are the minimum and maximum throughput which can be achieved under a RR policy with quantum=1 TS, respectively.*

Proof. There are three cases for the problem horizon T: 1) $T < \frac{m}{k}$, 2)$T \geq \frac{m}{k}$ and $\frac{kT}{m} \in Z$, and 3) $T \geq \frac{m}{k}$ and $\frac{kT}{m} \notin Z$

Case 1: If $T < \frac{m}{k} = p, T \leq p-1$. Since $min\left\{V^{RR}(T)\right\} \geq 0$ and $max\left\{V^{RR}(T)\right\} \leq kT \leq k(p-1) = m-k$, $max\left\{V^{RR}(T)\right\} - min\left\{V^{RR}(T)\right\} \leq m-k$. This proves the statement for this case.

Case 2: Denote by U_j the nodes scheduled in TS j where $j \leq p = \frac{m}{k}$ and $S_m = \bigcup_{j=1}^{p} U_i$. All RR policies have same length period p. Denoted by τ_l^{RR} the l^{th} period of RR, namely, $\tau_l^{RR} = [(l-1)p+1, lp]$. Assume that $T_1, T_2 \in \tau_l^{RR}$ and $T_1 < T_2$ where T_1 and T_2 are the TSs when a node s_i is scheduled l^{th} time by the FC under two different RR policies with quantum=1 TS, π^{RR1} and π^{RR2}, respectively.

By Remark 3, efficiency of π^{RR2} in T_2 is not lower than that of π^{RR1} in T_1 for the node s_i since π^{RR2} schedules the node later than π^{RR1} does. By Remark 3, if a node s_i cannot send data in T_1 and can send in T_2, then it would certainly have data to send when it is scheduled in $T_1 + p$ instead of T_2. Therefore, $V_i^{RR1}(T_1) \leq V_i^{RR2}(T_2) \leq V_i^{RR1}(T_1 + p)$ for $\forall s_i \in S_m$.

This means that giving each node one more TS, any RR policy can achieve maximum throughput achieved by most efficient RR. In other words, the least efficient RR can achieve the throughput of the most efficient RR by continuing only one period more. Note that since U_p is the nodes scheduled last under a RR policy, they achieve maximum throughput which can be achieved under RR policy by Remark 3. Therefore, the least efficient RR uses only $m-k$ TSs more than other RR policies to guarantee same throughput. By using the extra $m-k$ TSs which the least efficient RR used, the most efficient RR policy can have throughput $m-k$ more than it has. By considering the last period during the problem horizon T, Theorem 3 will be proved for this case.

Assume that $T = sp = t + p$ where $s \in Z$. Considering the last period $[t+1, t+p]$, the worst performance of RR occurs when the set of nodes U_j can transmit no data in TS $t+j$; however, they get ready for transmission in TS $t+j+1$ ($B_i(t+j+1) \geq 1$). Since there is no next TS for U_p, nodes of U_p cannot improve their battery states. Therefore, the throughput difference is determined by nodes $s_i \in S - U_p$. Since $|S - U_p| = m - k$, the difference is $m - k$. Hence, it is proved for this case.

Case 3: Assume that $T = sp + c$ where $0 < c < p$, $s \in Z$. In case 2, it is shown that the maximum difference is $m - k$ in TS sp. In the interval $[sp+1, sp+c]$, $S_c = \bigcup_{j=1}^{c} U_j$ is scheduled. For the nodes $s_i \in U_j \subset S_c$, $B_i(t) \geq 1$ in TS sp. If $B_i(sp+j) \geq 2 \; \forall s_i \in U_j \subset S_c$, the throughput difference remains as $m - k$. Unless $B_i(sp+j) \geq 2 \; \forall s_i \in U_j \subset S_c$, the difference remains same or decreases depending on other nodes $s_i \in S - S_c$. This concludes the proof. □

As the myopic policies (MP) in [47, 49] are also RR policies with quantum=1 TS, they have almost same efficiency as any other RR policy with quantum=1 TS. Since the difference between throughputs of two arbitrary RR policies with quantum=1 TS is $m - k$, the difference between efficiencies of two arbitrary RR policies with quantum=1 TS is $\frac{m-k}{V^{fe}(T)} = \frac{m-k}{V^{*}(T)}$ (Recall that $\pi^* = \pi^{fe}$ unless the scheduling capacity is exceeded). Considering large T, the difference becomes little (in fact 0 as $T \to \infty$). Therefore, instead of MPs in [47, 49], an arbitrary RR policy with quantum=1 TS will be used in the comparisons of scheduling policies in Section 2.7 for simplicity.

In Section 2.4, we investigate optimal omniscient policies which give us motivation to find a near optimal policy for the scheduling problem at hand in Section 2.5.

2.4 Optimal Omniscient Policies

For the EH scheduling problem, [47, 49] propose RR-based Myopic Policy (MP) and prove that the MP is optimal for certain specific cases. However, Theorem 2 and Theorem 3 state that RR-based policies with quantum=1 TS (including the MP in [47, 49]) become suboptimal when $D_i^{(t)} > 1$ for some sensor i although an 100% efficient policy exists ($D^{(t)} \leq 1$). The EH scheduling problem resembles a simplified unicast switch scheduling problem. Like unicast switch scheduling problems, this problem has input queues (energy queues) and feasible activation sets are such that at most k users are scheduled. Different from usual unicast switch scheduling problem setups, buffer (battery) states are not known in this problem; therefore, switch scheduling policies that assume the availability of state information cannot be applied directly. However, these provide intuition for finding an *omniscient scheduling* policy (i.e. one which knows the current battery states) for the EH scheduling problem.

For unicast switch scheduling problems, the following approaches are well-known: Maximum Size Matching (MSM) and Maximum Weight Matching (MWM) [54], [55]. Maximum Size Matching selects in each TS an activation set with the max number of nonempty queues. On the contrary, Maximum Weight Matching also respects queue size not only whether queues are empty or not. Maximum Size Matching may sometimes cause starvation due to head-of-line (HOL) blocking which limits its throughput to below 100% in some cases [54] and [56]. On the other hand, Maximum Weight Matching policies always guarantee 100% throughput for all admissible traffic (with analogy, $D^{(t)} \leq 1$ in our problem) and two MWM algorithms are offered to achieve 100% throughput in [54]. However, due to lower computational complexity, MSM policies are sometimes preferred [57].

Different from unicast switch scheduling problems, there is no preffered output for packets in the EH scheduling problem. All k lines correspond to the same output port to which any packet can be sent. This implies that HOL blocking does not occur in the EH scheduling problem, so both MSM and MWM will provide 100% throughput in our problem. Due to lower computational complexity, MSM is preferable. To find an omniscient policy for the EH scheduling problem, we assume that FC knows whether each node can transmit data or not in any TS. With this knowledge, there is no unique optimal omniscient policy for this problem. We shall concentrate on one optimal policy which provides intuition to find a near optimal, nonomniscient and online policy later.

To find such a policy, we map the problem onto a variation of block-packing game Tetris. A different Tetris model which we are inspired by was previously used in multicast switch scheduling problems [58] and [59]. In this model, packets from same input are sent to different output ports. In our case, different from the Tetris model of [58] and [59], the packets from same input are sent to same output port if the input is scheduled to transmit data to that output port in our model (The model is shown in Figure 2.4.). That is the critical point which provide us intuition to find a simple, near optimum, nonomniscient and online policy in the next section.

Based on our tetris model, we propose an omniscient, optimum scheduling policy, *Uniformizing Policy (UP)* for all admissible EH process. Considering nonuniform

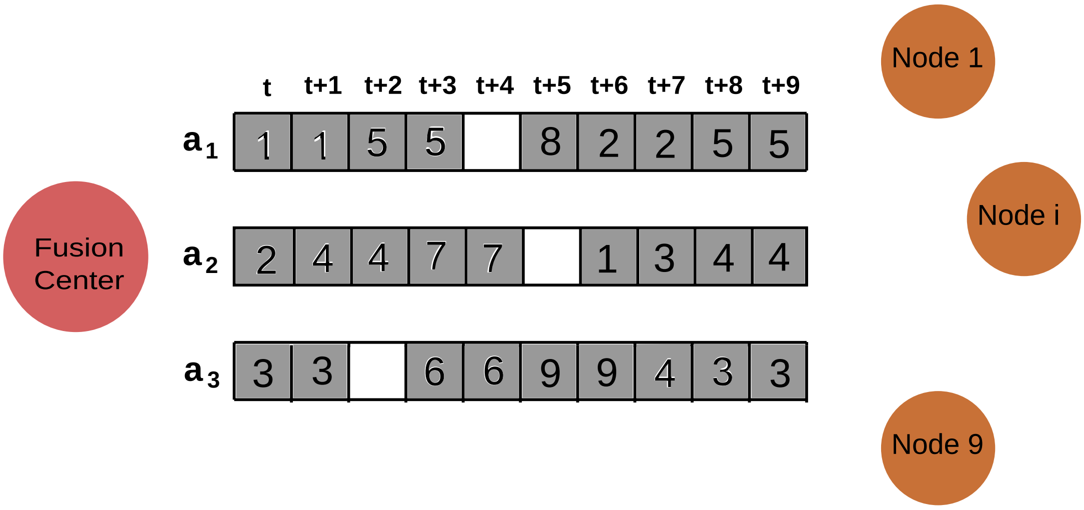

Figure 2.4: An example scheduling table kept by the fusion center (FC) for $m = 9$, $k = 3$ during the interval $[t, t + 9]$. Dark colored TSs represent busy slots labeled by node ID using the slot, and the white ones represent idle ones. 3 of 30 slots are idle even under an optimum omniscient policy (UP) ($D^{(t)} = 0.9$). UP allocates the slots in order to leave the least number of slots idle: resembling a Tetris game. Note that each node can use only one channel at a time slot.

EH processes at all m nodes, UP uses the empty output ports to schedule the nodes in each TS. If there are some nodes which are scheduled in previous TS but does not have enough energy to transmit data in current TS, UP schedules new nodes. By scheduling new nodes, UP prevents output ports to remain idle and balances the load in each of k output ports. Hence, UP *uniformizes* the nonuniform EH processes of m nodes such that all packets are scheduled in each of k output port almost equally. By this almost equal partition of the packets sent by nodes, UP makes *uniformization* and provides 100% throughput under all admissible uniform and non-uniform EH processes.

The operation of UP is summarized below:

1. Order the nodes arbitrarily and use this order throughout problem horizon.

2. Schedule the first k nodes in the ordering that have enough energy to transmit a packet.

3. At the beginning of the next TS, check the k nodes that were just scheduled. Replace those without energy to transmit a packet with new ones, respecting the initial order. If less than k nodes with enough energy can be found, schedule those nodes only.

4. Continue in a cyclic way.

2.5 A Near-Optimal Online Policy

2.5.1 Uniformizing Random Ordering Policy (UROP)

Assuming that all energy harvesting process is known in previous section, an optimal omniscient solution is proposed for the energy harvesting scheduling problem. However, the battery states of the nodes are not known in the exact energy harvesting scheduling problem. Therefore, we propose a near-optimal online scheduling policy by using Lemma 1 (stated below) for all admissible energy harvesting processes $D^{(t)} < 1$.

$D^{(t)} < 1$ means that there exists always idle TSs over a problem horizon even if an optimal policy is applied. Lemma 1 states that if a scheduled node cannot transmit data in TS t, an 100% efficient policy is applied to that node until TS t. Therefore, we propose Uniformizing Random Ordering Policy (UROP) which uses the idle TSs to determine battery state of the scheduled nodes (whether a node has enough energy to transmit data or not).

Since energy harvesting processes are completely unpredictable for some energy harvesting sources [1, 3], UROP orders the nodes randomly before starting to schedule them.

UROP operates as below:

1. Schedule the first k nodes according to initially determined random order.

2. If a scheduled node transmits data to FC in that TS, then it continues to be sched-

uled.

3. Otherwise, FC starts to schedule the nodes which are on the top in the remaining list of nodes according to initial cyclic random order replacing previously scheduled nodes.

4. Continue in a cyclic way.

To schedule all nodes once, the fusion center uses m energy harvesting nodes to complete a period (all nodes are scheduled once). As $D \to 1$, the ratio of idle TSs over whole problem horizon decreases. As $D \to 0$, the ratio of idle TSs over whole problem horizon increases. The algorithm, UROP, whose operation is described above is hence an adaptive and near optimal policy. In this section, the efficiency of UROP is investigated by assuming that no node behaves as *an elephant node* (defined below). In Section 2.6, it is shown that UROP is asymptotically optimal over infinite horizon for all admissible energy harvesting processes.

Definition 1 (Elephant node): If the node who is next in line for selection by the FC happens to be already transmitting continuously since its last selection, the node is said to behave as an *elephant node* between the previous selection (scheduling) time and the current selection time. In this case, FC selects the next node to schedule for one of the empty channels and the elephant node continues to transmit on its assigned channel as before. Figure 2.5 represents an elephant node.

2.5.2 Efficiency of UROP in Finite Horizon Case

In this part, the efficiency of UROP is investigated in a quite general case of energy harvesting process. First, several lemmas are stated and proved. Then, the lemmas will be used to prove Theorem 4 and Theorem 5.

Lemma 1. (Partial Optimality) *If $B_i(t) < 1$ for a sensor s_i at the end of TS t, an optimal policy has been applied for node s_i and efficiency of the scheduling policy is 100% for node s_i up to TS t.*

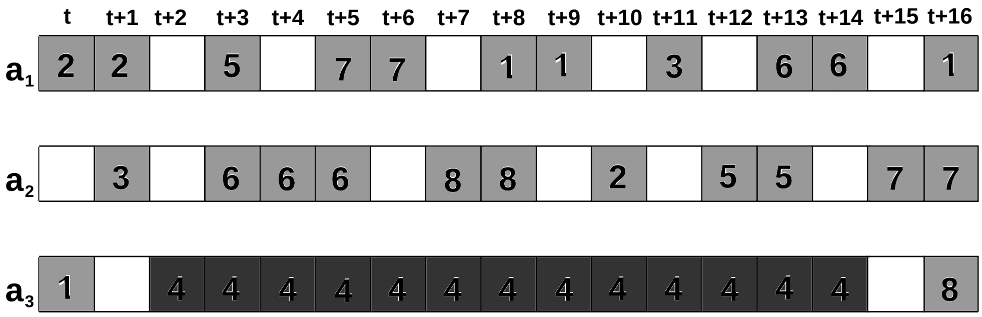

Figure 2.5: An example scheduling table kept by the fusion center (FC) for $m = 8$,$k = 3$ during the interval $[t, t + 16]$. Dark colored TSs represent busy slots labeled by node ID, and the white ones represent idle ones. Node 4 behaves as an elephant node since it does not idle within a round continues transmission from $t + 2$, until $t + 14$. Note that it has already transmitted data in $t + 12$ when it is next supposed to be scheduled.

Proof. The number of data packets which could be sent by node s_i with the remaining energy in TS t is $\lfloor B_i(t) \rfloor$. If s_i has transmitted all data packets which could be sent with $E_i(t)$ by TS t ($\lfloor B_i(t) \rfloor = 0$ or equivalently $B_i(t) < 1$), and efficiency is 100% for node s_i until TS t. □

Remark 4. *If $E_i(t)$ is the total amount of harvested energy in sensor s_i until TS t and $V_i^*(t)$ is the number of packets (throughput) which could be sent by sensor s_i until TS t under π^*, $V_i^*(t) = \lfloor E_i(t) \rfloor$. Recall that $\pi^* = \pi^{fe}$ for $0 \leq D \leq 1$.*

Recall that UROP benefits from idle time slots to schedule the nodes efficiently. Now, we will define some new parameters related to idle time slots and these will be used in Lemma 2, Lemma 3, Lemma 4 and Theorem 4. $A_{idle}(j, l)$ is the pair of the j^{th} channel of the FC and l^{th} idle TS for the j^{th} channel. $A_{idle}(j, l)$ occurs in TS γ_l^j. In this TS γ_l^j, FC drops a node using j^{th} channel and start to schedule another node in same channel. In the idle TSs, FC drops some of the k nodes and starts to schedule other nodes in their place. T_I is the set which consists of all pairs $A_{idle}(j, l)$. Figure 2.6 represents the transmission channel-idle time slot pairs in an example scheduling table.

Let's denote by $\xi_i^{(f)}$ and $\xi_i^{(f-1)}$ the idle TSs when FC starts to schedule node s_i for the last time and for the second last time, respectively. F_1 and F_2 are the set of all pairs $A_{idle}(u, v)$ such that $\gamma_v^u = \xi_i^{(f)}$ for a $s_i \in S$ and the set of all pairs $A_{idle}(u, v)$ such that $\gamma_v^u = \xi_i^{(f-1)}$ for a $s_i \in S$. As there are m nodes, $|F_1| = |F_2| = m$. G_1 is the set of all pairs $A_{idle}(p, q)$ such that $\gamma_q^p \neq \xi_i^{(f)}$ for $s_i \in S$. Moreover, G_2 is the set of

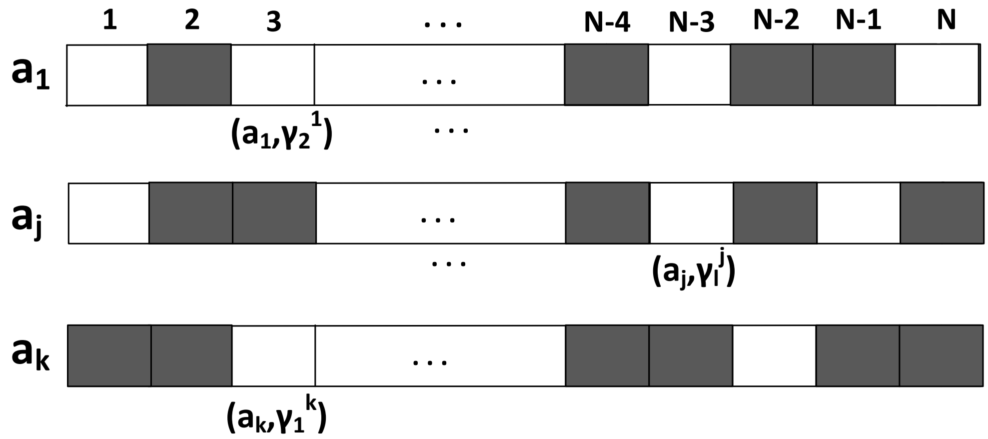

Figure 2.6: An example scheduling table kept by the fusion center (FC) for all k channels over problem horizon $T = N$ time slots. Dark colored TSs represent busy time slots (the time slot in which FC could receive a data packet from the scheduled (selected) user.), and the white colored TSs represent idle time slots (the slot in which FC could not receive a data packet from the scheduled (selected) user.)

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all pairs $A_{idle}(p,q)$ such that $\gamma_q^p \neq \xi_i^{(f)}$ and $\gamma_q^p \neq \xi_i^{(f-1)}$ for $s_i \in S$. In other words, $G_1 = T_I - F_1$ and $G_2 = T_I - (F_1 \cup F_2)$.

Lemma 2. *If* $A_{idle}(u,v) \in (F_1 \cup F_2)$*,*

i) There does not exist such a pair $A_{idle}(p,q) \in G_1$ *that* $\gamma_q^p > \gamma_v^u$ *for some* $A_{idle}(u,v) \in F_1$.

ii) There does not exist such a pair $A_{idle}(p,q) \in G_2$ *that* $\gamma_q^p > \gamma_v^u$ *for some* $A_{idle}(u,v) \in (F_1 \cup F_2)$.

Proof. ***Part i)*** Assume that there is such a pair $A_{idle}(p,q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u,v) \in F_1$. Since $\gamma_q^p \neq \xi_i^{(f)}$ $\forall s_i \in S$, the node s_r which is selected by the FC in TS γ_q^p will be selected by the FC at least once more ($\gamma_q^p < \xi_r^{(f)}$). According to UROP, a node s_r which is selected in TS T_1 cannot be selected by the FC in TS T_2 unless $\forall s_i \in S - s_r$ are selected in the time interval $[T_1, T_2]$. Since $\gamma_q^p > \gamma_v^u = \xi_i^{(f)}$ for some s_i, these nodes cannot be selected by the FC in the time interval $[\gamma_q^p, \xi_j^{(f)}]$. Therefore, there does not exist such a pair $A_{idle}(p,q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u,v) \in F_1$.

Part ii) $G_1 = T_I - F_1$ and $G_2 = T_I - (F_1 \cup F_2) = (T_I - F_1) - F_2$. Replacing $T_I - F_1$ and F_2 with T_I and F_1 , respectively, in Part i, we can said that there exists no $A_{idle}(p,q) \in G_2$ such that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u,v) \in F_2$. By Part i, there exists no $A_{idle}(p,q) \in F_2$ such that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u,v) \in F_1$. Therefore, there does not exist such a pair $A_{idle}(p,q) \in G_2$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u,v) \in (F_1 \cup F_2)$.

□

Lemma 3. *If $\zeta_i^{(f)}$ is the idle TS when FC stops to schedule node s_i for the last time and L is the set of the idle TSs $\zeta_i^{(f)}$, $L \subset (F_1 \cup F_2)$.*

Proof. Recall that $(F_1 \cup F_2) \subseteq T_I$. It can be said that FC starts to schedule a node iff it leaves (stops to schedule) another node. $(F_1 \cup F_2)$ includes two consecutive time (the last and second last time) when FC starts to schedule a node for all nodes. Assume that FC schedules a node s_i. Unless FC stops to schedule the node s_i, it cannot start to schedule the node s_i again. Therefore, $(F_1 \cup F_2)$ includes at least one departure time for each node. Since $(F_1 \cup F_2)$ includes the latest $2m$ idle TSs and at least one departure time for each node, $\zeta_i^{(f)} \in (F_1 \cup F_2)$ for $\forall s_i$. Hence, $L \subset (F_1 \cup F_2)$. □

Now, we state Lemma 4 and Lemma 5 which will help us find the worst case and expected efficiency bounds of UROP.

Lemma 4. *Assume that $S_k \subset S$ is the set of k nodes which are scheduled last by the FC in the problem horizon T, each node $s_i \in S_k$ transmits $\left(T - \xi_i^{(f)}\right)$ data packets in the time interval $\left(\xi_i^{(f)}, T\right]$.*

Proof. If $S_k \subset S$ is the set of last k nodes which are scheduled by the FC in problem horizon T, there will be no other selection so no idle TS until deadline of problem horizon T. Since each node can transmit at most one packet in each TS, each node $s_i \in S_k$ transmits $\left(T - \xi_i^{(f)}\right)$ data packets in the interval $\left(\xi_i^{(f)}, T\right]$. □

Lemma 5. *Assume that $T_1, T_2 \in (0,T]$ and $T_1 < T_2$. If s_i is not scheduled in interval $(T_1, T_2]$, $V_i^*(T_1) \leq V_i^*(T_2)$ where $V_i^*(t)$ is the number of packets (throughput) which could be sent by sensor s_i until TS t under optimal policy π^*.*

Proof. By Remark 4, $V_i^*(T_1)$ and $V_i^*(T_2)$ can be written as

$$\begin{aligned} V_i^*(T_1) &= \lfloor E_i(T_1) \rfloor \\ V_i^*(T_2) &= \lfloor E_i(T_2) \rfloor \end{aligned} \tag{2.16}$$

From Remark 3 (No battery leakage), the inequality below is written for all $s_i \in S$,

$$\begin{aligned} E_i(T_1) &\leq E_i(T_2) \\ \lfloor E_i(T_1) \rfloor + \{E_i(T_1)\} &\leq \lfloor E_i(T_2) \rfloor + \{E_i(T_2)\}\,. \end{aligned} \tag{2.17}$$

By substituting (2.16) into (2.17),

$$V_i^*(T_1) + \{E_i(T_1)\} \leq V_i^*(T_2) + \{E_i(T_2)\} \tag{2.18}$$

By using (2.18), it is shown that $V_i^*(T_1) \leq V_i^*(T_2)$ is possible; however, $V_i^*(T_1) > V_i^*(T_2)$ is not possible. There are three cases as below:

i) $V_i^*(T_1) = V_i^*(T_2) \Rightarrow \{E_i(T_1)\} \leq \{E_i(T_2)\}$ as $E_i(T_1) \leq E_i(T_2)$.

ii) $V_i^*(T_1) < V_i^*(T_2) \Rightarrow E_i(T_1) < E_i(T_2)$ as $0 \leq \{E_i(T_1)\}, \{E_i(T_2)\} < 1$ and $V_i^*(T_1), V_i^*(T_2) \in Z$.

iii) $V_i^*(T_1) > V_i^*(T_2) \Rightarrow E_i(T_1) > E_i(T_2)$ as $0 \leq \{E_i(T_1)\}, \{E_i(T_2)\} < 1$ and $V_i^*(T_1), V_i^*(T_2) \in Z$. This situation contradicts with (2.18).

Hence, $E_i(T_1) \leq E_i(T_2)\ \forall s_i \in S$ and $V_i^*(T_1) \leq V_i^*(T_2)\ \forall s_i \in S$. □

By Theorem 4, the worst case efficiency of UROP is analysed for quite general energy harvesting process. For this analysis, we consider the last $2m$ idle time slots and previous lemmas.

Theorem 4. (Efficiency Bounds of UROP) *Last departure time of the node s_j which satisfies $\zeta_j^{(f)} \leq \zeta_i^{(f)}\ \forall s_i \in S - \{s_j\}$ is denoted by $\zeta_j^{(f)} = T_0$. In problem horizon T, the efficiency of UROP is bounded as*

$$1 - \frac{k(T - T_0)}{\sum_{i=1}^{m} V_i^*(T)} \leq \eta_{UROP} \leq 1, \tag{2.19}$$

where $V_i^*(T)$ is the number of packets (throughput) which could be transmitted by node s_i until TS t (included) under optimal policy π^*.

Proof. $V_i(t)$ is the number of packets (throughput) which have been sent by sensor s_i until TS t. $V_i^{(f)}$ is the number of packets (throughput) which could be transmitted by sensor s_i in the interval $\left[\zeta_i^{(f)}, T\right]$. In fact, $V_i^{(f)} = V_i^{\left(\zeta_i^{(f)}\right)}$. We use $V_i^{(f)}$ for simplicity of notation.

$V_i^* = V_i\left(\zeta_i^{(f)}\right) + V_i^{(f)}$ can be written for $\forall s_i \in S$. By Lemma 1, $V_i\left(\zeta_i^{(f)}\right)$ is the throughput in TS $\zeta_i^{(f)}$ until when an optimum policy π^* is applied to node s_i. Therefore, $V_i^{(f)}$ is the only factor for throughput loss of node $s_i \in S - S_k$. For $s_i \in S_k$, the throughput loss by $V_i^{(f)}$ decreases by $\left(T - \xi_i^{(f)}\right)$ by Lemma 4.

Hence, the efficiency of UROP in problem horizon T can be written as

$$\begin{aligned} \eta_{UROP} &= \frac{\sum_{i=1}^{m} V_i\left(\zeta_i^{(f)}\right) + \sum_{s_i \in S_k}\left(T - \xi_i^{(f)}\right)}{\sum_{i=1}^{m} V_i^*(T)} \\ &= \frac{\sum_{i=1}^{m} V_i\left(\zeta_i^{(f)}\right) + \sum_{s_i \in S_k}\left(T - \xi_i^{(f)}\right)}{\sum_{i=1}^{m} V_i\left(\zeta_i^{(f)}\right) + \sum_{i=1}^{m} V_i^{(f)}}. \end{aligned} \tag{2.20}$$

By using Lemma 4, the term $\sum_{s_i \in S_k}\left(T - \xi_i^{(f)}\right)$ is added to the numerator in (2.20) since $s_i \in S_k$ are not considered to be left by the fusion center in TS T. It is assumed that $\zeta_i^{(f)} < T \; \forall s_i \in S_k$.

By (2.20), we can upper bound η_{UROP}.

i. Upper bound for efficiency of UROP

Efficiency of a policy cannot be more than 100% ($\eta \leq 1$). From (2.20), $\eta_{UROP} = 1$ only if

$$\sum_{s_i \in S_k}\left(T - \xi_i^{(f)}\right) = \sum_{i=1}^{m} V_i^{(f)} \tag{2.21}$$

is satisfied.

(2.21) comes true only if

$$V_i^{(f)} = \begin{cases} 0 & \text{if } s_i \in S - S_k \\ \left(T - \xi_i^{(f)}\right) & \text{if } s_i \in S_k \end{cases} \tag{2.22}$$

is satisfied.

If nodes harvest energy such that (2.22) is satisfied, $\eta_{UROP} = 1$. Therefore, upper bound of η_{UROP} is 100%, namely, $\eta_{UROP} \leq 1$.

By (2.20), let's find the lower bound of η_{UROP}.

ii. Lower bound for efficiency of UROP

The inequalities below can be written for a long problem horizon T.

To find the lower bound of η_{UROP}, we will define a loss function V_{loss} in (2.23) according to (2.20) and maximize V_{loss} by considering the worst case,

$$V_{loss} = \sum_{i=1}^{m} V_i^{(f)} - \sum_{s_i \in S_k} \left(T - \xi_i^{(f)}\right). \tag{2.23}$$

In (2.23), V_{loss} can be maximized by minimizing $\sum_{s_i \in S_k} \left(T - \xi_i^{(f)}\right)$. Since $\xi_i^{(f)} \leq T$ $\forall s_i \in S_k$,$\sum_{s_i \in S_k} \left(T - \xi_i^{(f)}\right) \geq 0$. This occurs only if $\xi_i^{(f)} = T \; \forall s_i \in S_k$.

By Equation (2.5),

$$V_i^{(f)} = \left\lfloor B_i\left(\zeta_i^{(f)}\right) + \sum_{t=\zeta_i^{(f)}+1}^{T} E_i^h(t) \right\rfloor \tag{2.24}$$

Since $\sum_{s_i \in S_k} \left(T - \xi_i^{(f)}\right) \geq 0$, V_{loss} is maximized if $\sum_{s_i \in S_k} \left(T - \xi_i^{(f)}\right) = 0$. Then (2.23) converts into

$$V_{loss} = \sum_{s_i \in S} V_i^{(f)}. \tag{2.25}$$

We denote by $S_k^{(lf)}$ the set of k nodes which satisfy $\zeta_i^{(f)} \leq \zeta_j^{(f)}$ $\forall s_i \in S_k^{(lf)}$ and $s_j \in S - S_k^{(lf)}$. V_{loss} can be written as

$$\begin{aligned} V_{loss} &= \sum_{s_i \in S} V_i^{(f)} \\ &= \sum_{s_i \in S_k^{(lf)}} V_i^{(f)} + \sum_{s_i \in S - S_k^{(lf)}} V_i^{(f)}. \end{aligned} \tag{2.26}$$

While maximizing V_{loss}, (2.27) must be considered for all nodes because the efficiency of the scheduling policies are analyzed under the assumption that the scheduling capacity of the communication system is not exceeded according to Theorem 1

(Scheduling Capacity Theorem).

$$V^{(\zeta_i^{(f)})} \leq k(T - \zeta_i^{(f)}), \forall s_i \in S \tag{2.27}$$

From (2.27), FC can accumulate maximum k data packets. This scheduling capacity can be achieved if there is an energy harvesting process such that k out of m nodes can transmit one data packet in each TS and the remaining nodes can transmit no packet.

In this case, V_{loss} becomes maximum when each node $s_i \in S_k^{(lf)}$ harvests 1 unit energy and the other nodes $s_i \in S - S_k^{(lf)}$ harvest almost no energy in each TS.It can be shown as below in (2.28). By putting (2.25) in (2.26), (2.28) can be written as

$$V_{loss} = \sum_{s_i \in S_k^{(lf)}} \left\lfloor B_i\left(\zeta_i^{(f)}\right) + \sum_{t=\zeta_i^{(f)}+1}^{T} E_i^h(t) \right\rfloor + \sum_{s_i \in S - S_k^{(lf)}} \left\lfloor B_i\left(\zeta_i^{(f)}\right) + \sum_{t=\zeta_i^{(f)}+1}^{T} E_i^h(t) \right\rfloor . \tag{2.28}$$

Last departure time of the node $s_j = s_0$ which satisfies $\zeta_i^{(f)} \leq \zeta_j^{(f)}$ $\forall s_i \in S - \{s_j\}$ is denoted by $\zeta_j^{(f)} = T_0$. By using Lemma 5 and (2.28), we write an upper bound for V_{loss} as

$$V_{loss}^{'} = \sum_{s_i \in S_k^{(lf)}} \left\lfloor B_i(T_0) + \sum_{t=T_0+1}^{T} E_i^h(t) \right\rfloor + \sum_{s_i \in S - S_k^{(lf)}} \left\lfloor B_i(T_0) + \sum_{t=T_0+1}^{T} E_i^h(t) \right\rfloor \geq V_{loss}. \tag{2.29}$$

To maximize V_{loss}, maximizing $V_{loss}^{'}$ will be enough so take $V_{loss} = V_{loss}^{'}$. To satisfy this equality, we assume that $T_i = T_0$ for $s_i \in S_k^{(lf)}$. By using (2.27),

$$V^{(T_0)} = \sum_{s_i \in S} V_i^{(T_0)} \leq k(T - T_0) \tag{2.30}$$

can be written. Hence,

$$V^{(T_0)} = \sum_{s_i \in S_k^{(lf)}} V_i^{(T_0)} + \sum_{s_i \in S - S_k^{(lf)}} V_i^{(T_0)} \leq k(T - T_0) \tag{2.31}$$

$$V^{(T_0)} = \sum_{s_i \in S_k^{(lf)}} \left[V_i^{(T_0)} - V_i^{(f)} + V_i^{(f)}\right]$$
$$+ \sum_{s_i \in S - S_k^{(lf)}} \left[V_i^{(T_0)} - V_i^{(f)} + V_i^{(f)}\right] \leq k(T - T_0) \tag{2.32}$$

Since $T_0 = \zeta_i^{(f)}\ \forall s_i \in S_k^{(lf)}$,

$$V_i^{(T_0)} - V_i^{(f)} = 0, \forall s_i \in S_k^{(lf)} \tag{2.33}$$

Hence, the inequality (2.32) converts into

$$V^{(T_0)} = \sum_{s_i \in S_k^{(lf)}} V_i^{(f)} + \sum_{s_i \in S - S_k^{(lf)}} \left[V_i^{(T_0)} - V_i^{(f)} \right] + \sum_{s_i \in S - S_k^{(lf)}} V_i^{(f)} \leq k(T - T_0). \tag{2.34}$$

By using (2.26) and (2.29) for V'_{loss} in (2.34), one obtains

$$V^{(T_0)} = V'_{loss} + \sum_{s_i \in S - S_k^{(lf)}} \left[V_i^{(T_0)} - V_i^{(f)} \right] \leq k(T - T_0). \tag{2.35}$$

Since $T_0 \leq \zeta_i^{(f)}\ \forall s_i \in S - S_k^{(lf)}$, by Lemma 5,

$$V_i^*(T_0) \leq V_i^* \left(\zeta_i^{(f)} \right), \forall s_i \in S - S_k^{(lf)}, \tag{2.36}$$

$$V_i^{tot}(T) - V_i^*(T_0) \geq V_i^*(T) - V_i^* \left(\zeta_i^{(f)} \right), \forall s_i \in S - S_k^{(lf)}, \tag{2.37}$$

$$V_i^{(T_0)} \geq V_i^{(f)}, \forall s_i \in S - S_k^{(lf)}. \tag{2.38}$$

By (2.35), to maximize V'_{loss}, $\sum_{s_i \in S - S_k^{(lf)}} \left[V_i^{(T_0)} - V_i^{(f)} \right]$ should be minimized. By (2.38),

$$V_i^{(T_0)} - V_i^{(f)} \geq 0. \tag{2.39}$$

If $V_i^{(T_0)} - V_i^{(f)} = 0$, (2.35) converts into

$$V^{(T_0)} = V'_{loss} \leq k(T - T_0). \tag{2.40}$$

By using (2.29) and (2.40),

$$V_{loss} \leq k(T - T_0) \tag{2.41}$$

By (2.20), efficiency of UROP can be written as below:

$$\eta_{UROP} = 1 - \frac{\sum_{i=1}^{m} V_i^{(f)} - \sum_{s_i \in S_k} \left(T - \xi_i^{(f)} \right)}{\sum_{i=1}^{m} V_i \left(\zeta_i^{(f)} \right) + \sum_{i=1}^{m} V_i^{(f)}} \tag{2.42}$$

Recall that $\sum_{s_i \in S_k} \left(T - \xi_i^{(f)} \right) \geq 0$. By using (2.42) and (2.23), (2.43) can be derived,

$$\begin{aligned} \eta_{UROP} &\geq 1 - \frac{V_{loss}}{\sum_{i=1}^{m} V_i^*(T)} \\ &\geq 1 - \frac{\sum_{i=1}^{m} V_i^{(f)}}{\sum_{i=1}^{m} V_i^*(T)} \\ &\geq 1 - \frac{k(T - T_0)}{\sum_{i=1}^{m} V_i^*(T)}. \end{aligned} \tag{2.43}$$

Hence, Theorem 4 is proven and the worst case efficiency bounds of UROP are found as

$$1 - \frac{k(T - T_0)}{\sum_{i=1}^{m} V_i^*(T)} \leq \eta_{UROP} \leq 1. \tag{2.44}$$

When elephant nodes are present: Regular nodes scheduled by UROP, give rise to at least one idle TS in a period (frame). However, this does not hold for elephant nodes. If there are nodes that behave as elephant nodes in a period, these do leave any TS empty in that period. Consequently, for these nodes UROP behaves as UP, which does not give up TS to determine the battery states of nodes. Hence, efficiency bounds in Theorem 4 are also valid in case of elephant nodes. □

Considering *the worst case* in Theorem 4, we found lower and upper bounds for the efficiency of UROP in terms of parameters. k is known and $V_i^*(T)$ can be found for each node s_i by Remark 4. However, the parameter T_0 cannot be determined unless all details of scheduling in problem horizon is known. Due to the incertainty of T_0, Theorem 4 does not give sufficient information about efficiency of UROP. As we mentioned in Section 2.1, expected average reward is a suitable performance measure for the EH scheduling policy over finite or infinite horizon [51]. Considering T_0 (and the other departure times of nodes) as ergodic processes depending on EH processes, we take expectation of the bounds of UROP in Theorem 5. Hence, the bounds of UROP can be determined in expected manner.

Theorem 5. (Expected Efficiency Bounds of UROP) *For $0 < D < 1$, expected efficiency of UROP is bounded as*

$$1 - \frac{2m}{(1-D)DTk} \leq E\left\{\eta_{UROP}\right\} \leq 1, \tag{2.45}$$

where D, T, m, and k are density, problem horizon length, number of the nodes, number of the orthogonal channels of the FC, respectively.

Proof. By Theorem 4, the efficiency of UROP can be written as

$$1 - \frac{k(T-T_0)}{\sum_{i=1}^{m} V_i^*(T)} \quad \leq \quad \eta_{UROP} \leq 1 \tag{2.46}$$

$$1 - \frac{k(T-T_0)}{V^*(T)} \quad \leq \quad \eta_{UROP} \leq 1. \tag{2.47}$$

Recall that the efficiency of UROP is analyzed for the systems satisfying $D^{(t)} < 1$ $\forall t < T$. Remember that $\pi^* = \pi^{fe}$ if $D^{(t)} < 1$ $\forall t < T$. Therefore, $V^*(T) = V^{fe}(T) = DTk$ $D^{(t)} < 1$. In this analysis, a scenario is assumed and EH process is determined but not known by the FC. Therefore, D, T, k and so $V^*(T)$ are determined.

In the following inequality, an expectation is taken over $(T - T_0)$ which depends on the scheduling policy of the FC, not on the parameters D, T, k and so $V^*(T)$. Therefore, $E\left\{V^*(T)\right\} = V^*(T)$.

$$1 - E\left\{\frac{k(T-T_0)}{V^*(T)}\right\} \quad \leq \quad E\left\{\eta_{UROP}\right\} \leq 1 \tag{2.48}$$

$$1 - kE\left\{\frac{(T-T_0)}{V^*(T)}\right\} \quad \leq \quad E\left\{\eta_{UROP}\right\} \leq 1 \tag{2.49}$$

$$1 - \frac{kE\left\{(T-T_0)\right\}}{V^*(T)} \quad \leq \quad E\left\{\eta_{UROP}\right\} \leq 1 \tag{2.50}$$

We denote by $\tau_{ar,i}$ and $\tau_{dep,i}$, elapsed time between two consecutive selection of same sensor s_i and elapsed time between two consecutive departure of same sensor s_i. For long problem horizons, $E\left\{\tau_{ar,i}\right\}$=$E\left\{\tau_{dep,i}\right\}$ $\forall i$. By Lemma 3, $L \subset (F_1 \cup F_2)$. By

Lemma 2, none of nodes $s_i \in S - S_k$ can be selected (started to schedule) more than twice by the FC in the time interval $(T_0, T]$; therefore, 2.51 can be written as

$$E\left\{T - T_0\right\} < 2E\left\{\tau_{ar}\right\}. \tag{2.51}$$

None of the nodes $s_i \in S_k$ can be left (stopped to schedule) more than once by the FC in interval $\left(\zeta_i^{(f)}, T\right]$; therefore, one obtains

$$E\left\{T - \zeta_i^{(f)}\right\} < 2E\left\{\tau_{dep}\right\} \tag{2.52}$$

Hence, (2.50) is converted into

$$1 - \frac{2kE\left\{\tau_{ar}\right\}}{V(T)} \leq E\left\{\eta_{UROP}\right\} \leq 1. \tag{2.53}$$

Let D and k denote, the density during problem horizon T and the number of orthogonal channels of the FC, respectively. By definition of D, $V^*(T) = DTk$. Hence,

$$D = \frac{kE\left\{\tau_{ar}\right\} - m}{kE\left\{\tau_{ar}\right\}} \tag{2.54}$$

$$E\left\{\tau_{ar}\right\} = \frac{m}{k(1-D)} \tag{2.55}$$

By using (2.53) and (2.55), (2.56) is written as

$$\begin{aligned} 1 - \frac{2k\left(\frac{m}{k(1-D)}\right)}{DTk} &< E\left\{\eta_{UROP}\right\} \leq 1 \\ 1 - \frac{2m}{(1-D)\,DTk} &< E\left\{\eta_{UROP}\right\} \leq 1. \end{aligned} \tag{2.56}$$

□

Note: As $D = 0$ means no harvested energy in the whole communication network, it is trivial case and not considered in our calculations. $D = 1$ means that there is no idle TS if the fusion center apply the 100% efficient policy (π^{fe}). However, UROP benefits from idle TSs to schedule the sensors as mentioned in Section 2.5. From Theorem 1, no π^{fe} exists for $D > 1$. Therefore, we investigate $0 < D < 1$.

As you may notice that the expected lower bound becomes negative for the case $m \geq \frac{(1-D)DTk}{2}$. However, we know that expected efficiency is nonnegative.

2.6 Extension to the Infinite-Horizon Case

As in (2.13) and (2.14), efficiency of RR-based policies (also MP in [47, 49]) depend on not only sensor densities D and $D^{(t)}$ but also partial sensor densities D_i and $D_i^{(t)}$ and cannot improve as problem horizon goes to infinity. Also, it is proved that batteries of nodes for which $D_i > 1$ and $D_i^{(t)} > 1$ will overflow over infinite horizon. However, efficiency of UROP in finite horizon case improves and converges to 1 (100% efficiency) for $0 < D < 1$ as the problem horizon increase and goes to infinity. By Theorem 5 and the relation $V^*(T) = DTk$, efficiency of UROP is, for $0 < D < 1$,

$$\lim_{T\to\infty}\left(1 - \frac{2m}{(1-D)\,DTk}\right) < \lim_{T\to\infty} E\left\{\eta_{UROP}\right\} \leq 1 \tag{2.57}$$

Hence, $\lim_{T\to\infty} E\left\{\eta_{UROP}\right\} = 1$, which shows that UROP is *asymptotically optimal* in the infinite horizon for general energy harvesting processes.

2.7 Numerical Results

In this section, efficiency achieved by RR and UROP policies are compared for independent (Poisson) and correlated (Markovian) energy harvesting processes under high density (D=0.975) and low density (D=0.2) energy harvesting processes first. RR and UROP are then compared under a fairness criterion for independent (Poisson) and correlated (Markovian) energy harvesting processes under high density (D=0.975). We focus on the region $D^{(t)} \leq 1$ so $\eta_* = \eta_{fe} = 1$.

To begin with, we compare efficiencies of these policies under both infinite and finite battery assumption for four cases. To create a realistic scenario, we take $m = 100$,

Table 2.1: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery $B_i = 50$ assumptions for uniform independent low density energy arrivals ($D_i = D = 0.2\ \forall i$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

Efficiency	Infinite battery	Finite battery
Efficiency of Round-Robin ($\frac{m}{k} \in Z$)	99.83	99.83
Efficiency of UROP ($\frac{m}{k} \in Z$)	99.58	99.58
Efficiency of UROP ($\frac{m}{k} \notin Z$)	99.41	99.41

Table 2.2: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery $B_i = 50$ assumptions for uniform independent high density energy arrivals ($D_i = D = 0.975\ \forall i$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

Efficiency	Infinite battery	Finite battery
Efficiency of Round-Robin ($\frac{m}{k} \in Z$)	99.64	99.64
Efficiency of UROP ($\frac{m}{k} \in Z$)	99.45	99.45
Efficiency of UROP ($\frac{m}{k} \notin Z$)	99.37	99.37

$k = 10$, $T = 2000$ for both policies. We also investigate the efficiency of UROP by taking $m = 103$ and $k = 10$. Note that we compare efficiency of UROP with an arbitrary RR since $\eta_{RR} \cong \eta_{MP}$ for long problem horizons (Theorem 3). In this section, we investigate the efficiencies of both policies under both an uniform and nonuniform EH processes. First, uniform, low and high density independent traffic are formed by taking $D_i = 0.2$ for all nodes. Under these EH processes, both UROP and RR achieves nearly 100% efficiency as shown in Table 2.1 and Table 2.2. Then, uniform, low and high density Markovian traffic are formed by taking $D_i = 0.975$ for all nodes. Under these EH processes, both UROP and RR achieves nearly 100% efficiency as shown in Table 2.3 and Table 2.4. Secondly, nonuniform, high density traffic is formed by taking $D_i = 3$ for 25 of the nodes and $D_i = 0.3$ for the remaining ones (Recall that D_i is partial density of sensor s_i as defined in Section 2.2). Moreover, low density, nonuniform traffic is formed by taking $D_i = 2.1$ for 5 nodes and $D_i = 0.1$ for the remaining nodes. Independent EH processes are modelled as Poisson. Markov EH process are modelled by a state space $M_i = \{0, 1, 2\}, \forall s_i$ and a 3×3 transition matrix P such that $P_{ii} = 0.9\ \forall i$ and $P_{ij} = 0.05$ for $i \neq j$. The harvested energy for node s_i in TS t, $E_i^h(t)$, is determined by M_i such that $E_i^h(t) = D_i \times M_i(t)$ (Note that each transmission requires unit energy.).

Table 2.3: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery $B_i = 50$ assumptions for uniform Markovian low density energy arrivals ($D_i = D = 0.2\ \forall i$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

Efficiency	Infinite battery	Finite battery
Efficiency of Round-Robin ($\frac{m}{k} \in Z$)	99.79	99.79
Efficiency of UROP ($\frac{m}{k} \in Z$)	99.67	99.67
Efficiency of UROP ($\frac{m}{k} \notin Z$)	99.61	99.61

Table 2.4: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery $B_i = 50$ assumptions for uniform Markovian high density energy arrivals ($D_i = D = 0.975\ \forall i$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

Efficiency	Infinite battery	Finite battery
Efficiency of Round-Robin ($\frac{m}{k} \in Z$)	99.63	99.63
Efficiency of UROP ($\frac{m}{k} \in Z$)	99.51	99.51
Efficiency of UROP ($\frac{m}{k} \notin Z$)	99.47	99.47

In Figure 2.7 (Low density, independent energy harvesting process), UROP has nearly 100% efficiency whereas RR has approximately 80% efficiency. In Figure 2.8 (High density, independent energy harvesting process), UROP continues to attain nearly 100% efficiency whereas the efficiency of RR has dropped below 50%. This is an expected result since Theorem 2 states that as the number of nodes s.t. $D_i > 1$ increases, efficiency of RR decreases. By Remark 2, efficiency of RR is expected to be $\eta_{RR} = 48.7\%$ and $\eta_{RR} = 72.5\%$ for the low and high density energy harvesting process, respectively.

In Figure 2.9(Low density, Markov energy harvesting process), UROP has nearly 100% efficiency whereas RR has nearly 70% efficiency. In Figure 2.10 (High density, Markov energy harvesting process), UROP has nearly 100% efficiency whereas RR has nearly 50% efficiency. When the energy harvesting process has memory, we observe similar results, except that the performance of RR drops further. The efficiency of UROP is more robust to memory in harvest process, as compared to RR (Note that $P_{ii} = 0.9, \forall i$).

Considering all four figures, we wish to make three additional remarks. First, the efficiency of UROP converges to 100% as $T \to \infty$, as shown in Section 2.6 (UROP

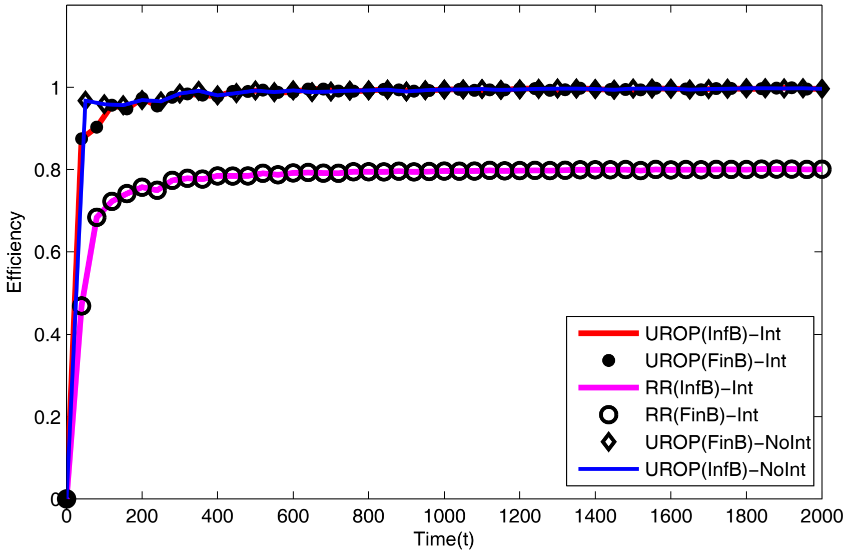

Figure 2.7: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery B_i=50 assumptions for nonuniform independent low density energy arrivals ($D = 0.2$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

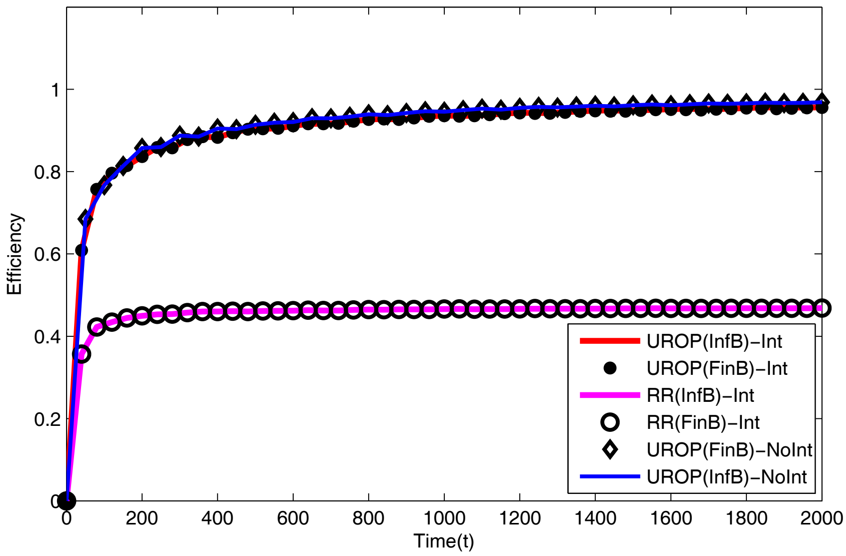

Figure 2.8: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery B_i=50 assumptions for nonuniform independent high density energy arrivals ($D = 0.975$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

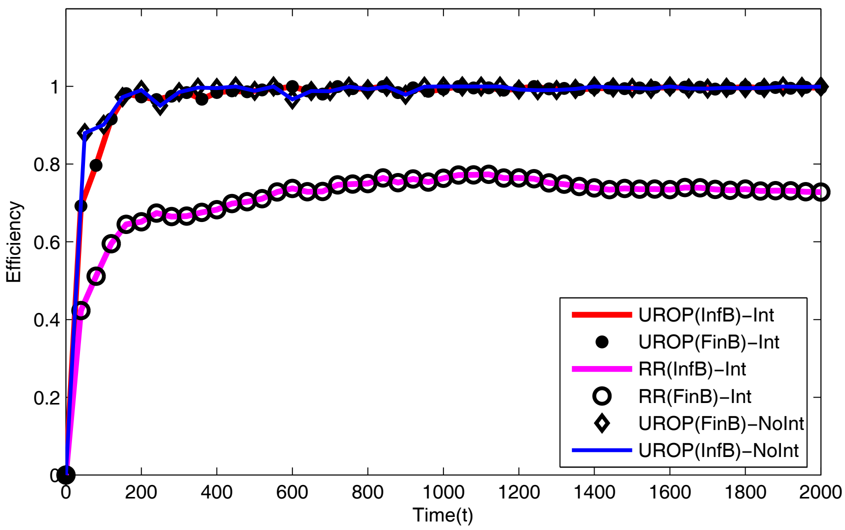

Figure 2.9: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery B_i=50 assumptions for nonuniform Markov low density energy arrivals ($D = 0.2$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

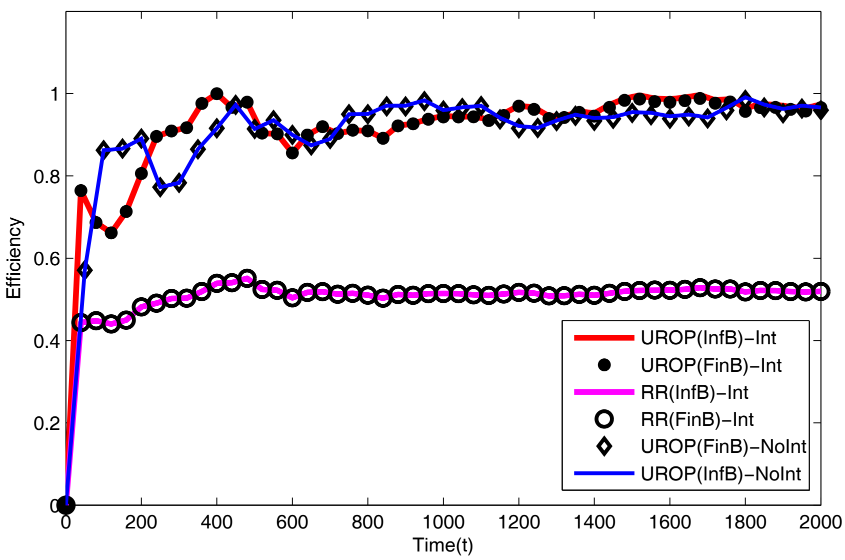

Figure 2.10: Efficiencies (ratio of total throughput by a policy to total throughput by optimal policy) of UROP, RR under infinite and finite battery B_i=50 assumptions for nonuniform Markov high density energy arrivals ($D = 0.975$) such that $m/k \in Z$. Efficiency of UROP is also shown for m/k taking a noninteger value.

is asymptotically optimal). Secondly, efficiency of UROP with a reasonable-sized finite battery B_i=50 is almost same as that with infinite battery. Finally, UROP can achieve nearly 100% throughput both for $m/k \in Z$ and $m/k \notin Z$ cases, while RR needs $m/k \in Z$ assumption for optimality. We conclude that UROP is more adaptive and efficient than RR (and MP proposed in [47, 49] by Theorem 3).

In addition to throughput, the performances of RR and UROP are also compared in terms of fairness, which is often an important issue for scheduling policies. We apply Jain's Fairness index [60],

$$f(x) = \frac{[\sum_{i=1}^{m} x_i(t)]^2}{m \sum_{i=1}^{m} x_i^2(t)}, \tag{2.58}$$

where $x_i(t)$ is the i^{th} user allocation up to TS t. Adopting the *proportionate progress* (P-fairness) criterion in [61], we scale the resource allocation $x_i(t)$ over users as

$$x_i(t) = \frac{V_i(t)}{V_i^*(t)}. \tag{2.59}$$

RR is usually known as a fair policy since it schedules users periodically. RR is 100% fair for uniform EH processes. However, RR may not be very fair for nonuniform EH processes. In fact, from 2.13 and 2.14 the efficiency of RR is expected to be $FI_{RR} = 89.3\%$ for high density $D = 0.975$, nonuniform arrivals. On the other hand, UROP schedules the users proportionally to their loads as well as respecting same or periodically. Consequently, UROP can achieve 100% fairness for general case of EH process. This is evident on Figure 2.11 and Figure 2.12. It is also observed that UROP is nearly 100% fair also for m/k noninteger case.

2.8 Computational Complexity of the Scheduling Policies

In addition to throughput and fairness, computational complexity is very important for scheduling policies. Therefore, computational complexities of RR, UROP and UP (uniformizing policy, the omniscient policy proposed in Section 2.4) are compared in this section. RR has complexity $O(1)$. Besides achieving almost 100% throughput and 100% fairness for various EH processes, UROP has low-complexity as well. In each TS, UROP checks the k nodes which are scheduled in previous TS thus it makes

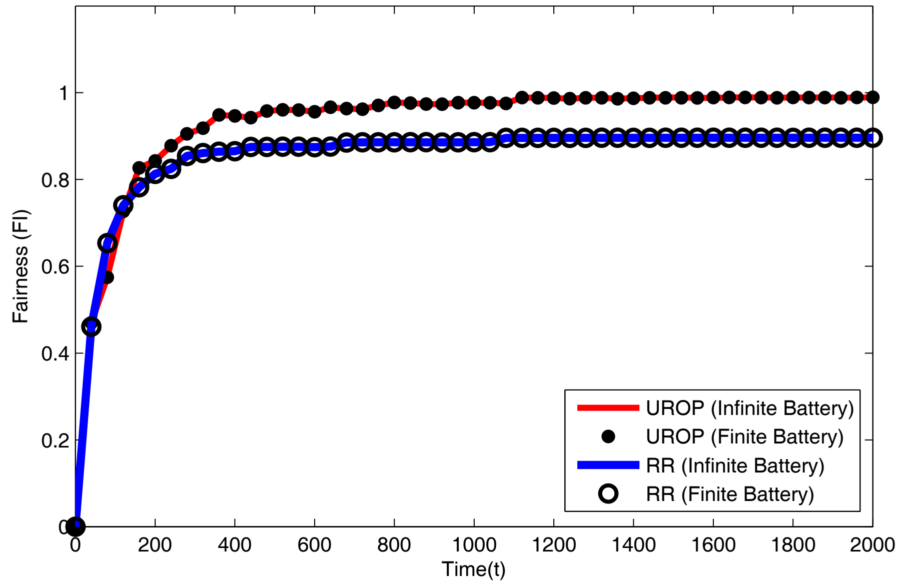

Figure 2.11: Fairness of UROP, RR under infinite and finite battery B_i=50 assumptions for high density $D = 0.975$ and independent EH process by m/k integer assumption.

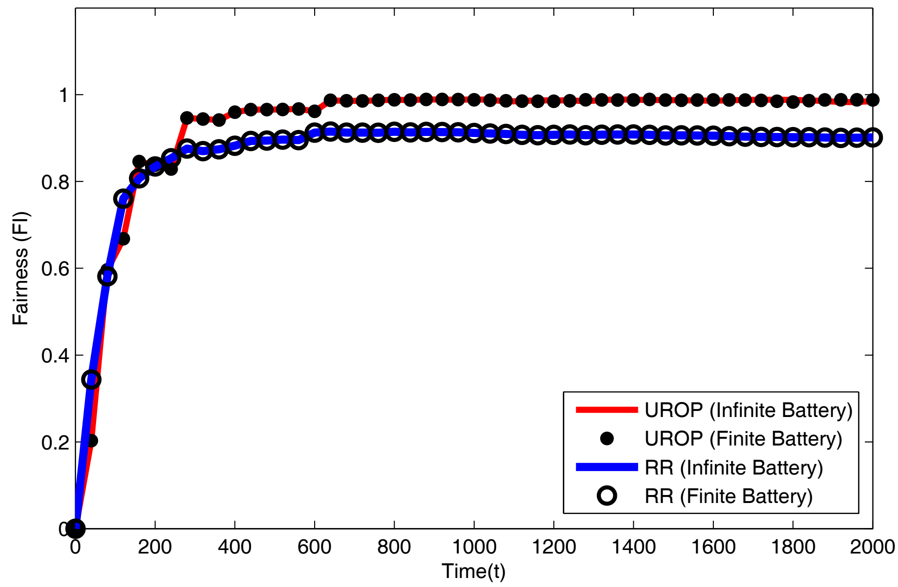

Figure 2.12: Fairness of UROP, RR under infinite and finite battery B_i=50 assumptions for high density $D = 0.975$ and Markov EH process by m/k integer assumption.

only k computations in each TS. Therefore, computational complexity of UROP is $O(kT)$.

It is also interesting to compare UROP with UP in terms of computational complexity. UP is an optimal omniscient policy. In each TS, UP checks the k nodes scheduled in previous TS and looks for replacement nodes if some of the k nodes cannot transmit data in that TS. As FC schedules k nodes in each TS, it can find k nodes which can transmit data to the FC in that TS by checking at least battery states of k nodes. If the first checked k nodes includes some nodes which cannot transmit data in that TS, then FC continue to check the remaining nodes until it find k nodes to transmit data. Note that if the number of nodes which can transmit data to the FC is less than k, FC check battery states of all nodes and schedules k nodes including all nodes which can transmit data in that TS. Therefore, the number of computation which UP makes in each TS is between k and m. Hence, UP has a computational complexity between $O(kT)$ and $O(mT)$.

The results show that UP may have complexity $O(mT)$ to achieve 100% throughput whereas UROP has complexity $O(kT)$ to achieve nearly 100% throughput. This implies that UP may have $\frac{m}{k}$ times more computation than UROP to achieve the same throughput performance. In other words, UROP achieves the same performance as UP with up to $\frac{m}{k}$ times lower complexity.

CHAPTER 3

ACHIEVING NEARLY 100% THROUGHPUT WITHOUT FEEDBACK IN ENERGY HARVESTING WIRELESS NETWORKS

In this chapter, we investigate a similar network scheduling problem with the scheduling problem in previous chapter except that there is no data backlog assumption in this problem. Recall the other assumptions stated in the previous chapter. In the network, a fusion center (FC) schedules a set of energy harvesting nodes to collect data from them. Fusion center does not know the instantaneous battery states of nodes or the statistics of random energy harvesting processes. Fusion center only knows the history of previous transmission attempts. The batteries of the nodes have infinite battery capacity and there is no leakage from the batteries.

This chapter is organized as follows. The problem formulation is made precise in Section 3.1. In Section 3.2, we investigate the scheduling capacity of the system. In Section 3.3, we show that RR-based policies are suboptimal under many non-uniform energy harvesting and data arrival processes. In Section 3.4, we describe and generalize the Uniformizing Random Ordered Policy (UROP) to operate under arbitrary energy harvesting and data arrival processes under an infinite battery assumption. In Section 3.5, we compare UROP and myopic policies in [47], [49], [53] through simulations.

3.1 System Model and Problem Formulation

We consider a single-hop wireless network in which a Fusion Center (FC) collects data packets from m energy harvesting (EH) nodes surrounding it. The wireless network operates in a TDMA fashion over time slots (TSs) of equal duration, and can schedule up to k nodes in each TS.

When a node is scheduled for transmission, it transmits if it has at least unit of energy and one data packet in its buffer. For simplicity, data is sent in the form of *unit sized* packets which take *unit energy* to transmit, and each transmission is successful with probability 1. Data becomes available at nodes according to an arbitrary process, corresponding to the nodes collecting measurements from their environment and encoding them as data packets to be sent to the fusion center.

We denote by $S = \{s_1, s_2, .., s_m\}$ the set of nodes. The EH processes are assumed to be independent for each node. The amount of energy harvested by node s_i during TS t is denoted by $E_i^h(t)$, and the total energy harvested by time t by $E_i^{tot}(t)$. The number of new data packets becoming available at node s_i in slot t is denoted by $D_i^a(t)$, and the total number of packets collected at node s_i up to TS t by $Q_i^{tot}(t)$. Both battery and buffer sizes are assumed to be unlimited. Moreover, we denote by $B_i(t)$ and $Q_i(t)$, the energy remaining in the battery of node s_i and the number of packets remaining in the buffer of node s_i at TS t. The number of packets transmitted by node s_i in TS t is denoted by $W_i(t) = I(s_i \in S_{sc}(t))I(B_i(t) \geq 1)I(Q_i(t) \geq 1) \in \{0, 1\}$ where $I(A)$ is indicator function and the set of k nodes scheduled by FC in TS t, are $S_{sc}(t) \subset S$. In each TS t, $S_{sc}(t)$ are determined by a policy π.

In the wireless network, $V(t)$ is the total number of data packets which FC received from nodes from TS 1 to TS t. In general (consistently with previous literature [47], [49], [53]), the objective is to maximize the total throughput (expected discounted reward when considering decision theory literature) over the problem horizon:

$$\max_{S_{sc}(t),t=1,..,T} V(t) = \max_{S_{sc}(t),t=1,..,T} E\left[\sum_{t=1}^{T} \beta^{t-1} \sum_{s_i \in S} I(s_i \in S_{sc}(t))I(B_i(t) \geq 1)I(Q_i(t) \geq 1)\right] \tag{3.1}$$

where $0 < \beta \leq 1$ is the discount factor. The discount factor corresponds to placing lower value on data that is delayed. Additionally in this case, as the FC schedules the nodes according to both their energy and their packets, β could be considered to correspond to delay and battery leakage. Ignoring delay and leakage (which tends to be quite negligible in time frames typical for transmitting a packet [2]) and focusing purely on throughput, we shall set $\beta = 1$ and convert problem (3.1) to problem (3.2) (average reward, a suitable performance measure for delay-insensitive communication problems [51]):

$$\max_{S_{sc}(t),t=1,..,T} \frac{V(t)}{T} = \max_{S_{sc}(t),t=1,..,T} E\left[\frac{1}{T}\sum_{t=1}^{T}\sum_{s_i \in S} I(s_i \in S_{sc}(t)) I(B_i(t) \geq 1) I(Q_i(t) \geq 1)\right] \tag{3.2}$$

Several definitions are in order: A *fully efficient policy* (alternatively, *100% efficient policy*) ensures that the nodes use up all of the harvested energy such that $B_i(T) < 1$ $\forall s_i \in S$, or the nodes transmit all their data. Efficiency of a policy π (η) is defined as the ratio of total throughput achieved by π and the throughput achieved by a fully efficient policy π^{fe} within the problem horizon ($\eta_{fe} = 1$). An *optimal policy* π^* is the scheduling policy that maximizes throughput by using the harvested energy. It is important to our study to understand, for a given case of energy harvests and data arrivals, whether there exists an both optimal and fully efficient policy (to find the region where $\pi^* = \pi^{fe} = 1$).

This paper shows near optimality of Uniformizing Random Ordered Policy, proposed in [32], for a broad class of energy harvesting and data arrival processes. UROP goes through nodes by *self-adapting* to their energy harvest and data arrival rate, and in this way stands in contrast to Round Robin (RR) policies. In particular, a RR policy with quantum=1 is a policy that goes through nodes in a cyclic order, giving each node one time slot at a round (cycle). By [32], efficiency of any RR policy with quantum=1 π^{RR} (η_{RR}) is almost the same as that of myopic policies π^{MP} (η_{MP}) proposed in [47], [49], [53]. Then, efficiency of UROP π^{UROP} will be compared with that of an arbitrary RR Policy with quantum=1 TS π^{RR} in Section 3.5. Recall that a Round Robin Policy with quantum=1 TS is a policy which allocates each node 1 TS during a round (cycle). A RR Policy with quantum=2 TS allocates each node 2 TS during a round. A RR Policy with quantum=3 TS allocates each node 3 TS during a round, so on.

Before moving on to Section 3.2, it will be useful to introduce some more terminology that will be used in the rest of paper. *Density of node i* (D_i) is the number of packets sent by the node s_i with π^{fe} normalized by $\frac{kT}{m}$ during problem horizon T. Partial Density of node s_i ($D_i^{(t)}$) is the total number of packets sent by the node s_i with π^{fe} normalized by $\frac{k(T-t)}{m}$ in the time interval $(t, T]$. Density (D) is the average of densities of all nodes during problem horizon T. Partial Density ($D^{(t)}$) is the average of partial densities of all nodes in the interval $[t, T]$. By definition, $D, D^{(t)} \leq 1$.

3.2 Scheduling Capacity

As the FC has access to k channels, it can schedule at most k nodes in each TS. If the system harvests too much energy, then the scheduling capacity of the system is exceeded and no 100% efficient policy exists. We denote by $V_i^{(t)}$ and $V^{(t)}$ the number of packets which could be sent by node s_i and by all nodes, respectively in the interval $(t, T]$. $V_i^{(t)}$ and $V^{(t)}$ can be represented as

$$V_i^{(t)} = min\left\{ \left\lfloor B_i(t) + \sum_{j=t+1}^{T} E_i^h(j) \right\rfloor, Q_i(t) + \sum_{j=t+1}^{T} D_i^a(j) \right\}, \tag{3.3}$$

$$V^{(t)} = \sum_{s_i \in S} V_i^{(t)}. \tag{3.4}$$

In the following, we record the condition on the value of the total amount of energy harvested and the number of data packets arrived so that a 100% efficient policy is possible.

Theorem 6. (Scheduling Capacity) *Assume* $0 \leq t < T$*,*

i. If $V^{(t)} > k(T-t)$*, no policy can achieve 100% efficiency, all possible policies have efficiency below 100%.*

ii. If $V^{(t)} \leq k(T-t)$*, a 100% efficient policy that maximizes throughput exists.*

Proof. i)

$$V^{(t)} > k(T-t) \tag{3.5}$$

As scheduling capacity of the FC is k packets per slot, FC can receive at most $k(T-t)$ packets from the nodes in the interval $(t,T]$. Assume a policy π which can achieve up to scheduling capacity. Then, efficiency of π equals the maximum efficiency in the condition (3.5), and it is represented as

$$\begin{aligned} \eta_* &= \frac{min\left\{k(T-t), V^{(t)}\right\}}{V^{(t)}} \\ &= \frac{k(T-t)}{V^{(t)}}. \end{aligned} \tag{3.6}$$

If (3.5) is satisfied, the scheduling capacity is exceeded. By (3.5) and (3.6), $\eta_* < 1$. This means that optimum policy cannot achieve 100% (fully) efficiency. Therefore, there is no 100% efficient policy which makes FC receive all $V^{(t)}$ packets from the nodes.

ii)

$$V^{(t)} \leq k(T-t) \tag{3.7}$$

As scheduling capacity of the fusion center (FC) is k data packets per time slot, FC can accumulate at most $k(T-t)$ data packets from the nodes in the time interval $(t,T]$. Consider an omniscient offline policy: it will not leave an idle TSs as long as there is a node with energy and data available, who is currently not scheduled. Hence, if there is an idle TS, this is because all available energy is being used. Trivially, this scheduling policy achieves 100% efficiency if $D^{(t)} \leq 1$,

$$\begin{aligned} \eta_* &= \frac{min\left\{k(T-t), V^{(t)}\right\}}{V^{(t)}} \\ &= \frac{V^{(t)}}{V^{(t)}} \\ &= 1. \end{aligned} \tag{3.8}$$

If (3.7) is satisfied, the scheduling capacity of the fusion center is not exceeded. By (3.8), there is an 100% efficient policy which makes the fusion center accumulate all $V^{(t)}$ data packets from the nodes. □

3.3 Efficiency of RR-based Policies

The scheduling problem is also investigated in [47], [49], [53] for certain scenarios. These papers propose myopic policies (MP) which are a kind of RR-based policies with quantum=1 TS and show that RR-based myopic policies is optimal in certain specific cases as mentioned in introduction.

First, we will investigate the efficiency of RR-based policies with quantum=1 TS in Theorem 7. There is only a slight difference between the efficiencies of any two RR-based policies in long problem horizon $T(\frac{m}{k} \ll T)$ (as proven in Theorem 3 in previous chapter). [32] Hence, the efficiency of RR-based myopic policies in [47], [49], [53] are investigated. It is shown that the policies in [47], [49], [53] are generally suboptimal.

For the case that each node has a battery arger than unit energy size or a buffer larger than one packet size, there is no known myopic policy in the literature. Therefore, we will compare UROP only with myopic policies in [47], [49], [53] in terms of efficiency.

Theorem 7. *Suppose that $T \gg \frac{m}{k} \in Z$ and the scheduling capacity of the FC is not exceeded by Theorem 6 ($V_i^{(t)} \leq (T-t)\ \forall s_i \in S, \forall t$ and $V^{(t)} \leq k(T-t)\ \forall t$). If there are some sensors $s_i \in S$ such that $V_i^{(t)} > \frac{k(T-t)}{m}$, all RR-based policies with quantum=1 TS will have efficiency below 100% although a fully efficient policy (π^{fe}) exists. Moreover, batteries of some nodes will overflow.*

Proof. In this proof, RR policy implies RR policies with quantum=1 TS. We study efficiency of RR in two possible cases:

i. If $\sigma = \frac{kT}{m} \notin Z$, RR allocates some nodes $\lfloor \sigma \rfloor + 1$ TSs and other nodes $\lfloor \sigma \rfloor$ TSs for data transmission.

ii. If $\sigma = \frac{kT}{m} \in Z$, RR allocates each node σ TSs for data transmission.

Assume that $V_i^{(t)} > \frac{k(T-t)}{m}, \exists s_i \in S$ and H is the set of these nodes. By definition of density, $D_i^{(t)} > 1\ \forall s_i \in H$.

i. If the FC schedules m nodes by RR policy in the problem horizon T, RR policy allocates some nodes $\lfloor\sigma\rfloor + 1$ TSs and other nodes $\lfloor\sigma\rfloor$ TSs for data transmission where $\sigma = \frac{kT}{m} \notin Z$ and $\{\sigma\} \triangleq \sigma - \lfloor\sigma\rfloor$. To maximize efficiency of RR policy, we assume that each node $s_i \in H$ can transmit at most $\lfloor\sigma\rfloor + 1$ data packets. However, each node cannot transmit $V_i^{(t)} - \lfloor\sigma\rfloor - 1$ data packets although $V^{(t)} \leq k(T-t)$ which means that a both optimum and 100% efficient policy exists. On the other hand, each node $s_i \in S - H$ can transmit all $V_i^{(t)}$ data packets. Efficiency of RR policy is represented as

$$\eta_{RR} = \frac{\sum_{s_i \in S} min\left\{V_i^{(t)}, \sigma\right\}}{\sum_{s_i \in S} V_i^{(t)}} \tag{3.9}$$

$$= \frac{\sum_{s_i \in H}(\lfloor\sigma\rfloor + 1) + \sum_{s_i \in S-H} V_i^{(t)}}{\sum_{s_i \in S} V_i^{(t)}} \tag{3.10}$$

$$= 1 - \frac{\sum_{s_i \in H}(V_i^{(t)} - \lfloor\sigma\rfloor - 1)}{\sum_{s_i \in S} V_i^{(t)}}. \tag{3.11}$$

By definition of $D_i^{(t)}$, η_{RR} is also stated as

$$\eta_{RR} = 1 - \frac{\sum_{s_i \in H}(D_i^{(t)}\sigma - \lfloor\sigma\rfloor - 1)}{\sum_{s_i \in S} D_i^{(t)}\sigma} \tag{3.12}$$

$$= 1 - \frac{\sum_{s_i \in H}(D_i^{(t)} - 1)\sigma - (1 - \{\sigma\}))}{\sum_{s_i \in S} D_i^{(t)}\sigma}. \tag{3.13}$$

As $D_i^{(t)} > 1$ for $s_i \in H$ and $\sigma \gg 1 - \{\sigma\}$, $(1 - \{\sigma\}) < (D_i^{(t)} - 1)\sigma$. Hence, $\eta_{RR} < 1$, i.e., RR is suboptimal.

ii. As $\sigma \in Z$, RR allocates each node $\sigma = \lfloor\sigma\rfloor$ TSs for data transmission. None of nodes can use $\lfloor\sigma\rfloor + 1$ TSs for data transmission. Therefore, efficiency of RR policies in this case can be represented as

$$\eta_{RR} = 1 - \frac{\sum_{s_i \in H}(V_i^{(t)} - \sigma)}{\sum_{s_i \in S} V_i^{(t)}} \tag{3.14}$$

instead of (3.11). By definition of $D_i^{(t)}$, η_{RR} is stated as

$$\eta_{RR} = 1 - \frac{\sum_{s_i \in H}(D_i^{(t)} - 1)}{\sum_{s_i \in S} D_i^{(t)}}. \tag{3.15}$$

Since $D_i^{(t)} > 1$ and $D^{(t)} \leq 1 \, \forall s_i \in H$, $\eta_{RR} < 1$. Hence, RR policies with quantum=1

TS are suboptimal because an optimal policy achieves fully efficiency ($\pi^* = \pi^{fe}$) when $D^{(t)} \leq 1$ by Theorem 6. □

3.4 A Near-Optimal Online Solution

The following Lemma forms the basis of our policy, UROP.

Lemma 6. (Partial Optimality) *If $min\{B_i(t), Q_i(t)\} < 1$ for a node s_i at TS t, it can be said that an optimal policy π^* has been applied for the node s_i and efficiency is 100% for the node s_i up to TS t.*

Proof. For a data packet transmission, buffer of a node s_i must not be empty and the node must have at least unit energy. If $Q_i(t) = 0$, s_i has no data packet to send. If $B_i(t) < 1$, there is not enough energy for data transmission. By TS t, the node s_i has transmit all data packets which could be sent with the total harvested energy up to TS t, $E_i^{tot}(t)$, and efficiency is 100% for the node s_i up to TS t. □

$D < 1$ implies that there exists always idle TSs over a problem horizon even if π^{fe} is applied. Lemma 6 states that if a scheduled node cannot transmit data in TS t (idle TS occurs), a 100% efficient policy is applied to that node until TS t. By Lemma 6, UROP will be proposed based on this observation: *UROP uses idle TSs to determine the battery states of scheduled nodes.*

3.4.1 Uniformizing Random Ordered Policy (UROP)

Considering that the energy harvesting and data arrival processes may be unpredictable, UROP orders the nodes randomly before starting to schedule them. The first k nodes in the ordering are scheduled to transmit. If a scheduled node can transmit a packet to the FC (because it has enough energy and data to transmit) in one TS, then it will continue to be scheduled in the next TS. Otherwise, FC schedules the next node in the ordering in its place. FC completes a scheduling round when all m nodes are scheduled once. In part B, efficiency of UROP is studied for finite horizon case.

In part C, it is shown that UROP is *asymptotically optimal* under a broad set of energy harvesting and data arrival processes.

3.4.2 Efficiency of UROP in Finite Horizon Case

In this part, the worst case and expected efficiency of UROP is studied in quite general energy harvesting and data arrival processes. First, several lemmas are stated. Then, these lemmas are used to prove Theorem 8 and Theorem 9.

Remark 5. *If $E_i^{tot}(t)$ and $Q_i^{tot}(t)$ are the total harvested energy and arrived packets in node s_i up to TS t and $V_i^*(t)$ is the number of data packets which could be sent by node s_i until TS t under π^*, $V_i^*(t) = min\left\{\lfloor E_i^{tot}(t)\rfloor, Q_i^{tot}(t)\right\}$.*

Now, we will define some new parameters related to idle time slots and these will be used in Lemma 7, Lemma 8, Theorem 8 and Theorem 9. $A_{idle}(j,l)$ is the pair of the j^{th} channel of the FC and l^{th} idle TS for the j^{th} channel. $A_{idle}(j,l)$ occurs in TS γ_l^j. In this TS γ_l^j, FC drops a node using j^{th} channel and start to schedule another node in same channel. In the idle TSs, FC drops some of the k nodes and starts to schedule other nodes in their place. T_I is the set which consists of all pairs $A_{idle}(j,l)$. Figure 3.1 represents the transmission channel-idle time slot pairs in an example scheduling table.

Let's denote by $\xi_i^{(f)}$ and $\xi_i^{(f-1)}$ the idle TSs when FC starts to schedule node s_i for the last time and for the second last time, respectively. F_1 and F_2 are the set of all pairs $A_{idle}(u,v)$ such that $\gamma_v^u = \xi_i^{(f)}$ for a $s_i \in S$ and the set of all pairs $A_{idle}(u,v)$ such that $\gamma_v^u = \xi_i^{(f-1)}$ for a $s_i \in S$. As there are m nodes, $|F_1| = |F_2| = m$. G_1 is the set of all pairs $A_{idle}(p,q)$ such that $\gamma_q^p \neq \xi_i^{(f)}$ for $s_i \in S$. Moreover, G_2 is the set of all pairs $A_{idle}(p,q)$ such that $\gamma_q^p \neq \xi_i^{(f)}$ and $\gamma_q^p \neq \xi_i^{(f-1)}$ for $s_i \in S$. In other words, $G_1 = T_I - F_1$ and $G_2 = T_I - (F_1 \cup F_2)$.

Lemma 7. *If $A_{idle}(u,v) \in (F_1 \cup F_2)$,*

i) There does not exist such a pair $A_{idle}(p,q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u,v) \in F_1$.

ii) There does not exist such a pair $A_{idle}(p,q) \in G_2$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u,v) \in$

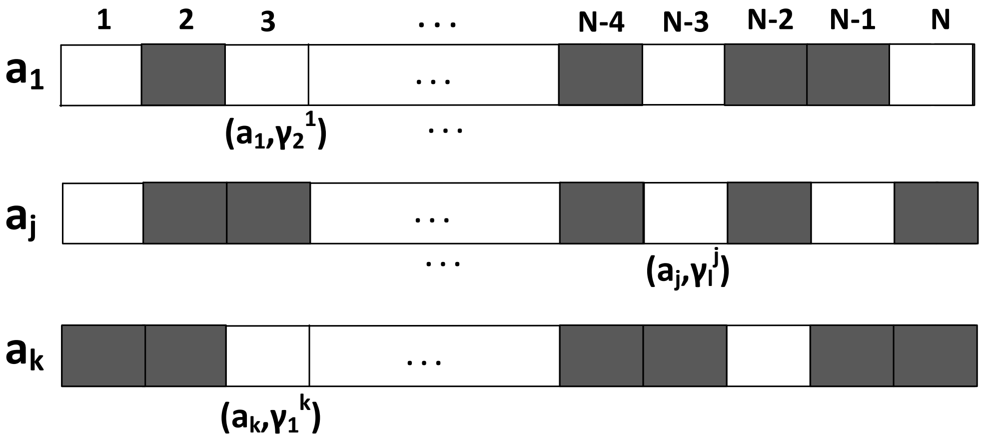

Figure 3.1: An example scheduling table kept by the fusion center (FC) for all k channels over problem horizon $T = N$ time slots. Dark colored TSs represent busy time slots, and the white ones represent idle ones.

$(F_1 \cup F_2)$.

Proof. ***Part i)*** Assume that there is such a pair $A_{idle}(p, q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_1$. Since $\gamma_q^p \neq \xi_i^{(f)}$ $\forall s_i \in S$, the node s_r which is selected by the FC in TS γ_q^p will be selected by the FC at least once more ($\gamma_q^p < \xi_r^{(f)}$). According to UROP, a node s_r which is selected in TS T_1 cannot be selected by the FC in TS T_2 unless $\forall s_i \in S - s_r$ are selected in the time interval $[T_1, T_2]$. Since $\gamma_q^p > \gamma_v^u = \xi_i^{(f)}$ for some s_i, these nodes cannot be selected by the FC in the time interval $[\gamma_q^p, \xi_j^{(f)}]$. Therefore, there does not exist such a pair $A_{idle}(p, q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_1$.

Part ii) $G_1 = T_I - F_1$ and $G_2 = T_I - (F_1 \cup F_2) = (T_I - F_1) - F_2$. Replacing $T_I - F_1$ and F_2 with T_I and F_1 , respectively, in Part i, we can said that there exists no $A_{idle}(p, q) \in G_2$ such that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_2$. By Part i, there exists no $A_{idle}(p, q) \in F_2$ such that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_1$. Therefore, there does not exist such a pair $A_{idle}(p, q) \in G_2$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in (F_1 \cup F_2)$.

□

Lemma 8. *If $\zeta_i^{(f)}$ is the idle TS when FC stops to schedule node s_i for the last time and L is set of $\zeta_i^{(f)}$s, $L \subset (F_1 \cup F_2)$.*

Proof. Recall that $(F_1 \cup F_2) \subseteq T_I$. It can be said that FC starts to schedule a node iff it leaves (stops to schedule) another node. $(F_1 \cup F_2)$ includes two consecutive time (the last and second last time) when FC starts to schedule a node for all nodes. Assume that FC schedules a node s_i. Unless FC stops to schedule the node s_i, it cannot start to schedule the node s_i again. Therefore, $(F_1 \cup F_2)$ includes at least one departure time for each node. Since $(F_1 \cup F_2)$ includes the latest $2m$ idle TSs and at least one departure time for each node, $\zeta_i^{(f)} \in (F_1 \cup F_2), \forall s_j$. Hence, $L \subset (F_1 \cup F_2)$. □

Theorem 8. (Efficiency Bounds of UROP) *Final departure time of the node s_j which satisfies $\zeta_j^{(f)} \leq \zeta_i^{(f)}$ $\forall s_i \in S - \{s_j\}$ is denoted by $\zeta_j^{(f)} = T_0$. In problem horizon T, efficiency of UROP is bounded as*

$$1 - \frac{k(T - T_0)}{\sum_{i=1}^{m} V_i^*(T)} \leq \eta_{UROP} \leq 1, \tag{3.16}$$

where $V_i^*(T)$ is the number of data packets which could be transmitted by node the s_i up to TS t under an optimal policy π^*.

Proof. Due to space constraints, the proof is omitted here. Please see the proof of Theorem 4 in previous chapter. □

Considering *the worst case*, efficiency of UROP is bounded as shown in Theorem 8. k is known and $V_i^*(T)$ can be found for each node s_i by Remark 5. However, T_0 cannot be determined unless all details of scheduling in problem horizon is known. Due to the uncertainty of T_0, Theorem 8 does not provide sufficient information about efficiency of UROP. Remember that average reward is a suitable performance measure for the scheduling policy over finite or infinite horizon [51]. Considering T_0 (and the other departure times of nodes) as ergodic processes depending on energy harvesting and data arrival processes, efficiency of UROP is bounded in expectation manner.

Theorem 9. *For $0 < D < 1$, expected efficiency of UROP is bounded as*

$$1 - \frac{2m}{(1-D)DTk} \leq E\left\{\eta_{UROP}\right\} \leq 1, \tag{3.17}$$

where T, m, k and D are problem horizon length, number of nodes, number of mutually orthogonal channels and density, respectively.

Proof. Recall that $V^*(T) = \sum_{i=1}^{m} V_i^*(T)$. By Theorem 8, efficiency of UROP can be written as

$$1 - \frac{k(T - T_0)}{V^*(T)} \leq \eta_{UROP} \leq 1. \tag{3.18}$$

$$1 - \frac{kE\left\{T - T_0\right\}}{V^*(T)} \leq E\left\{\eta_{UROP}\right\} \leq 1. \tag{3.19}$$

We denote by $\tau_{ar,i}$ and $\tau_{dep,i}$, elapsed time between two consecutive selection of same node s_i and elapsed time between two consecutive departure of same node s_i. For long problem horizons, $E\left\{\tau_{ar,i}\right\}$=$E\left\{\tau_{dep,i}\right\}$ $\forall i$. By Lemma 8, $L \subset (F_1 \cup F_2)$. By Lemma 7, if none of nodes $s_i \in S - S_k$ can be selected (started to schedule) more than twice by the FC in the interval $[T_0, T]$; therefore, $E\left\{T - T_0\right\} < 2E\left\{\tau_{ar}\right\}$. None of the nodes $s_i \in S_k$ can be left (stopped to schedule) more than once by the FC in time interval $\left[\zeta_i^{(f)}, T\right]$; therefore, the inequality 3.20 can be written all nodes:

$$\begin{aligned} E\left\{T - \zeta_i^{(f)}\right\} &< 2E\left\{\tau_{dep}\right\} \\ &< 2E\left\{\tau_{ar}\right\} \end{aligned} \tag{3.20}$$

Hence, (3.19) turns into

$$1 - \frac{2kE\left\{\tau_{ar}\right\}}{V^*(T)} \leq E\left\{\eta_{UROP}\right\} \leq 1 \tag{3.21}$$

By definition of D in the system model, the total throughput by an optimal policy, $V^*(T)$, can be written as

$$V^*(T) = DTk \tag{3.22}$$

and also the density can be found as

$$D = \frac{kE\left\{\tau_{ar}\right\} - m}{kE\left\{\tau_{ar}\right\}}. \tag{3.23}$$

Thus, one obtains

$$E\left\{\tau_{ar}\right\} = \frac{m}{(1 - D)k}. \tag{3.24}$$

By putting (3.24) into (3.21),

$$\begin{aligned} 1-\frac{2k\frac{m}{(1-D)k}}{DTk} &< E\left\{\eta_{UROP}\right\} \leq 1, \\ 1-\frac{2m}{(1-D)\,DTk} &< E\left\{\eta_{UROP}\right\} \leq 1. \end{aligned} \tag{3.25}$$

□

Note: As $D = 0$ means no harvested energy in the whole communication network, it is trivial case and not considered in our calculations. $D = 1$ means that there is no idle TS if the fusion center apply the 100% efficient policy (π^{fe}). However, UROP benefits from idle TSs to schedule the sensors as mentioned in Section 3.4. From Theorem 6, no π^{fe} exists for $D > 1$. Therefore, we investigate $0 < D < 1$.

As you may notice that the expected lower bound becomes negative for the case $m \geq \frac{(1-D)DTk}{2}$. However, we know that expected efficiency is nonnegative.

3.4.3 Extension to the Infinite-Horizon Case

By (3.25), as $1 - D$, D, k, and $m \in R_+$, $E\{\eta_{UROP}\} \to 1$ as $T \to \infty$. Hence, UROP is *asymptotically optimal* in infinite horizon for a broad class of energy harvesting and data arrival processes.

3.5 Numerical Results

In this section, efficiencies of RR and UROP are compared for independent and Markov energy harvesting (EH) and data arrival (DA) processes under high and low density energy harvesting and data arrival processes. As $D \leq 1$, $\eta_* = \eta_{fe} = 1$. In each case, we compare these policies under both infinite and finite battery assumption. To make a realistic scenario, we take $m = 100$, $k = 10$, $T = 2000$ for both policies. Note that we compare efficiency of UROP with a RR which is not necessarily MP proposed in [47], [49], [53] since $\eta_{RR} \cong \eta_{MP}$ for long problem horizons [38]. We investigate efficiency of both policies under nonuniform EH and DA process (Both have nearly 100% efficiency under uniform EH and DA processes). High

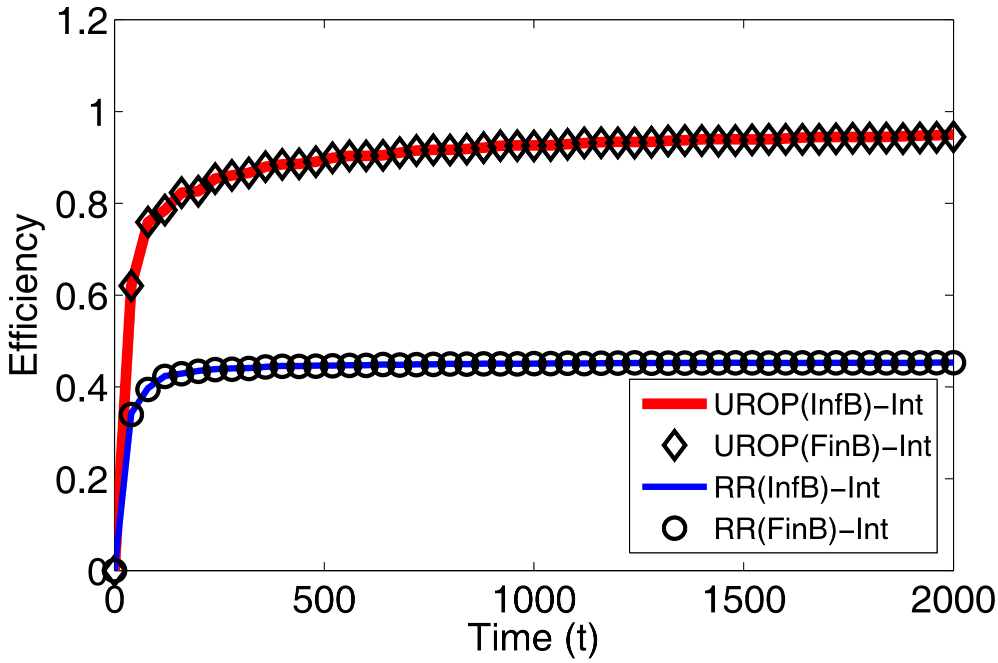

Figure 3.2: Efficiencies of UROP, RR with infinite battery, infinite buffer and finite buffer $Q_i = 50$, finite battery $B_i = 50$ for high density ($D = 0.975$) Independent energy harvesting and data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

density energy harvesting and data arrival processes are formed by taking $D_i = 3$ for 25 nodes and $D_i = 0.3$ for remaining nodes. Also, low density energy harvesting and data arrival processes are formed by taking $D_i = 2.1$ for 5 nodes and $D_i = 0.1$ for remaining nodes. Independent EH and DA processes are modelled as Poisson distribution for each node separately. Markov EH and DA processes are modelled for each node s_i by a state vector M_i=[0 D_i $2D_i$] and a 3×3 transition matrix P such that $p_{kk} = 0.9$ and $p_{jk} = 0.05$ for $j \neq k$.

Considering Figure 2 (a) and (b) (Independent EH and DA process), UROP has nearly 100% efficiency whereas RR has 80% efficiency for low density and below 50% efficiency for high density. Considering Figure 3 (a) and (b) (Markov EH and DA process), UROP has more than 95% efficiency whereas RR has 70% efficiency for low density and below 60% efficiency for high density. Simulations show that UROP is asymptotically optimal as proved in previous section. By Theorem 7, as the number of nodes satisfying $D_i > 1$ increases, efficiency of RR decreases. Therefore, the results are expected. Notice that efficiency of UROP is almost same under finite

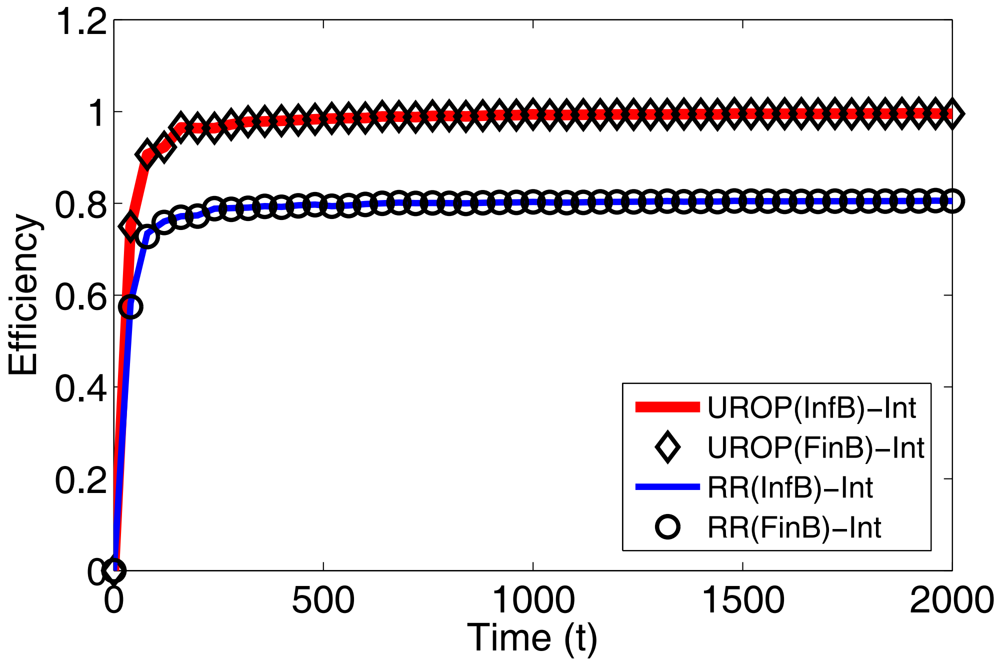

Figure 3.3: Efficiencies of UROP, RR with infinite battery, infinite buffer and finite buffer $Q_i = 50$, finite battery $B_i = 50$ for low density ($D = 0.2$) Independent energy harvesting and data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

battery $B_i = 50$ and finite buffer $Q_i = 50$ assumption as that under infinite battery and infinite buffer assumption.

We also investigate the efficiency of UROP by taking $m = 103$ and $k = 10$. UROP achieves nearly 100% throughput for the case that m/k is not an integer for quite general energy harvesting and data arrival processes. Therefore, UROP does not need m/k integer assumption which RR-based myopic policies in [47], [49], [53] need.

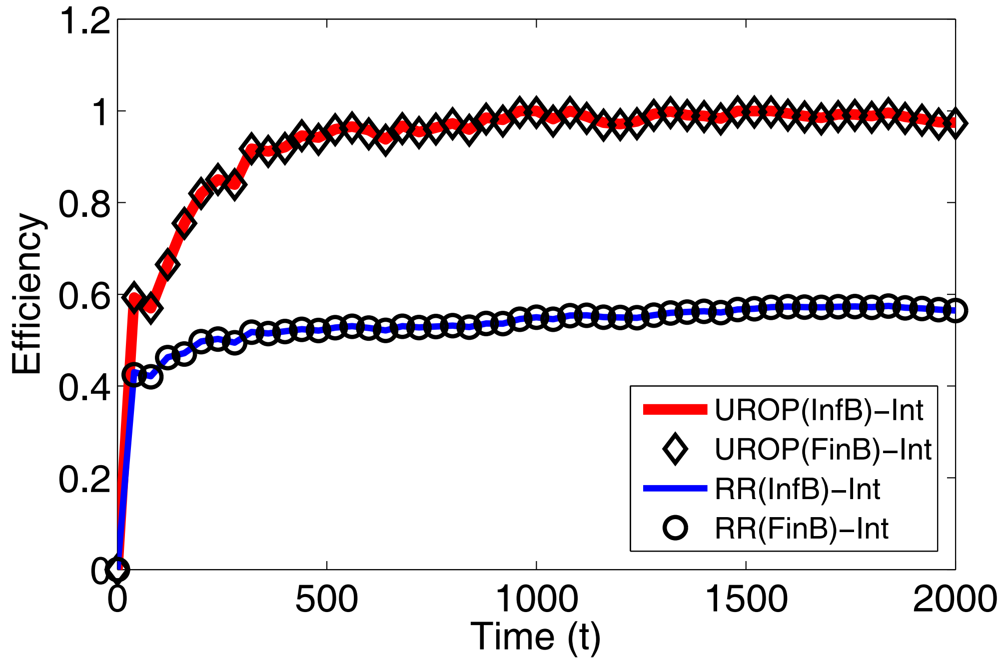

Figure 3.4: Efficiencies of UROP, RR with infinite battery, infinite buffer and finite buffer $Q_i = 50$, finite battery $B_i = 50$ for high density ($D = 0.975$) Markovian energy harvesting and data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

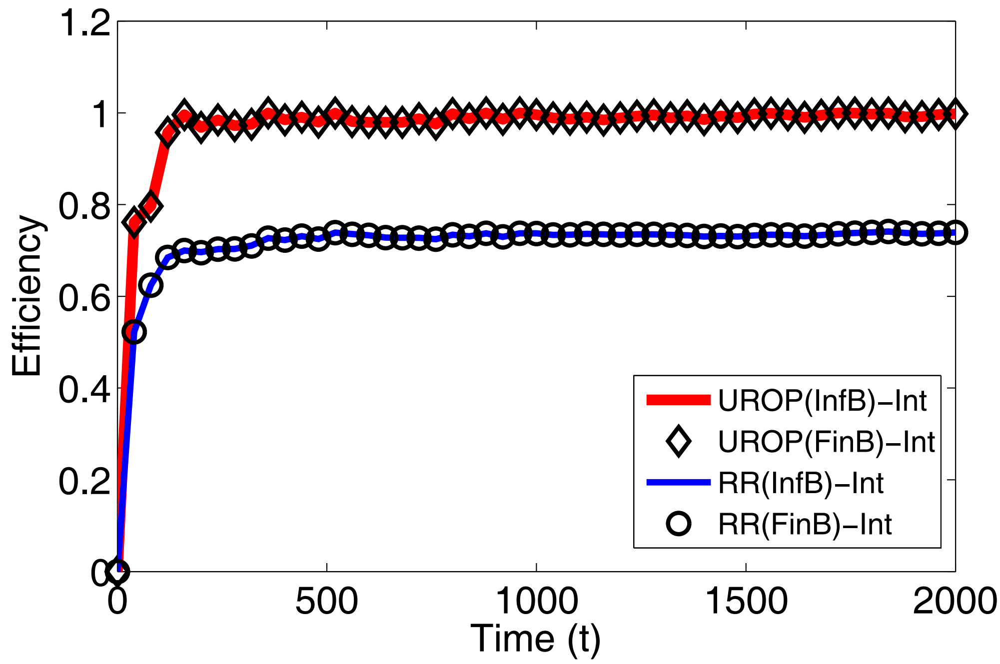

Figure 3.5: Efficiencies of UROP, RR with infinite battery, infinite buffer and finite buffer $Q_i = 50$, finite battery $B_i = 50$ for low density ($D = 0.2$) Markovian energy harvesting and data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

CHAPTER 4

ACHIEVING NEAR OPTIMALITY WITHOUT FEEDBACK IN COMMUNICATION NETWORKS

In this chapter, we investigate a dual network scheduling problem with the scheduling problem in the second chapter. In the network, a centralized controller (CC) schedules a set of nodes to collect data from them. Centralized controller does not know the instantaneous buffer states of nodes or the statistics of random data arrival processes. Centralized controller only knows the history of previous transmission attempts. The buffers of the nodes have infinite buffer capacity.

This chapter is organized as follows. The problem formulation is made precise in Section 4.1. In Section 4.2, we investigate the scheduling capacity of the system. In Section 4.3, we show that RR-based policies are suboptimal under many non-uniform data arrival processes. In Section 4.4, we describe and generalize the Uniformizing Random Ordered Policy (UROP) to operate under arbitrary data arrival processes under an infinite buffer assumption. In Section 4.5, we compare UROP and the myopic policy in [53] through simulations.

4.1 System Model and Problem Formulation

We consider a single-hop communication network in which a centralized controller (CC) collects data packets from m nodes surrounding it. The wireless network operates in a TDMA fashion over time slots (TSs) of equal duration, and can schedule up to k nodes in each TS.

When a node is scheduled for transmission, it transmits if it has at least one data packet in its buffer. For simplicity, data is sent in the form of *unit sized* packets and each transmission is successful with probability 1. Data becomes available at nodes according to an arbitrary process, corresponding to the nodes collecting measurements from their environment and encoding them as data packets to be sent to the centralized controller.

We denote by $S = \{s_1, s_2, .., s_m\}$ the set of nodes. The data arrival processes are assumed to be independent for each node. The number of new data packets becoming available at node s_i in slot t is denoted by $D_i^a(t)$, and the total number of packets collected at node s_i up to TS t by $Q_i^{tot}(t)$. Both buffer sizes are assumed to be unlimited. Moreover, we denote by $Q_i(t)$, the number of packets remaining in the buffer of node s_i at TS t. The number of packets transmitted by node s_i in TS t is denoted by $W_i(t) = I(s_i \in S_{sc}(t))I(Q_i(t) \geq 1) \in \{0, 1\}$ where $I(A)$ is indicator function and the set of k nodes scheduled by CC in TS t, are $S_{sc}(t) \subset S$. In each TS t, $S_{sc}(t)$ are determined by a policy π.

In the communication network, $V(t)$ is the total number of data packets which CC received from nodes from TS 1 to TS t. In general (consistently with previous literature [47], [49], [53]), the objective is to maximize the total throughput (expected discounted reward when considering decision theory literature) over the problem horizon:

$$\max_{S_{sc}(t),t=1,..,T} V(t) = \max_{S_{sc}(t),t=1,..,T} E\left[\sum_{t=1}^{T} \beta^{t-1} \sum_{s_i \in S} I(s_i \in S_{sc}(t))I(Q_i(t) \geq 1)\right] \tag{4.1}$$

where $0 < \beta \leq 1$ is the discount factor. The discount factor corresponds to placing lower value on data that is delayed. Additionally in this case, as the CC schedules the nodes according to the number of their packets, β could be considered to correspond to delay. Ignoring delay and focusing purely on throughput, we shall set $\beta = 1$ and convert problem (4.1) to problem (4.2) (average reward, a suitable performance measure for delay-insensitive communication problems [51]):

$$\max_{S_{sc}(t),t=1,..,T} \frac{V(t)}{T} = \max_{S_{sc}(t),t=1,..,T} E\left[\frac{1}{T}\sum_{t=1}^{T} \sum_{s_i \in S} I(s_i \in S_{sc}(t))I(Q_i(t) \geq 1)\right] \tag{4.2}$$

Several definitions are in order: A *fully efficient policy* (alternatively, *100% efficient policy*) ensures that the nodes transmit all of their packets such that $Q_i(T) = 0 \; \forall s_i \in S$. Efficiency of a policy π (η) is defined as the ratio of total throughput achieved by π and the throughput achieved by a fully efficient policy π^{fe} within the problem horizon ($\eta_{fe} = 1$). An *optimal policy* π^* is the scheduling policy that maximizes throughput. It is important to our study to understand, for a given case of data arrivals, whether there exists an both optimal and fully efficient policy (to find the region where $\pi^* = \pi^{fe} = 1$).

This paper shows near optimality of Uniformizing Random Ordered Policy, proposed in [32], for a broad class of data arrival processes. UROP goes through nodes by *self-adapting* to their data arrival rate, and in this way stands in contrast to Round Robin (RR) policies. In particular, a RR policy with quantum=1 TS is a policy that goes through nodes in a cyclic order, giving each node one time slot at a round (cycle). By [32], efficiency of any RR policy with quantum=1 TS π^{RR} (η_{RR}) is almost the same as that of myopic policies π^{MP} (η_{MP}) proposed in [47], [49], [53]. Then, efficiency of UROP π^{UROP} will be compared with that of an arbitrary RR Policy with quantum=1 TS π^{RR} in Section 4.5. Recall that a Round Robin Policy with quantum=1 TS is a policy which allocates each node 1 TS during a round (cycle). A RR Policy with quantum=2 TSs allocates each node 2 TSs during a round. A RR Policy with quantum=3 TSs allocates each node 3 TSs during a round, so on.

Before moving on to Section 4.2, it will be useful to introduce some more terminology that will be used in the rest of paper. *Density of node i* (D_i) is the number of packets transmitted by the node s_i with π^{fe} normalized by $\frac{kT}{m}$ during problem horizon T. Partial Density of node s_i ($D_i^{(t)}$) is the total number of packets transmitted by the node s_i with π^{fe} normalized by $\frac{k(T-t)}{m}$ in the time interval $(t, T]$. Density (D) is the average of densities of all nodes during problem horizon T. Partial Density ($D^{(t)}$) is the average of partial densities of all nodes in the interval $(t, T]$. By definition, $D, D^{(t)} \leq 1$.

4.2 Scheduling Capacity

As the CC has access to k channels, it can schedule at most k nodes in each TS. If data arrival to the system becomes too much, then the scheduling capacity of the system is exceeded and no 100% efficient policy exists. We denote by $V_i^{(t)}$ and $V^{(t)}$ the number of packets which could be transmitted by node s_i and by all nodes, respectively in the interval $(t, T]$. $V_i^{(t)}$ and $V^{(t)}$ can be represented as

$$V_i^{(t)} = Q_i(t) + \sum_{j=t+1}^{T} D_i^a(j), \tag{4.3}$$

$$V^{(t)} = \sum_{s_i \in S} V_i^{(t)}. \tag{4.4}$$

In the following, we record the condition on the value of the total number of arrived packets so that a 100% efficient policy is possible.

Theorem 10. (Scheduling Capacity) *Assume* $0 \leq t < T$,

i. If $V^{(t)} > k(T-t)$, *no policy can achieve 100% efficiency, all possible policies have efficiency below 100%.*

ii. If $V^{(t)} \leq k(T-t)$, *a 100% efficient policy that maximizes throughput exists.*

Proof. i.

$$V^{(t)} > k(T-t) \tag{4.5}$$

As scheduling capacity of the centralized controller (CC) is k packets per time slot, CC can receive at most $k(T-t)$ packets from the nodes in the interval $(t, T]$. Assume a policy π which can achieve up to scheduling capacity. Then, efficiency of π equals the maximum efficiency in the condition (4.5), and it is represented as below:

$$\begin{aligned} \eta_* &= \frac{min\left\{k(T-t), V^{(t)}\right\}}{V^{(t)}} \\ &= \frac{k(T-t)}{V^{(t)}} \end{aligned} \tag{4.6}$$

If (4.5) is satisfied, the scheduling capacity is exceeded. By (4.5) and (4.6), $\eta_* < 1$. This means that optimum policy cannot achieve 100% (fully) efficiency. Therefore, there is no 100% efficient policy which makes CC receive all $V^{(t)}$ packets from the nodes.

ii.

$$V^{(t)} \leq k(T-t) \tag{4.7}$$

As scheduling capacity of the centralized controller (CC) is k data packets per time slot, CC can accumulate at most $k(T-t)$ data packets from the nodes in the time interval $(t,T]$. Consider an omniscient offline policy: it will not leave an idle TSs as long as there is a node with data available, who is currently not scheduled. Hence, if there is an idle TS, this is because all available data packets are being transmitted. Trivially, this scheduling policy achieves 100% efficiency if $D^{(t)} \leq 1$:

$$\begin{aligned} \eta_* &= \frac{min\left\{k(T-t), V^{(t)}\right\}}{V^{(t)}} \\ &= \frac{V^{(t)}}{V^{(t)}} \\ &= 1 \end{aligned} \tag{4.8}$$

If (4.7) is satisfied, the scheduling capacity of the centralized controller is not exceeded. By (4.8), there is an 100% efficient policy which makes the centralized controller accumulate all $V^{(t)}$ data packets from the nodes. □

4.3 Efficiency of RR-based Policies

The scheduling problem is also investigated in [53] for certain scenarios. This paper propose myopic policy (MP) which is a kind of RR-based policies with quantum=1 TS and show that the RR-based myopic policy is optimal in certain specific cases as mentioned in introduction.

First, we will investigate the efficiency of RR-based policies with quantum=1 TS in Theorem 11. There is only a slight difference between the efficiencies of any two RR-based policies in long problem horizon $T(\frac{m}{k} \ll T)$ (as proven in Theorem 3 in Chapter 2). [32] Hence, the efficiency of RR-based myopic policy in [53] is investigated. It is shown that the policy in [53] is generally suboptimal.

For the case that each node has a buffer larger than one packet size, there is no known myopic policy in the literature. Therefore, we will compare UROP only with myopic policy in [53] in terms of efficiency.

Theorem 11. *Suppose that $T \gg \frac{m}{k} \in Z$ and the scheduling capacity of the FC is not exceeded by Theorem 1 ($V_i^{(t)} \leq (T-t)\ \forall s_i \in S, \forall t$ and $V^{(t)} \leq k(T-t)\ \forall t$). If there are some sensors $s_i \in S$ such that $V_i^{(t)} > \frac{k(T-t)}{m}$, all RR-based policies with quantum=1 TS will have efficiency below 100% although a fully efficient policy (π^{fe}) exists. Moreover, buffers of some sensors will be unstable.*

Proof. In this proof, RR policy implies RR policies with quantum=1 TS. We study efficiency of RR in two possible cases:

i. If $\sigma = \frac{kT}{m} \notin Z$, RR allocates some nodes $\lfloor \sigma \rfloor + 1$ TSs and other nodes $\lfloor \sigma \rfloor$ TSs for data transmission.

ii. If $\sigma = \frac{kT}{m} \in Z$, RR allocates each node σ TSs for data transmission.

Assume that $V_i^{(t)} > \frac{k(T-t)}{m}$ for some $s_i \in S$ and H is the set of these nodes. By definition of density, $D_i^{(t)} > 1\ \forall s_i \in H$.

i. If the CC schedules m nodes by RR policy in the problem horizon T, RR policy allocates some nodes $\lfloor \sigma \rfloor + 1$ TSs and other nodes $\lfloor \sigma \rfloor$ TSs for data transmission where $\sigma = \frac{kT}{m} \notin Z$ and $\{\sigma\} \triangleq \sigma - \lfloor \sigma \rfloor$. To maximize efficiency of RR policy, we assume that each node $s_i \in H$ can transmit at most $\lfloor \sigma \rfloor + 1$ data packets. However, each node cannot transmit $V_i^{(t)} - \lfloor \sigma \rfloor - 1$ data packets although $V^{(t)} \leq k(T-t)$ which means that a both optimum and 100% efficient policy exists. On the other hand, each node $s_i \in S - H$ can transmit all $V_i^{(t)}$ data packets. Efficiency of RR policy is represented as

$$\eta_{RR} = \frac{\sum_{s_i \in S} min\left\{V_i^{(t)}, \sigma\right\}}{\sum_{s_i \in S} V_i^{(t)}} \tag{4.9}$$

$$= \frac{\sum_{s_i \in H}(\lfloor \sigma \rfloor + 1) + \sum_{s_i \in S-H} V_i^{(t)}}{\sum_{s_i \in S} V_i^{(t)}} \tag{4.10}$$

$$= 1 - \frac{\sum_{s_i \in H}(V_i^{(t)} - \lfloor \sigma \rfloor - 1)}{\sum_{s_i \in S} V_i^{(t)}}. \tag{4.11}$$

By definition of $D_i^{(t)}$, η_{RR} is also stated as

$$\eta_{RR} = 1 - \frac{\sum_{s_i \in H}(D_i^{(t)}\sigma - \lfloor \sigma \rfloor - 1)}{\sum_{s_i \in S} D_i^{(t)}\sigma} \tag{4.12}$$

$$= 1 - \frac{\sum_{s_i \in H}(D_i^{(t)} - 1)\sigma - (1 - \{\sigma\}))}{\sum_{s_i \in S} D_i^{(t)}\sigma}. \tag{4.13}$$

As $D_i^{(t)} > 1$ for $s_i \in H$ and $\sigma \gg 1 - \{\sigma\}$, $(1 - \{\sigma\}) < (D_i^{(t)} - 1)\sigma$. Hence, $\eta_{RR} < 1$, i.e., RR is suboptimum.

ii. As $\sigma \in Z$, RR allocates each node $\sigma = \lfloor \sigma \rfloor$ TSs for data transmission. None of nodes can use $\lfloor \sigma \rfloor + 1$ TSs for data transmission. Therefore, efficiency of RR policies in this case can be represented as

$$\eta_{RR} = 1 - \frac{\sum_{s_i \in H}(V_i^{(t)} - \sigma)}{\sum_{s_i \in S} V_i^{(t)}} \tag{4.14}$$

instead of (4.11).

By definition of $D_i^{(t)}$, η_{RR} is stated as

$$\eta_{RR} = 1 - \frac{\sum_{s_i \in H}(D_i^{(t)} - 1)}{\sum_{s_i \in S} D_i^{(t)}}. \tag{4.15}$$

As $D_i^{(t)} > 1$ and $D^{(t)} \leq 1 \; \forall s_i \in H$, $\eta_{RR} < 1$. Hence, RR policies with quantum=1 TS are suboptimum because an optimal policy achieves fully efficiency ($\pi^* = \pi^{fe}$) when $D^{(t)} \leq 1$ by Theorem 10. □

4.4 A Near-Optimal Online Solution

The following Lemma forms the basis of our scheduling policy which is described in last subsection.

Lemma 9. (Partial Optimality) *If* $Q_i(t) = 0$ *for a node* s_i *at TS* t*, it can be said that an optimal policy* π^* *has been applied for the node* s_i *and efficiency is 100% for the node* s_i *up to TS* t*.*

Proof. For a data packet transmission, buffer of a node s_i must not be empty. If $Q_i(t) = 0$, s_i has no data packet to send. Efficiency is 100% for the node s_i up to TS t. □

$D < 1$ implies that there exists always idle TSs over a problem horizon even if π^{fe} is applied. Lemma 9 states that if a scheduled node cannot transmit data in TS t (idle TS occurs), a 100% efficient policy is applied to that node until TS t. By Lemma 9, UROP will be proposed based on this observation: *UROP uses idle TSs to determine the buffer states of scheduled nodes.*

4.4.1 Uniformizing Random Ordered Policy (UROP)

Considering that the data arrival process may be unpredictable, UROP orders the nodes randomly before starting to schedule them. The first k nodes in the ordering are scheduled to transmit. If a scheduled node can transmit a packet to the CC (because it has enough data to transmit) in one TS, then it will continue to be scheduled in the next TS. Otherwise, CC schedules the next node in the ordering in its place. CC completes a scheduling round when all m nodes are scheduled once. In part B, efficiency of UROP is studied for finite horizon case. In part C, it is shown that UROP is *asymptotically optimal* under a broad set of data arrival process.

4.4.2 Efficiency of UROP in Finite Horizon Case

In this part, the worst case and expected efficiency of UROP is studied in quite general data arrival process. First, several lemmas are stated. Then, these lemmas are used to prove Theorem 12 and Theorem 13.

Remark 6. *If $Q_i^{tot}(t)$ is the total arrived packets in node s_i up to TS t and $V_i^*(t)$ is the number of data packets which could be sent by node s_i until TS t under π^*, $V_i^*(t) = Q_i^{tot}(t)$.*

Now, we will define some new parameters related to idle time slots and these will be used in Lemma 10, Lemma 11 and Theorem 13. $A_{idle}(j, l)$ is the pair of the j^{th} channel of the FC and l^{th} idle TS for the j^{th} channel. $A_{idle}(j, l)$ occurs in TS γ_l^j. In this TS γ_l^j, FC drops a node using j^{th} channel and start to schedule another node in same channel. In the idle TSs, FC drops some of the k nodes and starts to schedule other nodes in their place. T_I is the set which consists of all pairs $A_{idle}(j, l)$. Figure 4.1 represents the transmission channel-idle time slot pairs in an example scheduling table.

Let's denote by $\xi_i^{(f)}$ and $\xi_i^{(f-1)}$ the idle TSs when FC starts to schedule node s_i for the last time and for the second last time, respectively. F_1 and F_2 are the set of all pairs $A_{idle}(u, v)$ such that $\gamma_v^u = \xi_i^{(f)}$ for a $s_i \in S$ and the set of all pairs $A_{idle}(u, v)$ such that $\gamma_v^u = \xi_i^{(f-1)}$ for a $s_i \in S$. As there are m nodes, $|F_1| = |F_2| = m$. G_1 is the set of all pairs $A_{idle}(p, q)$ such that $\gamma_q^p \neq \xi_i^{(f)}$ for $s_i \in S$. Moreover, G_2 is the set of all pairs $A_{idle}(p, q)$ such that $\gamma_q^p \neq \xi_i^{(f)}$ and $\gamma_q^p \neq \xi_i^{(f-1)}$ for $s_i \in S$. In other words, $G_1 = T_I - F_1$ and $G_2 = T_I - (F_1 \cup F_2)$.

Lemma 10. *If $A_{idle}(u, v) \in (F_1 \cup F_2)$,*

i) There does not exist such a pair $A_{idle}(p, q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_1$.

ii) There does not exist such a pair $A_{idle}(p, q) \in G_2$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in (F_1 \cup F_2)$.

Proof. ***Part i)*** Assume that there is such a pair $A_{idle}(p, q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some

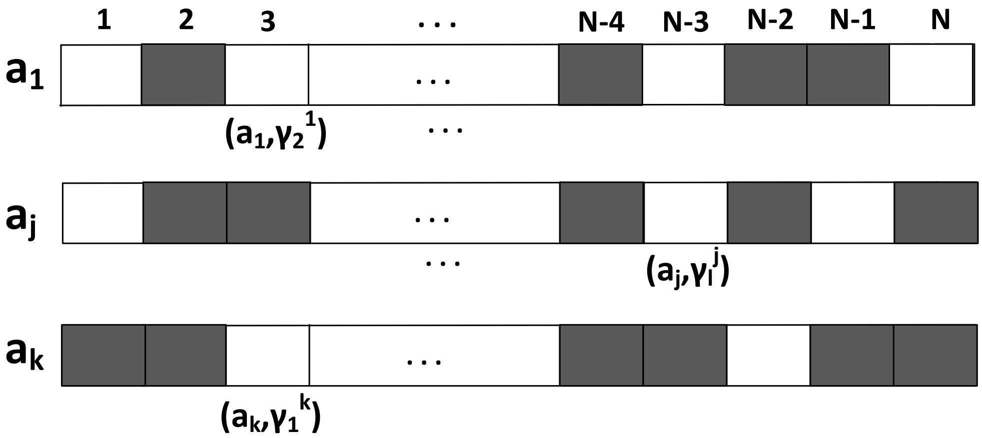

Figure 4.1: An example scheduling table kept by the centralized controller (CC) for all k channels over problem horizon $T = N$ time slots. Dark colored TSs represent busy time slots, and the white ones represent idle ones.

$A_{idle}(u, v) \in F_1$. Since $\gamma_q^p \neq \xi_i^{(f)}$ $\forall s_i \in S$, the node s_r which is selected by the FC in TS γ_q^p will be selected by the FC at least once more ($\gamma_q^p < \xi_r^{(f)}$). According to UROP, a node s_r which is selected in TS T_1 cannot be selected by the FC in TS T_2 unless $\forall s_i \in S - s_r$ are selected in the time interval $[T_1, T_2]$. Since $\gamma_q^p > \gamma_v^u = \xi_i^{(f)}$ for some s_i, these nodes cannot be selected by the FC in the time interval $[\gamma_q^p, \xi_j^{(f)}]$. Therefore, there does not exist such a pair $A_{idle}(p, q) \in G_1$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_1$.

Part ii) $G_1 = T_I - F_1$ and $G_2 = T_I - (F_1 \cup F_2) = (T_I - F_1) - F_2$. Replacing $T_I - F_1$ and F_2 with T_I and F_1 , respectively, in Part i, we can said that there exists no $A_{idle}(p, q) \in G_2$ such that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_2$. By Part i, there exists no $A_{idle}(p, q) \in F_2$ such that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in F_1$. Therefore, there does not exist such a pair $A_{idle}(p, q) \in G_2$ that $\gamma_q^p > \gamma_v^u$ for some $A_{idle}(u, v) \in (F_1 \cup F_2)$.

□

Lemma 11. *If $\zeta_j^{(f)}$ is the idle TS when CC stops to schedule node s_j for the last time and L is set of $\zeta_j^{(f)}$s, $L \subset (F_1 \cup F_2)$.*

Proof. Recall that $(F_1 \cup F_2) \subseteq T_I$. It can be said that CC starts to schedule a node iff it leaves (stops to schedule) another node. $(F_1 \cup F_2)$ includes two consecutive time (the last and second last time) when CC starts to schedule a node for all nodes. Assume that CC schedules a node s_i. Unless CC stops to schedule the node s_i, it cannot start to schedule the node s_i again. Therefore, $(F_1 \cup F_2)$ includes at least one departure time for each node. Since $(F_1 \cup F_2)$ includes the latest $2m$ idle TSs and at least one departure time for each node, $\zeta_j^{(f)} \in (F_1 \cup F_2), \forall s_j$. Hence, $L \subset (F_1 \cup F_2)$. □

Theorem 12. (Efficiency Bounds of UROP) *Final departure time of the node s_j which satisfies $\zeta_j^{(f)} \leq \zeta_i^{(f)}$ $\forall s_i \in S - \{s_j\}$ is denoted by $\zeta_j^{(f)} = T_0$. In problem horizon T, efficiency of UROP is bounded as*

$$1 - \frac{k(T - T_0)}{\sum_{i=1}^{m} V_i^*(T)} \leq \eta_{UROP} \leq 1, \tag{4.16}$$

where $V_i^*(T)$ is the number of data packets which could be transmitted by node the s_i up to TS t under an optimal policy π^*.

Proof. Due to space constraints, the proof is omitted here. Please see Theorem 4 in previous chapter. □

Considering *the worst case*, efficiency of UROP is bounded as shown in Theorem 12. k is known and $V_i^*(T)$ can be found for each node s_i by Remark 6. However, T_0 cannot be determined unless all details of scheduling in problem horizon is known. Due to the uncertainty of T_0, Theorem 12 does not provide sufficient information about efficiency of UROP. Remember that average reward is a suitable performance measure for the scheduling policy over finite or infinite horizon [51]. Considering T_0 (and the other departure times of nodes) as ergodic processes depending on data arrival process, efficiency of UROP is bounded in expectation manner.

Theorem 13. *For $0 < D < 1$, expected efficiency of UROP is bounded as*

$$1 - \frac{2m}{(1 - D)DTk} \leq E\left\{\eta_{UROP}\right\} \leq 1, \tag{4.17}$$

where T, m, k and D are problem horizon length, number of nodes, number of mutually orthogonal channels and density, respectively.

Proof. Recall that $V^*(T) = \sum_{i=1}^{m} V_i^*(T)$. By Theorem 12, efficiency of UROP can be written as below:

$$1 - \frac{k(T - T_0)}{V^*(T)} \leq \eta_{UROP} \leq 1 \tag{4.18}$$

$$1 - \frac{kE\{T - T_0\}}{V^*(T)} \leq E\{\eta_{UROP}\} \leq 1 \tag{4.19}$$

We denote by $\tau_{ar,i}$ and $\tau_{dep,i}$, elapsed time between two consecutive selection of same node s_i and elapsed time between two consecutive departure of same node s_i. For long problem horizons, $E\{\tau_{ar,i}\}$=$E\{\tau_{dep,i}\}$ $\forall i$. By Lemma 11, $L \subset (F_1 \cup F_2)$. By Lemma 10, if none of nodes $s_i \in S - S_k$ can be selected (started to schedule) more than twice by the CC in the interval $[T_0, T]$; therefore, $E\{T - T_0\} < 2E\{\tau_{ar}\}$. None of the nodes $s_i \in S_k$ can be left (stopped to schedule) more than once by the CC in time interval $\left[\zeta_i^{(f)}, T\right]$; therefore, the inequality 4.20 can be written for all nodes:

$$\begin{aligned} E\left\{T - \zeta_i^{(f)}\right\} &< 2E\{\tau_{dep}\} \\ &< 2E\{\tau_{ar}\} \end{aligned} \tag{4.20}$$

Hence, (4.19) turns into

$$1 - \frac{2kE\{\tau_{ar}\}}{V^*(T)} \leq E\{\eta_{UROP}\} \leq 1. \tag{4.21}$$

By definition of D in the system model, the total throughput by an optimal policy, $V^*(T)$, can be written as

$$V^*(T) = DTk \tag{4.22}$$

and also the density is

$$D = \frac{kE\{\tau_{ar}\} - m}{kE\{\tau_{ar}\}}. \tag{4.23}$$

Thus, $E\{\tau_{ar}\}$ is obtained as

$$E\{\tau_{ar}\} = \frac{m}{(1 - D)k}. \tag{4.24}$$

By putting (4.24) into (4.21), one concludes

$$\begin{aligned} 1 - \frac{2k\frac{m}{(1-D)k}}{DTk} &< E\{\eta_{UROP}\} \leq 1, \\ 1 - \frac{2m}{(1-D)\,DTk} &< E\{\eta_{UROP}\} \leq 1. \end{aligned} \tag{4.25}$$

□

Note: As $D = 0$ means no harvested energy in the whole communication network, it is trivial case and not considered in our calculations. $D = 1$ means that there is no idle TS if the fusion center apply the 100% efficient policy (π^{fe}). However, UROP benefits from idle TSs to schedule the sensors as mentioned in Section 4.4. From Theorem 10, no π^{fe} exists for $D > 1$. Therefore, we investigate $0 < D < 1$ in this paper.

As you may notice that the expected lower bound becomes negative for the case $m \geq \frac{(1-D)DTk}{2}$. However, we know that expected efficiency is nonnegative.

4.4.3 Extension to the Infinite-Horizon Case

By (4.25), as $1 - D$, D, k, and $m \in R_+$, $E\{\eta_{UROP}\} \to 1$ as $T \to \infty$. Hence, UROP is *asymptotically optimal* in infinite horizon for a broad class of data arrival process.

4.5 Numerical Results

In this section, efficiencies of RR and UROP are compared for independent and Markov data arrival processes under high and low density data arrival process. As $D \leq 1$, $\eta_* = \eta_{fe} = 1$. In each case, we compare these policies under both infinite and finite buffer assumption. To make a realistic scenario, we take $m = 100$, $k = 10$, $T = 2000$ for both policies. Note that we compare efficiency of UROP with a RR which is not necessarily MP proposed in [53] since $\eta_{RR} \cong \eta_{MP}$ for long problem horizons [38]. We investigate efficiency of both policies under nonuniform data arrival process (Both have nearly 100% efficiency under uniform data arrival processes). High density data arrival process is formed by taking $D_i = 3$ for 25 nodes

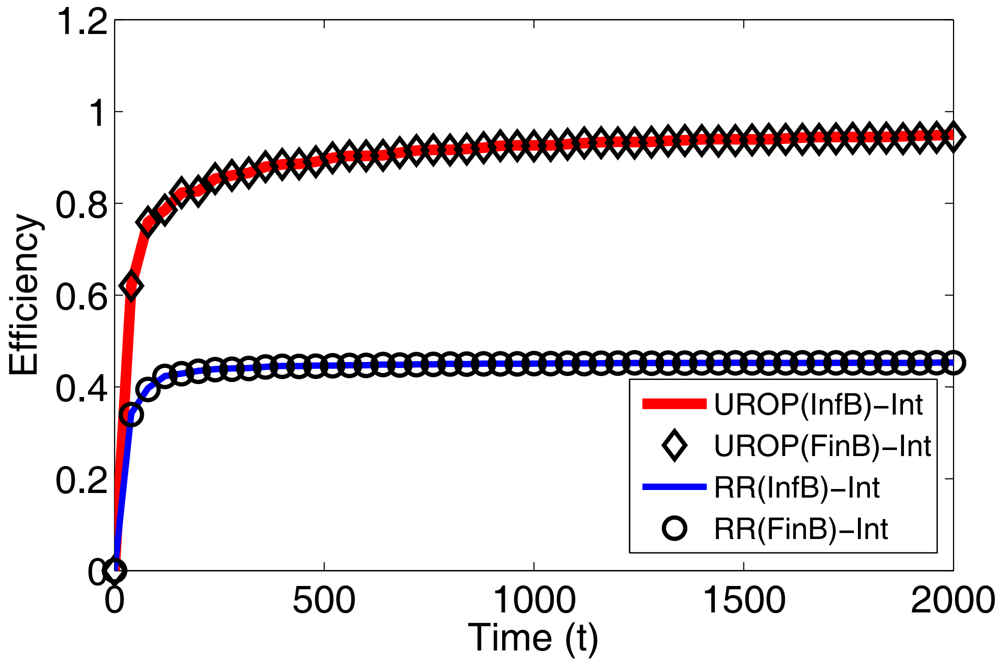

Figure 4.2: Efficiencies of UROP, RR with infinite buffer and finite buffer $Q_i = 50$ for high density ($D = 0.975$) Independent data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

and $D_i = 0.3$ for remaining nodes. Also, low density data arrival process is formed by taking $D_i = 2.1$ for 5 nodes and $D_i = 0.1$ for remaining nodes. Independent data arrival process is modelled as Poisson distribution for each node separately. Markov data arrival process is modelled for each node s_i by a state vector M_i=[0 D_i $2D_i$] and a 3×3 transition matrix P such that $p_{kk} = 0.9$ and $p_{jk} = 0.05$ $\forall j \neq k$.

Considering Figure 4.2 and 4.3 (Independent data arrival process), UROP has nearly 100% efficiency whereas RR has 80% efficiency for low density and below 50% efficiency for high density. Considering Figure 4.4 and 4.5 (Markov data arrival process), UROP has more than 95% efficiency whereas RR has 70% efficiency for low density and below 60% efficiency for high density. Simulations show that UROP is asymptotically optimal as proved in previous section. By Theorem 11, as the number of nodes satisfying $D_i > 1$ increases, efficiency of RR decreases. Therefore, the results are expected. Notice that efficiency of UROP is almost same under finite buffer $Q_i = 50$ assumption as that under infinite buffer assumption.

We also investigate the efficiency of UROP by taking $m = 103$ and $k = 10$. UROP

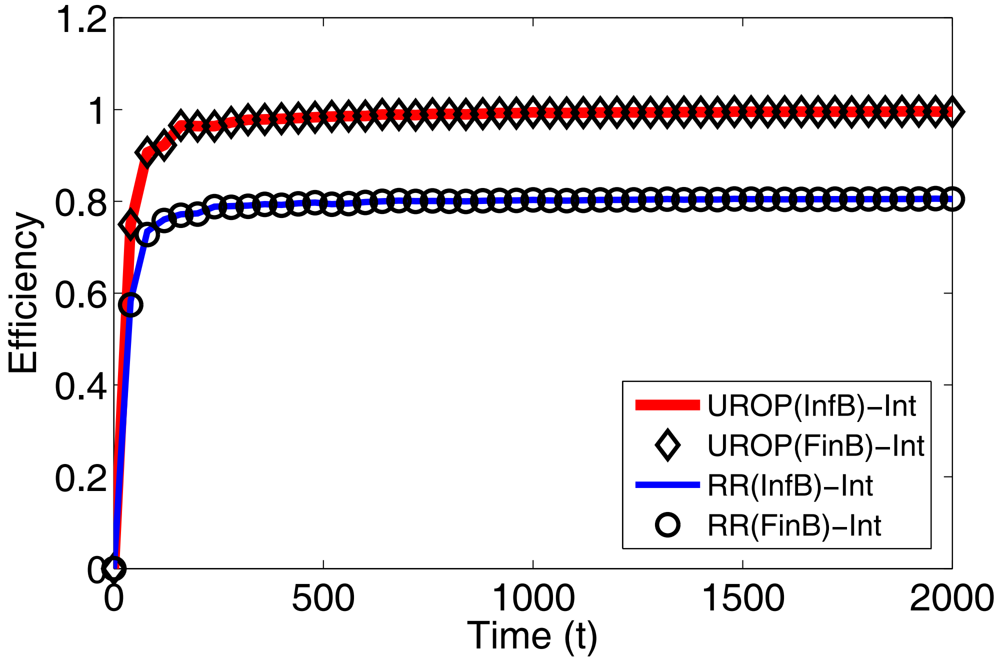

Figure 4.3: Efficiencies of UROP, RR with infinite buffer and finite buffer $Q_i = 50$ for low density ($D = 0.2$) Independent data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

achieves nearly 100% throughput for the case that m/k is not an integer for quite general data arrival processes. Therefore, UROP does not need m/k integer assumption which the RR-based myopic policy in [53] needs.

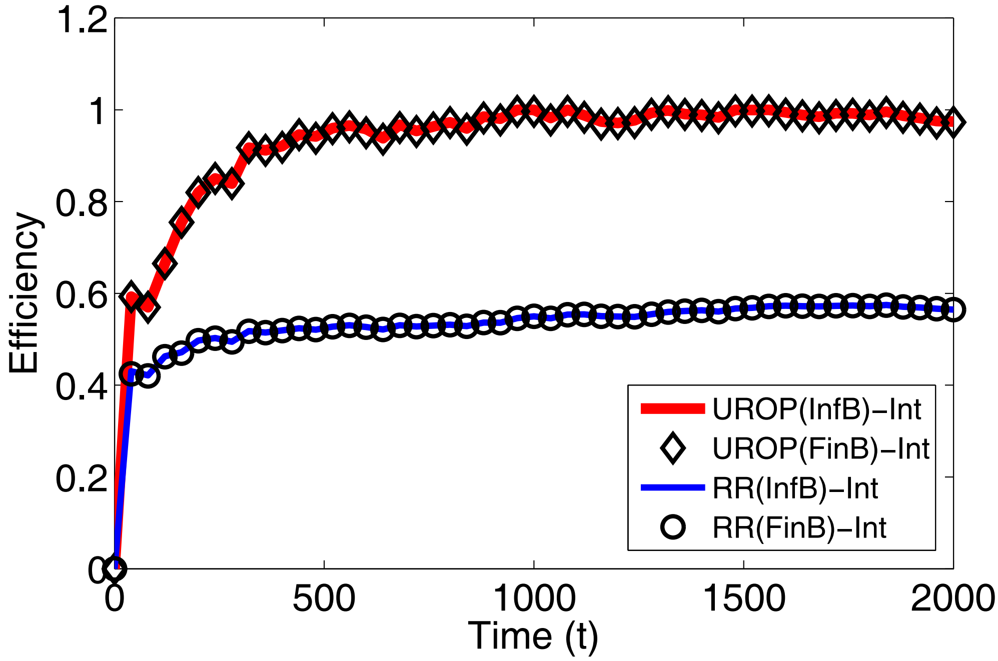

Figure 4.4: Efficiencies of UROP, RR with infinite buffer and finite buffer $Q_i = 50$ for high density ($D = 0.975$) Markovian data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

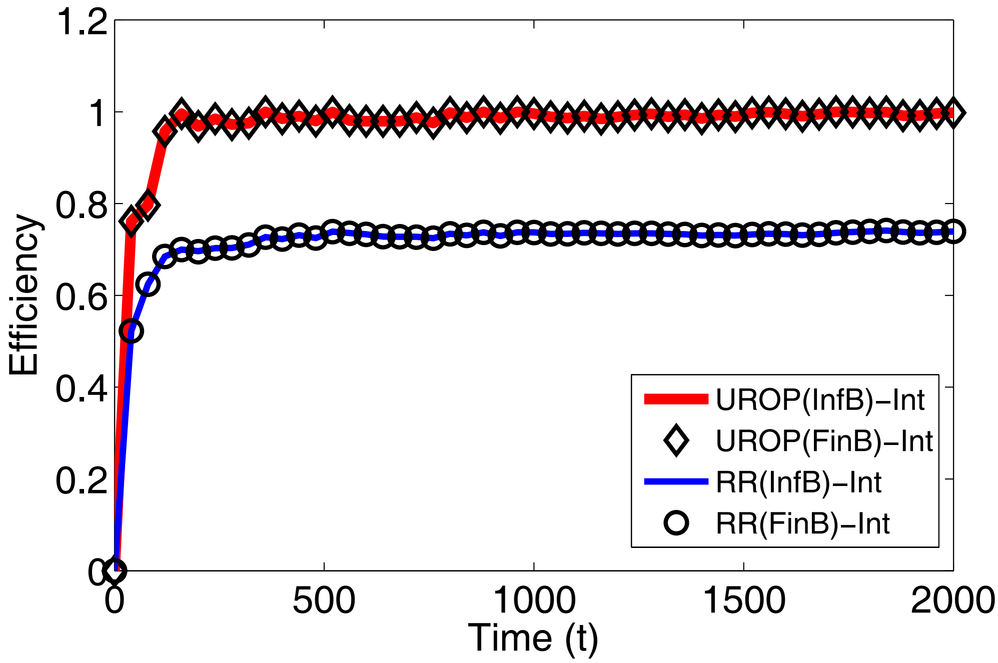

Figure 4.5: Efficiencies of UROP, RR with infinite buffer and finite buffer $Q_i = 50$ for low density ($D = 0.2$) Markovian data arrival processes under m/k integer assumption. Efficiency of UROP is also shown for m/k taking a noninteger value.

CHAPTER 5

CONCLUSION

In this thesis, three variations of a scheduling problem are studied. First, we investigated a scheduling problem for a single-hop wireless network, where a fusion center (FC) schedules a set of energy harvesting nodes to receive data from them. Fusion center does not know the instantaneous battery states of nodes. Batteries get recharged according to random energy harvesting processes, whose statistics are not available to the FC, and there is no leakage from the batteries. Under an infinite battery capacity assumption, we exhibit a near-optimal online scheduling policy for a broad set of energy harvesting processes (Markovian, independent, uniform, nonuniform, etc).

Secondly, we investigated a scheduling problem for a single-hop wireless network, where a fusion center schedules a set of EH nodes to collect data from them without feedback. By making infinite battery, buffer and no leakage assumptions, we consider this scheduling problem. In fact, this problem is the same with the first scheduling problem except the assumption that there is no data backlog in the system.

Thirdly, we studied a scheduling problem for a single-hop wireless network, where a centralized controller schedules a set of nodes to collect data from them without feedback. By making infinite buffer assumption, we investigated this scheduling problem. In fact, this problem is a dual version of first scheduling problem.

The scheduling problems are set up as an average reward maximization problem. It is shown that Round Robin (RR) based policies are generally suboptimal (do not guarantee 100% throughput) for nonuniform energy harvesting and data arrival processes.

It is also shown that policies proposed in previous literature (namely, myopic policies in [47], [49], [53]) have almost equal efficiency as any other RR policy with quantum=1 time slot.

Next, a low-complexity scheduling policy, Uniformizing Random Ordered Policy (UROP), is proposed for these scheduling problems. It is shown that UROP is asymptotically optimal regardless of energy harvesting and data arrival process, in the infinite problem horizon. Even in the finite horizon, UROP achieves nearly 100% throughput without requiring feedback about battery and buffer states of nodes.

As this problem can be considered as a type of restless multi-armed bandit (RMAB) problem, the simple self-adapting scheduling technique of UROP could find potential applications in problems other than communication networks, whenever the performance measure is average reward and the queues store a flexible resource such as energy and data.

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