DESIGN AND OPTIMIZATION OF A RATE ADAPTATION ALGORITHM FOR ENERGY HARVESTING TRANSMITTERS

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

BY

CIHAN EMRE KEMENT

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

SEPTEMBER 2014

Approval of the thesis:

DESIGN AND OPTIMIZATION OF A RATE ADAPTATION ALGORITHM FOR ENERGY HARVESTING TRANSMITTERS

submitted by **CIHAN EMRE KEMENT** in partial fulfillment of the requirements for the degree of **Master of Science in Electrical and Electronics Engineering Department, Middle East Technical University** by,

Prof. Dr. Canan Özgen
Dean, Graduate School of **Natural and Applied Sciences** ______________

Prof. Dr. Gönül Turhan Sayan
Head of Department, **Electrical and Electronics Eng.** ______________

Prof. Dr. Elif Uysal Bıyıkoğlu
Supervisor, **Electrical and Electronics Eng.Dept.,METU** ______________

Examining Committee Members:

Prof. Dr. Kemal Leblebicioğlu
Electrical and Electronics Engineering Department, METU ______________

Prof. Dr. Elif Uysal Bıyıkoğlu
Electrical and Electronics Engineering Department, METU ______________

Prof. Dr. Buyurman Baykal
Electrical and Electronics Engineering Department, METU ______________

Assoc. Prof. Dr. Ali Özgür Yılmaz
Electrical and Electronics Engineering Department, METU ______________

Selami Çiftçi, MSc
ARGELA A.Ş. ______________

Date: ______________

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: CIHAN EMRE KEMENT

Signature :

ABSTRACT

DESIGN AND OPTIMIZATION OF A RATE ADAPTATION ALGORITHM FOR ENERGY HARVESTING TRANSMITTERS

Kement, Cihan Emre
M.S., Department of Electrical and Electronics Engineering
Supervisor : Prof. Dr. Elif Uysal Bıyıkoğlu

September 2014, 61 pages

The need for energy efficient communication frameworks is growing. Energy harvesting communication constitutes an important part among such systems. This thesis aims to design and optimize a rate adaptation algorithm for transmitters of such systems in order to achieve energy efficiency. An optimal offline rate scheduling problem with battery constraints is solved by using iterative and heuristic techniques. Furthermore, it is shown that an additional energy saving is possible by changing the optimization problem to minimize both energy usage and energy waste. In addition to this, an online energy-efficient and energy harvesting-aware routing protocol for energy harvesting ad-hoc wireless sensor networks is developed. The protocol is observed to achieve a longer lifetime than some of the most popular current routing methods.

Keywords: Energy Harvesting Wireless Sensor Networks, Transmission Rate

Adaptation, Sequential Unconstrained Minimization Technique, Genetic Algorithm, Energy Efficient Routing

ÖZ

ENERJİ HASATLI VERİCİLER İÇİN HIZ UYARLAMASI ALGORİTMASI TASARIMI VE ENİYİLEMESİ

Kement, Cihan Emre
Yüksek Lisans, Elektrik ve Elektronik Mühendisliği Bölümü
Tez Yöneticisi : Prof. Dr. Elif Uysal Bıyıkoğlu

Eylül 2014 , 61 sayfa

Her geçen gün, çevreye duyarlı ve enerji verimli iletişim sistemlerine olan ihtiyaç artmaktadır. Bu tür sistemler içerisinde enerji hasatlı sistemler önemli bir yer teşkil etmektedir. Bu tez enerji harmanlayan vericiler için hız uyarlaması algoritması tasarımı ve optimizasyonunu amaçlamaktadır. Çalışma kapsamında; çevrimdışı iletim hızı uyarlaması ile enerji kullanımı enküçültme problemi, pil kısıtları göz önünde bulundurularak, yinelemeli ve sezgisel metodlar kullanılarak çözülmüştür. Ayrıca; optimizasyon problemi enerji kullanımı ile birlikte enerji israfını da azaltacak şekilde güncellenerek, ekstra enerji kazancı sağlanabileceği gösterilmiştir. Bunlara ek olarak; enerji hasat eden kablosuz sensör ağları için enerji hasadına duyarlı ve enerji verimli çevrimiçi bir iletim algoritması geliştirilmiştir. Bu algoritmanın güncel ve kabul görmüş algoritmalarla karşılaştırıldığında sensör ağının ömrünü daha çok uzattığı görülmüştür.

Anahtar Kelimeler: Enerji Hasat Eden Kablosuz Sensör Ağları, İletim Hızı Adaptasyonu, Ardışık Kısıtsız Optimizasyon Tekniği, Genetik Algoritma, Enerji Verimli İletim

To my beloved family

ACKNOWLEDGMENTS

I would like to thank my supervisor Professor Elif Uysal Bıyıkoğlu for her support and guidance. I also would like to thank Professor Buyurman Baykal and Professor Kemal Leblebicioğlu for their excellent teaching skills which helped me extend my academical knowledge. Thanks to all METU staff who run this institution brilliantly.

This work is also supported by TÜBİTAK-BİDEB scholarship (2210). I would also like to thank TÜBİTAK-BİDEB for their support.

My family also deserves to be mentioned here because they made me who I am. I would like to thank especially to my wife Mervenur Kement for being there for me since elementary school.

And finally very special thanks to my gang who are guilty of studying Electrical and Electronics Engineering and are now scattered all over the world, seeking redemption.

TABLE OF CONTENTS

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

ICT	Information and Communications Technology
ST	Save-then-Transmit
WSN	Wireless Sensor Network
SUMT	Sequential Unconstrained Minimization Technique
LEACH	Low-Energy Adaptive Clustering Hierarchy
PEGASIS	Power-Efficient Gathering in Sensor Information Systems
HEED	Hybrid Energy-Efficient Distributed Clustering
GC	Generic Clustering
GA	Genetic Algorithm
DTMC	Discrete Time Markov Chain
SNR	Signal-to-Noise Ratio
FORM	First Order Radio Model
EMARE	Energy and Mobility Aware Routing Scheme for Energy Harvesting Wireless Sensor Networks

CHAPTER 1

INTRODUCTION

Energy efficiency is an important goal for almost every field in today's world. Especially, as one of the most energy consuming sectors, ICT is a key player in energy efficiency. Energy efficient implementation of ICT infrastructure will be very important for the future of the technology, as its energy demand increases continually. *Energy efficient networking* has a great value due to the exponential increase in global networking and the amount of data that travels on it. Another thing that makes energy efficient networking so important is the fact that over the history of network design, energy efficiency was not taken into consideration until recently. Emergence of the mobile and battery powered networked devices with high energy demands during the last two decades has put energy efficiency among the top priority design aspects. Consequently, starting with [1], [2], [3], this issue also made an explosive effect on scholarly research in the field of communications and information theory recently. Especially, energy efficiency for wireless networks, where communication entities tend to be mobile and energy constrained, has gained much attraction.

Increasing energy demand of communication systems with battery-powered entities or *nodes* has forced the scientists to come up with alternative energy sources for the cases where electrical energy is not ubiquitous. One of the most important alternative methods is environmental energy harvesting. This method is realizable with rechargeable batteries that can generate energy from environmental sources such as solar, vibrational and thermal energy. Energy efficient networking shares the same purpose with energy harvesting, which is to prolong network entity's lifetime. It can be argued that energy efficiency is likely to be more critical for energy harvesting nodes, because energy harvesting is in general deployed by nodes which have energy shortage. This study therefore focuses on energy efficiency in energy harvesting communication systems.

Energy harvesting wireless communication systems consist of transceiver nodes which use batteries as the primary energy source. These batteries are supplied by the harvested environmental energy. The reason for such a mechanism is that the amount and the timing of energy harvests are ruled by the nature and hence may not follow at a steady state. On the other hand, network entities usually transmit packets that has to be transmitted before a deadline due to delay constraints. Therefore, even when the energy arrivals can be predicted to some extent, it is hard to make the transmission schedule and energy arrival schedule coincide. Hereby, between the harvested energy and used energy, there is an energy buffer, i.e. a battery. Although battery seems to be a perfect subsidiary, it brings its own problems: namely *charge/discharge inefficiency* and *leakage current*. Also, using environmental energy does not automatically guarantee unlimited lifetime. A certain energy policy should be constructed so that it is guaranteed for the energy harvesting node to operate perpetually.

Time variability of channel conditions, available energy, required energy and harvested energy bring complexity into construction of an energy efficient policy. However, these variations also present some opportunities which, if used wisely, can result in energy efficient or even perpetual operation. In order to use such opportunities, resource usage must be tuned according to them. This brings us to *scheduling* the transmission rate or power according to present, past, and future variations so that the resource usage is minimized. This is what was studied at the first part of this work. Building the solution to the problem of minimizing energy usage of an energy harvesting node by tuning transmission rate over the course of the transmission is alternatively called *optimum transmission rate scheduling*. As the solution is achieved by using the past,present and future data; it is called an *offline* solution. The problem of finding the optimal offline schedule which minimizes the transmission energy while ensuring perpetual operation is studied thoroughly. In addition, an online energy harvesting aware energy efficient method for energy harvesting wireless sensor network is studied.

The thesis consists of 5 chapters, first of which is the introduction chapter. The following chapter explains the study on optimal offline scheduling. The system model and problem definition, followed by the solution with SUMT are provided. Then, the same problem is handled by using a genetic algorithm. The chapter ends with the solution of a second optimization formulation that places more emphasis on saving energy. The fourth chapter focuses on the online routing protocol EMARE. Firstly, energy efficient protocols in general are explained. Then, the system model that includes energy dissipation, energy harvesting and data aggregation models is explained. The chapter concludes with performance evaluation of the algorithm. Finally, the fifth chapter is conclusion which includes outcomes of the study and possible future research areas.

CHAPTER 2

LITERATURE REVIEW

In [4], power management in sensor networks that utilize environmental energy has been studied. The study emphasizes that energy management in battery powered sensor networks and energy harvesting sensor networks must differ from each other due to distinct energy characteristics of these two types of networks. The main difference between these two types of networks was noted such that while battery powered sensor networks have the limit on the maximum amount of energy, energy harvesting sensor networks have the limit on the maximum rate at which the harvested energy can be utilized. According to [4] another distinctive feature of the energy harvesting sensor networks is the energy availability which fluctuates over time and is hard to predict exactly. This makes the characterization of energy metric harder than conventional sensor networks which operate on battery. In addition to these two, uneven energy harvesting opportunities of energy harvesting nodes (due to different environmental conditions etc.) makes it a necessity to come up with a characterization of energy which is coherent with the nature of energy harvesting sensor networks.

Under the light of these arguments, [4] presents the concept of Energy Neutral Operation: The operation of the network such that the used energy is always less than the harvested energy. When such energy neutral operation is achieved, it guarantees that the energy harvesting sensor network stays alive indefinitely. [4] aims to achieve maximum performance under the condition that energy neutrality is always preserved. However; the fact that energy consumption profile, which is shaped by the activity of the sensor network, is independent from energy harvesting profile, which is shaped by the environmental energy source, makes it difficult to achieve energy neutrality. Therefore, according to [4] it is necessary to utilize an intermediate energy buffer and to modify the energy consumption profile. By doing so, [4] maximizes the average duty cycle of an energy harvesting sensor network that scavenges solar energy. It also considers battery imperfections and proposes a low complexity optimal solution given the complete future energy harvesting knowledge.

[5] builds upon [4] and tries to maximize the throughput as well as to minimize the transmission time of a point-to-point communication in a wireless fading channel. The transmitter is an energy harvesting node and has limited battery capacity. It is assumed that energy harvesting occurs at random times by random amounts. [5] also considers that the battery has to have enough space for each energy harvesting period in order not to waste energy. Throughput maximization is achieved using an optimal offline algorithm called directional water-filling. The transmission time minimization objective is solved by using its relation with the throughput maximization problem.

[6] considers a system of communication that has an energy harvesting transmitter. Assuming that the energy harvesting process is known beforehand by the transmitter, it maximizes the amount of data transmitted within a certain transmission time. The battery leakage and imperfections are taken into account in addition to battery size constraints.

The study in [7] utilizes different advantages of batteries and super-capacitors by using both in an energy harvesting transmitter. The transmitter is assumed to be capable of selecting where the harvested energy is going to be stored. The offline throughput maximization objective is analyzed for a point-to-point communication. The two constraints coming from the battery and the super-capacitor are reduced to one constraint and the problem is solved by utilizing the directional water-filling algorithm.

[8] extends previous studies on throughput maximization by examining an energy harvesting two-hop communication system for which optimal power usage and scheduling are studied. In this work, both source node and the relay node harvest

energy from the environment. The harvested energy is assumed to arrive at the source node twice ($N = 2$), whereas harvested energy arrives at the relay node multiple times ($N > 2$). [8] shows that the multiple energy arrival at the relay node can equivalently be represented as two energy arrivals and thus the optimal transmission policy can be found by using previous work [9] which finds the optimal policy for the case of two energy arrivals at the relay.

One of the recent works about optimal transmission protocols for energy harvesting wireless transmitters is [10] which is concerned with rechargeable batteries' inability to charge and discharge simultaneously. Building upon this constraint, a protocol named save-then-transmit (ST) is introduced. This protocol saves a fracture of time p to energy harvesting and reserves the remaining $(1 - p)$ fraction to data transmission. Energy harvesting transmitters are assumed to have 2 energy storage units, one being a battery and one being a super-capacitor. Therefore, energy storage inefficiency of batteries is also taken into account. The study minimizes the system outage performance by finding the optimal save-ratio under Rayleigh fading channel.

[11] considers an energy harvesting communication system under AWGN Broadcast Channel and the transmission completion minimization problem is studied. All of the data is assumed to be available at the beginning of the transmission. Also, steady channel gain is assumed. The study states that the optimal schedule saves energy from each energy harvest, in order to use it at the later part of the transmissiion. A modified version of the iterative offline algorithm *FlowRight* [2] is shown to solve the problem. It was observed that the optimal schedule's power allocation is non-decreasing in time.

The study in [12] seeks optimal solutions to transmission time minimization and transmission energy minimization problems of both AWGN broadcast and point-to-point fading channels. Certain variables such as energy harvests, data arrivals and channel state changes are assumed to be known beforehand. An important outcome of the study is that in an optimal schedule, transmission rate remains constant within certain time intervals. One thing to note about this study is that it assumes perfect battery for energy harvesters, which is not applicable in reality. The study also includes an online scheduling algorithm TriMod [12], which takes energy harvesting into account and outperforms traditional scheduling algorithms in terms of energy efficiency.

In [13] authors study the transmission completion time minimization problem of an energy harvesting transmitter with multiple (M) receivers. The paper analyzes the single receiver case and proves that the optimal strategy is the same for the single receiver and multiple receiver cases. The transmission power allocated for the closest receiver is based on a cut-off level. If the available power for transmission is higher than this cut-off level, the remaining power is used for transmission to the second closest receiver. If this remaining power is more than a second cut-off level, the remaining power is allocated for the third closest receiver and so on. Based on this structure, a method deriving the optimal offline transmission policy which minimizes the transmission time is developed.

Another study by Kansal et al. [14] investigates key points of designing a solar energy harvesting wireless network. Several important aspects such as battery inefficiency, energy leakage, solar cell characteristics, energy harvesting hardware design as well as power management regarding energy harvesting are studied. Authors consider solar cell characteristics, different energy storage techniques, harvesting circuits and energy measurement capabilities to come up with an energy harvesting framework. This framework is implemented by using Heliomote energy harvesting sensor nodes and by evaluating its performance; it has been shown that the efficiency of the sensor network is improved by energy harvesting-aware design.

The study in [15] presents information about various energy harvesting techniques, current commercial products that harvest energy from various sources as well as design considerations regarding energy harvesting hardware. Existing commercial energy harvesting products exemplified here include thermogenerators, piezoelectric harvesters, a combination of solar and piezoelectric harvesters and electromagnetic energy harvesters. Voltage and current characteristics of such harvesters, as well as power consumption and energy storage issues are investigated. It is concluded that Voltage and Current levels of electrical circuits must be lowered in energy harvesting devices so that the limited energy harvested from the environment can be enough to power them. In addition, energy harvesting transducers must have different operation modes in order to minimize energy consumption. Lastly, leakage currents must be handled carefully in order to increase energy efficiency.

A comprehensive survey of wireless sensor neworks (WSNs), which also contains a comparison of energy efficient routing protocols in terms of parameters including cost, scalability and power consumption is [16]. The study mentions well-known methods such as Flooding and Gossiping, as well as other popular methods like SPIN[17] and LEACH[18]. Although protocols presented here intend to achieve energy efficiency, they do not take energy harvesting into account while constructing routes. It is deduced in this study that the surveyed protocols need to be improved, or new methods should be developed, in order to meet the requirements imposed by topology changes, power consumption and scalability.

One of the benchmarks of power-aware routing schemes is LEACH, which has first been presented in [18]. This protocol aims to prolong a wireless sensor network's lifetime by constructing clusters within which a *cluster head* collects all the data, aggregates it, and sends it to the sink. With this technique, only cluster heads establish a long-range communication with the sink, enabling the other nodes to save energy. For uniform dissipation of energy, cluster heads are chosen randomly amongst sensor nodes. Only a certain fraction $P \quad (0 < P < 1)$ of nodes can be cluster heads at the same time, and once a node becomes a cluster head, it cannot be a cluster head again for the next $1/P$ rounds of communication. These measures are claimed to help LEACH to outperform direct transmission scheme "by as much as 8x"[18]. The performance of LEACH, along with the simple energy dissipation model used for simulating LEACH, which is called First Order Radio Model, has made the protocol a benchmark for its successors.

PEGASIS [19] is one of the methods that are compared with LEACH in terms of sensor network lifetime. It is declared to perform up to 3 times better than

LEACH by reducing the number of nodes that communicate with the sink down to 1. This one *cluster head* sends all the data collected from other sensor nodes after aggregating them. Therefore, only 1 node makes a long-distance transmission that demands a high amount of energy. The other nodes form a *chain* by linking up with their closest unlinked neighbor, and pass their data to the next node in the chain. The routing structure (chain) is built by passing a token among sensor nodes. As in LEACH, in order to achieve uniform energy usage, sensor nodes become cluster heads in turn. Downsides of the method are; assuming that all nodes (including the cluster head) send a data packet of the same size (see *Complete Redundancy* in Section 4.2.3), not taking energy harvesting into account, and building the chain such that it minimizes individual transmission distances instead of minimizing the total transmission distance as in the traveling salesman problem.

A survey of more recent power-aware routing protocols is provided in [20]. Many protocols including LEACH and PEGASIS have been mentioned in this study. There, an energy-efficient and distributed cluster-based routing protocol, namely HEED [21], stood out amongst others. HEED is a distributed cluster-based routing algorithm which takes two metrics into account while selecting cluster heads: Residual energy and a secondary parameter such as proximity or node degree. It claims to achieve uniform energy distribution, low message overhead and termination in $O(1)$ iterations [21]. Similar with LEACH, HEED randomly elects cluster heads. However, instead of using a fixed election probability, it sets the probability depending on node's residual energy. Therefore, a node with small residual energy has a small chance of being a cluster head. The second parameter is used to "break ties"[21] when a node is in the range of two cluster heads. HEED is compared with methods such as LEACH and Generic Clustering (GC) in [21], and it is claimed to outperform those protocols under certain network conditions.

CHAPTER 3

OPTIMUM OFFLINE TRANSMISSION SCHEDULING FOR ENERGY HARVESTING TRANSMITTERS WITH BATTERY CONSTRAINTS

Energy harvesting transmitters are used primarily in applications where energy is not abundant. Battery-powered communication systems constitute most of such transmitters. As the available energy is limited in such applications, power management becomes critical. Especially for applications such as energy harvesting sensor networks, where the performance of the system is dependent on the life of individual nodes, energy dissipation should be minimized in order to maximize the efficiency of the network. It is widely known that the wireless transmission is the most energy demanding process in a wireless transceiver [22]. Therefore, minimizing the transmission energy is critical for such devices. One of the most common practices to minimize transmission energy is to adjust the transmission rate for certain time intervals (i.e *epochs*) so that a certain amount of data is transmitted with minimum energy within a specified transmission time. This practice is commonly called as transmission rate adaptation or scheduling [1][2][23].

To calculate the optimum transmission rate schedule, future occurrences such as channel gain change and the amount of energy harvested over transmission time need to be known in advance. Therefore, transmission rate scheduling is an *offline* [1] process. The benefit of calculating the optimal offline schedule is that it gives insight about the attributes of a decent online power management scheme. It also provides the upper boundary on the achievable performance level. Furthermore, in applications where variables such as channel state and energy harvests are predictable, optimal offline schedules can be used to achieve energy efficient transmissions. However, in order for the optimal offline schedule to be realistic, it should also include battery constraints such as charge/discharge inefficiency and leakage [24], which are covered in this study. More specifically, *energy neutral operation*, which is presented in [4], is adapted in order to formulize optimization problems solved throughout this chapter.

3.1 System Model

A point-to-point communication over a wireless fading channel is considered. Transmitter runs on battery and is supplied by energy harvests occurring at arbitrary times and arbitrary amounts. A zero-mean (white) unit-variance Gaussian noise is assumed. Over any time interval (epoch), the baseband equivalent of received signal is given by [5][10]

$$y = \sqrt{h}x + n \tag{3.1}$$

where y is the received signal, x is the transmitted signal, h is the squared channel gain and n is the zero-mean unit-variance Gaussian noise. Data packets and Energy packets arrive at arbitrary times and arbitrary amounts. All energy and data arrivals are assumed to be known beforehand. Energy storage unit (battery) of the transmitter is assumed to be non-ideal with charge/discharge efficiency η and constant leakage power P_{leak}.

Changes in the channel gain, energy arrivals and data arrivals are called as *events*, and the time interval between two successive events is defined as an *epoch* [1]. Therefore, the epoch i is the time interval $[t_i, t_{i+1})$ where t_i and t_{i+1} are the times when i^{th} and $(i+1)^{th}$ events take place. Note that during an epoch i, the squared channel gain h_i remains constant. The length of epoch i is represented by $T_i = t_{i+1} - t_i$.

Following the Gaussian channel capacity formula, at time t the maximum rate at which a reliable communication is achievable with a arbitrarily small probability of error is known as:

$$r(t) = \frac{1}{2}\log(1 + h(t)p(t))\text{bit/s/channel use} \tag{3.2}$$

From eq. (3.2), during i^{th} epoch of length T_i, the number of bits transmitted by sending the signal x with power p_i is $\frac{T_i}{2}\log(1 + h_i p_i)$. Similarly, the power p_i required to transmit data at a rate r_i is:

$$p_i(r_i) = \frac{2^{2r_i} - 1}{h_i} \tag{3.3}$$

3.2 Problem Definition by Adopting Energy Neutrality

Energy Neutral Operation is defined in [4] as to "operate such that the energy used is always less than the energy harvested". This is analogous with the energy causality concept, i.e. a device cannot use the energy that has not been available yet. Consider an energy harvesting transmitter with an ideal energy storage. Then, energy neutrality imposes that for all non-negative values of T [4]:

$$\int_0^T P_c(t)dt \leq \int_0^T P_s(t)dt + B_0 \qquad \forall T \in [0, \infty) \tag{3.4}$$

where $P_c(t)$ is the consumed power, $P_s(t)$ is the stored power and B_0 is the initial energy stored in the ideal battery. The case in (3.4) is not sufficient to model the real-life battery-powered systems, as current energy storage units have charge/discharge efficiency strictly less than 1 and they lose energy through leakage [24]. Therefore, a more realistic energy neutrality constraint can be stated as follows: [4]

$$B_0 + \eta\int_0^T [P_s(t) - P_c(t)]^+dt - \int_0^T [P_c(t) - P_s(t)]^+dt - \int_0^T P_{leak}(t)dt \geq 0 \quad \forall T \in [0, \infty) \tag{3.5}$$

The inequality in (3.5) can be modified into discrete-time as follows:

$$B_0 + \eta\sum_{i=1}^{k}[E_h(i) - E_u(i)]^+ - \sum_{i=1}^{k}[E_u(i) - E_h(i)]^+ - \sum_{i=1}^{k} P_{leak}T_i \geq 0 \quad \forall k \in 1, 2, ..., K \tag{3.6}$$

Where $E_h(i)$ is the energy harvested at the beginning of epoch i, $E_u(i)$ is the energy used during epoch i, K is the minimum number of epochs in which the transmission can be completed and T_i is the length of epoch i. Note that this inequality should hold for all k, meaning that energy causality is preserved during each epoch. Note that energy arrival is an event, therefore $E_h(i)$ is the harvested energy at the beginning of epoch i. Therefore, this model assumes that only the excess energy is stored in the battery with efficiency η.

Contemporary energy harvesting transmitters need an intermediate energy buffer in order to regulate the energy in accordance with the voltage and current need of the transmitter [24]. In order to avoid immediate energy loss due to inefficiency of the batteries, supercapacitors which have efficiency close to 1 are used. However, energy capacities of current supercapacitors are lower than batteries of comparable dimension. In addition, supercapacitors have typically higher leakage current than batteries. Therefore, a good system design may call for combining supercapacitors(high efficiency, small capacity, high leakage), and batteries (lower efficiency, larger capacity, smaller leakage) together. Equation (3.6) represents energy causality for such a transmitter. In case when $E_h(i)$ is smaller than $E_u(i)$, all of $E_h(i)$ is immediately used via the supercapacitor without losing any energy to inefficiency. Using harvested energy immediately also prevents losing energy to leakage. Similarly, when $E_h(i)$ is larger than $E_u(i)$, the harvested energy is immediately used and the remaining is stored in the battery. This indicates that the supercapacitor and the battery are the primary and secondary energy supplier, respectively.

In this energy causality model, the excess of energy harvested at the beginning of epoch i is sent to the battery at the end of the *same* epoch. Hence, inefficiency of the battery is preferred over leakage power of the supercapacitor. if the supercapacitor had bigger capacity and smaller leakage, it could be more efficient to store energy at the supercapacitor for longer durations. However, today's supercapacitors have small capacities and high leakage currents compared with batteries [25], leaving a small room for trade-off analysis. Hence, this discussion is left for further studies.

In addition to energy, data to be transmitted should be available before it was transmitted. This is called data causality, which is represented as follows:

$$\sum_{i=1}^{k} r_i T_i \leq \sum_{i=1}^{k} D(i) \quad \forall k \in 1, 2, ..., K \tag{3.7}$$

Where r_i is the transmission rate adopted during epoch i and the $D(i)$ is the data arrived at the beginning of epoch i. One thing to notice is that the rate r_i is constant throughout the epoch. It was proven in [11] that the transmission completion time minimization of an energy harvesting broadcast system yields a solution at which the power levels stay constant during epochs. Similarly, in [12], the same is shown to be true for a point-to-point communication time minimization problem. It was also stated in [12] that the solution of the time minimization problem (T_{opt}) yields the same schedule with the energy minimization problem with time constraint T_{opt}. Thus, it was proven that the power (or rate) levels remain constant on an optimal schedule that minimizes energy usage. It can also be deduced from the convexity of the power function given in (3.3). Another condition that the optimal schedule must meet is transmitting the data completely, which is stated below:

$$\sum_{i=1}^{K} r_i T_i = \sum_{i=1}^{K} D(i) \tag{3.8}$$

Combining these constraints, a constrained optimization problem which minimizes the energy usage while preserving energy and data causality can be stated as follows:

Minimize:

$$\sum_{i=1}^{K} E_u(i) = \sum_{i=1}^{K} p_i(r_i) T_i \tag{3.9}$$

subject to:

$$r_i \geq 0 \tag{3.9a}$$

$$\eta \sum_{i=1}^{k} [E_h(i) - E_u(i)]^+ - \sum_{i=1}^{k} [E_u(i) - E_h(i)]^+ - \sum_{i=1}^{k} P_{leak} T_i \geq 0 \tag{3.9b}$$

$$\sum_{i=1}^{k} r_i T_i \leq \sum_{i=1}^{k} D(i) \tag{3.9c}$$

$$\sum_{i=1}^{K} r_i T_i = \sum_{i=1}^{K} D(i) \tag{3.9d}$$

The constraint (3.9a) comes from the fact that the transmission power cannot be negative. Equation (3.2) directly deduces that transmission rate should also be nonnegative. Equations (3.9b) to (3.9d) follow from energy and data causality constraints.

Lemma 3.2.1. *Problem (3.9) is a convex optimization problem.*

Proof. see Appendix A. □

3.3 Solution of Problem (3.9) by Using SUMT

Sequential Unconstrained Minimization Technique [26] [27] is used to solve computationally complex constrained minimization problems by converting them into a sequence of unconstrained minimization problems. Penalty and barrier functions are in general used to replace the constraints.

Suppose that the problem is to minimize $f(x) : \mathbb{R}^J \to \mathbb{R}$ subject to $x \in C$. In order to replace this problem with an unconstrained one, a penalty function $f_p : \mathbb{R}^J \to \mathbb{R}$ is introduced such that $f_p \geq 0$ and $f_p = 0 \iff x \in C$. Then, this penalty function is added to the objective function with a coefficient k resulting in the unconstrained minimization problem:

$$\text{minimize} \quad g_k(x) = f(x) + k f_p(x) \tag{3.10}$$

which is solved for each positive integer k. If the constrained problem is convex, as $k \to \infty$ the sequence of solutions $\{x^k\}$ converges to $x^* \in C$ which solves the constrained problem.

Problem (3.9) is converted into an unconstrained minimization problem by adding the constraints (3.9a), (3.9b), (3.9c), (3.9d) into the objective function as a penalty function. The resulting minimization problem is as follows:

$$\text{Minimize:} \quad G(\mathbf{r}) = \sum_{i=1}^{K} p_i(r_i)T_i + \mu\Gamma(\mathbf{r}), \tag{3.11}$$

$$\text{where:} \quad \Gamma(\mathbf{r}) = \sum_{i=1}^{K} \max(0, -r_i)^2$$
$$+ \sum_{i=1}^{K} \max\Big(0, -\sum_{i=1}^{k} (\eta[E_h(i) - E_u(i)]^+ - [E_u(i) - E_h(i)]^+ - P_{leak}T_i)\Big)^2$$
$$+ \sum_{i=1}^{K} \max\Big(0, \sum_{i=1}^{k} (r_iT_i - D(i))\Big)^2 + \Big(\sum_{i=1}^{K} (r_iT_i - D(i))\Big)^2$$

It has been proven in [26] that, the sequence of unconstrained minimization problems converge to the solution x^* of the original constrained problem if the solution space is convex; or failing that, converge to the constrained minimum. As the original problem (3.9) is convex, SUMT results in a sequence which converges to the solution of the original problem.

Note that $\Gamma(\mathbf{r})$ is equal to zero if and only if all of the constraints in Problem (3.9) are satisfied. The vector $\mathbf{r}$ is of size K and it represents the transmission rate schedule. The SUMT algorithm to solve (3.11) is initialized with a random $\mathbf{r_{init}}$, ignoring the constraints. An unconstrained search technique is called at each iteration in order to find the $\mathbf{r}$ that minimizes (3.11). Depending on which constraints this $\mathbf{r}$ violates, some of the addends in $\Gamma(\mathbf{r})$ becomes zero and hence the objective function $G(\mathbf{r})$ changes. Therefore, the unconstrained search is repeated with an updated objective function and updated μ at the next iteration. The coefficient μ is initialized as μ_{init}, and increased by a factor $\phi \geq 1$ at each iteration. Thus, the penalty function gets bigger at each iteration, pushing the sequence of solutions towards the constrained region. The violating terms in $\Gamma(\mathbf{r})$ are squared in order to penalize violating terms more harshly so that the solution converges into the constrained region more quickly. Normally, when $\mu \to \infty$ the optimal solution is reached. In this study, however, due to practical reasons the iterations stop when μ reaches a certain large μ_{max}.

The SUMT algorithm used for problem (3.11) can be summarized as follows:

Algorithm 1 Sequential Unconstrained Minimization Technique

$\mathbf{r} \leftarrow \mathbf{r_{init}}$

$\mu \leftarrow \mu_{init}$

repeat

  $\mathbf{r} \leftarrow Newton(\mathbf{r})$

  $\mu \leftarrow \phi\mu$

until $\mu \geq \mu_{max}$

Note that in Algorithm 1, Newton's Method is used to find the unconstrained minimum at each iteration. Hence Newton's Method itself is an iterative method, Newton's iterations are called *inner iterations*. At inner iteration i, $\mathbf{r}_{i+1}$ is calculated as follows:

$$\mathbf{r}_{i+1} = \mathbf{r}_i - [\mathbf{H}G(\mathbf{r}_i)]^{-1}\nabla G(\mathbf{r}_i) \tag{3.12}$$

where ∇ represents the gradient vector and $\mathbf{H}$ represents the Hessian matrix. The stopping criteria for inner iterations is the *Newton decrement* $\lambda(\mathbf{r}_i) = \left(\nabla G(\mathbf{r}_i)^T[\mathbf{H}G(\mathbf{r}_i)]^{-1}\nabla G(\mathbf{r}_i)\right)^{1/2}$ being smaller than a certain ϵ_s, which is a typical stopping condition for Newton's method.

3.4 Numerical Results

Consider the sample event sequence in Figure 3.1. The initial energy the transmitter have is $15J$. It can also be considered as the energy harvested at first epoch. Harvested energies arrive at $T = \{7, 8, 11, 12, 14, 17\}$ The bandwidth is $W = 1kHz$.

The first case is when charge/discharge efficiency $\eta = 1$ and $P_{leak} = 0$, i.e. the ideal case. The squared channel gain h is also kept constant at 1 (no attenuation) to see the result under ideal conditions. The resulting optimal schedule is given

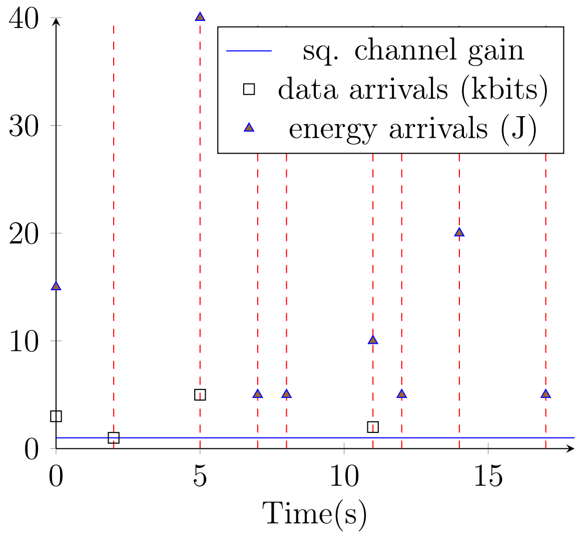
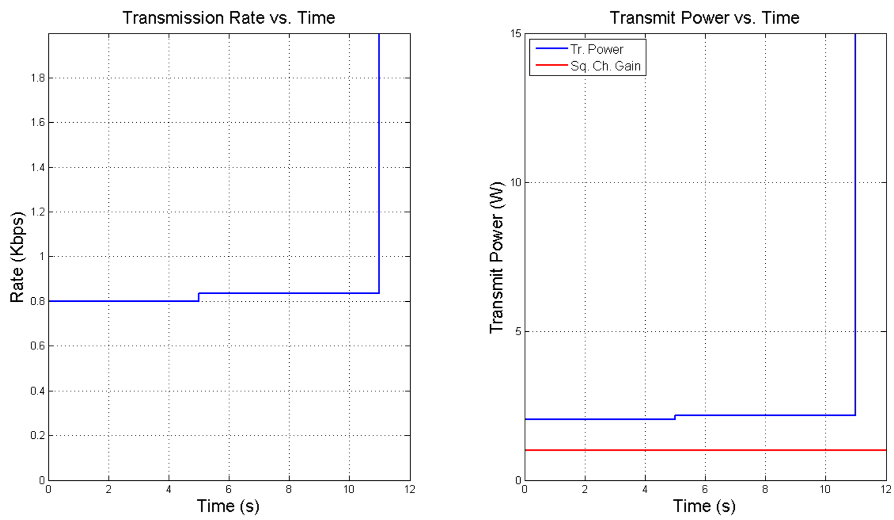


Figure 3.1: Sample event sequence

as in Figure 3.2. Note that the sum of consumed energy and remaining energy add up to $75J$ which is the sum of E_h's of first six epochs.

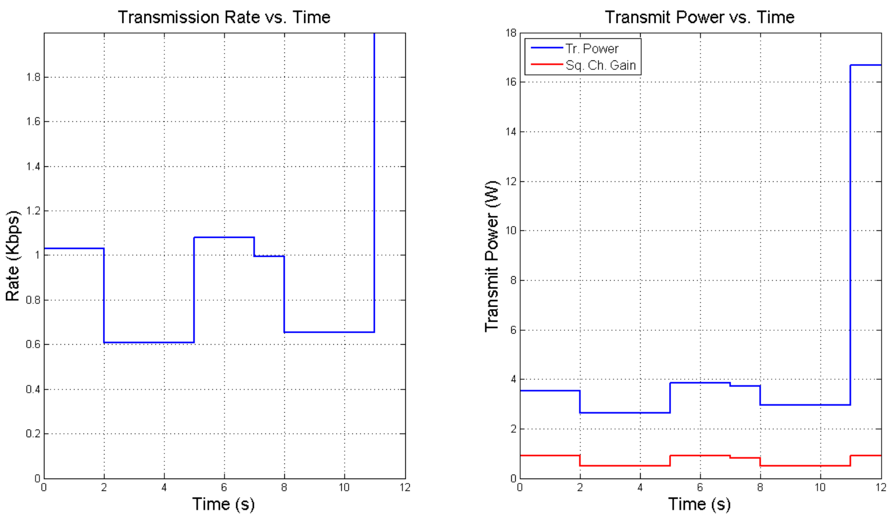


Total energy consumption: 38.2052 Joules
Remaining energy: 36.7948 Joules
Total data transmitted: 11 kbits

Figure 3.2: Optimal Offline Schedule: Ideal case

During the 6th epoch ($T = [11, 12)$), $2kbits$ arrive at the transmitter and subsequently the transmission rate increases to $2kbps$. As the transmission power increases exponentially with transmission rate (see Equation (3.3)), a high amount of energy ($15J$) is spent only at the last epoch. Those $2kbits$ could be transmitted with less energy by increasing transmission time (i.e. using 7 or more epochs). However, K is defined in (3.9) as the minimum number of epochs during which the transmission can be completed. Such a constraint is necessary while finding the optimal solution, because theoretically without a time constraint any amount of finite data can be transmitted with infinitesimal amount of energy over an infinite duration.

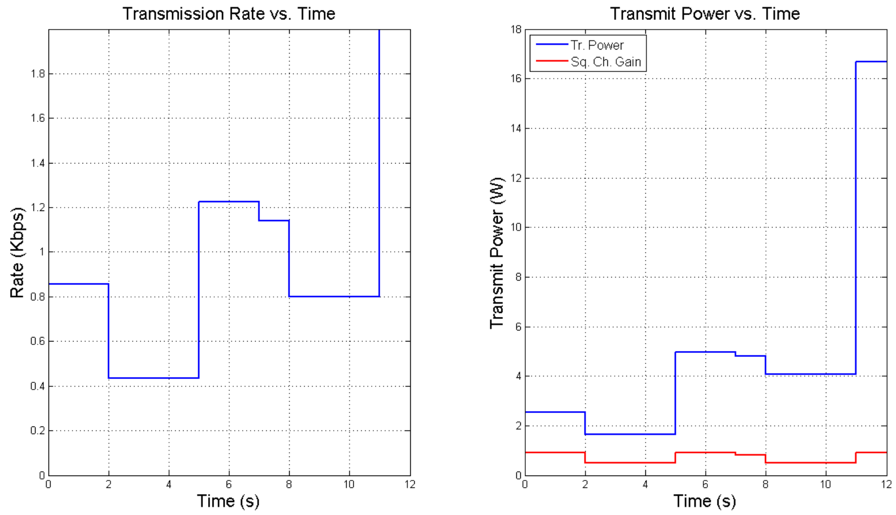
Next, the channel gain is reduced strictly below 1, which corresponds to more signal attenuation. The resulting schedule is given in Figure 3.3. The optimal schedule takes advantage of epochs with higher channel gain and increases transmission rate accordingly. Note that the total energy consumption increases as the decreased channel gain demands more energy to be spent on transmission. In this case, the battery efficiency η is equal to 1 and P_{leak} is $0W$.



Total energy consumption: 51.9205 Joules
Remaining energy: 23.0795 Joules
Total data transmitted: 11 kbits

Figure 3.3: Optimal Offline Schedule: Variable Channel Gain

Now let us relax the ideal battery assumption and increase P_{leak} to $1W$. Although it is a high value for leakage, it makes the observation of the effects of leakage easier. The optimal schedule with $P_{leak} = 1W$ is given in Figure 3.4.



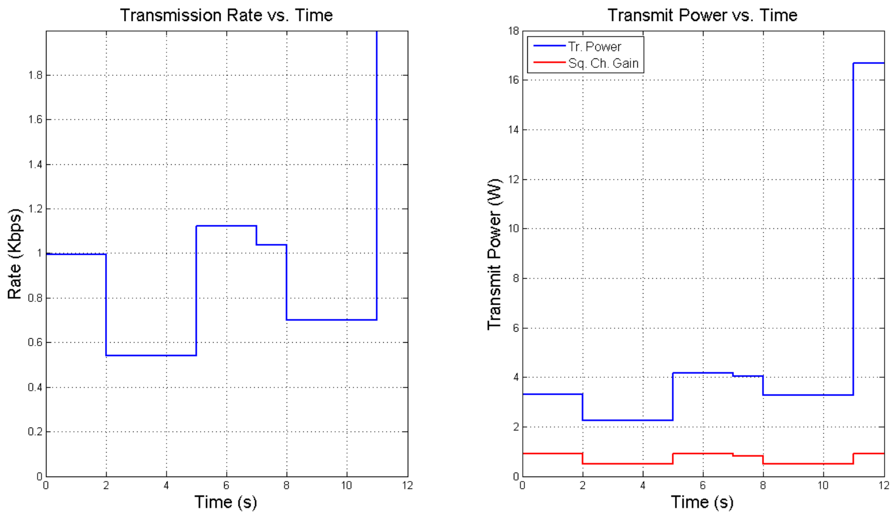
Total transmission energy: 53.5769 Joules
Remaining energy: 9.4231 Joules
Total data transmitted: 11 kbits

Figure 3.4: Optimal Offline Schedule: Battery with Leakage

The effect of the leakage can be seen especially during the first two epochs. The available energy at that time is $15J$ and $5J$ is lost to the leakage, which in return results in reduced transmission rate. In order to compensate for it, transmission rates at following three epochs are increased. These changes in the schedule cause an increase in total transmission energy.

The next case is when the battery efficiency is reduced to 0.8, a typical value for Li-ion batteries [28]. Leakage power is ignored so that the sole effect of battery inefficiency on optimal schedule can be seen. The result in Figure 3.5 is obtained for $\eta = 0.8$, $P_{leak} = 0$.

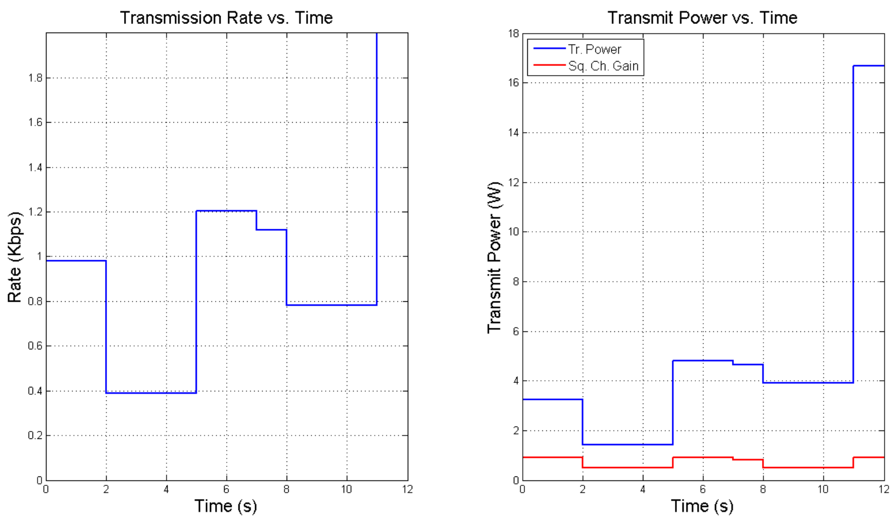
The optimal schedule again changes due to the imperfection of the battery. Note that although total transmission energy changes slightly, the remaining energy decreases significantly. How the behavior of the optimal schedule changes when efficiency is further reduced to 0.5 can be seen on Figure 3.6. Note that as the efficiency decreases, the optimal schedule is inclined to spend the arrived energy



Total transmission energy: 52.1652 Joules
Remaining energy: 14.6261 Joules
Total data transmitted: 11 kbits

Figure 3.5: Optimal Offline Schedule: Battery with $\eta = 0.8$

immediately. This is because if the energy is not spent at the same epoch, it is stored in the battery which loses a significant amount of energy in vain.



Total transmission energy: 53.3372 Joules
Remaining energy: 2.0057 Joules
Total data transmitted: 11 kbits

Figure 3.6: Optimal Offline Schedule: Battery with $\eta = 0.5$

3.5 Evolutionary Optimization Approach to Obtain the Optimal Offline Schedule

Evolutionary Algorithm is a heuristic optimization scheme which adopts techniques inspired from biological evolution such as crossover, mutation, selection and reproduction [29]. Among numerous Evolutionary algorithms, *Genetic Algorithm* [30] is one of the most popular ones. It pursues the solution in the form of *chromosomes*, i.e. string of numbers, which it derives from a certain *population* by simulating biological phenomena such as *crossover* and *mutation*. A typical Genetic Algorithm follows the steps given in Algorithm 2.

For the problem (3.9), the array of transmission rates are adopted as chromosomes without any alteration. For example; a transmission rate schedule $r_i = \{1, 3, 0.2, 2, 1.4, 1.8\}$kbps is represented as chromosome $c_i = [1, 3, 0.2, 2, 1.4, 1.8]$. Note that r_i has 7 elements and hence it represents a schedule that spans 7 epochs. The length of the schedule is the same for each schedule/chromosome and it is determined as the least number of epochs during which the transmission can be completed.

An initial population of $n = 100$ chromosomes are created in accordance with Algorithm 2. The transmission rate in epoch k is constrained between:

$$\left(0, \min\left\{\frac{W}{2}\log\left(1 + h_k P_{cum}(k)\right), \frac{\sum_{i=1}^{k} D(i)}{T_k}\right\}\right) \tag{3.13}$$

where $P_{cum}(k) = \dfrac{\sum_{i=1}^{k} E_h(i)}{T_k}$, $D(i)$ is the data arrived at the beginning of epoch k, T_k and h_k are the duration and channel gain of epoch k, respectively. This constraint is due to the energy and data causality constraints of the problem. Note that charge/discharge inefficiency and energy leakage are not taken into account. This means that some elements of the chromosomes will violate energy neutrality constraints. Those energy neutrality constraints are later dictated by the fitness function. Therefore, the aim of this constraint on the transmission rate is not to meet the constraints in (3.9), but rather to have a head start by creating an initial population that does not contain chromosomes with irrelevant elements.

Algorithm 2 Genetic Algorithm

1: A population of randomly generated n chromosomes is created. Each chromosome represents a possible solution to the optimization problem. In other words, any solution candidate is encoded into a chromosome, which is a string of numbers.

2: According to an application specific fitness function F_{fit}, fitness of each chromosome is calculated. The fitness function is specified such that the fitness of a chromosome is proportional to the proximity of the corresponding solution to the optimal solution.

3: If the fitness of a chromosome is greater than a certain threshold θ_f, **stop**. The solution corresponding to this chromosome is in the proximity of the optimal solution. Else, **continue**.

4: **repeat** following steps:

5: **Select two chromosomes from the population.** The probability of a chromosome being selected is proportional with its fitness.

6: **Perform a crossover with a probability $\mathbf{p_c}$.** The crossover can be single point or multiple point. In case of single point crossover, chromosomes are broken into two at a specific point and a new chromosome is formed by taking the first and the second parts from the first and the second *parent* chromosomes, respectively.

7: **Perform a mutation on the new chromosome with a probability $\mathbf{p_m}$.** Mutation is the change in random elements (numbers) of the chromosome. It is generally performed, when chromosomes are made of binary numbers, by replacing zeros with ones and vice versa.

8: **until** n offspring are produced.

9: Replace the current population with the new generation of n chromosomes.

10: Go to state 2

A resolution of 0.001 is used while determining the elements of the chromosomes. Therefore, the k^{th} element of the chromosome can take one of the values $\left\{0, 0.001, 0.002, \cdots, \min\left\{\frac{W}{2}\log\left(1+h_k P_{cum}(k)\right), \frac{\sum_{i=1}^{k} D(i)}{T_k}\right\}\right\}$. Using such a resolution in this problem makes calculations simpler. In addition, contemporary transmitters can adjust their transmission rates in a discrete fashion. Therefore, discrete transmission rates are more useful in real-life applications.

After the initial population is generated, chromosomes are evaluated by using a fitness function F_{fit} such that the fitness of the chromosome is a weighted sum of Heaviside (step) functions of constraints and total energy usage as below:

$$\begin{aligned}
F_{fit}(\mathbf{c}) = & x_1 \prod_{k=1}^{K} \mathcal{H}(\eta \sum_{i=1}^{k} [E_h(i) - E_u(i)]^+ - \sum_{i=1}^{k} [E_u(i) - E_h(i)]^+ - \sum_{i=1}^{k} P_{leak} T_i) \\
& + x_2 \prod_{k=1}^{K} \mathcal{H}(\sum_{i=1}^{k} D(i) - r_i T_i) \\
& + x_3 \sum_{i=1}^{K} \mathcal{H}(\epsilon - |D(i) - r_i T_i|) \\
& + x_4 \sum_{i=1}^{K} -E_u(i)
\end{aligned} \tag{3.14}$$

where $\mathcal{H}$ is the unit step function and x_i are coefficients with $x_1 + x_2 + x_3 = 1$. Note that the 4th addend is negative. This is because the chromosome which spends less energy should be more fit. One should also note that the coefficient x_4 is kept small compared with the other three, so that the first three addends remain dominant. As a solution *must* meet the constraints in (3.9), the first three addends in (3.14) accounts for most of the fitness. Therefore, according to (3.14), a schedule that uses a small amount of energy is represented by a chromosome which has fitness close to 1. The constraint (3.9a) is ignored as it is automatically met by allowing nonnegative transmission rate values only.

After all chromosomes are assigned with their fitness values, two chromosomes are randomly selected and with a probability p_c single-point crossover is applied between these chromosomes. The resulting chromosomes are added to the new generation chromosomes. The probability that a chromosome is selected is adjusted to be proportional with its fitness value. The point where the crossover takes place is also chosen randomly. After the crossover, all elements of new chromosomes are mutated with probability p_m. The mutation process is critical in acquiring the optimal solution, because the population consists of only 100 chromosomes and it is highly unlikely that the optimal rates corresponding to each epoch is chosen in the initial population. The process of selection, crossover and mutation continues until a new population of n chromosomes are generated. This cycle of assigning fitness and creating a new population continues until a generation with average fitness higher than a certain threshold is obtained. Among this group, the fittest chromosome is chosen as the solution.

Example 3.5.1. *Crossover at 3rd element*

$$\begin{aligned} c_1 &= [6, 2.2, 3, 8, 5.4, 2, 0.2, 3.3] & & & c_1' &= [6, 2.2, 3, 9, 4, 1.5, 8.1, 5] \\ & & &\xrightarrow{crossover} & & \\ c_2 &= [6.3, 1, 2.7, 9, 4, 1.5, 8.1, 5] & & & c_2' &= [6.3, 1, 2.7, 8, 5.4, 2, 0.2, 3.3] \end{aligned}$$

Example 3.5.2. *Mutation*

$$\begin{aligned} c_1' &= [\mathbf{6}, 2.2, 3, \mathbf{9}, 4, 1.5, 8.1, 5] & & & c_1' &= [\mathbf{6.01}, 2.2, 3, \mathbf{9.02}, 4, 1.5, 8.1, 5] \\ & & &\xrightarrow{mutation} & & \\ c_2' &= [6.3, \mathbf{1}, 2.7, 8, 5.4, \mathbf{2}, 0.2, 3.3] & & & c_2' &= [6.3, \mathbf{0.9}, 2.7, 8, 5.4, \mathbf{2.4}, 0.2, 3.3] \end{aligned}$$

In order to evaluate the effectiveness of this heuristic, it is compared with the optimal offline solution found earlier. A sequence of events as in Figure 3.7 is assumed and for that sequence, both SUMT and GA methods are run. The battery efficiency η and leakage power P_{leak} are assumed as 0.8 and $1mW$, respectively.

The resulting schedule with SUMT and GA can be compared in Figure 3.8. Note that the schedule produced by GA is very close to the schedule produced by SUMT. This is expected as the Genetic Algorithm converges to the the global optimum. On the other hand, normally SUMT method converges to the local optima along with the other gradient-based methods. Here, however, SUMT too reaches the global minimum due to the convexity of the optimization problem. The energy used by the optimal schedule is $52.1664J$ whereas the GA schedule

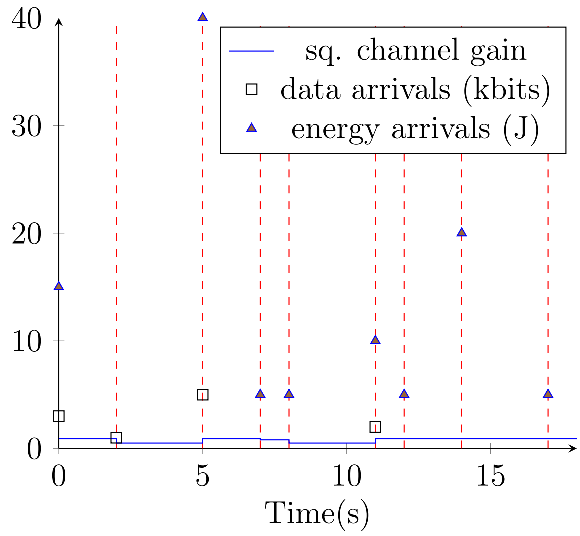


Figure 3.7: Another sample event sequence

spends 52.168J for transmitting the same amount of data. The small difference of transmission energy can be linked with the discrete set of rate values that a chromosome is allowed to take. This comparison shows that SUMT method indeed reaches the optimum solution. It should be noted that the convergence time of GA in this case is much longer than that of SUMT method.

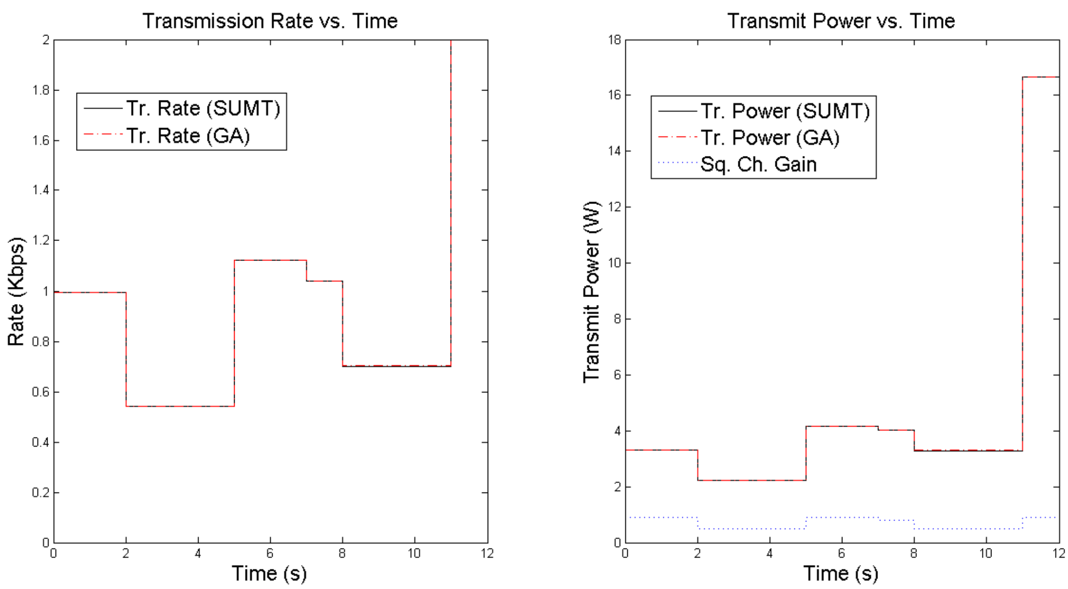


Figure 3.8: Offline Schedules: SUMT vs. GA

3.6 Maximization of Saved Energy by Using SUMT

It was observed in Section 3.4 that the change in the transmission energy and the remaining energy are not commensurate. At some cases, the transmission energy increases slightly while the remaining energy decreases rapidly. Likewise, the transmission energy can change immensely while the remaining energy is not affected as much. A further tweaking with the numbers showed that it was possible to *increase remaining energy* by changing the optimal transmission schedule, i.e. by *increasing transmission energy.* What was the problem? It turns out that, in the presence of battery imperfections, the algorithm that only focuses on minimizing transmission energy does not fully compile with the aim of energy saving. The optimization problem in such a case should try to maximize the energy that remains after the transmission. In other words, it should minimize the sum of transmission energy and the energy that is wasted. Therefore, the optimization problem (3.11) should be re-written as follows:

$$\text{Minimize:} \quad G(\mathbf{r}) = \sum_{i=1}^{K} \left(p_i(r_i)T_i + E_w(i)\right) + \mu\Gamma(\mathbf{r}), \tag{3.15}$$

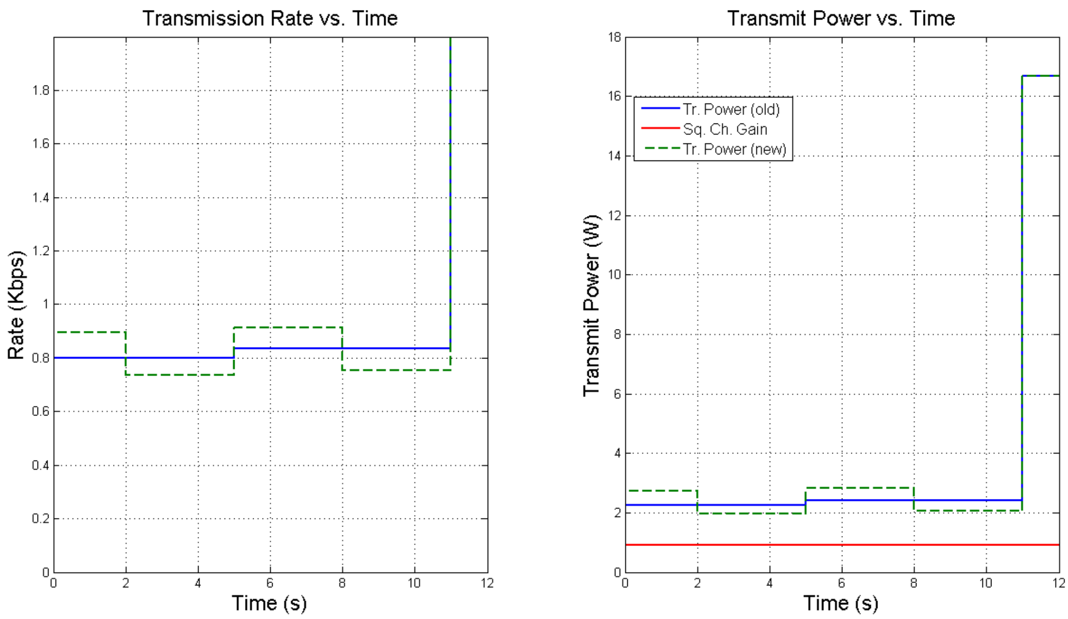
$$\text{where} \quad \Gamma(\mathbf{r}) = \sum_{i=1}^{K} \max(0, -r_i)^2$$

$$+ \sum_{i=1}^{K} \max\left(0, -\sum_{i=1}^{k} \left(\eta[E_h(i) - E_u(i)]^+ - [E_u(i) - E_h(i)]^+ - P_{leak}T_i\right)\right)^2$$

$$+ \sum_{i=1}^{K} \max\left(0, \sum_{i=1}^{k} (r_iT_i - D(i))\right)^2 + \left(\sum_{i=1}^{K} (r_iT_i - D(i))\right)^2$$

$$\text{where} \quad E_w(i) = (1-\eta)[E_h(i) - E_u(i)]^+ + P_{leak}T_i$$

E_w stands for energy wasted, and it can be seen that it is a constant when $(E_h - E_u) \leq 0$, and a linearly increasing function of $(E_h - E_u)$ when $(E_h - E_u) > 0$, therefore it can be seen that as long as $\eta \geq 0$, the convexity is not affected. Also, note that under ideal conditions ($\eta = 1, P_{leak} = 0$), $E_w = 0$ and the problem (3.15) becomes identical with problem (3.11). When this new optimization problem is solved and compared with the old one, the result is



Total transmission energy: 42.4501 Joules (old), 42.6845 Joules (new)
Remaining energy: 22.8906 Joules (old), 23.0991 Joules (new)
Total data transmitted: 11 kbits (old, new)

Figure 3.9: Offline Schedules: Old vs. New

obtained as in Figure 3.9.

The event sequence in Figure 3.10 is used in the comparison. Battery efficiency η and leakage power P_{leak} are taken as 0.8 and $1mW$, respectively. Note that the new optimal schedule is more aggressive during epochs at which energy arrival occurs. At the first ($E_h = 15J$) and third ($E_h = 40J$) epochs, the transmission rates are increased. This is due to the fact that if the harvested energy is not used at the same epoch, then it is stored at the battery and hence lose energy to charge/discharge inefficiency. Consequently, during the second, fourth and fifth epochs where there is a small energy harvest or no harvest at all, the transmission rate is reduced. It turns out that although the transmission energy is increased by the new schedule, the remaining energy is also increased.

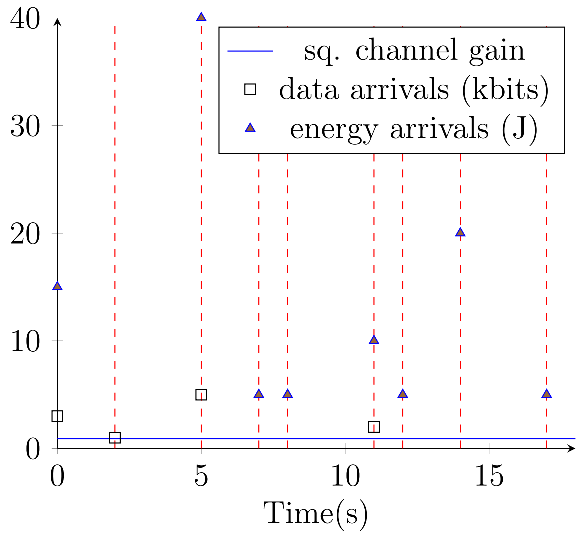


Figure 3.10: An event sequence

The comparison in Figure 3.9 is made with stable channel gain assumption. To relax that, optimal offline schedules for a sequence as in Figure 3.11 are calculated.

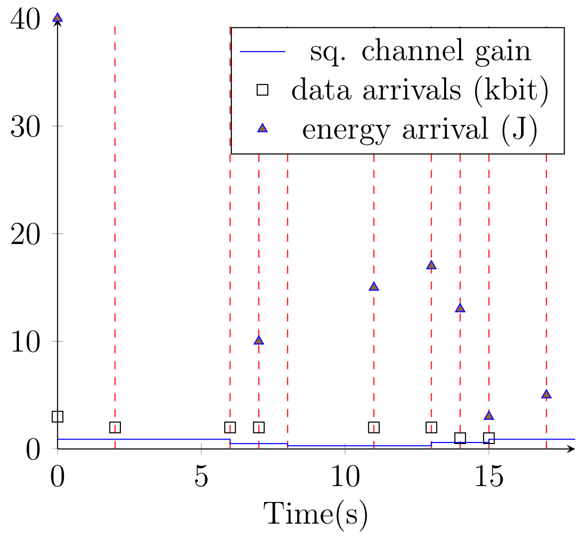
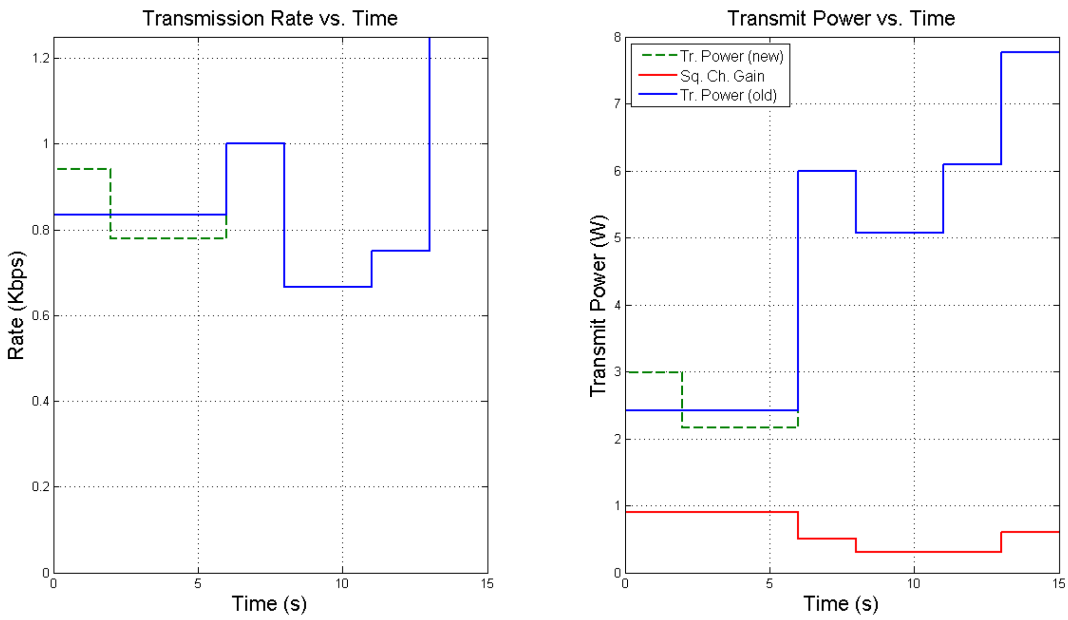


Figure 3.11: Another sample event sequence

Battery efficiency η and leakage power P_{leak} are kept the same (0.8 and $1mW$), and the resulting schedules in Figure 3.12 show that the new optimal schedule



Total transmission energy: 69.4093 Joules (old), 69.5295 Joules (new)
Remaining energy: 43.9325 Joules (old), 44.0386 Joules (new)
Total data transmitted: 13 kbits (old, new)

Figure 3.12: Offline Schedules: Old vs. New

does not completely differ from the old one. In this case, the new schedule is increased at the first epoch, consequently decreased at the second, and remained the same with the old schedule for the rest of the epochs. This minor change saved $0.1J$ of energy.

For the same event sequence in Figure 3.11, the solution of problem (3.15) for different η values, as well as the solution of problem (3.11) for $\eta = 1$ are plotted in Figure 3.13. The first thing to be noticed is that both of the problems (3.11) and (3.15) yield the *same* result for $\eta = 1$. This had been algebraically explained earlier. In addition, Figure 3.13 reveals the behavior of the optimal offline schedule against decreasing battery efficiency.

The leakage power P_{leak} was $1mW$ during the simulations in Figure 3.13. Although when the value of P_{leak} is significant it changes the outcome of problem (3.15), it gives the same result as problem (3.11). This is expected as P_{leak} is added as a constant to E_w in (3.15), therefore a change in P_{leak} does not alter

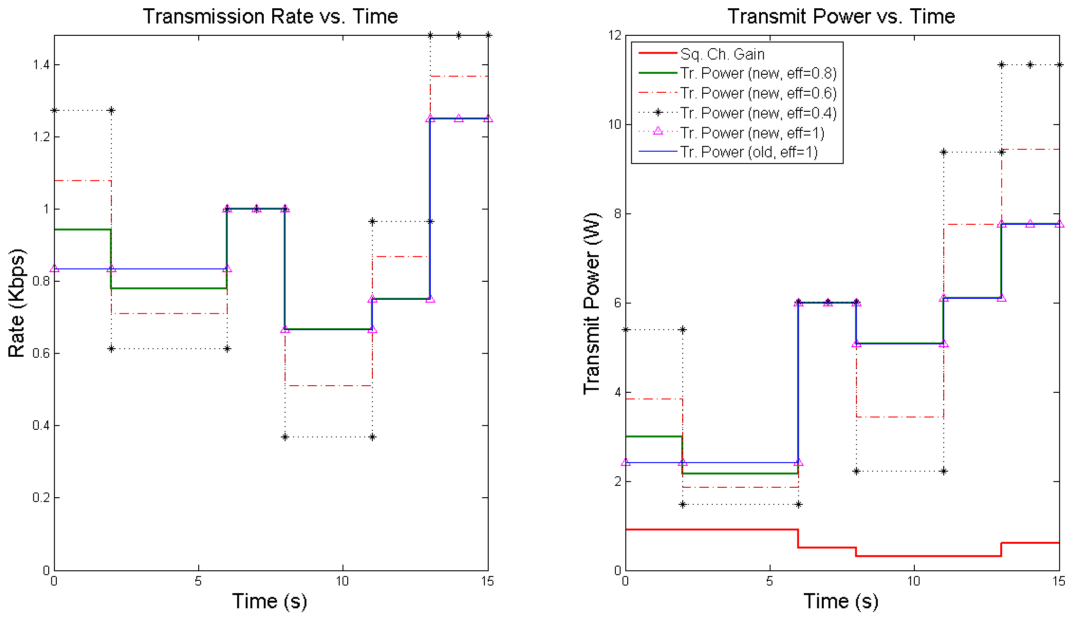


Figure 3.13: Optimal offline schedules under various battery efficiencies (η)

the optimal solution.

Main outcomes of this chapter can be divided into three. Firstly, it was observed that the battery imperfections affect the outcome of the optimal offline schedule that minimizes energy consumption. Especially, a high charge/discharge inefficiency causes the optimal schedule to be more aggressive in terms of using energy. This is due to the fact that if the harvested energy is not used immediately, it is stored in the battery which causes a certain percentage of the stored energy to be lost. Secondly, it was observed that this problem is suitable for evolutionary heuristics. By using Genetic Algorithm, the optimal solution can be obtained at the cost of processing power and time. The solution with Genetic Algorithm verified that SUMT successfully reaches the global minimum. Lastly, it was shown that by changing the optimization problem such that it minimizes energy usage *and* energy waste, more energy can be saved. In other words, optimal schedules that minimize transmission energy and maximize remaining energy slightly differ from each other. Increased battery inefficiency is observed to enhance the difference between these schedules.

CHAPTER 4

EMARE: ENERGY AND MOBILITY-AWARE ROUTING SCHEME FOR ENERGY HARVESTING WIRELESS SENSOR NETWORKS

Adapting transmission power is merely one of the methods that increase energy efficiency in an energy harvesting network. Techniques such as data reduction, protocol overhead reduction, energy efficient routing, duty cycling and topology control are some examples on alternative methods [31]. Although such practices are well studied for regular battery-powered networks, a few research has been made for energy harvesting systems. The absence of such studies encouraged us to come up with an energy efficient routing algorithm which differs from others by taking energy harvesting into account.

4.1 Energy Efficient Routing in Wireless Sensor Networks

Wireless sensor nodes are often small and minimal in design. As they are usually deployed abundantly over large areas, the cost of a single sensor node should be insignificant in order for the network to be feasible. This implies many constraints on wireless sensor nodes such as limited computational power, limited energy storage and so on. In addition to this, wireless sensor nodes are expected to last for a long time without maintenance. These constraints motivate researchers to come up with methods that can prolong wireless sensor networks' lifetime. Energy efficient routing protocols deal with it by finding the most efficient route from the transmitter sensor node to the sink node.

Consider a wireless sensor network of n nodes. Depending on the use of the sensor network, these nodes transmit data either periodically or when they are triggered by an external source which is generally the sensed phenomenon itself. In any case, for an operational network these nodes have to convey their data to the sink. Studies indicate that data transmission is very expensive in terms of energy when compared with other operations of a sensor node such as sensing and data processing [22]. Therefore, minimizing the transmission cost of a sensor node is essential for an energy efficient operation. Let the following (used in [32], [33]) roughly govern the energy spent for sending a packet over a distance d:

$$E_{tx}(d) = E_t + E_d * d^n \tag{4.1}$$

where E_t is the energy dissipated per bit by the transmitter circuitry and $E_d * d^n$ is the energy per bit spent by the radio amplifier. It is usually considered that $2 \leq n \leq 4$ [34]. It can be observed that the transmission energy increases exponentially with the distance. Therefore, for a wireless sensor node an intuitive approach would be to shorten the singular transmission distance between the node and the sink by using other sensor nodes as intermediate nodes, thus breaking a long distance transmission into multiple short distance transmissions. In case of wireless Ad-Hoc networks this would work fine as the communication is many-to-many, i.e. nodes communicate with each other in a uniform manner. However, in wireless sensor networks communication is many-to-one, where all sensor nodes communicate with the sink. Therefore, such an approach would cause the nodes closer to the sink to perform more transmissions, and hence to lose energy faster. This non-uniform energy drainage acts against the aim of the sensor networks by causing blackouts at the areas closer to the sink. Therefore, reducing individual sensor nodes' transmission energies is usually not sufficient. An ideal method maximizes the sensor network's lifetime by minimizing the overall energy consumption while ensuring that the sensor nodes die (run out of energy) at random places over the sensor field, preventing blackouts.

As the aim of energy efficient methods is to prolong the wireless sensor network's lifetime, their primary objective is to reduce the overall energy consumption of the network. Energy efficient routing protocols designed to achieve this can be classified as: data-centric, opportunity-based, geographical and hierarchical protocols[31].

Data-centric routing protocols attempt to reduce energy consumption by using the content of the data to be sent by the sensor node. Data packets are routed through sensor nodes which are interested with the information within these packets. These methods assume that the network operates under a query driven fashion. In a sample case, a node sends an advertisement message indicating the availability of data and interested nodes send responses for the packet. The node transmits its data to the interested node(s), which makes it possible to transmit data to interested nodes with less number of transmissions.

Opportunity based protocols exploit the characteristics of certain wireless sensor networks in order to reduce energy consumption. These characteristics include sensor node mobility, sink mobility and network geometry. A routing protocol designed specifically for wireless sensor networks with mobile nodes can outperform other generic routing protocols. However, such protocols have rather narrow area of use as they require specific features from wireless sensor networks. For example, [32] develops a routing strategy which outperforms classical routing protocols and is near-optimal for one-dimensional wireless sensor networks. As [32] uses the optimal number of hops for a linear wireless sensor network found in [35] by approximating its number of hops to it, however, [32] provides energy efficient routing only for networks with sensor nodes aligned over a line. It is outperformed by other protocols when sensor networks are spread over a two-dimensional area or a three-dimensional space.

Geographical protocols take advantage of wireless sensor nodes' location information in order to calculate energy optimal routes. These methods have a certain advantage over non-geographical protocols which use flooding based techniques to calculate routes. Using flooding causes extra messages which add to the energy consumption, i.e. setup cost, and it is less likely to be as scalable as geographical protocols due to connectivity issues. On the other hand, innate minimalistic wireless sensor nodes are usually not equipped with GPS modules due to their cost to the system. In addition, GPS modules tend to perform poorly in the absence of a line of sight link to GPS satellites. Therefore, methods that do not use geographical data span a larger portion of the current wireless sensor networks.

Wireless sensor networks vary in their number of sensor nodes, whereas there is usually one sink which collects all the sensors' data. If the network's size is large, this causes a dense data traffic towards the sink. Hierarchical routing protocols overcome this problem by arranging clusters where cluster heads collect data, merge it and transmit it to the sink. Thus, the sink receives less number of transmissions and the multiple access complexity for the sink node at the link layer is reduced. In addition, hierarchical protocols are shown to reduce the overall data consumption by having less number of shorter distance transmissions despite the message overhead caused by cluster construction.

4.2 System Model

Energy efficient routing protocols are often compared by using computer-aided simulations. In order to conduct these simulations, certain features of wireless sensor networks need to be mathematically modeled. Among these are Energy dissipation model, Energy harvesting model and Data aggregation model.

4.2.1 Energy Dissipation Model

Accurate modeling of the energy dissipation is important for a healthy comparison of various protocols' energy performances. A commonly used model firstly introduced in [18] is known as the First Order Radio Model. According to this model; the energy a transmitter spends to send k bits a distance d is:

$$\begin{aligned} E_{Tx}(k,d) &= E_{elec-Tx}(k) + E_{amp-Tx}(k,d) \\ &= E_{elec}.k + E_{amp}.k.d^2 \end{aligned} \tag{4.2}$$

where $E_{elec-Tx}(k)$ is the energy spent by the electrical circuitry of the transmitter, whereas $E_{amp-Tx}(k,d)$ is the energy consumed by the amplifier of the transmitter node. Likewise, at the receiving side the receiver node spends:

$$
\begin{aligned}
E_{Rx}(k) &= E_{elec-Rx}(k) \\
&= E_{elec}.k
\end{aligned} \tag{4.3}
$$

where $E_{elec-Rx}(k)$ is the energy required by the electrical circuitry to receive the message. Many studies such as [19] and [36] take E_{elec} as $50nJ/bit$ and E_{amp} as $100pJ/bit/m^2$ in accordance with [18].

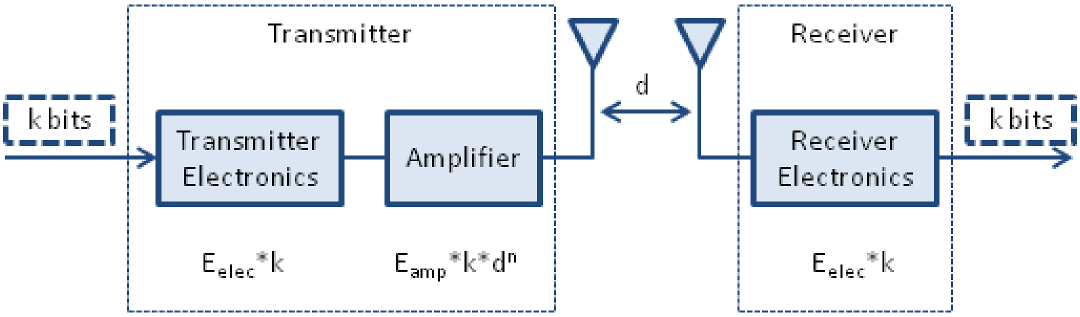


Figure 4.1: Energy Dissipation Model

more realistic model for the radio hardware energy consumption is presented in [37], where both free space and the multipath fading channels are considered. According to this model, the transmission energy is as follows:

$$
E_{Tx}(l,d) = \begin{cases} l * E_{elec} + l * \epsilon_{fs} * d^2, & \text{if } d < d_{crossover} \\ l * E_{elec} + l * \epsilon_{mp} * d^4, & \text{if } d \geq d_{crossover} \end{cases} \tag{4.4}
$$

In this model, depending on the transmission distance d, the energy model of the transmitter changes. When d is less than a certain threshold $d_{crossover}$, the free space channel model applies. Otherwise, the multipath fading channel model which has the d^4 term and therefore is more sensitive to the distance applies. The reason for using this model instead of the one used in Chapter 3 is that First Order Radio Model (FORM) is used in methods including LEACH [18] and PEGASIS [19], with which EMARE is compared. The model in Chapter 3 and FORM are quite different from each other. In FORM, modulation and coding are fixed and only signal amplification is used in order to achieve a certain SNR at the receiver. On the other hand, in the former model the transmission distance was fixed, and the code rate was being adjusted according to the transmit power level which had been resulted from the optimal scheduling algorithm. In other words, FORM ignores the effects of parameters such as coding and modulation, except the received SNR. Despite all, it is used to evaluate EMARE for a fair comparison with other methods.

4.2.2 Energy Harvesting Model

One of the key features of environmental energy is its unpredictability. Environmental energy depends on the type of the source (solar, wind, vibration etc.) as well as the geographical location and other environmental factors. This unpredictability necessitates a probabilistic modeling of energy harvesting in order to be studied accurately. Although these energy sources are available at random times at random amounts, it is possible to represent them using stochastic processes. Some environmental energy sources which are less unpredictable than the others are easier to be represented as a probabilistic model. One such example is solar energy, whose daily energy graph is highly correlated with its previous days' graphs. As it is also one of the most abundant energy sources, the energy harvesting model in this study is based on solar energy harvesting.

Markov chain is used by researchers to model previous meteorological data in order to predict future data [38] [39], as meteorological events tend to have memory. As solar energy is an outcome of such events, a discrete-time Markov chain (Figure 4.2) is used to represent the solar energy harvesting in this study.

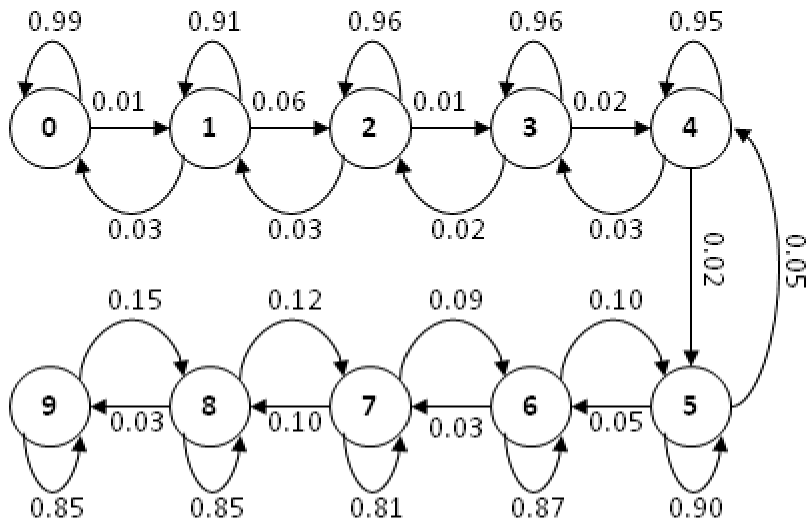


Figure 4.2: DTMC Energy Harvesting Model

In order to obtain the DTMC model, a current data generated by a solar energy harvester throughout a day is obtained from SensorScope [40] project. Then, similarly with [39], this data is used to obtain energy versus time graph. The amount of generated energy which varies from 0 to E_{max} is divided into 10 equal portions, each of which will correspond to a state of the Markov chain. If the amount of energy produced during a time interval (10 seconds) is within the same portion as the one from the previous interval, then the state in the Markov chain is assumed to be the same with the previous one. Otherwise, the state is changed to the one which corresponds to the portion that contains the produced energy. Due to the continuous behavior of solar energy, the new state is either one-up or one-down. If the changes in the amount of harvested solar energy were major or if the Markov chain had more than 10 states, the changes in states could be more diverse.

The frequencies of state changes are counted and normalized in order to be represented as probabilities. The resulting Markov chain with calculated probabilities is used as the energy harvesting model in this study.

4.2.3 Data Aggregation Model

Transmission of data from source to the destination in a multi-hop fashion enables the modification of data while being routed by intermediate nodes. As the intermediate nodes also send their data to the same destination, combining the node's own data with the data to be routed can reduce the total traffic of the network thus reduce the overall energy consumption.

Different types of sensor networks sense and send different types of data. The correlation of data that runs through the network determines how much aggregation can be done. Therefore, the amount of aggregation depends on the type of the sensor network. A sensor network generally falls into one of the following three categories in terms of data correlation [41]:

No Redundancy The information sent by individual sensor nodes completely differ from the others. In other words, data packets coming from different sensor nodes have no common attributes which can be merged into a single attribute. Sensor networks which collect individual temperature data from all their nodes is an example to this class.

Complete Redundancy Sensor nodes' messages are identical. This case is valid for sensor networks where sink sends a query and expects "Yes" or "No" messages from sensor nodes. An example is a military sensor network planted over an area to detect vehicles from the vibration they create. In this case, "Yes" or "No" messages can be merged into a single one, as the sink is primarily interested in whether there is a sensed phenomenon or not.

Intermediate Level Redundancy This is the case where two packets from different nodes can partly be merged. Therefore the resulting packet is longer than any one of the packets. It is practically the most common case, because usually some parts of network packets such as headers and footers are redundant.

Most of the current studies including [18] and [19] assume that a sensor node can collect any number of packets from other sensor nodes and, after processing those packets along with its own packet, produces a single packet of the same size. Although this assumption makes the performance analysis simpler, it is only valid for sensor networks that have complete redundancy mentioned above. In general, it is expected that the size of the aggregated packet grows with the number of packets that are being aggregated. Therefore, a more realistic aggregation model is needed for an accurate analysis.

The following aggregation model covers all three redundancy cases [42]:

$$\chi(x) = mx + c \tag{4.5}$$

where x is the number of aggregated packets, m is the compression ratio, c is the aggregation overhead and $\chi(x)$ is the number of packets after the aggregation. It is assumed that packets are of the same size, which is feasible as it is generic for sensor nodes, including TinyOS-operated motes [43] [44]. In addition, assuming that $0 \leq m \leq 1$ is reasonable as data aggregation aims to compress the data, limiting m between 0 and 1.

In an aggregation model, if $m = 0$ then it is the case when any number of packets can be reduced into a packet of fixed size c. This is the case used in numerous researches such as [18] and [19] and it corresponds to the complete redundancy case in real life applications. When $m = 1$, it means that there is no aggregation. This can be the case when there is no redundancy between data packets sent by different nodes. The case $0 < m < 1$ is the most realistic one, as in real-life networks certain parts such as headers can be reduced by aggregating two or more packets.

4.3 EMARE Algorithm

EMARE is a cluster-based routing protocol, where cluster heads constitute a backbone that reaches to the base station or the sink. Therefore, the communication between cluster heads and the sink is multi-hop, whereas intra-cluster communication is single-hop. Cluster head selection and cluster formation phases are conducted simultaneously in a flooding-like fashion.

In EMARE, the sink initiates the cluster selection-formation by broadcasting a *beacon* message with a certain transmission power. Sensor nodes which receive this *beacon* immediately label their route as the sink, therefore constituting the first cluster which has the sink as its cluster head.

Sensor nodes that had labeled their route are identified as *connected* nodes as they are connected to a cluster head. Similar to the sink node, *connected* nodes opportunistically broadcast *beacon* messages to continue the cluster formation. These *beacon* messages are dropped by *connected* nodes and responded by nodes that have not yet labeled their route. Such nodes are called *unconnected* for the obvious reason. By receiving the responses, a *connected* node learns its neighbors. If the *connected* node has any *unconnected* neighbors, it broadcasts an *info* signal which includes the following:

- Transmitter node's ID
- IDs of transmitter node's *unconnected* neighbors
- Transmitter node's energy metric

info signal is received only by *connected* nodes and dropped by *unconnected* nodes and cluster heads. *connected* nodes which receive the information signal check if the nodes pointed out in the *info* signal are covered by themselves; if one of them finds out that it also covers these nodes and its energy metric is higher, it immediately broadcasts a *notification* signal and becomes a cluster head. Otherwise, the node that had broadcasted the *info* signal broadcasts the *notification* signal (after waiting for a pre-determined time) and becomes a cluster head. *unconnected* nodes which receive *notification* signal become *connected* by labeling their route as the source of the broadcast.

This procedure continues until every *connected* node checks its *unconnected* neighbors. In the end, all nodes become either *connected* nodes or cluster heads (assuming that all nodes are inside the transmission radius of at least one other node). Pseudocodes for *unconnected* and *connected* nodes are given in Algorithms 3 and 4 A sample sensor network connected by PEGASIS, LEACH, HEED and EMARE is given in Figure 4.3.

Algorithm 3 EMARE Algorithm, Unconnected Nodes

procedure UNCONNECTEDNODE K

upon receiving a *beacon* message:

respond with ID: $\{ID_k\}$

upon receiving *notification* message from node i:

$route \leftarrow ID_i$

become *connected*

break

end procedure

One of the novel approaches of this method is the energy metric which affects the cluster head decision. It is defined as the weighted sum of the sensor node's current residual energy and the amount of energy harvested for the last τ time intervals:

$$M(t,\tau) = \alpha E_s(t) + (1-\alpha)E_h(t,\tau) \tag{4.6}$$

Here, M represents the energy metric while $E_s(t)$ represents the amount of energy stored by the sensor node at time t and $E_h(t,\tau)$ represents the amount of energy harvested during the period $[(t-\tau), t]$. Moreover, α is the weight coefficient which can be tuned according to the type of the sensor network. As *number of rounds* replaces the time axis in similar studies, in this setup a discrete energy metric $M[n,i] = \alpha E_s[n] + (1-\alpha)E_h[n,i] \quad n,i \in \mathbb{N}^+$ is used. In accordance with Equation (4.6), $E_s[n]$ is the amount of stored energy at the n^{th} round and $E_h[n,i]$ is the amount of harvested energy during the last i rounds of communication.

If the availability of ambient energy source is rather continuous (such as solar energy), this implies that between rounds of communication, amounts of harvested energy are highly correlated with each other. In such a case, E_h can be taken as the amount of harvested energy since the last round of communication ($i = 1$). Such an E_h gives enough insight about the amount of energy that will be harvested at the next interval. Similarly, a smaller α can be chosen due to the fact that E_h gives significant clues about the potential lifetime of the network.

On the other hand, if the ambient energy source is discrete and sparse (such

Algorithm 4 EMARE Algorithm, Connected Nodes

procedure ConnectedNode c

broadcast *beacon* message

upon receiving $\{ID_x\}$ from *unconnected node* x:

$\{ID_{UCc}\} \leftarrow \{ID_{UCc}\} \cup \{ID_x\}$

upon receiving *info* signal $\{ID_y, ID_{UCy}, M_y\}$ from *connected node* y:

if $\{ID_{UCc}\} \neq \emptyset$ **then**

if $\{ID_{UCc}\} = \{ID_{UCy}\}$ **then**

if $M_c > M_y$ **then**

broadcast surpassing *notification* message

become *cluster head*

break

end if

else if $\{ID_{UCc}\} \supset \{ID_{UCy}\}$ **then**

broadcast surpassing *notification* message

become *cluster head*

break

end if

end if

wait for $T_{backoff}$

if $\{ID_{UCc}\} \neq \emptyset$ **then**

broadcast *info* signal $\{ID_c, ID_{UCc}, M_c\}$

wait for T_w

if no surpassing *notification* message received **then**

broadcast *notification* message

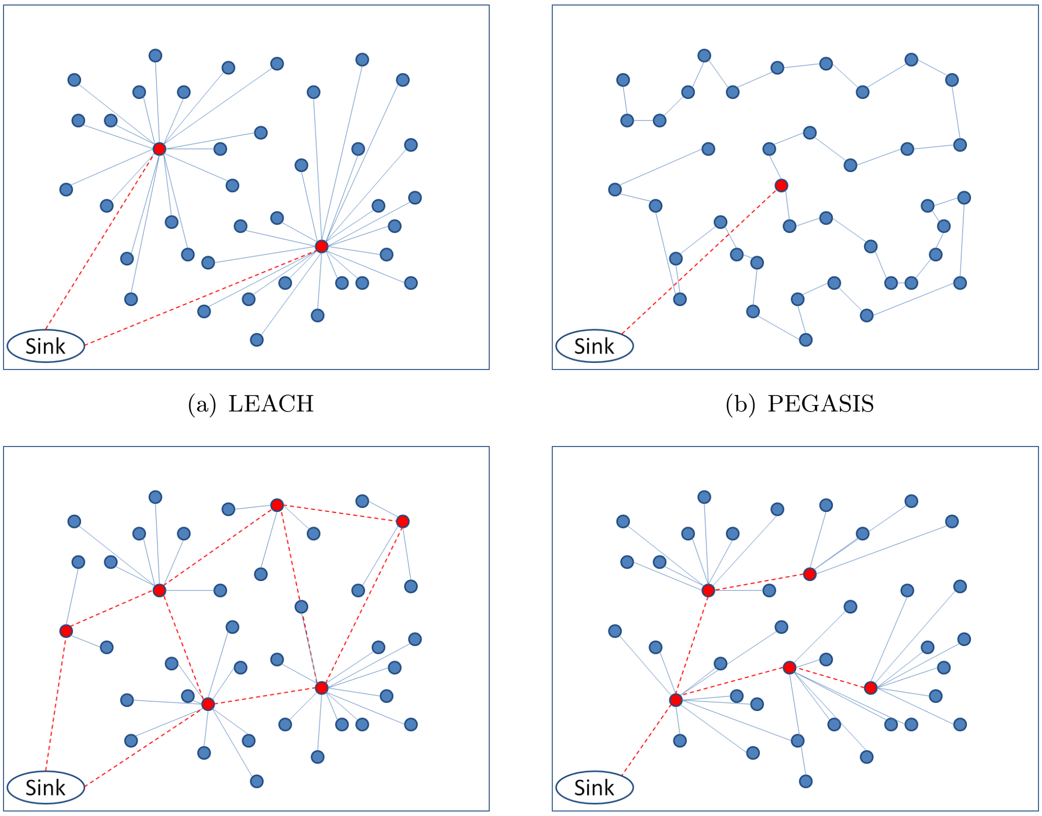
become *cluster head*

break

end if

end if

end procedure



(a) LEACH

(b) PEGASIS

(c) HEED

(d) EMARE

Figure 4.3: Cluster formation of various methods

as vibrational energy in a car park) E_h can be taken as the sum or (moving) average of the amount of energy harvested during the last $(i \gg 1)$ rounds of communication. As in such cases the recent energy harvests do not give much clue about the incoming energy harvests, taking former harvests into account can give better insight about the frequency and hence the probability of energy harvests. Again, α can also be adapted according to the correlation between energy harvests.

4.4 Performance Evaluation

A group of 100 sensor nodes are randomly scattered over a $(100m \times 100m)$ area as in Figure 4.4. E_{elec} and E_{amp} are taken as $50nJ/bit$ and $100pJ/bit/m^2$, respectively. The coverage radius of nodes are assumed as $20m$. Initially, no energy harvest and data aggregation is assumed. All nodes are started with $0.1J$ of initial energy. At each iteration, $2kbits$ of information is sent to the sink from every node. The sink is located at $(-100, -100)$, which is at least $140m$ away from the closest node, as all the nodes are located between coordinates $(0,0), (0,100), (100,0), (100,100)$. The resulting performance of the network under EMARE, LEACH, PEGASIS, HEED and direct transmission schemes is given in Figure 4.5.

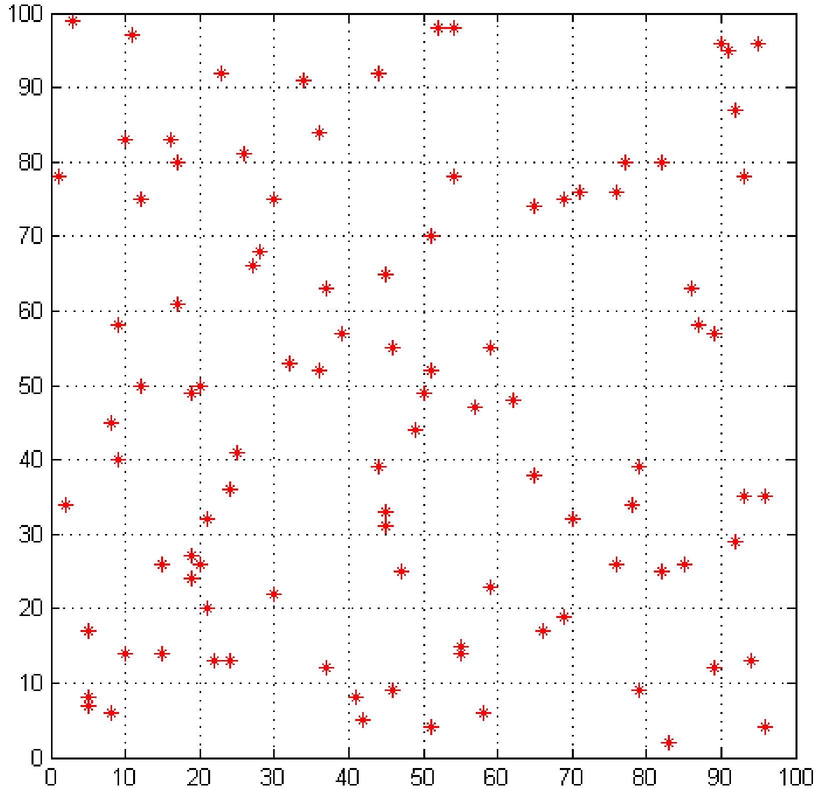


Figure 4.4: Coordinates of randomly placed 100 nodes

It can be seen that EMARE outperforms all other protocols at *last node to die*. Although the direct transmission has the best performance in terms of *first node to die*, it is the first protocol to lose all of its nodes. Note that the network lifetimes are different from what was claimed in original works [18][19] which is due to assumed *complete redundancy* data aggregation that is described earlier.

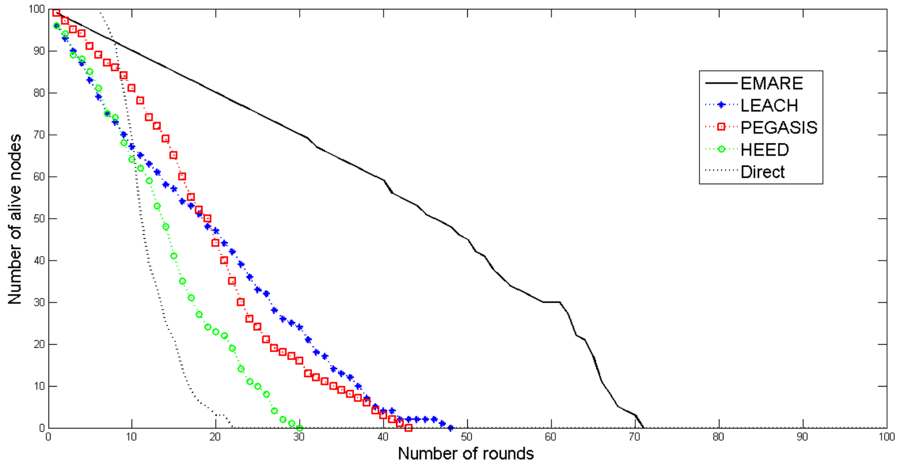


Figure 4.5: Numbers of alive nodes per round when sink is at $(-100, -100)$

Almost all protocols such as LEACH and PEGASIS assume a sink node that is far away from the network. The main reason for this is that when the sink is close, the cost of direct transmission is less than making shorter multi-hop transmissions according to the first order radio model. In order to observe this phenomena, next comparison is made with the sink node at $(0, 0)$. Sensor network lifetimes under that condition is observed as in Figure 4.6.

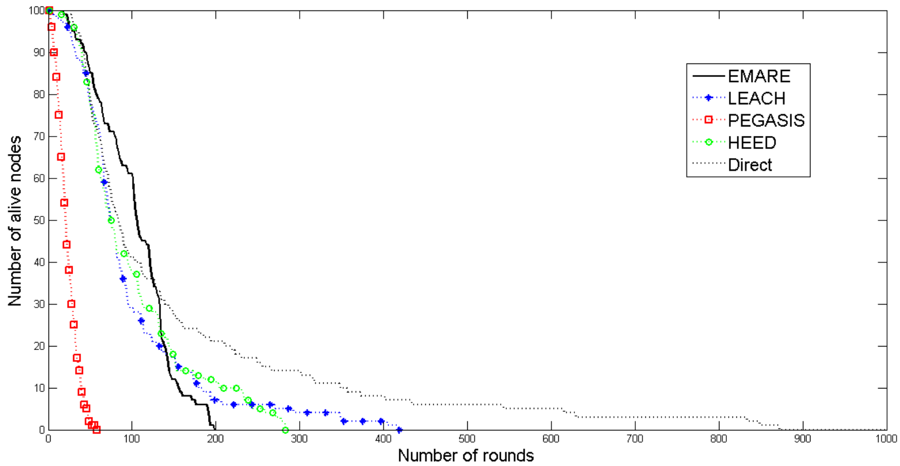


Figure 4.6: Numbers of alive nodes per round when sink is at $(0, 0)$

As expected, the direct transmission performed best in terms of last node to die. It can be seen that a small amount of nodes survive for a very long time. Those nodes are the ones close to coordinates $(0, 0)$. This result indicate that hierarchical protocols are useful when the sink node is far away. Therefore, the sink is replaced back to $(-100, -100)$, and this time energy harvesting is enabled. The resulting performances are given in Figure 4.7.

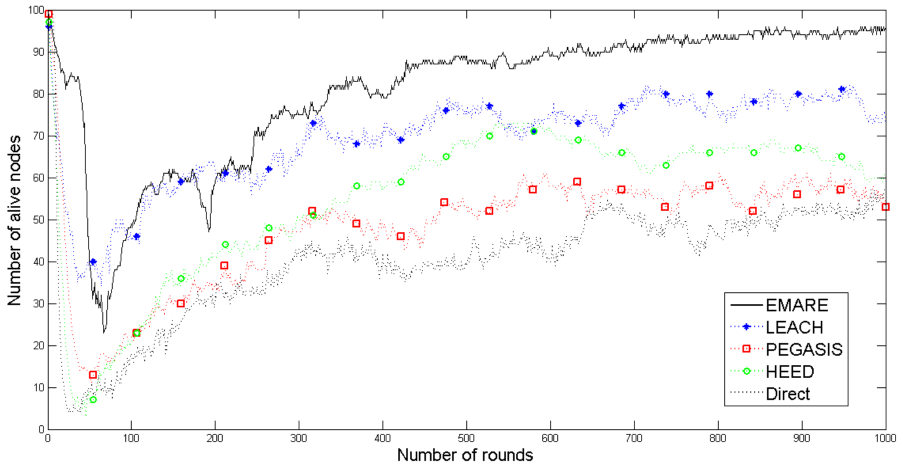


Figure 4.7: Numbers of alive nodes per round with energy harvesting

It can be seen that after the networks reach a stable state, EMARE contains the most alive nodes among the others. The initial fall at the number of alive nodes is due to the initial energy of $0.1J$ per node. The *dead* nodes become alive again when they harvest energy from the environment. LEACH is the second after EMARE in terms of alive nodes at steady state. The superiority of EMARE over other methods can be linked with the fact that it uses both residual energy *and* recent energy harvest information to elect cluster heads. Therefore, it can select cluster heads with accurately estimated life expectancy.

CHAPTER 5

CONCLUSIONS

The main purpose of this thesis is to find insight and develop effective ways to achieve energy efficiency for energy harvesting communication systems. Two of the many ways to achieve this; namely transmission rate scheduling and energy efficient routing were investigated. The research led us to study complex offline optimization problems and energy efficient online routing protocols. While doing these, imperfections of such real-life systems are taken into consideration in order to take the research to another level. These studies are resulted in finding the optimal offline transmission rate schedule for energy harvesting transmitters with battery imperfections, along with an online energy harvesting and mobility-aware routing protocol for energy harvesting wireless sensor networks. The summary of the process and deductions are given below.

The first investigation was on energy efficient transmission for energy harvesting transmitters. Energy efficiency is aimed to be achieved by scheduling the transmission rate, and hence the transmission power. A point-to-point communication scheme under fading channel conditions are assumed. Adapting the *energy neutrality* definition from [4], a convex constrained optimization problem has been obtained. In this problem, battery charge/discharge efficiency and leakage current along with energy causality and data causality are taken into account. The problem is turned into an unconstrained one by using penalty functions and solved by using one of the classic iterative methods, namely Sequential Unconstrained Minimization Technique (SUMT) [26]. It was shown that the optimal transmission rate schedule changes when the battery imperfections are taken into account.

One problem of SUMT was that in general, gradient-based optimization methods converge to the local optima instead of the global optimum. Although the problem in this study is shown to be convex, a cross-check would ensure the effectiveness of the SUMT method. Therefore, an alternative method which converges to the global optimum is investigated. The Genetic Algorithm (GA), which is a heuristic method that mimics the process of biological evolution was used to solve the transmission energy minimization problem. Again considering battery imperfections and energy neutrality, the optimal solution to the minimization problem was achieved with this heuristic. It was observed that the two solutions are almost identical, proving the accuracy of SUMT method for this problem.

Later during these studies, it was observed that the earlier optimization problem which focuses on transmission energy minimization can be upgraded and schedules with more energy saving can be achieved. This was due to the fact that battery inefficiency could be taken into consideration not only as a part of the energy causality constraint, but also an energy waste which should also be minimized. After re-writing the optimization problem as minimization of energy usage *and* energy wastage, and solving it by using SUMT, it was demonstrated that a little more energy can be saved with the resulting optimal schedule.

The extensive research conducted for the first part of the thesis gave insight and know-how about energy efficient methods, especially for energy harvesting communication devices with limited storage and processing capabilities. Therefore, an additional effort was made in order to come up with an online algorithm which is simple enough to be used by such devices and is also energy efficient. Among many ways to achieve this, energy efficient routing protocols for wireless sensor networks had been shown to be highly effective. However, next to none studies were there for routing protocols customized for *energy harvesting* wireless sensor networks. Therefore, an energy harvesting aware clustering scheme, namely EMARE, was developed for energy harvesting wireless sensor nodes. This protocol constructs a connected backbone between sensor nodes and sink, improving connectivity and scalability. In addition, cluster heads are elected based on their expected lifetime, which does not singularly depend on residual energy but also depends on recent energy harvests. These traits are shown to be effective by results depicting that EMARE outperforms other reputed protocols, in cases with and without energy harvesting.

The next step of these studies can be more implementation-oriented. For the optimal offline scheduling, theoretical results that has been found can be sought experimentally. In addition, an online scheduling algorithm that takes battery inefficiencies into account can be developed and its performance can be compared with the theoretical minimum. As for the genetic algorithm that was used to solve the optimal scheduling problem, it can be developed further by including other techniques such as *elitism*. Thus, the convergence time of the heuristic can be reduced. There is more to build on about EMARE, as it is only compared with some other protocols in terms of network lifetime. EMARE can also be implemented on an energy harvesting sensor network, which has not been accomplished due to hardware constraints. Thereby, its performance can be seen on a real-life application. In addition, EMARE can be improved further by finding the optimal transmission radius for energy harvesting wireless sensor nodes. Also, the *energy metric* can be defined not only for solar but also for other types of energy harvesting. Delay and throughput analysis can also be made and compared with other popular protocols. The mobility issue can be expanded by using modeling techniques such as random waypoint model. The effect of mobility on connectivity, as well as a relation between mobility and route re-calculation frequency for preserving connectivity can be studied.

REFERENCES

[1] Balaji Prabhakar, Elif Uysal Biyikoglu, and Abbas El Gamal. Energy-efficient transmission over a wireless link via lazy packet scheduling. In *INFOCOM 2001. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, volume 1, pages 386–394. IEEE, 2001.

[2] Elif Uysal-Biyikoglu and Abbas El Gamal. On adaptive transmission for energy efficiency in wireless data networks. *Information Theory, IEEE Transactions on*, 50(12):3081–3094, 2004.

[3] Maruti Gupta and Suresh Singh. Greening of the internet. In *Proceedings of the 2003 conference on Applications, technologies, architectures, and protocols for computer communications*, pages 19–26. ACM, 2003.

[4] Aman Kansal, Jason Hsu, Sadaf Zahedi, and Mani B Srivastava. Power management in energy harvesting sensor networks. *ACM Transactions on Embedded Computing Systems (TECS)*, 6(4):32, 2007.

[5] Omur Ozel, Kaya Tutuncuoglu, Jing Yang, Sennur Ulukus, and Aylin Yener. Transmission with energy harvesting nodes in fading wireless channels: Optimal policies. *Selected Areas in Communications, IEEE Journal on*, 29(8):1732–1743, 2011.

[6] Bertrand Devillers and Deniz Gunduz. A general framework for the optimization of energy harvesting communication systems with battery imperfections. *Communications and Networks, Journal of*, 14(2):130–139, 2012.

[7] Omur Ozel, Khurram Shahzad, and Sennur Ulukus. Optimal scheduling for energy harvesting transmitters with hybrid energy storage. In *Information Theory Proceedings (ISIT), 2013 IEEE International Symposium on*, pages 1784–1788. IEEE, 2013.

[8] Oner Orhan and Elza Erkip. Energy harvesting two-hop networks: Optimal policies for the multi-energy arrival case. In *Sarnoff Symposium (SARNOFF), 2012 35th IEEE*, pages 1–6. IEEE, 2012.

[9] Oner Orhan and Elza Erkip. Optimal transmission policies for energy harvesting two-hop networks. In *Information Sciences and Systems (CISS), 2012 46th Annual Conference on*, pages 1–6. IEEE, 2012.

[10] Shixin Luo, Rui Zhang, and Teng Joon Lim. Optimal save-then-transmit protocol for energy harvesting wireless transmitters. *Wireless Communications, IEEE Transactions on*, 12(3):1196–1207, 2013.

[11] Mehmet Akif Antepli, Elif Uysal-Biyikoglu, and Hakan Erkal. Optimal packet scheduling on an energy harvesting broadcast link. *Selected Areas in Communications, IEEE Journal on*, 29(8):1721–1731, 2011.

[12] Fatih Mehmet Özçelik. Optimal and implementable transmission schemes for energy harvesting networks. Master's thesis, Middle East Technical University, Turkey, 2012.

[13] Jing Yang, Omur Ozel, and Sennur Ulukus. Broadcasting with an energy harvesting rechargeable transmitter. *Wireless Communications, IEEE Transactions on*, 11(2):571–583, 2012.

[14] Vijay Raghunathan, Aman Kansal, Jason Hsu, Jonathan Friedman, and Mani Srivastava. Design considerations for solar energy harvesting wireless embedded systems. In *Proceedings of the 4th international symposium on Information processing in sensor networks*, page 64. IEEE Press, 2005.

[15] Peter Spies, Markus Pollak, and Günter Rohmer. Energy harvesting for mobile communication devices. In *Telecommunications Energy Conference, 2007. INTELEC 2007. 29th International*, pages 481–488. IEEE, 2007.

[16] Ian F Akyildiz, Weilian Su, Yogesh Sankarasubramaniam, and Erdal Cayirci. Wireless sensor networks: a survey. *Computer networks*, 38(4):393–422, 2002.

[17] Wendi Rabiner Heinzelman, Joanna Kulik, and Hari Balakrishnan. Adaptive protocols for information dissemination in wireless sensor networks. In *Proceedings of the 5th annual ACM/IEEE international conference on Mobile computing and networking*, pages 174–185. ACM, 1999.

[18] Wendi Rabiner Heinzelman, Anantha Chandrakasan, and Hari Balakrishnan. Energy-efficient communication protocol for wireless microsensor networks. In *System Sciences, 2000. Proceedings of the 33rd Annual Hawaii International Conference on*, pages 10–pp. IEEE, 2000.

[19] Stephanie Lindsey and Cauligi S Raghavendra. Pegasis: Power-efficient gathering in sensor information systems. In *Aerospace conference proceedings, 2002. IEEE*, volume 3, pages 3–1125. IEEE, 2002.

[20] Canay Özkan. Implementation of the heed clustering protocol with sleep scheduling in tinyos 2 on a wireless sensor network testbed. Master's thesis, Middle East Technical University, Turkey, 2013.

[21] Ossama Younis and Sonia Fahmy. Heed: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks. *Mobile Computing, IEEE Transactions on*, 3(4):366–379, 2004.

[22] Ziaul Hasan, Hamidreza Boostanimehr, and Vijay K Bhargava. Green cellular networks: A survey, some research issues and challenges. *Communications Surveys & Tutorials, IEEE*, 13(4):524–540, 2011.

[23] Aruna Prem Bianzino, Claude Chaudet, Dario Rossi, and J Rougier. A survey of green networking research. *Communications Surveys & Tutorials, IEEE*, 14(1):3–20, 2012.

[24] Bertrand Devillers and D Gunduz. Energy harvesting communication system with battery constraint and leakage. In *GLOBECOM Workshops (GC Wkshps), 2011 IEEE*, pages 383–388. IEEE, 2011.

[25] Massoud Pedram and Qing Wu. Design considerations for battery-powered electronics. In *Proceedings of the 36th annual ACM/IEEE Design Automation Conference*, pages 861–866. ACM, 1999.

[26] A.V. Fiacco and G.P. McCormick. *Nonlinear Programming: Sequential Unconstrained Minimization Techniques*. Classics in Applied Mathematics. Society for Industrial and Applied Mathematics (SIAM, 3600 Market Street, Floor 6, Philadelphia, PA 19104), 1990.

[27] Charles L Byrne. Sequential unconstrained minimization: A survey. 2013.

[28] Carl Johan Rydh and Björn A Sandén. Energy analysis of batteries in photovoltaic systems. part ii: Energy return factors and overall battery efficiencies. *Energy conversion and management*, 46(11):1980–2000, 2005.

[29] David B Fogel. An introduction to simulated evolutionary optimization. *Neural Networks, IEEE Transactions on*, 5(1):3–14, 1994.

[30] Lawrence Davis et al. *Handbook of genetic algorithms*, volume 115. Van Nostrand Reinhold New York, 1991.

[31] Ridha Soua and Pascale Minet. A survey on energy efficient techniques in wireless sensor networks. In *Wireless and Mobile Networking Conference (WMNC), 2011 4th Joint IFIP*, pages 1–9. IEEE, 2011.

[32] Marco Zimmerling, Waltenegus Dargie, and Johnathan M Reason. Energy-efficient routing in linear wireless sensor networks. In *Mobile Adhoc and Sensor Systems, 2007. MASS 2007. IEEE Internatonal Conference on*, pages 1–3. IEEE, 2007.

[33] Mao Ye, Chengfa Li, Guihai Chen, and Jie Wu. Eecs: An energy efficient clustering scheme in wireless sensor networks. *IEEE International*, 24:535–540, 2005.

[34] Swarup Kumar Mitra and Mrinal Kanti Naskar. Comparative study of radio models for data gathering in wireless sensor network. *International Journal of Computer Applications*, 27(4), 2011.

[35] Manish Bhardwaj, Timothy Garnett, and Anantha P Chandrakasan. Upper bounds on the lifetime of sensor networks. In *Communications, 2001. ICC 2001. IEEE International Conference on*, volume 3, pages 785–790. IEEE, 2001.

[36] Yang Yang, Hui-Hai Wu, and Hsiao-Hwa Chen. Short: shortest hop routing tree for wireless sensor networks. *International Journal of Sensor Networks*, 2(5):368–374, 2007.

[37] Wendi B Heinzelman, Anantha P Chandrakasan, and Hari Balakrishnan. An application-specific protocol architecture for wireless microsensor networks. *Wireless Communications, IEEE Transactions on*, 1(4):660–670, 2002.

[38] Dusit Niyato, Ekram Hossain, and Afshin Fallahi. Sleep and wakeup strategies in solar-powered wireless sensor/mesh networks: Performance analysis and optimization. *Mobile Computing, IEEE Transactions on*, 6(2):221–236, 2007.

[39] Alex E Susu, Andrea Acquaviva, David Atienza, and Giovanni De Micheli. Stochastic modeling and analysis for environmentally powered wireless sensor nodes. In *Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks and Workshops, 2008. WiOPT 2008. 6th International Symposium on*, pages 125–134. IEEE, 2008.

[40] Guillermo Barrenetxea, Henri Dubois-Ferriere, Roger Meier, and John Selker. A weather station for sensorscope. In *The Fifth International Conference on Information Processing in Sensor Networks (IPSN 2006)*, number LCAV-CONF-2007-010, 2006.

[41] Bhaskar Krishnamachari, Deborah Estrin, and Stephen Wicker. Modelling data-centric routing in wireless sensor networks. In *IEEE infocom*, volume 2, pages 39–44, 2002.

[42] Vivek Mhatre and Catherine Rosenberg. Design guidelines for wireless sensor networks: communication, clustering and aggregation. *Ad Hoc Networks*, 2(1):45–63, 2004.

[43] Samuel Madden, Michael J Franklin, Joseph M Hellerstein, and Wei Hong. Tag: A tiny aggregation service for ad-hoc sensor networks. *ACM SIGOPS Operating Systems Review*, 36(SI):131–146, 2002.

[44] Rabindra Bista, Yong-Ki Kim, and Jae-Woo Chang. A new approach for energy-balanced data aggregation in wireless sensor networks. In *Computer and Information Technology, 2009. CIT'09. Ninth IEEE International Conference on*, volume 2, pages 9–15. IEEE, 2009.

[45] Mokhtar S Bazaraa, Hanif D Sherali, and Chitharanjan Marakada Shetty. *Nonlinear programming: theory and algorithms*. John Wiley & Sons, 2013.

APPENDIX A

PROOF OF LEMMA 1

A standard convex minimization problem is defined as [45]:

$$\begin{aligned} &\underset{x}{\text{minimize}} && f(x) \\ &\text{subject to} && g_i(x) \leq 0,\ i = 1, \ldots, m \\ & && h_i(x) = 0,\ i = 1, \ldots, n. \end{aligned} \tag{A.1}$$

where $f, g_1, \ldots, g_m$ are *convex*, and $h_1, \ldots, h_n$ are *affine*. Therefore, to show that problem (3.9) is convex, the objective function along with constraints (3.9a),...,(3.9d) should be convex or linear. Let us start with the convexity of the objective function:

$$\text{define} \quad \mathbf{r}^c \triangleq \alpha \mathbf{r}^a + (1-\alpha)\mathbf{r}^b \quad \text{of length } K$$

$$\begin{aligned} \sum_{i=1}^{K} E_u^c(i) &= \sum_{i=1}^{K} p(r_i^c) T_i \\ &= \sum_{i=1}^{K} p(\alpha r_i^a + (1-\alpha) r_i^b) T_i \\ &\leq \sum_{i=1}^{K} [p(\alpha r_i^a) + p((1-\alpha) r_i^b)] T_i && \text{(A.2)} \\ &= \sum_{i=1}^{K} [\alpha p(r_i^a) + (1-\alpha) p(r_i^b)] T_i \\ &= \alpha \sum_{i=1}^{K} p(r_i^a) T_i + (1-\alpha) \sum_{i=1}^{K} p(r_i^b) T_i \\ &= \alpha \sum_{i=1}^{K} E_u^a(i) + (1-\alpha) \sum_{i=1}^{K} E_u^b(i) \qquad \square && \text{(A.3)} \end{aligned}$$

In A.2, the inequality comes from the convexity of the power function which had been defined in Equation (3.3). Due to this inequality, the objective function is convex.

The constraint (3.9a) can be adapted to the definition in A.1 as follows:

$$g_1(r_i) = -r_i \leq 0 \tag{A.4}$$

As $g_1(r_i)$ is a linear function of r_i it is convex (and concave, actually). □

The constraint (3.9b) also can be represented as follows:

$$g_2(\mathbf{r}) = -\eta \sum_{i=1}^{k} [E_h(i) - E_u(i)]^+ + \sum_{i=1}^{k} [E_u(i) - E_h(i)]^+ + \sum_{i=1}^{k} P_{leak} T_i \leq 0 \tag{A.5}$$

This function is handled for two different cases due to the rectifier terms inside the function:

$$\begin{aligned}
&\text{Case 1: } E_h(i) \geq E_u(i) \\
&\Rightarrow g_2(\mathbf{r}) = -\eta \sum_{i=1}^{k} (E_h(i) - E_u(i)) + \sum_{i=1}^{k} 0 + \sum_{i=1}^{k} P_{leak} T_i \\
&\qquad = -\eta \sum_{i=1}^{k} (E_h(i) - E_u(i)) + 0 + const_1 \\
&\qquad = -\eta \sum_{i=1}^{k} E_h(i) + \eta \sum_{i=1}^{k} E_u(i) + const_1 \\
&\qquad = -const_2 + \eta \sum_{i=1}^{k} E_u(i) + const_1 \\
&\qquad = \eta \sum_{i=1}^{k} E_u(i) + constant
\end{aligned} \tag{A.6}$$

Case 2: $E_u(i) > E_h(i)$

$$\begin{aligned}
\Rightarrow g_2(\mathbf{r}) &= -\eta \sum_{i=1}^{k} 0 + \sum_{i=1}^{k}(E_u(i) - E_h(i)) + \sum_{i=1}^{k} P_{leak} T_i \\
&= 0 + \sum_{i=1}^{k}(E_u(i) - E_h(i)) + const_1 \\
&= \sum_{i=1}^{k} E_u(i) - \sum_{i=1}^{k} E_h(i) + const_1 \\
&= \sum_{i=1}^{k} E_u(i) - const_2 + const_1 \\
&= \sum_{i=1}^{k} E_u(i) + constant
\end{aligned} \tag{A.7}$$

It was shown in A.3 that $\sum_{i=1}^{k} E_u(i)$ is convex. As in both cases (A.7, A.8), $g_2(\mathbf{r})$ is a linear function of $\sum_{i=1}^{k} E_u(i)$, $g_2(\mathbf{r})$ itself is a convex function. □

The next constraint (3.9c) is represented as:

$$g_3(\mathbf{r}) = \sum_{i=1}^{k} r_i T_i - \sum_{i=1}^{k} D(i) \leq 0 \tag{A.8}$$

As $g_3(\mathbf{r})$ is a linear function of $\mathbf{r}$, it is convex. Similarly, the last constraint (3.9d) is:

$$h_1(\mathbf{r}) = \sum_{i=1}^{K} r_i T_i - \sum_{i=1}^{K} D(i) = 0 \tag{A.9}$$

where $h_1(\mathbf{r})$ is affine (linear), hence it satisfies the convexity requirement.

Following the result in A.3, along with convexities of A.4, A.5, A.8 and linearity of A.9, the optimization problem in (3.9) is convex. ■