Resource Management in
Energy Harvesting
Wireless Sensor Networks

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 pursue 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


2.1 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 $N_{\text{sun}}$ 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 $\delta$ 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>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.6</td>
<td>Numerical Results</td>
<td>95</td>
</tr>
<tr>
<td>3.6.1</td>
<td>Performance Improvement due to Improved-HEUE</td>
<td>95</td>
</tr>
<tr>
<td>3.6.2</td>
<td>Energy Neutral Operation</td>
<td>96</td>
</tr>
<tr>
<td>3.6.3</td>
<td>Average Channel Throughput</td>
<td>99</td>
</tr>
<tr>
<td>3.6.4</td>
<td>Convergence Rate to Optimality</td>
<td>103</td>
</tr>
<tr>
<td>3.6.5</td>
<td>Computational Complexities</td>
<td>104</td>
</tr>
<tr>
<td>3.7</td>
<td>Summary</td>
<td>106</td>
</tr>
<tr>
<td>4</td>
<td>Energy Neutral Directed Diffusion for Energy Harvesting Wireless</td>
<td>107</td>
</tr>
<tr>
<td>4.1</td>
<td>Introduction</td>
<td>108</td>
</tr>
<tr>
<td>4.2</td>
<td>Related Works</td>
<td>110</td>
</tr>
<tr>
<td>4.2.1</td>
<td>Energy Harvesting Aware Routing Protocols</td>
<td>110</td>
</tr>
<tr>
<td>4.2.2</td>
<td>Query Driven Routing Protocols</td>
<td>112</td>
</tr>
<tr>
<td>4.3</td>
<td>System Model and Notations</td>
<td>113</td>
</tr>
<tr>
<td>4.3.1</td>
<td>Network Topology</td>
<td>113</td>
</tr>
<tr>
<td>4.3.2</td>
<td>Sensor Energy Dissipation Model</td>
<td>114</td>
</tr>
<tr>
<td>4.3.3</td>
<td>Network-level Energy Neutral Management</td>
<td>115</td>
</tr>
<tr>
<td>4.4</td>
<td>Energy Neutral Directed Diffusion (ENDD)</td>
<td>116</td>
</tr>
<tr>
<td>4.4.1</td>
<td>Preliminaries</td>
<td>117</td>
</tr>
<tr>
<td>4.4.2</td>
<td>ENDD-Two Phase Pull (ENDD-T)</td>
<td>119</td>
</tr>
<tr>
<td>4.4.3</td>
<td>ENDD-One Phase Pull (ENDD-O)</td>
<td>127</td>
</tr>
<tr>
<td>4.4.4</td>
<td>Real-time Energy Consumption Estimation</td>
<td>133</td>
</tr>
<tr>
<td>4.4.5</td>
<td>Upper Bounds on the Control Message Overheads</td>
<td>139</td>
</tr>
<tr>
<td>4.5</td>
<td>Empirical Studies</td>
<td>142</td>
</tr>
</tbody>
</table>
### 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 Sensors 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
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 $\eta^*_V$ ....... 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 ($\eta^*_V$) .... 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
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.3</td>
<td>Calculation of $T_m(t)$ for different OIs</td>
</tr>
<tr>
<td>4.4</td>
<td>Accumulated Node Failure Time using the three protocols</td>
</tr>
<tr>
<td>4.5</td>
<td>Distinct packet delivery ratio comparison</td>
</tr>
<tr>
<td>4.6</td>
<td>Average end-to-end packet delivery delay comparison</td>
</tr>
<tr>
<td>5.1</td>
<td>Cluster Members and Cluster Head Groups</td>
</tr>
<tr>
<td>5.2</td>
<td>Operation timeline of the ENC algorithm</td>
</tr>
<tr>
<td>5.3</td>
<td>Six clusters formed using ENC</td>
</tr>
<tr>
<td>5.4</td>
<td>Six equal sized clusters formed using ENC*</td>
</tr>
<tr>
<td>5.5</td>
<td>Accumulated Cluster Failure Time with $R = 50m$</td>
</tr>
<tr>
<td>5.6</td>
<td>Accumulated Cluster Failure Time with $R = 100m$</td>
</tr>
<tr>
<td>5.7</td>
<td>Accumulated Cluster Failure Time with $R = 150m$</td>
</tr>
<tr>
<td>5.8</td>
<td>Average TAIB gathered with $R = 50m$</td>
</tr>
<tr>
<td>5.9</td>
<td>Average TAIB gathered with $R = 100m$</td>
</tr>
<tr>
<td>5.10</td>
<td>Average TAIB gathered with $R = 150m$</td>
</tr>
<tr>
<td>5.11</td>
<td>Number of control message exchanged with $R = 100m$</td>
</tr>
</tbody>
</table>
**List of Tables**

1.1 Approaches and Proposed Schemes ............................................ 13

2.1 Matching Deviation under different $D_{\text{min}}$ .......................... 56

2.2 Average BREL deviations from $2000J (\delta_{2000})$ ......................... 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

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABAP</td>
<td>Adaptive Budget Assignment Policy</td>
</tr>
<tr>
<td>ABAP*</td>
<td>Improved Adaptive Budget Assignment Policy</td>
</tr>
<tr>
<td>ACT</td>
<td>Average Channel Throughput</td>
</tr>
<tr>
<td>AMP</td>
<td>ACT Maximization Problem</td>
</tr>
<tr>
<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
</tr>
<tr>
<td>AWL</td>
<td>Adaptive Water Level</td>
</tr>
<tr>
<td>BCL</td>
<td>Battery Cycle Life</td>
</tr>
<tr>
<td>BREL</td>
<td>Battery Residual Energy Level</td>
</tr>
<tr>
<td>CH</td>
<td>Cluster Head</td>
</tr>
<tr>
<td>CHG</td>
<td>Cluster Head Group</td>
</tr>
<tr>
<td>CM</td>
<td>Cluster Member</td>
</tr>
<tr>
<td>CN</td>
<td>Center Node</td>
</tr>
<tr>
<td>DWF</td>
<td>Directional Water Filling</td>
</tr>
<tr>
<td>EDP</td>
<td>Exploratory Data Packet</td>
</tr>
<tr>
<td>EHAM</td>
<td>Energy Harvesting Aware Management</td>
</tr>
<tr>
<td>EHAR</td>
<td>Energy Harvesting Aware Routing</td>
</tr>
<tr>
<td>EH-Sensor</td>
<td>Energy Harvesting Wireless Sensor</td>
</tr>
<tr>
<td>EH-WSN</td>
<td>Energy Harvesting Wireless Sensor Network</td>
</tr>
<tr>
<td>ENC</td>
<td>Energy Neutral Clustering</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Full Form</td>
</tr>
<tr>
<td>--------------</td>
<td>-----------</td>
</tr>
<tr>
<td>ENC*</td>
<td>Improved Energy Neutral Clustering</td>
</tr>
<tr>
<td>ENDD</td>
<td>Energy Neutral Directed Diffusion</td>
</tr>
<tr>
<td>ENM</td>
<td>Energy Neutral Management</td>
</tr>
<tr>
<td>ENO</td>
<td>Energy Neutral Operation</td>
</tr>
<tr>
<td>HEUE</td>
<td>Harvested Energy Utilization Efficiency</td>
</tr>
<tr>
<td>INI</td>
<td>Initial Interest</td>
</tr>
<tr>
<td>LP</td>
<td>Linear Programming</td>
</tr>
<tr>
<td>LEACH</td>
<td>Low Energy Adaptive Clustering Hierarchy</td>
</tr>
<tr>
<td>MAC</td>
<td>Multiple Access Control</td>
</tr>
<tr>
<td>Max-NIG</td>
<td>Network Information Gathering Maximization</td>
</tr>
<tr>
<td>MEMS</td>
<td>Micro-Electro-Mechanic System</td>
</tr>
<tr>
<td>NDP</td>
<td>Non-exploratory Data Packet</td>
</tr>
<tr>
<td>OI</td>
<td>One-phase Interest</td>
</tr>
<tr>
<td>OPPD</td>
<td>One Phase Pull Diffusion</td>
</tr>
<tr>
<td>P-FREEN</td>
<td>Prediction FREE Energy Neutral management</td>
</tr>
<tr>
<td>RI</td>
<td>Reinforcement Interest</td>
</tr>
<tr>
<td>TPPD</td>
<td>Two Phase Pull Diffusion</td>
</tr>
<tr>
<td>WSN</td>
<td>Wireless Sensor Network</td>
</tr>
</tbody>
</table>
Mathematical Symbols

$\eta_S$ 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

$\eta$ Harvested Energy Utilization Efficiency

$\sigma_D$ 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

$\frac{1}{\lambda^*_t}$ Adaptive Water Level for a time slot $t$

$\eta_V$ Improved-HEUE

$\eta'_V$ Current estimated Improved-HEUE for a time slot $t$

$\eta^*_V$ 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
Glossary

\begin{itemize}
  \item \(d\) \hspace{1cm} Distance between two sensor nodes
  \item \(E_{P}(t)\) \hspace{1cm} Current Projected Energy Consumption
  \item \(E_{A}(m)\) \hspace{1cm} Additional energy consumption
  \item \(\phi^{\text{total}}(t)\) \hspace{1cm} Total number of data packets that a sensor is suppose to receive and transmit in a time slot \(t\)
  \item \(\phi^{\text{total}}_{m}(t)\) \hspace{1cm} Total number of packets that is supposed to be relayed by a sensor in a time slot \(t\) for admitting an interest \(m\)
  \item \(R_{m}\) \hspace{1cm} Data packet transmission rate specified by interest \(m\)
  \item \(T_{m}(t)\) \hspace{1cm} Portion of the event duration specified by interest \(m\) that lies within the current time slot \(t\)
  \item \(\beta_{re}\) \hspace{1cm} Expected packet retransmission constant
  \item \(\phi^{\text{oh}}(t)\) \hspace{1cm} Expected number of packet overhearing in time slot \(t\)
  \item \(E_{\text{idle}}(t)\) \hspace{1cm} Energy consumed due to idle listening in time slot \(t\)
  \item \(G\) \hspace{1cm} A network graph with \(|V|\) vertices and \(|E|\) edges
  \item \(\Delta(G)\) \hspace{1cm} Maximum degree of a vertex in the network graph \(G\)
  \item \(N\) \hspace{1cm} Notation of Normal Distribution
  \item \(N\) \hspace{1cm} Total number of sensors in the network
  \item \(R\) \hspace{1cm} Radius of the sensor deployment field
  \item \(\hat{d}\) \hspace{1cm} Crossover distance
  \item \(\varepsilon_{e-tx}\) \hspace{1cm} Energy consumed in the transmitter electronics to transmit one bit of information
  \item \(\varepsilon_{e-rx}\) \hspace{1cm} Energy consumed in the receiver electronics to receive one bit of information
  \item \(\varepsilon_{Sx}\) \hspace{1cm} Energy consumed to sense one information bit
  \item \(\varepsilon_{DA}\) \hspace{1cm} A constant (Joule/bit/signal) used in the data aggregation process
  \item \(E_{CM}^{n}\) \hspace{1cm} Energy needed for a Cluster Member \(n\) to sense and transmit one bit of information
  \item \(E_{CH}^{n}\) \hspace{1cm} Energy needed for a Cluster Head \(n\) to handle one bit of information
  \item \(E_{CM}^{TX/b}\) \hspace{1cm} Amount of energy needed for a CM to transmit one bit of information
\end{itemize}
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_{CH}^{Tx/b}$</td>
<td>Amount of energy needed for a CH to transmit one bit of information</td>
</tr>
<tr>
<td>$E_H^n(t)$</td>
<td>Energy harvested by sensor $n$ in a time slot $t$</td>
</tr>
<tr>
<td>$E_B^n(t)$</td>
<td>Energy Budget for a sensor $n$ in a time slot $t$</td>
</tr>
<tr>
<td>$K$</td>
<td>Number of clusters expected to be formed in the network</td>
</tr>
<tr>
<td>$N_{CM}^k$</td>
<td>Number of Final Cluster Members in a cluster $k$</td>
</tr>
<tr>
<td>$N_{IC}^k$</td>
<td>Number of Initial Cluster Members in a cluster $k$</td>
</tr>
<tr>
<td>$N_G^k$</td>
<td>Number of CHG-Nodes in a cluster $k$</td>
</tr>
<tr>
<td>$L^n(t)$</td>
<td>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</td>
</tr>
<tr>
<td>$B_{max}^k(t)$</td>
<td>Maximum amount of information bits that can be gathered by a cluster $k$ in time slot $t$</td>
</tr>
<tr>
<td>$T_A^n$</td>
<td>The time duration for a CHG-Node $n$ to wake up and take up the role as an Active-CH</td>
</tr>
<tr>
<td>$T_{DX}$</td>
<td>Amount of time a network spent in data information transmission during a time slot</td>
</tr>
<tr>
<td>$N_{CM}$</td>
<td>Expected number of Final-CMs in a cluster</td>
</tr>
<tr>
<td>$N_G$</td>
<td>Expected size of the CHG in a cluster</td>
</tr>
<tr>
<td>$\xi[E_B(t)]$</td>
<td>Expected Energy Budget for a sensor in a time slot $t$</td>
</tr>
<tr>
<td>$d_{toCH}$</td>
<td>Distance between a Cluster Member and a Cluster Head</td>
</tr>
<tr>
<td>$d_{toBS}$</td>
<td>Distance between a Cluster Head and the Base Station</td>
</tr>
<tr>
<td>$R_e$</td>
<td>Expected radius of a cluster formed in the network</td>
</tr>
<tr>
<td>$L_t$</td>
<td>Expected number of information bits that a Final-CM can send to its CH without compromising its Energy Neutral state in time slot $t$</td>
</tr>
</tbody>
</table>
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

![Wireless Sensor Networks Diagram](image)

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
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 vari-
  ations. 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 re-
  lying on predicted energy harvesting information, the energy management
  mechanism for the EH-WSN has to be carefully designed so that it can dy-
  namically 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 consid-
ering a definite energy constraint (the amount of energy stored in batteries)
as in conventional WSN, for the energy management of an EH-WSN, mul-
tiple energy constraints have to be taken into consideration. Network wide
cordinations 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
  of the EH-WSN.
1.3 Existing Solutions

- **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.
1.3. Existing Solutions

![Diagram showing categories of existing solutions]

**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
1.3. Existing Solutions

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
1.3. Existing Solutions

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

<table>
<thead>
<tr>
<th>Energy Neutral Management</th>
<th>Approach</th>
<th>Proposed Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node-level</td>
<td>Linear Mathematical Optimization</td>
<td>P-FREEN</td>
</tr>
<tr>
<td></td>
<td>Non-linear Adaptive Control</td>
<td>ABAP</td>
</tr>
<tr>
<td>Network-level</td>
<td>Query Driven Admission Control</td>
<td>ENDD</td>
</tr>
<tr>
<td></td>
<td>Continuous Network Clustering</td>
<td>ENC</td>
</tr>
</tbody>
</table>

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-
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 nonlinear 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
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


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
2.1. Introduction

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
2.2 Related Works

- 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
2.2. Related Works

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 $\eta_S$, 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. System Model and Notations

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 $t = 1, ..., N_D$ 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:

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

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 $E_{\max}$.
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:

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

(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
2.4. Average Duty Cycle Maximization

Energy consumption is thus determined by the maximum and minimum duty cycle where \( E_{\text{min}} = D_{\text{min}} \times E_c \) and \( E_{\text{max}} = D_{\text{max}} \times E_c \).

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 \( \eta_S \) 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

\[
E^+_U = \eta_S D(t) \times T \times (P_H(t) - P_c) + D(t) \times T \times P_c
\]

\[
= D(t)(\eta_S \times (E_H(t) - E_c) + E_c) = D(t)(\eta_S X(t) I(X(t)) + E_c)
\]  (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

\[
E^-_U = D(t) \times T \times P_H(t) = D(t) \times E_H(t)
\]

\[
= D(t)E_c + D(t) \times E_H(t) - D(t)E_c = D(t)(E_c + X(t)I(-X(t)))
\]  (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:

\[
E^{active}_U(t) = D(t)[\eta_S X(t) I(X(t)) + E_c + X(t)I(-X(t))]
\]  (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 \( E^{sleep}_U \) under this
situation can be represented as:

$$E_{U}^{\text{sleep}}(t) = (1 - D(t))\eta_SE_H(t) \quad (2.6)$$

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

$$E_U(t) = E_U^{\text{active}}(t) + E_U^{\text{sleep}}(t)$$

$$= D(t)[\eta_S X(t)I(X(t)) + E_c + X(t)I(-X(t))] + (1 - D(t))\eta_SE_H(t) \quad (2.7)$$

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

*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:

$$E_U^{\text{max}}(t) = E_c + \eta_S(E_H(t) - E_c) \geq E_c \quad (2.8)$$
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 $E_U^{\text{max}}(t) = \eta_s E_H(t) E_c / (E_c - (1 - \eta_s) E_H(t))$.

*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:

$$E_U(t) = D(t) E_H(t) + (1 - D(t)) \eta_s E_H(t)$$

(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:

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

(2.10)

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

$$D(t) \leq \frac{\eta_s E_H(t)}{E_c - (1 - \eta_s) E_H(t)}$$

(2.11)

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

$$E_U(t) \leq \frac{\eta_s E_H(t) E_c}{E_c - (1 - \eta_s) E_H(t)} = E_U^{\text{max}}(t)$$

(2.12)

Based on Lemma 1 and Lemma 2, we further classify the time slot $t$ into two
categories, the Darkslot and the Sunslot, by the following method:

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

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:

\[
\max \frac{1}{N_{O} \times N_{D}} \sum_{i=1}^{N_{O}} \sum_{t=(i-1)\times N_{D}+1}^{i \times N_{D}} D(t) \quad (2.13)
\]

\[ s.t. \]
\[ D(t) \geq D_{\text{min}}, t = 1, 2, ... N_{t} \quad (2.14) \]
\[ D(t) \leq D_{\text{max}}, t = 1, 2, ... N_{t} \quad (2.15) \]
\[
\sum_{i=1}^{N_{O}} \sum_{t=(i-1)\times N_{D}+1}^{i \times N_{D}} E_{U}(t) \geq \sum_{i=1}^{N_{O}} \sum_{t=(i-1)\times N_{D}+1}^{i \times N_{D}} E_{B}(t) 
\]

(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. Furthermore, 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:

\[
\xi[D(E_B(t))] = D(\xi[E_B(t)])
\]  

(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

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

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

\[ \xi[D(E_B(t))] \leq D \left( \frac{1}{N_t} \sum_{t=1}^{N_t} E_U(t) \right) = \frac{1}{N_t E_e} \sum_{t=1}^{N_t} E_U(t) \] (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 $\eta$) for one OC ($N_D$ time slots) is thus defined as follows:

$$\eta = \frac{\sum_{t=1}^{N_D} E_U(t)}{\sum_{t=1}^{N_D} E_H(t)} = \frac{\sum_{t=1}^{N_D} E_H(t) - \sum_{t=1}^{N_D} E_{Loss}(t)}{\sum_{t=1}^{N_D} E_H(t)}$$

where $E_{S_{loss}}(t)$ 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*. $E_{N_{loss}}(t)$ 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:

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

where

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

Thus, minimizing \( EN_{\text{loss}}(t) \) requires

\[
E_B(t) = D(t)E_c \leq E_U(t) \tag{2.22}
\]

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)):

\[
ES_{\text{Loss}}(t) = E_H(t) - E_U(t) \\
= (1 - \eta_S)(1 - D(t))E_H(t) + (1 - \eta_S)D(t)[E_H(t) - E_c]^+ \tag{2.23}
\]

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 ($\eta$) is in fact the minimization of $ES_{Loss}(t) + EN_{loss}(t)$ in each time slot, which has two scenarios:

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

$$ES_{Loss}(t) = (1 - \eta_S)(E_H(t) - D(t) \times E_c) = E_c(1 - \eta_S) \left( \frac{E_H(t)}{E_c} - D(t) \right) \geq E_c(1 - \eta_S)(1 - D(t))$$

(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 $\eta$.

**Scenario 2:** $E_H(t) \leq E_c$. 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
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 $E_{U}^{\text{max}}(t)$, whereby the value of $E_{U}^{\text{max}}(t)$ is given in lemma 2.2. Since it is the maximum amount possible, use $E_{U}^{\text{max}}(t)$ as the energy budget can thus minimize $E S_{\text{Loss}}(t)$. In addition, we note that according to condition \( (2.22) \), assign an energy budget that is no more than $E_{U}^{\text{max}}(t)$ will also minimize $E N_{\text{loss}}(t)$. From here, we can conclude that $E_{U}^{\text{max}}(t)$ should be used as the energy budget to maximize $\eta$. Take the maximum and minimum energy budget constraints into consideration, energy budget assignment method to maximize $\eta$ in this scenario is:

\[
E_{B}(t) = \begin{cases} 
E_{\text{max}} & \text{if } E_{U}^{\text{max}}(t) > E_{\text{max}} \\
E_{U}^{\text{max}}(t) & \text{if } E_{\text{min}} < E_{U}^{\text{max}}(t) \leq E_{\text{max}} \\
E_{\text{min}} & \text{if } E_{U}^{\text{max}}(t) \leq E_{\text{min}}
\end{cases}
\] (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 $E_{U}^{\text{max}}$. Thus, it is intuitive that we will want to minimize the differences between the energy budget assigned and the utilizable energy $E_{U}^{\text{max}}(t)$, 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 $E_{U}^{\text{max}}(t)$ 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 $E_{\text{max}}$ 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 $E_{\text{min}}$ as the energy budget for Darkslots. By the definition of Darkslot, using $E_{\text{min}}$ 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:

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

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 $E_{\text{min}}$ 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 $E_{\text{min}}$ to be the energy budget.

2. (a) For a Sunslot, if there is insufficient energy $E_r$ reserved in the battery,
assign $E_{\text{min}}$ 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 $B_{\text{PFL}}$, indicates that the battery is fully charged. The Operational Full Level (OFL), denoted by $B_{\text{OFL}}$, indicates that the system has reserved sufficient energy ($E_r$) that is required for Darkslots
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-FRENE 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 $B(t)$.

![Battery energy level model](image)

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:

\[ E_{gap} = (N_D - N_{sun})(E_{min} + \int_{\tau}^{\tau+T} \rho(\tau)d\tau) \]  \hspace{1cm} (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 \( N_{sun}(d) \) denote the number of Sunslots that we have observed today, \( N_{sun}(d-1) \) for yesterday and \( N_{sun}(d-2) \) for the day before yesterday and so on. Then the updated number of Sunslots \( N_{sun}(d+1) \) for tomorrow (the next OC), will be:

\[ N_{sun}(d+1) = a[N_{sun}(d) + (1-a)N_{sun}(d-1) + (1-a)^2N_{sun}(d-2) + ...] \]  \hspace{1cm} (2.28)

where \( N_{sun}(0) = N_D/2 \) (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.
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
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:

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

where

- \( Condition(A) : B(t) < B_{OFL} \)
- \( Condition(B) : E_{U}^{\text{max}}(t-1) < E_{\text{min}} \)

(\( \overline{A} \)) 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 $E_{\text{min}}$ 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 $E_{\text{min}}$ 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 $E_{\text{min}}$ (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 $E_{\text{min}}$ 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 $B_{\text{OFL}}$ 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 $E_{\text{U}t}^{\text{max}}(t)$ 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 $E_{\text{min}}$ 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 $E_{\text{gap}}$ easily by using equation (2.27) and determine the Bonus Energy by $E_{\text{bon}} = 2 \times E_{\text{gap}}$. 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 $BOEL$ unless under some extreme weather conditions. Thus, in order to benefit from Shallow Recharge, it is preferred to set $BOEL$ to be above certain percentage of the total battery capacity. The battery capacity $BC$ can thus be calculated as follows:

$$BC \geq (E_{bon} + E_{gap})/\sigma_D$$

(2.29)

where $\sigma_D$ is a percentage value that represents the depth of discharge. Shallow Recharge require the $\sigma_D$ 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 $600 - 1300 mAh$, 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
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:

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

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 $E_L$ due to the differences
2.5. Prediction Free Energy Neutral Management

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

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

From this equation we can observe that the performance deviation of P-FREEN is directly determined by variance \(\sigma_T^2\), 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, \((D(t) = 1 \text{ for example})\), 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 \(E_{min}\). 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.

52
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 $D_{\text{max}}$ 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. $N_{\text{sun}}$ 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 $E_{\text{max}}^u(t)$ 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

Table 2.1: Matching Deviation under different $D_{min}$

<table>
<thead>
<tr>
<th>$\delta_M^{average}$</th>
<th>$D_{max} = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$D_{min} = 0.1$</td>
</tr>
<tr>
<td>Data Set 1</td>
<td></td>
</tr>
<tr>
<td>Kansal-Ideal</td>
<td>11.0J</td>
</tr>
<tr>
<td>P-FREEN</td>
<td>12.9J</td>
</tr>
<tr>
<td>Kansal-Actual</td>
<td>16.9J</td>
</tr>
<tr>
<td>Data Set 2</td>
<td></td>
</tr>
<tr>
<td>Kansal-Ideal</td>
<td>13.7J</td>
</tr>
<tr>
<td>P-FREEN</td>
<td>14.2J</td>
</tr>
<tr>
<td>Kansal-Actual</td>
<td>19.7J</td>
</tr>
<tr>
<td>Data Set 3</td>
<td></td>
</tr>
<tr>
<td>Kansal-Ideal</td>
<td>10.7J</td>
</tr>
<tr>
<td>P-FREEN</td>
<td>11.4J</td>
</tr>
<tr>
<td>Kansal-Actual</td>
<td>13.0J</td>
</tr>
</tbody>
</table>

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

We also record the matching deviation (denoted by $\delta_M$) 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 2000 J, we let the battery level to keep accumulating (capped at 2300 J) 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 2000 J (denoted by $\delta_{2000}$) is 160 J per time slot under Kansal-Actual, which is larger as compared with the deviation of 128 J 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 $D_{\text{min}} = 0.1$ 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 63.4$J$, 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 $D_{\text{min}}$ 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 \( D_{\text{min}} = 0.3 \) for DS1

<table>
<thead>
<tr>
<th>( \delta_{2000} )</th>
<th>( D_{\text{max}} = 1 )</th>
<th>( D_{\text{min}} = 0.1 )</th>
<th>( D_{\text{min}} = 0.2 )</th>
<th>( D_{\text{min}} = 0.3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Set 1</td>
<td>Kansal-Ideal</td>
<td>63.4J</td>
<td>335J</td>
<td>724J</td>
</tr>
<tr>
<td></td>
<td>P-FREEN</td>
<td>128J</td>
<td>210J</td>
<td>477J</td>
</tr>
<tr>
<td></td>
<td>Kansal-Actual</td>
<td>160J</td>
<td>390J</td>
<td>736J</td>
</tr>
<tr>
<td>Data Set 2</td>
<td>Kansal-Ideal</td>
<td>69J</td>
<td>237J</td>
<td>406J</td>
</tr>
<tr>
<td></td>
<td>P-FREEN</td>
<td>129J</td>
<td>157J</td>
<td>193J</td>
</tr>
<tr>
<td></td>
<td>Kansal-Actual</td>
<td>168J</td>
<td>293J</td>
<td>451J</td>
</tr>
<tr>
<td>Data Set 3</td>
<td>Kansal-Ideal</td>
<td>35J</td>
<td>44J</td>
<td>125J</td>
</tr>
<tr>
<td></td>
<td>P-FREEN</td>
<td>57J</td>
<td>43J</td>
<td>117J</td>
</tr>
<tr>
<td></td>
<td>Kansal-Actual</td>
<td>67J</td>
<td>64J</td>
<td>146J</td>
</tr>
</tbody>
</table>

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

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 \( D_{\text{min}} \) 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

It still causes a higher $\delta_{2000}$ 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 $\delta_{2000}$ 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) ($\sigma_{H}$) 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 $\eta_{S}$ 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 $D_{\text{min}} = 0.1$ using DS1

Figure 2.10: HEUE comparison with $D_{\text{min}} = 0.2$ 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 $D_{\text{min}}$ increases. That is because the energy consumption is higher with higher $D_{\text{min}}$, 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 $D_{\text{min}} = 0.3$ using DS1

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 $D_{\text{min}}$ 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 $D_{\text{min}}$ constraint, there might not be sufficient energy harvested to sustain even the minimum duty cycle for OCs that are experiencing bad weather condition. Battery
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 $D_{\text{min}}$ 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
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 polices 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 polices 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
3.1. Introduction

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.
3.2. System Model and Notations

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 $t = 1, 2, ..., N_t$ 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 $\mathbb{E}[E_H]$, where $\mathbb{E}[\cdot]$ 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
3.2. System Model and Notations

...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 $\{H\} = \{h_1, h_2, ..., h_N\}$ 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:

$$C(t) = W \log \left( 1 + \frac{h_t E_B(t)}{N_0 W T} \right) = W \log \left( 1 + \frac{h_t E_B(t)}{\beta} \right)$$

(3.1)

where $W$ is the bandwidth, $N_0W$ is the noise power spectral density in $W/Hz$, $\frac{E_B(t)}{T}$ is the signal power in $Watt$ and $\beta = N_0W \times T$ 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 $\eta$) is estimated by:

$$\eta = \frac{\xi[E_U]}{\xi[E_H]} \tag{3.2}$$

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

We define the *Battery Energy Storage Efficiency* $\eta_S$, 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 $\eta_S$ 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:

$$\eta = \frac{\xi[E_U]}{\xi[E_H]} = \frac{\eta_S \xi[E_H]}{\xi[E_H]} = \eta_S \tag{3.3}$$
3.2. System Model and Notations

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

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 $t = 1, 2, 3, ..., N_t$. 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 mount 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 $N_t$. 

76
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:

\[
\max \frac{1}{N_t} \sum_{t=1}^{N_t} C(t) \tag{3.5}
\]

s.t.

\[
B(t) \geq B_0, \quad t = 1, 2, 3, \ldots, N_t \tag{3.6}
\]

\[
0 \leq B(t) \leq B_c, \quad t = 1, 2, 3, \ldots, N_t \tag{3.7}
\]

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 \(B_c >> E_B(t)\). 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 \(B_c >> E_H(t)\). 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:

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

s.t.

$$
B(N_t) \geq B_0 \tag{3.10}
$$

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 $E^*_B(t) = \beta \left( \frac{1}{X^*} - \frac{1}{m} \right)^+$ is used as the energy budget for a time slot $t$, where $\frac{1}{X^*}$ 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:

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

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

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

**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 $(l = 1, 2, 3, \ldots, L)$ 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:

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

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

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 ($\eta$) 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:

$$E_B(t) = \min \left( \left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{h_t} \right)^+ - \delta \right)^+ , (B(t-1) - B_0) \right)$$  \hspace{1cm} (3.17)

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

$$\sum_{k=1}^{t} \beta \left( \frac{1}{\lambda_t} - \frac{1}{h_k} \right)^+ = \eta_S \sum_{k=0}^{t-1} (E_H(k))$$  \hspace{1cm} (3.18)

where $t = 1, 2, ..., N_t$, $\delta$ is a small positive constant and $E_H(0) = 0$. Since the water level $\frac{1}{\lambda_t}$ is calculated adaptively using the values of $E_H(k)$ observed in the past time slots ($k = 0, 1, 2, ..., t - 1$), we refer to water level $\frac{1}{\lambda_t}$ 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 \( \left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{\mu_t} \right)^+ - \delta \right)^+ > (B(t - 1) - B_0) \),

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

\[
B(t) = B(t - 1) + E_U(t) - (B(t - 1) - B_0)
\]

\[
= \eta_S E_H(t) + B_0 \geq B_0
\]

For a time slot $t$, if \( \left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{\mu_t} \right)^+ - \delta \right)^+ \leq (B(t - 1) - B_0) \),

\( \left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{\mu_t} \right)^+ - \delta \right)^+ \) will be used as the energy budget, which means the BREL at the end of this time slot $t$ will be calculated by:

\[
B(t) = B(t - 1) + E_U(t) - \left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{\mu_t} \right)^+ - \delta \right)^+
\]

\[
\geq B(t - 1) + \eta_S E_H(t) - (B(t - 1) - B_0)
\]

\[
= \eta_S E_H(t) + B_0 \geq B_0
\]

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.

\( \square \)

**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 \( \left( \frac{1}{\lambda_t} \right) \) converges to the
3.4. Online Asymptotic Throughput Maximization Policies

*Optimal Water Level (\(\frac{1}{\lambda_t}\)).*

**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:

\[
\lim_{t \to N^*} \beta \sum_{k=1}^{L} \left( \frac{1}{\lambda_t} - \frac{1}{h_k} \right)^+ \approx N^* \beta \sum_{l=1}^{L} p_l \left( \frac{1}{\lambda_t} - \frac{1}{h_l} \right)^+ \quad (3.19)
\]

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:

\[
\lim_{t \to N^*} \eta_s \sum_{k=0}^{t-1} (E_{H}(k)) \approx N^* \eta_s \xi [E_H] = N^* \xi [E_U] \quad (3.20)
\]

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

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

From here we observe that the expression for \(\frac{1}{\lambda_t}\) 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 \(\frac{1}{\lambda_t}\) converges to OWL \(\frac{1}{\lambda^*}\) when the number of time slots elapsed is sufficiently large. \[\square\]
Theorem 3.2.

Proof. Based on equation (3.17), we can see that for time slots with
\[
\left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{h_t} \right)^+ - \delta \right)^+ \leq (B(t) - B_0), \quad \left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{h_t} \right)^+ - \delta \right)^+ \]
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 \( \delta \) less amount of energy as the energy budget. Thus, this \( \delta \) 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 \( \hat{N} = \max(N', N^*) \leq N_t \)), \( \left( \beta \left( \frac{1}{\lambda^*} - \frac{1}{h_t} \right)^+ - \delta \right)^+ \) amount of energy will be assigned as the energy budget for a time slot \( t \). Note that since \( \delta \) 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 $\delta$ Constant

As stated in the proof of Theorem 3.2, when the number of time slot elapsed is sufficiently large, $\left( \beta \left( \frac{1}{N} - \frac{1}{n} \right)^+ - \delta \right)^+$ amount of energy will be used to assign the energy budget. The concept of using the small $\delta$ constant is similar to that in [45], where the $\delta$ is assumed be to an arbitrarily small value so that the ACT can be arbitrarily close to the maximized level. However, although $\delta$ is a small positive number, it still causes a kind of energy wastage. In addition, since $\delta$ amount of energy is expected to be accumulated in the battery for time slots that use $\left( \beta \left( \frac{1}{N} - \frac{1}{n} \right)^+ - \delta \right)^+$ 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 $\delta$ 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 $B_c >> E_H(t)$ as discussed in Section 3.2, an energy buffer of $0.25B_c$ should
be sufficiently large to accommodate the variances of $E_H(t)$. In this way, we can use $\beta \left( \frac{1}{\lambda} - \frac{1}{\eta} \right)^+$ 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 $\eta_s$. As a result, the expected utilizable energy in one time slot is $\xi[E_U] = \eta_s \xi[E_H]$, which means that only $\eta_s$ 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 $\eta_S$). 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 \( \gamma = (\xi[\xi[E_H]])^{-1} \).

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

\[
\xi[E_U] = P_+ \int_{\xi[E_B]}^{\infty} E_U(t) \frac{f(E_H(t), \gamma)}{P_+} d(E_H(t)) + P_- \int_{0}^{\xi[E_B]} E_U(t) \frac{f(E_H(t), \gamma)}{P_-} d(E_H(t))
\]

\[
= \int_{\xi[E_B]}^{\infty} (\eta_S E_H(t) + (1 - \eta_S)\xi[E_B]) e^{-\gamma E_H(t)} d(E_H(t)) + \int_{0}^{\xi[E_B]} E_H(t) \gamma e^{-\gamma E_H(t)} d(E_H(t))
\]

\[
= \eta (\xi[E_B] + \frac{1}{\gamma}) e^{-\gamma \xi[E_B]} + (1 - \eta_S)\xi[E_B] e^{-\gamma \xi[E_B]} - (\xi[E_B] + \frac{1}{\gamma}) e^{-\gamma \xi[E_B]} + \frac{1}{\gamma}
\]

\[
= \frac{1}{\gamma} - (1 - \eta_S) e^{-\gamma \xi[E_B]} \tag{3.23}
\]

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 \( \eta_V \)). 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*)

Optimal Improved-HEUE achievable by using the energy harvest-use(store) method, which is denoted by $\eta^*_V$.

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 ($\eta^*_V$).

**Theorem 3.3.** The Optimal Improved-HEUE $\eta^*_V$ achievable by using energy harvest-use(store) method can be estimated by 

$$
\eta^*_V = (1 - P^*) \times \eta_S + P^* \left( 1 - (1 - \eta_S) e^{-\frac{\eta^*_V}{E}} \right),
$$

where $P^*$ is the probability of the Optimal Water Level $\frac{1}{X}$ 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 $\frac{1}{X}$. According to Lemma 3.1, for a time slot $t$, if $\frac{1}{h_t} \geq \frac{1}{X}$, 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 $\frac{1}{h_t} < \frac{1}{X}$, the energy budget assigned to this time slot will not be zero. Since no energy will be allocated to time slots with $\frac{1}{h_t} \geq \frac{1}{X}$, (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 $\frac{1}{h_t} < \frac{1}{X}$. 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 $\frac{1}{\lambda_i} < \frac{1}{\lambda^*_i}$.

Hence, based on equation (3.24), the Optimal Improved-HEUE $\eta^*_V$ is estimated by:

$$\eta^*_V = (1 - P^*) \times \left( 1 - \eta_S e^{-\frac{\eta^*_V \xi[E_H]}{P^*}} \right) + P^* \left( 1 - \eta_S e^{-\frac{\eta^*_V \xi[E_H]}{P^*}} \right)$$

$$= (1 - P^*) \times (1 - \eta_S)e^0 + P^* \left( 1 - \eta_S e^{-\frac{\eta^*_V}{P^*}} \right)$$

$$= (1 - P^*) \times \eta_S + P^* \left( 1 - \eta_S e^{-\frac{\eta^*_V}{P^*}} \right) \quad (3.26)$$

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

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 $\frac{1}{\lambda_i} < \frac{1}{\lambda^*_i}$. Hence,
3.5. Improved Adaptive Budget Assignment
Policy (ABAP*)

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

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

$$
\eta_v^*(i) = (1 - P_v^*) \times \eta_S + P_v^*(1 - (1 - \eta_S)e^{-\frac{\eta_v^*(i)}{H}})
$$

(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 ($\eta_v^*$) 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, $\eta_v^*$ can be obtained within 4 iterations.

3.5.3 Improved-ABAP

The estimation of $\eta_v^*$ 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
sensor deployment, $\eta_k^\dagger$ 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 $\eta_k^t$) 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:

$$E_B(t) = \min \left( \left( \beta \left( \frac{1}{\lambda_t} - \frac{1}{h_t} \right) - \delta \right)^+, (B(t-1) - B_0) \right)$$  \hspace{1cm} (3.28)

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

$$\sum_{k=1}^{t} \beta \left( \frac{1}{\lambda_t} - \frac{1}{h_k} \right)^+ = \eta_k^t \sum_{k=0}^{t-1} (E_H(k))$$  \hspace{1cm} (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 ($\frac{1}{\lambda_t}$) calculated in ABAP* converges to the Optimal Water Level ($\frac{1}{\lambda^\dagger}$).

**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, $\eta_k^t$ will be sufficiently
3.5. Improved Adaptive Budget Assignment Policy (ABAP*)

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

$$\lim_{t \to \bar{N}} \eta^*_V \sum_{k=0}^{t-1} (E_H(k)) \approx \bar{N} \eta^*_V \xi[E_H] = \bar{N} \xi[E_U]$$

(3.30)

Thus, similar to the proof of Lemma 3.3, the AWL $\frac{1}{\lambda}$ 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.

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

**Proof.** The proof is similar to the proof of Theorem 3.2.

**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.

Note that additional computational complexity will be involved if we estimate $\eta^*_V$ at the beginning of every time slot. As stated in the proof of Lemma 3.4, $\eta^*_V$ will converge to $\eta^*_V$ when the number of time slots grows to $\bar{N}$. Thus, $\eta^*_V$ 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 $\eta^*_V$ to converge to $\eta^*_V$ 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 2000\(J\) (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 1000\(J\). We choose the \(\delta\) constant to be one. However, we will set \(\delta\) to zero when the BREL exceeds 1500\(J\) (0.75\(B_c\) as discussed in Section 3.4.2). For the convenience of comparison, the channel bandwidth is chosen to be 1\(MHz\) 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 30\(J\) (1\(J/Sec\)). 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 \(\eta_S\) 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 \(\langle H \rangle\) of 1, ABAP* can achieve an ACT of 0.62 \(Mbps\)
3.6. Numerical Results

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 phenomena 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 ($\eta_V$) to compute the energy budget. As $\eta_V$ is much higher than the corresponding $\eta_S$, higher energy budget will be assigned
3.6. Numerical Results

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 $\delta$ as discussed in the proof of Theorem 3.2.

As stated in Section 3.5.3, ABAP* use $\eta_V^*$ (which converges to $\eta_V^*$) to calculate
the energy budget, which is different from the $\eta_S$ 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 $\eta^*_V$ 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 $\eta^*_V$ to some values that are different from the Optimal Improved-HEUE ($\eta^*_V$), 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 ($\eta^*_V$) in this case is 0.839. As shown in Figure 3.4, the BREL is very sensitive to the value of $\eta^*_V$ we chose to assign energy budget for ABAP*. When $\eta^*_V$ 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 2000 $J$ 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 $\eta^*_V$, which in turn decreases the ACT. On the other hand, when $\eta^*_V$ 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 $\eta^*_V$ 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 $\eta^*_V = 0.839$. 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 $\eta^*_V$ is an accurate estimation of
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 ($\eta^*_U$) based on the historical information at the beginning of each time slot. The HEUE achieved by the
3.6. Numerical Results

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 ($\eta^*_v$) 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
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.
3.6. Numerical Results

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 ($\eta'_V$) 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 ($\eta'_V$) to converge to the Optimal Improved-HEUE ($\eta^*_V$). As shown in Figure 3.9, $\eta'_V$ converges to $\eta^*_V$ after 300 time slots under various communication channels. It verifies that we can fix $\eta'_V$ 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.

![Convergence of the Current Estimated Improved-HEUE](image1)

**Figure 3.9:** Convergence of the Current Estimated Improved-HEUE ($\eta^t_V$)

![Convergence of Adaptive Water Level](image2)

**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 $\eta''_V$ as stated in Section 3.5.3, this kind of estimation is also not needed when the AWL converges to the Optimal Water Level $\frac{1}{\hat{N}_t}$. 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-
4.2 Related Works

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. Related Works

4.2.2 Query Driven Routing Protocols

In the literature, Directed Diffusion (DD) \cite{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 \cite{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 deliver the EDPs with the lowest empirical delay.

In \cite{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 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
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 $e_{\text{tx}}$ 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 $\varepsilon_{sp}$ and $\varepsilon_{mp}$ 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:

$$E_{Rx} = L \times e_{\text{rx}}$$ (4.2)

where $e_{\text{rx}}$ 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:

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

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

<table>
<thead>
<tr>
<th>Interest Packet</th>
<th>Data Packet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest ID</td>
<td>Data Packet ID</td>
</tr>
<tr>
<td>Interest Type</td>
<td>Interest ID</td>
</tr>
<tr>
<td>Source ID</td>
<td>Data Type</td>
</tr>
<tr>
<td>Destination ID</td>
<td>Source ID</td>
</tr>
<tr>
<td>Packet Rate</td>
<td>Destination ID</td>
</tr>
<tr>
<td>Start Time</td>
<td>Sent Time</td>
</tr>
<tr>
<td>End Time</td>
<td></td>
</tr>
<tr>
<td>Hops Count</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.1: Fields in the packet headers

<table>
<thead>
<tr>
<th>Cache Table</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Entry_1</strong></td>
</tr>
<tr>
<td><strong>Entry_2</strong></td>
</tr>
<tr>
<td><strong>Entry_3</strong></td>
</tr>
<tr>
<td><strong>Entry,...</strong></td>
</tr>
</tbody>
</table>

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)

<table>
<thead>
<tr>
<th>Interest Cache</th>
<th>Data Cache</th>
<th>Rejection Cache</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest ID</td>
<td>Data Packet ID</td>
<td>Interest ID</td>
</tr>
<tr>
<td>Interest Type</td>
<td>Interest ID</td>
<td>Interest Type</td>
</tr>
<tr>
<td>Source ID</td>
<td>Source ID</td>
<td>Source ID</td>
</tr>
<tr>
<td>Packet Rate</td>
<td>Data Type</td>
<td>Data Type</td>
</tr>
<tr>
<td>Start Time</td>
<td>Delay</td>
<td>Start Time</td>
</tr>
<tr>
<td>End Time</td>
<td></td>
<td>End Time</td>
</tr>
<tr>
<td>Hops Count</td>
<td></td>
<td>Hops Count</td>
</tr>
</tbody>
</table>

Table 4.3: Fields in the cache entries

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

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
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**
  - **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**

**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](image-url)
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 of 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
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 previously 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

```plaintext
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
        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.
Algorithm 4.3: Rejection Message Handling for ENDD-T

\begin{algorithm}
\textbf{foreach} Rejection Message \textit{r} received by node \textit{n} \textbf{do}
\begin{algorithmic}
\State Check the ICT maintained by \textit{n}
\If \textit{r} corresponds to an RI \textit{m} that \textit{n} has sent before
\State Select the next Best Neighbor
\If no Best Neighbor is found
\State Create an entry in RCT for RI \textit{m}
\State Broadcast a Rejection Message
\Else
\State Resend RI \textit{m} to the Best Neighbor
\EndIf
\Else
\State Create an entry in RCT for \textit{r}
\EndIf
\EndFor
\end{algorithmic}
\end{algorithm}

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 \textit{A}'s neighbors rejected the RI sent by \textit{A}, \textit{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

1. \(My.ID \leftarrow ID\) of the node \(n\)
2. \(ITD.ID \leftarrow \text{“Destination ID” in } d\)
3. \(RI.ID \leftarrow \text{“Interest ID” in } d\)

if \(My.ID = ITD.ID\) then

1. Check the ICT maintained by \(n\)
2. if an RI Entry in ICT has same Interest ID as \(RI.ID\) then

   1. Denote this RI Entry as \(h_{RI}\)
   2. Check the DCT maintained by \(n\)
   3. if a matching entry is found for \(d\) then

      1. Discards NDP \(d\)
   else

      1. \(D.ID \leftarrow \text{“Source ID” in } h_{RI}\)
      2. Send NDP \(d\) to node \(D.ID\)
      3. Create an entry for \(d\) in the DCT

   else

   1. Discard NDP \(d\)

else

1. 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.
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 \( HC(A) = 1 \). 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.
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 $\Delta T$. 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. $\Delta T$ 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

```plaintext
foreach sensor node n do
    Periodically check the ICT with an interval of ΔT
    foreach entry in the ICT do
        m ← The OI that this entry corresponds to
        T_c ← Current system time
        T_{m start} ← “Start Time” of OI m
        if T_{m start} + ΔT ≤ 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
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. 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 $\phi^{\text{total}}(t)$ that this sensor is supposed to receive and then transmit in this time slot $t$ can be estimated by:

$$\phi^{\text{total}}(t) = \sum_{m=1}^{M} \phi^{\text{total}}_{m}(t) = \sum_{m=1}^{M} R_m \times T_m(t)$$  \hspace{1cm} (4.4)

where $\phi^{\text{total}}_{m}(t)$ 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](image)

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)

<table>
<thead>
<tr>
<th>$T_m(t)$</th>
<th>$T_m^{start} \geq T_m^{end}$</th>
<th>$T_m^{end} \geq T_m^{start}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_m^{start} &gt; T_m^{start}$</td>
<td>$T_m^{end} - T_m^{start}$</td>
<td>$T_m^{end} - T_m^{start}$</td>
</tr>
<tr>
<td>$T_m^{start} &lt; T_m^{start}$</td>
<td>$T_m^{end} - T_m^{start}$</td>
<td>$T_m^{end} - T_m^{start}$</td>
</tr>
</tbody>
</table>

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 $T_m^{start}(t)$) 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 $T_m^{end}(t)$). In this scenario $T_m(t) = T_m^{end}(t) - T_m^{start}$. 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 $t$ ($T_m^{start} < T_m^{start}(t)$), and ends before the end time of time slot $t$ ($T_m^{end} < T_m^{end}(t)$).

In this scenario, $T_m(t) = T_m^{end} - T_m^{start}$. 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 $t$ ($T_m^{start} < T_m^{start}(t)$) but ends after the end time of time slot $t$ ($T_m^{end} \geq T_m^{end}(t)$).

In this scenario, $T_m(t) = T_m^{end}(t) - T_m^{start}(t)$.

**Scenario 4:** The event queried by OI $m$ starts after the start time of time slot $t$ ($T_m^{start} \geq T_m^{start}(t)$) but it ends before the end time of time slot $t$ ($T_m^{end} < T_m^{end}(t)$).

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 $\beta_{re}$) 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 at time $T_a$, the expected packet retransmission constant $\beta_{re}$ can be estimated by:

$$\beta_{re} = \frac{\Phi'_{Tx}}{\Phi_{Tx}} \tag{4.5}$$

where $\Phi'_{Tx}$ is the number of data packets that have been actually transmitted by the sensor in the current time slot at time $T_a$. $\Phi_{Tx}$ 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.

$\Phi'_{Tx}$ and $\Phi_{Tx}$ 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 $\Phi'_{Tx}$ will be incremented whenever the sensor node transmits a data packet. The counter for $\Phi_{Tx}$ 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 ($T_a$), $\beta_{re}$ 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 $\beta_{re}\phi^{total}(t)$. 

136
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:

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

(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:

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

(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:

\[
E_{idle}(t) = P_{idle} \times D(t) \times T
\]

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:

\[
E_P(t) = \left( E[\phi_{oh}] + \phi_{total}(t) \right) E_{Rx} + \beta_{re} E_{total}(t) E_{Tx} + E_{idle}(t)
\]

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:

$$E_A(m) = \beta_{rc} \phi^{total}_m(t) E_{Tx} + \phi^{total}_m(t) E_{Rx}$$  \hspace{1cm} (4.9)

where $\phi^{total}_m(t)$ 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-
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
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 \( e \geq 1 \).

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 \( \Delta(G)|V| \).

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” filed. 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. Empirical Studies

4.5.1 Simulation Setup

50 energy harvesting sensor nodes are deployed randomly (following uniform distribution) in a 100\(m\) x 100\(m\) field. Each sensor node has a maximum radio transmission range of 20\(m\). 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.
4.5. Empirical Studies

<table>
<thead>
<tr>
<th>Communication Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Packet Length</td>
<td>1024 bits</td>
</tr>
<tr>
<td>Control Message Packet Length</td>
<td>256 bits</td>
</tr>
<tr>
<td>$\epsilon_{e-tx}$</td>
<td>$21 \times 10^{-8}$ J/bit</td>
</tr>
<tr>
<td>$\epsilon_{e-rx}$</td>
<td>$35 \times 10^{-8}$ J/bit</td>
</tr>
<tr>
<td>$P_{idle}$</td>
<td>10 mW</td>
</tr>
<tr>
<td>$\epsilon_{sp}$</td>
<td>$2 \times 10^{-9}$ J/(bit \cdot m^2)</td>
</tr>
</tbody>
</table>

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, $\beta_{re}$ 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 protocol’s 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.
4.5. Empirical Studies

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](image)

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
4.5. Empirical Studies

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
4.5. Empirical Studies

![Distinct packet delivery ratio comparison](image)

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 outperform 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...
4.5. Empirical Studies

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.
4.5. Empirical Studies

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.
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

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

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

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 implemented 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.
5.2. Related Works

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.
5.2. Related Works

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 depletes 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 $\pi R^2$ 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:

$$E_{Tx/b} = \begin{cases} 
\varepsilon_{e-tx} + \varepsilon_{spd^2} & \text{if } d < \hat{d} \\
\varepsilon_{e-tx} + \varepsilon_{mpd^4} & \text{if } d \geq \hat{d}
\end{cases}$$

(5.1)

where constant $\varepsilon_{e-tx}$ 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
can be approximated as a two ray multi-path propagation model with \( d^4 \) power attenuation. Constants \( \varepsilon_{sp} \) and \( \varepsilon_{mp} \) 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:

\[
E_{Rx/b} = \varepsilon_{e-rx}
\]

(5.2)

where constant \( \varepsilon_{e-rx} \) 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:

\[
E_{CM}^n = \varepsilon_{Sx} + E_{CM}^{Tx/b}
\]

(5.3)

where \( \varepsilon_{Sx} \) 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:

$$E_{CH}^n = E_{Rx/b}^n + \alpha \varepsilon_{DA} + \frac{E_{CH}^{Tx/b}}{\alpha}$$

(5.4)

where $E_{Rx/b}^n$ is the amount of energy spent to receive this one bit of information. $\varepsilon_{DA}$ 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. $\alpha$ 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 $t = 1, 2, \ldots N_t$. 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 $n = 1, 2, 3, \ldots, N$), 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
5.4 Energy Neutral Clustering

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

\[ \sum_{t=1}^{N_t} E^n_B(t) \leq \sum_{t=1}^{N_t} \eta E^n_H(t) \]  

(5.5)

where \( \eta \) 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
5.4. Energy Neutral Clustering

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

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

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.
5.4. Energy Neutral Clustering

Algorithm 5.1: ENC Algorithm-Initialization

**INITIALIZATION:**

```plaintext
foreach sensor node do
    myID ≜ Node ID for this sensor
    myDistoBS ≜ Relative distance to Base Station
    myBudget ≜ Energy Budget in current time slot
    p ≜ random(0, 1)
    if p ≤ PK then
        myRole ≜ Center Node
    else
        myRole ≜ 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:

\[
P_K = \frac{K}{N}
\]

(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” ← myID
        Broadcast the “CLUSTER” message
    else if T_C < CURRENT TIME < T_C + T_J then
        Upon receiving a “JOIN” message
        CID ← ‘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

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 ← ‘Cluster ID’ in “CLUSTER”
            myDistoCH ← Estimated relative distance to CH
        end
    else if T_C < CURRENT TIME < T_C + T_J then
        ‘Node ID’ in “JOIN” ← myID
        ‘Cluster ID’ in “JOIN” ← myCH
        ‘DistanceToBS’ in “JOIN” ← myDistoBS
        ‘DistanceToCH’ in “JOIN” ← myDistoCH
        ‘EnergyBudget’ in “JOIN” ← 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
5.4. Energy Neutral Clustering

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 $N^k_G$, (the way to estimate $N^k_G$ will be elaborated later in Section 5.4.3). This CN will next choose $N^k_G - 1$ 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.
5.4. Energy Neutral Clustering

Algorithm 5.3: ENC Algorithm-Finalization

**FINALIZATION:**

```plaintext
definalization:
    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 \(N^k_G\). The number of Final-CMs \((N^k_{CM})\) in this cluster \(k\) follows:

\[
N^k_{CM} = N^k_{IC} + 1 - N^k_G
\] (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 \(B^k_{max}(t)\) 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:

\[
B^k_{max}(t) = \sum_{n=1}^{N^k_{CM}} L^n(t) = \sum_{n=1}^{N^k_{CM}} \frac{E^n_B(t)}{E^n_{CM}}
\] (5.8)

where \(L^n(t) = \frac{E^n_B(t)}{E^n_{CM}}\) 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. \(E^n_{CM}\) is the energy consumed by a Final-CM \(n\) to sense and transmit one bit of information. \(E^n_B(t)\) is the amount of energy budget assigned to Final-CM \(n\) in time slot \(t\). The value of \(E^n_B(t)\) for each Final-CM in the cluster can be retrieved from the ‘EnergyBudget’ field contained in the “JOIN” messages. \(E^n_{CM}\) 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 \(N^k_G\) CHG-Nodes, we have the following constraint:

\[
\sum_{n=1}^{N^k_G} \frac{E^n_B(t)}{E^n_{CM}} \geq B^k_{max}(t)
\] (5.9)
where $E_{n}^{CH}$ 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, $\frac{E_{n}^{CH}(t)}{E_{n}^{CH}}$ 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 $N_{k}^{G}$ 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 $N_{k}^{G}$ 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 $\frac{1}{N_{CM}}$ fraction of a second during each second until the end of the
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 ($D^n_{T_x}(t)$) of a Final-CM $n$ in time slot $t$ can be estimated by:

$$D^n_{T_x}(t) = \frac{L^n(t)}{\frac{T_{DX}}{N_{CM}^k}} = \frac{E^r_t(t)N_{CM}^k}{T_{DX}E^n_{CM}}$$  \hspace{1cm} (5.10)$$

Since the $\frac{B^k_{max}(t)}{T_{DX}}$ 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 $\frac{B^k_{max}(t)}{T_{DX}}$ to make sure the consistent relay of the received information. Thus, for a CHG-Node $n$, during the period of time ($T^n_A$) that it is acting as an Active-CH, we have:

$$\frac{B^k_{max}(t)}{T_{DX}}T^n_A = \frac{E^r_t(t)}{E^n_{CH}}$$  \hspace{1cm} (5.11)$$

where $\frac{B^k_{max}(t)}{T_{DX}}T^n_A$ is the amount of information bits that a CHG-Node $n$ has to handle during $T^n_A$ period time. $\frac{E^r_t(t)}{E^n_{CH}}$ 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

$$\sum_{n=1}^{N_G} T^n_A = \sum_{n=1}^{N_G} \frac{E^r_t(t)}{E^n_{CH}} \geq T_{DX}$$  \hspace{1cm} (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 $T^n_A$ seconds. We can also observe from inequality (5.12) that the sum of the time for all CHG-Nodes to act as Active-CHs ($\sum_{n=1}^{N_G} T^n_A$) 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 analysis 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:

$$N_{CM} = \frac{N}{K} - N_G$$ \hspace{1cm} (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:

$$K \pi R_c^2 = \pi R^2$$ \hspace{1cm} (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 \( \rho(r, \theta) = \frac{1}{\pi R^2} = \frac{K}{\pi R^2} \). 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 \( \xi[d^2_{toCH}] \) and the expected quadratic distance \( \xi[d^4_{toCH}] \) from the Final-CMs to a CHG-Node can be estimated by:

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

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

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

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:

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

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:

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

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

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

$$\xi[E_{CH}^{Tx/b}] = \begin{cases} 
\epsilon_{e-1x} + \epsilon_{sp} \frac{R^2}{2} & \text{if } \xi[d_{toBS}] < \hat{d} \\
\epsilon_{e-1x} + \epsilon_{mp} \frac{R^4}{3} & \text{if } \xi[d_{toBS}] \geq \hat{d} 
\end{cases}$$ (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:

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

(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 $t$:

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

(5.25)

5.5.2 Maximised 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:

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

(5.26)

subject to:

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

(5.27)

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

(5.28)

$$1 \leq \frac{N}{K} - N_G$$

(5.29)

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

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

(5.30)

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

Additional Complement Slackness Conditions are as follows:

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

(5.31)

and

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

(5.32)

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

\[
\frac{\Delta L}{\Delta L_t} = 0, \quad \frac{\Delta L}{\Delta K} = 0, \quad \frac{\Delta L}{\Delta N_G} = 0
\]

(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

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_{r-x}$</td>
<td>$5 \times 10^{-8}$ J/bit</td>
</tr>
<tr>
<td>$e_{t-x}$</td>
<td>$5 \times 10^{-8}$ J/bit</td>
</tr>
<tr>
<td>$e_{DA} = $</td>
<td>$5 \times 10^{-9}$ J/bit</td>
</tr>
<tr>
<td>$e_{S_x} = $</td>
<td>$1 \times 10^{-10}$ J/bit</td>
</tr>
<tr>
<td>$e_{sp} = $</td>
<td>$1 \times 10^{-10}$ J/(bit $\times m^2$)</td>
</tr>
<tr>
<td>$e_{mp} = $</td>
<td>$1.3 \times 10^{-15}$ J/(bit $\times m^2$)</td>
</tr>
<tr>
<td>$d$</td>
<td>277.35m</td>
</tr>
<tr>
<td>$R$</td>
<td>50-150m</td>
</tr>
<tr>
<td>$N$</td>
<td>100-200 nodes</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>($L_t^<em>, K^</em>, N_G^*$)</th>
<th>$N = 100$</th>
<th>$N = 200$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R = 50m$</td>
<td>$(17 \times \xi[E_B(t)], 3, 17)$</td>
<td>$(17 \times \xi[E_B(t)], 4, 24)$</td>
</tr>
<tr>
<td>$R = 100m$</td>
<td>$(15 \times \xi[E_B(t)], 5, 10)$</td>
<td>$(16 \times \xi[E_B(t)], 7, 15)$</td>
</tr>
<tr>
<td>$R = 150m$</td>
<td>$(12 \times \xi[E_B(t)], 4, 12)$</td>
<td>$(13 \times \xi[E_B(t)], 6, 16)$</td>
</tr>
</tbody>
</table>

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.

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.
5.6. Extensions

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
5.6. Extensions

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 $E_{n}(t) = 54 + X$ 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

<table>
<thead>
<tr>
<th>Name</th>
<th>CH Re-selections</th>
<th>Packet Transmission Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEACH-A10</td>
<td>10/time slot</td>
<td>10 pkts/s</td>
</tr>
<tr>
<td>LEACH-B5</td>
<td>5/time slot</td>
<td>20 pkts/s</td>
</tr>
<tr>
<td>LEACH-B10</td>
<td>10/time slot</td>
<td>20 pkts/s</td>
</tr>
<tr>
<td>LEACH-C5</td>
<td>5/time slot</td>
<td>40 pkts/s</td>
</tr>
<tr>
<td>LEACH-C10</td>
<td>10/time slot</td>
<td>40 pkts/s</td>
</tr>
<tr>
<td>LEACH-D10</td>
<td>10/time slot</td>
<td>60 pkts/s</td>
</tr>
</tbody>
</table>

Table 5.5: Simulation setups

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$N = 100$</th>
<th>$N = 200$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R = 50m$</td>
<td>Setup 1</td>
<td>Setup 2</td>
</tr>
<tr>
<td>$R = 100m$</td>
<td>Setup 3</td>
<td>Setup 4</td>
</tr>
<tr>
<td>$R = 150m$</td>
<td>Setup 5</td>
<td>Setup 6</td>
</tr>
</tbody>
</table>

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
longer a primary concern.

Since we assume that all clustering protocols adopt P-FREEN, a sensor $n$ can gain access to $E_n^{n_B}(t)$ amount of energy in a time slot $t$. Hence, if this sensor consumes $E_n^{n_B}(t)$ 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.
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 base 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
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
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).
5.7. Performance Evaluations

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.
6.1. Conclusions

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 FREEe En-
energy 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 \textit{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 \textit{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
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.


6.2. Recommendations for Further Research


References


REFERENCES


REFERENCES


