Resource management in energy harvesting wireless sensor networks

Peng, Shuai

2015

Peng, S. (2015). Resource management in energy harvesting wireless sensor networks.
Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/65361>

<https://doi.org/10.32657/10356/65361>

Resource Management in Energy Harvesting Wireless Sensor Networks

PENG SHUAI

PENG SHUAI

School of Electrical and Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of

Doctor of Philosophy

2015

©2015 by Peng Shuai. All rights reserved.

To my family

Acknowledgments

This thesis could not be finished without the help and support of many people who are gratefully acknowledged here.

At the very first, I am honored to express my deepest gratitude to my dedicated supervisor, Prof. Low Chor Ping for helping me so much to become a PhD. I believe I am not able to complete this thesis without his continuous support and inspiring encouragement. He has offered me valuable suggestions and criticisms with his profound knowledge and rich research experience. His patience and kindness are greatly appreciated.

Thanks are also due to my friends, especially to Dr. Wang Ting and Mr Luo Wuqiong, who never failed to give me great encouragement and suggestions. I benefited from the collaboration and discussions with the postgraduate students of Communication Research Lab, Nanyang Technological University. I had a great time working with them and learned a lot from the group interactions.

At last but not least, I would like to thank my parents, who raised me up so I can pursuit my dreams. I am thankful to all my family members for their support all the way from the very beginning of my life. And most of all for my loving wife, whose encouragement and thoughtfulness are much appreciated.

Table of Contents

List of Figures	xi
List of Tables	xv
Summary	xvii
Glossary	xxi
1 Introduction	1
1.1 An Overview of Wireless Sensor Networks	2
1.2 Energy Harvesting and Management Issues	4
1.3 Existing Solutions	8
1.3.1 Energy Harvesting Aware Management	9
1.3.2 Energy Neutral Management	10
1.4 Our Approaches and Contributions	13
1.4.1 Mathematical Optimization	13
1.4.2 Adaptive Control	14
1.4.3 Admission Control	15
1.4.4 Network Clustering	16
1.5 Thesis Organization	18

TABLE OF CONTENTS

2	Prediction Free Energy Neutral Management for Energy Harvest-	
	ing Wireless Sensors	19
2.1	Introduction	20
2.2	Related Works	23
2.3	System Model and Notations	26
2.3.1	Energy Harvesting and Storage Method	26
2.3.2	Slotted System Time and Energy Budget	28
2.3.3	Duty Cycle	30
2.4	Average Duty Cycle Maximization	31
2.4.1	Utilizable Energy	31
2.4.2	Sensor Average Duty Cycle Maximization	35
2.4.3	Alternative Maximization Condition	36
2.4.4	Harvested Energy Utilization Efficiency	37
2.4.5	Maximizing Harvested Energy Utilization Efficiency	40
2.4.6	Budget Assigning Principles	41
2.5	Prediction Free Energy Neutral Management	43
2.5.1	Battery Energy Levels	43
2.5.2	Energy Budget Generation	46
2.5.3	Capacity of the Battery	49
2.5.4	Performance Deviation Due to Variations in $E_H(t)$	50
2.5.5	Maximizing the Linear Performance Level	52
2.6	Performance Analysis and Evaluation	53
2.6.1	Energy Matching Ability	54
2.6.2	Battery Residual Energy Level Variations	57
2.6.3	Harvested Energy Utilization Efficiency Comparison	60

TABLE OF CONTENTS

2.6.4	Impact of the Time Slot Duration	63
2.6.5	Impact of the N_{sun} Estimation Accuracy	64
2.6.6	Computational Complexity	65
2.7	Summary	67
3	Asymptotically Throughput Maximized Energy Neutral Manage-	
	ment for Energy Harvesting Wireless Sensors	69
3.1	Introduction	70
3.2	System Model and Notations	73
3.2.1	Harvested Energy and Energy Budget	73
3.2.2	Communication Channel Throughput	74
3.2.3	Harvested Energy Utilization Efficiency (HEUE)	75
3.2.4	Energy Neutral Operation	76
3.3	Throughput Maximization under Ideal Conditions	77
3.3.1	Average Channel Throughput Maximization	77
3.3.2	Constraints Relaxations	77
3.3.3	Low Complexity Offline Solutions	79
3.4	Online Asymptotic Throughput Maximization Policies	82
3.4.1	Adaptive Budget Assignment Policy (ABAP)	82
3.4.2	The δ Constant	86
3.5	Improved Adaptive Budget Assignment	
	Policy (ABAP*)	87
3.5.1	Improved-HEUE	87
3.5.2	Offline Estimation of the Optimal Improved-HEUE	90
3.5.3	Improved-ABAP	92

TABLE OF CONTENTS

3.6	Numerical Results	95
3.6.1	Performance Improvement due to Improved-HEUE	95
3.6.2	Energy Neutral Operation	96
3.6.3	Average Channel Throughput	99
3.6.4	Convergence Rate to Optimality	103
3.6.5	Computational Complexities	104
3.7	Summary	106
4	Energy Neutral Directed Diffusion for Energy Harvesting Wireless Sensor Networks	107
4.1	Introduction	108
4.2	Related Works	110
4.2.1	Energy Harvesting Aware Routing Protocols	110
4.2.2	Query Driven Routing Protocols	112
4.3	System Model and Notations	113
4.3.1	Network Topology	113
4.3.2	Sensor Energy Dissipation Model	114
4.3.3	Network-level Energy Neutral Management	115
4.4	Energy Neutral Directed Diffusion (ENDD)	116
4.4.1	Preliminaries	117
4.4.2	ENDD-Two Phase Pull (ENDD-T)	119
4.4.3	ENDD-One Phase Pull (ENDD-O)	127
4.4.4	Real-time Energy Consumption Estimation	133
4.4.5	Upper Bounds on the Control Message Overheads	139
4.5	Empirical Studies	142

TABLE OF CONTENTS

4.5.1	Simulation Setup	143
4.5.2	Network-level Energy Neutral Management	144
4.5.3	Distinct Packet Delivery Ratio	146
4.5.4	Average End-to-End Packet Delivery Delay	148
4.5.5	Control Message Overhead	149
4.6	Summary	151
5	Energy Neutral Clustering for Energy Harvesting Wireless Sen-	
	sors Networks	153
5.1	Introduction	154
5.2	Related Works	156
5.3	System Models and Notations	158
5.3.1	Network Setup	158
5.3.2	Sensor Energy Consumption Model	159
5.3.3	Energy Budget	161
5.4	Energy Neutral Clustering	162
5.4.1	Cluster Head Group	162
5.4.2	Energy Neutral Clustering (ENC) protocol	164
5.4.3	Size of the Cluster Head Group	170
5.4.4	Scheduling the Final-CMs and the CHG-Nodes	172
5.5	Optimum Number of Clusters	174
5.5.1	Energy Neutrality Constraints	174
5.5.2	Maximized Network Information Gathering	177
5.6	Extensions	180
5.7	Performance Evaluations	183

TABLE OF CONTENTS

5.7.1	Simulation Setup	183
5.7.2	Energy Neutral State	184
5.7.3	Total Amount of Information Bits Gathered	187
5.7.4	Control Message Overhead	190
5.8	Summary	191
6	Conclusions and Future Work	193
6.1	Conclusions	193
6.2	Recommendations for Further Research	198
	Authors Publications	201
	References	203

List of Figures

1.1	Topologies for different categories of Wireless Sensor Networks . . .	3
1.2	Categories of existing solutions	9
2.1	Observed solar radiation power. Drawn based on the data retrieved from TEXAS Solar Radiation Database [1]	22
2.2	Duty Cycle, Time Slot and Operation Cycle	29
2.3	Battery energy level model	44
2.4	Histogram of z	51
2.5	Energy matching ability comparison for Kansal-Ideal and Kansal- Acutal using DS1	55
2.6	Energy matching ability comparison for P-FREEN and Kansal-Ideal using DS1	56
2.7	BREL comparison with $D_{min} = 0.1$ for DS1	58
2.8	BREL comparison with $D_{min} = 0.3$ for DS1	59
2.9	HEUE comparison with $D_{min} = 0.1$ using DS1	61
2.10	HEUE comparison with $D_{min} = 0.2$ using DS1	61
2.11	HEUE comparison with $D_{min} = 0.3$ using DS1	62
2.12	HEUE comparison using DS2	62

LIST OF FIGURES

2.13	HEUE comparison using DS3	63
2.14	Average HEUE with different time slot duration using DS1	64
2.15	Average HEUE with different time slot duration using DS2	65
2.16	Average HEUE with different time slot duration using DS3	66
3.1	Convergence of $\eta_V^*(i)$ under different fading channels	92
3.2	Average Channel Throughput (ACT) improvements in (a): Rayleigh Fading Channel ($\xi[H] = 1$). (b): Rayleigh Fading Channel ($\xi[H] = 0.2$). (c): Nakagami Fading Channel ($\xi[H] = 0.3$)	96
3.3	Battery Residual Energy Level variations in: (a) Rayleigh Fading Channel ($\xi[H] = 1$) (b) Rayleigh Fading Channel ($\xi[H] = 0.2$) (c) Nakagami Fading Channel ($\xi[H] = 0.3$)	97
3.4	Battery Residual Energy Level variations with different η_V^t	99
3.5	Average Channel Throughput comparison based on harvest-store-use method (Rayleigh fading, $\xi[H] = 1$)	100
3.6	Average Channel Throughput comparison based on harvest-use(store) method (Rayleigh fading, $\xi[H] = 1$)	101
3.7	Average Channel Throughput comparison based on harvest-use(store) method (Rayleigh fading, $\xi[H] = 0.2$)	102
3.8	Average Channel Throughput comparison based on harvest-use(store) method (Nakagami fading, $\xi[H] = 0.3, m = 3$)	103
3.9	Convergence of the Current Estimated Improved-HEUE (η_V^t)	104
3.10	Convergence of Adaptive Water Level	104
4.1	Admission and rejection of Reinforcement Interests	121
4.2	Propagation of One-phase Interests	131

LIST OF FIGURES

4.3	Calculation of $T_m(t)$ for different OIs	134
4.4	Accumulated Node Failure Time using the three protocols	145
4.5	Distinct packet delivery ratio comparison	147
4.6	Average end-to-end packet delivery delay comparison	148
4.7	Control message overhead comparison. (A: “EDDD”, B: “ENDD- O”, C: “DD”, D: “ENDD-T”.)	151
5.1	Cluster Members and Cluster Head Groups	164
5.2	Operation timeline of the ENC algorithm	165
5.3	Six clusters formed using ENC	181
5.4	Six equal sized clusters formed using ENC*	182
5.5	Accumulated Cluster Failure Time with $R = 50m$	185
5.6	Accumulated Cluster Failure Time with $R = 100m$	185
5.7	Accumulated Cluster Failure Time with $R = 150m$	186
5.8	Average TAIB gathered with $R = 50m$	189
5.9	Average TAIB gathered with $R = 100m$	189
5.10	Average TAIB gathered with $R = 150m$	190
5.11	Number of control message exchanged with $R = 100m$	190

List of Tables

1.1	Approaches and Proposed Schemes	13
2.1	Matching Deviation under different D_{min}	56
2.2	Average BREL deviations from 2000J (δ_{2000})	59
4.1	Fields in the packet headers	117
4.2	Structure of a cache table maintained by a sensor	117
4.3	Fields in the cache entries	118
4.4	Utilities of the fields contained in packet headers and cache entries .	118
4.5	Calculation of $T_m(t)$	135
4.6	Communication related parameters	144
5.1	Control Message configurations	165
5.2	Network parameters	179
5.3	Optimal solutions for the Max-NIG problem	179
5.4	LEACH with different parameters	184
5.5	Simulation setups	184

Summary

With the emergence of energy harvesting techniques, it is now possible for wireless sensor networks to operate perpetually while supporting certain performance levels. Due to the renewable but non-deterministic nature of the energy harvesting source, the way to manage the harvested energy and provide such perpetual operation becomes a major challenge. Thus, in this thesis, we focus on the energy resource management mechanisms for energy harvesting wireless sensor networks.

In order to achieve perpetual operations, an *Energy Neutral Management* (ENM) mechanism is needed to make sure that the harvested energy will be able to replenish the energy that is being consumed by a sensor. Based on different performance maximization goals, we identify two levels of energy neutral management, namely *Node-level ENM* and *Network-level ENM*.

For Node-level ENM, we study the ways to efficiently utilize the harvested energy so that a sensor can operate perpetually with desired sensor performance level. We firstly consider the case when the sensor performance level (such as the duty cycle) has a linear relationship with the amount of energy consumed by the sensor. We analytically derive a set of energy allocation principles to maximize the amount of harvested energy that can be utilized by a sensor, in the presence of battery storage inefficiencies. These principles in turn maximize the sensor

average duty cycle while maintaining its energy neutral state. Since the energy harvesting information is not always available before sensor deployment, we develop a Prediction-FRee Energy Neutral (P-FREEN) management mechanism to implement the derived energy allocation principles based solely on current observed energy harvesting rate and battery residual energy level, which enables perpetual sensor operation with maximized sensor performance level.

We next consider the case when the sensor performance level (such as the communication channel throughput) has a non-linear relationship with the amount of energy consumed by the sensor. An off-line optimal energy allocation mechanism, which maximizes the average channel throughput while maintaining the energy neutral state of the sensor, is developed via convex optimization. Based on this optimal mechanism, we propose an on-line Adaptive Energy Budget Assignment Policy (ABAP) that asymptotically maximizes the average channel throughput by using the historical energy harvesting and channel state information observed by the sensor. We also study a method to reduce the energy loss caused by the battery energy storage inefficiencies. The fraction of the harvested energy that can be utilized by using this method is analytically derived and is integrated into ABAP to provide improved average channel throughput.

For Network-level ENM, we study the network layer routing protocols that coordinately control the energy consumption of sensors in the network, (by controlling the routing paths of the data traffic), so that perpetual network operations can be achieved with improved network performance levels. We focus on developing routing protocols based on two widely used data delivery models, namely the *Query Driven Model* and the *Continuous Model*. Using the query driven model, only data queried by the user will be sensed and delivered to the destination, which prevents

the delivery of non-desired data and is thus highly energy efficient. Hence, we propose a query driven Energy Neutral Directed Diffusion (ENDD) protocol to provide Network-level ENM. ENDD employs the traffic flow admission control mechanism to regulate the traffic load carried by a sensor based on its energy harvesting status, which in turn prevents sensors from shutting down due to excessive usage of energy. In this way, routing path failures can be prevented, which ensures the data delivery consistency and improves the network data throughput.

Continuous model is used for applications that require the periodical sensing and delivery of data information. Clustering protocols are suitable for such data delivery model as it can enable in-network data aggregations and thus reduces energy wastage caused by the delivery of the redundant data information. We develop an Energy Neutral Clustering (ENC) protocol to group the network into several clusters with the goal of providing perpetual network operation with consistent data delivery. ENC employs a novel Cluster Head Group (CHG) mechanism that allows a cluster to use multiple cluster heads to share the heavy traffic load. This CHG mechanism can help reduce the frequency of cluster re-formations, which in turn reduces the control message overhead. The optimum number of clusters that maximizes the amount of information gathered from the network is mathematically derived via convex optimization. Based on this optimum number of clusters, an extension to ENC is proposed to group the network into equal sized clusters so that maximized network information gathering can be achieved.

The performance of our proposed energy management mechanisms is verified through theoretical analysis and extensive empirical studies. We believe that these mechanisms and their results make important contributions to the study of the energy management mechanisms in energy harvesting wireless sensor networks.

Glossary

Abbreviations

ABAP	Adaptive Budget Assignment Policy
ABAP*	Improved Adaptive Budget Assignment Policy
ACT	Average Channel Throughput
AMP	ACT Maximization Problem
AWGN	Additive White Gaussian Noise
AWL	Adaptive Water Level
BCL	Battery Cycle Life
BREL	Battery Residual Energy Level
CH	Cluster Head
CHG	Cluster Head Group
CM	Cluster Member
CN	Center Node
DWF	Directional Water Filling
EDP	Exploratory Data Packet
EHAM	Energy Harvesting Aware Management
EHAR	Energy Harvesting Aware Routing
EH-Sensor	Energy Harvesting Wireless Sensor
EH-WSN	Energy Harvesting Wireless Sensor Network
ENC	Energy Neutral Clustering

ENC*	Improved Energy Neutral Clustering
ENDD	Energy Neutral Directed Diffusion
ENM	Energy Neutral Management
ENO	Energy Neutral Operation
HEUE	Harvested Energy Utilization Efficiency
INI	Initial INterest
LP	Linear Programming
LEACH	Low Energy Adaptive Clustering Hierarchy
MAC	Multiple Access Control
Max-NIG	Network Information Gathering Maximization
MEMS	Micro-Electro-Mechanic System
NDP	Non-exploratory Data Packet
OI	One-phase Interest
OPPD	One Phase Pull Diffusion
P-FREEN	Prediction FREe Energy Neutral management
RI	Reinforcement Interest
TPPD	Two Phase Pull Diffusion
WSN	Wireless Sensor Network

Mathematical Symbols

η_S	Battery Energy Storage Efficiency
B_0	Initial BREL upon sensor deployment
B_C	Battery capacity
t	Index of a time slot
T	Time slot duration
N_t	Total number of time slots under consideration
$E_H(t)$	Amount of energy harvested in time slot t
$P_H(t)$	Energy harvesting power rate in time slot t
$E_B(t)$	Energy Budget for a time slot t
$D(t)$	Duty Cycle achieved in a time slot t
$E_U(t)$	Utilizable Harvested Energy in a time slot t
$\xi[\cdot]$	Sign of expectation
η	Harvested Energy Utilization Efficiency
σ_D	Depth of discharge
h_t	Communication channel gain in a time slot t
$C(t)$	Channel throughput in a time slot t
$B(t)$	BREL at the end of a time slot t
$E_B^*(t)$	Optimal Energy Budget for a time slot t
$\frac{1}{\lambda^*}$	Optimal Water Level
$\frac{1}{\hat{\lambda}_t}$	Adaptive Water Level for a time slot t
η_V	Improved-HEUE
η_V^t	Current estimated Improved-HEUE for a time slot t
η_V^*	Off-line Optimal Improved-HEUE
E_{Tx}	Amount of energy needed to transmit a data packet
E_{Rx}	Amount of energy needed to receive a data packet

d	Distance between two sensor nodes
$E_P(t)$	Current Projected Energy Consumption
$E_A(m)$	Additional energy consumption
$\phi^{total}(t)$	Total number of data packets that a sensor is suppose to receive and transmit in a time slot t
$\phi_m^{total}(t)$	Total number of packets that is supposed to be relayed by a sensor in a time slot t for admitting an interest m
R_m	Data packet transmission rate specified by interest m
$T_m(t)$	Portion of the event duration specified by interest m that lies within the current time slot t
β_{re}	Expected packet retransmission constant
$\phi^{oh}(t)$	Expected number of packet overhearing in time slot t
$E_{idle}(t)$	Energy consumed due to idle listening in time slot t
G	A network graph with $ V $ vertices and $ E $ edges
$\Delta(G)$	Maximum degree of a vertex in the network graph G
$\mathcal{N}$	Notation of Normal Distribution
N	Total number of sensors in the network
R	Radius of the sensor deployment field
$\hat{d}$	Crossover distance
ε_{e-tx}	Energy consumed in the transmitter electronics to transmit one bit of information
ε_{e-rx}	Energy consumed in the receiver electronics to receive one bit of information
ε_{Sx}	Energy consumed to sense one information bit
ε_{DA}	A constant (Joule/bit/signal) used in the data aggregation process
E_{CM}^n	Energy needed for a Cluster Member n to sense and transmit one bit of information
E_{CH}^n	Energy needed for a Cluster Head n to handle one bit of information
$E_{CM}^{Tx/b}$	Amount of energy needed for a CM to transmit one bit of information

$E_{CH}^{Tx/b}$	Amount of energy needed for a CH to transmit one bit of information
$E_H^n(t)$	Energy harvested by sensor n in a time slot t
$E_B^n(t)$	Energy Budget for a sensor n in a time slot t
K	Number of clusters expected to be formed in the network
N_{CM}^k	Number of Final Cluster Members in a cluster k
N_{IC}^k	Number of Initial Cluster Members in a cluster k
N_G^k	Number of CHG-Nodes in a cluster k
$L^n(t)$	The amount of information bits that a Final-CM n can sense and transmit in a time slot t without compromising its Energy Neutral state
$B_{max}^k(t)$	Maximum amount of information bits that can be gathered by a cluster k in time slot t
T_A^n	The time duration for a CHG-Node n to wake up and take up the role as an Active-CH
T_{DX}	Amount of time a network spent in data information transmission during a time slot
N_{CM}	Expected number of Final-CMs in a cluster
N_G	Expected size of the CHG in a cluster
$\xi[E_B(t)]$	Expected Energy Budget for a sensor in a time slot t
d_{toCH}	Distance between a Cluster Member and a Cluster Head
d_{toBS}	Distance between a Cluster Head and the Base Station
R_c	Expected radius of a cluster formed in the network
L_t	Expected number of information bits that a Final-CM can send to its CH without compromising its Energy Neutral state in time slot t

Chapter 1

Introduction

With the advancements in technologies and the overwhelming demand of data information, there is a large scale research and engineering focus in the area of wireless sensor networks in the past decades. By extracting useful information from the physical world, wireless sensor network provides practical usefulness in a large number of applications. However, for traditional wireless sensor networks powered by batteries or super-capacitors, a major issue is the limited, non-renewable energy resource. In recent years, the emergence of the energy harvesting technology has made it possible for wireless sensor networks to gain access to theoretically infinite amount of energy resource. By efficiently managing the harvested energy, wireless sensor networks with energy harvesting capabilities will finally be able to achieve fully automated, untethered and unattended perpetual operation.

Our research focuses on the energy management for energy harvesting wireless sensor networks. In this chapter, we introduce the background, together with existing solutions to this energy management problem, before more details of our proposed schemes and results are discussed in the latter part of this thesis.

1.1 An Overview of Wireless Sensor Networks

The phenomenal advancements in the Micro-Electro-Mechanic System (MEMS) and the wireless communication technologies have lead to the development of low-power, low-cost, small sized wireless sensors. A wireless sensor has the capability of gathering information from its ambient environment through its sensing component, which consists of one or more sensing devices. In addition, it can also process the gathered information and communicate with other sensor nodes through its computing/processing unit and communication component, respectively.

A *Wireless Sensor Network* (WSN) is a network of wireless sensors that are operating in a co-operative manner to sense and collect ambient information [2]. Being deployed into various areas, WSNs are able to extract valuable information from the physical world and deliver the gathered information to a destination (usually a manned base station) for further analysis. As shown in Figure 1.1, WSN can be classified into two categories [3]:

- Category 1 (WSN-C1): mesh-based network with multi-hop radio connectivity among or between wireless sensors. This category of WSN has been used in various applications, such as military target tracking and surveillance [4, 5], disaster relief [6, 7], infrastructure monitoring [8, 9], as well as habitat and environmental monitoring [10, 11, 12, 13].
- Category 2 (WSN-C2): point-to-point or multipoint-to-point (star-based) systems with single-hop radio connectivity to wireless sensor. This category of WSN is useful in small scaled applications such as health monitoring [14, 15] and home applications [16].

1.1. An Overview of Wireless Sensor Networks

Figure 1.1: Topologies for different categories of Wireless Sensor Networks

Conventionally, wireless sensors are powered by batteries or super-capacitors, which can only provide limited energy resource. Since most of the WSNs are deployed into areas that are hard or dangerous for human to reach, replacing these batteries or super-capacitors becomes costly or sometimes even impossible. A sensor will be *dead* if it depletes its energy resource and the network performance will degrade severely when one or more sensors in the network are dead. Hence, the energy consumption is a major concern for conventional WSN [17]. There has been a significant amount of research efforts on developing energy efficient mechanisms that provide improved network performance levels, such as the network lifetime, network data throughput, etc. These mechanisms include (but not limited to) energy-efficient routing and MAC protocols [18, 19, 20, 21], duty cycling strategies [22, 23] as well as hierarchical topology control [24, 25, 26]. However, since the energy resource is limited, no matter how efficient these mechanisms or protocols are, a WSN will eventually depletes all energy resources and stops functioning.

1.2 Energy Harvesting and Management Issues

The emergence of energy harvesting techniques provide a way of solving the energy limitation problem in WSN. By harvesting energy from the ambient environment, a WSN will be able to gain access to theoretically infinite amount of energy resource. As a result, the energy harvesting technique has opened a whole new research dimension for the design, deployment and management of WSNs. Our proposed mechanisms, protocols and results in this thesis apply to a general wireless sensor network with energy harvesting capabilities.

The term *Energy Harvesting* refers to the process of scavenging energy or converting energy from one form to another. Equipped with energy harvesting devices, such as a solar panel, a wireless sensor will be able to harness energy from ambient environment and then convert this kind of energy into electrical energy, which will be used to support sensor operations. Throughout this thesis, we refer to a wireless sensor with energy harvesting capability as an *Energy Harvesting Sensor* (EH-Sensor). A WSN that consists of entirely EH-Sensors is referred to as an *Energy Harvesting Wireless Sensor Network* (EH-WSN).

There are different kinds of energy sources for EH-Sensors to harvest from, which include (but not limited to) solar radiation energy [27, 28], vibration energy [29, 30] and RF energy [31, 32]. Since these energy resource are generally *renewable* in nature, an EH-Sensor can gain access to theoretically infinite amount of energy resource. However, it does not imply that a sensor can consume arbitrarily amount of energy — the renewable energy can only be harvested at a limited rate.

One naive approach to overcome this limitation is to let the sensor to carry an energy harvesting device that is large or efficient enough to provide higher energy

1.2. Energy Harvesting and Management Issues

harvesting rate than the maximum energy consumption rate required by the sensor. This solution is not feasible in practice due to the size constraint on the sensor, which also constraints the size of the energy harvesting device. What's more, for some energy source, such as solar radiation energy, the energy harvesting rate during the night would be zero, which thus can never be larger than the maximum energy consumption rate required by the sensor.

Hence, a more reasonable approach is to carefully manage the energy consumption of the EH-Sensors according to the limit on the energy harvesting rate. *Energy resource management* is thus needed for an EH-Sensor or an EH-WSN. For a single sensor, the energy management involves estimating the energy harvesting rate and tuning a sensor's parameter, (such as sampling rate, transmit power, duty cycle, etc.), so that it will not consume more energy than the amount of energy that can be harvested from the ambient environment.

Energy resource management is also needed at the network level to coordinately control the consumption of the harvested energy for every sensor in the network and thus provides improved network performance. It is shown in [33] that the energy consumed in relaying (receiving/transmitting) the network traffic directly determines the energy consumption of the sensors in the WSNs. Hence, network layer routing protocol ([19, 34]), which controls the routing of network data traffic flows, plays a vital role in managing the energy resource at the network level. By carefully designing these routing protocols, sensors in the network will not consume more energy than that can be harvested due to the relaying of excessive traffic flows. As a result, it is possible for an EH-WSN to operate perpetually with maximized network performance levels (such as maximized network data throughput). Other than routing protocols, there are also other strategies and mechanisms that can be

1.2. Energy Harvesting and Management Issues

utilized to manage the energy consumption for an EH-WSN, such as the Multiple Access Control (MAC) protocols and the Sensor Deployment Mechanisms [35].

We note that the EH-WSN exhibits the following distinct natures that make the energy resource management extremely challenging:

- *Non-controllable energy harvesting source:* Most of the energy harvesting sources are non-controllable in nature, which means the energy harvesting source cannot be controlled to yield energy at desired time instances. The availability of the energy harvesting source shows temporal and spatial variations. Although the temporal energy availability for some of the energy harvesting source can be predicted, such as the widely used solar radiation energy, such prediction involves a lot of errors due to unforeseeable changes in the ambient environment. Also, since the energy harvesting condition may vary at different locations (spatial variations), the large scale deployment of the EH-Sensors (especially for WSN-C1) makes it impossible to predict the energy availability for all EH-Sensors in the network. Hence, instead of relying on predicted energy harvesting information, the energy management mechanism for the EH-WSN has to be carefully designed so that it can dynamically adapt to the variations and uncertainties in the energy harvesting source.
- *Multiple energy constraints:* Since wireless sensors are designed to be small in size, the size of its onboard energy harvesting device is thus constrained. Hence, during a finite period of time, there will be a limit on the amount of energy that can be harvested and converted for sensor operation. Since the energy harvesting condition shows spatial and temporal variations, a sensor

1.2. Energy Harvesting and Management Issues

will experience several different constraints on the energy harvesting rate at different time instances and different locations. Hence, instead of only considering a definite energy constraint (the amount of energy stored in batteries) as in conventional WSN, for the energy management of an EH-WSN, multiple energy constraints have to be taken into consideration. Network wide coordinations are needed to manage the energy consumption for each EH-Sensor and more computational efforts have to be done in order to achieve perpetual operation.

- *Non-ideal energy storage technology*: Since the energy harvesting source is non-controllable, it is impossible for the sensor to consume energy at a rate that is exactly the same as the energy harvesting (power) rate. Hence, an energy buffer is needed to store the harvested energy if the energy harvesting rate is higher than the energy consumption rate. On the other hand, a sensor can also draw energy from the energy buffer when necessary. However, in practical implementations, the energy buffer, which is usually a rechargeable battery or a super-capacitor, is non-ideal [36]: the storage capacity is limited; the charging efficiency, which is also referred to as the *Battery Energy Storage Efficiency*, is less than 1 (hence energy loss will occur during the energy storage process); some energy will be lost over time due to battery energy leakage. These limitations brought by non-ideal energy storage technology will put up another type of constraint on the amount of harvested energy that would be available for sensor usage, which in turn impacts on the performance the EH-WSN.

- *Unique performance optimization goal*: In conventional WSNs, due to the limited energy resource, the goal of simultaneously optimizing the *Network Lifetime*, (which is measured by the time elapsed before the first sensor or a fraction of sensors in the WSN are dead), and other network performance levels (such as network data throughput) can hardly be achieved. For EH-WSN, since the network can gain access to theoretically infinite amount of energy resource, it has the potential of achieving perpetual operation (i.e., unlimited network lifetime) while optimizing other network performance (such as maximized network data throughput). Since the purpose of maintaining perpetual operation is to gather more high quality information from the ambient environment, achieving the goal of simultaneous optimizing the network lifetime and other network performance is highly desirable when managing the harvested energy for EH-WSN.

1.3 Existing Solutions

The existing energy resource management schemes for EH-WSNs can be categorized into two groups based on their ways of treating the harvested energy, namely *Energy Harvesting Aware Management* (EHAM) and *Energy Neutral Management* (ENM). Fig 1.2 shows the detailed mechanisms/protocols under each category. In this section, we briefly introduce and compare the related works in both categories. More details of the related works will be discussed with each piece of our work in the following chapters.

Figure 1.2: Categories of existing solutions

1.3.1 Energy Harvesting Aware Management

With *Energy Harvesting Aware Management*, the harvested energy is treated as a supplementary to the battery energy. Thus, the harvested energy is used to improve the network performance level, such as extending the network lifetime. Under this category, *Energy Harvesting Aware Routing* (EHAR) protocols are extensively studied to exploit the advantages brought by the energy harvesting technology.

Early EHAR protocols ([37, 38]) consider the case when only some of the sensors in the network are EH-Sensors. For this kind of network, EH-Sensors are more likely to be chosen to relay data traffic since it can gain access to additional amount of energy. More recent protocols, such as the ones in [39, 40], incorporate the energy harvesting rate into the cost metrics to compute traffic route and sensors with better energy harvesting status will be chosen to relay network traffic. There are also energy harvesting aware hierarchical routing protocols [41, 42] that choose sensors with better energy harvesting status to act as cluster head to carry heavy

network traffic.

We note that, since these EHAR protocols still aim at improving the traditional network performance levels such as the network lifetime, they only provide incremental improvements over battery powered WSN. For EH-WSN, since the availability of the energy resource is infinite, it is more desirable that the energy management mechanisms can exploit this unique feature and provide perpetual operation with unlimited network lifetime.

1.3.2 Energy Neutral Management

With *Energy Neutral Management* (ENM), the harvested energy is treated as the primary source of energy and the battery/supercapacitor is used as an energy buffer. The term *Energy Neutral* [36] refers to the situation when an EH-Sensor consumes no more energy than the amount of harvested energy that is available for sensor utilization during a certain period of time. In this situation, a sensor will be able to operate perpetually with a certain performance level. Hence, with energy neutral management, the energy consumption of the EH-Sensor is carefully controlled so that desired performance levels can be supported perpetually for an EH-Sensor as well as an EH-WSN. In this thesis, we categorize the Energy Neutral Management schemes into two levels, namely *Node-level ENM* and *Network-level ENM*, based on different energy management objectives.

1.3.2.1 Node-level ENM

Node-level ENM aims at estimating and maximizing the *Utilizable Energy*, which is the amount of energy that can be harvested and then utilized by a sensor, in the

presence of temporal variations in the energy harvesting rate and inefficiencies in the energy storage techniques. In addition, it also provides a method to allocate the utilizable energy so that a sensor can achieve maximized performance levels while maintaining its energy neutral state. Node-level ENM can be directly applied to WSN-C2 where point to point communication is considered.

Node-level ENM can be further categorized based on different energy consumption models, namely *Linear Energy Consumption* (LEC) model and the *Non-linear Energy Consumption* (NEC) model. With the LEC model, the sensor performance level (such as the sensor *Duty Cycle*) has a linear relationship with the amount of energy consumed by this sensor. Node-level ENMs that aim at maximizing such performance metric are studied in [36, 43]. With the NEC model, we consider the case when the sensor performance level (such as the *Communication Channel Throughput*) has a non-linear, concave relationship with the amount of energy consumed by this sensor. Node-level ENMs that maximize such performance metric are studied in [44, 45, 46, 47].

1.3.2.2 Network-level ENM

Network-level ENM coordinately manages the energy consumption of every sensor in the network in the presence of spatial variations in the energy harvesting rate, with the aim of preventing sensors that are actively involved in the network operations from shutting down due to excessive use of energy. This in turn provides consistent network service (such as data sensing and delivery) and improved network performance (such as network data throughput). Network-level ENM can be applied to WSN-C1 where multi-hop communications are considered.

We note that, since Node-level ENM addresses the temporal variations in the

energy harvesting rate and determines the maximized amount of harvested energy that a sensor could consume without compromising its energy neutrality, it serves as an underlaying mechanism for Network-level ENM to determine the maximum amount of energy that each sensor in the network could consume during a certain period of time, without being forced to shut down.

One way of implementing the Network-level ENM is to manage the network traffic through network layer routing protocols, so that sensors that are actively involved in network operations will not be forced to shut down due to the carrying of excessive traffic loads. In the meantime, each sensor in the network will be carrying as much network traffic as possible (without compromising its energy neutrality) to provide higher network data throughput.

Routing protocols can be categorized based on different *Data Delivery Models*, which include *Query Driven*, *Event Driven*, *Continuous* and *Hybrid* model. Continuous model is used for applications, such as the habitat and environmental monitoring [10], that require the periodical delivery of data information to the destination for further analysis. Query/Event driven model is applicable for some other applications, such as target tracking [34], in which the information will be sensed and delivered by the network only when a specific event happens or when a specific query is generated by the end user. The hybrid model is a combination of the aforementioned models. Currently, to the best of our knowledge, there are two energy neutral routing protocols available: the continuous model based routing protocol proposed in [48] and the event driven based opportunistic routing protocol proposed in [49].

1.4 Our Approaches and Contributions

In this thesis, we aim at providing energy neutral management at both node level and network level. At the node level, we provide two energy neutral management schemes based on the linear and non-linear energy consumption models, respectively. At the network level, we propose two different routing protocols that are based on the Query Driven data delivery model and the Continuous data delivery model, respectively. Our approaches include *Mathematical Optimization*, *Adaptive Control*, *Admission Control* and *Network Clustering*. Table 1.1 shows the proposed approaches which correspond to the energy neutral management schemes/protocols that are proposed in this thesis.

Table 1.1: Approaches and Proposed Schemes

Energy Neutral Management		Approach	Proposed Scheme
Node-level	Linear	Mathematical Optimization & Adaptive Control	P-FREEN
	Non-linear		ABAP
Network-level	Query Driven	Admission Control	ENDD
	Continuous	Network Clustering	ENC

1.4.1 Mathematical Optimization

As stated in Section 1.3.2.1, for the Node-level ENM, the goal is to control the energy consumption of a sensor so that it can operate perpetually in the Energy Neutral state with maximized sensor performance levels. We achieve this goal through *Mathematical Optimization*, which is a way of finding best solutions to a mathematically defined problem with one or more constraints [50]. Two optimiza-

1.4. Our Approaches and Contributions

tion problems are formulated to maximize the sensor performance levels based on the linear energy consumption model (sensor average duty cycle) and the non-linear energy consumption model (communication channel throughput), respectively. In these optimization problems, both the energy harvesting rate limitation and the battery energy storage inefficiencies are considered in the constraints.

We firstly solve the linear optimization problem that is formulated based on the linear energy consumption model, by analysing the relations between the objective function and the constraints. We next use the *Convex optimization* [51] technique to solve the optimization problem that is formulated based on the non-linear energy consumption model. Based on the solutions to these two optimization problems, two optimal energy budget assignment policies are developed to control the energy consumption of the sensors (regarding to the two different energy consumption models), so that maximized sensor performance levels can be achieved while maintaining the sensor in the energy neutral state.

1.4.2 Adaptive Control

In the formulation of the aforementioned two optimization problems, energy harvesting information is needed to impose constraints on the energy consumption rate of the sensor. However, such energy harvesting information is not always available before sensor deployment. Thus, the aforementioned optimal budget assignment policies cannot be implemented directly. As mentioned in section 1.2, predicting the energy harvesting information is difficult (if not impossible). Hence, we use the *Adaptive Control* [52, 53] technique to adaptively adjust the energy consumption of a sensor based on the historical and current information learned by the

1.4. Our Approaches and Contributions

sensor. For the linear energy consumption model, we propose a Prediction FREe Energy Neutral (P-FREEN) management mechanism to implement the optimal energy budget assignment policies obtained through the solution of the linear optimization problem. P-FREEN uses the current observed energy harvesting rate and battery residual energy level to adaptively control the energy consumption of a sensor so that near optimal sensor performance level can be achieved. For the non-linear energy consumption model, we develop the Adaptive Budget Assignment Policy (ABAP) to control the energy consumption of a sensor based on historical information observed by the sensor. ABAP assigns energy budget in a way that, with sufficiently amount of information observed by the sensor, the energy budget assigned by ABAP will converge to the optimal energy budget assignment obtained from the solution of the convex optimization problem. This in turn indicates that ABAP will be able to asymptotically achieve maximized sensor performance level while maintaining the sensor's energy neutral state.

1.4.3 Admission Control

At the network level, we firstly study a way to provide energy neutral management through the network routing protocol that is based on the *Query Driven* data delivery model. With this model, queries will be injected into the network and traffic flows will be generated accordingly. If excessive queries are injected into the network, sensors will not be able to carry the heavy traffic flows generated and stop functioning due to energy shortage. This in turn compromise the consistency of the network data delivery for those queries that are already injected into the network. In order to solve this problem, the *Admission Control* [54, 55] technique

1.4. Our Approaches and Contributions

is used to dynamically control the amount of queries injected into the network. We propose an Energy Neutral Directed Diffusion (ENDD) protocol that provides consistent network service by implementing admission controls at every sensor in the network. Instead of controlling the number of flows according to the channel capacity limitations in traditional wired/wireless network [56, 57], admission control implemented in ENDD controls the traffic flows according to the energy harvesting rate limitations on each sensor. A real-time realistic sensor energy consumption model is developed to compute the energy required to carry the traffic flow generated by a query. Based on this energy consumption model, a sensor will be able to determine if it is able to admit a specific query without compromising its energy neutral state. In this way, all queries admitted into the network will be guaranteed with consistent network service. In addition, since no sensor will be forced to shut down due to the excessive consumption of energy, fewer packet loss would occur due to sensor failures. This in turn improves the amount of information that can be successfully delivered to the destination.

1.4.4 Network Clustering

We next develop the way to provide Network-level ENM for applications that requires the continuous delivery of data. One problem about the continuous data delivery is that redundant data information might be generated and delivered by the network, which results in a large amount of energy wastage [34]. We approach this problem by using the *Network Clustering* technique. Using this technique, sensors will be grouped into several clusters and in-network data information aggregation can be carried out at the cluster heads, which in turn reduces the amount

1.4. Our Approaches and Contributions

of redundant information that will be delivered by the network. Taking the energy neutral management into consideration, we propose an Energy Neutral Clustering (ENC) protocol to cluster the EH-WSN in a way that the information sensed by sensors in the network will be delivered consistently to the destination. Since the cluster heads will have to take up the additional data reception and aggregation tasks, it will consume energy much faster than the rest of the sensors in the cluster. Hence, we propose a Cluster Head Group mechanism that allows each cluster to have more than one cluster heads to share the heavy traffic load. The size of the CHG is computed in a way that, at any given time instance, there will be at least one sensor in the CHG having sufficient energy to process and relay the traffic load for the cluster. The size of the CHG as well as the information transmission rate at each sensors are computed locally at each CHG. We also mathematically derived, through convex optimization, the optimal number of clusters that the network should be grouped into, so that maximum amount of data information can be gathered and consistently delivered by the network.

1.5 Thesis Organization

The structure of this thesis is as follows. In Chapter 2, we develop a Node-level ENM for sensors with linear energy consumption model. A Prediction FREe Energy Neutral (P-FREEN) management mechanism is proposed to maximize the sensor performance level based solely on the historical and current information observed by the sensor. The Node-level ENM for sensors with a non-linear energy consumption model is studied in Chapter 3. An Adaptive Budget Assignment Policy (ABAP) is proposed to assign the energy budget in a way that the sensor performance level, in terms of the average channel throughput, can be asymptotically maximized when sufficient historical information is observed by the sensor. We next propose a query driven routing protocol, namely Energy Neutral Directed Diffusion (ENDD) in Chapter 4, to provide Network-level ENM for applications that employ the query driven data delivery model. Admission control is used by ENDD to regulate the traffic flows carried by sensors in the network, which in turn ensures the consistent network service and provides improved network performance. The Energy Neutral Clustering (ENC) protocol that provides Network-level ENM for applications with continuous data delivery model is proposed in Chapter 5. In this chapter, we also analytically derive the optimal number of clusters that maximizes the amount of information that can be gathered by the network. Last but not least, we present our conclusions and discuss the future research directions in Chapter 6.

Chapter 2

Prediction Free Energy Neutral Management for Energy Harvesting Wireless Sensors

For Energy Harvesting Wireless Sensors, an Energy Neutral state can be achieved so that desired performance level can be supported perpetually. Current prediction based energy neutral management mechanisms suffer from inevitable prediction errors, which in turn degrade the sensor performance in real implementations. To circumvent such problems, we propose a fundamental framework to efficiently manage the harvested energy in a prediction free manner. In particular, we theoretically derive a set of Budget Assigning Principles (BAPs) to maximize the amount of harvested energy that can be utilized by a sensor in the presence of battery energy storage inefficiencies, which in turn maximize the sensor's performance level in terms of the sensor's average duty cycle. A Prediction FREE Energy Neutral (P-FREEN) management mechanism is then proposed to implement the BAPs based solely on current observed energy harvesting rate and battery residual energy level. The performance of P-FREEN is verified via theoretical analysis and extensive computer simulations using real life energy harvesting data sets.

2.1 Introduction

Powered by batteries with finite energy storage capacity, traditional wireless sensors usually have a limited *Lifetime*, which is defined by the period of time elapsed before a sensor's *Battery Residual Energy Level* (BREL) reaches zero. The BREL indicates the amount of residual energy in the battery. When its BREL reaches zero, a sensor node is called *dead* and it stops performing any tasks. Thus, conventional researches ([58, 59, 60, 61, 62]) focus on extending the lifetime of a sensor by utilizing the energy stored in the batteries more efficiently. However, due to the finite energy storage capacity, no matter how carefully the energy management mechanisms or communication protocols are designed, sensors will eventually stop working. Battery replacement is thus required for these sensors, which may be costly and difficult to be done due to environmental or physical constraints [49].

In view of this, energy harvesting techniques have been introduced for wireless sensors in recent years to provide an additional source of energy. Sensor nodes are equipped with energy harvesting devices (solar panels, etc.) to harvest energy from the ambient environment. The harvested energy can be used to re-charge the sensor's battery if necessary. As a result, the lifetime of a sensor is less of a critical issue as it is possible for sensors to operate perpetually in an *Energy Neutral* [36] state, in which the amount of energy consumed by the sensor is no more than that can be harvested in a given period of time. Several energy management mechanisms, such as those in [44, 45, 46], have been proposed to provide such energy neutral operations. Besides maintaining the energy neutral state of a sensor, these mechanisms also aim at maximizing the sensor performance levels, such as the sensor average duty cycle or communication channel throughput, by efficiently

utilizing the harvested energy.

However, one common problem with the above energy management mechanisms is that they are all offline optimization mechanisms. In particular, they all make use of predicted energy harvesting information or assume the energy harvesting statistics to be known in advance to provide optimized system performance level and energy neutral operation. While energy harvesting information may be predictable for various energy sources such as solar power and wind power, getting such predicted information for each sensor might be time consuming. Even if the predictions are available upon deployment of sensors, these predictions may not be easily done with high level of accuracy. As a matter of fact, the actual amount of energy harvested at a given period of time usually deviates greatly from the predicted value. Figure 2.1 shows the observed 2 weeks' solar radiation power information obtained from US Texas Solar Radiation Lab [1]. From this figure we can see that the amount of energy that a sensor can actually harvest shows a large fluctuation. As a result, a system operating with a prediction based energy management mechanism may underuse or overuse the energy harvested. The system performance will be sub-optimal as there may not be sufficient amount of energy available at a given period of time due to over usage of energy resource. In addition, batteries with larger capacities have to be used to accommodate the larger fluctuations in the battery residual energy levels caused by these prediction errors, which will increase the size and cost of the wireless sensors.

To circumvent the problems stated above, a Prediction FREE Energy Neutral (P-FREEN) management mechanism is proposed in this chapter to provide energy neutral operation with maximized sensor performance level (in terms of sensor average duty cycle). In order to develop a theoretical energy management framework

Figure 2.1: Observed solar radiation power. Drawn based on the data retrieved from TEXAS Solar Radiation Database [1]

for P-FREEN, we firstly formulate the sensor’s average duty cycle maximization as a Linear Programming (LP) problem. We define a *Harvested Energy Utilization Efficiency* (HEUE) to represent the fraction of the harvested energy that can be effectively utilized by the system in the presence of battery energy storage inefficiencies. By analyzing the characteristics of HEUE, we solve the LP program and propose a set of Budget Assigning Principles (BAPs) that maximize the HEUE, which in turn maximize the average duty cycle of a sensor. With the assumption that two consecutive time slots usually experience similar energy harvesting condition, P-FREEN implements BAPs based solely on the observed energy harvesting rate and current battery residual energy level. The novel features of P-FREEN are:

- Energy Neutral management without the need to predict future energy harvesting profile

- Improved sensor performance level (average duty cycle), which is achieved through fast adaption to the fluctuations of the energy harvesting power rate, in the presence of battery energy storage inefficiencies
- Reduced Battery Residual Energy Level variations, which reduces the capacity of the battery required and improves battery cycle life
- Low computational complexity and easy implementation

The rest of this chapter is organized as follows. We review the recent researches that are related to our proposed mechanism in Section 2.2. Section 2.3 discusses the system model and some preconditions we assumed. In Section 2.4, the condition to maximize the sensor average duty cycle is theoretically analyzed. The details about the implementation of P-FREEN are presented in Section 2.5. Theoretical analysis and computer simulations that evaluate the performance of P-FREEN are presented in Section 2.6. We summarize this chapter in Section 2.7.

2.2 Related Works

In the literature, recent energy management mechanisms for energy harvesting wireless sensors can be classified according to their performance maximization goals, such as communication channel throughput maximization, source rate maximization, the sensor duty cycle maximization, etc.

In [63], optimal sleep and wake up policies that maximize the channel throughput for wireless sensors are obtained by using Game Theory. The energy harvesting process is modeled using the finite state Markov model. Joseph et al [64] also tried to maximize the channel throughput while maintaining the stable data queue of

the sensor network, using sleep and wake up strategies. Unlike the finite state Markov model used in [63], a more general stochastic model is used to model the energy harvesting process.

More works have been done in maximizing the theoretical communication channel throughput with optimal data transmission policies. In [45], an optimal energy management policy is proposed to maximize the channel throughput while maintaining a stable data queue at the sensor. In [46] and [65], optimum data transmission schedules of the sensor has been explored to maximize the theoretical communication channel capacity for fading communication channels, where convex optimization techniques are used in order to get optimal data transmission and energy allocation policies. Battery inefficiencies and limitations are considered in [44] and [47] when designing the optimal transmission policies. An optimal energy allocation algorithm is proposed in [66] to maximize the total throughput on a finite time horizon with a finite data buffer. In [67], an error-energy tradeoff energy management mechanism is proposed, with a goal of maximizing the successful data transmission probability while minimizing the probability of depleting the harvested energy for a body sensor network. The mutual information rate optimization policies for energy harvesting nodes with multi-antenna are explored in [68].

Other than the channel throughput maximization, in [69], a distributed sampling rate control algorithm is proposed to maximize the sensor sampling rate for rechargeable sensor nodes while taking the limited battery capacity into consideration. An energy neutral source-channel coding algorithm is proposed in [70] to balance the signal distortion and the data backlog size for multiple sensors.

Besides proposing the concept of energy neutral operation [36], Kansal et al.

provided in [71] an energy neutral management mechanism that improves the average duty cycle of a sensor in the presence of battery energy storage inefficiencies. The occurrence of battery energy storage inefficiencies is due to the fact that energy harvested from the energy harvesting device cannot be fully stored into batteries for utilization, which in turn causes energy loss. Kansal's mechanism employs an exponential weighted moving average filter to predict the amount of energy that can be harvested in the future. A dynamic duty cycle adaption algorithm is proposed to ensure the energy neutrality when the actual amount of energy deviates from the predicted values. Other prediction based energy management mechanisms that aim at improving the utilization efficiency of the harvested energy and improving sensor performance can be found in [72, 73, 74]

The work that is closest to our proposed mechanism is the one proposed in [43], in which a battery residual energy level based, prediction free energy neutral mechanism is proposed. This mechanism uses a linear-quadratic tracker to reduce the average deviation of the battery residual energy level. As a result, the chance for a battery being depleted is minimized as the system will tend to use minimum amount of energy when the battery residual energy level is very low. The limitation for this mechanism is that, it did not take battery energy storage inefficiencies into consideration. By using this mechanism, the harvested energy is stored into batteries before used by the sensor. As the harvested energy cannot be fully stored into batteries due to the battery energy storage inefficiencies, energy loss may occur and the performance of this mechanism may be degraded in real implementation.

2.3 System Model and Notations

2.3.1 Energy Harvesting and Storage Method

There are many different types of ambient energy that are available for harvesting. Among these energy resources, solar energy harvesting through photo-voltaic effect has emerged as a technology of choice for many sensor nodes [75, 76]. Therefore in this chapter, we will use the solar energy as the energy harvesting source. The amount of solar radiation energy that can be harvested has a periodical characteristic as shown in Figure 1.

We note that, due to battery energy storage inefficiencies, only a fraction of the energy harvested can be stored into energy storage devices. We refer to this fraction as the *Battery Energy Storage Efficiency* η_S , where $0 < \eta_S < 1$. Using the commonly used harvest-store-use [35] method to handle the harvested energy, the system will always suffer an energy loss of $1 - \eta_S$. In view of this problem, based on the concept discussed in [36], we proposed a harvest-use(store) mechanism in [77] that ensures the system to use as much energy as possible directly from the energy harvesting device before storing it. Only surplus energy harvested will be stored and the sensor will draw energy from the energy storage device if the energy harvested is not sufficient for sensor operation. We will adopt this harvest-use(store) method into our proposed energy management mechanism.

Rechargeable battery and Super-capacitor are two widely used energy storage mediums for energy harvesting wireless sensors due to their small size and high energy density. While super-capacitor has high energy storage efficiencies (higher than 95% [78]), it however suffers from high self-discharge rate (more than 50%

in a few days or weeks [79]). As a result, large amount of stored energy will be lost if it is not used immediately. Thus, we adopt the rechargeable batteries as the energy storage device in this chapter as it has lower self-discharge rate as compared to super-capacitors. As discussed in [35, 36], Li-ion rechargeable batteries require high pulse charging current (up to $1C/h$, where C is the battery capacity in mAh [80]), which is not suitable for the wireless sensors as the small energy harvesting device on these sensors might not be able to provide sufficient charging current. NiMH or Ni-Cd battery are recommended to store the harvested energy for its low charging current requirement (less than $100mA$ [81]) and small self-discharge rate (less than 20% in one month [35]).

We assume that upon deployment, the rechargeable battery carried by a sensor will have an initial Battery Residual Energy Level of B_0 . The value of B_0 can be equal to the battery residual energy level ($C \times V$ Joules where V is the nominal working voltage of the battery) for a fully charged battery, since it is a common practice that the batteries will be fully charged upon deployment. Note that for energy neutral management, the rechargeable batteries are considered as an energy buffer to deal with extreme weather conditions or prediction errors. The available energy in the rechargeable battery upon deployment is relatively small as compared to the total amount of energy that can be harvested in future operations for a large number of time slots. Thus, using the same assumption as in many other energy neutral management mechanisms ([36], [44]), the initial energy available in the rechargeable battery upon deployment is not taken into consideration as an energy source when designing energy neutral management mechanisms.

2.3.2 Slotted System Time and Energy Budget

Due to the weather condition and the day-night differences, solar energy harvesting system will experience large variances in the harvested energy input at different time instances. We thus divide the system time into small time slots and we use t to represent the time slot index, where $t = 1, \dots, N_D$ and N_D is total number of time slots for a typical day (24 hours). In this way, we can track the energy input variations and control the system energy consumption rate with higher accuracy. We denote the time elapsed from slot 1 to slot N_D as an **Operation Cycle** (OC). The relationships among Duty Cycle (DC), OC and time slots are depicted in Figure 2.2. The time slot duration is denoted by T . In this section, we choose T to be 1 hour and thus $N_D = 24$ (we do this for the convenience of calculation and analysis; the optimal length of the slot will be discussed in Section 2.6.4). Thus, for a time slot t , the total amount of energy $E_H(t)$ harvested from the energy harvesting device can be expressed as:

$$E_H(t) = \int_{\tau}^{\tau+T} P_H(t) d\tau \quad (2.1)$$

where $P_H(t)$ is the energy harvesting (power) rate in time slot t .

Note that for most sensor applications, there will be a minimum performance requirement, such as the minimum duty cycle, or the maximum delay. Intuitively, when operating at the minimum performance level, the energy consumption of a sensor is the lowest. We define the amount of energy that is consumed when the sensor is operating at the minimum performance level for one time slot as E_{min} . On the other hand, a system will also impose a cap on the maximum amount of energy that it is allowed to use and we denote this cap as E_{max} .

Figure 2.2: Duty Cycle, Time Slot and Operation Cycle

We assume here that the long term average solar energy harvesting power is sufficient for the sensor to operate at minimum performance level. Otherwise there will not exist any energy management mechanism that can maintain the energy neutral state of a sensor.

We also define the amount of energy that is allocated, by the energy management mechanism, to be used in a time slot t as the **Energy Budget** $E_B(t)$. The energy budget is calculated at the beginning of the time slot t . The calculation method will be elaborated in Section 2.5.2. Since the slot duration T is fixed, once we have determined the energy budget $E_B(t)$ for time slot t , the power budget can be calculated as $P_B(t) = \frac{1}{T}E_B(t)$. The energy neutral operation should ensure that the total amount of energy budget granted to a sensor will not exceed the total amount of harvested energy that can be utilized by this sensor in a given period of time.

2.3.3 Duty Cycle

Duty Cycle (DC) is the fraction of time a sensor spends in the active state as compared with the total time under consideration. If we only want to maintain the energy neutral state, we can just allow the sensors to consume minimal energy (by setting a very low duty cycle) or even shut them down. This is however not the case, as we would also want to maximize the amount of information a sensor can transmit or receive in a given period of time. When sensors are operating at a fixed power consumption level, the amount of information that can be transmitted or received by a sensor is determined by how long the system can stay in the active state, which is reflected by the length of the duty cycle. In addition, for a wireless sensor network, higher sensor average duty cycle means smaller end to end transmission delay, as more sensors in the network can stay active at a given instance for relaying information. Thus, we use the sensor average duty cycle as the sensor performance metric in this chapter.

The communication channel is assumed to be a non-fading channel with Additive White Gaussian Noise (AWGN). The sensor is assumed to be operating at a constant power level P_c (the same as in [36]) when the sensor is in the active state. The energy consumption for the sleep (inactive) state is neglected as it is very low as compared to P_c .

With $E_B(t)$ assigned as the energy budget for time slot t , the Duty cycle $D(E_B(t))$ for time slot t is defined as follows:

$$D(t) = D(E_B(t)) = \frac{1}{E_c} E_B(t) \quad (2.2)$$

where $E_c = P_c \times T$ is a predefined constant to represent the energy consumption if the sensor is running on a full duty cycle ($D(t) = 1$). The maximum and minimum

energy consumption is thus determined by the maximum and minimum duty cycle where $E_{min} = D_{min} \times E_c$ and $E_{max} = D_{max} \times E_c$.

2.4 Average Duty Cycle Maximization

In this section we will develop the energy budget assignment principles needed to maximize an energy harvesting sensor's average Duty Cycle (DC).

2.4.1 Utilizable Energy

Before defining the duty cycle maximization problem, we firstly present the way to calculate the *Utilizable Energy*, which represents the amount of harvested energy that can actually be utilized by the sensor using the energy harvest-use(store) method as mentioned in Section 2.3.1, in the presence of battery energy storage inefficiencies.

We firstly define $X(t) = E_H(t) - E_c$, which represents the surplus harvested energy (when $X(t) > 0$) that has to be stored in time slot t by using the energy harvest-use(store) method.

An indicator function $I(\cdot)$ is defined as:

$$I(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

During the active state of a time slot (with duration $D(t) \times T$), if $X(t) \geq 0$ so that $I(X(t)) = 1$, it means $E_H(t) \geq E_c$. As a result, the energy harvesting rate (power) $P_H(t)$ will also be no less than P_c . Using the harvest-use(store) method, in this active state, the sensor will be using $D(t) \times T \times P_c$ amount of

2.4. Average Duty Cycle Maximization

harvested energy directly from the energy harvesting device. The surplus energy $D(t) \times T \times (P_H(t) - P_c)$ will be stored into the battery. Because of the energy storage inefficiencies, only η_S fraction of the surplus energy can be stored into batteries for future use. We refer to this situation as the surplus situation and the actual amount of utilizable energy E_U^+ in this situation can be expressed as

$$\begin{aligned} E_U^+ &= \eta_S D(t) \times T \times (P_H(t) - P_c) + D(t) \times T \times P_c \\ &= D(t)(\eta_S \times (E_H(t) - E_c) + E_c) = D(t)(\eta_S X(t)I(X(t)) + E_c) \end{aligned} \quad (2.3)$$

During the this active state of a time slot, if $X(t) < 0$ so that $I(-X(t)) = 1$, the amount of energy harvested in time slot t is less than the energy budget of slot t . Thus, we have $P_H(t) < P_c$. Using the harvest-use(store) method, the sensor will be using $D(t) \times T \times P_H(t)$ amount of energy from the energy harvesting device. It means that all harvested energy will be utilized directly by the sensor without being stored into the batteries first. We refer to this situation as the shortfall situation and the actual utilizable energy E_U^- in this situation can be expressed as

$$\begin{aligned} E_U^- &= D(t) \times T \times P_H(t) = D(t) \times E_H(t) \\ &= D(t)E_c + D(t) \times E_H(t) - D(t)E_c = D(t)(E_c + X(t)I(-X(t))) \end{aligned} \quad (2.4)$$

By analyzing the structure of (2.3) and (2.4), we represent the amount of utilizable energy during the active state of a time slot as:

$$E_U^{active}(t) = D(t)[\eta_S X(t)I(X(t)) + E_c + X(t)I(-X(t))] \quad (2.5)$$

During the inactive (sleep) state, with time duration of $(1 - D(t))T$, the sensor is not consuming any energy ($E_c = 0$). Thus, all harvested energy will be stored into batteries. As a result, the actual amount of utilizable energy E_U^{sleep} under this

2.4. Average Duty Cycle Maximization

situation can be represented as:

$$E_U^{sleep}(t) = (1 - D(t))\eta_S E_H(t) \quad (2.6)$$

By combining (2.5) and (2.6), the amount of utilizable energy for one time slot can be calculated by:

$$\begin{aligned} E_U(t) &= E_U^{active}(t) + E_U^{sleep}(t) \\ &= D(t)[\eta_S X(t)I(X(t)) + E_c + X(t)I(-X(t))] + (1 - D(t))\eta_S E_H(t) \end{aligned} \quad (2.7)$$

According to the above equation, the amount of utilizable energy in a time slot t varies with different values of $D(t)$. When the amount of energy harvested $E_H(t)$ in time slot t is known, we are able to derive the maximum amount of utilizable energy $E_U^{max}(t)$ in this time slot, as stated in the following lemmas.

Lemma 2.1. *For a time slot t , when $E_H(t) \geq E_c$, the maximum amount of utilizable energy follows $E_U^{max}(t) = E_c + \eta_S(E_H(t) - E_c) \geq E_c$.*

Proof. When $E_H(t) \geq E_c$, P_c will be no more than $P_H(t)$. Thus, even if the sensor is running on full duty cycle ($D(t) = 1$), it will be consuming E_c amount of energy. In this situation we have $X(t) > 0$. Thus, $I(X(t)) = 1$ and $I(-X(t)) = 0$. From equation (2.7), the maximum amount of energy this sensor can actually harvest and utilize (by setting $D(t) = 1$) in this time slot follows:

$$E_U^{max}(t) = E_c + \eta_S(E_H(t) - E_c) \geq E_c \quad (2.8)$$

□

2.4. Average Duty Cycle Maximization

Lemma 2.2. *For a time slot t , when $E_H(t) < E_c$, the maximum amount of utilizable energy follows $E_U^{max}(t) = \frac{\eta_S E_H(t) E_c}{E_c - (1 - \eta_S) E_H(t)}$.*

Proof. When $E_H(t) < E_c$, we have $X(t) < 0$. Thus $I(X(t)) = 0$ and $I(-X(t)) = 1$.

According to equation (2.7), the amount of utilizable energy in this time slot is:

$$E_U(t) = D(t)E_H(t) + (1 - D(t))\eta_S E_H(t) \quad (2.9)$$

For energy neutral operation, we should at most use all the utilizable energy in time slot t as the energy budget for this time slot. Thus, we have:

$$E_B(t) = D(t) \times E_c \leq E_U(t) \quad (2.10)$$

Combining equation (2.9) and (2.10), we have the following constraint on $D(t)$:

$$D(t) \leq \frac{\eta_S E_H(t)}{E_c - (1 - \eta_S) E_H(t)} \quad (2.11)$$

From (2.9) we can see that $E_U(t)$ can be increased with larger duty cycle $D(t)$. Thus, by combining (2.9) and (2.11), we have the maximum amount of utilizable energy $E_U^{max}(t)$ under this situation as:

$$E_U(t) \leq \frac{\eta_S E_H(t) E_c}{E_c - (1 - \eta_S) E_H(t)} = E_U^{max}(t) \quad (2.12)$$

□

Based on Lemma 1 and Lemma 2, we further classify the time slot t into two

2.4. Average Duty Cycle Maximization

categories, the Darkslot and the Sunslot, by the following method:

$$t = \begin{cases} \text{Sunslot}, & E_U^{max}(t) \geq E_{\min} \\ \text{Darkslot}, & E_U^{max}(t) < E_{\min} \end{cases}$$

2.4.2 Sensor Average Duty Cycle Maximization

We next formulate the Linear Optimization (LP) problem for the sensor average Duty Cycle (DC) maximization as follows:

$$\max \quad \frac{1}{N_O \times N_D} \sum_{i=1}^{N_O} \sum_{t=(i-1) \times N_D + 1}^{i \times N_D} D(t) \quad (2.13)$$

s.t.

$$D(t) \geq D_{min}, t = 1, 2, \dots, N_t \quad (2.14)$$

$$D(t) \leq D_{max}, t = 1, 2, \dots, N_t \quad (2.15)$$

$$\sum_{i=1}^{N_O} \sum_{t=(i-1) \times N_D + 1}^{i \times N_D} E_U(t) \geq \sum_{i=1}^{N_O} \sum_{t=(i-1) \times N_D + 1}^{i \times N_D} E_B(t) \quad (2.16)$$

where N_O is the total number of operation cycles (days) under consideration and i is the index number to indicate which operation cycle is being considered in the summations. $N_t = N_O \times N_D$ is the total number of time slots under consideration.

We refer to this Sensor Average Duty Cycle Maximization problem as **DC-Max** problem. The objective function (2.13) represents the average DC per time slot for N_O operation cycles (N_t time slots) by using $E_B(t)$ amount of energy (duty cycle $D(t)$) in time slot t . Condition (2.14) and condition (2.15) impose the minimum and maximum duty cycle constraints, respectively, which in turn impose the minimum and maximum energy constraints as we discussed in Section 2.3.2.

Condition (2.16) is the energy neutrality constraint. The LHS of (2.16) shows

2.4. Average Duty Cycle Maximization

the amount of utilizable energy by using the harvest-use(store) method for N_O operation cycles. The RHS of (2.16) is the total energy budget assigned during N_O operation cycles, it should be less than or equal to the LHS of (2.16) to ensure the energy neutrality of the whole system.

2.4.3 Alternative Maximization Condition

We note that, due to the non-linear $I(\cdot)$ function, constraint (2.16) is in fact non-linear, which makes it difficult to solve the DC-Max problem. Further more, for the solutions of the DC-Max problem to be optimal, the number of operation cycles under consideration should be infinite, which makes the DC-Max problem not tractable. Thus, we have the following lemma that provides an alternative maximization approach for the DC-Max problem:

Lemma 2.3. *Maximization of LHS of constraint (2.16) maximizes the objective function (2.13).*

Proof. Since $D(E_B(t))$ is a linear function of variable $E_B(t)$, according to Jensen's inequality [48], we have:

$$\xi[D(E_B(t))] = D(\xi[E_B(t)]) \quad (2.17)$$

where $\xi[\cdot]$ is the sign of expectation.

As we mentioned in Section 2.3.2, an energy neutral management mechanism should ensure that the total energy budget assigned does not exceed the amount

2.4. Average Duty Cycle Maximization

of utilizable energy in a given period of time. Thus, we have

$$\xi[E_B(t)] = \frac{1}{N_t} \sum_{t=1}^{N_t} E_B(t) \leq \frac{1}{N_t} \sum_{t=1}^{N_t} E_U(t) \quad (2.18)$$

By combining (2.2), (2.17) and (2.18), we have

$$\xi[D(E_B(t))] \leq D \left(\frac{1}{N_t} \sum_{t=1}^{N_t} E_U(t) \right) = \frac{1}{N_t E_c} \sum_{t=1}^{N_t} E_U(t) \quad (2.19)$$

The Left Hand Side of equation (2.19) is the average duty cycle achieved by using energy budgets assigned by the energy management mechanism in N_t time slots.

It is easy to see from (2.18) that the equality of (2.19) is achieved when all utilizable energy $\sum_{t=1}^{N_t} (E_U(t))$ are used to assign energy budgets for N_t time slots. Thus, maximizing sensor's average duty cycle (objective function (2.13)) is as a matter of fact maximizing the amount of harvested energy that can be utilized by the sensor in N_t time slots, which is equivalent to maximize the LHS of (2.16) when $N_t = N_O \times N_D$ as in (2.13). $\square$

2.4.4 Harvested Energy Utilization Efficiency

Due to the diurnal characteristic of the solar energy harvesting, the energy harvesting rates in each time slot show a periodical profile. That is, the energy harvesting rates of the same time in each day is similar to one another. Thus, tracking and analyzing the energy neutral operation within one operation cycle (corresponding to one day) is a good approximation of the DC-max problem.

2.4. Average Duty Cycle Maximization

From here, we define the notion of *Harvested Energy Utilization Efficiency* (HEUE), which is a measure of the system's ability to utilize the harvested energy to assign energy budget during one Operation Cycle (OC). According to Lemma 2.3, we analyze the energy budget assigning conditions that maximize HEUE, which in turn maximize the sensor average duty cycle.

The amount of utilizable energy during one OC can be computed by using the total amount of energy harvested minus the total energy loss experienced during one OC. HEUE (denoted by η) for one OC (N_D time slots) is thus defined as follows:

$$\begin{aligned}\eta &= \frac{\sum_{t=1}^{N_D} E_U(t)}{\sum_{t=1}^{N_D} E_H(t)} = \frac{\sum_{t=1}^{N_D} E_H(t) - \sum_{t=1}^{N_D} E_{Loss}(t)}{\sum_{t=1}^{N_D} E_H(t)} \\ &= \frac{\sum_{t=1}^{N_D} E_H(t) - \sum_{t=1}^{N_D} ES_{loss}(t) - \sum_{t=1}^{N_D} EN_{loss}(t)}{\sum_{t=1}^{N_D} E_H(t)}\end{aligned}\tag{2.20}$$

where $ES_{loss}(t)$ is the amount of energy loss when storing harvested energy into batteries and we refer to this kind of energy loss as the *Energy Storage Loss*. $EN_{loss}(t)$ is the amount of energy loss caused by using more energy than the amount of utilizable energy during a time slot t . We refer to this kind of as the *Energy Neutrality Loss* for a time slot t .

When the amount of energy $E_B(t)$ consumed by the sensor is larger than the amount of utilizable energy $E_U(t)$ in time slot t , there will be $E_B(t) - E_U(t)$ amount of energy overused by the system during one time slot, where the overused energy is drawn from the battery. To maintain the energy neutrality, the system has to store this amount of energy back into battery in the subsequent time slots. Due to

2.4. Average Duty Cycle Maximization

the battery energy storage inefficiencies, it will require $[E_B(t) - E_U(t)]^+ / \eta_S$ amount of harvested energy to restore the battery residual energy level, which will result in an energy neutrality loss of:

$$EN_{loss}(t) = (1/\eta_S - 1) \times [E_B(t) - E_U(t)]^+ \quad (2.21)$$

where

$$[x]^+ = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

Thus, minimizing $EN_{loss}(t)$ requires

$$E_B(t) = D(t)E_c \leq E_U(t) \quad (2.22)$$

This condition actually means that, in order to avoid the energy neutrality loss, the energy consumption during one time slot should be less than the amount of harvested energy that can be utilized in this time slot, which is intuitive.

The energy storage loss during one time slot can be calculated by using the total amount of energy harvested $E_H(t)$ minus the total amount of energy $E_U(t)$ utilizable by the sensor (as calculated in equation (2.7)) :

$$\begin{aligned} ES_{Loss}(t) &= E_H(t) - E_U(t) \\ &= (1 - \eta_S)(1 - D(t))E_H(t) + (1 - \eta_S)D(t)[E_H(t) - E_c]^+ \end{aligned} \quad (2.23)$$

The first term of the RHS of equation (2.23) is the energy loss occurred when the sensor is in the inactive state of a time slot t . All energy harvested during this state $(1 - D(t))E_H(t)$ has to be stored into batteries as the sensor is not consuming any energy, which will result in energy loss of $(1 - \eta_S)(1 - D(t))E_H(t)$. The second term of the RHS of equation (2.23) is the energy loss occurred when the energy harvesting rate is higher than the energy consuming rate during the active period

2.4. Average Duty Cycle Maximization

of a time slot t . The excess energy $D(t)(E_H(t) - E_c)$ during the period will be stored into batteries, which causes energy loss of $(1 - \eta_S)D(t)(E_H(t) - E_c)$.

2.4.5 Maximizing Harvested Energy Utilization Efficiency

From (2.20) we can see that the maximization of HEUE (η) is in fact the minimization of $ES_{Loss}(t) + EN_{loss}(t)$ in each time slot, which has two scenarios:

Scenario 1: $\mathbf{E_H(t)} \geq \mathbf{E_c}$. Energy storage loss for this time slot t can be rewritten from (2.23) as

$$\begin{aligned} ES_{Loss}(t) &= (1 - \eta_S)(E_H(t) - D(t) \times E_c) = E_c(1 - \eta_S) \left(\frac{E_H(t)}{E_c} - D(t) \right) \\ &\geq E_c(1 - \eta_S)(1 - D(t)) \end{aligned} \quad (2.24)$$

From equation (2.2), we know that $E_B(t) = D_t \times E_c$. Thus, we can see directly from equation (2.24) that minimizing $ES_{Loss}(t)$ requires $D(t)$ to be as large as possible, which implies $D(t) = 1$.

Meanwhile, from Lemma 1 we can see that with $D(t) = 1$, $E_B(t) = E_c \leq E_U(t)$. With $D(t) = 1$, $EN_{loss}(t)$ will also be minimized according to condition (2.22).

However, as mentioned in Section 2.4.2, there will be a maximum duty cycle constraint D_{max} . Thus, we conclude that in this scenario, $D(t) = D_{max}$ minimizes $EN_{loss}(t) + ES_{Loss}$, which implies $E_B(t) = E_{max}$ will be the ideal assignment of energy to maximize η .

Scenario 2: $\mathbf{E_H(t)} \leq \mathbf{E_c}$. The total energy loss under this situation can be recalculated from (2.23):

$$ES_{Loss}(t) = (1 - \eta_S)(1 - D(t)) E_H(t)$$

We can observe that $ES_{Loss}(t)$ can be reduced by choosing a $D(t)$ as high as

2.4. Average Duty Cycle Maximization

possible, which requires the energy budget assigned to be as high as possible. We note that the maximum amount of utilizable energy for one time slot is $E_U^{max}(t)$, whereby the value of $E_U^{max}(t)$ is given in lemma 2.2. Since it is the maximum amount possible, use $E_U^{max}(t)$ as the energy budget can thus minimize $ES_{Loss}(t)$. In addition, we note that according to condition (2.22), assign an energy budget that is no more than $E_U^{max}(t)$ will also minimize $EN_{loss}(t)$.

From here, we can conclude that $E_U^{max}(t)$ should be used as the energy budget to maximize η . Take the maximum and minimum energy budget constraints into consideration, energy budget assignment method to maximize η in this scenario is:

$$E_B(t) = \begin{cases} E_{max} & \text{if } E_U^{max}(t) > E_{max} \\ E_U^{max}(t) & \text{if } E_{min} < E_U^{max}(t) \leq E_{max} \\ E_{min} & \text{if } E_U^{max}(t) \leq E_{min} \end{cases} \quad (2.25)$$

2.4.6 Budget Assigning Principles

It is shown in the last section that we will be able to utilize more harvested energy if we try to use as much energy as possible subject to the constraints on E_U^{max} . Thus, it is intuitive that we will want to minimize the differences between the energy budget assigned and the utilizable energy $E_U^{max}(t)$, so that more energy can be drained directly from the energy harvesting device to avoid the energy storage loss. We denote the absolute deviation between $E_B(t)$ and $E_U^{max}(t)$ as the **Matching Deviation** of an energy management mechanism. Thus, if an energy management mechanism can achieve a smaller matching deviation, the sensor's average duty cycle can be improved.

However, in real implementations, there will be minimum and maximum performance requirements as in constraints (2.14) and (2.15), which make it impossible to achieve zero matching deviation even when future energy harvesting information

2.4. Average Duty Cycle Maximization

is available in advance. Due to constraint (2.15), only E_{max} amount of energy can be used as the energy budget even if there are more energy harvested in the same time slot. On the other hand, due to constraint (2.14), we have to use at least E_{min} as the energy budget for Darkslots. By the definition of Darkslot, using E_{min} as the energy budget will result in more energy being used than the amount of utilizable energy during Darkslots. In order to maintain the energy neutrality, the amount of energy overused in the Darkslots has to be reserved by assigning smaller energy budget for the Sunslots so that total energy consumed will not exceed the amount of utilizable energy during one OC. We refer this process as the *Energy Reservation Process*.

The amount of energy E_r that is needed to be reserved for Darkslots during one OC is calculated as follows:

$$E_r = \sum_{t \in \text{Darkslots}} (E_{min} - E_U^{max}(t)) \quad (2.26)$$

One simple way of carrying out the energy reservation process is to reserve this amount of energy at the first few Sunslots of an OC until E_r amount of energy has been accumulated in the battery. This is done by assigning E_{min} to be the energy budget for these Sunslots, once the energy reservation process has been completed, the energy budgets for the subsequent Sunslots should be assigned according to equation (2.25).

From here we conclude that the Budget Assigning Principles (BAPs) that maximize the sensor average duty cycle while maintaining the energy neutral state are:

1. For a Darkslot, assign E_{min} to be the energy budget.
2. (a) For a Sunslot, if there is insufficient energy E_r reserved in the battery,

2.5. Prediction Free Energy Neutral Management

assign E_{min} to be the energy budget.

- (b) For a Sunslot, if there is sufficient energy E_r reserved in the battery, follow the rules stated in equation (2.25).

2.5 Prediction Free Energy Neutral Management

Traditional ways to implement BAPs are to predict the $E_H(t)$ for each time slot and then assign energy budget accordingly. In this section, we introduce a Prediction FREE Energy Neutral (P-FREEN) management mechanism that implements BAPs without the need of the predicted energy harvesting information. P-FREEN adjusts the energy budget of each time slot adaptively according to the observed energy harvesting rate and the battery residual energy level. The energy harvesting rate monitoring function has already been implemented in some commercially available energy harvesting wireless sensor node such as the Helimote [35]. In addition, the method to measure battery residual energy level has been widely studied in many battery operated systems and energy aware protocols, such as in [82] and [83]. As such, we will not further discuss about these measurement methods.

2.5.1 Battery Energy Levels

We firstly define several battery energy levels that are needed for P-FREEN. The battery energy level model is shown in Figure 2.3.

The *Physical Full Level* (PFL), denoted by B_{PFL} , indicates that the battery is fully charged. The *Operational Full Level* (OFL), denoted by B_{OFL} , indicates that the system has reserved sufficient energy (E_r) that is required for Darkslots

2.5. Prediction Free Energy Neutral Management

usage. The *Operational Empty Level* (OEL), denoted by B_{OEL} , indicates that the system has used up all the reserved energy E_r . Thus, the difference between B_{OFL} and B_{OEL} , denoted by the *Energy Gap* E_{gap} , is equal to the amount of energy E_r reserved for Darkslots as we defined in Section 2.4.6. The difference between PFL and OFL is denoted by the *Bonus Energy* E_{bon} , which accounts for the extra energy stored into batteries during Sunslots due to under-allocated energy budget.

For energy neutral operation, the system will try to prevent the Battery Residual Energy Level (BREL) from dropping down below B_{OEL} , as it would mean that the sensor is consuming more energy than the amount of utilizable energy during one OC. However, under extreme weather condition, BREL might still drop below B_{OEL} , and the *Fail Safe Energy* is then used to prevent the system from shutting down. Once this situation happened, P-FREEN will recover the BREL by assigning less energy budget for each time slot until the BREL reaches B_{OFL} again. We denote the BREL **at the beginning** of a time slot t as $B(t)$.

Figure 2.3: Battery energy level model

The value of Energy Gap for each OC is updated at the time when the first

2.5. Prediction Free Energy Neutral Management

Sunslot is observed. It is estimated as follows:

$$E_{\text{gap}} = (N_D - N_{\text{sun}})(E_{\text{min}} + \int_{\tau}^{\tau+T} \rho(\tau) d\tau) \quad (2.27)$$

where $\rho(\tau)$ is the battery self discharging rate. N_D is the total number of time slots in one OC and N_{sun} is the number of Sunslots in one OC. Since the self discharge rate is very low for rechargeable batteries as stated in Section 2.3.1, we neglect it by setting $\rho(\tau) = 0$.

The Exponentially Weighted Moving Average (EWMA) filter can be used to calculate the value of N_{sun} . Let $N_{\text{sun}}(d)$ denote the number of Sunslots that we have observed today, $N_{\text{sun}}(d-1)$ for yesterday and $N_{\text{sun}}(d-2)$ for the day before yesterday and so on. Then the updated number of Sunslots $N_{\text{sun}}(d+1)$ for tomorrow (the next OC), will be:

$$N_{\text{sun}}(d+1) = a[N_{\text{sun}}(d) + (1-a)N_{\text{sun}}(d-1) + (1-a)^2N_{\text{sun}}(d-2) + \dots] \quad (2.28)$$

where $N_{\text{sun}}(0) = N_D/2$ (an initial guess of the number of Sunslots) and $0 < a < 1$ is the weight assigned to the previous day. In practice, a will be chosen to be close to 1 because the number of Sunslots observed yesterday is more relevant as compared to the older observed values.

However, we note that D_{min} is usually set at a very low level (such as 0.1). Hence, even if there is some difference between the actual number of Sunslots and the estimated number of Sunslots for a specific OC, the impact on the value of E_{gap} is limited. As a result, the impact of the estimation accuracy of N_{sun} on the performance of the proposed mechanism is limited. We will verify this effect in Section 2.6.5. We note here that in real implementations, N_{sun} can be set to a reasonable fixed value.

2.5. Prediction Free Energy Neutral Management

We set at the beginning $E_{bon} = 2 \times E_{gap}$ and adjust OFL and OEL according to the frequency in which the BREL reaches PFL. If the BREL is charged to PFL, the system will experience energy loss as any additional harvested energy cannot be stored into the batteries. Thus, when the BREL has reached PFL at least once in one OC, we will decrease the level of OFL by E_{gap} at the end of this OC to increase E_{bon} . In this way, more energy buffer place can be provided for the next OC to prevent the BREL from reaching PFL again. Note that because E_{gap} is the energy reserved for the Darkslots, it should not be changed once it is estimated using equation (2.27). Since E_{gap} is measured by the difference of OFL and OEL, if we decreased the value of OFL by E_{gap} at the end of one OC, we will also have to decrease the value of OEL by E_{gap} to keep the value of E_{gap} unchanged.

2.5.2 Energy Budget Generation

For solar energy harvesting, the energy harvesting power rate varies greatly as there are day and night differences. However, as the weather condition usually does not change quickly over a short period of time, the energy harvesting power rate also evolves slowly at the same time [36]. Thus, we have the following assumption:

Assumption 2.1. *With a sufficiently small time slot duration, the energy harvesting power rate for two consecutive time slots are similar.*

The appropriate time slot duration will be discussed later in Section 2.6.4.

With Assumption 2.1, we can assume that if the previous time slot $t - 1$ is a Sunslot (or a Darkslot), then it is highly possible that the current time slot t will also be a Sunslot (or a Darkslot). Exceptions can happen when there is a

2.5. Prediction Free Energy Neutral Management

sudden change in weather condition so that two consecutive time slots may not be experiencing similar energy harvesting power rate, which is very rare. It can also happen when the time slots are shifting from Darkslot to Sunslot (when the sun is rising) at dawn or shifting from Sunslot to Darkslot at dusk. However, these situations can also be considered to be rare condition as it can only happen twice a day (an OC).

From here we introduce the prediction free energy budget generation method that implements BAPs. This method is carried out once at the beginning of each time slot. We use the energy harvesting rate observed in the previous time slot (time slot $t - 1$) to estimate whether the current slot t is a Sunslot or a Darkslot. The Battery Residual Energy Level (BREL) is used to determine whether there is sufficient energy reserved for the Darkslots. The energy budget for a time slot t (current time slot) is given by:

$$E_B(t) = \begin{cases} E_{min} & \text{if } (A) \text{ or } (B) \\ \min\{E_U^{max}(t-1), E_{max}\} & \text{if } (\overline{A}) \text{ and } (\overline{B}) \end{cases}$$

where

$$Condition(A) : B(t) < B_{OFL}$$

$$Condition(B) : E_U^{max}(t-1) < E_{min}$$

$(\overline{A})$ is the complementary of Condition (A) . $(\overline{B})$ is the complementary of Condition (B) .

The above energy budget generation equations correspond to three different scenarios:

1. Current BREL $B(t)$ is below B_{OFL} (Condition (A)): If BREL is below OFL, one possible case is that the sensor is using the energy reserved for Dark-

2.5. Prediction Free Energy Neutral Management

slots. This can happen when the current time slot is a Darkslot and the sensor should use E_{min} as the energy budget, as specified in BAPs-(1). Another possibility is that the current time slot is a Sunslot but the energy accumulated in the battery is not sufficient for the energy budget reservation of Darkslots. In this case, sensor should be operating at E_{min} to reserve energy for Darkslots as specified in BAPs-(2a).

2. Energy harvested in previous time slot $t - 1$ is less than the minimum energy requirement E_{min} (Condition (B)): In this case, the previous time slot is a Darkslot and it is highly possible that the current time slot is also a Darkslot. Following BAPs-(1), the sensor should use E_{min} as energy budget to minimize the amount of energy drawn from the battery, which in turn avoids energy loss caused by battery energy storage inefficiencies.
3. Current BREL $B(t)$ is higher than B_{OFL} and previous time slot is a Sunslot (Condition $(\bar{A})$ and $(\bar{B})$): For this case, the sensor is operating in a Sunslot with sufficient energy reserved for Darkslots already. In this situation, we will have to follow BAPs-(2b). As we have assumed that the energy harvesting rate for two consecutive time slots are similar, we use the amount of energy harvested in previous time slot $t - 1$ to calculate the $E_U^{max}(t)$ for current time slot t .

Note that when some extreme weather condition happens during some OCs, the energy harvested might not be able to support even the minimum performance level. As a result, short term energy neutrality (for one OC) might be compromised and the BREL may drop below OEL. That is why we have the Fail Safe Energy reserved to account for this kind of situation. Sensors under such a situation

2.5. Prediction Free Energy Neutral Management

will use E_{min} as energy budgets for every time slot (according to Condition (A)) to conserve energy when the weather condition improves, until the BREL has reached OFL. In this way, we can ensure the long term energy neutrality (for many OCs), in the presence of exceptional weather conditions.

2.5.3 Capacity of the Battery

In [36], a battery capacity calculation method is proposed. This method is based on the predicted long term average energy harvesting power rate, the maximum and the minimum possible instant energy harvesting rate. However, since we try to implement a prediction free energy management mechanism, this battery capacity calculation method described in [36] is not applicable for our proposed mechanism.

For a rechargeable battery, there will be a battery cycle life limit. *Battery Cycle Life* (BCL) is defined by the number of “fully charge to fully discharge” cycles a battery can perform before its useable capacity falls below 80% of its original rated capacity. Thus, higher BCL means longer operation time for the wireless sensor. Typically, the number of BCL is closely related to the depth of discharge of a battery. *Depth of Discharge* (DOD) is a measure of how deep a battery has been discharged before recharging again. As the relation of BCL and DOD is logarithmic, a *Shallow Recharge*, which means a smaller DOD, will yield a higher BCL [84]. Thus, it is preferable for the sensors to adopt this shallow recharge method.

Before the deployment of sensors, we know the minimum and maximum performance requirements for the sensors. Thus, we can estimate the value of E_{gap} easily by using equation (2.27) and determine the Bonus Energy by $E_{bon} = 2 \times E_{gap}$. Under normal operation, the BREL will be increasing (battery charging) during

2.5. Prediction Free Energy Neutral Management

Sunslots and dropping during Darkslots. Since there are sufficient energy reserved for Darkslots, the BREL will usually reach OEL at the last Darkslot of an OC. As a result, the BREL will not drop below B_{OEL} unless under some extreme weather conditions. Thus, in order to benefit from Shallow Recharge, it is preferred to set B_{OEL} to be above certain percentage of the total battery capacity. The battery capacity B_C can thus be calculated as follows:

$$B_C \geq (E_{bon} + E_{gap})/\sigma_D \quad (2.29)$$

where σ_D is a percentage value that represents the depth of discharge. Shallow Recharge require the σ_D to be set at a small value (20% for example [84]) to increase the BCL. As a result, the battery capacity should be several times larger than $E_{bon} + E_{gap}$. A typical AA-sized NiCd [81] battery usually has a capacity of $600 - 1300mAh$, which is enough for a typical wireless sensor (such as CC1000[85]) to operate for several days. It provides sufficient battery capacity to support the shallow recharge requirements of our proposed battery model.

2.5.4 Performance Deviation Due to Variations in $E_H(t)$

For two consecutive Sunslots, we assumed that the amount of energy harvested in these two Sunslots are similar in Section 2.5.2. In real implementation, the energy harvested in two consecutive Sunslots might not be exactly the same, which in turn results in deviations on the performance of P-FREEN from the optimal value. Let z to denote the difference in the amount of energy harvested in two consecutive Sunslots (t and $t - 1$), we have $z = E_H(t) - E_H(t - 1)$.

Using the same data as used in Figure 2.1, we plot the histogram of z in Figure 2.4. As shown in this figure, z can be treated as a random variable of a random

2.5. Prediction Free Energy Neutral Management

Figure 2.4: Histogram of z

process Z with a normal probability density distribution. The variance of Z is closely related to the time slot duration. As the probability of weather change within a smaller time duration is in fact smaller, it is reasonable to assume that variance of Z is smaller with a smaller time slot duration. We denote the variance of Z as $\sigma_T^2 \propto T$, where T is the time slot duration. The probability density function of Z is thus:

$$f(z) = \frac{1}{\sigma_T \sqrt{2\pi}} e^{-\frac{z^2}{2\sigma_T^2}}$$

When $z > 0$, $E_H(t-1) < E_H(t)$. Using P-FREEN, $E_H(t-1)$ (instead of $E_H(t)$) will be used to calculate $E_U^{max}(t)$ and assign the energy budget for time slot t accordingly (this is because $E_H(t)$ is not available at the beginning of time slot t). This can result in causing an energy loss of $(1 - \eta_S) \times z$ as the excess energy z will be stored into battery. On the other hand, when $z < 0$, an energy loss of $(1/\eta_S - 1) \times (-z)$ will occur because the additional energy consumption will be drawn from the battery. Thus, the expected energy loss EL due to the differences

2.5. Prediction Free Energy Neutral Management

in the amount of harvested energy between two consecutive time slots are:

$$EL = \int_0^\infty (1 - \eta_S)zf(z)dz + \int_{-\infty}^0 (\frac{1}{\eta_S} - 1)(-z)f(z)dz = \frac{(\frac{1}{\eta_S} - \eta_S)\sigma_T}{\sqrt{2\pi}} \quad (2.30)$$

From this equation we can observe that the performance deviation of P-FREEN is directly determined by variance σ_T^2 , which is proportional to the length of the time slot duration. We will verify this kind of relationship later in Section 2.6.4.

2.5.5 Maximizing the Linear Performance Level

We note that besides maximizing the sensor average duty cycle, P-FREEN is also applicable to other performance metrics that have a *Linear* relationship with the amount of energy consumed by a sensor. For example, as stated in [86], the amount of data packets that a sensor will be able to relay (receive/transmit) is linearly related to the amount of energy consumed by a sensor, once the distance between the transmitting sensor and the receiving sensor is known and fixed. Using $L[E_B(t)]$ to denote the amount of data packets that a sensor can relay by consuming $E_B(t)$ amount of energy, according to Lemma 2.3, we can maximize the average value of $L[E_B(t)]$ by maximizing the utilizable energy, (so that higher energy budgets can be assigned). Since the goal is to maximize average $L[E_B(t)]$ instead of maximizing average $D(t)$, we can set $D(t)$ to a certain fixed value, ($D(t) = 1$ for example), and make the sensor energy consumption in a time slot E_c to be equal to the value of $E_B(t)$, which is adjustable in between E_{min} and E_{max} . In this way, we can recalculate $E_U^{max}(t)$ for each time slot according to method we used in the proof of Lemma 2.1 and Lemma 2.2. Based on the recalculated $E_U^{max}(t)$, P-FREEN can then be applied to maximize the average amount of data packets that a sensor can relay in a time slot.

2.6 Performance Analysis and Evaluation

In this section, we evaluate the performance of P-FREEN via empirical studies. The LQ-tracker based battery centric method proposed in [43] does not consider battery energy storage inefficiencies, thus it is not fair to compare it with P-FREEN. Kansal's method [36] is an effective energy neutral management mechanism that focuses on maximizing a sensor's average DC in the presence of battery energy storage inefficiencies. Thus we compare our proposed P-FREEN against Kansal's method via computer simulations. Kansal's mechanism employs an Exponential Weighted Moving Average filter to predict the amount of energy that can be harvested in the future. Using this exponential EWMA filter, Kansal's mechanism predicts the amount of energy harvested in each time slot in the next operation cycle, and then uses a dynamic duty cycle adaption algorithm to try to meet the energy neutrality constraints when the actual amount of energy harvested deviates from the predicted values. For comparison purpose, we further divide the Kansal's method into two different scenarios: Kansal-Ideal and Kansal-Actual. Kansal-Ideal assumes that the full future energy harvesting information is available in advance (which is an ideal case). Kansal-Actual uses the EWMA filter based method as described in [36] to predict the future energy harvesting information.

For the computer simulations we conduct in this section, three sets of solar radiation data are used. Data Set 1 (DS1) and Data Set 2 (DS2) are retrieved from the database maintained by US Texas Solar Radiation Lab [1] and the location where those two sets of data are observed and recorded is the Canyon, Texas. DS1 contains the data recorded from July 1st to August 1st, 2002 and DS2 contains

2.6. Performance Analysis and Evaluation

the data recorded from January 1st to February 1st, 2003. Data Set 3 (DS3) is retrieved from the US National Solar Radiation Database [87], which contains the data observed from July 1st to August 1st, 2010 in Las Vegas, Nevada. DS1 and DS2 can reflect the temporal variations in the weather conditions. DS1 and DS3 can reflect the spatial variations in the weather condition. In this way, we will be able to fully test P-FREEN under different climate conditions.

We assume that the sensor is carrying a $5cm \times 5cm$ solar power receiving panel. We also assume that 10% of the total solar radiation can be captured by the solar panel and 10% of the captured solar radiation can be converted into electricity. The duration of a time slot is set to be one hour if not otherwise specified. The maximum duty cycle D_{max} is set to be 1 throughout all the simulations and the energy consumption E_c for the sensor to run at full duty cycle for one time slot is set to be $60J$, which means the sensor will be running with a power consumption of approximately $16.7mW$ (CC1000 sensor [85]) during active state. N_{sun} is set at 10 if not specified otherwise, which is a reasonable guess as usually there are 10 hours of strong sunlight (from 8am to 6pm) during a day. The battery is assumed to have an energy capacity of $2000J$ (similar to a 660mAh AA sized NiCd battery at 1.2 V [81]) and we assume the battery is fully charged upon deployment. The simulations are carried out using MatLab [88].

2.6.1 Energy Matching Ability

As stated in Section 2.4.6, the Matching Deviation (MD), which is the absolute deviation between $E_B(t)$ and $E_U^{max}(t)$ for time slot t , reflects the sensor's ability to avoid energy storage loss. We thus compare in this section the matching devia-

2.6. Performance Analysis and Evaluation

Figure 2.5: Energy matching ability comparison for Kansal-Ideal and Kansal-Actual using DS1

tion under different energy management mechanisms. The battery energy storage efficiency is chosen to be 0.8 (NiCd battery [35]) in the simulations.

Figure 2.5 shows a detailed comparison of the resulted energy matching ability for Kansal-Ideal and Kansal-Actual mechanisms for 5 consecutive OCs chosen from DS1, when the minimum duty cycle is set to be 0.1. Label Max-EU denotes the maximum amount of energy that can be utilized by the sensor, which is calculated from equations (2.8) and (2.12), given the full knowledge of the amount of energy harvested in each time slot. We can see that the energy matching ability for Kansal-Actual is much worse than that of Kansal-Ideal. This is because Kansal-Actual is based on the estimation of future energy availability using EWMA filter, which suffers from inevitable prediction errors. Figure 2.6 shows the energy matching ability of Kansal-Ideal and our proposed P-FREEN for the same 5 consecutive OCs chosen from DS1. P-FREEN can provide a similar energy matching as Kansal-Ideal, which verifies that P-FREEN is more energy efficient than Kansal-Actual as

2.6. Performance Analysis and Evaluation

Figure 2.6: Energy matching ability comparison for P-FREEN and Kansal-Ideal using DS1

$\delta_M^{average}$		$D_{max} = 1$		
		$D_{min} = 0.1$	$D_{min} = 0.2$	$D_{min} = 0.3$
Data Set 1	Kansal-Ideal	11.0J	13.7J	17.5J
	P-FREEN	12.9J	17.1J	21.3J
	Kansal-Actual	16.9J	18.6J	22.1J
Data Set 2	Kansal-Ideal	13.7J	16.0J	21.2J
	P-FREEN	14.2J	18.0J	24.3J
	Kansal-Actual	19.7J	22.5J	25.9J
Data Set 3	Kansal-Ideal	10.7J	13.2J	15.9J
	P-FREEN	11.4J	14.7J	17.5J
	Kansal-Actual	13.0J	15.7J	17.9J

Table 2.1: Matching Deviation under different D_{min}

it can track the fluctuations in actual amount of energy harvested in real time.

We also record the matching deviation (denoted by δ_M) for all three data sets under evaluation. The average matching deviation per slot is calculated by:

$$\delta_M^{average} = \frac{1}{N_t} \sum_{t=1}^{N_t} |E_U^{max}(t) - E_B(t)|$$

where N_t denotes the total number of time slots under consideration and $|\cdot|$ is the

2.6. Performance Analysis and Evaluation

sign of absolute value. Table 2.1 shows the matching deviation comparisons under different minimum duty cycle requirements. We can see that P-FREEN achieves smaller Matching Deviation than Kansal-Actual in all three data sets, which in turn implies improved sensor average duty cycle. The difference in performance between P-FREEN and Kansal-Actual in terms of the matching deviation decreases as we increase the minimum duty cycle requirements. We will explain the reason for this phenomenon together with the HEUE comparison in Section 2.6.3.

2.6.2 Battery Residual Energy Level Variations

We next examine the battery residual energy level variations by using P-FREEN and Kansal’s mechanism. Note that although we define the battery capacity to be $2000J$, we let the battery level to keep accumulating (capped at $2300J$) even if the battery residual energy level is larger than the battery capacity. That is because we want to compare the actual variations of the battery residual energy level without being limited by the constraint of the battery capacity.

We first compare and visualize the detailed battery residual energy level (BREL) variations with a small D_{min} using DS1. As shown in Figure 2.7, Kansal-Actual experiences greater BREL variations than the other two mechanisms with $D_{min} = 0.1$. As shown in Table 2.2, the average absolute deviation of the BREL with reference to $2000J$ (denoted by δ_{2000}) is $160J$ per time slot under Kansal-Actual, which is larger as compared with the deviation of $128J$ under P-FREEN. This is also true for the BREL variations under different D_{min} . That is because Kansal-Actual is insensitive to the BREL variations as it is assigning energy budget solely based on the estimated amount of energy harvested. When the actual amount of energy

2.6. Performance Analysis and Evaluation

Figure 2.7: BREL comparison with $D_{min} = 0.1$ for DS1

harvested is not the same as predicted, the prediction error will cause the overusage or underusage of energy, which causes bigger variances in BREL. Assigning budget with reference to the BREL, P-FREEN is able to maintain the BREL at a much lower variance with the dynamic adjustments of OEL in the first few operation cycles. Lower variance in the BREL means that a smaller battery capacity will be needed for the sensor's operation. The battery's cycle life will also be increased due to the Shallow Recharge effect as explained in Section 2.5.3. BREL under Kansal-Ideal shows a deviation of $63.4J$, which is smaller than that under P-FREEN. This is because Kansal-Ideal assumes the full knowledge of future energy harvesting information and thus does not suffer from prediction errors.

We next examine and visualize the BREL variations under each mechanism when there are insufficient energy harvested to support even the minimum duty cycle using DS1. To do this, we increase D_{min} requirement to be 0.3. We can see from Figure 2.8 that only P-FREEN can successfully recover the BREL back to OEL when some extreme weather conditions occur from time slot 96 to 168 and

2.6. Performance Analysis and Evaluation

Figure 2.8: BREL comparison with $D_{min} = 0.3$ for DS1

δ_{2000}		$D_{max} = 1$		
		$D_{min} = 0.1$	$D_{min} = 0.2$	$D_{min} = 0.3$
Data Set 1	Kansal-Ideal	63.4J	335J	724J
	P-FREEN	128J	210J	477J
	Kansal-Actual	160J	390J	736J
Data Set 2	Kansal-Ideal	69J	237J	406J
	P-FREEN	129J	157J	193J
	Kansal-Actual	168J	293J	451J
Data Set 3	Kansal-Ideal	35J	44J	125J
	P-FREEN	57J	43J	117J
	Kansal-Actual	67J	64J	146J

Table 2.2: Average BREL deviations from 2000J (δ_{2000})

from time slot 220 to 270. In these time slots, the BREL is dropping severely because the energy harvested is not sufficient to support the high D_{min} constraint. Because both Kansal-Ideal and Kansal-Actual are not BREL aware mechanisms, when there is more energy used than harvested during an OC, the system will not recover the BREL back in the following OCs. That is why, as shown in Table 2.2, although Kansal-Ideal assumes full knowledge of future energy harvesting informa-

2.6. Performance Analysis and Evaluation

tion, it still causes a higher δ_{2000} as compared with P-FREEN when $D_{min} = 0.2$ and $D_{min} = 0.3$. As a result, if there are more OCs that are experiencing bad weather conditions, the battery might be depleted under Kansal's mechanisms. This in turn implies that P-FREEN has a stronger ability to maintain the long term energy neutral state of a sensor. The δ_{2000} data for DS2 and DS3 as shown in Table 2.2 confirms that P-FREEN can maintain a small BREL variation in different seasons and locations, which in turn confirms the high robustness of P-FREEN.

2.6.3 Harvested Energy Utilization Efficiency Comparison

We next verify the Harvested Energy Utilization Efficiency (HEUE) (σ_H) under different battery energy storage efficiencies (ranging from 0.7 to 1) for Kansal-Ideal, Kansal-Actual and P-FREEN. We record the HEUE for each OC and calculate the average HEUE to represent the overall performance of each mechanism as shown in Figures 2.9 to 2.13.

In general, the average HEUE for the above three mechanisms increases when we increase the battery energy storage efficiency. However, we can see there is a big difference between the average HEUE of Kansal-Ideal and Kansal-Actual. As shown in Figure 2.9, when η_S is 0.7 (NiMH Battery) and $D_{min} = 0.1$, the average HEUE for Kansal-Ideal is 0.90 while the average HEUE for Kansal-Actual is 0.83, which is nearly 10% lower. Showing an average HEUE of 0.87 at $\eta_S = 0.7$ using DS1, P-FREEN has an improvement of 5% over Kansal-Actual when $D_{min} = 0.1$. This is due to the fact that P-FREEN is generating the energy budget adaptively according to real time energy harvesting rate, which is not just an estimation of the energy available in each time slot. This kind of HEUE improvement can be

2.6. Performance Analysis and Evaluation

Figure 2.9: HEUE comparison with $D_{min} = 0.1$ using DS1

Figure 2.10: HEUE comparison with $D_{min} = 0.2$ using DS1

observed through Figures 2.9 to 2.13 under all data sets that are being evaluated. Kansal-Ideal exhibits highest HEUE using all three data sets as it assumes ideal energy harvesting information to be known in advance.

We notice that HEUE for all the three mechanisms decreases as D_{min} increases. That is because the energy consumption is higher with higher D_{min} , which results in higher energy storage loss as we have to store more energy into the battery in

2.6. Performance Analysis and Evaluation

Figure 2.11: HEUE comparison with $D_{min} = 0.3$ using DS1

Figure 2.12: HEUE comparison using DS2

Sunslots to maintain the energy neutral state.

We can also observe, from Figures 2.9, 2.10 and 2.11, that the difference between the performance of P-FREEN and Kansal-Actual becomes smaller as D_{min} increases using DS1. Same phenomenon can be observed using DS2 and DS3, as shown in Figures 2.12 and Figure 2.13. As discussed in Section 2.6.2, with higher D_{min} constraint, there might not be sufficient energy harvested to sustain even the minimum duty cycle for OCs that are experiencing bad weather condition. Battery

2.6. Performance Analysis and Evaluation

Figure 2.13: HEUE comparison using DS3

residual energy level will drop below OEL under extreme weather condition, which in turn results in P-FREEN forcing the sensor to operate with minimum duty cycle for a long period, until the BREL has been restored to OFL. As a result, during this period, more energy storage loss is experienced by P-FREEN because D_{min} is assigned as the energy budget even if the current energy harvesting rate is high. Kansal-Ideal and Kansal-Actual will however continue assigning energy budget according to the predicted energy harvesting information of the current OC, irrespective of the BREL. As a result, although the average HEUE for Kansal-Actual can be slightly increased, it is at the cost of lowering the BREL as shown in Figure 2.8, which might risk depleting the battery in the long run. In addition, it can also cause the battery to go through deep discharge-charge cycles, which decreases the battery cycle life as we mentioned in Section 2.5.3.

2.6.4 Impact of the Time Slot Duration

As stated in Section 2.5.4, the slot duration will have an impact on the performance of P-FREEN. We thus examine the HEUE of P-FREEN under different time slot

2.6. Performance Analysis and Evaluation

Figure 2.14: Average HEUE with different time slot duration using DS1

durations with $D_{min} = 0.1$ using the three different data sets and the results are shown in Figures 2.14, 2.15 and 2.16. It is verified that, under different weather conditions, P-FREEN can always adapt to the weather change faster if the time slot duration is smaller and thus improve the HEUE. However, as shown in Figures 2.14, 2.15 and 2.16, the improvement in HEUE is not obvious when we decrease the time slot duration from 30 minutes to 5 minutes. In real implementation, smaller time slot duration will require more frequent measurements of the BREL and the energy harvesting rate, which in turn implies higher computational complexity. Thus, considering the trade-off between the improvements in HEUE and the extra complexity involved in smaller time slot duration, a time slot duration of 10 to 30 minutes is recommend for our proposed mechanism.

2.6.5 Impact of the N_{sun} Estimation Accuracy

We also carry out the simulations to evaluate the impact of fixing N_{sun} to 10 (time slot duration is set to be 60 minutes for the convenience of analysis) for every OC as

Figure 2.15: Average HEUE with different time slot duration using DS2

compared with estimating N_{sun} using EWMA filter as mentioned in Section 2.5.1. We find the differences in the HEUE between the two methods are within 1%. The standard deviation of the actual N_{sun} observed for 31 OCs is approximately 3 time slots, which makes the standard deviation of the number of Darkslots to be 3 time slots as well. From equation (2.27) we know that a 3 time slots deviation can result in increasing or decreasing the E_{gap} for only $3 \times E_c \times D_{min}$. Even if we choose a D_{min} as high as 0.3, this deviation will still be less than E_c , which is a fairly small value and we can recover it with the energy harvested in one Sunslot. Thus, the system can firstly use EWMA filter for certain days to choose a reasonable N_{sun} and then fix it to that value instead of evaluating it every day.

2.6.6 Computational Complexity

In terms of computational complexity, Kansal's mechanism will require the estimation of the amount of energy harvested in each time slot and then do a sorting

2.6. Performance Analysis and Evaluation

Figure 2.16: Average HEUE with different time slot duration using DS3

operation with average complexity of $O(n \log n)$, where n is the number of time slots during one OC. In order to adapt to the prediction errors, a dynamic energy consumption adjustment algorithm has to be implemented with additional sorting and comparing operation with additional complexity of at least $O(n \log n)$.

As mentioned in last section, for P-FREEN, when the time slot duration T is decreased, the number of time slots per OC will be increased and more frequent measurements of the battery residual energy level and energy harvesting rate will be required. However, once the time slot duration is fixed, the complexity of P-FREEN in computing the energy budget for each time slot is constant $O(1)$. That is because P-FREEN only requires the recording of energy harvesting information for the previous time slot and the current battery residual energy level, and then do a simple comparison with the predefined energy budget generation policy. Thus, P-FREEN has a lower computational complexity as compared to Kansal's mechanism.

2.7 Summary

We discuss and verify in this chapter that the current prediction based energy neutral management mechanisms are facing the deficiencies caused by prediction errors. In order to overcome this problem, we develop a Prediction Free Energy Neutral (P-FREEN) management mechanism that aims at maximizing the sensor's average duty cycle in the presence of battery energy storage inefficiencies. By analyzing the conditions to maximize the Harvested Energy Utilization Efficiency (HEUE), we develop a set of Budget Assigning Principles (BAPs) that maximize a sensor's average duty cycle while maintaining the energy neutral state. P-FREEN implements BAPs based solely on observed energy harvesting information and the battery residual energy level. Its computational complexity is also lower as compared with existing prediction based energy neutral management mechanisms. P-FREEN can also be applied to maximize other performance metric that has a linear relationship with the sensor energy consumption.

Extensive empirical studies are carried out to verify the performance of P-FREEN and to compare it with other energy management mechanisms using real life data sets taken from various time and locations. P-FREEN outperforms the prediction based mechanisms, in terms of average sensor average duty cycle, as it can adapt to the weather condition dynamically. It is verified that P-FREEN can recover the battery residual energy level even under extreme weather conditions, which enhances the sensor's long term energy neutrality. P-FREEN can also help the sensor to benefit from shallow recharge and thus improve the sensor battery's battery cycle life. It is also verified that, with appropriate time slot duration, the performance of P-FREEN can be further improved.

Chapter 3

Asymptotically Throughput Maximized Energy Neutral Management for Energy Harvesting Wireless Sensors

Besides the linear energy consumption model that we have studied in Chapter 2, there are other sensor performance levels, such as the sensor communication channel throughput, that have a non-linear relationship with the sensor energy consumption. Hence, in this chapter, we propose a low complexity energy neutral management policy that asymptotically maximizes the point-to-point communication channel throughput by using the historical information observed by each sensor. Furthermore, we study a method to reduce the energy loss caused by battery energy storage inefficiencies. The fraction of the harvested energy that can be utilized by using this method is analytically derived and integrated into our proposed energy neutral management policy to provide improved average channel throughput. Extensive empirical studies are carried out to compare the performance of our proposed energy neutral management policies with current energy neutral management mechanisms.

3.1 Introduction

While operating in the energy neutral state, it is also highly desirable for a sensor to transmit/receive more information to/from its neighboring sensor(s) in a given period of time. During this period of time, the amount of information that can be transmitted or received by a sensor is usually limited by the communication channel throughput (capacity) of the wireless link(s) established among this sensor and its neighboring sensor(s). Due to the logarithmic relationship between the channel throughput and the energy consumption of the sensor, the energy consumption model considered in this chapter is non-linear. Hence, the energy neutral management mechanism has to be specially designed for this type of energy consumption model, so that the channel throughput can be maximized with the limited amount of harvested energy available in this period of time.

In the literature, many efforts have been put on developing such communication channel throughput maximization policies for wireless sensors with energy harvesting capabilities. In [89], a general mathematical framework is derived via dynamic programming to provide optimal data transmission policies under different energy replenishment models. In [45], the system time is divided into discrete time slots and the energy harvesting process is characterized as a stationary, ergodic process. Based on the statistical information about the energy harvesting process as well as the channel state, throughput optimal data transmission policies are obtained while maintaining a stable data queue in the sensor. The constraints of maintaining a stable data queue are removed in [65], in which an optimal energy allocation scheme is studied to provide theoretically maximized channel throughput under different channel characteristics. Continuous time model is considered in [47], which pro-

vides channel throughput maximization policies for static channels, while taking the battery capacity constraint into consideration. [46] considers fading channels and provides optimal policies via dynamic programming.

For the above mentioned energy management policies, a predicted energy harvesting profile is needed to determine the amount of energy that can be harvested and then allocated in the given amount of time. However, as discussed in previous chapters, such predicted information may not always be available before sensor deployment. In addition, various factors, such as location, time, altitude, etc., may affect a sensor's energy harvesting profile. Thus, sensors may have different energy harvesting profiles and it is time consuming to predict the energy harvesting profiles for all sensors. What's more, the statistical channel state information for fading communication channels may also not be available before sensor deployment. As a result, these off-line optimization policies, which require the full knowledge of the energy harvesting profile and the statistical channel state information, might not be feasible for practical implementation.

Some on-line optimization policies have been proposed in [46] and [65]. Such policies employ the Dynamic Programming techniques [90] to achieve maximized channel throughput based on current available information. However, as mentioned in [46], due to the inherent complexity of dynamic programming, these optimal online policies involve computationally intensive tasks, which may not be feasible for wireless sensors with limited computational power. Several sub-optimal low complexity online policies were proposed in [46], namely the Constant Water Level policy and the Energy Adaptive Water-Filling policy. However, with the lowered computational complexity, these policies suffer from lowered channel throughput as compared to the optimal online policies. Thus, an open issue is whether can we

find a low complexity online energy neutral management mechanism that provides near-optimal channel throughput.

As stated in Chapter 2, due to the limitation of current battery technology, only a fraction of the harvested energy can be stored into the batteries. As a result, the currently widely used energy *harvest-store-use* method [35], which stores the harvested energy into batteries before utilization, will result in energy loss. Hence, we adopt the same energy harvest-use(store) method as studied in Chapter 2. Using this method, a sensor will use as much energy as possible from the amount of energy that has been harvested from the sensor's energy harvesting device, before storing any surplus energy into the battery. Hence, another open issue is to determine the fraction of the harvested energy that can be utilized (i.e., the Harvested Energy Utilization Efficiency) by using this energy harvest-use(store) method, when the non-linear energy consumption model is considered.

In view of this, our focus in this chapter is to study and propose energy management policies that address the aforementioned problems. The main contributions of this chapter are:

- An online energy neutral management policy that asymptotically maximizes the average channel throughput. This policy involves low computational complexities.
- Analytically derived Harvested Energy Utilization Efficiency (HEUE) achievable by using the energy harvest-use(store) method. Using this HEUE, an improved energy neutral management policy is proposed to further improve the average channel throughput in the presence of battery energy storage inefficiencies.

The rest of the chapter is organized as follows. The next section discusses the system model and notations we use. In Section 3.3, the optimization problem which addresses the maximization of the communication channel throughput is formulated and solved. An online adaptive energy management policy that asymptotically achieves maximized communication channel throughput is presented in Section 3.4. An improved energy management policy that considers the battery storage inefficiencies is proposed in Section 3.5. Empirical studies that verify the performance of our proposed policies are discussed in Section 3.6. This chapter will then be summarized in Section 3.7.

3.2 System Model and Notations

3.2.1 Harvested Energy and Energy Budget

The system time is divided into time slots indexed by t , where $t = 1, 2, \dots, N_t$ and N_t is the total number of time slots under consideration. The duration (T) of a time slot is chosen in a way that the energy harvesting power can be considered to be constant within this time slot. The amount of energy that can be harvested from the environment is referred to as the *Harvested Energy*. The harvested energy in a time slot t is denoted by $E_H(t)$. In this chapter, we model the harvested energy in each time slot as a stationary, ergodic random process $\{E_H\}$ as in [45]. The expected harvested energy in a time slot is denoted by $\xi[E_H]$, where $\xi[\cdot]$ denotes the expectation of a random process.

The amount of energy allocated to a sensor for usage in a time slot t is referred to as the *Energy Budget* and is denoted by $E_B(t)$. The energy budget will be used

to control the energy consumption of a sensor.

3.2.2 Communication Channel Throughput

We focus on maximizing the channel throughput of a sensor node that is transmitting information generated by its own sensing activities. All the energy harvesting sensors considered in this chapter are randomly deployed in a static location. Fading wireless communication channel is considered in this chapter. We assume that the channel experiences flat fading during a time slot [45]. The channel gain for a time slot t is denoted by h_t and the channel fading level in this time slot is thus $\frac{1}{h_t}$. The channel gains are assumed to be independent in different time slots and the sequence $\{H\} = \{h_1, h_2, \dots, h_{N_t}\}$ is stationary, ergodic. Both transmitter and receiver know the current Channel State Information (CSI) at the beginning of a time slot t , (this is done by a feedback from the receiver). The sequence $\{H\}$ is assumed to follow the Rayleigh or the Nakagami distribution with a Mean Channel Gain of $\xi[H]$ in this chapter. The channel noise is assumed to be Additive White Gaussian Noise. All source nodes are assumed to have saturated traffic to transmit. Shannon's channel capacity function [91] can thus be used to determine the channel throughput $C(t)$ that can be achieved by using $E_B(t)$ amount of energy in each time slot as follows:

$$\begin{aligned} C(t) &= W \log \left(1 + \frac{h_t}{N_0 W} \frac{E_B(t)}{T} \right) \\ &= W \log \left(1 + \frac{h_t E_B(t)}{\beta} \right) \end{aligned} \quad (3.1)$$

where W is the bandwidth, $N_0 W$ is the noise power spectral density in W/Hz , $\frac{E_B(t)}{T}$ is the signal power in *Watt* and $\beta = N_0 W \times T$ is a constant.

3.2.3 Harvested Energy Utilization Efficiency (HEUE)

Due to the non-ideal rechargeable battery carried by a sensor, only a fraction of the harvested energy will be available for sensor utilization. For clarification, throughout this chapter, we use the term *Utilizable Energy* to refer to the amount of harvested energy that can actually be utilized for sensor operations. We denote the utilizable energy in a time slot t by $E_U(t)$. We also define the *Harvested Energy Utilization Efficiency* (HEUE) to be the fraction of the harvested energy that is expected to be utilized in one time slot. Hence, the HEUE (denoted by η) is estimated by:

$$\eta = \frac{\xi[E_U]}{\xi[E_H]} \quad (3.2)$$

where $\xi[E_U]$ is the expected utilizable energy in one time slot.

We define the *Battery Energy Storage Efficiency* η_S , where $0 < \eta_S < 1$, to be the fraction of the harvested energy that can be stored into batteries. We do not consider battery self-discharging as this amount is negligible for rechargeable batteries [36]. Thus, by using the energy *harvest-store-use* method [35], the utilizable energy in a time slot t is $E_U(t) = \eta_S E_H(t)$, (since all harvested energy is stored into the battery before it can be utilized for sensor operations). Since η_S is a constant, by the definition of expectation, we also have $\xi[E_U] = \eta_S \xi[E_H]$. Hence, the HEUE achieved by using the harvest-store-use method is as follows:

$$\eta = \frac{\xi[E_U]}{\xi[E_H]} = \frac{\eta_S \xi[E_H]}{\xi[E_H]} = \eta_S \quad (3.3)$$

3.2.4 Energy Neutral Operation

The battery capacity is denoted by B_c and a battery will have an initial *Battery Residual Energy Level* (BREL) of B_0 upon deployment. We use $B(t)$ to denote the BREL **at the end** of time slot t , which is calculated by:

$$B(t) = B(t-1) + E_U(t) - E_B(t) \quad (3.4)$$

where $t = 1, 2, \dots, N_t$, $B(0) = B_0$.

A sensor maintains the *Strict Energy Neutral Operation* (Strict-ENO) if the BREL at the end of every time slot is no less than the initial BREL, i.e., $B(t) \geq B_0$ for $t = 1, 2, 3, \dots, N_t$. A sensor maintains the *Long Term Energy Neutral Operation* (Long-Term-ENO) if the BREL at the end of time slot N_t is no less than the initial BREL, i.e., $B(N_t) \geq B_0$.

Long-Term-ENO ensures that the total amount of energy consumed by the sensor in N_t time slots is no more than the utilizable energy for N_t time slots. This definition of Long-Term-ENO is similar to the definition of energy neutral operation as stated in [36]. It is intuitive that a sensor maintains the Strict-ENO also maintains the Long-Term-ENO. However, a sensor that maintains Long-Term-ENO may not be able to maintain Strict-ENO. With Long-Term-ENO, at the end of a time slot t ($t \neq N_t$), the sensor might be consuming more energy than the amount of harvested energy it can utilize, which causes the BREL to drop below B_0 . If this situation happens, the sensor will have to use less energy than the amount of harvested energy it can utilize for the remaining time slots ($t+1$ to N_t) to restore the BREL to B_0 and thus maintain the Long-Term-ENO. This means that, with Long-Term-ENO, the BREL might be dropping below B_0 at some time slots before building up to no less than B_0 at the end of time slot N_t .

3.3 Throughput Maximization under Ideal Conditions

3.3.1 Average Channel Throughput Maximization

Our goal is to maximize the Average Channel Throughput (ACT) while maintaining the energy neutral state for N_t time slots. The *Average Channel Throughput* measures the average amount of channel throughput (bps) achieved in one time slot, which is estimated by $\frac{1}{N_t} \sum_{t=1}^{N_t} C(t)$. Thus, the ACT maximization problem can be expressed as:

$$\max \frac{1}{N_t} \sum_{t=1}^{N_t} C(t) \quad (3.5)$$

s.t.

$$B(t) \geq B_0, t = 1, 2, 3, \dots, N_t \quad (3.6)$$

$$0 \leq B(t) \leq B_c, t = 1, 2, 3, \dots, N_t \quad (3.7)$$

Constraints (3.6) ensure the Strict Energy Neutral Operation. Constraints (3.7) ensure that the BREL will not exceed the battery capacity nor will it drop below zero for each time slot. We refer to this ACT Maximization Problem as AMP.

3.3.2 Constraints Relaxations

Due to the concavity of the objective function (3.5), the optimal solutions for AMP exist and the results have been discussed in [46]. However, for AMP, the number of constraints included in (3.6) and (3.7) increases as number of time slots (N_t)

3.3. Throughput Maximization under Ideal Conditions

under consideration increases. Thus, a larger number of constraints will have to be considered to obtain the optimal energy budget for each time slot as the value of N_t increases. As a result, the optimal solutions provided in [46] suffer from levied complexity with a larger value for N_t . In view of this, we relax the constraints (3.6) and (3.7) so that the number of constraints will not increase with N_t . These relaxed constraints will then be used to formulate a maximization problem with low computational complexities.

We firstly remove constraints (3.7) by assuming that the battery capacity is sufficiently large. In practice, the amount of energy stored in a fully charged AAA sized battery can usually support the sensor to operate for several days [45] (more than a hundred time slots if $T = 3600s$). This means $B_c \gg E_B(t)$. It is intuitive that for energy neutral operations, the value of the energy budget for a time slot should be in the same range as the amount of energy harvested in a time slot. Hence, we have $E_B(t) \simeq E_H(t)$ and thus $B_c \gg E_H(t)$. Thus, if the initial BREL is set at a reasonable value, for example $B_0 = 0.5B_c$, the energy buffer of $0.5B_c$ will be sufficiently large to accommodate the fluctuations in the amount of energy harvested in a time slot. As a result, no energy overflow or depletion in the battery would occur, which in turn implies that constraints (3.7) can be removed.

We next relax the constraints (3.6) as follows:

$$B(N_t) \geq B_0 \tag{3.8}$$

Constraint (3.8) ensures the Long Term Energy Neutral Operation of the sensor for N_t time slots under consideration. Since constraint (3.8) does not ensure the Strict Energy Neutral Operation for every time slot, the BREL at the end of some time slots (except for time slot N_t) might be smaller than the initial BREL B_0 .

3.3. Throughput Maximization under Ideal Conditions

However, since B_0 is assumed to be sufficiently large, even if BREL was smaller than B_0 in certain time slots, the BREL will not be dropping down to zero and thus forces the sensor to shut down. Hence, with the relaxation of constraints (3.6) to constraint (3.8), the sensor can still operate normally without being forced to shut down. Thus, we conclude that this constraint relaxation is also feasible in real implementation.

3.3.3 Low Complexity Offline Solutions

With the relaxed constraints, the AMP can be reformulated as:

$$\max \frac{1}{N_t} \sum_{t=1}^{N_t} C(t) \quad (3.9)$$

s.t.

$$B(N_t) \geq B_0 \quad (3.10)$$

We refer to this maximization problem as the Relaxed-AMP.

Assuming that the full knowledge of the statistical channel state information and the energy harvesting profile are available, we have the following lemmas:

Lemma 3.1. *The average channel throughput for a fading channel can be maximized if the water filling solution $E_B^*(t) = \beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t} \right)^+$ is used as the energy budget for a time slot t , where $\frac{1}{\lambda^*}$ is the Optimal Water Level.*

Proof. It is shown in [92] that, using the Lagrangian method, Relaxed-AMP can be solved using the water filling solution. The **Optimal Energy Budget** ($E_B^*(t)$)

3.3. Throughput Maximization under Ideal Conditions

for a time slot t is:

$$E_B^*(t) = \beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t} \right)^+ \quad (3.11)$$

where $(x)^+ = x$ if $x \geq 0$, otherwise $(x)^+ = 0$.

$\frac{1}{\lambda^*}$ is the **Optimal Water Level**, which can be obtained by solving the following equation:

$$\sum_{t=1}^{N_t} \beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t} \right)^+ = \sum_{t=1}^{N_t} E_U(t) \quad (3.12)$$

where $\sum_{t=1}^{N_t} E_U(t)$ is the total amount of utilizable energy in N_t time slots. $\square$

Lemma 3.2. *When N_t is sufficiently large, the Optimal Water Level $\frac{1}{\lambda^*}$ is independent of N_t .*

Proof. In practice, there is a limited number of fading levels available in the fading channel. Assuming that there are L fading levels, we denote the l -th ($l = 1, 2, 3, \dots, L$) fading level by h_l . We also denote the probability of the wireless channel experiencing a fading level of h_l to be p_l . It is shown in [93] that the Optimal Water Level can also be computed in an alternative approach based on statistical channel state information as follows:

$$\sum_{t=1}^{N_t} \beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t} \right)^+ = N_t \beta \sum_{l=1}^L p_l \left(\frac{1}{\lambda^*} - \frac{1}{h_l} \right)^+ \quad (3.13)$$

3.3. Throughput Maximization under Ideal Conditions

with

$$\sum_{l=1}^L p_l = 1 \quad (3.14)$$

When the number of time slots N_t under consideration is sufficiently large, by the definition of expectation, we have

$$\sum_{t=1}^{N_t} E_U(t) \approx N_t \xi[E_U] \quad (3.15)$$

Combining equations (3.12), (3.13) and (3.15), the Optimal Water Level can be calculated by:

$$\beta \sum_{l=1}^L p_l \left(\frac{1}{\lambda^*} - \frac{1}{h_l} \right)^+ = \xi[E_U] \quad (3.16)$$

We can observe from equation (3.16) that when N_t is sufficiently large, the calculation of Optimal Water Level does not involve the actual value of N_t . $\square$

Hence, in order to obtain the Optimal Energy Budget, we have to get the accurate energy harvesting profile and the HEUE (η) to estimate the value of $\xi[E_U]$, (since $\xi[E_U] = \eta \xi[E_H]$). In addition, we also need the statistical channel state information to estimate p_l for each fading level. However, the energy harvesting profile or the statistical channel state information might not be easily retrievable before sensor deployment. Thus, we propose in the next section an online budget assignment policy that asymptotically maximizes the channel throughput, without the need of the predicted energy harvesting profile or the statistical channel state information before the deployment of sensors.

3.4 Online Asymptotic Throughput Maximization Policies

In this section, we do not assume the availability of the predicted energy harvesting profile or the statistical channel state information before sensor deployment. Instead, we propose an energy budget assignment policy that learns the channel state information and the energy harvesting profile over time and adaptively assign energy budget so that the ACT will gradually converge to the maximum value. Throughout this section, we assume that the energy harvest-store-use method is used, which means the HEUE $\eta = \eta_S$.

3.4.1 Adaptive Budget Assignment Policy (ABAP)

At the **beginning** of a time slot t , the energy budget for this time slot will be assigned according to the following policy:

$$E_B(t) = \min \left(\left(\beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_t} \right)^+ - \delta \right)^+, (B(t-1) - B_0) \right) \quad (3.17)$$

with the water level $\frac{1}{\hat{\lambda}_t}$ calculated at the beginning of time slot t as follows:

$$\sum_{k=1}^t \beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_k} \right)^+ = \eta_S \sum_{k=0}^{t-1} (E_H(k)) \quad (3.18)$$

where $t = 1, 2, \dots, N_t$, δ is a small positive constant and $E_H(0) = 0$. Since the water level $\frac{1}{\hat{\lambda}_t}$ is calculated adaptively using the values of $E_H(k)$ observed in the past time slots ($k = 0, 1, 2, \dots, t-1$), we refer to water level $\frac{1}{\hat{\lambda}_t}$ as the **Adaptive Water Level** (AWL). We refer to policy (3.17) as the *Adaptive Budget Assignment Policy* (ABAP).

3.4. Online Asymptotic Throughput Maximization Policies

Theorem 3.1. *ABAP ensures the Strict Energy Neutral Operation of a sensor.*

Proof. For a time slot t , if $\left(\beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+ > (B(t-1) - B_0)$,

$B(t-1) - B_0$ will be used as the energy budget, which means the BREL at the end of this time slot t will be calculated by:

$$\begin{aligned} B(t) &= B(t-1) + E_U(t) - (B(t-1) - B_0) \\ &= \eta_S E_H(t) + B_0 \geq B_0 \end{aligned}$$

For a time slot t , if $\left(\beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+ \leq (B(t-1) - B_0)$,
 $\left(\beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+$ will be used as the energy budget, which means the BREL at the end of this time slot t will be calculated by:

$$\begin{aligned} B(t) &= B(t-1) + E_U(t) - \left(\beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+ \\ &\geq B(t-1) + \eta_S E_H(t) - (B(t-1) - B_0) \\ &= \eta_S E_H(t) + B_0 \geq B_0 \end{aligned}$$

Thus, for any time slot t , the BREL at the end of this time slot will be no less than the initial BREL B_0 . This ensures the Strict Energy Neutral Operation for every time slot, which in turn ensures the Long Term Energy Neutral Operation.

□

Lemma 3.3. *As the number of time slots elapsed approaches a sufficiently large value N^* (assuming $N^* \leq N_t$), the Adaptive Water Level $(\frac{1}{\hat{\lambda}_t})$ converges to the*

3.4. Online Asymptotic Throughput Maximization Policies

Optimal Water Level ($\frac{1}{\lambda^*}$).

Proof. When the number of time slots elapsed approaches a sufficiently large value N^* , sufficient fading levels will be experienced by the sensor. As a result, the p_l values estimated by the sensor for the L fading levels will be sufficiently close to the theoretical value. Thus, similar to equation (3.13), the LHS of equation (3.18) can be rewritten as:

$$\lim_{t \rightarrow N^*} \sum_{k=1}^t \beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_k} \right)^+ \approx N^* \beta \sum_{l=1}^L p_l \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_l} \right)^+ \quad (3.19)$$

where p_l is the probability for the wireless channel to experience a fading level of h_l and $\sum_{l=1}^L p_l = 1$.

Meanwhile, by the definition of expectation, the RHS of equation (3.18) can be rewritten as:

$$\lim_{t \rightarrow N^*} \eta_S \sum_{k=0}^{t-1} (E_H(k)) \approx N^* \eta_S \xi[E_H] = N^* \xi[E_U] \quad (3.20)$$

Combining equations (3.18), (3.19) and (3.20), we have

$$\beta \sum_{l=1}^L p_l \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_l} \right)^+ = \xi[E_U] \quad (3.21)$$

From here we observe that the expression for $\frac{1}{\hat{\lambda}_t}$ in the above equation (3.21) is the same as the expression for the Optimal Water Level (OWL) in equation (3.16) (in the proof of Lemma 3.2). Thus we conclude that AWL $\frac{1}{\hat{\lambda}_t}$ converges to OWL $\frac{1}{\lambda^*}$ when the number of time slots elapsed is sufficiently large. $\square$

3.4. Online Asymptotic Throughput Maximization Policies

Theorem 3.2.

Proof. Based on equation (3.17), we can see that for time slots with

$\left(\beta \left(\frac{1}{\lambda_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+ \leq (B(t) - B_0)$, $\left(\beta \left(\frac{1}{\lambda_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+$ will be used as the energy budget. For these time slots, although $\beta \left(\frac{1}{\lambda_t} - \frac{1}{h_t}\right)^+$ amount of energy can be used without compromising the energy neutrality, the sensor is actually using δ less amount of energy as the energy budget. Thus, this δ amount of energy is expected to be accumulated in the battery in each of these time slots. Hence, $B(t)$ will be building up as t increases since the sensor is using less energy than the amount of harvested energy that it can actually utilize. As a result, after a certain number of time slots (denoted by N' , where $N' \leq N_t$), $B(t) - B_0$ will be larger than $\left(\beta \left(\frac{1}{\lambda_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+$. Consequently, ABAP will always use $\left(\beta \left(\frac{1}{\lambda_t} - \frac{1}{h_t}\right)^+ - \delta\right)^+$ amount of energy as the energy budget in the subsequent time slots.

Meanwhile, when the number of time slots elapsed approaches a sufficiently large value N^* , according to Lemma 3.3, $\frac{1}{\lambda_t}$ will converge to the Optimal Water Level $\frac{1}{\lambda^*}$.

Thus, when the number of time slots elapsed grows to a sufficiently large value $\hat{N}$ (where $\hat{N} = \max(N', N^*) < N_t$), $\left(\beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t}\right)^+ - \delta\right)^+$ amount of energy will be assigned as the energy budget for a time slot t . Note that since δ is chosen to be a small positive constant, it can be neglected as compared to $\beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t}\right)^+$. Hence, the energy budget assigned by ABAP approaches $\beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t}\right)^+$ as the number of

3.4. Online Asymptotic Throughput Maximization Policies

time slots elapsed approaches a sufficiently large value $\hat{N}$, which is equal to the Optimal Energy Budget as discussed in the proof of Lemma 1. Since the Optimal Energy Budget assignment provides maximized ACT as stated in Lemma 1, we can conclude that the ACT achieved by ABAP asymptotically approaches the maximized ACT as the number of time slots elapsed approaches a sufficiently large value $\hat{N}$. $\square$

3.4.2 The δ Constant

As stated in the proof of Theorem 3.2, when the number of time slot elapsed is sufficiently large, $\left(\beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t}\right)^+ - \delta\right)^+$ amount of energy will be used to assign the energy budget. The concept of using the small δ constant is similar to that in [45], where the δ is assumed to be an arbitrarily small value so that the ACT can be arbitrarily close to the maximized level. However, although δ is a small positive number, it still causes a kind of energy wastage. In addition, since δ amount of energy is expected to be accumulated in the battery for time slots that use $\left(\beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t}\right)^+ - \delta\right)^+$ as the energy budget, the BREL will be built up to B_c after a large number of time slots. When BREL is built up to B_c , energy harvested from the energy harvesting device will not be able to be stored into the battery anymore. This in turn results in another kind of energy wastage.

In order to reduce these two kinds of energy wastage, we set the value of δ to zero when the BREL has been built up to a sufficiently large level. For example, $0.75B_c$ would be an appropriate choice, which give us an energy buffer of $0.25B_c$. Since $B_c \gg E_H(t)$ as discussed in Section 3.2, an energy buffer of $0.25B_c$ should

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

be sufficiently large to accommodate the variances of $E_H(t)$. In this way, we can use $\beta \left(\frac{1}{\lambda^*} - \frac{1}{h_t} \right)^+$ as the energy budget for a time slot to maximize the ACT while preventing the BREL from building up to B_c .

3.5 Improved Adaptive Budget Assignment Policy (ABAP*)

As discussed in Section 3.2.3, by using the energy harvest-store-use method, the Harvested Energy Utilization Efficiency (HEUE) achieved is only η_S . As a result, the expected utilizable energy in one time slot is $\xi[E_U] = \eta_S \xi[E_H]$, which means that only η_S fraction of harvested energy is expected to be utilized in a time slot. This in turn leads to large amount of energy loss. In view of this, we study an alternative approach, which we refer to as the energy *harvest-use(store)* method, to improve the HEUE and thus reduce this kind of energy loss.

3.5.1 Improved-HEUE

The energy harvest-use(store) method allows the sensor to use as much energy as possible directly from the energy harvesting device and only store the remaining surplus amount of harvested energy into the battery. Using this method, there will be two scenarios:

1. $E_H(t) \geq E_B(t)$. The sensor uses $E_B(t)$ amount of energy directly from the energy harvesting device and stores the unused portion of the harvested energy ($E_H(t) - E_B(t)$) in the battery. As a result, $\eta_S(E_H(t) - E_B(t))$ amount of energy will be stored into battery for future use.

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

2. $E_H(t) < E_B(t)$. All the harvested energy ($E_H(t)$) will be used directly from the energy harvesting device.

Thus, when the energy harvest-use(store) method is used, the amount of harvested energy that could be utilized by the sensor includes the amount of energy that is directly drained from the energy harvesting device, as well as the unused portion of the harvested energy (if any) that is stored into the battery. Hence, the utilizable energy in a time slot $E_U(t)$, can be estimated as follows:

$$E_U(t) = \begin{cases} \eta_S(E_H(t) - E_B(t)) + E_B(t), & \text{Condition +} \\ E_H(t), & \text{Condition -} \end{cases}$$

where “Condition +” refers to the situation when $E_H(t) \geq E_B(t)$ and “Condition -” refers to the situation when $E_H(t) < E_B(t)$.

From the above expression we find that the HEUE achieved by using the energy harvest-use(store) method cannot be obtained directly, (unlike the case for the energy harvest-store-use method that achieves an HEUE of η_S). By the definition of HEUE, we have $\eta = \xi[E_U]/\xi[E_H]$. Thus, in order to calculate the HEUE, we have to estimate the value of $\xi[E_U]$ achieved by using the harvest-use(store) method. We denote the expected energy budget for a time slot by $\xi[E_B]$. For a time slot t , we denote the probability for $E_H(t) \geq \xi[E_B]$ to be P_+ and the probability for $E_H(t) < \xi[E_B]$ to be P_- . Using conditional expectations [94], the expected utilizable energy in one time slot is calculated as follows:

$$\xi[E_U] = P_+ \xi[E_U(t) | \{E_H(t) \geq \xi[E_B]\}] + P_- \xi[E_U(t) | \{E_H(t) < \xi[E_B]\}] \quad (3.22)$$

As stated in Section 3.2, $\{E_H\}$ is assumed to be an ergodic and stationary random process. It is stated in [45] that exponential distribution function is one

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

suitable Probability Density Function (PDF) for $\{E_H\}$, which is as follows:

$$f(E_H(t), \gamma) = \begin{cases} \gamma e^{-\gamma E_H(t)} & \text{if } E_H(t) \geq 0 \\ 0 & \text{if } E_H(t) < 0 \end{cases}$$

where $\gamma = (\xi[E_H])^{-1}$.

Based on the PDF of $\{E_H\}$ and equation (3.22), $\xi[E_U]$ can be computed as follows:

$$\begin{aligned} \xi[E_U] &= P_+ \int_{\xi[E_B]}^{\infty} E_U(t) \frac{f(E_H(t), \gamma)}{P_+} d(E_H(t)) \\ &\quad + P_- \int_0^{\xi[E_B]} E_U(t) \frac{f(E_H(t), \gamma)}{P_-} d(E_H(t)) \\ &= \int_{\xi[E_B]}^{\infty} (\eta_S E_H(t) + (1 - \eta_S) \xi[E_B]) \gamma e^{-\gamma E_H(t)} d(E_H(t)) \\ &\quad + \int_0^{\xi[E_B]} E_H(t) \gamma e^{-\gamma E_H(t)} d(E_H(t)) \\ &= \eta (\xi[E_B] + \frac{1}{\gamma}) e^{-\gamma \xi[E_B]} + (1 - \eta_S) \xi[E_B] e^{-\gamma \xi[E_B]} - (\xi[E_B] + \frac{1}{\gamma}) e^{-\gamma \xi[E_B]} + \frac{1}{\gamma} \\ &= \frac{1}{\gamma} - \frac{1}{\gamma} (1 - \eta_S) e^{-\gamma \xi[E_B]} \end{aligned} \tag{3.23}$$

As $\gamma = (\xi[E_H])^{-1}$, by dividing the both sides of equation (3.23) using $\xi[E_H]$, we have the HEUE achieved by using the energy harvest-use(store) method estimated as follows:

$$\eta = \frac{\xi[E_U]}{\xi[E_H]} = 1 - (1 - \eta_S) e^{-\frac{\xi[E_B]}{\xi[E_H]}} \tag{3.24}$$

Since $-\frac{\xi[E_B]}{\xi[E_H]} \leq 0$, we have $\eta \geq 1 - (1 - \eta_S) = \eta_S$. Thus, we name the HEUE efficiency achieved by using the energy harvest-use(store) method as the *Improved-HEUE* (denoted by η_V). When the full knowledge of the energy harvesting profile and statistical channel state information are available to accurately estimate $\xi[E_B]$ and $\xi[E_H]$, the Improved-HEUE calculated by using equation (3.24) will be the *Op-*

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

imal Improved-HEUE achievable by using the energy harvest-use(store) method, which is denoted by η_V^* .

3.5.2 Offline Estimation of the Optimal Improved-HEUE

In this section, we derive several results for the offline estimation of the Optimal Improved-HEUE (η_V^*).

Theorem 3.3. *The Optimal Improved-HEUE η_V^* achievable by using energy harvest-use(store) method can be estimated by $\eta_V^* = (1 - P^*) \times \eta_S + P^* \left(1 - (1 - \eta_S) e^{-\frac{\eta_V^*}{P^*}} \right)$, where P^* is the probability of the Optimal Water Level $\frac{1}{\lambda^*}$ being larger than the fading level $\frac{1}{h_t}$ of a time slot t .*

Proof. Assume that we have obtained the value of the Optimal Water Level $\frac{1}{\lambda^*}$. According to Lemma 3.1, for a time slot t , if $\frac{1}{h_t} \geq \frac{1}{\lambda^*}$, the energy budget assigned to this time slot is 0 (due to the $(x)^+$ function). Thus, the expected energy budget ($\xi[E_B]$) for time slots under this condition is also zero. With the statistical channel state information, we will be able to determine the probability for the sensor experiencing this kind of condition, which is denoted as $(1 - P^*)$.

On the other hand, for a time slot t , if $\frac{1}{h_t} < \frac{1}{\lambda^*}$, the energy budget assigned to this time slot will not be zero. Since no energy will be allocated to time slots with $\frac{1}{h_t} \geq \frac{1}{\lambda^*}$, (i.e., the energy budgets for these time slots are zero), all harvested energy that can be utilized by the sensor in N_t time slots will be used to assign the energy budgets for time slots with $\frac{1}{h_t} < \frac{1}{\lambda^*}$. Hence, the expected energy budget for

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

time slots under this condition follows:

$$\xi[E_B] = \frac{1}{P^* \times N_t} \sum_{t=1}^{N_t} (E_U(t)) \approx \frac{1}{P^*} \xi[E_U] = \frac{\eta_V^*}{P^*} \xi[E_H] \quad (3.25)$$

where P^* denotes the probability for a time slot experiencing $\frac{1}{h_t} < \frac{1}{\lambda^*}$.

Hence, based on equation (3.24), the Optimal Improved-HEUE η_V^* is estimated by:

$$\begin{aligned} \eta_V^* &= (1 - P^*) \times \left(1 - (1 - \eta_S) e^{-\frac{0}{\xi[E_H]}} \right) + P^* \left(1 - (1 - \eta_S) e^{-\frac{\eta_V^* \xi[E_H]}{P^* \xi[E_H]}} \right) \\ &= (1 - P^*) \times (1 - (1 - \eta_S) e^0) + P^* \left(1 - (1 - \eta_S) e^{-\frac{\eta_V^*}{P^*}} \right) \\ &= (1 - P^*) \times \eta_S + P^* \left(1 - (1 - \eta_S) e^{-\frac{\eta_V^*}{P^*}} \right) \end{aligned} \quad (3.26)$$

□

According to Theorem 3.3, the value of η_V^* can be obtained only if the value of $\frac{1}{\lambda^*}$ is available to estimate P^* . However, as discussed in the proof of Lemma 3.2, the value of $\frac{1}{\lambda^*}$ can be obtained if the value of $\xi[E_U]$ is available, which depends on the value of η_V^* (according to equation (3.24)). As a result, the value of η_V^* cannot be obtained directly. We thus provide an iterative method to obtain the value of η_V^* .

We start the iteration by using $\eta_V^*(0) = 1$ as the initial value. $\eta_V^*(i)$ is used to denote the Improved-HEUE estimated in the i -th iteration, where $i \geq 1$.

In the i -th iteration, we firstly estimate $\xi[E_U]$ based on the $\eta_V^*(i-1)$ obtained from the last iteration. Based on this estimated $\xi[E_U]$, the Current Water Level (CWL) $\frac{1}{\lambda_i}$ will be obtained using equation (3.16). Using $\frac{1}{\lambda_i}$, we will be able to determine the probability (denoted by P_i^*) of a time slot whereby $\frac{1}{h_t} < \frac{1}{\lambda_i}$. Hence,

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

Figure 3.1: Convergence of $\eta_V^*(i)$ under different fading channels

the probability of $\frac{1}{h_t} \geq \frac{1}{\lambda_i}$ for a time slot is $1 - P_i^*$. With the value of P_i^* obtained, $\eta_V^*(i)$ can be estimated based on equation (3.26) as follows:

$$\eta_V^*(i) = (1 - P_i^*) \times \eta_S + P_i^* (1 - (1 - \eta_S) e^{-\frac{\eta_V^*(i)}{P_i^*}}) \quad (3.27)$$

As the single variable in equation (3.27), $\eta_V^*(i)$ can be obtained by using Newton's Method [95].

As a matter of fact, $\eta_V^*(i)$ converges to the Optimal Improved-HEUE (η_V^*) in just a few iterations. We show in Figure 3.1 the convergence of $\eta_V^*(i)$ under different fading channels (with $\xi[E_H] = 30$). In all scenarios, η_V^* can be obtained within 4 iterations.

3.5.3 Improved-ABAP

The estimation of η_V^* as shown in Theorem 3.3 depends on the full knowledge of the statistical channel state information as well as the expected amount of energy that can be harvested in one time slot. Since this information is not available before

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

sensor deployment, η_V^* cannot be obtained directly for online implementation.

Using the same technique as in ABAP, we let the sensor to learn the energy harvesting profile to estimate $\xi[E_H]$. The sensor will also learn the historical fading levels experienced to estimate the p_l for each fading level. In this way, at the beginning of a time slot t , using the channel state information and the energy harvesting information observed, the value of the *Current Estimated Improved-HEUE* (denoted by η_V^t) can be estimated using the iterative method as discussed in Section 3.5.2. Hence, when the energy harvest-use(store) method is used, the budget assignment policy is as follows:

$$E_B(t) = \min \left(\left(\beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_t} \right)^+ - \delta \right)^+, (B(t-1) - B_0) \right) \quad (3.28)$$

with the **Adaptive Water Level** (AWL) $\frac{1}{\hat{\lambda}_t}$ calculated at the beginning of time slot t as follows:

$$\sum_{k=1}^t \beta \left(\frac{1}{\hat{\lambda}_t} - \frac{1}{h_k} \right)^+ = \eta_V^t \sum_{k=0}^{t-1} (E_H(k)) \quad (3.29)$$

We denote this policy as the **ABAP*** policy.

Lemma 3.4. *When the energy harvest-use(store) method is used, as the number of time slots elapsed approaches a sufficiently large value, the Adaptive Water Level ($\frac{1}{\hat{\lambda}_t}$) calculated in ABAP* converges to the Optimal Water Level ($\frac{1}{\lambda^*}$).*

Proof. When the number of time slots elapsed is sufficiently large, sufficient channel fading information and energy harvesting information will be observed by the sensor. In this situation, the estimated $\xi[E_H]$ and p_l for each fading level will be sufficiently close to the theoretical values. As a result, η_V^t will be sufficiently

3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

close to the Optimal Improved-HEUE (η_V^*). Hence, when the number of time slots elapsed grows to a sufficiently large value $\bar{N}$, the RHS of equation (3.29) becomes:

$$\lim_{t \rightarrow \bar{N}} \eta_V^t \sum_{k=0}^{t-1} (E_H(k)) \approx \bar{N} \eta_V^* \xi[E_H] = \bar{N} \xi[E_U] \quad (3.30)$$

Thus, similar to the proof of Lemma 3.3, the AWL $\frac{1}{\lambda_t}$ calculated in ABAP* will also converge to the Optimal Water Level $\frac{1}{\lambda^*}$ when the number of time slots elapsed approaches a sufficiently large value. $\square$

Theorem 3.4. *ABAP* asymptotically achieves maximized ACT.*

Proof. The proof is similar to the proof of Theorem 3.2. $\square$

Lemma 3.5. *ABAP* achieves a higher ACT than that achieved by ABAP.*

Proof. Since $\eta_V^* \geq \eta_S$, $\xi[E_U]$ achieved by ABAP* will be higher than that achieved by ABAP. As a result, the Adaptive Water Level achieved by using ABAP* is also higher, which results in a higher energy budget assigned. This in turn implies that ABAP* achieves a higher ACT than that achieved by ABAP. $\square$

Note that additional computational complexity will be involved if we estimate η_V^t at the beginning of every time slot. As stated in the proof of Lemma 3.4, η_V^t will converge to η_V^* when the number of time slots grows to $\bar{N}$. Thus, η_V^t can be fixed to the value estimated at time slot $\bar{N}$ for the remaining time slots (from $\bar{N}$ to N_t) to reduce the computational complexity. We will verify the convergence rate for η_V^t to converge to η_V^* later in Section 3.6.4.

3.6 Numerical Results

Empirical studies are carried out to evaluate the performance of our proposed ABAP and ABAP* using Matlab [88]. Throughout the empirical studies, we assume that the sensor carries a rechargeable battery with an energy capacity of $2000J$ (a typical 700mAh AAA sized NiMH battery at 1.2 V [96]). We also assume that the initial Battery Residual Energy Level (BREL) upon deployment of the sensor is set to be $1000J$. We choose the δ constant to be one. However, we will set δ to zero when the BREL exceeds $1500J$ ($0.75B_c$ as discussed in Section 3.4.2). For the convenience of comparison, the channel bandwidth is chosen to be $1MHz$ and the Noise Power Spectrum Density is normalized to be $1 W/Hz$. The duration for a time slot is assumed to be 30 seconds and $\{E_H\}$ is assumed to be exponentially distributed with a mean of $30J$ ($1J/Sec$). Channel gains in different time slots are generated by Rayleigh distribution or Nakagami distribution, with different mean channel gains.

3.6.1 Performance Improvement due to Improved-HEUE

We firstly verify the performance improvements achieved by using ABAP* (based on the energy harvest-use(store) method) as compared to ABAP (based on the energy harvest-store-use method). Simulations are carried out under a range of values for the battery energy storage efficiency η_S with $N_t = 1000$ time slots.

It is shown in Figure 3.2 that ABAP* achieves a much higher Average Channel Throughput (ACT) as compared to ABAP under various kinds of fading channels. For example, as shown in Figure 3.2(a), when Rayleigh fading channels are used with a mean channel gain ($\xi[H]$) of 1, ABAP* can achieve an ACT of $0.62 Mbps$

Figure 3.2: Average Channel Throughput (ACT) improvements in (a): Rayleigh Fading Channel ($\xi[H] = 1$). (b): Rayleigh Fading Channel ($\xi[H] = 0.2$). (c): Nakagami Fading Channel ($\xi[H] = 0.3$)

when $\eta_S = 0.66$ (typical NiMH battery [35]). This is an improvement of 16.9% as compared to the ACT of 0.53 *Mbps* achieved by ABAP. For Rayleigh fading channels with $\xi[H] = 0.2$ (shown in Figure 3.2(b)), ABAP* can achieve an ACT of 0.182 *Mbps* with $\eta_S = 0.66$. This is an improvement of 15.1% as compared to the ACT of 0.158 *Mbps* achieved by ABAP. As for Nakagami fading channels with $\xi[H] = 0.3$ (shown in Figure 3.2(c)), ABAP* can achieve an ACT of 0.232 *Mbps* with $\eta_S = 0.66$. This is an improvement of 22.1% as compared to the ACT of 0.19 *Mbps* achieved by ABAP. These phenomenons also indicate that ABAP* achieves a higher HEUE than that achieved by ABAP, (since the ACT is dependent on $\xi[E_U]$, which in turn depends on the HEUE as shown in equation (3.2)).

3.6.2 Energy Neutral Operation

In ABAP*, we use the Improved-HEUE (η_V) to compute the energy budget. As η_V is much higher than the corresponding η_S , higher energy budget will be assigned

Figure 3.3: Battery Residual Energy Level variations in: (a) Rayleigh Fading Channel ($\xi[H] = 1$) (b) Rayleigh Fading Channel ($\xi[H] = 0.2$) (c) Nakagami Fading Channel ($\xi[H] = 0.3$)

by ABAP* than that assigned by ABAP. Since assigning higher energy budget may risk compromising the energy neutrality of the sensor, we next examine the Battery Residual Energy Level (BREL) variations of the sensor under ABAP and ABAP* to verify its energy neutral status maintenance. If not otherwise stated, we assume that the sensor carries an NiMH rechargeable battery with battery storage efficiency $\eta_S = 0.66$ [35].

As shown in Figure 3.3, the BREL never drops below the initial BREL of $1000J$ under various communication channels, which confirms that both ABAP and ABAP* can efficiently maintain Strict Energy Neutral Operation. Furthermore, we can observe from Figure 3.3 that the BREL shows an increasing trend in the first few hundred time slots. After about 500 time slots, the BREL is sustained in a stable region above $1500J$. This confirms the battery energy accumulations due to the small constant δ as discussed in the proof of Theorem 3.2.

As stated in Section 3.5.3, ABAP* use η_V^t (which converges to η_V^*) to calculate

the energy budget, which is different from the η_S value used by ABAP. However, as shown in Figure 3.3, with the same experimental setup, the BREL variations under ABAP are very similar to those under the ABAP*. This actually verifies that η_V^* is an accurate estimation of the HEUE when energy harvest-use(store) method is used. In order to further illustrate this point, we also examined the BREL variations for ABAP*, by assigning η_V^t to some values that are different from the Optimal Improved-HEUE (η_V^*), which is calculated using the method described in Theorem 3.3.

We recorded the BREL variations for ABAP* when Rayleigh fading channel with $\xi[H] = 1$ is used and the Optimal Improved-HEUE (η_V^*) in this case is 0.839. As shown in Figure 3.4, the BREL is very sensitive to the value of η_V^t we chose to assign energy budget for ABAP*. When η_V^t is assigned to a value of 0.8, which is slightly less than the optimal value of 0.839, the BREL approaches the value of $2000J$ at a faster rate as less energy is consumed by the sensor due to a lower water level. As a result, smaller energy budgets will be assigned due to the lower water level calculated based on a smaller η_V^t , which in turn decreases the ACT. On the other hand, when η_V^t assigned is larger than the optimal value of 0.839, the resultant water level might be higher. Although a higher water level will result in an increased ACT, it is at the risk of compromising the energy neutral state of the sensor. As shown in Figure 3.4, when η_V^t is chosen to be 0.88, which is a little higher than the optimal value of 0.839, the BREL is substantially lower than that when $\eta_V^t = 0.839$. This phenomenon indicates that the sensor consumes more energy than the amount of harvested energy it can actually utilize, which might compromise the energy neutrality of the sensor in the long run and results in the deterioration of ACT. Hence, it is confirmed that η_V^* is an accurate estimation of

Figure 3.4: Battery Residual Energy Level variations with different η_V^t

the HEUE when the energy harvest-use(store) method is used.

3.6.3 Average Channel Throughput

Other than maintaining the energy neutrality of a sensor for perpetual operation, we would also want to maximize the Average Channel Throughput (ACT). Thus, we next compare the ACT achieved by our proposed policies against four other policies: the Simple policy, the Energy Adaptive (EA) policy, the Directional Water Filling (DWF) policy and the Ideal policy.

The **Simple** policy simply uses the amount of utilizable energy in the previous time slot $t - 1$ as the energy budget of current time slot t , which means $E_B(t) = E_U(t - 1)$ (assuming $E_U(0) = 0$). The **Energy Adaptive** (EA) policy uses the current estimated average amount of utilizable energy in one time slot as the energy budget. This kind of estimation is based on the historical energy harvesting information observed, which means $E_B(t) = \frac{1}{t} \sum_{k=0}^{t-1} E_U(k)$ (assuming $E_U(0) = 0$). The **Directional Water Filling** (DWF) policy is an off-line throughput

3.6. Numerical Results

Figure 3.5: Average Channel Throughput comparison based on harvest-store-use method (Rayleigh fading, $\xi[H] = 1$)

maximization policy proposed in [46], which requires the full knowledge of the energy harvesting profile and statistical channel state information to achieve the optimality. We use the Optimization Toolbox in Matlab [88] to solve the concave optimization problem and thus obtain the optimal energy budget assignments for DWF. The **Ideal** policy uses the energy budget obtained in Lemma 3.1, assuming that full knowledge of the energy harvesting profile and statistical channel state information are known in advance.

Similar to the last section, we assume that the sensor carries an NiMH rechargeable battery with energy storage efficiency $\eta_S = 0.66$. For the purpose of fair comparison, we firstly compare ABAP with the four other policies, assuming that the energy harvest-store-use method is used. The ACTs achieved by using these polices are shown in Figure 3.5. We also compare ABAP* with the four other policies, assuming that all policies adopt the energy harvest-use(store) method. ABAP* calculates the Current Estimated Improved-HEUE (η_V^t) based on the historical information at the beginning of each time slot. The HEUE achieved by the

Figure 3.6: Average Channel Throughput comparison based on harvest-use(store) method (Rayleigh fading, $\xi[H] = 1$)

four other policies is set to the Optimal Improved-HEUE (η_V^*) as calculated using the method discussed in Theorem 3.3. Figures 3.6, 3.7 and 3.8 illustrate the ACT achieved by each policy under different fading channels.

Under all conditions, the Simple policy always performs the worst. This is because the Simple policy is strictly suboptimal since it does not assign the energy budget by taking the expected amount of utilizable energy $\xi[E_U]$ into consideration. It also does not consider the impact of the channel fading levels. Although the Energy Adaptive policy uses the adaptively calculated expected amount of utilizable energy in one time slot to assign the energy budget, it does not consider the impact of the channel fading levels. As a result, EA achieves a higher ACT than that achieved by the Simple policy but lower than that achieved by other policies.

With the full knowledge of the statistical channel state information and the energy harvesting profile, the Ideal policy does perform the best under all situations. Since the DWF policy requires additional energy constraints, (which are similar to the ones as in constraints (3.6)), it performs worse than the Ideal policy under

Figure 3.7: Average Channel Throughput comparison based on harvest-use(store) method (Rayleigh fading, $\xi[H] = 0.2$)

all situations. As shown in Figure 3.5, without the need of the prior knowledge about the statistical channel state information as well as the energy harvesting profile, our proposed ABAP still performs similarly to the DWF policy when energy Harvest-Store-Use method is used.

When the energy harvest-use(store) method is used, ABAP* also performs similarly to the DWF when the Rayleigh fading channel has a mean channel gain of 1 as shown in Figure 3.6. In addition, as shown in Figure 3.7, when the mean channel gain of the Rayleigh fading channel decreases to 0.2, ABAP* performs better than DWF after $t = 1000$ time slots. For example, at $t = 1000$, ABAP* achieves an ACT of 0.182 Mbps as compared to the 0.175 Mbps achieved by DWF. ABAP* also performs better than DWF when Nakagami fading channels with a mean channel gain of 0.3 is used. As shown in Figure 3.8, at $t = 1000$, ACT achieved by ABAP* is 0.232 Mbps as compared to 0.226 Mbps of ACT achieved by DWF.

Figure 3.8: Average Channel Throughput comparison based on harvest-use(store) method (Nakagami fading, $\xi[H] = 0.3, m = 3$)

3.6.4 Convergence Rate to Optimality

In ABAP*, two parameters are dynamically computed at the beginning of a time slot: the Current Estimated Improved-HEUE (η_V^t) and the Adaptive Water Level (AWL). When these two parameters converge to the optimal values, the sensor will be using the Optimal Water Level to assign energy budgets, which in turn maximizes the ACT.

We firstly examine the convergence speed for the Current Estimated Improved-HEUE (η_V^t) to converge to the Optimal Improved-HEUE (η_V^*). As shown in Figure 3.9, η_V^t converges to η_V^* after 300 time slots under various communication channels. It verifies that we can fix η_V^t to the latest updated value after a number of time slots as stated in Section 3.5.3 to reduce the computational complexity.

The convergence of the Adaptive Water Level (AWL) in ABAP* is shown in Figure 3.10. AWL also converges to the Optimal Water Level (which is calculated based on the method discussed in the proof of Lemma 3.1) after around 300 time

3.6. Numerical Results

slots, which is a very short period of time. It in turn indicates that ABAP* can asymptotically achieve maximized ACT in a short period of time.

Figure 3.9: Convergence of the Current Estimated Improved-HEUE (η_V^t)

Figure 3.10: Convergence of Adaptive Water Level

3.6.5 Computational Complexities

For the off-line policies, as mentioned in [46], the DWF policy employs dynamic programming to obtain the Optimal Energy Budget. Due to the “Curse of Di-

mensionality” [97] inherent by dynamic programming, DWF involves high computational complexities. In addition, the number of constraints involved in solving the optimization problem for DWF increases with the number of time slots under consideration. This in turn further increases the computational complexity when the number of time slots under consideration increases. As for the Ideal policy, as shown in Section 3.3, the number of constraints required by solving the optimization problem (Relaxed-TMP) is greatly reduced. As a result, the Optimal Energy Budget can be obtained directly through the methods discussed in the proof of Lemma 3.1. Thus, the Ideal policy involves less computational complexities.

For the online budget assignment policies, the Simple policy has the least computational complexity. A sensor just have to record the utilizable energy in the last time slot and then use it as the energy budget for the current time slot. The EA policy requires the sensor to record the utilizable energy for all the previous time slots and then calculate the energy budget for the current time slot. It thus requires more computational power than that needed by the Simple policy. Taking channel fading levels into consideration, our proposed ABAP and ABAP* calculate the AWL $\frac{1}{\lambda_t}$ to assign energy budget for a time slot. At the first few hundred time slots, the sensor will be learning the statistics of the channel fading levels as well as the energy harvesting profile to estimate AWL. However, similar to the way we estimate the Current Estimated Improved-HEUE η_V^t as stated in Section 3.5.3, this kind of estimation is also not needed when the AWL converges to the Optimal Water Level $\frac{1}{\lambda^*}$. Thus, our proposed ABAP and ABAP* involve a slightly higher computational complexity as compared to the EA and Simple policy. However, since ABAP and ABAP* do not require computational intensive dynamic programming technique, the computational complexity of in our proposed ABAP

and ABAP* are much lower than that of the off-line DWF policy.

3.7 Summary

Based solely on the historical information observed by a sensor, a low complexity Adaptive Budget Assignment Policy (ABAP) is proposed in this chapter to provide energy neutral management, without the need of the statistical channel state information and the predicted energy harvesting profile before sensor deployment. It is shown analytically that ABAP asymptotically maximizes the Average Channel Throughput (ACT) for fading communication channels, which has a non-linear relationship with the energy consumption of a sensor. That is, without the predicted information, ABAP is able to asymptotically achieve the optimal channel throughput as that achieved by the ideal water filling mechanism. We also derive a way to estimate the Harvested Energy Utilization Efficiency (HEUE) achieved by using the energy harvest-use(store) method. Based on this HEUE, an ABAP* policy is proposed to further improve the ACT in the presence of battery inefficiencies.

We verify through empirical studies the substantial ACT improvements achieved by using our proposed ABAP* policy as compared to ABAP policy. It is also confirmed that ABAP and ABAP* can successfully maintain the energy neutral state of a sensor. We also find that our proposed ABAP and ABAP* can perform better, in terms of ACT, as compared to the off-line optimal Directional Water Filling policy. In addition, empirical studies also indicate that ABAP and ABAP* can asymptotically achieve maximized ACT within a small number of time slots.

Chapter 4

Energy Neutral Directed Diffusion for Energy Harvesting Wireless Sensor Networks

Besides providing the Node-level Energy Neutral Management for sensor nodes as discussed in Chapter 2 and 3, it is also possible to provide the Network-level Energy Neutral Management, which enables the perpetual operation of the whole network. In this chapter, we propose a query driven Energy Neutral Directed Diffusion (ENDD) protocol that aims at providing perpetual and consistent network operation with improved network performance level. In order to control the energy consumption of the sensors in the network, ENDD employs traffic flow admission controls to regulate the data traffic flows carried by each sensor. The admission control procedure is carried out locally at each sensor based on its own energy harvesting status, which prevents sensors from shutting down due to excessive usage of energy. A real-time realistic energy consumption estimation model is also proposed to improve the reliability of the admission control procedure. Extensive simulations are also carried out to evaluate and compare the performance of our proposed ENDD protocol against other query driven routing protocols.

4.1 Introduction

Powered by small batteries/supercapacitors, one of the biggest problems faced by traditional Wireless Sensor Network (WSN) is the limited energy resource. A sensor will be *dead* when the energy resource stored in its battery is depleted. As a dead sensor cannot perform any kind of tasks, the performance of the WSN will degrade severely when one or more sensors are dead. Thus, the *Network Lifetime*, which is measured by the amount of time elapsed before the first sensor node (or a fraction of sensor nodes) is dead, is used as an important performance metric for traditional WSNs.

As the amount of data traffic carried by a sensor node will directly determine its energy consumption, the lifetime of a network can be extended by using energy efficient network layer routing protocols. As discussed in Section 1.3.2.2, based on different data delivery models, routing protocols can be classified into three categories: *Continuous*, *Event Driven*, *Query Driven* and *Hybrid Model* [34].

Using the continuous model, (such as the ones in [98, 99, 100, 101]), data information sensed by sensors will be delivered to the destinations periodically with a specific data packet transmission rate. Using the event/query driven model (such as the ones in [102, 103, 104, 105, 106]), the transmission of data will be triggered only when a specific event occurs or when a query is generated by the user. The hybrid model is the combination of continuous model and event/query driven model [107, 108]. We note that using the query driven model, only data queried by the user will be sensed and then delivered to the destination. Hence, less data will be transmitted when the query driven model is employed as compared to the continuous model. This in turn implies that the query driven model is highly

energy efficient and thus has the potential of providing longer network lifetime. Energy aware query driven routing protocols ([109, 110]) have also been proposed to further extend the lifetime of the network. However, no matter how energy efficient these routing protocols are, sensors will eventually deplete their batteries and stop functioning, which results in inevitable network failure.

With the emergence of energy harvesting techniques, wireless sensor nodes are equipped with energy harvesting devices so that it can gain access to theoretically infinite amount of energy source from the ambient environment. As discussed in Chapter 1, with this energy harvesting technology, it is now possible for an Energy Harvesting WSN (EH-WSN) to operate perpetually with unlimited network lifetime.

Thus, the research interest has been recently shifted from the energy aware routing to *Energy Harvesting Aware* routing. Several energy harvesting aware routing protocols (such as the ones in [39, 111, 112]) that are based on the continuous data delivery model have been proposed in the literature. However, to the best of our knowledge, there has not been any work on energy neutral routing protocols that are based on the query driven data delivery model. Due to the inherited high energy efficiency, a query driven routing protocol has the potential of further enhancing the performance of a sensor network with energy harvesting capabilities. In view of this, we study in this chapter a query driven routing protocol that aims at providing Network-level Energy Neutral Management for an EH-WSN. The main contributions of this chapter are:

- A query driven Energy Neutral Directed Diffusion (ENDD) routing protocol. Admission controls are carried out locally at each node based on its energy harvesting status to admit or reject data traffic routing requests. Us-

ing ENDD, the Network-level Energy Neutral Management can be achieved, which provides unlimited network lifetime and consistent network service.

- A realistic energy consumption estimation model to improve the accuracy of the admission control procedure, which in turn enhances the reliability of the sensor energy neutral state guarantee.
- Analytically derived upper bound on the amount of control messages exchanged for route establishment. This upper bound has a linear relationship with the network size, which means ENDD scales well with the network size.

The rest of the chapter is organized as follows. Previous related works are reviewed in Section 4.2. Section 4.3 contains the system models and notations we use. Operations of our proposed ENDD protocol are presented in Section 4.4. Empirical studies are carried out in Section 4.5 to evaluate the performance of our proposed ENDD protocol. This chapter will be summarized in Section 4.6.

4.2 Related Works

4.2.1 Energy Harvesting Aware Routing Protocols

In recent years, several continuous data delivery model based energy harvesting aware protocols have been proposed. Lin et al. presented the Energy-opportunistic Weighted Minimum Energy (E-WME) [111] routing protocol which assigns each energy harvesting sensor with a cost that is related to the energy harvesting rate and then calculate the shortest path according to each node's cost. The Randomized Minimum Path Recovery Time (R-MPRT) routing protocol [112] proposed by

Lattanzi et al. assigns a cost to each edge that is related to the energy required to transmit a packet and the energy harvesting rate. Hasenfratz et al. compared in [39] the above two protocols and found that if we calculate the cost in R-MPRT with respect to the available energy instead of the energy harvesting rate, its performance will be better than that of E-WME. These routing protocols determine the appropriate routing path by considering the battery residual energy and the energy harvesting rate. In this way, the network traffic can be routed on energy harvesting sensors that have better energy status. In [113], a multiple path routing protocol is proposed to improve the data collection quality and the routing sustainability in an energy harvesting wireless sensor network. In [114], the transmission quality, energy consumption and energy wastage are considered to improve the energy efficiency of the routing protocol designed for energy harvesting WSN. There are also energy harvesting aware hierarchical routing and clustering protocols [42, 115] that choose sensors with better energy harvesting status to act as cluster head to carry heavy network traffic.

A joint energy management and routing protocol has been proposed in [48] to compute the optimal routes so that the overall data transmission capacity at all energy harvesting sensors can be maximized, while maintaining the energy neutrality of all the energy harvesting sensors. The proposed maximization problem is solved by using dual decomposition method and a distributive implementation of the method is proposed for a network with a special structure, namely the directed acyclic network graph (DAG).

4.2.2 Query Driven Routing Protocols

In the literature, Directed Diffusion (DD) [102] is an important query driven based routing protocol for traditional wireless sensor networks. It uses a publish and subscribe mechanism to efficiently pull desired data information. In order to create a query, *Interest* packets will be generated at the sink(s). These interests will diffuse across the network to find the sensor nodes that have sensed the desired information.

The original Directed Diffusion proposed in [102] uses a *Two Phase Pull Diffusion* (TPPD) model. In the first phase, interests will be diffusing across the network to pull down low quality information from the data source. Upon receiving these interests, the data source will send back the queried low quality information in the form of data packets (with a very low packet transmission rate), which are referred to as the *Exploratory Data Packets* (EDPs). The second phase begins once the sink receives these EDPs and it will send out reinforcement interests to pull down high quality information. The high quality information (in the form of data packets with a high packet transmission rate) will be sent back to the sink via the *Empirically Lowest Delay Path*, which consists of sensors that delivers the EDPs with the lowest empirical delay.

In [116], an *One Phase Pull Diffusion* (OPPD) model is proposed to extend the original DD protocol. Using this model, hops count will be recorded by the sensor when the interests are diffusing in the network. Once these interests are received by the data sources, they will directly send back data packets with a high data packet transmission rate. These data packets are routed to the sink via the sensors that have lower hops count to the sink. Since no reinforcements or

exploratory data packets are needed, the One Phase Pull Diffusion model has a lower control message overhead as compared with the Two Phase Pull Diffusion model. However, as indicated in [109], the low delay path established by using hops counts (instead of the empirical delays) might not be the lowest delay path. Thus, higher end-to-end data delivery delays might be experienced using OPPD model as compared to TPPD model.

Since the original and the modified version of DD always choose the low delay path to carry traffic flows, sensors along this path will die faster than the rest of the sensors. This will in turn result in a shorter network lifetime. In [109], an Energy Differentiated Directed Diffusion (EDDD) is proposed based on the OPPD model. This protocol can achieve global energy balance of sensors so that the network lifetime can be improved. Sensors with higher amount of residual battery energy will be chosen to carry the traffic load by using a Best Effort filter. Some other researches ([110], [117]) on energy aware query driven protocols took the similar approach in extending the system lifetime (as the one in [109]). Since the energy availability (instead of the data delivery delay) becomes the primary concern in selecting routing paths, these energy aware DD protocols might suffer from longer end-to-end packet delivery delays.

4.3 System Model and Notations

4.3.1 Network Topology

We assume that N energy harvesting sensor nodes are randomly deployed (following the uniform distribution) in a field. A data sink is placed at the center of the

4.3. System Model and Notations

field. The network formed by the sensor nodes and the data sink can be represented by an undirected graph $G = (V, E)$, where V is the set of vertices ($|V| = N + 1$) and E is the set of edges (wireless communication links) in G . A pair of nodes is connected with each other when the nodes are within each other's maximum radio transmission (interference) range. The maximum radio transmission range is set to a value so that the minimum Signal to Noise Ratio (SNR) at the receiver side is able to maintain the desired Bit Error Rate. We assume that the maximum radio transmission ranges for all nodes (sensor nodes and sink node) are the same.

4.3.2 Sensor Energy Dissipation Model

Every energy harvesting sensor is assumed to carry a rechargeable battery with an initial battery residual energy level of B_0 . The *Battery Residual Energy Level* (BREL) measures the amount of energy remaining in the battery. A sensor node stops sensing or relaying messages when its BREL drops to zero. We assume that the sink has access to an unlimited power source as the sink node is usually a manned station that is connected to a power grid.

To compute the energy needed for the communication process between sensor nodes, we adopt the widely used path loss energy dissipation model as proposed in [86]. A sensor node will spend energy to run the radio electronic as well as the radio amplifier. We assume that the information sensed by a sensor node will be aggregated into data packets with a length of L bits. The energy E_{Tx} needed to transmit one data packet is calculated by:

$$E_{Tx} = \begin{cases} L \times \varepsilon_{e-tx} + L \times \varepsilon_{sp} \times d^2 & \text{if } d < \hat{d} \\ L \times \varepsilon_{e-tx} + L \times \varepsilon_{mp} \times d^4 & \text{if } d \geq \hat{d} \end{cases} \quad (4.1)$$

4.3. System Model and Notations

where ε_{e-tx} is the energy consumed by the transmitter electronics of the sensor to perform tasks such as modulation, data processing, code spreading, etc. d is the distance between the transmitting sensor and the receiving sensor. When d is smaller than the crossover distance $\hat{d}$, the path loss can be treated as Friis free space loss with d^2 power attenuation. When d is larger than $\hat{d}$, the path loss model can be approximated as a two ray multi-path propagation model with d^4 power attenuation. Constants ε_{sp} and ε_{mp} will be set according to the required SNR at the receiver so that the bit error rate is acceptable.

The energy needed to receive one data packet, which is denoted by E_{Rx} is calculated by:

$$E_{Rx} = L \times \varepsilon_{e-rx} \quad (4.2)$$

where ε_{e-rx} is the energy consumed by the receiver electronics.

4.3.3 Network-level Energy Neutral Management

In order to monitor the harvested energy dynamically, the system time is divided into time slots with a duration of T seconds. The amount of energy harvested in a time slot t is denoted by $E_H(t)$. We define the *Energy Budget* $E_B(t)$ as the amount of energy that can be used by a sensor node in time slot t . Thus, in order to achieve the *Energy Neutral* state [36], we have the following constraint for an energy harvesting sensor:

$$\sum_{t=1}^{N_t} E_B(t) \leq \sum_{t=1}^{N_t} \eta E_H(t) \quad (4.3)$$

where N_t is the total number of time slots under consideration, η is the Harvested Energy Utilization Efficiency (HEUE) as discussed in Chapter 2 and Chapter 3.

4.4. Energy Neutral Directed Diffusion (ENDD)

We can observe from equation (4.1) that, when the distance between the transmitting node and the receiving node is fixed, the total information bits that can be transmitted by a single sensor in a time slot n will have a linear relationship with the Energy Budget allocated to this time slot. This means that the Linear Energy Consumption model can be used in this chapter and P-FREEN can thus be utilized to provide Node-Level ENM as discussed in Chapter 2. In particular, P-FREEN can be used by a sensor to determine its energy budget in a time slot. Since P-FREEN maximizes the amount of harvested energy that is available for sensor utilization, it can improve the maximum amount of data packets that a sensor can relay in a time slot.

However, since the energy harvesting status varies at different sensor nodes (due to the spatial variations), the energy budgets assigned by P-FREEN to different sensors also varies. Hence, our focus in this chapter is to provide Network-Level ENM through network layer routing protocols, which coordinately controls the utilization of the energy budget assigned by Node-Level ENM and handles the spatial variations in the energy harvesting rate experienced by different sensors. For simplicity, we assume that the battery energy storage efficiency $\eta_S = 1$.

4.4 Energy Neutral Directed Diffusion (ENDD)

In this section, the design of our proposed Energy Neutral Directed Diffusion (ENDD) protocol will be presented. Based on the two different data pulling models as described in Section 4.2.2, two variations of ENDD, namely ENDD-T (based on the Two Phase Pull Diffusion model) and ENDD-O (based on the One Phase Pull Diffusion model), are proposed to meet different design requirements.

4.4. Energy Neutral Directed Diffusion (ENDD)

Interest Packet	Data Packet
Interest ID	Data Packet ID
Interest Type	Interest ID
Source ID	Data Type
Destination ID	Source ID
Packet Rate	Destination ID
Start Time	Sent Time
End Time	
Hops Count	

Table 4.1: Fields in the packet headers

Cache Table				
Entry_1	Field_1	Field_2	Field_3	Field_...
Entry_2	Field_1	Field_2	Field_3	Field_...
Entry_3	Field_1	Field_2	Field_3	Field_...
Entry_...	Field_1	Field_2	Field_3	Field_...

Table 4.2: Structure of a cache table maintained by a sensor

4.4.1 Preliminaries

Two types of packets will be used in ENDD, namely the *Interest Packet* and the *Data Packet*. Interest packet is used to query desired data information. It contains information that describes the attributes of the desired event information. Such attributes include event type, event location, event duration, etc. Data packets contain the desired information queried by the sink. Detailed packet header configurations for the interest packet and the data packet can be found in Table 4.1.

Cache tables will be maintained at every sensor in the network to record necessary information. The general structure of a cache table is shown in Table 4.2. A sensor node will maintain three kinds of cache tables, *Interest Cache Table* (ICT), *Rejection Cache Table* (RCT) and *Data Cache Table* (DCT). ICT holds the information contained in the interest packets that are received and accepted by a

4.4. Energy Neutral Directed Diffusion (ENDD)

Interest Cache	Data Cache	Rejection Cache
Interest ID	Data Packet ID	Interest ID
Interest Type	Interest ID	Interest Type
Source ID	Source ID	Source ID
Packet Rate	Data Type	Packet Rate
Start Time	Delay	
End Time		
Hops Count		

Table 4.3: Fields in the cache entries

Field Names	Utility
Interest ID	Unique identifier for an interest packet
Interest Type	Initial Interest/Reinforcement Interest/Rejection Message
Source ID	ID of the node that sends the packet
Destination ID	ID of the node that is selected to receive the packet
Data Packet ID	Unique identifier for a data packet
Packet Rate	Data packet transmission rate at the data source
Start Time	Start time of the event queried
End Time	End time of the event queried
Data Type	Exploratory Data Packet/ Non-exploratory Data Packet
Sent Time	The time when the Target Sensor sent the data packet
Delay	Packet delivery delay experienced by a data packet

Table 4.4: Utilities of the fields contained in packet headers and cache entries

sensor node. RCT holds the information contained in the *Rejection Message* received from neighboring sensors. (Rejection Message is used for rejecting certain interests during the admission control procedure, which will be further discussed later.) DCT is used to cache the information of the data packets that are transmitted by the sensor node. The fields contained in the three kinds of cache tables can be found in Table 4.3.

Detailed descriptions of the fields contained in the packet headers and cache entries can be found in Table 4.4.

For a newly received interest packet, there might be a situation where the values contained in the “Interest ID” and the “Interest Type” fields in the packet

4.4. Energy Neutral Directed Diffusion (ENDD)

header of this interest are identical to the values contained in the corresponding two fields in a cache entry stored in the ICT or the RCT. We refer to such entry as a *Matching Entry* for this interest packet. Similarly, for a newly received data packet, it has a matching entry in the DCT if the values contained in the “Data Packet ID” and the “Data Type” field in this data packet header are identical to the values contained in the corresponding two fields of an entry stored in the DCT.

4.4.2 ENDD-Two Phase Pull (ENDD-T)

We firstly present the ENDD-T protocol based on the Two Phase Pull Diffusion model as we discussed in Section 4.2.2. ENDD-T algorithm operates in the following three phases:

4.4.2.1 Setting Up Phase

ENDD-T is initiated when the sink generates the initial interests that diffuse through the network to query the desired event information. *INitial Interest* (INI) is a type of interest packet that specifies a very low data packet transmission rate to pull down low quality information at the desired data source.

Following Algorithm 4.1, a sensor node that receives a new INI (no matching entry in the ICT) will create a corresponding entry in its ICT. As shown in Table 4.3, this newly created entry will be storing the node ID of the sensor (that sends the INI) in the “Source ID” field to create a reply link to this sensor. The *Reply Link* specifies the direction (from a sensor to its neighbor that sends the INI) in which to send data packets. After creating this entry, this INI will be rebroadcasted.

On the other hand, if a node receives an INI that has been received by this

4.4. Energy Neutral Directed Diffusion (ENDD)

Algorithm 4.1: Network Setting Up for ENDD-T

```
foreach INI i received by node n do
    Check the ICT maintained by n
    if no matching entry is found then
        Create an entry for i in the ICT
        Rebroadcast i
    else if a matching entry exists in the ICT then
         $ID \leftarrow$  ID of the node from which i is received
        Add  $ID$  into the “Source ID” field of the matching entry
        Discard i
    end
    if Node n has sensed the desired information queried by INI i then
        Node n becomes the target sensor
        Send out EDPs at the specified event starting time
    end
end

foreach EDP e received by node n do
    Create an entry for e in DCT
    Rebroadcast e
end
```

node previously (a matching entry is found in the ICT), the ID of the sensor that sent this received INI will be added into the “Source ID” field of this matching entry in the ICT to create a new reply link. After that, this INI will be discarded. In this way, each node will broadcast an INI only once while setting up the reply links to all its neighbors.

A sensor node will become a *Target Sensor* when it receives a new INI and finds out that it has sensed information that matches the attributes of the information queried by this INI. *Exploratory Data Packet* (EDP) will be generated at the target sensor and will be transmitted following the low data packet transmission rate as specified in the INI. These EDPs generated at the target sensor will be flooded across the network until they reach the sink.

4.4. Energy Neutral Directed Diffusion (ENDD)

A sensor node that receives an EDP for the first time will create an entry for it in its DCT. Unlike receiving an INI, a sensor node that receives an EDP that has a matching entry in the DCT will still create a new entry in the DCT for this newly received EDP. In this way, a sensor will be able to determine packet delivery delays for receiving the same EDP from different neighbors, which will be utilized to find the empirically lowest delay path in the Admission Control Phase. After creating the corresponding cache entry in the DCT, this EDP will then be rebroadcasted to all its neighbors.

When the sink receives the EDP(s), it will generate *Reinforcement Interest* (RI) to pull down high quality data information (with higher packet transmission rate) from the target sensor(s). RI will be sent from the sink to a selected neighboring node that sent EDP packet(s) to the sink with the lowest delay. For example, as shown in Figure 4.1, the sink chose to send the RI to sensor A since A sent EDP packet(s) to the sink with the lowest delay. The network will then enter the Admission Control Phase.

Figure 4.1: Admission and rejection of Reinforcement Interests

4.4. Energy Neutral Directed Diffusion (ENDD)

4.4.2.2 Admission Control Phase

When a sensor node receives an RI, it will check the value under the “Destination ID” field in the header of this RI to determine whether it is the intended recipient of this RI. If this sensor node is the intended recipient, it will carry out the admission control procedure to decide if it can admit this RI.

As shown in Algorithm 4.2, this admission control procedure is comprised of three steps. In the first step, the sensor will check its current energy consumption status by estimating the *Current Projected Energy Consumption* $E_P(t)$. $E_P(t)$ represents the total amount energy that the sensor will consume during time slot t with the current number of RIs admitted. In step two, the sensor will estimate the *Additional Energy Consumption* $E_A(m)$, which is the additional amount of energy that will be consumed to relay the additional data packets after admitting a new RI m . The detailed way to estimate these two variables will be discussed in Section 4.4.4. In the third step, the sensor will compare if its energy budget $E_B(t)$ for this time slot t is larger than the sum of $E_A(m)$ and $E_P(t)$. If $E_B(t) \geq E_P(t) + E_A(m)$, it means the sensor will have sufficient energy to route the additional data packets queried by this new RI m without compromising its energy neutral state. In this situation, this sensor will admit RI m . Otherwise it will reject the RI m .

This admission control procedure is also illustrated using examples shown in Figure 4.1. After receiving a new RI m sent from the sink (step 1 in Figure 4.1), A will check its Current Projected Energy Consumption $E_P(t)$ and the Additional Energy Consumption $E_A(m)$ for admitting this RI m . Assume that $E_A(m) + E_P(t) \leq E_B(t)$. A will accept this RI m and create an entry for this RI in its ICT. Then A will next resend this RI to its Best Neighbor (step 2 in Figure 4.1) to relay

4.4. Energy Neutral Directed Diffusion (ENDD)

this RI to the target sensor.

A *Best Neighbor* of a sensor n must meet the following two criteria:

- It is delivering EDPs with the lowest delivery delay among all n 's neighbors
- It has not perviously rejected an RI that contains the same Interest ID as that contained in the RI that n is trying to send out

Assume that B is A 's best neighbor and it receives the RI from A . However, assume that node B rejects this RI because admitting this RI will compromise its energy neutral state. B will broadcast a *Rejection Message* (RM) corresponding to this RI to inform all its neighbors that it cannot sustain the data packet transmission rate specified by this RI in current time slot (step 3 in Figure 4.1). The neighboring nodes of B will then record the information contained in this RI in their RCT. As a result, in the same time slot, these neighboring nodes will not send another RI to node B again if the data packet transmission rate specified in this RI is higher than what B can sustain. This will help to reduce the control message overhead, which will be further discussed in Section 4.4.5.

Upon receiving this RM, A will select its best neighbor again (excluding neighbor B) and resend the corresponding RI (step 4 in Figure 4.1) to the reselected best neighbor (assumed to be node C). If C accepts this RI, it will decide its own best neighbor. The same admission control process will continue (step 5 in Figure 4.1) until the RI reaches the corresponding target sensor.

4.4. Energy Neutral Directed Diffusion (ENDD)

Algorithm 4.2: Admission Control for ENDD-T

```
foreach Reinforcement Interest m received by node n do
   $My\_ID \leftarrow$  ID of node  $n$ 
   $ITD\_ID \leftarrow$  Value of “Destination ID” field in  $m$ 
  if  $My\_ID = ITD\_ID$  then
    Check the ICT maintained by  $n$ 
    if a matching entry is found then
      This RI  $m$  has been received by  $n$  before
      Discard  $m$ 
    else if no matching entry is found then
      Estimate  $E_P(t)$  for current time slot  $t$ 
      Estimate  $E_A(m)$  for RI  $m$ 
      if  $E_P(t) + E_A(m) \leq E_B(t)$  then
        Create an entry for  $m$  in ICT
        Select the Best Neighbor
        if no Best Neighbor is found then
          Create an entry in RCT for  $m$ 
          Broadcast a Rejection Message
        else
          Send  $m$  to the Best Neighbor
        end
      else
        Create an entry in RCT for  $m$ 
        Broadcast a Rejection Message
      end
    end
  else
    RI  $m$  is not intended for  $n$ 
    Discard RI  $m$ 
  end
end
```

Choosing the Best Neighbor in this way will help ensure that the RIs are relayed to the target sensor via a *Feasible Empirically Lowest Delay Path*. Using this path, in the data propagation phase, data packets will be delivered to the sink with the lowest packet delivery delay possible, without compromising the energy neutral state of the sensors along this path.

4.4. Energy Neutral Directed Diffusion (ENDD)

Algorithm 4.3: Rejection Message Handling for ENDD-T

```
foreach Rejection Message r received by node n do
    Check the ICT maintained by n
    if r corresponds to an RI m that node n has sent before then
        Select the next Best Neighbor
        if no Best Neighbor is found then
            Create an entry in RCT for RI m
            Broadcast a Rejection Message
        else
            Resend RI m to the Best Neighbor
        end
    else
        Create an entry in RCT for r
    end
end
```

Note that if a sensor finds that all its neighbors rejects the RI it sent, it will also broadcast an RM corresponding to this RI. For example, if all *A*'s neighbors rejected the RI sent by *A*, *A* will broadcast an RM that corresponds to this RI which it received from the sink (this situation is not shown in Figure 4.1) to reject this RI. The detailed algorithm of handling the RMs can be found in Algorithm 4.3. We also note that there may be a chance that the RI generated by the sink is rejected by all its neighbors (due to their energy constraints) and thus the query cannot be completed. This ensures that no excessive routing tasks will be injected into the network, which in turn prevents network failure.

4.4.2.3 Data Propagation Phase

Data propagation phase begins when a target sensor receives an RI that queries the information it has sensed. This target sensor will begin to send back the queried information using Non-exploratory Data Packets (NDPs). These NDPs are sent

4.4. Energy Neutral Directed Diffusion (ENDD)

Algorithm 4.4: Data Propagation

```
foreach NDP d received by node n do
  My_ID  $\leftarrow$  ID of the node n
  ITD_ID  $\leftarrow$  "Destination ID" in d
  RI_ID  $\leftarrow$  "Interest ID" in d
  if My_ID = ITD_ID then
    Check the ICT maintained by n
    if an RI Entry in ICT has same Interest ID as RI_ID then
      Denote this RI Entry as hRI
      Check the DCT maintained by n
      if a matching entry is found for d then
        Discards NDP d
      else
        D_ID  $\leftarrow$  "Source ID" in hRI
        Send NDP d to node D_ID
        Create an entry for d in the DCT
      end
    else
      Discard NDP d
    end
  else
    Discard NDP d
  end
end
```

according to the high data packet transmission rate specified in the RI. Unlike the EDPs, NDPs are not broadcasted to all neighbors. Instead, NDPs will only be sent to the sensor that relays the corresponding RI. This corresponding RI contains the same Interest ID as the one carried by these NDPs.

Following Algorithm 4.4, upon receiving an NDP, a sensor will first check if it is the intended recipient. If this sensor is the intended recipient, the interest ID carried by this NDP will be searched in all RI Entries in the ICT. (We denote a cache entry in the ICT that corresponding to an RI as the *RI Entry*). This NDP will be discarded if no RI Entry has the same interest ID as that carried by this

4.4. Energy Neutral Directed Diffusion (ENDD)

NDP. (Since it would indicate that this sensor has never admitted the RI that queries this NDP.) Otherwise, an RI entry (denoted by h_{RI}) in the ICT will be found with the same Interest ID as that carried by this NDP. In this situation, this NDP will be checked against the DCT. If no matching entry is found in the DCT, this NDP will be transmitted to the next hop node. The ID of this next hop node is set to the value under the “Source ID” field in h_{RI} . In this way, NDP will be routed back to the sink via the sensors that has admitted and relayed the corresponding RI. (This in turn means that the NDPs will be delivered on the Feasible Empirically Lowest Delay Path). On the other hand, if a matching entry is found in the DCT, it would indicate that the same NDP has been previously received by this node and this NDP will thus be discarded.

4.4.3 ENDD-One Phase Pull (ENDD-O)

Similar to ENDD-T, ENDD-One phase pull protocol (ENDD-O) also performs admission control using the same energy consumption estimation method. However, no Exploratory Data Packets, Reinforcement Interests or Rejection Messages are needed for ENDD-O, (which makes it a lighter weight protocol as compared with ENDD-T). ENDD-O only makes use of one type of interest packet, which specifies a high data packet transmission rate (similar to the RI in ENDD-T). We refer to this kind of interest as the *One-phase Interest* (OI). ENDD-O operates in the following two phases:

4.4. Energy Neutral Directed Diffusion (ENDD)

4.4.3.1 Interest Propagation and Admission Control Phase

As shown in Figure 4.2 step 1, the sink will broadcast an OI that diffuses across the network to query desired data. The “Hops Count” field in the header of this OI is set to be 0. For a sensor node n , if it receives an OI from a neighboring node, two conditions will be considered based on Algorithm 4.5:

Condition 1: If it is the first time for sensor node n to receive OI m (no matching entry in the ICT for OI m), admission control will be performed. Sensor n will firstly estimate the Current Projected Energy Consumption $E_P(t)$ and the Additional Energy Consumption $E_A(m)$. (The way of estimating these two values will be further discussed in Section 4.4.4.) If sensor node n cannot admit an OI m due to the energy budget constraint, it will discard OI m and keep silent. (For example, sensors with the *Rejected* label as in Figure 4.2 belongs to this case). Otherwise, when OI m is admitted by the node n , an entry will be created in the ICT to record the information carried in the header of this OI.

The “Hops Count” field in the header of OI m will be used in ENDD-O to record the number of hops traversed by this OI. We denote the value in this field by $HC(m)$. After admitting OI m , a new entry will be created in the ICT of node n . In this entry, the “Hops Count” field will be used to record the number of hops between node n and the sink. We denote the value in this field by using $HC(n)$ and $HC(n)$ will be set to $HC(m) + 1$. Node n will then rebroadcast OI m with the “Hops Count” in the header of OI m modified to be $HC(m) + 1$. For example, following step 2 in Figure 4.2, sensor A will rebroadcast OI m with the value of the “Hops Count” in the header of OI m set to be 1. The value of the “Hops Count” in the ICT entry created for OI m in sensor A will be set to be 1.

4.4. Energy Neutral Directed Diffusion (ENDD)

Algorithm 4.5: Admission Control for ENDD-O

```

foreach One-Phase Interest  $m$  received by node  $n$  do
    Check the ICT maintained by  $n$ 
    if no matching entry is found (Condition 1) then
        Estimate  $E_P(t)$  for current time slot  $t$ 
        Estimate  $E_A(m)$  required by  $m$ 
        if  $E_A(m) + E_P(t) \leq E_B(t)$  then
             $HC(m) \leftarrow$  "Hops Count" field of OI  $m$ 
            Create an entry in ICT for  $m$ 
             $HC(n) \leftarrow$  "Hops Count" field in this newly created entry
            Set  $HC(n)$  to be  $HC(m) + 1$ 
            Increment  $HC(m)$  in OI  $m$  to be  $HC(m) + 1$ 
            Re-broadcast  $m$  to all neighbors
        else
            Discard OI  $m$ 
        end
    else if a matching entry is found (Condition 2) then
         $HC(n) \leftarrow$  "Hops Count" in this matching entry
         $HC(m) \leftarrow$  "Hops Count" carried by OI  $m$ 
        if  $HC(n) > HC(m) + 1$  then
            Update  $HC(n)$  to be  $HC(m) + 1$ 
            Update "Source ID" of this matching entry using the ID of the
            node that sent OI  $m$ 
            Increment  $HC(m)$  in OI  $m$  to be  $HC(m) + 1$ 
            Re-broadcast  $m$  to all neighbors
        else
            Discard OI  $m$ 
        end
    end
end

```

Condition 2: It is not the first time for sensor n to receive OI m , (a matching entry is found in the ICT). In this case, no admission control is needed since the sensor has already admitted an OI with the same Interest ID. The sensor will directly compare the value of the "Hops Count" field in the header of this OI m (denoted by $HC(m)$) and the value of the "Hops Count" field (denoted by $HC(n)$)

4.4. Energy Neutral Directed Diffusion (ENDD)

in this matching entry in the ICT of n .

If $HC(m) + 1 < HC(n)$, it means that OI m has traversed less number of hops before reaching node n as compared to OI(s) (with the same Interest ID) that are received by node n prior to OI m . Thus, node n will update the “Hops Count” field in this matching entry in ICT by setting $HC(n) = HC(m) + 1$. The “Source ID” field in this matching entry will also be updated to the ID of the node that sent this OI m . After this, OI m will be rebroadcasted to sensor node n ’s neighbors, with the “Hops Count” field in the packet header incremented by 1. For example, as shown in Figure 4.2, assuming that sensor C receives an OI m from sensor A with $HC(m) = 1$. We also assume that for this OI m , a matching entry is found in the ICT of sensor C with $HC(C) = 3$. Since $HC(m) + 1 < HC(C)$, sensor C will update the “Hops Count” in this matching entry in the ICT to be 2. Sensor C will also update the “Source ID” field in the matching entry to be the ID of sensor A . Following step 3 in Figure 4.2, C will then rebroadcast the OI to all its neighbors.

On the other hand, when $HC(m) + 1 \geq HC(n)$, m will be discarded and the sensor will keep silent. For example, for sensor D in Figure 4.2, assuming $HC(D) = 1$ and it receives an OI m from A with $HC(m) = 1$. Since $HC(m) + 1 = 2 > HC(D)$, this OI m will be discarded and sensor D will keep silent.

Hence, in ENDD-O, a node n will only record the node ID of its neighbor that is broadcasting an OI m with the smallest $HC(m)$ value, (if m can be admitted). This neighboring node is actually the node that relays OI m from sink to node n via the minimum number of hops possible. If more than one neighboring nodes sent OI m to sensor n with the same number of hops count, (if m can be admitted), n will choose the record the node ID of the neighbor from which it receives OI m first. This chosen neighboring node will be selected as the node to relay the data

4.4. Energy Neutral Directed Diffusion (ENDD)

Figure 4.2: Propagation of One-phase Interests

packets queried by OI m in the data propagation phase. In this way, the data packets generated at the target sensor node will be routed back to the sink via a *Feasible Minimum Hop Path*. Using this path, in the data propagation phase, data packets will be delivered to the sink via minimum number of hops possible, without compromising the energy neutral state of the sensors along this path.

4.4.3.2 Data Propagation Phase

When a sensor node receives an OI that queries the information it has sensed, it will become a target sensor and start transmitting its sensed information back to the sink with a high data packet transmission rate. The network thus enters the data propagation phase. The operation of the data propagation phase of ENDD-O is similar to that of ENDD-T, which can be found in Algorithm 4.4. A slight difference is that for ENDD-O, the data packets will be routed following the feasible minimum hop path established by the diffusing of OIs (step 4 as in Figure 4.2).

4.4. Energy Neutral Directed Diffusion (ENDD)

4.4.3.3 Exclusion of Redundant OIs

We note that the OIs in ENDD-O are rebroadcasted to all neighbors instead of sending to a specific best neighbor as in ENDD-T. As a result, nodes in ENDD-O might receive and admit some *Redundant OIs*. Data packets queried by these Redundant OIs will not be relayed by these sensor nodes in the data propagation phase. This is due to the fact that some nodes may admit and relay an OI with a larger hops count value as compared with other nodes. Such nodes will thus be excluded from the data routing path to make sure that the data packets are routed back to the sink via minimum number of hops possible. As a result, although some OIs are admitted and included in the calculation of Current Projected Energy Consumption of these nodes, the data packets queried by these OIs will not be relayed by these nodes.

In order to maintain the accuracy of the admission control procedure, we have to exclude these Redundant OIs from the energy consumption calculations. The detailed way of excluding a Redundant OI is shown in Algorithm 4.6. The checking and exclusion of a Redundant OI will be carried out periodically with a time interval of ΔT . If the data packets queried by an OI m have not been received by the sensor at the time of performing the Redundant OIs Exclusion, the entry in the ICT that corresponds to this OI m will be removed from the ICT. ΔT can be set to be several times larger than the packet delivery delay from the source to the sink. (The packet delivery delay from the source to the sink can be estimated once the sink receives a data packet.) In this way, we can ensure that a data packet intended to be relayed by a node n will reach this node before carrying out the Redundant OIs Exclusion process. This in turn ensures that the OI corresponding to this data

4.4. Energy Neutral Directed Diffusion (ENDD)

Algorithm 4.6: Exclusion of Redundant OIs for ENDD-O

```
foreach sensor node n do
    Periodically check the ICT with an interval of  $\Delta T$ 
    foreach entry in the ICT do
         $m \leftarrow$  The OI that this entry corresponds to
         $T_c \leftarrow$  Current system time
         $T_m^{start} \leftarrow$  "Start Time" of OI  $m$ 
        if  $T_m^{start} + \Delta T \leq T_c$  then
            Check the DCT to see if there is any entry that matches the data
            packets queried by  $m$ 
            if no matching entry is found then
                Delete the entry from the ICT
            end
        else
            Wait for the next checking
        end
    end
end
```

packet will not be undesirably excluded.

4.4.4 Real-time Energy Consumption Estimation

For our proposed ENDD-T and ENDD-O protocols, an accurate and realistic energy consumption model is required for the admission control to estimate the Current Projected Energy Consumption $E_P(t)$ as well as the Additional Energy Consumption $E_A(m)$ for admitting a new RI/OI m . Since the way to estimate $E_P(t)$ and $E_A(m)$ for admitting a new OI is similar to that for admitting a new RI, we only present in this section the way to estimate $E_P(t)$ and $E_A(m)$ for admitting a new OI.

For a sensor that is communicating with the other sensors in a network, energy is consumed when performing tasks such as the data packet transmission, reception

4.4. Energy Neutral Directed Diffusion (ENDD)

as well as the idle listening. Once the amount of energy that is required to transmit (E_{Tx}) or receive (E_{Rx}) one data packet is determined as discussed in Section 4.3.2, the energy consumed by the sensor to perform data transmission or reception tasks can be estimated by the number of packets that are being transmitted or received.

Assume that when the admission control is carried out to determine whether or not to admit a new One-phase Interest (OI) for ENDD-O, the sensor node has already admitted M OIs in current time slot t . At this point of time, the total number of data packets $\phi^{total}(t)$ that this sensor is supposed to receive and then transmit in this time slot t can be estimated by:

$$\phi^{total}(t) = \sum_{m=1}^M \phi_m^{total}(t) = \sum_{m=1}^M R_m \times T_m(t) \quad (4.4)$$

where $\phi_m^{total}(t)$ is the total number of packets that is supposed to be relayed by a sensor in time slot t for admitting an OI m . R_m is the data packet transmission rate (pkts/sec) specified by m . $T_m(t)$ is the portion of the event duration specified by m that lies within the current time slot t (the shaded area in Figure 4.3).

Figure 4.3: Calculation of $T_m(t)$ for different OIs

As shown in Table 4.5, the following four scenarios are to be considered for the calculation of $T_m(t)$.

Scenario 1: The start time of the event queried by an OI m (denoted by

4.4. Energy Neutral Directed Diffusion (ENDD)

$T_m(t)$	$T_m^{end} \geq T^{end}(t)$	$T_m^{end} < T^{end}(t)$
$T_m^{start} \geq T^{start}(t)$	$T^{end}(t) - T_m^{start}$	$T_m^{end} - T_m^{start}$
$T_m^{start} < T^{start}(t)$	$T^{end}(t) - T^{start}(t)$	$T_m^{end} - T^{start}(t)$

Table 4.5: Calculation of $T_m(t)$

T_m^{start} is larger (later) than or equal to the start time of the time slot t (denoted by $T^{start}(t)$) and the end time of the event queried by OI m (denoted by T_m^{end}) is also larger (later) than or equal to the end time of the time slot t (denoted by $T^{end}(t)$). In this scenario $T_m(t) = T^{end}(t) - T_m^{start}$. OI m'' shown in Figure 4.3 belongs to this scenario.

Scenario 2: The event queried by OI m starts before the start time of time slot t ($T_m^{start} < T^{start}(t)$), and ends before the end time of time slot t ($T_m^{end} < T^{end}(t)$). In this scenario, $T_m(t) = T_m^{end} - T^{start}(t)$. OI m shown in Figure 4.3 belongs to this case.

Scenario 3: The event queried by OI m starts before the start time of time slot t ($T_m^{start} < T^{start}(t)$) but ends after the end time of time slot t ($T_m^{end} \geq T^{end}(t)$). In this scenario, $T_m(t) = T^{end}(t) - T^{start}(t)$.

Scenario 4: The event queried by OI m starts after the start time of time slot t ($T_m^{start} \geq T^{start}(t)$) but it ends before the end time of time slot t ($T_m^{end} < T^{end}(t)$). In this scenario, $T_m(t)$ will be calculated by $T_m^{end} - T_m^{start}$. OI m' shown in Figure 4.3 belongs to this scenario.

Note that since the number of interest packets relayed by a sensor is comparably smaller than the amount of data packets relayed, the amount of energy consumed to relay the interested packet is neglected. The amount of interested packets exchanged is further studied in Section 4.4.5. In the real implementation, the sensor will have to transmit or receive more data packets than $\phi^{total}(t)$ as computed from

4.4. Energy Neutral Directed Diffusion (ENDD)

equation (4.4). This is due to the packet collisions and overhearing.

Packet Collisions: When two neighboring sensors are transmitting at the same time, data packet loss will occur due to *Packet Collision*. Data packet retransmission mechanism is thus implemented in the underlying MAC protocols to recover the lost packets. We define the Packet Retransmission Constant (denoted as β_{re}) to represent the number of data packets that are actually transmitted in order to successfully transmit one unique data packet. When performing the Admission Control of an OI m at time T_a , the expected packet retransmission constant β_{re} can be estimated by:

$$\beta_{re} = \frac{\Phi'_{Tx}}{\Phi_{Tx}} \quad (4.5)$$

where Φ'_{Tx} is the number of data packets that have been actually transmitted by the sensor in the current time slot at time T_a . Φ_{Tx} is the number of data packets that are supposed to be transmitted by the sensor according to the admitted OIs at time of performing the admission control.

Φ'_{Tx} and Φ_{Tx} can be estimated by implementing simple packet transmission counters that are initialized to be 0 at the beginning of each time slot. The counter for Φ'_{Tx} will be incremented whenever the sensor node transmits a data packet. The counter for Φ_{Tx} will be incremented when the sensor node has correctly received a data packet that is intended for it to relay to the next hop. At the time of performing the admission control (T_a), β_{re} will be evaluated by using the values in the counters. Then the expected number of packets that will actually be transmitted when the sensor is suppose to transmit $\phi^{total}(t)$ packets will be estimated by $\beta_{re}\phi^{total}(t)$.

4.4. Energy Neutral Directed Diffusion (ENDD)

Packet Overhearing: Due to the broadcasting nature of the wireless communications, a packet transmitted by a sensor can be heard by all sensors that lie within the transmission range of this sensor. As a result, a sensor may receive a packet that is not intended for it and this phenomenon is referred to as the *Packet Overhearing*. It is shown in [118] that the overhearing of a packet will result in an energy consumption that is equal to the energy consumed to receive this packet. Hence, for the calculation of the amount of energy consumed during the data packet reception process, an important factor to consider is the occurrence packet overhearing.

At the time (T_a) of performing the admission control, we estimate the expected number of packet receptions per second due to overhearing in a time slot t as follows:

$$\phi^{oh}(t) = \frac{\hat{\phi}^{oh}}{T_a} \quad (4.6)$$

where $\hat{\phi}^{oh}$ is the number of packets that the sensor has actually overheard in time slot t at time T_a .

$\hat{\phi}^{oh}$ can also be estimated by implementing a packet counter that is initialized to be 0 at the beginning of each time slot. This counter will be incremented every time the sensor node receives a data packet that is not intended for it to receive. Thus, at time T_a , based on the estimated $\phi^{oh}(t)$, the expected number of packets that are overheard by a sensor during time slot t is estimated by:

$$E[\phi^{oh}] = \phi^{oh}(t) \times T = \hat{\phi}^{oh} + \phi^{oh}(t)(T - T_a) \quad (4.7)$$

where $E[\cdot]$ is the sign of expectation. $\hat{\phi}^{oh}$ is the number of packets that are actually overheard at time T_a . $\phi^{oh}(t)(T - T_a)$ is the number of packet that are expected

4.4. Energy Neutral Directed Diffusion (ENDD)

to be overheard for the rest of the time $(T - T_a)$ in this time slot.

Idle Listening: We also note that, when the sensor is not transmitting or receiving data packets, it still consumes a certain amount of energy as its radio has to be turned on for potential data receptions. We refer to this scenario as the *Idle Listening*. It is shown in [58] that the idle listening is a major source of energy wastage for a sensor. *Duty Cycle* mechanism is proposed to reduce such energy waste. This mechanism let the sensor to turn off (go to sleep state) for a period of time to avoid the idle listening. A duty cycle refers to the fraction of time a sensor spends in the active state in one time slot. Thus, the energy consumed due to the idle listening during one time slot t can be estimated by:

$$E_{idle}(t) = P_{idle} \times D(t) \times T \quad (4.8)$$

where P_{idle} is the idle power consumption in Watt. $D(t)$ is the duty cycle in time slot t and T is the duration of time slot t in seconds.

The duration of the duty cycle will affect the amount of energy consumed due to idle listening and in turn will affect the overall network performance. However, as we focus on the developing the network layer routing protocol, we will not further discuss the suitable duration of the duty cycle as it might mask the performance of our proposed protocol. Thus, $D(t)$ is set to be one if not otherwise stated in this chapter.

From here, the Current Projected Energy Consumption $E_P(t)$ in a time slot t for the admitted M OIs can be estimated based on equations (4.4) to (4.8) by:

$$E_P(t) = (E[\phi^{oh}] + \phi^{total}(t)) E_{Rx} + \beta_{re} \phi^{total}(t) E_{Tx} + E_{idle}(t)$$

where $((E[\phi^{oh}] + \phi^{total}(t)))$ is the total number of packets that are expected to be

4.4. Energy Neutral Directed Diffusion (ENDD)

received by a sensor in time slot t .

Additional Energy Consumption $E_A(m)$ for admitting a new OI m is estimated by:

$$E_A(m) = \beta_{re}\phi_m^{total}(t)E_{Tx} + \phi_m^{total}(t)E_{Rx} \quad (4.9)$$

where $\phi_m^{total}(t)$ is the number of packets that a sensor is suppose to receive and transmit for admitting a new OI m in time slot t .

In this way, the value of $E_P(t)$ and $E_A(m)$ can be estimated at the time of performing the admission control process and thus ensures the Network-level Energy Neutral operation for sensors using our proposed ENDD protocols.

4.4.5 Upper Bounds on the Control Message Overheads

In order to establish a data routing path, control messages, which include Initial INterests, Reinforcement Interests, Rejection Messages and Exploratory Data Packets for ENDD-T as well as the One-phase Interests for ENDD-O, will have to be exchanged among sensor nodes. Recall that in Section 4.3.1, we represent the network using a graph $G = (V, E)$. Based on this network graph, we have the following theorems on the number of control messages exchanged:

Theorem 4.1. *The total number of control messages exchanged using ENDD-T for establishing one data routing path from the target sensor to the sink is upper bounded by $(e \times \Delta(G) + 3)|V|$, where $e \geq 1$ and $\Delta(G)$ is the maximum degree of a vertex in the network graph G .*

Proof. To generate a query using ENDD-T, the sink will broadcast an Initial INter-

4.4. Energy Neutral Directed Diffusion (ENDD)

est (INI) and this INI will be diffusing across the network. As discussed in 4.4.2.1, each sensor in the network will rebroadcast this INI only once after receiving it from a neighbor for the first time. As a result, the total number of INIs that will be broadcasted by all the sensor in the network is capped at $|V|$.

As discussed in Section 4.4.2, when a node n in the network receives an RI and rejects it, it will broadcast an RM to all its neighbors. In this way, neighbors of n will not relay this RI back to node n again in the current time slot. Hence, when no feasible data routing path exists (which is the worst case scenario), each node in the network will receive the same intended RI at most once. This in turn indicates that there will be at most $|V|$ RIs exchanged in the network. Since an RM will be broadcasted only when an RI is being rejected, every sensor node in the network will broadcast an RM at most once. Thus, the total number of RIs and RMs exchanged in the network will be capped by $|V|$ RIs plus $|V|$ RMs ($2|V|$ in total).

With the Exploratory Data Packets (EDPs) are flooding in the network, a sensor node will receive an EDP from one of its neighbors and then rebroadcast it. Since the maximum degree of a vertex in the network graph G is $\Delta(G)$, a sensor in the network will have at most $\Delta(G)$ neighbors. Hence, for each sensor, the same EDP packet will be rebroadcasted for at most $\Delta(G)$ times. Assuming that e ($e \geq 1$) EDPs are generated at the target sensor within the event duration as specified by the INI, the total number of EDPs that will be broadcasted by all the

4.4. Energy Neutral Directed Diffusion (ENDD)

sensors in the network is upper bounded by $e \times \Delta(G)|V|$.

As a result, the upper bound on the number of control message exchanged for ENDD-T to establish the routing path for one query is $|V| + 2|V| + e \times \Delta(G)|V| = (e \times \Delta(G) + 3)|V|$, where $e \geq 1$. $\square$

Note that in practical implementations, e will be set to a very low value such as 1 to reduce the number of EDPs needed.

Theorem 4.2. *The total number of control messages exchanged using ENDD-O for establishing one data routing path from the target sensor to the sink is upper bounded by $\Delta(G)|V|$.*

Proof. When ENDD-O is employed, upon receiving an OI, the admission control will be performed by a sensor to determine whether or not to admit this OI. This OI will not be rebroadcasted if it is not admitted. Furthermore, even if the OI was admitted, it will be rebroadcasted only when the value of the “Hops Count” field in the corresponding ICT entry has been decreased due to the lower “Hops Count” value contained in this OI. Thus, a sensor node will not rebroadcast every OI it received from its neighbors. This in turn implies that a sensor will rebroadcast an OI for at most $\Delta(G)$ times. Hence, the upper bound on the number of control messages exchanged for ENDD-O to establish the routing path for one query is $\Delta(G)|V|$. $\square$

For ENDD-O, a sensor will be receiving OIs with the same Interest ID from different neighbors. Since these OIs will be traveling in the network via different

sensor nodes, they will carry different values in the “Hops Count” field. As lower hops count usually means lower packet delivery delay, OIs carrying a lower “Hops Count” value will tend to reach a sensor earlier than those carrying higher “Hops Count” values. Thus, it is highly possible that OIs that arrive later will not be rebroadcasted (due to the high hops count contained). As a result, the total number of OIs exchanged under ENDD-O could be much lower than the theoretical upper bound $\Delta(G)|V|$. It also means that ENDD-O requires much less control messages to establish a path as compared with ENDD-T, which is burdened by the flooding of the EDPs.

When the density of the sensor in the network is fixed, changing the network size ($|V|$) will not result in a change in $\Delta(G)$. In this case, we can find that the upper bounds $(e \times \Delta(G) + 3)|V|$ (ENDD-T) and $\Delta(G)|V|$ (ENDD-O) are linear to the network size $|V|$. Thus, increased network size does not affect the upper bound on the number of control messages sent by one sensor in the network, which means this protocol is highly scalable with the network size when the sensor density is fixed. We will verify the actual number of control messages exchanged under various circumstances through empirical studies in Section 4.5.

4.5 Empirical Studies

In this section, the performance of our proposed ENDD protocols (ENDD-T and ENDD-O) are compared through empirical studies with two query driven routing protocols, namely Directed Diffusion (DD) [102] and Energy Differentiated Directed Diffusion (EDDD) [109]. Simulations are carried out using the OMNeT++ simulator [119].

4.5.1 Simulation Setup

50 energy harvesting sensor nodes are deployed randomly (following uniform distribution) in a $100m \times 100m$ field. Each sensor node has a maximum radio transmission range of $20m$. A data sink is placed at the center of the sensor deployment field. In the generated network graph, a sensor has at most 8 neighbors ($\Delta(G) = 8$).

The duration of a time slot is set to 360 seconds. Different sensor will be experiencing different energy harvesting rates in a time slot. We assume that, in a time slot t , $E_H(t)$ for a sensor is randomly chosen by: $E_H(t) = 5.4 + X$, where X is a random variable and it follows the normal distribution with $X \sim \mathcal{N}(0, 0.16)$. In this way, the mean energy harvesting rate of a sensor is 5.4 Joule, which is the estimated average amount of solar radiation energy harvestable in one time slots (360 seconds) based on the data retrieved from the US TEXAS Solar Radiation Database [1]. Upon deployment, we assume that every energy harvesting sensor node carries a rechargeable battery with an initial battery residual energy level of 2000 Joule [81].

The duration of a queried event is set to 10 seconds. The data packet transmission rate specified in INIs is set to be 1 packet per 10 seconds. The data packet transmission rate specified in RIs and OIs is set to be 10 packets per second. The network traffic load is controlled by the **Interest Injection Interval**, which is a measure that reflects the number of interests that are generated and injected into the network from the sink. Within each Interest Injection Interval, six interests (6 INIs and 6 RIs for ENDD-T, 6 OIs for ENDD-O) will be injected into the network at a random time instance. For example, an Interest Injection Interval of 20 seconds means that six interests will be injected into the network at a random time

Communication Parameter	Value
Data Packet Length	1024 bits
Control Message Packet Length	256 bits
ϵ_{e-tx}	$21 \times 10^{(-8)} J/bit$
ϵ_{e-rx}	$35 \times 10^{(-8)} J/bit$
P_{idle}	10mW
ϵ_{sp}	$2 \times 10^{(-9)} J/(bit \cdot m^2)$

Table 4.6: Communication related parameters

(within the time interval) for every 20 seconds.

In order to provide a realistic simulation environment, we use CSMA/CD as the MAC layer protocol. Collisions may occur and packets might be dropped under heavy contentions. However, since the focus of this chapter is not on an efficient data packet retransmission mechanism, we assume that no data packet retransmission will be scheduled when packets are dropped due to heavy contention. Thus, β_{re} is set to be one. As a result, not all packets generated at the target sensor can be successfully delivered to the sink. We adopt the communication parameters from a commercially available wireless transceiver CC1000 443MHz [85], which can be found in Table 4.6.

4.5.2 Network-level Energy Neutral Management

We firstly carry out empirical studies to test the data delivery consistency under different routing protocols. This will in turn verify a protocols ability to ensure the Network-level Energy Neutral Management.

For fair comparison, we assume that all routing protocols employ P-FREEN for Node-level Energy Neutral Management. During one time slot, a sensor will be forced to shut down if it consumes more energy than the amount of energy budget

allocated to this time slot. We measure the *Node Failure Time* by the amount of time a node is forced to shut down within one time slot. A higher node failure time will in turn implies a more severe breach of the consistency in data delivery. Thus, we use the *Accumulated Node Failure Time* (ANFT), which is the sum of the node failure time for all sensor nodes in the network during one time slot to evaluate a routing protocol's ability to provide Network-level Energy Neutral Management.

Figure 4.4: Accumulated Node Failure Time using the three protocols

As shown in Figure 4.4, when the traffic load in the network is low (with an interest injection interval that is higher than 22 seconds), the network experiences a zero ANFT with the four protocols under evaluation. It means that the Network-level Energy Neutral Management can be provided by all the four routing protocols under low traffic load. When the interest injection interval drops below 20 seconds, the sensor network begins to experience node failures when DD is employed. This in turn implies that DD cannot provide the Network-level Energy Neutral Management with the higher traffic load under this situation. When EDDD is employed, the occurrence of node death begins when interest injection interval drops below

14 seconds. This means that although EDDD has a stronger ability of balancing the energy consumption as compared to DD, it cannot provide the Network-level Energy Neutral Management when the network traffic load is high. When the network traffic load is increased to a very high level with an interest injection interval of less than 10 seconds, the network experiences a high value of ANFT when either DD or EDDD is employed.

On the other hand, ENDD-T and ENDD-O can provide the Network-level Energy Neutral Management under all traffic loads with an ANFT of zero. This is due to the fact that although a large number of interests are injected into the network, sensor nodes using ENDD-T and ENDD-O will choose to reject certain interests if their energy neutral state would be compromised when these interests are admitted. As a result, sensor nodes using ENDD-T and ENDD-O will not relay more traffic flows than that they can actually handle. This in turn ensures the consistent delivery of data packets that are queried by the admitted interests and less node failure caused data packet loss will be experienced.

4.5.3 Distinct Packet Delivery Ratio

With the Network-level Energy Neutral Management, data packets can be consistently delivered to sinks without interruption. Beside the data delivery consistency, it is also desirable to efficiently utilize the available energy so that more data packets could be delivered back to the sink for further analysis. We thus carried out simulations to evaluate the *Distinct Packet Delivery Ratio* (DPDR) that could be achieved by using the four protocols under different traffic loads. Distinct Packet Delivery Ratio measures the portion of the unique data packets (sent from the

Figure 4.5: Distinct packet delivery ratio comparison

target sensor) that are successfully received by the sink.

When the traffic load is low (with an interest injection interval of higher than 20), the performance of ENDD-T, ENDD-O and DD are similar in terms of DPDR. When the traffic load is high (with an interest injection interval of less than 20), ENDD-T and ENDD-O outperforms DD. This is because, since DD cannot provide Network-level Energy Neutral Management under high traffic load, data packets might be dropped due to sensor failures, which in turn results in a lower DPDR.

EDDD performs the worst in terms of DPDR. This is due to the fact that, in order to prevent node death, EDDD allows sensors with higher BRELS to join the traffic routing path instead of choosing the nodes on the lowest delay path (as in DD). Thus, although EDDD achieves lower ANFT as compared with DD, it might choose a high delay routing path that consists of more sensor nodes. This means that a data packet will be relayed by a large number of sensors. Since the MAC layer contentions will be carried out at every sensor node, packets routed by EDDD will experience a higher chance of collisions. As a result, the packets loss

Figure 4.6: Average end-to-end packet delivery delay comparison

due to the elevated number collisions will result in a decrease in the DPDR when EDDD is employed, (which masks the positive contribution of the lower ANFT under EDDD as compared to DD).

4.5.4 Average End-to-End Packet Delivery Delay

Other than the DPDR, another important network performance metric is the packet delivery delay. We carry out the empirical studies to evaluate the average *End-to-End Packet Delivery Delay* experienced by the data packets when different protocols are employed. The end-to-end packet delivery delay is measured by the difference between the time the sink receives the data packet and the time this data packet was sent out by the target sensor. The delay of a lost data packet is ignored.

As shown in Figure 4.6, we find that EDDD performs the worst in terms of end-to-end delay due to its delay insensitive routing path selection. It only considers

the BREL of a sensor when making routing decisions. We also find that under higher traffic loads with an interest injection interval of smaller than 16 seconds, ENDD-T performs slightly better than DD although ENDD-T and DD use the same empirically lowest delay path selection mechanisms. This is due to the fact that ENDD-T will choose other path(s) to carry the additional traffic load when the traffic load increases to a point where the empirically lowest delay path is not sustainable. Thus, the length of the data packet queues (waiting for transmission) at the sensor node using ENDD-T will be smaller as compared to DD. As a result, the waiting time reduction in the data queues helps to lower the end-to-end packet delivery delay when ENDD-T is employed.

It is also confirmed in Figure 4.6 that ENDD-T performs better than ENDD-O in terms of end-to-end packet delivery delay. That is due to the fact that ENDD-T uses the feasible empirically lowest delay path. ENDD-O however sets up a feasible minimum hop path, which may not be the actual lowest delay path due to MAC layer contentions and back off mechanisms. Hence, if the application is delay sensitive, ENDD-T is preferred.

4.5.5 Control Message Overhead

A lower control message overhead is also important for routing protocols as it can reduce the energy cost in setting up routing paths and improve the scalability of the protocols. Hence, we record the actual number of control messages exchanged when different protocols are employed and the results are shown in Figure 4.7. For ENDD-T, the number of RIs and RMs are summed together and represented using the “RI” label.

Firstly we can verify from Figure 4.7 that the number of control messages exchanged using ENDD-T and ENDD-O is well bounded by the theoretical upper bound as specified in Theorem 4.1 and Theorem 4.2. For example, when the Interest Injection Interval is 18 seconds, the actual numbers of control messages exchanged are 32693 using ENDD-T and 6813 using ENDD-O. With $\Delta(G) = 8$, the theoretical upper bound for the number of control messages exchanged is 66000 using ENDD-T and 48000 using ENDD-O, which is well above the actual numbers recorded. Note that, as analyzed in Section 4.4.5 the actual number of control messages exchanged when ENDD-O is employed is much lower than the theoretical upper bound.

We can also observe from Figure 4.7 that, DD and ENDD-T are experiencing comparably larger amount of control messages than that experienced by EDDD and ENDD-O. This is due to the fact that DD and ENDD-T requires the flooding of EDPs to help establish empirically lowest delay path, which causes large amount of control message overhead. As for the one phase pull based protocols, EDDD requires much more control messages to establish traffic routes than that required by ENDD-O. This is because nodes using EDDD will rebroadcast an OI whenever a new route with higher Minimum Energy Node (MEN) is found. MEN refers to the node with the minimum BREL on the routing path. As a route with a high MEN is not necessarily the route with the minimum hops count, OIs have to be exchanged several times between sensors before the route with highest MEN node is found. This in turn results in large amount of control messages being exchanged. For the case of ENDD-O, sensors will keep silent if they cannot admit new OIs due to energy constraints. Thus the rebroadcasting of OIs will be suppressed for these sensors and hence the total number of OIs exchanged under ENDD-O is smaller.

Figure 4.7: Control message overhead comparison. (A: “EDDD”, B: “ENDD-O”, C: “DD”, D: “ENDD-T”.)

Hence, if the application is not delay sensitive, ENDD-O is preferred as it is a lighter weight protocol that requires less control messages.

4.6 Summary

In this chapter, a novel query driven Energy Neutral Directed Diffusion (ENDD) protocol is proposed with the goal of providing Network-level Energy Neutral Management and thus enabling perpetual operations for an energy harvesting wireless sensor network. ENDD employs admission controls to regulate the traffic load on each node according to its own energy harvesting status. In addition, a real-time realistic sensor energy consumption model is proposed to facilitate the admission control procedure. Based on different data pulling models, two variations of the ENDD protocol, namely ENDD-T and ENDD-O, are proposed to meet different

design requirements. ENDD-T can be used by applications that are sensitive to packet delivery delays, while ENDD-O is a lighter weight protocol designed for less delay-sensitive applications. We also prove that the control message overheads experienced by ENDD-T and ENDD-O are linearly upper bounded by the network size, which means our proposed protocols scale well with the network size.

Extensive empirical studies verify that our proposed ENDD protocols can effectively provide Network-level Energy Neutral Management so that data packets can be consistently delivered to destinations. It is also observed through empirical studies that, as compared to current available query driven protocols, our proposed ENDD-T protocol can provide lower end-to-end packet delivery delay and higher distinct packet delivery ratio. The actual number of control messages exchanged in the empirical studies is also consistent with the theoretical upper bound we derive. It is also shown that our proposed ENDD-O protocol has the lowest control message overhead among the query driven protocols under evaluation.

Chapter 5

Energy Neutral Clustering for Energy Harvesting Wireless Sensors Networks

Other than the query driven energy neutral routing protocol as studied in the previous chapter, a distributive Energy Neutral Clustering (ENC) protocol, which is specially designed for sensor networks that require the periodical delivery of data, is studied in this chapter. ENC employs a novel Cluster Head Group (CHG) mechanism that allows a cluster to use multiple cluster heads to share heavy traffic load. This CHG mechanism can help to reduce the frequency of cluster re-formations, which in turn reduces the control message overhead. The optimum number of clusters that maximizes the amount of information gathered from the network is mathematically derived using convex optimization. Based on this optimum number of clusters, an extension to ENC is proposed to group the network into equal sized clusters so that maximized network information gathering can be achieved. Extensive empirical studies show that ENC can provide Network-level Energy Neutral Management while achieving substantial improvements on the amount of information gathered as compared to traditional clustering protocols.

5.1 Introduction

As discussed in the previous chapters, powered by batteries/super-capacitors, traditional wireless sensors can only access to limited energy resource. A sensor will be *Dead* when the energy resource in its battery is depleted and it will stop functioning normally. Thus, mechanisms to prolong the *Network Lifetime*, which measures the amount time of elapsed before the first sensor (or a fraction of sensors) is dead, are being extensively studied in the past few decades.

Since the routing of data packets directly determines the energy consumption for a sensor, many network layer routing protocols have been proposed to efficiently utilize the available energy to prolong network lifetime. It is discussed in [34] that, for applications with continuous data delivery model, since the information is generated periodically at each sensor, redundant information will be sensed and delivered by the network. For this kind of applications, it is concluded in [86] that the hierarchical (clustering) routing protocol is the most efficient alternative since it can enable in network data aggregation. With these clustering protocols, sensors in the network will be grouped into a number of clusters. In each cluster, there will be a Cluster Head and several Cluster Members. A *Cluster Member* (CM) is the type of sensor that senses information from the environment and then sends the sensed information to the Cluster Head for further processing. The *Cluster Head* (CH) gathers and aggregates the information sent by the CMs. It will then send the aggregated information to the Base Station. By efficiently managing the selection of the CH and CMs, several clustering protocols (such as the ones in [86, 120, 121]) have been proposed to prolong the network lifetime. However, due to the limited energy resources available in the batteries, no matter how carefully these

clustering protocols are designed, sensors will eventually deplete their batteries and stop functioning.

As discussed in Chapter 4, the emergence of energy harvesting techniques provides the possibility of achieving unlimited lifetime for Energy Harvesting Wireless Sensor Networks (EH-WSNs). Several flat routing protocols ([49, 48, 122]) have been proposed in the literature to exploit the energy harvested from the environment. However, to the best of our knowledge, clustering protocol that aims at providing Network-level Energy Neutral Management for an EH-WSN has not been explored. As compared to flat routing protocols, clustering protocols possess the inherited advantages on energy efficiency and scalability [123]. Thus, a clustering protocol is proposed in this chapter to cluster an EH-WSN so that perpetual network operation can be achieved. The main contributions of this chapter are:

- An Energy Neutral Clustering (ENC) protocol that provides the Network-level Energy Neutral Management. ENC clusters the network with goal of providing perpetual network operation by controlling the size of the clusters as well as the data traffic load at each sensor. It can be implement distributively with a low protocol communication overhead.
- A Cluster Head Group (CHG) mechanism that allows one cluster to have multiple Cluster Heads. CHG helps reduce the number of cluster re-formations and Cluster Head re-selections needed. This in turn reduces the protocol control message overhead and enhances the consistency of data delivery.
- Mathematically derived optimum number of clusters that maximizes the amount of information that can be gathered from the network, while providing Network-level Energy Neutral Management.

The rest of the chapter is organized as follows. In the next section, some of the important works that are related to our proposed protocol are reviewed. Section 5.3 discusses the network topology as well as the energy model that are being used in this chapter. Our proposed ENC protocol will be presented in Section 5.4. The optimum number of clusters that maximizes the data information gathering is derived in Section 5.5. An extension to ENC is proposed in Section 5.6. Empirical studies that verify the performance of our proposed protocols are presented in Section 5.7. This chapter is then summarized in Section 5.8.

5.2 Related Works

In the literature, clustering protocols are being extensively studied in the past few decades. The Low Energy Adaptive Clustering Hierarchy (LEACH) [86] is an important clustering protocol that aims at prolonging the network lifetime. It points out that since a Cluster Head (CH) usually carries heavy processing tasks and traffic loads, it is more energy intensive as compared to Cluster Members (CMs). To address this problem, a *Cluster Head Reselection* (CH-Reselection) mechanism is included in LEACH. The system time is divided into *rounds* and the sensor network will be reorganized into new clusters at the beginning of each round. Sensors that have never been the CH before will have a higher chance of being selected as CHs for these newly formed clusters. Using this kind of CH-Reselection mechanism, energy consumption balance between CHs and CMs can be achieved and the network lifetime is thus improved.

However, one problem for LEACH is that the CHs that are far away from the Base Station usually consumes energy faster than the ones near the Base Station.

This in turn creates another form of imbalance in energy consumption. Thus, an Energy Efficient Clustering Scheme is proposed in [124] to solve this problem by allocating more CMs to those clusters that are near the Base Station and less CMs to those clusters that are far away from the Base Station. It is worth mentioning that in [41], a Solar-aware LEACH protocol is proposed to deal with the situation when a fraction of sensor nodes in the network have the capability of harvesting solar energy. Using this protocol, sensors with the energy harvesting capabilities will have a higher chance of being chosen as a CH. A centralized clustering protocol is proposed in [125] to control the size of the cluster and the location of the CH so that energy balance would be achieved.

Another issue is that LEACH assumes that all the CHs in the network communicate directly with the Base Station. The cost for this kind of single hop communication can be very expensive when the distance between CH and the Base Station is large. In [120], a Hybrid Energy Efficient Distributed (HEED) clustering protocol is proposed to address this problem by adopting a multihop inter-cluster communication model. Using this model, CHs that are closer to the Base Station will relay the information sent from CHs that are farther away from the Base Station. Several other protocols are also proposed based on the multi-hop inter-cluster communication model [126, 127, 128]. In this way, the expensive long distance communication will be replaced by several less-expensive short distance communications. However, by using HEED, CHs that are closer to the Base Station will have to relay additional traffic flows and will thus deplete energy much faster. To solve this problem, the unequal sized clustering techniques are being studied [121, 129, 130, 131]. Using this kind of technique, those clusters that are closer to the Base Station to have smaller clusters size so that the intra-cluster traf-

fic load for those clusters can be reduced. The energy consumption for this kind of multi-hop inter-cluster communication is comprehensively studied in [25, 132] to provide accurate control of the cluster size.

The clustering protocols mentioned above take numerous efforts to prolong the network lifetime. However, since the term network lifetime is no longer a primary concern for Energy Harvesting Wireless Sensor Networks (EH-WSNs), these clustering protocols might not be able to meet the special energy constraints put up by the energy harvesting sensors. Thus, a carefully designed clustering protocol is needed to meet these energy constraints so that unlimited network lifetime can be achieved.

5.3 System Models and Notations

5.3.1 Network Setup

N Energy Harvesting Sensors are assumed to be deployed randomly (following the uniform distribution) in a field. For the convenience of analysis, the shape of the field is assumed to be a disk area with a radius of R meters. The area of the field is thus πR^2 square meters. Sensors will be grouped into several clusters. In each cluster there will be one or more Cluster Heads (CHs) that gather and aggregate the information received from the Cluster Members (CMs). These CMs will be sending their sensed information directly to the CHs in the form of data packets with a certain data packet transmission rate. Sensors that are selected to be CHs will be exempted from information sensing tasks to reduce their energy consumptions. The Base Station is located at the center of the disk area. It is a

common practice that the Base Station can be a manned station with power grid connection, which means it can gain access to unlimited amount of energy.

Similar to LEACH [86], we assume in this chapter that the CHs will communicate directly with the Base Station. We do note that as discussed in Section 5.2, this kind of direct communication will not be as energy efficient as the multihop communication when the distance between the CH and the Base Stations is large. However, the multihop inter-cluster communication models [25] involve higher computational complexities and additional control message overheads. Thus, since the focus of this chapter is to propose the Energy Neutral clustering protocol that explores the additional research dimension provided by the energy harvesting technique (instead of the advantages brought by multihop communications), we choose the single hop communication model for its simplicity.

5.3.2 Sensor Energy Consumption Model

For the communication related energy consumptions (energy consumed in data packet transmissions or receptions), we adopt the energy dissipation model used by LEACH in [86]. The energy consumed by a sensor to transmit one bit of information (denoted by $E^{Tx/b}$) is estimated by:

$$E^{Tx/b} = \begin{cases} \varepsilon_{e-tx} + \varepsilon_{sp}d^2 & \text{if } d < \hat{d} \\ \varepsilon_{e-tx} + \varepsilon_{mp}d^4 & \text{if } d \geq \hat{d} \end{cases} \quad (5.1)$$

where constant ε_{e-tx} is the amount of energy consumed by the transmitter electronics to perform tasks such as the signal filtering, modulation and code spreading. d is the distance between the transmitting sensor and the receiving sensor. When d is smaller than the crossover distance $\hat{d}$, the path loss can be treated as Friis free space loss with d^2 power attenuation. When d is larger than $\hat{d}$, the path loss model

5.3. System Models and Notations

can be approximated as a two ray multi-path propagation model with d^4 power attenuation. Constants ε_{sp} and ε_{mp} will be set according to the required SNR at the receiver so that the bit error rate is acceptable. Note that equation 5.3 is a special case of equation 4.1 with $L = 1$.

The energy consumed by a sensor to receive one bit of information (denoted by $E^{Rx/b}$) is estimated by:

$$E^{Rx/b} = \varepsilon_{e-rx} \quad (5.2)$$

where constant ε_{e-rx} is the amount of energy consumed by the receiver electronics to receive one bit of information.

Due to different task requirements, the Cluster Member (CM) and the Cluster Head (CH) consume energy in different ways. For sensors that are selected to be the CM, energy will be spent on information sensing and data packet transmission. Thus, based on equation (5.1), the total amount of energy consumed by a CM n to sense and transmit one bit of information is estimated by:

$$E_{CM}^n = \varepsilon_{Sx} + E_{CM}^{Tx/b} \quad (5.3)$$

where ε_{Sx} is the amount of energy consumed to sense one information bit, $E_{CM}^{Tx/b}$ is the amount of energy needed for a CM to transmit one bit of information, which depends on the distance between this CM and the CH.

A CH will consume energy to receive and aggregate data packets sent from the CMs. It will also consume energy to send the aggregated data packets to the Base Station. The *Data Aggregation* technique can combine several correlated data signals into a smaller set of data signals without losing the effective information contained in the original data signals [86]. When perfect aggregation is assumed,

these correlated signals will be combined into one signal. Thus, for a cluster k , if it has N_{CM}^k CMs, the total amount of energy consumed by the CH n to *handle* (receive, aggregate and then transmit) one bit of information sent by the CMs is estimated as follows:

$$E_{CH}^n = E^{Rx/b} + \alpha \varepsilon_{DA} + \frac{E_{CH}^{Tx/b}}{\alpha} \quad (5.4)$$

where $E^{Rx/b}$ is the amount of energy spent to receive this one bit of information. ε_{DA} is the constant (Joule/bit/signal) used in the data aggregation process and $\alpha \varepsilon_{DA}$ is the amount of energy spent in aggregating one bit of information. $E_{CH}^{Tx/b}$ is the amount of energy needed for a CH to transmit one bit of information, which depends on the distance between this CH and the Base station. $\frac{E_{CH}^{Tx/b}}{\alpha}$ is thus the amount of energy spent in transmitting the aggregated information ($\frac{1}{\alpha}$ bit) to the Base Station. α is the aggregation factor, where $\alpha = N_{CM}^k$ means perfect aggregation and $\alpha = 1$ means no aggregation.

5.3.3 Energy Budget

The same as stated in Chapter 4, the system time is divided into time slots that are indexed by t , where $t = 1, 2, \dots, N_t$. The time duration for a time slot is T seconds. The amount of energy harvested in a time slot t by a sensor node n , (where $n = 1, 2, 3, \dots, N$), is denoted by $E_H^n(t)$ (Joule). To maintain the Energy Neutral state, the energy consumed by a sensor should be no more than the amount of energy harvested by its energy harvesting device during a certain period of time. The term *Energy Budget* is also used in this chapter to represent the amount of energy $E_B^n(t)$ that can be used by a sensor n in a time slot t , without compromising

the Energy Neutral state of the sensor. Thus, by the definition of Energy Neutral state, we have:

$$\sum_{t=1}^{N_t} E_B^n(t) \leq \sum_{t=1}^{N_t} \eta E_H^n(t) \quad (5.5)$$

where η is the Harvested Energy Utilization Efficiency as studied in Chapter 2.

The same as discussed in Chapter 4, the amount of information bits relayed by a sensor node has a linear relationship with the sensor energy consumption once the distance d between the transmitting sensor node and the receiving sensor node is fixed. This means that ENC can also employ P-FREEN to provide Node-level ENM. For simplicity, we also assume in this chapter that the battery energy storage efficient $\eta_S = 1$.

5.4 Energy Neutral Clustering

5.4.1 Cluster Head Group

Conventionally, in each cluster, there will be one *Cluster Head* (CH) and several *Cluster Members* (CMs). Since the distance between a CH and the Base Station is usually much larger than that between a CH and a CM, a CH usually consumes more energy on information transmission than that of a CM. As a CH will also perform additional data reception and aggregation tasks, it will deplete its battery much faster than CMs. *Cluster Failure* will happen when the CH depletes its battery and the information sensed by the CMs will not be relayed to the Base Station anymore. Thus, as mentioned in Section 5.2, traditional clustering protocols, such as LEACH and HEED, employ the *Cluster Head Reselection* (CH-Reselection)

scheme to solve this problem. Using this scheme, clusters will be re-formed periodically and CHs will be reselected when these new clusters are formed. As a result, all sensors (or sensors with high battery residual energy level) will be playing the role of the CH in turn to share the heavy energy consumption and thus delay the network failure.

For an EH-WSN, if a CH can harvest more energy than the amount of energy it consumes in one time slot, no CH-Reselection will be needed. However, due to the size constraint, in real practice the energy harvested by one sensor node in one time slot usually could not sustain the heavy energy consumption of being a CH for the whole time slot. One way to solve this problem is to employ the CH-Reselection scheme. However, the CH-Reselection scheme requires additional control messages to be exchanged when forming new clusters and selecting new CHs, which in turn results in additional energy consumption. In addition, data information transmission has to be suspended during the cluster reformations, which compromises the data delivery consistency. In view of this, we propose the concept of the **Cluster Head Group**, which is defined as follows:

Definition 1: A *Cluster Head Group* (CHG) is a set of sensor nodes that will take turns to act as the Cluster Head of a cluster during one time slot.

As shown in Figure 5.1, instead of having only one CH within each cluster, ENC allows a cluster to have more than one CHs to form a CHG (nodes lies in the dashed circles). A sensor that belongs to a CHG is referred to as a *CHG-node*. CHG-nodes will be scheduled to become the *Active Cluster Head* (Active-CH) in turn. When a CHG-node is scheduled to be an Active-CH, it will be playing the role as a traditional CH. Otherwise, it will turn off its radio and go to sleep to conserve energy. Thus, the traffic load carried by a single CH in a traditional

cluster is now shared by the set of CHG-nodes. As each CHG-node can harvest energy from its own energy harvesting device, it is easy to find a suitable size for the CHG so that the total amount energy required (to process and relay the sensed information from CMs) is no more than the total amount of energy harvested by the all the CHG-nodes during one time slot. We denote the size of the CHG, i.e., the number of CHG-nodes, in a cluster k to be N_G^k . The way to estimate N_G^k will be presented in Section 5.4.3.

Figure 5.1: Cluster Members and Cluster Head Groups

5.4.2 Energy Neutral Clustering (ENC) protocol

Based on the concept of the Cluster Head Group (CHG), we now present the detailed operation procedures for our proposed Energy Neutral Clustering (ENC) protocol. We assume that, upon deployment, each sensor node will be assigned with a unique sensor Node ID for identification. The location of each sensor is not required to be known in advance. However, each sensor will learn the relative distance between itself and the Base Station. This can be done by letting the Base

5.4. Energy Neutral Clustering

Table 5.1: Control Message configurations

Message Type	Fields	Utility
“CLUSTER”	‘Cluster ID’	ID of the cluster
“JOIN”	‘Node ID’	ID of the joining node
	‘Cluster ID’	ID of the intended cluster
	‘EnergyBudget’	Energy Budget of the joining node in current time slot
	‘DistanceToBS’	Distance between the joining node and the Base station
	‘DistanceToCH’	Distance between the joining node and the Center Node
“SCHEDULE”	‘Node_1 ID’	ID of the scheduled Node_1
	‘Node_1 Type’	CHG-Node/Final-CM
	‘Node_1 Schedule’	Period of time to wake up
	‘Node_2 ID’	ID of the scheduled Node_2
	‘Node_2 Type’	CHG-Node/Final-CM
	‘Node_2 Schedule’	Period of time to wake up
	‘Node_n ID’	ID of the scheduled Node_3
	‘Node_n Type’	CHG-Node/Final-CM
	‘Node_n Schedule’	Period of time to wake up

Station to broadcast a beacon message. A sensor will measure the received beacon signal strength and estimate the relative distance using the techniques described in [133].

Figure 5.2: Operation timeline of the ENC algorithm

As shown in Figure 5.2, ENC is carried out at the beginning of each time slot.

Algorithm 5.1: ENC Algorithm-Initialization

INITIALIZATION:

foreach *sensor node* **do**

$myID \leftarrow$ Node ID for this sensor

$myDistoBS \leftarrow$ Relative distance to Base Station

$myBudget \leftarrow$ Energy Budget in current time slot

$p \leftarrow random(0, 1)$

if $p \leq P_K$ **then**

$myRole \leftarrow$ Center Node

else

$myRole \leftarrow$ Initial-CM

end

end

It works in three phases:

Phase 1: Initialization. We assume that the network is expected to be clustered into K clusters, where the value of K is defined and controlled by the user. Thus, as shown in Algorithm 5.1, several sensor nodes will be randomly selected to be the Center Nodes of the initially spawned clusters. A *Center Node* (CN) is the sensor node that is located at the geographical center of the spawned cluster.

In order to select these CNs, a constant P_K is assigned to each sensor, which is calculated by:

$$P_K = \frac{K}{N} \quad (5.6)$$

where P_K denotes the probability of a sensor to be selected as a CN.

Each sensor will then generate a random number ranged from 0 to 1. A sensor will become a CN if it generates a number that is smaller than P_K . Hence, by the definition of expectation, the expected number of clusters generated in the network will be $N \times P_K = K$. The rest of the sensor nodes, (which generate numbers that

are larger than P_K), will become the Initial Cluster Members (Initial-CMs).

Phase 2: Cluster Formation. As shown in Algorithm 5.2, with every sensor decided its own role, a CN will begin broadcasting a “CLUSTER” message. As shown in Table 5.1, this “CLUSTER” message contains a ‘Cluster ID’ field, the value of which is assigned to be the same as the Node ID of this CN. To minimize collisions, a CN will randomly pick a time instance to send the “CLUSTER” message before a time deadline T_C .

An Initial-CM that receives only one “CLUSTER” message before deadline T_C will join the CN that sends this “CLUSTER” message. An Initial-CM that receives more than one “CLUSTER” message before deadline T_C will compare the signal strength of the received “CLUSTER” messages. It will choose to join the CN from which the received signal strength is the strongest (ties are broken randomly). Starting from time T_C , Initial-CMs will be sending “JOIN” messages at a randomly picked time instance before deadline $T_C + T_J$. As shown in Table 5.1, a “JOIN” message contains the Node ID of the sensor that is sending out this message and the ID of the CN (which is also the ID of the Cluster) that this node is intending to join. The “JOIN” message also contains: the ‘EnergyBudget’ field, which specifies the amount of energy budget assigned to this sensor node in the current time slot; the ‘DistanceToBS’ field, which stores the relative distance between this sensor node and Base Station (estimated upon the sensor deployment); the ‘DistanceToCH’ field, which stores the relative distance between this sensor node and Center Node (estimated by using the signal strength of the received “CLUSTER” message [133]). The information carried by these fields will be used later to form the CHG.

Algorithm 5.2: ENC Algorithm-Cluster Formation

CLUSTER FORMATION:

```

foreach Center Node do
  if  $CURRENT\ TIME < T_C$  then
    'Cluster ID' in "CLUSTER"  $\leftarrow myID$ 
    Broadcast the "CLUSTER" message
  else if  $T_C < CURRENT\ TIME < T_C + T_J$  then
    Upon receiving a "JOIN" message
     $CID \leftarrow$  'Cluster ID' contained in "JOIN"
    if  $myID = CID$  (Intended CN) then
      Record the information contained in "JOIN"
    else
      Not intended for this CN. Discard "JOIN"
    end
  end
end
foreach Initial-CM do
  if  $CURRENT\ TIME < T_C$  then
    Upon receiving a "CLUSTER" message
    if the signal strength of this message is higher than that of the previous received "CLUSTER" messages then
       $myCH \leftarrow$  'Cluster ID' in "CLUSTER"
       $myDistoCH \leftarrow$  Estimated relative distance to CH
    end
  else if  $T_C < CURRENT\ TIME < T_C + T_J$  then
    'Node ID' in "JOIN"  $\leftarrow myID$ 
    'Cluster ID' in "JOIN"  $\leftarrow myCH$ 
    'DistanceToBS' in "JOIN"  $\leftarrow myDistoBS$ 
    'DistanceToCH' in "JOIN"  $\leftarrow myDistoCH$ 
    'EnergyBudget' in "JOIN"  $\leftarrow myBudget$ 
    Send the "JOIN" message to  $myCH$  before deadline  $T_C + T_J$ 
  end
end

```

Upon receiving these "JOIN" messages, a CN will check if it is the intended recipient of this message by checking the value under the 'Cluster ID' field of this "JOIN" message. If this CN is the intended recipient, it will record the values under the fields contained in the "JOIN" message. Otherwise, (when this CN is not the

intended recipient of the “JOIN” message), this “JOIN” message will be discarded.

Phase 3: Finalization. At time $T_C + T_J$, “JOIN” messages sent by all Initial-CMs are supposed to be received by the corresponding CNs, which means that a CN will be able to determine the Initial-CMs that have registered with itself. A CN in a cluster k will then estimate the size of the Cluster Head Group N_G^k , (the way to estimate N_G^k will be elaborated later in Section 5.4.3). This CN will next choose $N_G^k - 1$ Initial-CMs that are closer to this CN (as compared to the rest of the Initial-CMs in the cluster), to form the CHG. Note that this CN will also become a CHG-Node. The rest of the Initial-CMs in the cluster will be chosen as *Final-CMs*, which will be transmitting their sensed information to the CHG. As shown in Algorithm 5.3, after determining the roles for all the sensor nodes inside the cluster, a CN will be broadcasting a “SCHEDULE” message at a random time instance before deadline $T_C + T_J + T_S$.

As shown in Table 5.1, a “SCHEDULE” message contains the roles (CHG-Node or Final-CM) and the wake up schedule for all sensors in the cluster. Based on different sensor roles, two types of scheduling information will be generated. The way to determine the appropriate schedules will be further discussed later in Section 5.4.4. Upon receiving a “SCHEDULE” message, a sensor will check the information contained in this message and find its own role. A sensor that is chosen to be a Final-CM will turn on its radio transceiver and transmit its sensed information during the wake up period specified in the “SCHEDULE” message and turn off its radio when otherwise. For a sensor that is chosen to be a CHG-Node, it will wake up and act as an Active-CH during the wake up period specified in the “SCHEDULE” message and go to sleep when otherwise.

Algorithm 5.3: ENC Algorithm-Finalization

FINALIZATION:

```

foreach Center Node at time  $T_C + T_J$  do
    This Center Node is in cluster  $k$ 
    Estimate the size of the CHG ( $N_G^k$ )
    Choose  $N_G^k - 1$  Initial-CMs (that are closer to this CN) as the
    CHG-Nodes
     $myRole \leftarrow$  CHG-Node
    Broadcast the "SCHEDULE" message at a random time instance before
    deadline  $T_C + T_J + T_S$ 
end
foreach Initial-CM do
    When it receives a "SCHEDULE" Message
    if It is scheduled to be a CHG-Node then
         $myRole \leftarrow$  CHG-Node
        Wake up and act as an Active-CH during the period of time as
        specified in the "SCHEDULE" message
    else
         $myRole \leftarrow$  Final-CM
        Transmit its sensed information during the period of time as
        specified in the "SCHEDULE" message
    end
end

```

5.4.3 Size of the Cluster Head Group

With the number of Initial-CMs determined in the Finalization Phase, the Center Node has to determine the size of the CHG so that, at any given time instance, there will be one CHG-Node having sufficient energy to act as an Active-CH. In this way, information gathered by the sensors in the cluster will be able to be relayed to Base Station without interruption.

We consider a cluster k ($1 \leq k \leq K$) in the network. Assuming that there are N_{IC}^k Initial-CMs registered at the Center Node (CN) at the beginning of the Finalization Phase, there will be $N_{IC}^k + 1$ sensors in total in this cluster k . We

5.4. Energy Neutral Clustering

denote the size of the CHG for this cluster k using N_G^k . The number of Final-CMs (N_{CM}^k) in this cluster k follows:

$$N_{CM}^k = N_{IC}^k + 1 - N_G^k \quad (5.7)$$

Since the number of control messages exchanged for cluster formations is small as compared to the number of data packets that will be sent in each time slot, we neglect the energy spent on exchanging these control messages. Hence, the maximum amount of information bits $B_{max}^k(t)$ that can be transmitted (to the CHG) by all Final-CMs in a cluster k in time slot t , without compromising their own Energy Neutral state, can be estimated as follows:

$$B_{max}^k(t) = \sum_{n=1}^{N_{CM}^k} L^n(t) = \sum_{n=1}^{N_{CM}^k} \frac{E_B^n(t)}{E_{CM}^n} \quad (5.8)$$

where $L^n(t) = \frac{E_B^n(t)}{E_{CM}^n}$ is the amount of information bits that a Final-CM n can sense and transmit in a time slot t without compromising its Energy Neutral state. E_{CM}^n is the energy consumed by a Final-CM n to sense and transmit one bit of information. $E_B^n(t)$ is the amount of energy budget assigned to Final-CM n in time slot t . The value of $E_B^n(t)$ for each Final-CM in the cluster can be retrieved from the ‘EnergyBudget’ field contained in the “JOIN” messages. E_{CM}^n for each Final-CM in the cluster can be estimated by the CN through equation (5.3), using the value of the ‘DistanceToCH’ field contained in the “JOIN” messages received and recorded by the CN.

To ensure the Energy Neutral state of the N_G^k CHG-Nodes, we have the following constraint:

$$\sum_{n=1}^{N_G^k} \frac{E_B^n(t)}{E_{CH}^n} \geq B_{max}^k(t) \quad (5.9)$$

5.4. Energy Neutral Clustering

where E_{CH}^n is the energy consumed by a CHG-Node n to *handle* (receive, aggregate and then transmit) one bit of information as stated in equation (5.4). Hence, $\frac{E_B^n(t)}{E_{CH}^n}$ is the amount of information bits that a CHG-Node n can handle without compromising its Energy Neutral state. Thus, the LHS of the inequality (5.9) represents the maximum amount of information bits that the CHG can handle without compromising the Energy Neutral state of the CHG.

As the value of N_G^k increases, the LHS of (5.9) will increase since more sensors are added into the CHG to handle information. On the other hand, $B_{max}^k(t)$ will decrease as N_G^k increases since fewer sensors will be chosen as the Final-CMs to gather information. The final size of the CHG is chosen to be the smallest integer value of N_G^k that fulfils the inequality (5.9). In this way, we can gather as much information as possible (with the largest feasible $B_{max}^k(t)$) without compromising the Energy Neutral state of the sensors in the network.

5.4.4 Scheduling the Final-CMs and the CHG-Nodes

As stated in Section 5.4.3, $B_{max}^k(t)$ amount of information bits will be sent from the Final-CMs to the CHG during a time slot t . Since no data information will be sent during the cluster formations, the $B_{max}^k(t)$ amount of information bits is actually sent in the period of time after ENC has been carried out at the beginning of a time slot. As shown in Figure 5.2, we use T_{DX} to represent this period of time, where $T_{DX} = T - (T_C + T_J + T_S)$.

During the T_{DX} period of time, the Final-CMs will be transmitting information to the CHG in turn. One way of scheduling the Final-CMs is to let each of them to transmit for $\frac{1}{N_{CM}^k}$ fraction of a second during each second until the end of the

5.4. Energy Neutral Clustering

time slot. This means that a Final-CM will have $\frac{T_{DX}}{N_{CM}^k}$ amount of time in a time slot to transmit the $L^n(t)$ amount information as estimated in (5.8). Thus, the data transmission rate ($D_{Tx}^n(t)$) of a Final-CM n in time slot t can be estimated by:

$$D_{Tx}^n(t) = \frac{L^n(t)}{\frac{T_{DX}}{N_{CM}^k}} = \frac{E_B^n(t)N_{CM}^k}{T_{DX}E_{CM}^n} \quad (5.10)$$

Since the $B_{max}^k(t)$ amount of information bits are consistently transmitted from the Final-CMs to the CHG, the data transmission rate of the CHG-Nodes is set to $\frac{B_{max}^k(t)}{T_{DX}}$ to make sure the consistent relay of the received information. Thus, for a CHG-Node n , during the period of time (T_A^n) that it is acting as an Active-CH, we have:

$$\frac{B_{max}^k(t)}{T_{DX}}T_A^n = \frac{E_B^n(t)}{E_{CH}^n} \quad (5.11)$$

where $\frac{B_{max}^k(t)}{T_{DX}}T_A^n$ is the amount of information bits that a CHG-Node n has to handle during T_A^n period time. $\frac{E_B^n(t)}{E_{CH}^n}$ is the amount of information that n is able to handle without compromising its Energy Neutral state.

By combining (5.9) and (5.11), we have

$$\sum_{n=1}^{N_G^k} T_A^n = \frac{\sum_{n=1}^{N_G^k} \frac{E_B^n(t)}{E_{CH}^n}}{\frac{B_{max}^k(t)}{T_{DX}}} \geq T_{DX} \quad (5.12)$$

According to equation (5.11), a CHG-Node n will not compromise its Energy Neutral state by waking up and acting as an active-CH for T_A^n seconds. We can also observe from inequality (5.12) that the sum of the time for all CHG-Nodes to act as Active-CHs ($\sum_{n=1}^{N_G^k} T_A^n$) is no less than T_{DX} . Hence, we can conclude that, with the wakeup time assignment following equation (5.11), at any given time instance within T_{DX} , there will be at least one CHG-Node acting as an Active-CH with

sufficient energy that supports the consistent delivery of data information.

5.5 Optimum Number of Clusters

In ENC, the network is expected to be grouped into K clusters and the value of K is predetermined and controlled by the end user. In this section, we formulate an optimization problem, the solution of which is the optimum number of clusters that the network should be grouped into, so that the amount of information gathered by the network can be maximized.

5.5.1 Energy Neutrality Constraints

Before formulating the optimization problem, we firstly derive the Energy Neutrality constraints for both Final-CMs and CHG-Nodes.

For analyzation purpose, we assume that K equal sized clusters are formed in the network. Hence, each cluster in the network is expected to contain $\frac{N}{K}$ sensor nodes. As a result, for each cluster we have:

$$N_{CM} = \frac{N}{K} - N_G \quad (5.13)$$

where N_{CM} is the expected number of Final-CMs in a cluster and N_G is the expected size of the CHG in a cluster.

For these K clusters in the network, we assume that each cluster is a disk area with a radius of R_c . Since the whole deployment field is assumed to be a disk area with a radius of R as stated in Section 5.3.1, we have:

$$K\pi R_c^2 = \pi R^2 \quad (5.14)$$

5.5. Optimum Number of Clusters

From the above equation we can get $R_c = \frac{R}{\sqrt{K}}$. Since the sensors are uniformly distributed, the node distribution probability is thus a constant, which can be expressed as $\rho(r, \theta) = \frac{1}{\pi R_c^2} = \frac{K}{\pi R^2}$. Assuming that the CHG-Nodes are located at the center area of the cluster (since the CHG-Node are distributed uniformly around the Center Node), the expected distance ($\xi[d_{toCH}]$), the expected squared distance ($\xi[d_{toCH}^2]$) and the expected quadratic distance ($\xi[d_{toCH}^4]$) from the Final-CMs to a CHG-Node can be estimated by:

$$\xi[d_{toCH}] = \int_{\theta=0}^{2\pi} \int_{r=0}^{R/\sqrt{k}} r \rho(r, \theta) r dr d\theta = \frac{2R}{3K} \quad (5.15)$$

$$\xi[d_{toCH}^2] = \int_{\theta=0}^{2\pi} \int_{r=0}^{R/\sqrt{k}} r^2 \rho(r, \theta) r dr d\theta = \frac{R^2}{2K} \quad (5.16)$$

$$\xi[d_{toCH}^4] = \int_{\theta=0}^{2\pi} \int_{r=0}^{R/\sqrt{k}} r^4 \rho(r, \theta) r dr d\theta = \frac{R^4}{3K} \quad (5.17)$$

where $\xi[\cdot]$ is the sign of expectation.

Based on equations (5.1), (5.15), (5.16) and (5.17), the expected amount of energy consumed $\xi[E_{CM}^{Tx/b}]$ for a Final-CM to transmit one bit of information to the CHG can be estimated as follows:

$$\xi[E_{CM}^{Tx/b}] = \begin{cases} \varepsilon_{e-tx} + \varepsilon_{sp} \frac{R^2}{2K} & \text{if } \xi[d_{toCH}] < \hat{d} \\ \varepsilon_{e-tx} + \varepsilon_{mp} \frac{R^4}{3K} & \text{if } \xi[d_{toCH}] \geq \hat{d} \end{cases} \quad (5.18)$$

Let L_t denotes the expected number of information bits that a Final-CM can send to its CH without compromising its Energy Neutral state in time slot t . Based on equation (5.3), we have the following constraint for a Final-CM:

$$L_t \times \xi[E_{CM}] = L_t \times (\varepsilon_{Sx} + \xi[E_{CM}^{Tx/b}]) \leq \xi[E_B(t)] \quad (5.19)$$

5.5. Optimum Number of Clusters

where $\xi[E_{CM}]$ is the expected amount of energy consumed by a Final-CM to sense and transmit one bit of information. $\xi[E_B(t)]$ is the expected energy budget for a sensor in a time slot t .

Since the Base Station is assumed to be located at the center of the network, the expected distance ($\xi[d_{toBS}]$), the expected squared distance ($\xi[d_{toBS}^2]$) and the expected quadratic distance ($\xi[d_{toBS}^4]$) from a CHG-Node to the Base Station can be estimated as follows:

$$\xi[d_{toBS}] = \int_{\theta=0}^{2\pi} \int_{r=0}^R r \rho'(r, \theta) r dr d\theta = \frac{2R}{3} \quad (5.20)$$

$$\xi[d_{toBS}^2] = \int_{\theta=0}^{2\pi} \int_{r=0}^R r^2 \rho'(r, \theta) r dr d\theta = \frac{R^2}{2} \quad (5.21)$$

$$\xi[d_{toBS}^4] = \int_{\theta=0}^{2\pi} \int_{r=0}^R r^4 \rho'(r, \theta) r dr d\theta = \frac{R^4}{3} \quad (5.22)$$

where $\rho'(r, \theta) = \frac{1}{\pi R^2}$ since we assume that the sensors are deployed uniformly across the entire deployment field with a radius of R .

Hence, the expected amount of energy consumed $\xi[E_{CH}^{Tx/b}]$ for a CHG-Node to transmit one bit of information to the Base Station can be estimated based on equations (5.1), (5.20), (5.21) and (5.22) as follows:

$$\xi[E_{CH}^{Tx/b}] = \begin{cases} \varepsilon_{e-tx} + \varepsilon_{sp} \frac{R^2}{2} & \text{if } \xi[d_{toBS}] < \hat{d} \\ \varepsilon_{e-tx} + \varepsilon_{mp} \frac{R^4}{3} & \text{if } \xi[d_{toBS}] \geq \hat{d} \end{cases} \quad (5.23)$$

In a cluster k , since each Final-CM will transmit L_t amount of information bits to the CHG, $N_{CM}L_t$ amount of information bits in total will be received by the CHG. Assuming that perfect aggregation is performed ($\alpha = N_{CM}$), based on equation (5.4), the expected amount of energy ($\xi[E_G]$) consumed for the CHG to

5.5. Optimum Number of Clusters

handle the $N_{CM}L_t$ amount of information can be estimated by:

$$\xi[E_G] = N_{CM}L_t \times \left(\varepsilon_{e-rx} + N_{CM}\varepsilon_{DA} + \frac{\xi[E_{CH}^{Tx/b}]}{N_{CM}} \right) \quad (5.24)$$

Since the expected amount of energy consumed by the CHG ($\xi[E_G]$) should not exceed the sum of expected amount of energy budget assigned to all the CHG-nodes in the CHG, we have the following Energy Neutrality constraint for the CHG of a cluster in a time slot t :

$$\xi[E_G] \leq \sum_{n=1}^{N_G} \xi[E_B(t)] \quad (5.25)$$

5.5.2 Maximized Network Information Gathering

For a sensor network, it is always desired to gather as much data information from the network as possible. We thus formulate our *Network Information Gathering Maximization* (Max-NIG) problem as follows:

$$\max \sum_{k=1}^K \left(\frac{N}{K} - N_G \right) \times L_t \quad (5.26)$$

subject to:

$$L_t \times (\varepsilon_{Sx} + \xi[E_{CM}^{Tx/b}]) \leq \xi[E_B(t)] \quad (5.27)$$

$$N_{CM}L_t \times \left(\varepsilon_{e-rx} + N_{CM}\varepsilon_{DA} + \frac{\xi[E_{CH}^{Tx/b}]}{N_{CM}} \right) \leq \sum_{n=1}^{N_G} \xi[E_B(t)] \quad (5.28)$$

$$1 \leq \frac{N}{K} - N_G \quad (5.29)$$

where $t = 1, 2, 3, \dots, N_t$, $N_{CM} = \left(\frac{N}{K} - N_G \right)$ and $N_G, K \geq 1$

The objective function (5.26) represents the amount of information that can be gathered at the CHG-Nodes from all Final-CMs in all the K clusters for one time slot t . Constraint (5.27) is the Energy Neutrality constraint (5.19) for the

5.5. Optimum Number of Clusters

Final-CM and constraint (5.28) is the Energy Neutrality constraint (5.25) for the CHG as defined in last section. Constraint (5.29) is to make sure that there will be at least one Final-CM in a cluster. It can be shown that the objective function (5.26) is concave and the constraints (5.27), (5.28) and (5.29) are convex. Thus, the Max-NIG problem is a convex optimization problem [51], which admits a unique optimal point (L_t^*, K^*, N_G^*) for a time slot t so that the objective function (5.26) can be maximized.

To solve the Max-NIG problem, we formulate the following Lagrangian function:

$$\begin{aligned} \mathcal{L} = & \sum_{k=1}^K \left(\frac{N}{K} - N_G \right) \times L_t + \lambda \left(L_t \times \left(\varepsilon_{Sx} + \xi[E_{CM}^{Tx/b}] \right) - \xi[E_B(t)] \right) \\ & + v \left(N_{CM} L_t \times \left(\varepsilon_{e-rx} + N_{CM} \varepsilon_{DA} + \frac{\xi[E_{CH}^{Tx/b}]}{N_{CM}} \right) - \sum_{n=1}^{N_G} \xi[E_B(t)] \right) \end{aligned} \quad (5.30)$$

where $\lambda \geq 0$ and $v \geq 0$ are the Lagrange Multipliers.

Additional Complement Slackness Conditions are as follows:

$$\lambda \left(L_t \times \left(\varepsilon_{Sx} + \xi[E_{CM}^{Tx/b}] \right) - \xi[E_B(t)] \right) = 0 \quad (5.31)$$

and

$$v \left(N_{CM} L_t \times \left(\varepsilon_{e-rx} + N_{CM} \varepsilon_{DA} + \frac{\xi[E_{CH}^{Tx/b}]}{N_{CM}} \right) - \sum_{n=1}^{N_G} \xi[E_B(t)] \right) = 0 \quad (5.32)$$

In order to find the optimal point, we have to apply the Karush-Kuhn-Tucker condition [51], which requires

$$\frac{\Delta \mathcal{L}}{\Delta L_t} = 0, \frac{\Delta \mathcal{L}}{\Delta K} = 0, \frac{\Delta \mathcal{L}}{\Delta N_G} = 0 \quad (5.33)$$

The optimal points can be found by solving the system of equations (5.31), (5.32) and (5.33). In real implementations, K^* and N_G^* should be positive integers. Thus, the values of K^* and N_G^* should be chosen to be the closest integer value

5.5. Optimum Number of Clusters

Table 5.2: Network parameters

Parameters	Value
ε_{e-rx}	$5 \times 10^{-8} J/bit$
ε_{e-tx}	$5 \times 10^{-8} J/bit$
$\varepsilon_{DA} =$	$5 \times 10^{-9} J/bit$
$\varepsilon_{Sx} =$	$1 \times 10^{-10} J/bit$
ε_{sp}	$1 \times 10^{-10} J/(bit \times m^2)$
ε_{mp}	$1.3 \times 10^{-15} J/(bit \times m^4)$
$\hat{d}$	$277.35m$
R	$50-150m$
N	$100-200$ nodes

of the optimal solutions, without breaking the energy neutrality constraints (5.27) and (5.28). Using the parameters as shown in Table 5.2, the optimal points under different network setups are shown in Table 5.3. (L_t^* is in *Mbits*.)

Table 5.3: Optimal solutions for the Max-NIG problem

(L_t^*, K^*, N_G^*)	$N = 100$	$N = 200$
$R = 50m$	$(17 \times \xi[E_B(t)], 3, 17)$	$(17 \times \xi[E_B(t)], 4, 24)$
$R = 100m$	$(15 \times \xi[E_B(t)], 5, 10)$	$(16 \times \xi[E_B(t)], 7, 15)$
$R = 150m$	$(12 \times \xi[E_B(t)], 4, 12)$	$(13 \times \xi[E_B(t)], 6, 16)$

Based on the results we obtained in Table 5.3, we have the following theorem.

Theorem 5.1. *When all the communication related parameters are fixed, the optimum number of clusters K^* that provides maximized network information gathering is the same for each time slot.*

Proof. From the optimal points shown in Table 5.3 we can see that the optimal number of clusters K^* for a time slot t is not a function of the expected energy budget $\xi[E_B(t)]$ for this time slot. This means that, when the communication pa-

rameters are fixed, the optimal number of clusters K^* that maximizes the network information gathering in a time slot t is not related to the expected energy budget of this time slot. It in turn indicates that for different time slots with different expected energy budgets, the optimum number of clusters K^* that maximizes the network information gathering remains unchanged. $\square$

Hence, in practice, we can firstly estimate the value of K^* before sensor deployment. Then ENC can be carried out by setting the K value to K^* in the Initialization Phase to provide maximized information gathering.

5.6 Extensions

As shown in last section, maximized amount of information can be gathered from the environment if we use the optimal solutions obtained by solving the Max-NIG problem. However, to achieve this kind of maximized information gathering, the network has to be grouped into exactly K^* clusters with equal cluster size and the CHGs are required to be located at the expected center locations. Using our proposed Energy Neutral Clustering protocol, the number of clusters formed in the network might not be exactly K^* due to the randomness in selecting the Center Nodes. The locations of the CNs are also randomly chosen. As a result, as shown in Figure 5.3, some Cluster Head Groups formed are far away from the Base Station while the others are closer to the Base Station. The number of sensors inside each cluster also varies greatly from one cluster to another. Thus, ENC will not be able to provide the theoretical maximized network information gathering due to the randomness in the selection of CNs.

Figure 5.3: Six clusters formed using ENC

In view of this, we propose an extension to our proposed ENC protocol to provide maximized network information gathering. We denote this extended ENC protocol as the ENC* protocol.

Using ENC*, sensors in the network will be grouped into K^* equal sized clusters with a cluster radius of $\frac{2R}{3}$ (following equation (5.20)). Many clustering protocols have been proposed to cluster the network into equal sized clusters. Since our focus in this chapter is not on developing protocols that generate equal sized clusters, we will not further discuss these protocols. We adopt the Algorithm for Cluster Establishment (ACE) proposed in [134] to form clusters with equal cluster size and minimum cluster overlapping. ACE can be implemented distributively without centralized controls. After forming the K^* equal sized clusters using ACE, we use Algorithm 5.3 to form the CHG and generate the schedules. The ways to estimate the size of the CHG and generate the schedules in ENC* are the same as the ones

Figure 5.4: Six equal sized clusters formed using ENC*

in ENC, which are shown in Section 5.4.3 and Section 5.4.4. A network that is clustered by using ENC* is shown in Figure 5.4.

However, we notice that by using ACE, several iterations are to be carried out before the network can be grouped into equal sized clusters. Since many control messages have to be exchanged during each iteration, the control message overhead will be large if we carry out ACE at the beginning of every time slot.

Based on Theorem 5.1, we notice that for ENC*, cluster reformations is not needed for every time slot. Since the optimum number of clusters K^* does not change from time slot to time slot, ENC* can be carried out only once upon sensor deployment with the K^* calculated beforehand. As a result, the number of control messages exchanged when ENC* is employed can be greatly reduced, which will be verified later in Section 5.7.4.

5.7 Performance Evaluations

Empirical studies are carried out in this section to evaluate the performance of our proposed ENC and ENC* protocols.

5.7.1 Simulation Setup

Simulations are carried out on Matlab platform [88]. For fair comparison, the communication related parameters used in the simulations are the same as the ones used in LEACH [86], which are shown in Table 5.2. The size of the data packets and the control messages are set to be 5000 bits/packet and 500 bits/packet, respectively.

We set the duration of a time slot (T) to be 3600 seconds. The amount of energy harvested by a sensor n in a time slot t is randomly chosen by $E_H^n(t) = 54 + X$ Joule, where X is a random variable that follows $X \sim \mathcal{N}(0, 4)$ and $\mathcal{N}$ denotes the Normal Distribution. We choose the value of 54 Joule since it is the estimated average amount of solar radiation energy harvestable in one time slot (3600 seconds) based on the data retrieved from the US TEXAS Solar Radiation Database [1]. For fair comparison, we assume that all clustering protocols adopts P-FREEN as the Node-level ENM mechanism.

We compare the performance of ENC and ENC* against LEACH [86], which is a well known clustering protocol that assumes direct communication between the Cluster Head (CH) and the Base Station. Using LEACH, in order to balance the energy consumption, a sensor will be acting as a CH for a short period of time. After that, clusters will be reformed and Cluster Head Re-selections will be performed to select other sensors to be the CH. We note that in [86], the frequency of the Cluster Head Re-selections as well as data packet transmission rate at the

5.7. Performance Evaluations

Table 5.4: LEACH with different parameters

Name	CH Re-selections	Packet Transmission Rate
LEACH-A10	10/time slot	10 pkts/s
LEACH-B5	5/time slot	20 pkts/s
LEACH-B10	10/time slot	20 pkts/s
LEACH-C5	5/time slot	40 pkts/s
LEACH-C10	10/time slot	40 pkts/s
LEACH-D10	10/time slot	60 pkts/s

Table 5.5: Simulation setups

	$N = 100$	$N = 200$
$R = 50m$	Setup 1	Setup 2
$R = 100m$	Setup 3	Setup 4
$R = 150m$	Setup 5	Setup 6

Cluster Members (CMs) are not specified. In order to fully compare LEACH with our proposed protocols, as shown in Table 5.4, we choose to test LEACH with different number of Cluster Head Re-selections per time slot and different packet transmission rates at the CMs. For example, using LEACH-C5, clusters will be re-formed and Cluster Head will be reselected 5 times during one time slot. Meanwhile, each CM will be transmitting data packets with a packet transmission rate of 40 packets per second (when it is scheduled to transmit).

Simulations are carried out under different network setups, which are categorized into six scenarios as shown in Table 5.5.

5.7.2 Energy Neutral State

The *Network Lifetime*, which measures the amount of time elapsed before a sensor node or a fraction of sensors in the network are dead, is used as an important performance metric in traditional sensor networks. However, for sensors with energy harvesting capability, since dead sensor can come back functioning again when sufficient energy has been accumulated in the battery, the network lifetime is no

5.7. Performance Evaluations

Figure 5.5: Accumulated Cluster Failure Time with $R = 50m$

Figure 5.6: Accumulated Cluster Failure Time with $R = 100m$

longer a primary concern.

Since we assume that all clustering protocols adopt P-FREEN, a sensor n can gain access to $E_B^n(t)$ amount of energy in a time slot t . Hence, if this sensor consumes $E_B^n(t)$ amount of energy before the end time of the current time slot, it will be forced to shut down and stop functioning until the beginning of the subsequent time slot. As mentioned in Section 5.4.1, if this sensor is a Cluster Head (CH) for LEACH or an Active-CH for ENC, cluster failures would occur

5.7. Performance Evaluations

Figure 5.7: Accumulated Cluster Failure Time with $R = 150m$

since the information sensed by the Cluster Members (CMs) will not be able to be relayed to the Base Station. We use the *Cluster Failure Time* to measure the amount of time a CH (or an Active-CH) of a cluster is forced to shut down (a cluster failure persists) in one time slot. Thus, the Accumulated Cluster Failure Time (ACFT) experienced by the sensor network is used in this chapter as a metric that measures a clustering protocol's ability to provide the Network-level Energy Neutral Management. The *Accumulated Cluster Failure Time* is calculated by the sum of the Cluster Failure Time experienced by all clusters in the network for one time slot. For clustered network, the cluster head is the most important sensor node, as the failure of the cluster head could result in the whole cluster failure and no useful information could be relayed back to the base station. Hence, a smaller ACFT means the clusters in the network can stay alive for a longer period of time, which in turn indicates that more data could be consistently relayed to the based station.

We compare the ACFT experienced by the network when ENC, ENC* and LEACH are employed. As shown in Figures 5.5, 5.6 and 5.7, both ENC and ENC*

can provide the Network-level Energy Neutral Management (with zero ACFT) under all network setups considered in the empirical studies. This in turn implies that when ENC and ENC* are being used, information will be delivered to the Base Station consistently without interruption.

When LEACH is employed, the network experiences zero ACFT only when LEACH-A10 is employed in Setup 1, Setup 3 and Setup 5, which are shown in Figure 5.5(A), Figure 5.6(A) and Figure 5.7(A), respectively. This is because LEACH-A10 let every sensor in the network to transmit at a very low packet transmission rate so that the energy consumption of the CH will be smaller than the energy budget. However, this is at the cost of lowering the total amount of information that can be gathered from the network, which is not desired.

When the packet transmission rate is higher (when LEACH-B10, LEACH-C10 or LEACH-D10 are employed), a high ACFT is experienced by the network in all the six scenarios as specified in Table 5.5. This means that LEACH cannot provide the Network-level Energy Neutral Management when the packet transmission rate is high, which compromises the data delivery consistency. We do note that higher frequency of Cluster Head Re-selections (LEACH-B10, LEACH-C10) can help reduce the ACFT (as compared to LEACH-B5, LEACH-C5). However, the frequent CH Re-selections will cause large amount of time spent in cluster formations and more control messages are needed, which are also not desired.

5.7.3 Total Amount of Information Bits Gathered

Besides providing the Network-level Energy Neutral Management that enables the consistent delivery of data, we also want to maximize the amount of information

5.7. Performance Evaluations

that can be gathered from the network. We thus carried out simulations to evaluate the Total Amount of Information Bits (TAIB) that can be received by all the CHG-Nodes in the network. For each clustering protocol, we recorded the TAIB gathered at the CHG-Nodes for 100 time slots. Figures 5.8, 5.9 and 5.10 show the average TAIB in one time slot under different network setups when different clustering protocols are employed.

It is verified through Figures 5.8 to 5.10 that, although LEACH-A10 is able to achieve zero ACFT when there are more than 8 clusters in the network, it is at the cost of greatly lowering the average TAIB gathered from the network. For LEACH, the average TAIB can be improved with a more frequent rotation of Cluster Head (comparing LEACH-C10 to LEACH-C5). Meanwhile, the average TAIB also shows an increasing trend when the packet transmission rate increases from 10 to 40 packets/second (LEACH-A10 to LEACH-C10). However, TAIB decreases when the packet transmission rate further increases from 40 to 60 packets/second (from LEACH-C10 to LEACH-D10). This is because, when LEACH-D10 is used, a high ACFT will be experienced as shown in the last section, which masks the positive contributions of the higher packet transmission rate.

We can observe from Figures 5.8 to 5.10 that the maximum TAIB achieved by ENC and ENC* is higher than that achieved by LEACH (when LEACH-C10 is employed). This is because ENC* and ENC allow every CM to maximize their transmission rate according to their own energy status, while at the same time preventing cluster failure. As discussed in Section 5.6, since equal sized clusters can be formed using ENC*, it achieves a higher maximum TAIB than that achieved by ENC. It is also verified in Figures 5.8 to 5.10 the validity of the optimum number of clusters that maximize the TAIB as calculated in Section 5.5. For example, with

5.7. Performance Evaluations

Figure 5.8: Average TAIB gathered with $R = 50m$

Figure 5.9: Average TAIB gathered with $R = 100m$

$N = 200$ and $R = 100m$, the optimum number of clusters calculated is 7 as shown in Table 5.3, which is consistent with the recorded maximum TAIB achieved around 7 clusters by ENC* and ENC as shown in Figure 5.9(B).

 Figure 5.10: Average TAIB gathered with $R = 150m$

 Figure 5.11: Number of control message exchanged with $R = 100m$

5.7.4 Control Message Overhead

We also recorded the number of control messages exchanged when different protocols are employed. As shown in Figure 5.11, ENC experiences a lower control message overhead than that experienced by LEACH. This is because the cluster formations will be carried out only once at the beginning of a time slot under ENC, while the cluster formations under LEACH will be carried out several times

in one time slot during the Cluster Head Re-selections. When ENC* is employed, clusters only have to be formed once upon sensor deployment. As a result, a constant number of control messages is exchanged when ENC* is employed, which is comparably smaller than that required by ENC and LEACH when the number of time slots elapsed approaches a large number.

5.8 Summary

In this chapter, we propose an Energy Neutral Clustering (ENC) protocol to group an energy harvesting wireless sensor network into a number of clusters, with the aim of providing Network-level Energy Neutral Management. ENC employs a novel Cluster Head Group (CHG) mechanism, which allows more than one Cluster Heads to reside in one cluster to share the heavy traffic load. The size of CHG in each cluster is computed locally, with the aim of ensuring that, at any given time instance, there will be an Active Cluster Head (chosen from the CHG) that has sufficient energy to handle the information sent from the Cluster Members. In this way, information sensed by the Cluster Members can be consistently relayed to the Base Station. With the CHG mechanism, frequent cluster formations and cluster head re-selections are not required, which reduce the time and computational complexities needed for the clustering protocol.

We also analytically derive the optimum number of clusters that maximizes the amount of information gathered from the network, while maintaining the perpetual network operation. Based on this optimum number of clusters, an ENC* protocol is proposed to extend ENC so that equal sized clusters can be formed in the network, which provides maximized network information gathering. ENC* also has a very

low control message overhead since the cluster formation process only has to be carried out once upon sensor deployment.

Extensive empirical studies verify that ENC and ENC* can successfully prevent cluster failures by providing Network-level Energy Neutral Management. As compared to LEACH, ENC and ENC* can provide higher amount of information gathered from the network while imposing a lower control message overhead. It is also shown in the empirical studies that the analytically derived optimum number of clusters indeed provides maximized network information gathering when ENC and ENC* are employed.

Chapter 6

Conclusions and Future Work

We conclude this thesis by summarising our contributions and recommending some directions for further research.

6.1 Conclusions

In this thesis, we explore the energy management mechanisms that are specially designed for Energy Harvesting Wireless Sensor Networks. In particular, we focus on carefully managing the harvested energy so that wireless sensors and sensor networks can operate perpetually in the energy neutral state, with improved sensor and network performance level. We classify such *Energy Neutral Management* mechanisms into two different levels: *Node-level* and *Network-level*. At the node level, we study a way to provide energy neutral management for sensor nodes while maximizing the sensor performance level, without the need of predicted energy harvesting information. At the network level, we propose energy neutral network layer routing protocols that aims at providing perpetual network operation with unlimited network lifetime, while maximizing the network data throughput.

Four different approaches, including *Mathematical Optimization*, *Adaptive Control*, *Admission Control* and *Network Clustering*, are adopted to design energy neutral management schemes on both node level and network level. We find that these approaches are very useful and effective in solving the problems imposed by the unique energy constraints faced by energy harvesting wireless sensor networks.

For a single sensor system or a sensor network that only involves single hop point to point transmissions, energy neutral operation can be achieved by the Node-level Energy Neutral Management mechanism that carefully manages the harvested energy. This is done by controlling the energy consumption of a sensor so that it will not consume more energy than the amount it can harvest and utilize in a certain period of time. While maintaining the energy neutral state of a sensor, it is also highly desired to improve the sensor performance level so that more information can be retrieved by the sensor. When the sensor performance level (such as sensor average duty cycle) is linearly related with the energy consumption of a sensor, we formulate in Chapter 2 a linear optimization problem that aims at maximizing the sensor average duty cycle while maintaining the energy neutral state of the sensor. We find that the sensor average duty cycle can be maximized when the amount of harvested energy that can be utilized by the sensor is maximized, (in the presence of battery energy storage inefficiencies). Hence, we propose and study an energy *harvest-use(store)* method that improves the fraction of harvested energy that can be made available for sensor utilization. Based on this method, we derive a set of *Budget Assignment Policies* (BAPs) that provides energy neutral management with maximized sensor average duty cycle, by assigning *Energy Budget* that regulates the energy consumption of the sensor. Since the predicted energy harvesting information is time consuming and inaccurate, we proposed a *Prediction FRee En-*

ergy Neutral (P-FREEN) management mechanism that implements BAPs based on observed energy harvesting information and the sensor's battery residual energy level. Extensive simulations are carried out to validate that P-FREEN is able to maintain an energy harvesting sensor in the energy neutral state with improved sensor average duty cycle.

We next consider in Chapter 3 the case when the sensor performance level, (such as the communication channel throughput), has a non-linear relationship with the sensor energy consumption. We formulate a convex optimization problem that aims at maximizing the communication channel throughput without compromising the energy neutral state of the sensor. Based on the solutions of this convex optimization problem, we propose an Adaptive Budget Assignment Policy (ABAP) that provides energy neutral management by assigning the energy budget adaptively to the observed energy harvesting and channel state information, which means ABAP is also prediction free. We analytically show that ABAP asymptotically achieves maximized channel throughput after a certain period of time. We also derive the fraction of harvested energy that can be utilized by the sensor through the energy harvest-use(store) method. Based on this derivation, we propose an ABAP* policy that provides improved channel throughput when battery energy storage inefficiency is considered. Empirical studies verify that ABAP and ABAP* can asymptotically achieve maximized channel throughput while maintaining the energy neutral state of the sensor. These two policies also involve less computational complexities as compared to current energy neutral channel throughput maximization policies.

Based on the Node-level Energy Management mechanisms, we explore a way to provide Network-level Energy Neutral Management for sensor networks that

involves multi-hop communications. In particular, we study network layer routing protocols that coordinately controls the energy consumption of each sensor in the network by regulating the data traffic it carries, with the goal of providing consistent and perpetual network operation. In Chapter 4, we focus on developing an *Energy Neutral Directed Diffusion* (ENDD) routing protocol that provides Network-level Energy Neutral Management based on the *query driven data delivery model*. For applications that use this kind of data delivery model, data information delivery will be triggered only when a specific query is generated by the end user. In order to regulate the traffic loads on each sensor in the network, ENDD uses the *admission control* technique to control the number of queries (traffic flows) that can be admitted by a sensor, according to the availability of its own energy budget, (the amount of energy budget available to a sensor node is determined by the Node-level Energy Management mechanism). In order to improve the network performance level, (such as the network data throughput), a sensor will admit as many queries as possible as long as it does not consume more energy than the amount of energy budget available. We also develop a real time realistic sensor energy consumption estimation model to account for the amount of energy that a sensor will consume by admitting a query, which enhances the reliability of the flow admission control and thus ensures the energy neutral state of every sensor in the network. Simulations show that ENDD can successfully provide Network-level Energy Neutral Management, which ensures the consistent delivery of data. It is also observed that, as compared to current available query driven protocols, ENDD can provide lower end-to-end packet delivery delay and higher distinct packet delivery ratio, while imposing a smaller control message overhead.

For applications that require periodical and continuous delivery of data (i.e.,

continuous data delivery model), redundant data information will be generated and delivered by the sensor network. Network clustering is thus used to reduce the amount of redundant data information that will be delivered by the network, by enabling data aggregations at the cluster head in each cluster. In Chapter 5, we propose an *Energy Neutral Clustering* (ENC) protocol that clusters a network with the goal of providing Network-level Energy Neutral Management. Since the cluster head usually carries much heavier traffic loads than the cluster members, it will deplete its energy source faster and results in network failure. Hence, ENC employs a novel *Cluster Head Group* (CHG) mechanism that allows each cluster to have more than one cluster head to share the heavy traffic load. The size of the CHG group and the data transmission rate for the cluster members are carefully managed, so that each sensor node in the CHG group will not deplete its energy budget when it is actively involved in network data delivery process. We also mathematically derive the optimum number of clusters that maximizes the amount of data information that can be gathered from the network. Based on this optimum number, an extension to ENC is proposed to cluster the network into equal sized clusters so that maximum data information gathering can be achieved. Simulations show that ENC can prevent network failures and thus enable perpetual network operations in different network setups, which in turn verifies that ENC can provide Network-level Energy Neutral Management. It is also shown that ENC achieves substantial improvements on the amount of information gathered from the network, as compared to current clustering protocols.

6.2 Recommendations for Further Research

We explore in this thesis the way of providing energy neutral management in energy harvesting wireless sensor networks. Since the wireless sensor networks are widely applied in many different scenarios and conditions, many problems are still open, especially in the new research dimension opened by the energy harvesting technique. In this section, we identify some potential areas for the future work.

Firstly, our research works can be further extended, and some of the potential extensions are listed as follows:

1. In Chapter 2, we use the sensor average duty cycle as the performance metric to demonstrate the effectiveness of P-FREEN. In future researches, P-FREEN may be used to maximize other sensor performance levels such as sensor coverage area and sensing reliability (sampling frequency). For example, if a sensor's sensing range model is based on the RF-power-density function for an isotropic antenna [135], its sensing coverage area is linear proportional to the available power [136]. Since the available power of a sensor is determined by the amount of energy budget assign to it in a time slot, P-FREEN can be extended to maximize the amount of energy budget assigned to a time slot, which in turn maximizes a sensor's sensing coverage area.
2. We provide a prediction free harvested energy allocation policies that maximize the communication channel throughput in Chapter 3. We implicitly assume that the transmission backlog is infinite, which means there is infinite amount of information bits awaiting for transmission. Another scenario that could be considered in the future researches is that there are finite information bits awaiting for transmission. The goal of the energy management for

6.2. Recommendations for Further Research

such scenario is to allocate the harvested energy in a way that the *transmission completion time* [46, 47], which is a measurement of the time elapsed before finishing the transmission of the last bit of information in the backlog, is minimized. In this way, the transmission delays can also be minimized, which is highly desirable for applications that are delay sensitive.

3. For the Energy Neutral Directed Diffusion (ENDD) protocol we proposed in Chapter 4, we assume that the network has one data sink to collect the data information gathered by the network. Although single sink model is widely used in many wireless sensor networks, some applications requires multiple sinks to collect the network data. Due to its distributive implementation, ENDD can be extended to deal with the situation when multiple data sinks are used [137]. Furthermore, ENDD can also be extended to provide multiple routing paths for the data traffic generated by one routing request (query). This kind of *multi-path routing* is very useful when the data traffic generated by a routing request can only be fulfilled by more than one routing paths, (due to the energy neutrality constraints). It will further improve the robustness of the network and provide higher network data throughput [138].
4. We use the single hop inter-cluster communication model to demonstrate that our proposed Energy Neutral Clustering (ENC) can successfully provide Network-level Energy Neutral Management. For large networks, it is shown that multi-hop inter-cluster communication is more energy efficient. Hence, ENC can be extended to employ the multi-hop inter-cluster communication model in future researches. Since a cluster head might have to relay inter-cluster data traffic, new algorithm has to be implemented to calculate the

6.2. Recommendations for Further Research

suitable size of the Cluster Head Group. Furthermore, for the multi-hop inter-cluster communication model, unequal cluster size should be considered to balance the energy consumption of the cluster heads. As a result, the optimum number of clusters and the cluster size should be recalculated to provide maximized network information gathering.

In addition to the current network-level energy neutral routing protocols based on the query driven and continuous data delivery model as discussed in Chapter 4 and 5, it is also possible to explore the network-level energy neutral routing protocols with other data delivery models, such as event-driven models and even hybrid model that combines the aforementioned data delivery models. Several other type of routing protocols, such as the opportunistic routing, could also be considered to provide network level energy neutral management.

Furthermore, some other techniques can be adopted to provide energy neutral management in energy harvesting wireless sensor networks. We note that the link-layer Multiple Access Control protocols [139, 140, 141], which controls the point to point data transmission schedules as well as the sleep-wakeup cycles of the EH-Sensors, also have a great impact on the energy consumption of a sensor. Hence, energy neutral MAC protocols will have a great potential of improving the network performance levels (such as packet delivery latency and data throughput), while enabling perpetual network operation. On the other hand, energy neutral management can also be carried out with the goal of maintaining the network coverage and connectivity [142], while minimizing the number of energy harvesting sensors needed in the network. As a result, the redundant deployment of sensors can be avoided without compromising the network coverage guarantees.

Author's Publications

This thesis is a monograph, which contains some unpublished material, but is mainly based on the following publications. In this thesis, these publications are referred to as [Px], where x is the sequence number in the following list.

- [P1] S. Peng and C. P. Low, “Prediction Free Energy Neutral Power Management for Energy Harvesting Wireless Sensor Nodes,” *Elsevier Ad Hoc Networks*, vol. 13, Part B, no. 0, pp. 351–367, 2014.
- [P2] S. Peng and C. P. Low, “Asymptotically Throughput Maximized Energy Neutral Management for Energy Harvesting Wireless Sensors,” *Elsevier Computer Communications*, submitted, 2015 (expected).
- [P3] S. Peng and C. P. Low, “Energy Neutral Directed Diffusion for Energy Harvesting Wireless Sensor Networks,” *Elsevier Computer Communications*, vol 63, pp. 40–52, 2015.
- [P4] S. Peng, T. Wang and C. P. Low, “Energy Neutral Clustering for Energy Harvesting Wireless Sensors Networks,” *Elsevier Ad Hoc Networks*, Vol 28, pp. 1-16, 2015.

6.2. Recommendations for Further Research

- [P5] S. Peng and C. P. Low, “Throughput Optimal Energy Neutral Management for Energy Harvesting Wireless Sensor Networks,” in *IEEE Wireless Communications and Networking Conference, (WCNC '12)*, pp. 2347–2351, Paris, 2012.
- [P6] S. Peng and C. P. Low, “Energy Neutral Routing for Energy Harvesting Wireless Sensor Networks,” in *IEEE Wireless Communications and Networking Conference (WCNC '13)*, pp. 2063–2067, Shanghai, 2013.
- [P7] S. Peng and C. Low, “Energy Neutral Clustering for Energy Harvesting Wireless Sensor Networks,” in *Proceedings of the 19th IEEE International Conference on Networks (ICON '13)*, pp. 1–6, Singapore, 2013.

References

- [1] *Canyon Solar Raditaion Dataset, TEXAS Solar Radiation Database*, retrieved on 1st May, 2013. Available at <http://www.me.utexas.edu/~solarlab/data/canyon/index.html>.
- [2] W. Dargie and C. Poellabauer, *Fundamentals of wireless sensor networks: theory and practice*. John Wiley & Sons, 2010.
- [3] K. Sohraby, D. Minoli, and T. Znati, *Wireless sensor networks: technology, protocols, and applications*. John Wiley & Sons, 2007.
- [4] M. Winkler, M. Street, K.-D. Tuchs, and K. Wrona, “Wireless sensor networks for military purposes,” in *Autonomous Sensor Networks*, vol. 13 of *Springer Series on Chemical Sensors and Biosensors*, pp. 365–394, Springer Berlin Heidelberg, 2013.
- [5] J. Branch, C. Giannella, B. Szymanski, R. Wolff, and H. Kargupta, “In-network outlier detection in wireless sensor networks,” *Knowledge and Information Systems*, vol. 34, no. 1, pp. 23–54, 2013.

REFERENCES

- [6] M. Uddin, H. Ahmadi, T. Abdelzaher, and R. Kravets, “Intercontact routing for energy constrained disaster response networks,” *IEEE Transactions on Mobile Computing*, vol. 12, pp. 1986–1998, Oct 2013.
- [7] I. M. Khalil, A. Khreishah, F. Ahmed, and K. Shuaib, “Dependable wireless sensor networks for reliable and secure humanitarian relief applications,” *Ad Hoc Networks*, vol. 13, Part A, no. 0, pp. 94 – 106, 2014.
- [8] M. Reyer, S. Hurlebaus, J. Mander, and O. Ozbulut, “Design of a wireless sensor network for structural health monitoring of bridges,” in *Wireless Sensor Networks and Ecological Monitoring*, vol. 3 of *Smart Sensors, Measurement and Instrumentation*, pp. 195–216, Springer Berlin Heidelberg, 2013.
- [9] N. Barroca, L. M. Borges, F. J. Velez, F. Monteiro, M. Grski, and J. Castro-Gomes, “Wireless sensor networks for temperature and humidity monitoring within concrete structures,” *Construction and Building Materials*, vol. 40, no. 0, pp. 1156 – 1166, 2013.
- [10] A. Mainwaring, D. Culler, J. Polastre, R. Szewczyk, and J. Anderson, “Wireless sensor networks for habitat monitoring,” in *Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*, pp. 88–97, ACM, 2002.
- [11] G. Sanchez-Azofeifa, C. Rankine, M. Marcos do Espirito Santo, R. Fatland, and M. Garcia, “Wireless sensing networks for environmental monitoring: Two case studies from tropical forests,” in *IEEE 7th International Conference on E-Science (e-Science '11)*, pp. 70–76, Dec 2011.

REFERENCES

- [12] R. Huang, W.-Z. Song, M. Xu, N. Peterson, B. Shirazi, and R. LaHusen, “Real-world sensor network for long-term volcano monitoring: Design and findings,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 23, pp. 321–329, Feb 2012.
- [13] R. Tan, G. Xing, J. Chen, W.-Z. Song, and R. Huang, “Fusion-based volcanic earthquake detection and timing in wireless sensor networks,” *ACM Transactions on Sensor Networks*, vol. 9, no. 2, p. 17, 2013.
- [14] H. Alemdar and C. Ersoy, “Wireless sensor networks for healthcare: A survey,” *Computer Networks*, vol. 54, no. 15, pp. 2688 – 2710, 2010.
- [15] X. Xu and M. Zhong, “Wireless body sensor networks with cloud computing capability for pervasive healthcare: Research directions and possible solutions,” in *Frontier and Future Development of Information Technology in Medicine and Education*, vol. 269 of *Lecture Notes in Electrical Engineering*, pp. 979–988, Springer Netherlands, 2014.
- [16] Y. Kim, T. Schmid, Z. M. Charbiwala, J. Friedman, and M. B. Srivastava, “Nawms: nonintrusive autonomous water monitoring system,” in *Proceedings of the 6th ACM conference on Embedded network sensor systems*, pp. 309–322, ACM, 2008.
- [17] J. Yick, B. Mukherjee, and D. Ghosal, “Wireless sensor network survey,” *Computer Networks*, vol. 52, no. 12, pp. 2292 – 2330, 2008.
- [18] A. Bachir, M. Dohler, T. Watteyne, and K. Leung, “Mac essentials for wireless sensor networks,” *IEEE Communications Surveys Tutorials*, vol. 12, pp. 222–248, Second 2010.

REFERENCES

- [19] N. Pantazis, S. Nikolidakis, and D. Vergados, “Energy-efficient routing protocols in wireless sensor networks: A survey,” *IEEE Communications Surveys Tutorials*, vol. 15, pp. 551–591, Second 2013.
- [20] M. A. Yigitel, O. D. Incel, and C. Ersoy, “Qos-aware mac protocols for wireless sensor networks: A survey,” *Computer Networks*, vol. 55, no. 8, pp. 1982 – 2004, 2011.
- [21] A. Liu, J. Ren, X. Li, Z. Chen, and X. S. Shen, “Design principles and improvement of cost function based energy aware routing algorithms for wireless sensor networks,” *Computer Networks*, vol. 56, no. 7, pp. 1951 – 1967, 2012.
- [22] M. Li, L. Mo, and Y. Liu, “Towards energy-fairness in asynchronous duty-cycling sensor networks,” in *IEEE International Conference on Computer Communications (INFOCOM ’12)*, pp. 801–809, March 2012.
- [23] K. Han, Y. Liu, and J. Luo, “Duty-cycle-aware minimum-energy multicasting in wireless sensor networks,” *IEEE/ACM Transactions on Networking*, vol. 21, no. 3, pp. 910–923, 2013.
- [24] C.-H. Lung and C. Zhou, “Using hierarchical agglomerative clustering in wireless sensor networks: An energy-efficient and flexible approach,” *Ad Hoc Networks*, vol. 8, no. 3, pp. 328–344, 2010.
- [25] D. Wei, Y. Jin, S. Vural, K. Moessner, and R. Tafazolli, “An energy-efficient clustering solution for wireless sensor networks,” *IEEE Transactions on Wireless Communications*, vol. 10, pp. 3973–3983, November 2011.

REFERENCES

- [26] H. Taheri, P. Neamatollahi, O. M. Younis, S. Naghibzadeh, and M. H. Yaghmaee, “An energy-aware distributed clustering protocol in wireless sensor networks using fuzzy logic,” *Ad Hoc Networks*, vol. 10, no. 7, pp. 1469–1481, 2012.
- [27] C. Alippi and C. Galperti, “An adaptive system for optimal solar energy harvesting in wireless sensor network nodes,” *IEEE Transactions on Circuits and Systems*, vol. 55, no. 6, pp. 1742–1750, 2008.
- [28] S. Bader and B. Oelmann, “Enabling battery-less wireless sensor operation using solar energy harvesting at locations with limited solar radiation,” in *Fourth International Conference on Sensor Technologies and Applications (SENSORCOMM '10)*, pp. 602–608, July 2010.
- [29] S. Saadon and O. Sidek, “A review of vibration-based mems piezoelectric energy harvesters,” *Energy Conversion and Management*, vol. 52, no. 1, pp. 500–504, 2011.
- [30] S. Kahrobaee and M. Vuran, “Vibration energy harvesting for wireless underground sensor networks,” in *IEEE International Conference on Communications (ICC '13)*, pp. 1543–1548, June 2013.
- [31] P. Nintanavongsa, U. Muncuk, D. R. Lewis, and K. R. Chowdhury, “Design optimization and implementation for rf energy harvesting circuits,” *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 2, no. 1, pp. 24–33, 2012.

REFERENCES

- [32] S. He, J. Chen, F. Jiang, D. Yau, G. Xing, and Y. Sun, “Energy provisioning in wireless rechargeable sensor networks,” *IEEE Transactions on Mobile Computing*, vol. 12, pp. 1931–1942, Oct 2013.
- [33] I. F. Akyildiz and M. C. Vuran, *Wireless sensor networks*, vol. 4. John Wiley & Sons, 2010.
- [34] K. Akkaya and M. Younis, “A survey on routing protocols for wireless sensor networks,” *Ad Hoc Networks*, vol. 3, no. 3, pp. 325 – 349, 2005.
- [35] S. Sudevalayam and P. Kulkarni, “Energy harvesting sensor nodes: Survey and implications,” *IEEE Communications Surveys Tutorials*, vol. 13, pp. 443–461, 2010.
- [36] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, “Power management in energy harvesting sensor networks,” *ACM Transactions on Embedded Computer Systems*, vol. 6, September 2007.
- [37] T. Voigt, H. Ritter, and J. Schiller, “Utilizing solar power in wireless sensor networks,” in *28th Annual IEEE International Conference on Local Computer Networks, (LCN’03)*, pp. 416–422, IEEE, 2003.
- [38] M. Jakobsen, J. Madsen, and M. Hansen, “Dehar: A distributed energy harvesting aware routing algorithm for ad-hoc multi-hop wireless sensor networks,” in *IEEE International Symposium on World of Wireless Mobile and Multimedia Networks, (WoWMoM ’10)*, pp. 1–9, June 2010.
- [39] D. Hasenfratz, A. Meier, C. Moser, J.-J. Chen, and L. Thiele, “Analysis, comparison, and optimization of routing protocols for energy harvesting wireless

REFERENCES

- sensor networks,” in *IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing (SUTC '10)*, pp. 19–26, June 2010.
- [40] L. Cai, Y. Liu, T. Luan, X. Shen, J. Mark, and H. Poor, “Sustainability analysis and resource management for wireless mesh networks with renewable energy supplies,” *IEEE Journal on Selected Areas in Communications*, vol. 32, pp. 345–355, February 2014.
- [41] T. Voigt, A. Dunkels, J. Alonso, H. Ritter, and J. Schiller, “Solar-aware clustering in wireless sensor networks,” in *Ninth International Symposium on Computers and Communications*, vol. 1, pp. 238–243 Vol.1, June 2004.
- [42] P. Zhang, G. Xiao, and H.-P. Tan, “Clustering algorithms for maximizing the lifetime of wireless sensor networks with energy-harvesting sensors,” *Computer Networks*, vol. 57, no. 14, pp. 2689–2704, 2013.
- [43] C. M. Vigorito, D. Ganesan, and A. G. Barto, “Adaptive control of duty cycling in energy-harvesting wireless sensor networks,” in *IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks*, pp. 21–30, June 2007.
- [44] S. Reddy and C. Murthy, “Dual-stage power management algorithms for energy harvesting sensors,” *IEEE Transactions on Wireless Communications*, vol. 11, pp. 1434–1445, April 2012.
- [45] V. Sharma, U. Mukherji, V. Joseph, and S. Gupta, “Optimal energy management policies for energy harvesting sensor nodes,” *IEEE Transactions on Wireless Communications*, vol. 9, pp. 1326–1336, April 2010.

REFERENCES

- [46] O. Ozel, K. Tutuncuoglu, J. Yang, S. Ulukus, and A. Yener, “Transmission with energy harvesting nodes in fading wireless channels: Optimal policies,” *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 8, pp. 1732–1743, 2011.
- [47] K. Tutuncuoglu and A. Yener, “Optimum transmission policies for battery limited energy harvesting nodes,” *IEEE Transactions on Wireless Communications*, vol. 11, pp. 1180 –1189, March 2012.
- [48] R.-S. Liu, P. Sinha, and C. Koksai, “Joint energy management and resource allocation in rechargeable sensor networks,” in *IEEE International Conference on Computer Communications, (ICC '10)*, pp. 1 –9, March 2010.
- [49] Z. A. Eu, H.-P. Tan, and W. K. Seah, “Opportunistic routing in wireless sensor networks powered by ambient energy harvesting,” *Computer Networks*, vol. 54, no. 17, pp. 2943 – 2966, 2010.
- [50] J. Snyman, *Practical mathematical optimization: An introduction to basic optimization theory and classical and new gradient-based algorithms*, vol. 97. Springer, 2005.
- [51] L. V. Stephen Boyd, *Convex Optimization*. Cambridge University Press, 2004.
- [52] K. J. Åström and B. Wittenmark, *Adaptive control*. Courier Dover Publications, 2013.

REFERENCES

- [53] P. Kumar and P. Varaiya, *Stochastic systems: estimation, identification, and adaptive control*. Prentice-Hall information and system sciences series, Prentice Hall, 1986.
- [54] J. Sarangapani, *Wireless ad hoc and sensor networks: protocols, performance, and control*. CRC Press, 2007.
- [55] S. Ghosh and A. Konar, *Call Admission Control in Mobile Cellular Networks*. Springer, 2013.
- [56] Y. Yang and R. Kravets, “Contention-aware admission control for ad hoc networks,” *IEEE Transactions on Mobile Computing*, vol. 4, pp. 363–377, July 2005.
- [57] Y. Qin, Y. Yang, C. L. Gwee, and X. He, “A flow admission control scheme for qos in wireless ad hoc networks,” in *IEEE Global Communications Conference (GLOBECOM '12)*, pp. 5734–5739, 2012.
- [58] W. Ye, J. Heidemann, and D. Estrin, “An energy-efficient mac protocol for wireless sensor networks,” in *IEEE International Conference on Computer Communications (INFOCOM '02)*, vol. 3, pp. 1567 – 1576, 2002.
- [59] R. P. Mann, K. R. Namuduri, and R. Pendse, “Energy-aware routing protocol for ad hoc wireless sensor networks,” *EURASIP Journal on Wireless Communications and Networking*, pp. 635–644, 2005.
- [60] Y.-J. Lu and T.-L. Sheu, “An efficient routing scheme with optimal power control in wireless multi-hop sensor networks,” *Computer Communications*, vol. 30, no. 14-15, pp. 2735–2743, 2007.

REFERENCES

- [61] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, “Energy conservation in wireless sensor networks: A survey,” *Ad Hoc Networks*, vol. 7, no. 3, pp. 537–568, 2009.
- [62] S. Ganeriwal, I. Tsigkogiannis, H. Shim, V. Tsiatsis, M. B. Srivastava, and D. Ganesan, “Estimating clock uncertainty for efficient duty-cycling in sensor networks,” *IEEE/ACM Transactions on Networking*, vol. 17, pp. 843–856, June 2009.
- [63] D. Niyato, E. Hossain, M. Rashid, and V. Bhargava, “Wireless sensor networks with energy harvesting technologies: a game-theoretic approach to optimal energy management,” *IEEE Transactions on Wireless Communications*, vol. 14, no. 4, pp. 90–96, 2007.
- [64] V. Joseph, V. Sharma, and U. Mukherji, “Optimal sleep-wake policies for an energy harvesting sensor node,” in *IEEE International Conference on Communications (ICC '09)*, pp. 1–6, 2009.
- [65] C. K. Ho and R. Zhang, “Optimal energy allocation for wireless communications with energy harvesting constraints,” *IEEE Transactions on Signal Processing*, vol. 60, no. 9, pp. 4808–4818, 2012.
- [66] S. Mao, M. H. Cheung, and V. Wong, “An optimal energy allocation algorithm for energy harvesting wireless sensor networks,” in *IEEE International Conference on Communications, (ICC '12)*, pp. 265–270, 2012.
- [67] A. Seyedi and B. Sikdar, “Energy efficient transmission strategies for body sensor networks with energy harvesting,” *IEEE Transactions on Communications*, vol. 58, no. 7, pp. 2116–2126, 2010.

REFERENCES

- [68] M. Gregori and M. Payaro, “Optimal power allocation for a wireless multi-antenna energy harvesting node with arbitrary input distribution,” in *IEEE International Conference on Communications (ICC '12)*, pp. 5794–5798, 2012.
- [69] Y. Zhang, S. He, J. Chen, Y. Sun, and X. Shen, “Distributed sampling rate control for rechargeable sensor nodes with limited battery capacity,” *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 3096–3106, 2013.
- [70] P. Castiglione, O. Simeone, E. Erkip, and T. Zemen, “Energy management policies for energy-neutral source-channel coding,” *IEEE Transactions on Communications*, vol. 60, no. 9, pp. 2668–2678, 2012.
- [71] J. Hsu, S. Zahedi, A. Kansal, M. Srivastava, and V. Raghunathan, “Adaptive duty cycling for energy harvesting systems,” in *Proceedings of the 2006 international symposium on Low power electronics and design (ISLPED '06)*, pp. 180–185, ACM, 2006.
- [72] A. Kansal, J. Hsu, M. Srivastava, and V. Raghunathan, “Harvesting aware power management for sensor networks,” in *Proceedings of the 43rd annual Design Automation Conference*, pp. 651–656, ACM, 2006.
- [73] C. Moser, D. Brunelli, L. Thiele, and L. Benini, “Real-time scheduling for energy harvesting sensor nodes,” *Real-Time Systems*, vol. 37, no. 3, pp. 233–260, 2007.
- [74] J. R. Piorno, C. Bergonzini, D. Atienza, and T. S. Rosing, “Prediction and management in energy harvested wireless sensor nodes,” in *1st International*

REFERENCES

- Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace Electronic Systems Technology*, pp. 6–10, IEEE, 2009.
- [75] V. Raghunathan, A. Kansal, J. Hsu, J. Friedman, and M. Srivastava, “Design considerations for solar energy harvesting wireless embedded systems,” in *ACM/IEEE international symposium on Information processing in sensor networks (IPSN '05)*, p. 64, IEEE Press, 2005.
- [76] V. Raghunathan, S. Ganeriwal, and M. Srivastava, “Emerging techniques for long lived wireless sensor networks,” *IEEE Communications Magazine*, vol. 44, no. 4, pp. 108–114, 2006.
- [77] S. Peng and C. P. Low, “Throughput optimal energy neutral management for energy harvesting wireless sensor networks,” in *IEEE Wireless Communications and Networking Conference, (WCNC '12)*, pp. 2347–2351, 2012.
- [78] C. Renner, J. Jessen, and V. Turau, “Lifetime prediction for supercapacitor-powered wireless sensor nodes,” *Proceedings of FGSN*, pp. 1–6, 2009.
- [79] B. Conway, *Electrochemical Supercapacitors: Scientific Fundamentals and Technological Applications*. Springer, 1999.
- [80] J. Li, E. Murphy, J. Winnick, and P. A. Kohl, “The effects of pulse charging on cycling characteristics of commercial lithium-ion batteries,” *Journal of Power Sources*, vol. 102, no. 1, pp. 302–309, 2001.
- [81] *NiCd Rechargeable Batteries: Product Fact Sheet*, retrieved in 2014. Available at http://www.gpina.com/pdf/NiCd_Rechargeable.pdf.

REFERENCES

- [82] M. Younis, M. Youssef, and K. Arisha, “Energy-aware routing in cluster-based sensor networks,” in *10th IEEE International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunications Systems (MASCOTS '02)*, pp. 129 – 136, 2002.
- [83] Y. J. Zhao, R. Govindan, and D. Estrin, “Residual energy scans for monitoring wireless sensor networks,” in *IEEE Wireless Communications and Networking Conference (WCNC '02)*, pp. 17–21, 2002.
- [84] D. Linden and T. B. Reddy, *Handbook of Batteries*. New York: McGraw-Hill, 2001.
- [85] *CC1000: Single Chip Very Low Power RF Transceiver Product Manual*, retrieved in 2014. Available at <http://www.ti.com/lit/ds/symlink/cc1000.pdf>.
- [86] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, “An application-specific protocol architecture for wireless microsensor networks,” *IEEE Transactions on Wireless Communications*, vol. 1, no. 4, pp. 660–670, 2002.
- [87] *Las Vegas Solar Radiation Dataset, US National Solar Radiation Data Base*, retrieved on 31st May, 2013. Available at http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2010/hourly/siteonthefly.cgi?id=723860.
- [88] MATLAB, *version 7.11.0 (R2010b)*. Natick, Massachusetts: The MathWorks Inc., 2010.

REFERENCES

- [89] J. Lei, R. Yates, and L. Greenstein, “A generic model for optimizing single-hop transmission policy of replenishable sensors,” *IEEE Transactions on Wireless Communications*, vol. 8, no. 2, pp. 547–551, 2009.
- [90] D. P. Bertsekas, *Dynamic Programming and Optimal Control*. Athena Scientific, 2007.
- [91] A. Goldsmith and P. Varaiya, “Capacity of fading channels with channel side information,” *IEEE Transactions on Information Theory*, vol. 43, pp. 1986–1992, Nov 1997.
- [92] D. Tse, *Fundamentals of wireless communication*. Cambridge University Press, 2005.
- [93] A. Goldsmith, *Wireless Communications*. Cambridge University Press, 2005.
- [94] R. D. Yates and D. J. Goodman, *Probability and stochastic processes*. Wiley New York, 1999.
- [95] C. Kelley, *Solving Nonlinear Equations with Newton’s Method*. Society for Industrial and Applied Mathematics, 2003.
- [96] *NiMH Rechargeable Batteries: Product Fact Sheet*, retrieved in 2014. Available at <http://data.energizer.com/PDFs/nh12-700.pdf>.
- [97] R. E. Bellman, *Dynamic Programming*. Courier Dover Publications, 2003.
- [98] J.-H. Chang and L. Tassiulas, “Maximum lifetime routing in wireless sensor networks,” *IEEE/ACM Transactions on Networking*, vol. 12, no. 4, pp. 609–619, 2004.

REFERENCES

- [99] R. Madan and S. Lall, “Distributed algorithms for maximum lifetime routing in wireless sensor networks,” *IEEE Transactions on Wireless Communications*, vol. 5, no. 8, pp. 2185–2193, 2006.
- [100] J. Park and S. Sahni, “An online heuristic for maximum lifetime routing in wireless sensor networks,” *IEEE Transactions on Computers*, vol. 55, no. 8, pp. 1048–1056, 2006.
- [101] F. Ren, J. Zhang, T. He, C. Lin, and S. Ren, “Ebrp: Energy-balanced routing protocol for data gathering in wireless sensor networks,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 22, pp. 2108–2125, Dec 2011.
- [102] C. Intanagonwiwat, R. Govindan, D. Estrin, J. Heidemann, and F. Silva, “Directed diffusion for wireless sensor networking,” *IEEE/ACM Transactions on Networks*, vol. 11, pp. 2–16, February 2003.
- [103] M. Chu, H. Haussecker, and F. Zhao, “Scalable information-driven sensor querying and routing for ad hoc heterogeneous sensor networks,” *International Journal of High Performance Computing Applications*, vol. 16, no. 3, pp. 293–313, 2002.
- [104] R. Shah and J. Rabaey, “Energy aware routing for low energy ad hoc sensor networks,” in *Wireless Communications and Networking Conference (WCNC ’02)*, vol. 1, pp. 350 – 355 vol.1, Mar. 2002.
- [105] N. Sadagopan, B. Krishnamachari, and A. Helmy, “Active query forwarding in sensor networks,” *Ad Hoc Networks*, vol. 3, no. 1, pp. 91–113, 2005.

REFERENCES

- [106] F. Yu, Y. Li, F. Fang, and Q. Chen, “A new tora-based energy aware routing protocol in mobile ad hoc networks,” in *3rd IEEE/IFIP International Conference in Central Asia on Internet (ICI '07)*, pp. 1–4, IEEE, 2007.
- [107] Z. J. Haas and M. R. Pearlman, “The performance of query control schemes for the zone routing protocol,” *IEEE/ACM Transactions on Networking*, vol. 9, no. 4, pp. 427–438, 2001.
- [108] S. Tilak, N. B. Abu-Ghazaleh, and W. Heinzelman, “A taxonomy of wireless micro-sensor network models,” *ACM Mobile Computing and Communications Review*, vol. 6, pp. 28–36, 2002.
- [109] M. Chen, T. Kwon, and Y. Choi, “Energy-efficient differentiated directed diffusion (eddd) in wireless sensor networks,” *Computer Communications*, vol. 29, no. 2, pp. 231–245, 2006.
- [110] Z. Xiangbin, “An improved energy aware directed diffusion algorithm for wireless sensor network,” in *Asia-Pacific Conference on Communications (APCC '07)*, pp. 385–388, 2007.
- [111] L. Lin, N. B. Shroff, and R. Srikant, “Asymptotically optimal energy-aware routing for multihop wireless networks with renewable energy sources,” *IEEE/ACM Transactions on Networking*, vol. 15, pp. 1021–1034, October 2007.
- [112] E. Lattanzi, E. Regini, A. Acquaviva, and A. Bogliolo, “Energetic sustainability of routing algorithms for energy-harvesting wireless sensor networks,” *Computer Communications*, vol. 30, pp. 2976–2986, October 2007.

REFERENCES

- [113] N. Dang, M. Roshanaei, E. Bozorgzadeh, and N. Venkatasubramanian, “Adapting data quality with multihop routing for energy harvesting wireless sensor networks,” in *International Green Computing Conference (IGCC '13)*, pp. 1–6, June 2013.
- [114] R. Cui, Z. Qu, and S. Yin, “Energy-efficient routing protocol for energy harvesting wireless sensor network,” in *IEEE International Conference on Communication Technology (ICCT '13)*, pp. 500–504, Nov 2013.
- [115] Y. Wu and W. Liu, “Routing protocol based on genetic algorithm for energy harvesting-wireless sensor networks,” *IET Wireless Sensor Systems*, vol. 3, pp. 112–118, June 2013.
- [116] F. Silva, J. Heidemann, R. Govindan, and D. Estrin, *Frontiers in Distributed Sensor Networks*, ch. Directed Diffusion. Boca Raton, Florida, USA: CRC Press, Inc., October 2003.
- [117] B. Guo, Z. Li, and D. Li, “Energy-aware improved directed diffusion algorithm for area event monitoring in wireless sensor network,” in *Distributed Computing and Internet Technology*, vol. 4317 of *Lecture Notes in Computer Science*, pp. 41–48, Springer Berlin Heidelberg, 2006.
- [118] L. M. Feeney and M. Nilsson, “Investigating the energy consumption of a wireless network interface in an ad hoc networking environment,” in *Twenty-First Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM '01)*, pp. 1548–1557, 2001.
- [119] *OMNet++ User Manual, version 4.1*, 2013.

REFERENCES

- [120] O. Younis and S. Fahmy, “Heed: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks,” *IEEE Transactions on Mobile Computing*, vol. 3, pp. 366 – 379, Oct.-Dec. 2004.
- [121] G. Chen, C. Li, M. Ye, and J. Wu, “An unequal cluster-based routing protocol in wireless sensor networks,” *Wireless Networks*, vol. 15, pp. 193–207, Feb. 2009.
- [122] S. Peng and C. P. Low, “Energy neutral routing for energy harvesting wireless sensor networks,” in *IEEE Wireless Communications and Networking Conference (WCNC '13)*, pp. 2063–2067, April 2013.
- [123] A. A. Abbasi and M. Younis, “A survey on clustering algorithms for wireless sensor networks,” *Computer Communications*, vol. 30, pp. 2826–2841, Oct. 2007.
- [124] M. Ye, C. Li, G. Chen, and J. Wu, “Eecs: an energy efficient clustering scheme in wireless sensor networks,” in *IEEE International Performance, Computing, and Communications Conference (IPCCC '05)*, pp. 535–540, April 2005.
- [125] S. D. Muruganathan, D. C. Ma, R. I. Bhasin, and A. Fapojuwo, “A centralized energy-efficient routing protocol for wireless sensor networks,” *IEEE Communications Magazine*, vol. 43, no. 3, pp. S8–13, 2005.
- [126] H. Huang and J. Wu, “A probabilistic clustering algorithm in wireless sensor networks,” in *IEEE Vehicular Technology Conference*, vol. 62, p. 1796, IEEE; 1999, 2005.

REFERENCES

- [127] S. Bandyopadhyay and E. J. Coyle, “An energy efficient hierarchical clustering algorithm for wireless sensor networks,” in *Twenty-Second Annual Joint Conference of the IEEE Computer and Communications (INFOCOM '03)*, vol. 3, pp. 1713–1723, IEEE, 2003.
- [128] A. M. Youssef, M. F. Younis, M. Youssef, and A. K. Agrawala, “Distributed formation of overlapping multi-hop clusters in wireless sensor networks,” in *IEEE Global Communications Conference (GLOBECOM '06)*, 2006.
- [129] S. Soro and W. B. Heinzelman, “Prolonging the lifetime of wireless sensor networks via unequal clustering,” in *19th IEEE International Parallel and Distributed Processing Symposium (IPDPS '05)*, pp. 8–pp, IEEE, 2005.
- [130] B. Gong, L. Li, S. Wang, and X. Zhou, “Multihop routing protocol with unequal clustering for wireless sensor networks,” in *ISECS International Colloquium on Computing, Communication, Control, and Management (CCCM'08)*, vol. 2, pp. 552–556, IEEE, 2008.
- [131] S. Lee, J. Lee, H. Sin, S. Yoo, S. Lee, J. Lee, Y. Lee, and S. Kim, “An energy-efficient distributed unequal clustering protocol for wireless sensor networks,” *Proceedings of World Academy of Science: Engineering and Technology (PWASET '08)*, vol. 48, 2008.
- [132] Y. Wang, T. Yang, and D. Zhang, “An energy efficient and balance hierarchical unequal clustering algorithm for large scale sensor networks,” *Information Technology Journal*, vol. 8, no. 1, 2009.
- [133] N. Patwari, A. O. H. Iii, M. Perkins, N. S. Correal, R. J. O'Dea, R. J. Odea, M. P. N. S. Correal, and R. J. O. Are, “Relative location estimation in

REFERENCES

- wireless sensor networks,” *IEEE Transactions on Signal Processing*, vol. 51, pp. 2137–2148, 2003.
- [134] H. Chan and A. Perrig, “Ace: An emergent algorithm for highly uniform cluster formation,” in *Wireless Sensor Networks*, pp. 154–171, Springer, 2004.
- [135] P. Martin, R. Galvan-Guerra, M. Egerstedt, and V. Azhmyakov, “Power-aware sensor coverage: An optimal control approach,” in *Proceedings of the 19th International Symposium on Mathematical Theory of Networks and Systems (MTNS ’10)*, vol. 5, 2010.
- [136] H. Jaleel, A. Rahmani, and M. Egerstedt, “Probabilistic lifetime maximization of sensor networks,” *IEEE Transactions on Automatic Control*, vol. 58, pp. 534–539, Feb 2013.
- [137] L. Mottola and G. P. Picco, “Muster: Adaptive energy-aware multisink routing in wireless sensor networks,” *IEEE Transactions on Mobile Computing*, vol. 10, no. 12, pp. 1694–1709, 2011.
- [138] M. Tao, D. Lu, and J. Yang, “An adaptive energy-aware multi-path routing protocol with load balance for wireless sensor networks,” *Wireless Personal Communications*, vol. 63, no. 4, pp. 823–846, 2012.
- [139] Z. A. Eu, H.-P. Tan, and W. K. Seah, “Design and performance analysis of mac schemes for wireless sensor networks powered by ambient energy harvesting,” *Ad Hoc Networks*, vol. 9, no. 3, pp. 300 – 323, 2011.

REFERENCES

- [140] H. Yoo, M. Shim, and D. Kim, “Dynamic duty-cycle scheduling schemes for energy-harvesting wireless sensor networks,” *IEEE Communications Letters*, vol. 16, pp. 202–204, February 2012.
- [141] F. Iannello, O. Simeone, and U. Spagnolini, “Medium access control protocols for wireless sensor networks with energy harvesting,” *IEEE Transactions on Communications*, vol. 60, no. 5, pp. 1381–1389, 2012.
- [142] S. Kumar, T. H. Lai, and J. Balogh, “On k-coverage in a mostly sleeping sensor network,” *Wireless Networks*, vol. 14, no. 3, pp. 277–294, 2008.