Neighbor Discovery in Energy Harvesting Wireless Sensor Networks

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Master of Science Thesis

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by

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Abstract

Homes, offices and vehicles are getting networked. This will enable context aware, autonomous operation of many support systems that could be controlled remotely. To achieve this there would be a large number of tiny devices – sensors and actuators – which are networked and they are termed generally as Internet of Things (IoT) devices. In future, they will be powered through harvested energy from the ambience to enable perennial lifetime and minimal manual maintenance. Some examples of energy sources are photovoltaic panels and piezoelectric crystals. Several challenges arise due to the nature of sources of energy. One of these challenges is that the devices (nodes) leave and re-enter networks due to fluctuating availability of harvested energy. This energy condition requires the adaptation of special means at every layer of the communication model. For example, as a result of fluctuating energy levels, the neighbor table maintained at each node changes quite often leading to complications in forming and maintaining routes. In fact initial neighbor discovery (ND) itself is a difficult task. Further, usage of directional antennas would affect the time taken to complete ND. Given the spatio-temporal variations in energy availability in harvesting environments, there are benefits of energy prediction. With the help of prediction, resource allocation within a single system and splitting of tasks between nodes in a network would be enhanced.

In order to identify the various parameters that affect ND we first describe a generic analytical model of an energy harvesting device. Next, we study a network of these devices through exhaustive simulation study considering these various parameters. We demonstrate the benefits and challenges of using directional antennas for ND. We present a scheme that nodes could use to discover their neighbors during initial deployment and another scheme that could be used for subsequent discovery on re-entry into the network. We show that a dedicated ND protocol is necessary for energy harvesting networks and that directional ND is beneficial in these networks under some circumstances. Finally, we present light-weight energy prediction solutions that can be used to improve the performance of the ND process in particular.

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Shruti Devasenapathy

To my Mother, for her support and courage
To my Father, for believing in me
To my Sister, for being an infinite ocean of Love

Chapter 1

Introduction

In today's connected world, we have several means of communicating with each other on the go, every where we go. We are on the verge of a future where there will be thousands of inanimate objects to each human that will ceaselessly communicate with each other in an "Internet of Things" (IoT). These are sensing and actuator devices that will work towards better home and office automation, maintenance and control of operations within systems such as vehicles, process industries, stock management at stores and industries and so on. Some examples of the benefits of using these devices are: better use of energy through seamless control of heating, lighting in homes and offices and of process operations in industries; improvements in preventive maintenance and so on.

We can enumerate the typical characteristics of IoT nodes[1] as follows: (i) Small in size and weight, as they often must be hidden from view or must be placed in areas that have low space availability (ii) Low processing capabilities, owing to limitations in size and weight (iii) Low memory availability, also because of size and weight limitations, (iv) Wireless connectivity, for ease of communications and to eliminate extensive cabling, (v) Low radio link range, because of power limitations and limitations on antenna size, (vi) perpetually operational without manual intervention – because of the nature of applications. The most crucial of these characteristics is of perpetual operation. It implies that nodes must be able to be able to form self-forming and self-healing networks. Importantly, it also implies that nodes must be able be powered by a source of energy that is perpetual.

Due to the nature of their application area or because they must be installed in existing structures, powering them through mains supplies is a waste of resources and often not possible. Their effective lifetime is severely limited if powered by batteries. However, nodes are deployed in environments that usually are rich with energy harvesting opportunities such as from sunlight, wind, vibration and temperature differentials. Thus, it is ideal if nodes can tap their rich environments for energy to power themselves.

[1] The words devices or nodes are used interchangeably.

In this chapter, we introduce energy harvesting nodes, their applications and the peculiarities of natural sources of energy for harvesting. Following this, we discuss the effect of harvesting and its peculiarities on the communication model and formulate our problem statement.

1-1 Energy Harvesting Nodes and Networks

The process of extracting energy from the environment in order to power devices is called energy harvesting (EH). Any device that operates on harvested energy is known as an Energy Harvesting System (EHS). An energy harvesting node in this study refers to a low power wireless sensor node that derives its power from an energy harvesting device. A network of these nodes is known as an energy harvesting wireless sensor network (EH-WSN).

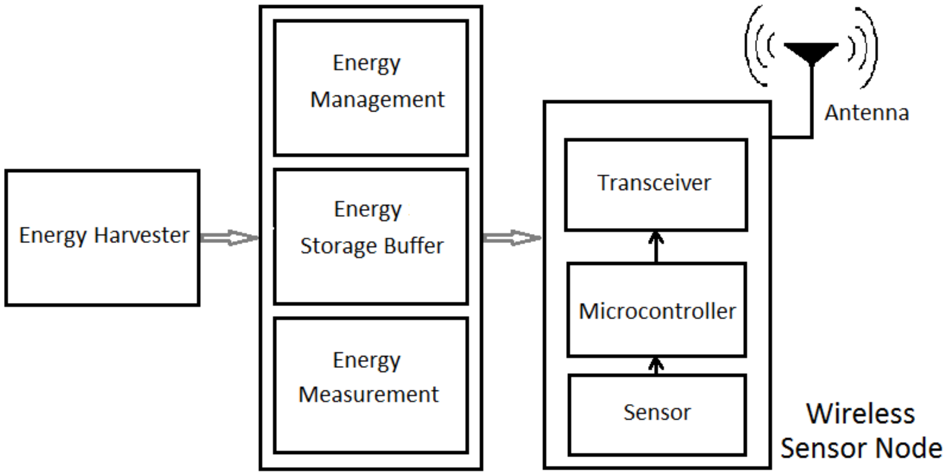


Figure 1-1: Block Diagram of a Typical Energy Harvesting Wireless Sensor Node

A typical energy harvesting wireless sensor node is depicted in blocks in Fig. 1-1. The wireless sensor node consists of a microcontroller, a transceiver chip and a sensor depending on the application. The energy harvesting system consists of a harvester or harvesting device such as a solar panel, thermo-electric generator, cantilever beams etc. Depending on the type of harvester, the raw output of the harvester is processed using components such as rectifiers, DC-DC converters for stepping the voltage level up or down, maximum power point tracking (MPPT) devices and so on. Next, the harvested power is stored in an energy storage buffer. Researchers have shown a preference for using supercapacitors to store energy in these systems for several reasons such as lack of a memory effect and charge cycles of the order of several thousands. There are also several options for rechargeable storage devices such as Nickel metal hydride batteries, Lithium ion batteries and thin-film cells. Frequently, an energy measurement sensor to enable software based energy management is also included in the system.

1-1-1 Applications of EH-WSNs

In order to understand the importance and relevance of an energy harvesting network, we must understand the various applications in which they have been used or proposed by researchers. A popular application scenario is in bridge and structural monitoring [1, 2]. Here, energy from micro-vibrations is extracted by special piezoelectric crystals and fed to sensor nodes that collect data on the health of the structure to a central entity. Other applications include railroad track monitoring [3], soil moisture measurement for information on whether irrigation is required in an agricultural field [4], monitoring of the health, habitat and habits of animals [5] and so on. Each of these applications is in an area where sufficient energy is available through vibrations, sunlight and wind. EH-WSNs are appropriate for indoor conditions such as in smart home settings [6, 7], within aircrafts [8] or other vehicles, where powering nodes through mains supply is not advisable due to need for wiring requirements - which must be avoided to prevent major changes in old buildings or for size and weight concerns in aircrafts. Even such environments are rich in energy from indoor lighting, thermal difference due to insulation and heating, vibration, motion and so on. Button presses and linear motion have also been found to be sources of usable energy [9].

1-1-2 Nature of Energy Sources

Let us understand the nature of energy availability in typical application scenarios. Solar energy is harvested by photovoltaic or solar panels. While panels that are capable of harvesting energy from indoor lighting have been developed, most photovoltaic panels are used for harvesting energy from sunlight. The conversion efficiency and electrical characteristics of existing photovoltaic panels are well studied [10]. Depending upon the season, geographical location and the presence or absence of shadow creating objects such as trees and buildings, solar power follows a trend such that it increases as the day progresses to a point of time where it is highest and then reduces steadily. Following this, a period of no energy availability follows after sunset.

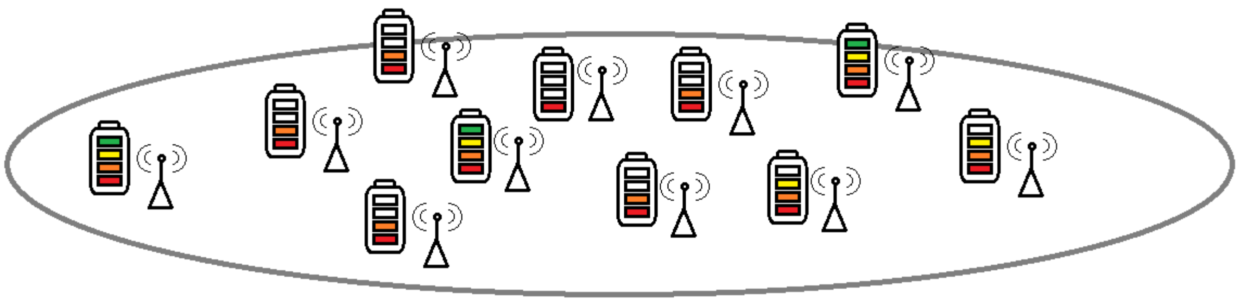


Figure 1-2: Energy Availability Varies With Location

Vibration energy is extracted by piezoelectric fibres that are typically made of lead zirconate titanate (PZT) that shows a pronounced piezoelectric effect. Roundy and others have demonstrated that these devices can extract upto the order of 100 μW/cm^3

[11]. If such a power output were to sustain for even a single second, state of the art sensor nodes could sense and transmit 30 bytes of data at a transmit power of +5dBm which is a typical application requirement in sensor networks. The rate and magnitude of energy harvested from these devices depends on where in a vibrating structure they are installed. Also, variations are seen at different times, for example, depending on the traffic on a bridge or the motion of people in a room.

Other energy harvesting sources include wind, RF power and temperature differentials. Again, these sources are highly random and are defined by parameters such as location, number of RF users in the area and weather respectively. Again, it can be argued that time of day or year has an impact on the energy outputs of some if not all of these sources. Thus, we can visualize a diversity in terms of energy opportunity at each node in a deployment as illustrated in Fig 1-2.

Clearly, energy availability varies in a harvesting network, with space and time. As we shall see, this important property of energy availability in the harvesting setup requires that special mechanisms be introduced in order to achieve the major objective of perennial operation.

1-1-3 Communication Model for EH-WSNs

Operating wireless sensor nodes on harvested energy is not without challenges. In general, environmental energy sources are random. Nodes in an EH-WSN typically have low computation capacity, low radio link range and little or no non-volatile memory storage. Apart from this, they now have the additional challenge of functioning with sporadic energy availability. A scenario in which nodes keep depleting their energy reserves in order to perform a fixed set of operations that are pre-programmed into it can occur frequently. In order to avoid such a situation, a node must be informed of its harvesting rate such that it can adapt its sensing and communication rate to it. With information on energy availability it can perform task scheduling based on the priorities.

In addition, in a network, energy conditions could exist such that one node enjoys an excess, while another suffers from want of energy. In such a scenario, it is not practical to expect all nodes in the network to assume equal responsibilities at all times. The distributed nature of the setup proves to be an additional obstacle as nodes are not aware of the fortunes of their neighbors. Thus, clever solutions must be devised for the various operations that are required to form a self-forming, self-maintaining network using these devices. Solutions include various techniques for power and energy management at node level. At network level, nodes must resort to cooperative methods and operate proactively whenever possible to reduce the burden on others.

The impact of such behavior is felt on every layer of the communication model. With respect to the networking stack, several efforts have been made towards the various aspects of an EH-WSN such as routing [12] and medium access [13]. Several of these solutions bank on information such as energy availability, harvesting rates, energy predictions and so on. In order for seamless operation within the network, each layer of the

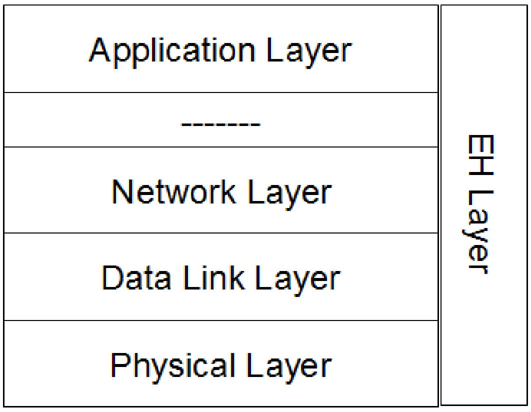


Figure 1-3: A Networking Stack for EH-WSNs

wireless sensor node's stack must be given these inputs. Measurements, calculations and computations that need to be performed to improve the operation of each layer of the traditional communication model can be designated to a module known as the EH layer seen in Fig. 1-3. The philosophy of using this vertical EH layer is that it would maintain the modular structure of an existing networking stack with minimal changes and yet provide inputs to every layer.

1-2 Problem Statement

In this thesis, we present solutions towards the realization of a dedicated communication model for EH-WSNs. We focus our attention on the problem of neighbor discovery in a network consisting of energy harvesting nodes. Neighbor Discovery (ND) is performed implicitly in traditional sensor networks. That is, it is performed while the sensor node attempts to transmit data to its neighbors. However, we shall see that neighbor discovery is no longer a trivial problem in EH-WSNs for several reasons. Firstly, a popular energy management technique in energy harvesting networks is duty cycle adaptation to the rate of energy arrival. Thus, it is no longer possible to predict the next time a node would be awake if it is present in the neighborhood. Secondly, though energy availability is perennial in an energy harvesting network, power availability is not guaranteed at every instant. Thus, energy harvesting nodes can leave and re-enter the network. Thus, ND is not performed just at the deployment stage of the network but is a continuous process across the network. These reasons motivate a ND protocol for energy harvesting sensor networks. One of the peculiarities of energy harvesting networks is that every node may see different energy availability. Such heterogeneity implies that the burden of ND could be handed to a node that sees more frequent or larger quantities of energy arrival. If nodes are equipped with prior knowledge of energy availability through a reliable energy prediction algorithm, they could pro-actively opt to take on neighbor discovery. Thus opportunities arise for a protocol that allows for distributed or cooperative neighbor discovery. Further, through the use of directional antennas for neighbor discovery, nodes can transmit at lower transmit powers, reducing their instantaneous power requirement and improvement over omnidirectional transmission because of reduced interference. The contributions of this thesis are as follows:

- We describe the concept and implementation of a simple two-way scheme for ND during initial deployment in an EH-WSN.
- We describe the concept and implementation of a one-way scheme for ND in nodes that are re-entering existing networks due to energy dynamics.
- Through analysis and parametric studies, we understand the effect of various factors on important metrics that can be used to measure performance of ND in EH-WSNs.
- Finally, we study and propose prediction algorithms that may be used to improve the ND process and behavior as well as a contribution to the EH layer of the network stack (Fig 1-3).

1-3 Literature Review

ND in wireless sensor networks is not considered to be a problem by itself as it is traditionally performed by MAC protocols as an implicit operation. However, as Dutta and others point out in [14], ND is not a trivial problem in networks where it is not easy or practical to predict if and when a node will find a neighbor nearby. These networks include mobile networks in which energy is a constraint – e.g., battery operated ad hoc networks [14]. The authors describe a protocol based on the birthday protocol method [15] for networks of mobile nodes that sleep and wake up at regular intervals. Their recommendation is that nodes choose their duty cycles as the sum of the reciprocals of two prime numbers that are distinct for each node. This duty cycle setting is performed based on the worst case discovery latency required by the applications.

Similarly Iyer et al., suggest that beaconing rate must be based on the estimate of the neighborhood size [16]. Such an estimate of neighborhood size is calculated using the *NetDetect* algorithm that uses a maximum likelihood estimator which is fed with the number of errors occurring on the wireless channel. However in case of energy harvesting networks, a popular technique adopted for energy management is to adapt the duty cycle to the rate of energy harvesting [17, 18]. Such a rate adaptation causes additional complexity in ND process.

ND process in EH networks is a two-fold problem. Immediately following deployment, nodes require to learn their environment in a short time span and use as little energy as possible to do so. Secondly, since energy availability is constantly changing, nodes tend to leave the network due to lack of energy and then re-enter it when they harvest enough energy. This causes ND to be a process that is being continuously performed in the network. Cohen and Kapchits describe a cooperative scheme for continuous ND which is performed by nodes in collaboration with known neighbors to find a node that may have recently entered the network [19]. Such a discovery process is different from the initial discovery process when no node is aware of the other. Again, the application of this scheme to energy harvesting networks is not straight forward as the nodes that have already been discovered by their neighbors would attempt to perform initial ND again. Thus, there would be a heavy overhead caused by nodes trying to discover neighbors who are already aware of them. A node that suffers heavy fluctuation between on and off state due to very low energy availability could potentially cause congestions by re-initiating the ND process in its vicinity repeatedly.

With respect to low or optimal energy consumption, Madan and Lall present a minimum energy method for ND [20]. Their solution rests on the computation of a minimum energy graph at design time by solving a stochastic shortest path problem. This method requires knowledge of topology and importantly does not address the issue of continuous ND. To the best of our knowledge, the issues in ND that are unique to energy harvesting wireless sensor networks have not been investigated in literature.

Discovery in wireless networks using directional antennas has been studied by Vasudevan and others [21] where the authors describe direct and gossip based algorithms. ND protocols in ad hoc wireless networks using directional antennas have been described by An and Hekmat [22]. They describe a hand shake based directional ND scheme and study its performance. An and others describe the various protocols that can be used for ND and the impact of beamwidth and link models on these protocols [23]. Each of these studies, describe the benefits of directional antennas in discovery and provide an analytical model for the same. However, they do not expand on a network in which nodes duty cycle due to non-availability of continuous source of power.

1-4 Organization of this Report

This report is organized into six chapters, including this introductory chapter.

Chapter 2 describes the system under study in the form of a general model. Next, two different ND schemes are detailed. Also described are the details of implementation of this model in our simulation engine and the performance metrics that we use.

In Chapter 3 the system is described as a stochastic model in which the various parameters that would influence performance are identified from probability expressions. The extent of their effect on performance is outlined with the help of numerical results.

Chapter 4 presents the results of extensive simulations. The effect of parameters identified in Chapter 3 is studied through these simulations. Several recommendations are provided to address these effects.

In Chapter 5, energy prediction algorithms are studied. Solutions for light-weight energy prediction mechanisms are described and recommendations on the use of these algorithms in the communication model are given with ND as a special case.

Chapter 6 concludes this report and lays emphasis on recommended future work that would contribute to creating our vision for real-world implementations of EH-WSNs.

Chapter 2

System Model and Simulation Details

In this chapter, we introduce the system models that we consider in this study. We begin with the description of a basic model and introduce the differences in this basic model when we consider omnidirectional or directional transmitters. All models are considered for a fledgling network in which nodes are yet to create neighbor tables. Further, the details of realizing these system models in the simulation setup are also discussed and simulation parameter choices are justified.

2-1 General System Model

In this section we describe the features that are common to every model under study and hence term this the general system model. Every case under study is a modification of this basic setup. We consider a system of nodes that are placed at random in a rectangular field (Fig. 2-1) on the same horizontal plane.

Every node in the network is powered by an energy harvester such as a photovoltaic panel, thermoelectric generator or vibration harvester. We assume that all nodes may or may not be powered by the same type of harvester. Thus the energy opportunities of each node in the network could be different from the other. In an indoor or home setting, we can visualize this heterogeneity if we consider that energy harvesting sensor nodes would be equipped with harvesting devices depending on where they are placed - if placed near windows they could use solar harvesting and if placed near the walls could use thermoelectric generation to bank on the difference in temperature in the insulation.

We focus our study on a single node in the energy harvesting network which has just begun the process of discovering its nearest neighbors. This node that we label the “finding node” or A and is represented as a red dot in Fig. 2-1. This node is placed at the center of a circle (represented by a large black circle in Fig. 2-1) whose radius defines its radio range. The other capabilities of this node may or may not exceed that of its neighbors, but we limit our discussions to the process of neighbor discovery alone. The nodes that fall in the radio range of the finding node are identified in our example Fig. 2-1 with black circles. Any of these nodes is termed as node B. The nodes that do not fall within the range of the finding node are seen as gray dots.

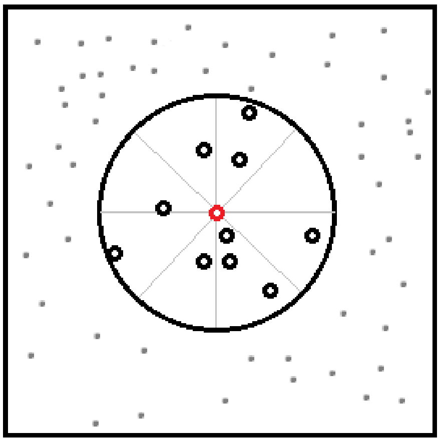


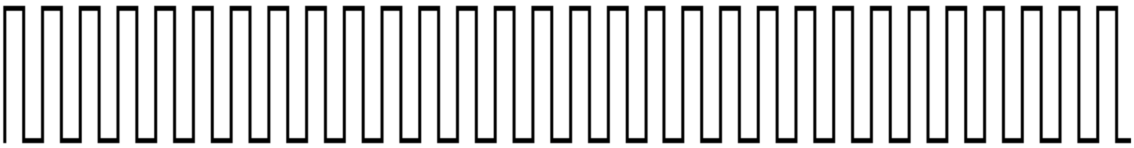
Figure 2-1: Example of Node Placement

We assume that each node is equipped with an antenna whose beamwidth can be electronically switched similar to SPIDA as described by Nilsson [24]. We assume that it is possible to choose the beamwidth at which the transmitter may transmit ranging from 45° to 360° at which the transmitter becomes an ideal omnidirectional transmitter and receive. We assume that there are ideal transmission conditions and link variations are not considered in this study.

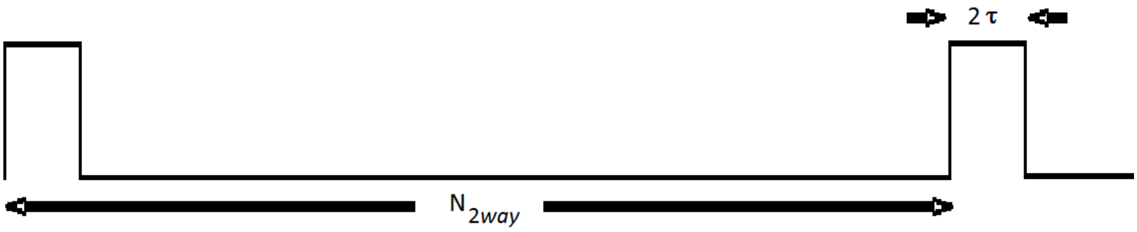
With respect to the timing , we assume that there is no synchronization between nodes but all nodes follow time-slotted operation. In our study a slot equals one millisecond as this is the smallest unit of measurement required in this study, the choice of which is justified as follows. The data rate as prescribed by the IEEE 802.15.4 protocol, used by most deployments of wireless sensor networks, is 250kbps. Thus, in order to transmit a packet consisting of node IDs, CRC bytes and some information on the node's energy condition, neighbor table etc. we would require a maximum of 30 bytes. Transmission of a 30 byte packet at 250kbps would require 960 microseconds which we round off to 1 millisecond. An illustration of this timed cycle is seen in Fig 2-2(a).

2-2 Two Way Neighbor Discovery

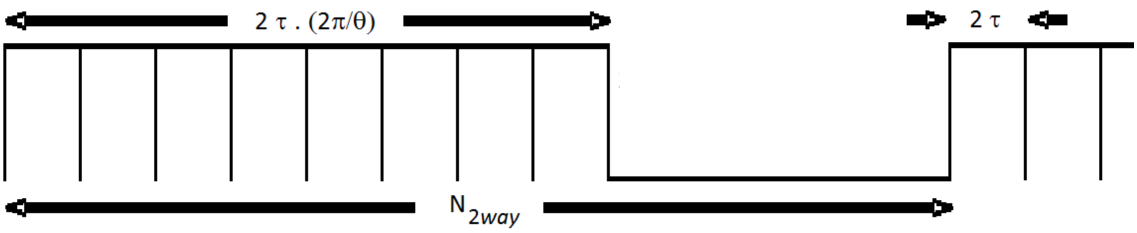
We focus our attention on an energy harvesting network that has just been deployed. In our study, we initially consider the neighbor discovery process occurring in a single node that we label the "finding node" or A. The assumption is that this node has been marked, before deployment, to perform this process and no other node attempts ND. In an actual setting this assumption may not be unrealistic as in a home setting, this node could a "super node" that acts as the home controller which is powered by a larger



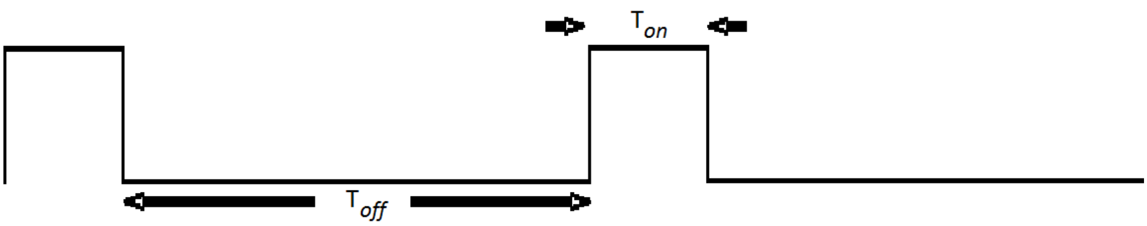
(a) Time is slotted in durations of 1 millisecond



(b) Omnidirectional Finding Node's Timing Diagram for Two Way ND



(c) Directional Finding Node's Timing Diagram for Two Way ND



(d) Neighbor Node's Timing Diagram for Two Way ND

Figure 2-2: Timing Diagrams

harvesting device than the other nodes in the network. However, a more homogeneous network must be modeled and studied for a truly ad hoc network.

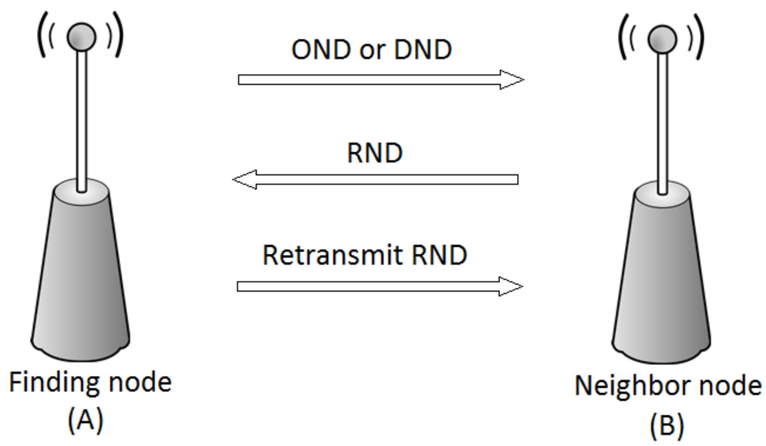


Figure 2-3: Two Way Neighbor Discovery

2-2-1 Omnidirectional Two-Way ND

First, we consider an omnidirectional finding node at the center of a circular field whose radius represents the radio link range of the node. This finding node attempts to find its immediate (single hop) neighbors which lie at random locations within the circular field as seen in Fig. 2-1. We assume that every node has a truly omnidirectional antenna. All nodes other than the finding node sleep for T_{off} milliseconds and are awake for T_{on} milliseconds as seen in Fig 2-2(d). The finding node transmits an Omnidirectional Neighbor Discovery (OND), whose duration is τ and waits for a Reply to ND packet (RND) for a duration τ. The finding node transmits an OND every N_{2way} milliseconds. This timing allocation is illustrated in Fig 2-2(b). The algorithmic steps followed during the ND process are listed out in Alg 1.

2-2-2 Directional Two-Way ND

Here we discuss the case where the finding node has a directional antenna with a beamwidth θ and thus the circular field is divided into $\frac{2\pi}{\theta}$ sectors. An example division into 8 sectors of 45° beamwidth is seen in Fig. 2-1 in grey lines. The finding node transmits a Directional Neighbor Discovery (DND) packet of duration τ and listens for τ milliseconds for an RND packet every N_{2way} milliseconds. The finding node transmits DND packets in a fashion similar to the wheeled-iteration method [22], i.e., the finding node transmits a DND packet and awaits an RND in each of the sectors 1 through $\frac{2\pi}{\theta}$ in sequence. Thus the total transmit time for the finding node is $2\tau \cdot \frac{2\pi}{\theta}$. The assumptions for the neighbor nodes remain the same as before. The algorithmic steps followed are listed in Alg 2

Algorithm 1 Omnidirectional Two-Way ND algorithm.

At the scanning node **A** when having sufficient energy in storage:
while all k neighbors are not found **do**
  Advertize a neighbor discovery (OND) packet using omnidirectional antenna
  Wait for Reply ND (RND) packet in the next τ ms
  if RND for a neighbor x is successfully received **then**
    Mark x as found
    Send a broadcast packet saying x has been found
  end if
  Sleep for $(\mathrm{N}_{2way} - 2\tau)$ ms
end while

At a neighbor node y with sufficient energy in storage:
if OND packet is received successfully **then**
  Send a Reply ND (RND) packet
  Wait for **A** to check if y is found
  if y is not found by **A** **then**
    Randomize the next wake-up time
  end if
end if

Algorithm 2 Directional Two-Way ND algorithm.

At the scanning node **A** when having sufficient energy in storage:
while all k neighbors are not found **do**
  for all s where s is a sector from sector 1 through sector $\frac{2\pi}{\theta}$ **do**
    Advertize a neighbor discovery (DND) packet using an directional antenna with beamwidth θ
    Wait for Reply ND (RND) packet in the next τ ms
    if RND for a neighbor x is successfully received **then**
      Mark x as found
      Send a broadcast packet saying x has been found
    end if
  end for
  Sleep for $(\mathrm{N}_{2way} - 2\tau.\frac{2\pi}{\theta})$ ms
end while

At a neighbor node y with sufficient energy in storage:
if DND packet is received successfully **then**
  Send a Reply ND (RND) packet
  Wait for **A** to check if y is found
  if y is not found by **A** **then**
    Randomize the next wake-up time
  end if
end if

The justification for use of directional antennas in energy harvesting sensor networks is that these antennas allow for lesser interference and thus less loss of energy across the network. SPIDA is an example of a directional antenna that can be used in low power devices such as wireless sensor nodes [24]. Since SPIDA uses parasitic elements that can be controlled with a micro-controller output using an FET, it does not consume DC power. Studies show that such a construction improves received signal strength at longer distances as is expected of these antennas. SPIDA also allows for omni-directional operation. Additional energy consumption of such a device if any, is yet to be investigated.

A new scenario arises with the use of directional antennas. Since the node would have to use lower energy to transmit over a smaller sector area, it can reach the same range as an omnidirectional transmitter at lower transmit powers. Thus, for a directional transmission, if the node increases its transmit power, it could reach a longer range [25]. This would cause the node to discover nodes that were not reachable by the omnidirectional antenna. While this is beneficial since it improves the connectivity of the network, the advantage is lost because nodes can no longer discover each other mutually. That is, unless the neighbor node found in the extended range chooses to transmit using the same power which would be possible only with the setting of the directional antenna, two way discovery is not possible. However, the purpose of use of a directional antenna in neighbor discovery for EHS is not increased transmission range but reduced instantaneous power consumption and lower interference among neighbors. For this reason, we only consider the longest range of the omnidirectional antenna and limit the directional antenna's range to the same by controlling the transmit power. In practice, such transmit power control for a directional antenna could be achieved using topology control schemes described by Hackmann et al. [26].

2-3 One-Way Neighbor Discovery

Let us consider a connected energy harvesting network, where nodes have discovered their neighbors and are now performing network operations such as sensing and data transmission. In an energy harvesting network, when nodes constantly leave and re-enter the network, storing a neighbor table in non-volatile flash memory is often too expensive for nodes to perform especially if node density is high. In such a case, it is economical and practical for a node to attempt to discover its neighbor nodes every time it re-enters the network. However, a two-way neighbor discovery process could be avoided in this case as most nodes are already aware of all their neighbor nodes.

We further motivate the necessity of a continuous ND scheme instead of the use of the two-way scheme with an example. Let us consider a connected EH-WSN in which a routing algorithm has arrived at the best possible multi-hop route to the destination or base-station. Let us assume that the route for a few nodes requires a node X as one of the several hops to the destination. Say, if X dies due to the lack of energy – which is to be expected in an EH device. Of course, a routing algorithm designed for use in an EH scenario would provide for such a situation and nodes would converge on

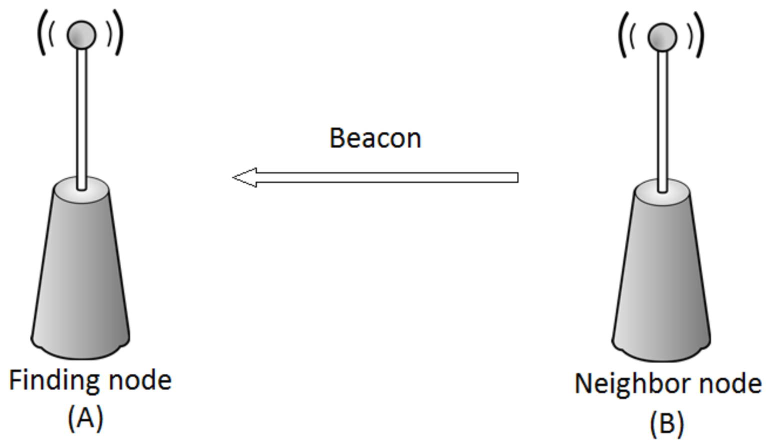


Figure 2-4: One Way ND

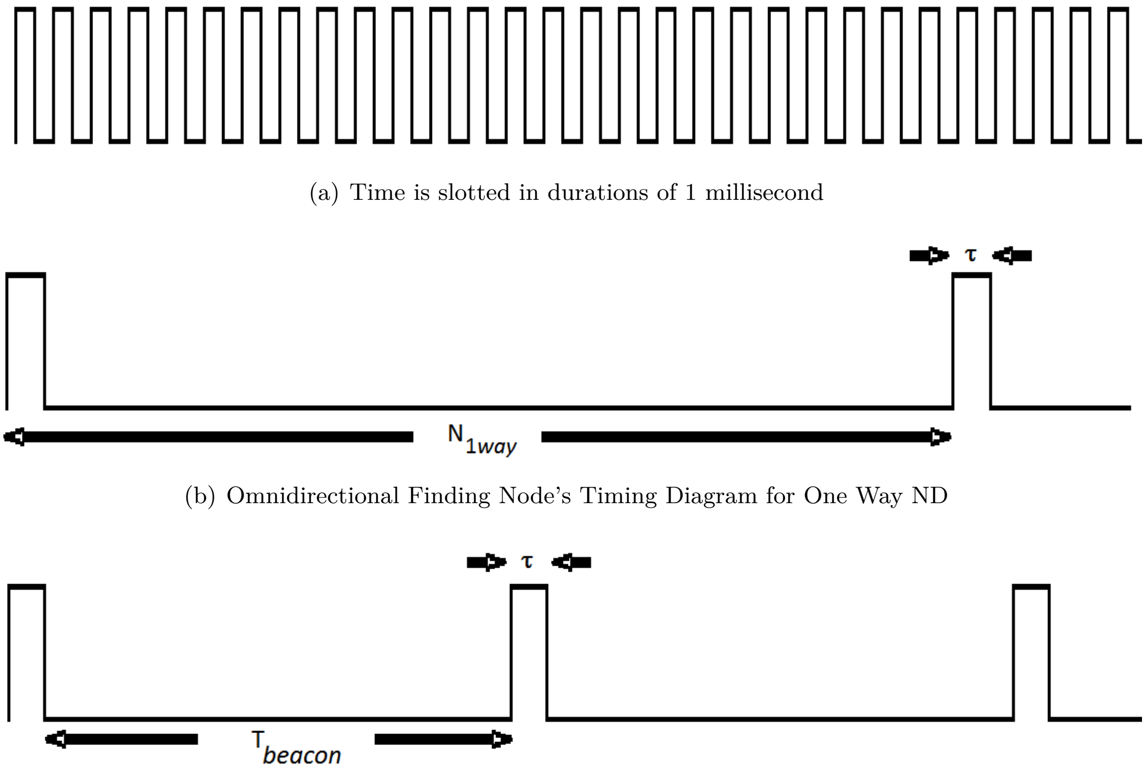
a new route to follow. However, when X revives with the arrival of energy, it would reinitiate ND process since it is no longer aware of its neighbors. If such a situation were faced by a group of nodes, the network would rapidly tend towards congestion as large sections of the network would be performing ND while others would be attempting data communication and other network operations. Such a possibility necessitates a mechanism that would allow re-entering nodes to discover their neighbors as non-intrusively as possible.

In this continuous ND scheme, we propose that all nodes in a connected network send out beacons. These beacons can then be heard by the newly "reborn" sensor node and used to discover its neighbors. Such a beaconing could be useful not just for neighbor discovery but also to convey important information such as synchronization as in S-MAC [27] and/or as a signal that a node is still active in the network. Since through this process, only the node that is listening for beacons discovers nodes, we label it a "one-way" scheme.

2-3-1 Omnidirectional One-Way ND

Here we consider a finding node at the center of a circular field whose radius is defined by the finding node's radio link range. Every other node within this circular field has participated in the initial neighbor discovery process and has a neighbor table of at least its immediate neighbors. The finding node listens for a beacon every N_{1way} milliseconds for τ milliseconds (seen in Fig 2-5(b) whereas every neighbor node transmits a beacon of duration τ milliseconds every T_{beacon} milliseconds on an average (as in Fig 2-5(c). The finding node acts as an omnidirectional receiver while every other node acts as an omnidirectional transmitting node.

The algorithmic steps involved in ND for the omnidirectional care are listed in Alg 3.



(a) Time is slotted in durations of 1 millisecond

(b) Omnidirectional Finding Node's Timing Diagram for One Way ND

(c) Neighbor Node's Timing Diagram for One Way ND

Figure 2-5: Timing Diagrams for One Way ND

Algorithm 3 Omnidirectional One-Way ND algorithm.

At the scanning node **A** when having sufficient energy in storage:
At every N_{1way} ms **do**
Wait for beacon in the next τ ms
if beacon for a neighbor x is successfully received **then**
  Mark x as found
end if
Sleep for (N_{1way} - τ) ms
end

At a neighbor node y with sufficient energy in storage:
Transmit a beacon at time t
Randomize t with a mean of T_{off} ms

2-3-2 Directional One-Way ND

The only difference from the omnidirectional one-way discovery is that the finding node listens for τ milliseconds in each of sectors 1 through $\frac{2\pi}{\theta}$ sectors in sequence every N_{1way} milliseconds. Neighbor nodes transmit omnidirectionally as before. The steps followed in this method are listed in Alg 4

Algorithm 4 Directional One-Way ND algorithm.

At the scanning node **A** when having sufficient energy in storage:
At every N_{1way} ms **do**
for all s where s is a sector from sector 1 through sector $\frac{2\pi}{\theta}$ **do**
  Wait for beacon in the next τ ms
  if beacon for a neighbor x is successfully received **then**
    Mark x as found
  end if
end for
Sleep for (N_{1way} - $\tau.\frac{2\pi}{\theta}$) ms
end

At a neighbor node y with sufficient energy in storage:
Transmit a beacon at time t
Randomize t with a mean of T_{off} ms

2-4 Energy Model

Here we describe the modeling of the energy arrival process, the energy consumed by the nodes and the behavior of the energy storage element.

2-4-1 Energy Arrival Process

We assume an energy arrival model at the harvesting node to follow a Poisson arrival process. That is the time between the arrival of two discrete packets of energy is exponentially distributed. We use the term energy Interarrival Time (IA) to indicate that the time between two consecutive arrivals of energy. Thus an energy regime that sees an interarrival time of 15 time slots is injected with a random quantity of energy every 15 time slots on an average. While it is difficult to visualize the arrival of energy in this manner at a solar panel, it is natural to observe this from a piezoelectric crystal harvesting energy from structural vibrations. Also, considering that most hardware solutions for harvesting electronics make use of DC-DC converters which require a minimum power level to begin operation, the arrival of energy assumed here could be caused by the fluctuation about the threshold value. The quantity of arrival is randomized to emulate a varying energy availability level similar to the varying power levels available from a solar panel at noon versus at sunset. This quantity of energy is of the order of up to 3mJ over one time slot.

2-4-2 Energy Consumption at Nodes

Table 2-1: Energy Consumed by Node for Various Operations

Event	**Energy Consumption**
Transmission of one OND or one RND	0.075mJ
Transmission of one DND ($\theta = 45°$)	0.054mJ
Transmission of one DND ($\theta = 90°$)	0.063mJ
Transmission of one DND ($\theta = 180°$)	0.069mJ
Transmission of $\frac{2\pi}{\theta}$ DNDs	Cost for DND x$\frac{2\pi}{\theta}$
Receive mode for 1 time slot	0.072mJ
Staying on (asleep) for 1 time slot	0.006mJ

The energy consumed for every relevant operation that we consider in our study is listed in the Table 2-1. The values assumed are taken from energy consumption by an Iris mote from Crossbow [28]. The energy consumption of one DND is less than one OND as we assume that the directional transmitter can transmit at a lower transmit power than the omnidirectional transmitter and cover the same approximate range. However, the cost for a series of transmissions to each sector for the directional transmitter would prove costlier as this cost for a single transmission would be multiplied by the number of sectors.

Each node is assumed to be aware of its energy availability in the storage buffer. A node initiates or responds to an ND process only if it has energy required for the entire process. For example, the directional finding node in the two-way discovery process would start transmission in sector 1 only if it has energy to transmit to and receive from all sectors.

2-4-3 Energy Storage Element

The energy storage element or storage buffer considered is a supercapacitor or ultra-capacitor which is usually an electric double layer capacitor with high farad capacity. This storage buffer is gaining popularity among researchers for use in energy harvesting devices due to its various advantages such as high power and energy density, low complexity charging circuitry and longer life. The disadvantage of the supercapacitor is that it suffers a leakage current that depletes the amount of usable energy over long periods. This leakage cannot be modeled easily as it is characterized by a complex non-linear behaviour [29]. We use a simple linear relationship between stored energy and leakage but Weddell et al. describe a complex model for accurate supercapacitor modeling [30] which could improve the study.

An energy buffer is of great importance in any Energy Harvesting System (EHS) deployed in a setting where energy availability is random and comes in bundles rather than in a steady deterministic flow. Since almost every source in nature is of the former kind, the energy buffer is recommended for use. With the presence of a storage element, the variations in energy availability are smoothened. We shall see in the results of our simulation and analytical models, how this impacts system performance.

For all our simulations, unless indicated otherwise, we consider that every node is equipped with a supercapacitor with a capacitance of $0.7F$ which translates to an energy capacity of $3mJ$. We assume leakage to be 5% of the available energy.

2-5 Conflict Resolution

Collisions occuring at the finding node due to multiple nodes transmitting at the same time has to be dealt with effectively for successful discovery. In the two-way discovery method discussed above, every RND received by the finding node is retransmitted to the neighbor nodes. Thus, if the neighbor nodes receive a packet that does not match the packet that it has just sent, it can detect that a collision has occurred. When such a collision is detected, the node randomly reschedules the instant at which it wakes up next. Since each node that detects this collision reschedules its timers, the probability of a collision during the next ND period is reduced. If the received and transmitted packet match, the node that transmitted the ND packet does not respond to any subsequent ND packets, thus as nodes are found, the rate at which collisions are experienced must reduce. In the one-way discovery process, as there is no feedback from the passive finding node, each neighbor node simply randomizes the time slot at which it transmits the next ND packet.

2-6 Performance Metrics

We expand on performance metrics used by An and others [23].

- **ND ratio** is the ratio of found nodes to total number of its immediate neighbor nodes. We assume that the node performing discovery is aware of the exact number of its immediate neighbors (k). Immediate neighbors are the nodes that can be reached over a single hop. Ideally, the ND ratio of each node in the network must be 1 or 100%. In practice, providing a node with the knowledge of its number of neighbors is unrealistic. In that case, we put a limit on the time for which the node performs neighbor discovery to ensure that at least 90% of its neighbors are discovered. The greater a node's ND ratio, the more connected it is and the higher is the redundancy of the network at this point.
- **ND time** is the time taken to find all k neighbor nodes. Since we treat time as divided into discrete slots, ND time is measured in slots. It is important for neighbors to be discovered as soon as possible when a network is deployed to enable other activities such as routing and data dissemination to begin to keep to application requirements. Further, in an energy harvesting network, it is important to keep this time to a minimum such that loss of stored energy because

of supercapacitor leakage does not impact this process. Thus, the ND time of a neighbor discovery protocol indicates its energy efficiency. Again, the assumption that number of immediate neighbors (k) is known can be avoided if we limit the ND time.

- **ND energy** is the energy required at the finding node to discover k number of neighbor nodes. It includes the energy required for the transmission of DND frames or OND packet, for reception and the cost for acknowledgments. ND energy defines the efficiency of the neighbor discovery protocol. However, this metric differs from ND time as energy-deficient nodes defer initiating or responding to ND processes. That is, there could be time slots at which the finding node was scheduled to perform neighbor discovery but did not, due to lack of energy. Such a deferment would add to the ND time but not to ND energy. An and others use ND overhead as a metric. But as the energy used for a DND frame would depend on the number of sectors are considered, we find that ND energy provides more information.

- **ND Collisions** Collisions allow us to understand the energy wasted within the immediate neighborhood of the finding node. In a case where number of ND collisions is large, the immediate neighborhood of the finding node is taxed and is more likely to fail due to lack of energy. Thus, when ND collisions are at a minimum, robustness is likely to be higher.

Chapter 3

Analytical Model

In order to analyze and further understand the system model described in the previous chapters, we detail the analytical model of the energy arrival process, the consumption process and the energy storage element and use these models to describe both the ND processes discussed previously for the omnidirectional and directional cases. Through this discussion, we aim to (i) describe the system under study, (ii) list the parameters that would have an effect on performance metrics especially ND time, (iii) understand and discuss the effect of these parameters through numerical analysis.

3-1 Energy Model

Energy arrival at a harvesting node in a natural environment is best modeled as a stochastic process due to the random nature of most natural sources such as sunlight and wind. Poggi and others demonstrate that the solar radiation recorded over a period of time can be mapped to a Markov process [31]. Similary Ho et al. provide the methodology to model harvested energy as a non-stationary Markov process with added context [32]. The modeling of the energy as well as traffic in terms of birth and death processes is described by Jing Lei et al [33] and a discrete Markov chain by Seyedi et al [34], while traffic at a sensor node has been modeled as a Markov chain by Medepally and others [35].

It has been common practice to model energy and node operations as stochastic processes as our examples above suggest. However, it is beneficial to model the processes of energy arrival, consumption and storage as a unified model. Here, we describe the modeling of these processes as a single queuing system where energy arrival is similar to packet arrival at the queue and service of packets is the equated to consumption of energy. The system queue is equated to the energy storage buffer that can store a finite number of discrete energy bundles.

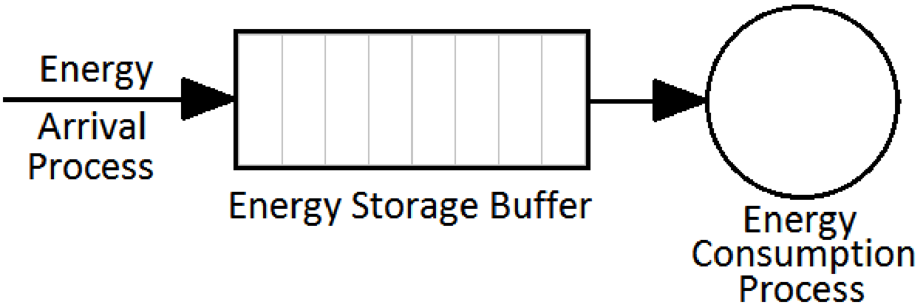


Figure 3-1: Energy Model

3-1-1 Arrival Process

We consider energy to arrive at the harvesting node's energy storage buffer in the form of discrete packets of equal size. The arrival process in a queuing system is characterized by the interarrival time of two consecutive packets. More specifically, the interarrival times of packets are independent and identically distributed (i.i.d.).

We consider interarrival times of energy as i.i.d. random variables and the mean interarrival time is denoted as IA. Thus, the mean energy arrival rate is given as $\lambda = \frac{1}{IA}$.

In our study, we assume that energy arrives as a Poisson arrival process. A Poisson process is one that has the characteristic of being memoryless. It can be argued that the energy arrival at an energy harvesting node is a memoryless process.

Thus far, we have discussed the *arrival times* of discrete energy packets. The *quantity of energy* in each arrival is also a random quantity in nature. At any given instant of time during the day, solar rays incident on a solar panel could vary allowing different quantities of energy to be harvested. In order to account for this, we consider the arrival at instant of time to be a random variable itself that we label B. Each harvesting device has a range of energy that it can possibly harvest according to its physical dimensions such as area for a solar panel. Let us assume that the current draw from the solar panel in use in our setup to allow for an energy range of 0 to E_{max} and B is uniformly distributed between these two values. Thus,

$$f(b) = \begin{cases} \frac{1}{E_{max}} & \text{for } 0 \leq b \leq E_{max} \\ 0 & \text{elsewhere} \end{cases} \tag{3-1}$$

and the mean value of B is $E[B] = \frac{1}{2}(E_{max})$.

The process is no longer a Poisson process, but is better represented as a compound Poisson arrival process which is described as follows:

If $N(t)$ is denotes the number of energy arrivals by time t, $X(t)$ denotes the total amount of energy arriving by time t, we have:

$$X(t) = \sum_{n=1}^{N(t)} B_n \tag{3-2}$$

And, the mean $E[X(t)]$ is given as

$$= E[N(t)]E[B] = \lambda t E[B] \tag{3-3}$$

In the Kendall notation, the compound Poisson process is represented as M^X.

The compound Poisson process while capable of efficiently describing our arrival process, is tough to model in our analysis and out of scope. Thus, we approximate the arrival process to a Poisson process, where every two discrete energy bundles that arrive can provide enough energy to perform a single ND process.

3-1-2 Departure Process

The service time distribution of a queue is characterized by the time at which the packet or customer is serviced or the mean rate at which they are serviced, μ. In our analogy, the service time is the instant at which a quantity of energy is used up. In the node, operations that it must perform are scheduled at fixed times, the departure process or energy consumption process can be modeled as a degenerate distribution:

$$f(k; k_0) = \begin{cases} 1 & \text{if } k = k_0 \\ 0 & \text{if } k \neq k_0 \end{cases} \tag{3-4}$$

The Kendall notation for the degenerate distribution is D.

If we consider the usage of energy for a periodic process to be N discrete packets of energy, the departure process would be best denoted as $N * D$. If the size of one discrete energy packet is xmJ which is the smallest quantity of energy that is used in the considered setup, the value of N is given as $N = E_{ND}/x$.

There are some scenarios where the departure process has a different behavior. For example, all of the various processes that consume energy come from different layers of the communication model at different scheduled times. Thus, we might approximate the consumption process to a Poisson arrival case. However, in our discussion here, we limit ourselves to the description of energy consumed due to ND process alone and model this as D.

3-1-3 Queuing process

The queue or buffer is characterized by two important parameters:
(a) the number of different queues, m - in our case since each node is equipped with a single storage buffer $m = 1$
(b) the number of positions in the queue - since the storage element has a fixed capacity, we take this to be K positions in the queue. Translating this into our analogy, the queue has $K = E_{max}/x$ positions.

Thus, the notation for the entire queue system that represents our energy arrival, usage and storage system is : $M^X/N * D/1/K$.

However, this queue is complicated to analyze. It is possible to simplify to a studied system - M/D/1/K by defining a single arrival or discrete packet to be of a fixed size - such that two of these packets is sufficient to carry out or respond to an ND packet. Thus, we require a queue of $K = E_{max}/(0.5 * E_{ND})$ positions.

In order to fully understand the analogy that we have adopted to describe the entire energy process, it is important to understand an important parameter - 'the traffic intensity' or 'load' or 'utilization', ρ of the queuing system. For a regular queuing process,

$$\rho = \frac{E[\text{Service Time}]}{E[\text{Interarrival Time}]} = \frac{\lambda}{\mu} \tag{3-5}$$

In a queuing system, the condition for stability is $\rho < 1$. In words, this means that the service rate is never lesser than the arrival rate. If there is a possibility that the arrival rate exceeds the service rate, the system is said to be unstable as the buffer content of such a queue keeps increasing. However, for an energy harvesting system, the requirement is that the rate of arrival of harvested energy must be greater than the rate at which the node consumes it. Most practical implementations define a scheduling scheme such that this condition is achieved. If the harvesting node maintains $\rho = 1$ the system is energy neutral and node design and operation that ensures such a condition is desirable as discussed in detail by Kansal et al. [17].

Energy Availability in the Buffer

With the definition of the energy model as a queuing system, it now becomes possible to obtain an expression for the probability that a fixed threshold of energy is available. This parameter is defined as the probability of the buffer occupancy. For the M/D/1/K when the arrival rate approaches the service rate, $\rho \to 1$. Under this condition, the pdf of buffer occupancy is given by Van Mieghem [36] as:

$$Pr[Q > m] \approx e^{-2m\frac{1-\rho}{\rho}} \tag{3-6}$$

In our system, it is important that ρ equals if not exceeds 1. Thus, it is not possible to calculate this probability for the various values of λ that we consider. In order to understand the behavior of the system, we observe the variations in $Pr[Q > m]$ with changes in ρ in Fig 3-2. It can be seen that the probability that 2 discrete packets of energy (which we assumed to be sufficient to run ND process once) is high for large ρ values, but depreciates very quickly. Thus, we understand that the value of ρ should be large for extended periods of operation - to sustain acceptable levels of performance.

It can be seen that the queuing model described above approximates the energy model described in the simulation setup. However, we use this model here as an explanation device and cannot expand on it in our analytical model. This is because our requirement for $\rho \geq 1$ is not studied for a traditional queuing system – since the queue is unstable under these conditions. In order to demonstrate the analytical model we show numerical

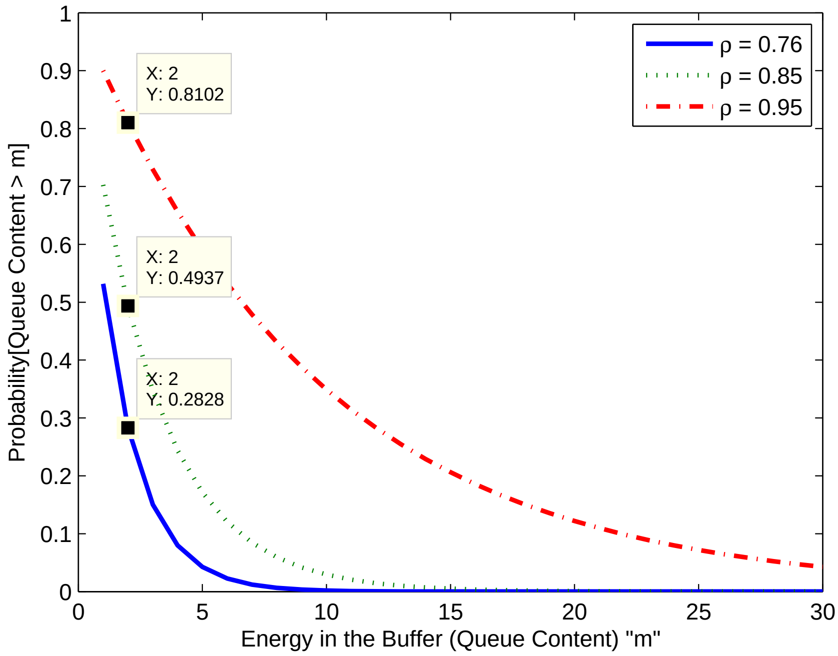


Figure 3-2: PDF of Buffer Occupancy

results for a buffer-less system. That is, we assume an ON-OFF system in which energy is either present or not. Implementation of this queuing system in our simulation engine is possible and we expand on the results in Chapter 4.

3-2 Analytical Model for Two-Way Omnidirectional Finding Node

Here we describe the analytical model for the case in which the finding node attempts to discover all of its neighbors using an omnidirectional transmitting antenna using the two-way ND process. At the center of a circular field is a node A that acts as the finding node and it must discover k nodes labeled B_1 to B_k (we refer to a single one of them simply as B).

In order to discover these nodes, A transmits with a probability P_{t_A} given as :

$$P_{t_A} = \frac{1}{N_{2way}} * P_{eA} \tag{3-7}$$

, where N_{2way} is the period at which A attempts ND and A transmits an ND message that lasts for 1 time slot and P_{eA} is the probability that A has the energy required to initiate and complete the ND process at that instant of time. This probability in a real system would be equal to the probability that the required amount of energy is present in the storage buffer.

Every node B listens for an ND message from A with a probability, P_{l_B} which is given as:

$$P_{l_B} = \frac{1}{T_B} * P_{eB} \tag{3-8}$$

, where T_B is the sleep duration of B_i and the node is ON for 1 time slot and P_{eB} is the probability that B has the energy to respond to the ND message.

Thus, the probability that an ND packet transmitted by A reaches B successfully is given as:

$$P_{A\to B} = P_{t_A} * P_{l_B} \tag{3-9}$$

This also gives the probability P_{t_B} that node B that receives this ND packet responds to it by sending an RND. In order for the discovery process to be completed, B_k nodes must respond to A without their RNDs colliding with each other. The probability that of i nodes that have not been discovered by A, only 1 responds is given as $(1 - P_{t_B})^{k-1}$. Thus the probability that only a single node reaches the finding node successfully (without collisions) is given as:

$$P_{B\to A} = \binom{k}{1} * P_{t_B} * (1 - P_{t_B})^{k-1} \tag{3-10}$$

From this expression it is possible to calculate the time required to find a given node B_i as :

$$\text{ND Time}(i) = \frac{1}{P_{B_i\to A}} \tag{3-11}$$

The total time that is required to find all k nodes is given as:

$$\text{ND Time} = \sum_{i=1}^{k} \frac{1}{P_{B_i\to A}} \tag{3-12}$$

, where i denotes the number of nodes out of k that have been found by A.

In Fig 3-3, we see numerical results from the analysis for ND time for the case that $k = 40$ under several energy availability probabilities $Pe = P_{eA} = P_{eB}$ for all nodes.

3-3 Analytical Model for Two-Way Directional Finding Node

In the case where the finding nodes employs a directional transmitting antenna while discovering its neighbors there are differences in the analysis. As in the omnidirectional case, the probability of transmission at directional finding node Ad is given as :

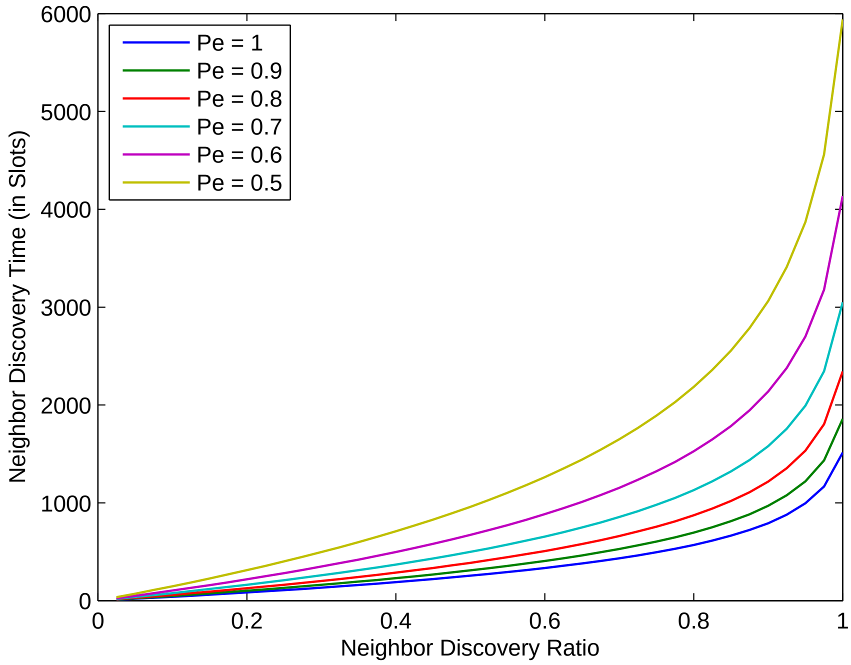


Figure 3-3: Omnidirectional Two-Way ND for Various Energy Probabilities

$$P_{t_{Ad}} = \frac{1}{N_{2way}} * P_{eAd} \tag{3-13}$$

and the probability that the neighbor node B is listening is given as :

$$P_{l_B} = \frac{1}{T_B} * P_{eB} \tag{3-14}$$

as before in the omnidirectional case. The probability that the node B is in the same sector as the finding node is given as $\frac{\theta}{2*\pi} = \frac{1}{N_s}$, where θ gives the beamwidth of the directional beam and N_s is the resultant number of sectors into which the circular field is divided.

Thus the probability that node B responds to the ND packet from Ad is given as $P_{t_B} * (1/N_s)$ where P_{t_B} is defined as before in the omnidirectional case. The probability that no other node responds to A depends on the number of nodes that fall within the beam of Ad. We define the probability that of k number of neighbor nodes there are j nodes in the same beam sector as our selected node B. In other words, the probability that the sector N_j containing node j is the same as sector N_B which contains node B is:

$$P_j = P[N_j = N_B] = \binom{N_s}{1}\binom{k-1}{j-1}\left(1 - \frac{1}{N_s}\right)^{k-j}\left(\frac{1}{N_s}\right)^{j} \tag{3-15}$$

It is interesting to observe this PDF for variations in k seen in Fig 3-4. The variation of P_j with k will help us understand the effect of node density on the ND time in numerical as well as simulation results that we shall see later. We see that the probability that a given number of nodes would occupy the same sector as a node B takes the form of a bell curve that gets wider and shorter with increasing k.

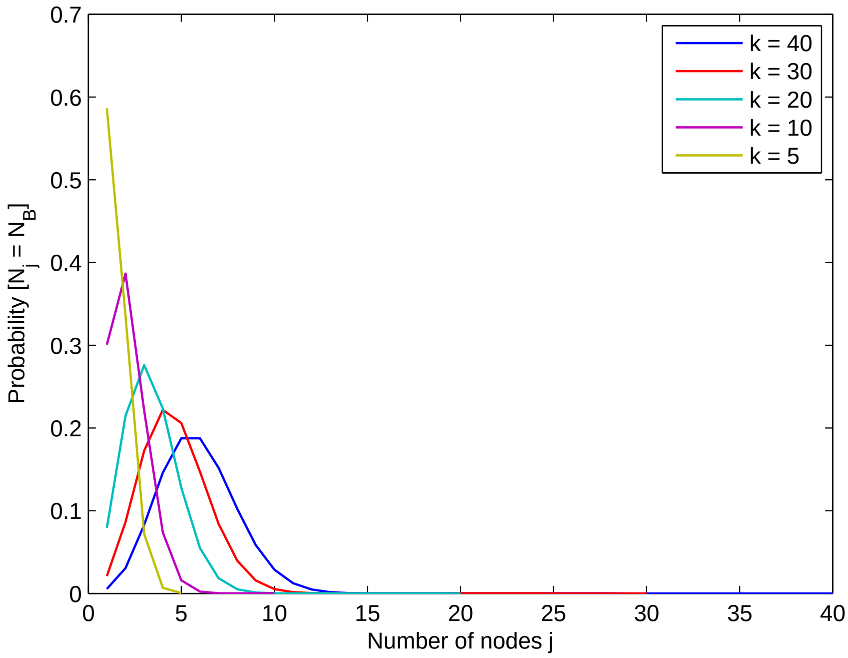


Figure 3-4: Effect of Node Density on Probability that Nodes Occupy the Same Sector

Similarly, the beamwidth of the directional finding node has an effect on the probability P_j (seen in Fig 3-5) which translates to a pronounced change in ND time with beamwidth. Again, the PDF is a bell curve that gets shorter and wider with increasing θ.

The implication of a short PDF curve is that the mean probability is low. But shortness goes with wideness which means that the variance increases. The reason for the curve to move to the right is that the probability that a higher number of nodes share the same sector is larger. Hence, we must prefer a taller, sharper PDF which stays on the left.

Finally, the probability that the node B is successfully discovered by node Ad is given as :

$$P_{B \to Ad} = \sum_{j=1}^{k} P_j * \binom{j}{1} * \frac{P_{t_B}}{N_s} * \left(1 - \frac{P_{t_B}}{N_s}\right)^{j-1} \tag{3-16}$$

and this reduces to Eq 3-10 for $N_s = 1$.

Again, the number of time slots required to discover a single node is given as $1/P_{B \to Ad}$ and the ND time for all k nodes is the summation for all nodes B_i :

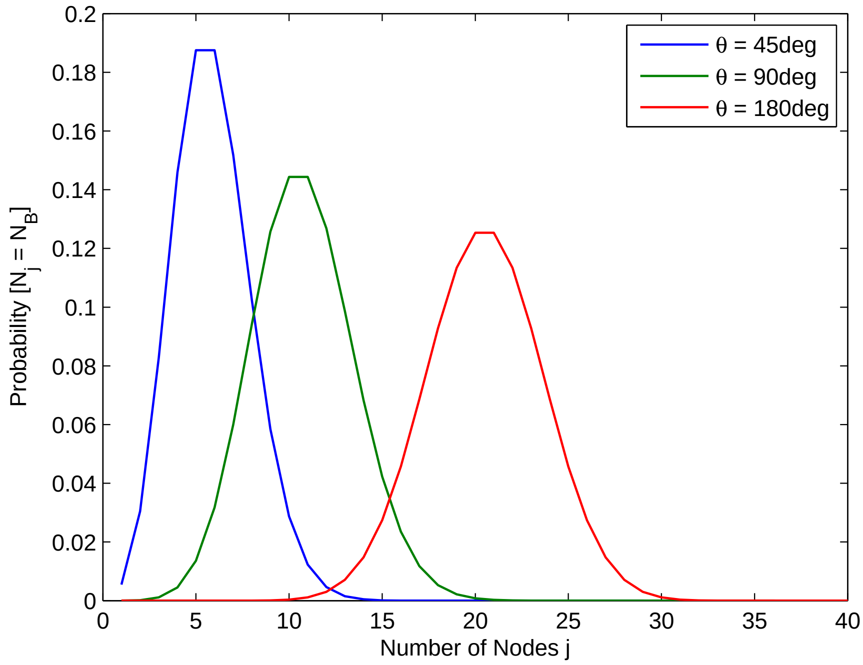


Figure 3-5: Effect of Beamwidth on Probability that Nodes Occupy the Same Sector

$$\text{ND Time} = \sum_{i=1}^{k} \frac{1}{P_{B_i \rightarrow Ad}} \tag{3-17}$$

where $i = 1, 2, ...k$ denotes the number of nodes found by node Ad.

The numerical results from this analysis for the case of varying energy availability probabilities and a finding node that has a beamwidth of $\theta = 45°$ is given in Fig 3-6.

As expected, with lower energy probabilities, the performance of ND deteriorates.

3-4 Discussion of Numerical Results

The behavior of the finding node under various scenarios depends on several factors as we have noted so far in the above analysis as the following:

- Energy availability
- Number of nodes or node density
- Node duty cycle
- Beamwidth

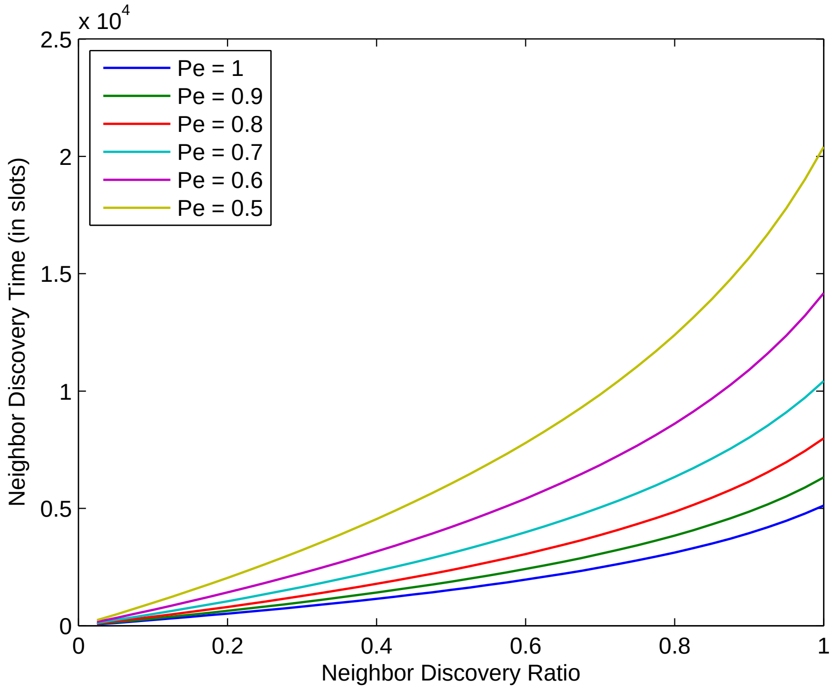


Figure 3-6: Directional Two-Way ND for Various Energy Probabilities

We have already seen the effects of variation in energy availability in the previous sections. In this section, we observe the performance of the omnidirectional and directional transmitter when subjected to variation in the other important factors, compare results and discuss the implications.

3-4-1 Node Density

The ND time for various values of k or node density for both an omnidirectional and directional transmitter is observed in Fig 3-7. As can be seen, the trend seems to saturate at higher values of k. This behavior is due to the fact that once a node has been found, it does not respond to subsequent ND packets of the finding node. This factor appears in Eq 3-12 and Eq 3-17 as the value of the number of nodes found i and varies as $i = 1, 2...k$.

3-4-2 Node Duty Cycle

Next, the duty cycle of the neighbor nodes plays an important role. The duty cycle gives the probability that a responding node B is awake and hence hears the message to respond to the ND packet from the finding node. Thus, the parameter of interest here is the probability that a neighbor node responds to the ND given by Eq 3-10 for the omnidirectional case and by Eq 3-16 for the directional case. Plotting the ND

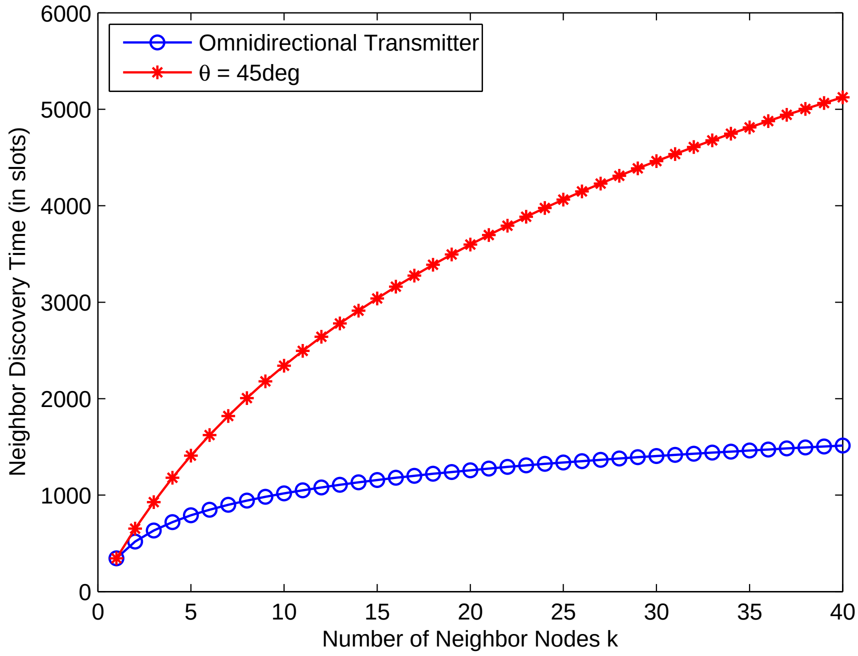


Figure 3-7: Performance of Two-Way ND for Various Node Densities

time against this parameter gives us insight into the great advantage that directional transmission would provide to the ND process.

On the one hand, we see in Fig 3-8 that the ND time increases dramatically, starting at the extremely low RND probability of 0.12. On the other hand, the directional transmitter benefits from the factor P_j as there is little impact of a high probability of response (in Fig 3-9. In other words, since there is a low probability of several of the k nodes occupying the same sector, the ND time is relatively unaffected by the response probability.

3-4-3 Beamwidth

Comparing Fig 3-6 showing variation in ND time at $\theta = 45°$ to Fig 3-3, showing the same for the omnidirectional transmitter, we see that the performance of the directional finding node is worse than the omnidirectional case. This leads us to observe the performance with respect to beamwidth. We can see in Fig 3-10 that the performance gets progressively worse with an increasing beamwidth. The major cause for this is the lower probability that at a given time node B is listening in the same sector as the one in which A transmits. Another important factor is the variability of energy availability. We shall see the ameliorating effect of a storage buffer through simulation results.

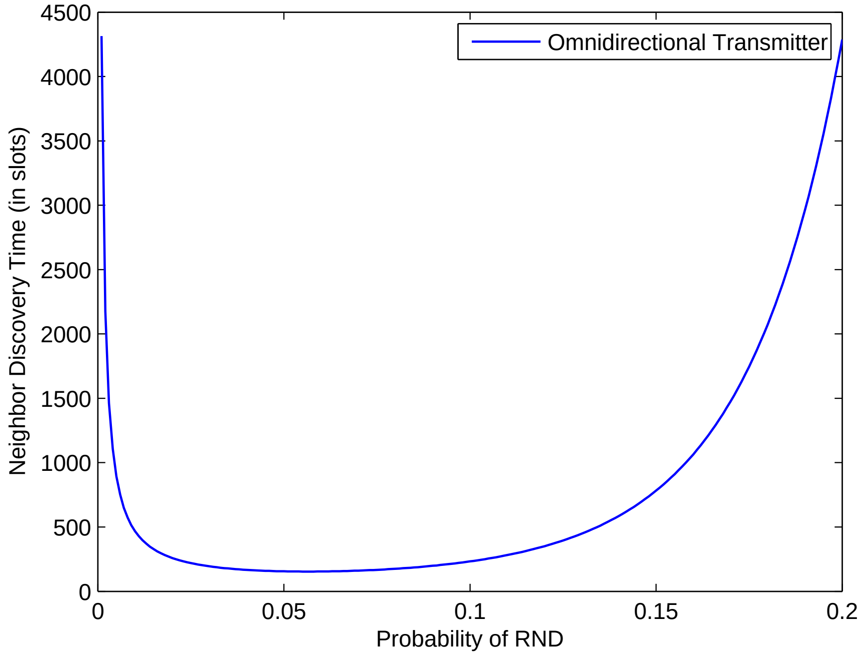


Figure 3-8: Effect of Response Probability on ND time for Omnidirectional Case

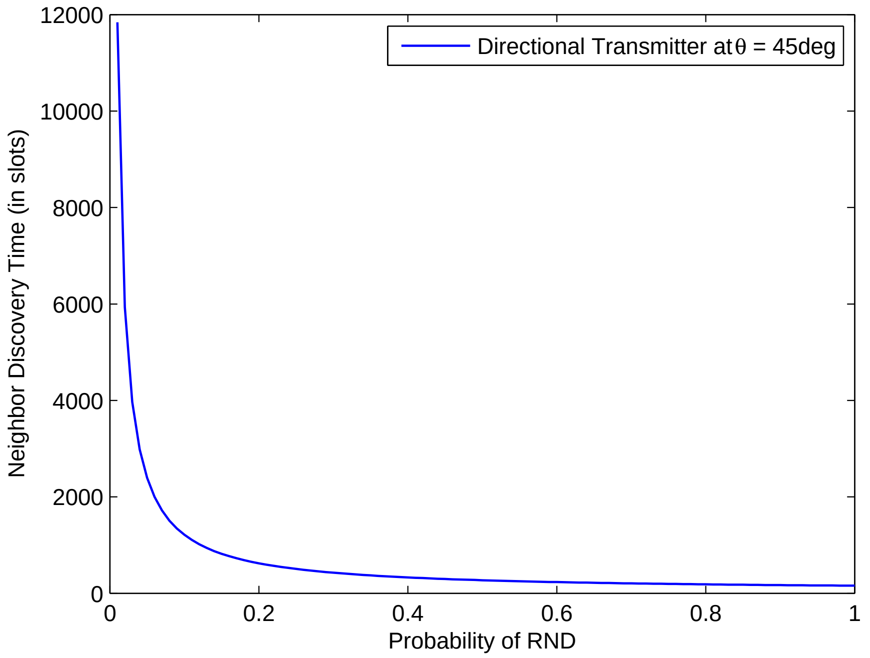


Figure 3-9: Effect of Response Probability on ND time for Directional Case

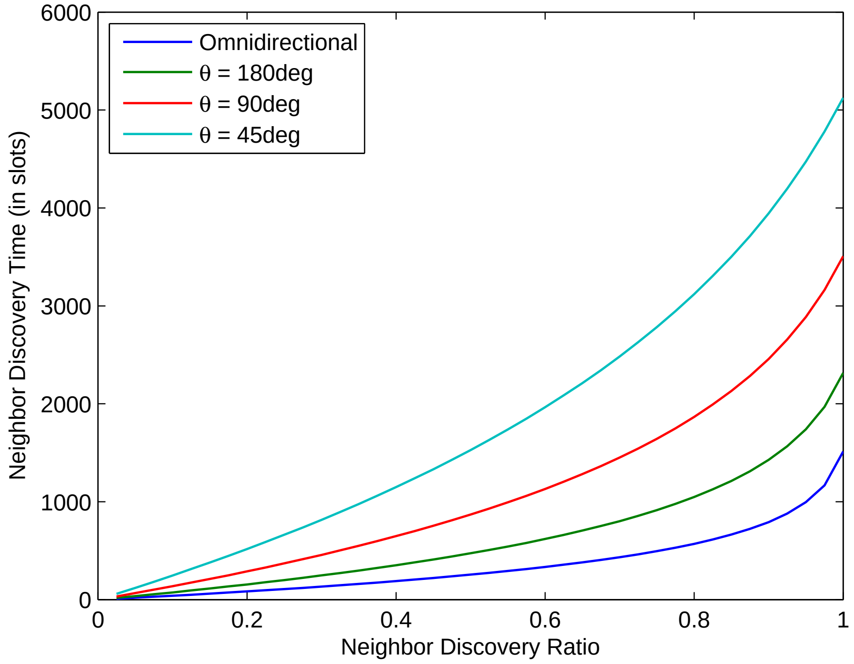


Figure 3-10: Two-Way ND for Various Beamwidths

3-4-4 Discussion

For practical implementation, collision avoidance tactics must be implemented. If, for example, a collision feedback mechanism is not put in place, the ND time would very well tend to infinity as nodes are not aware if a collision has occurred and would maintain their instant of wake up and sleep. Also, as we shall see later, collisions have a huge impact on the stored energy availability in nodes and even on the introduction of collision avoidance, a large effect is seen on the ND time.

We have seen that the response probability of neighbor nodes has a great impact on the ND time. Response probability of B is in turn heavily impacted by energy availability in a storage buffer. If this energy is wasted, for example on collisions, the effect on performance is high. Collisions and the associated heavy losses occur more often in an omnidirectional case than in a directional case due to the factor P_j (Eq 3-15).

As will be reiterated in the following chapter, the effect of node density and duty cycle on performance is large. The choice of these parameters must be taken into account during design and deployment in order to achieve best performance at least cost to the entire network. Since there is an obvious tradeoff between the node density and the duty cycle of neighbor nodes, it is important to choose one parameter given the other.

Finally, our numerical analysis suggests that though the directional transmitter sees lesser impact of response probability, it suffers heavily due to the decreased probability that nodes A and B are in the same sector at the same time. However, as we shall see later, apart from fewer collisions there are advantages of a smaller beamwidth even in terms of energy usage and savings.

Chapter 4

Parametric Study of the Neighbor Discovery Process in EH-WSNs

In order to understand the effect of various relevant parameters on the process of neighbor discovery in EH-WSNs, we perform a parametric study that is described in detail in this chapter. From lessons learnt through this study, we propose design-time and run-time recommendations for both omnidirectional and directional discovery. Furthermore, we describe the requirements, challenges and opportunities for a dedicated neighbor discovery protocol for this type of network. First, we address the effects of different beamwidths, node densities, duty cycles and of different energy interarrival times on the two-way omnidirectional and directional cases. Then we study the performance of the one-way neighbor discovery case at various energy regimes and discuss how it compares with two-way discovery.

4-1 Two-Way Neighbor Discovery

Our study starts with the effects of various parameters on the ND time, ND collisions and ND energy with respect to ND ratio as appropriate on the two-way neighbor discovery scheme. To recapitulate, we propose that such a scheme is used to perform neighbor discovery in the initial deployment phase of the network. As the name suggests, a node attempts discovery and through a three-way handshake both the finding node and its neighbor can add each other to their neighbor table. We introduce the use of an energy storage element which was not considered in arriving at numerical results in Chapter 3. With the introduction of the storage element (a supercapacitor), every deployed node checks if there is sufficient energy for it to perform an entire set of operations before starting them. For example, the two-way directional finding node would check for energy availability to transmit to all sectors, listen for responses and then transmit acknowledgments back before initiating ND in the very first sector. If this energy were not available, no ND process would occur at that instant of time and it would be postponed to the next scheduled instant.

4-1-1 Effect of Beamwidth

In order to understand if and how the beamwidth of the finding node antenna affects the neighbor discovery process, we conduct this study.

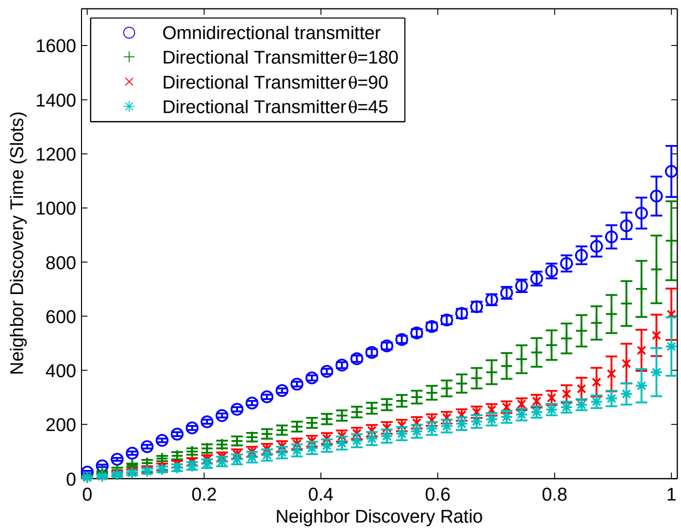


Figure 4-1: Effect of Beamwidth on ND time

The study of the effect of beamwidth was conducted in the case that $k = 40$ nodes and that all nodes, including the finding node, have excess energy availability i.e., IA is 0. Neighbor nodes operate at 20% duty cycle. The advantage of using a directional finding node is evident from Fig. 4-1 which shows the mean and standard deviation of the ND time required to find each neighbor node, taken from 1000 samples. The node with the lowest beamwidth at 45° provides the best performance in terms of ND time.

The energy required for finding all 40 nodes can be seen in fig.4-2. We assume that the finding node can transmit to the same link range for a smaller transmit power. Yet, the advantage that the finding node has in lower ND time for low beamwidth is offset by the higher energy consumption due to increased number of transmissions. Thus, at $\theta = 45°$ the quantity of energy spent by the finding node is highest and reduces with higher beamwidth.

As the beamwidth of the finding node decreases the number of collisions that occur among responding nodes goes down. Thus, the required neighbor discovery time can be seen to reduce. As the percentage of nodes discovered goes up, the deviation of the various samples from the mean value increases. Such an increase is the result of the randomization of the back-off time that is performed for the purpose of conflict resolution. In Fig. 4-3 we see the cumulative number of collisions that occurred before

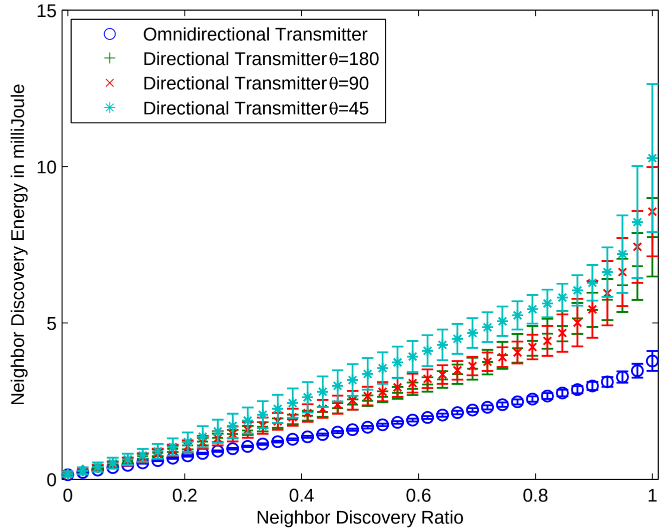


Figure 4-2: Effect of Beamwidth on ND energy

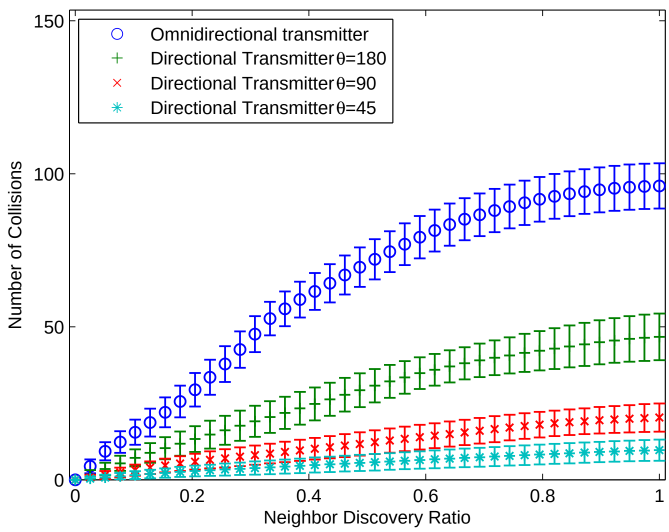


Figure 4-3: Effect of Beamwidth on ND collisions

discovery of each of the 40 nodes. For the omnidirectional finding node, a sharp rise can be seen in the number of collisions till about 40% of the nodes are found. Beyond this point, the number of collisions saturates visibly. The reason for this is that as each node is found, the probability of a collision keep reducing as the found node no longer responds to subsequent ND packets.

We can now conclude that the directional transmitter performs better in terms of ND time due to two reasons, both relating to interference: (i) Fewer collisions allow nodes to be found faster (ii) Nodes suffer lower loss of energy due to collisions, and thus do not deplete their storage buffer. Thus, they are likely to be able to respond more often.

4-1-2 Effect of Node Density

In investigating the effect of the number of neighbor nodes on the neighbor discovery time, from Fig. 4-4 it can be observed that it takes the same time for the finding node to discover a single neighbor node (i.e., $k = 1$) in both omnidirectional and directional cases. Here $\theta = 45°$, but the number of sectors scanned does not have an impact on the neighbor discovery time, since the rate at which all sectors are scanned is equal to the rate at which the omnidirectional transmitter transmits.

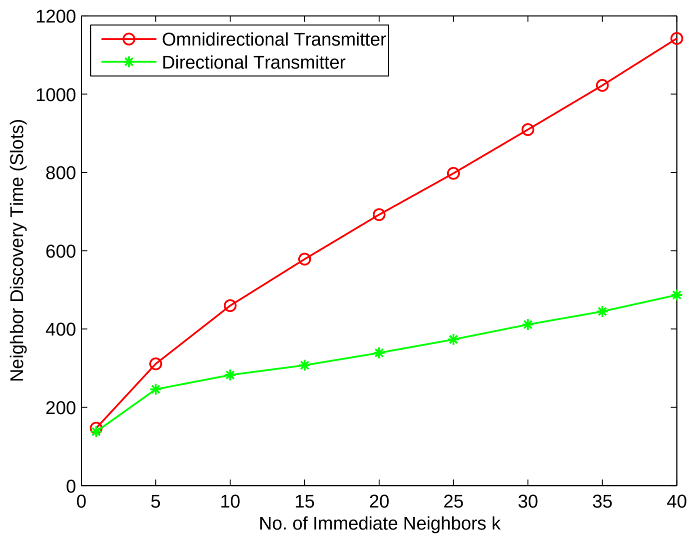


Figure 4-4: Effect of Node Density on ND time

However, as the number of nodes to be discovered (k) increases, the number of collisions between responses to the OND or DND messages increases (Fig. 4-5). The effect of these collisions is lower in the case of directional discovery since fewer nodes listen and respond to the DND messages and hence there are fewer RND messages. As before, the study was conducted for the case when excess energy is available (energy interarrival time = 0), neighbor nodes operate at 20% duty cycle and shown result is the mean of 1000 samples.

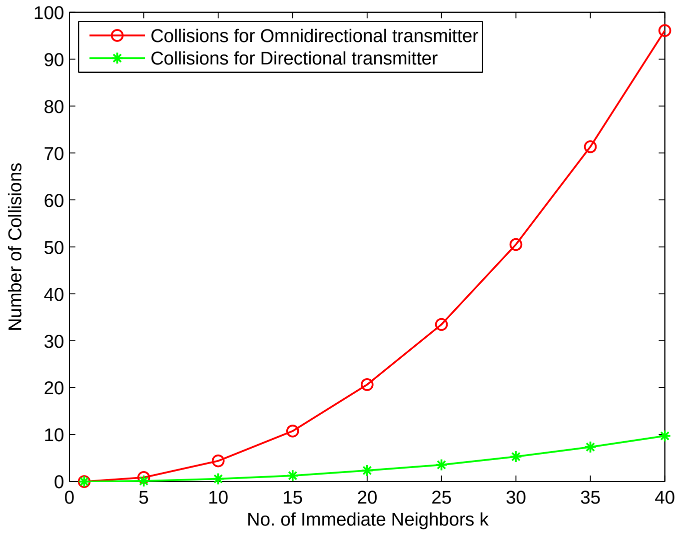


Figure 4-5: Effect of Node Density on ND collisions

4-1-3 Effect of Node Duty Cycle

As discussed previously, neighbor nodes operate at a fixed duty cycle (DC). For ease of study, we assume that all nodes choose to operate at the same duty cycle. This works since we assume that none of the neighbor nodes interact among each other. In order to understand what duty cycle suits our setting best, we plotted the neighbor discovery time for various node densities at different duty cycle settings. The time for which the node is awake is set and only the T_{off} changes.

The duty cycle at which neighbor nodes operate, has a bearing on the time taken for neighbor discovery as seen in Fig. 4-6. The study was conducted at the excess energy condition and shown results are the mean of 1000 samples. We consider cases in which nodes duty cycle at 20%, 10% and 5% and we see that it takes longest to discover nodes at 5%.

However for the 5% duty cycle, the number of collisions that are observed is the least. This lower collision count is simply because the neighbor nodes listen to and therefore respond to fewer OND or DND packets.

We do not study the effect of changing the rate at which the finding node sends ND packets as the effect of this would be simply an elongation of the time taken to discover nodes and does not provide any new findings.

4-1-4 Effect of Energy Interarrival Times

As we described previously, energy arrives at each of the nodes including the finding node as a Poisson arrival process with an interarrival time of 15, 10 and 5 time slots.

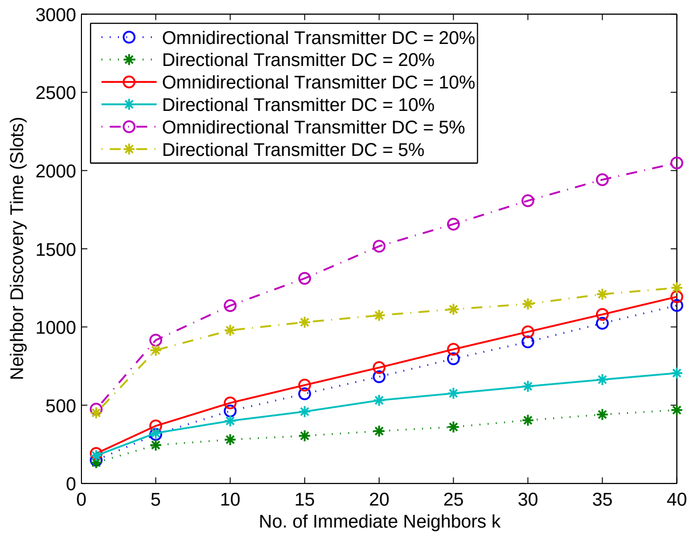


Figure 4-6: Effect of Node Duty Cycle on ND time

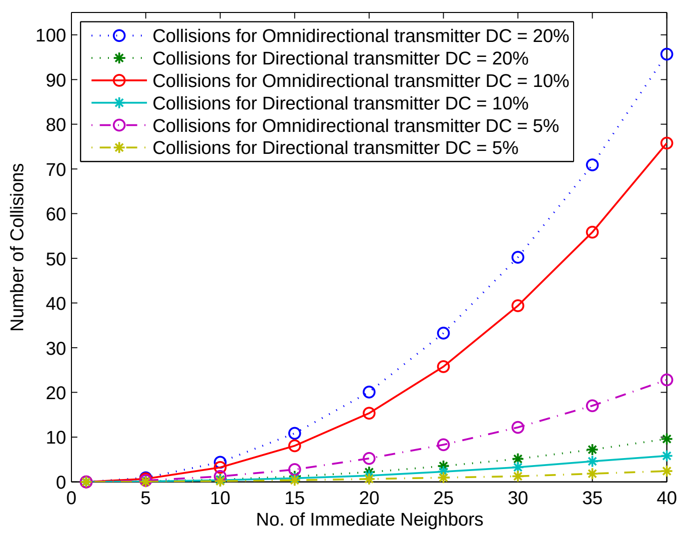


Figure 4-7: Effect of Node Duty Cycle on ND collisions

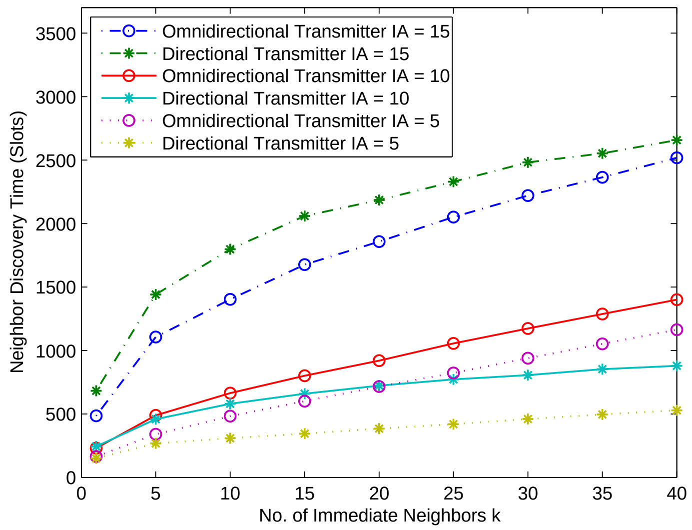


Figure 4-8: Effect of Energy Interarrival Times on ND time

The effect of energy interarrival times on the neighbor discovery time can be seen in Fig. 4-8. The time or number of slots required in each case to find neighbor nodes is recorded for both an omnidirectional and a directional finding node ($\theta = 45°$) in figure 4-8. As intuition suggests, the performance of the finding node in terms of neighbor discovery times is worse at low energy arrival rates. But it is interesting to see the behavior of the directional node versus the omnidirectional one.

When IA = 15, the omnidirectional finding node outperforms the directional node. This is caused by the excess energy that the directional node must spend in comparison with the omnidirectional node as seen in Fig 4-9 and the lower availability that the IA = 15 case offers. Since the nodes in the vicinity of the finding node in the IA = 15 case suffer from lack of energy, they respond less frequently to the ND packets of the finding node. As a result, the finding node bears the brunt and has to spend a longer time and energy attempting discovery. Furthermore, as the directional node defers the ND process to a time when it has sufficient energy to carry out discovery in all sectors, there is a further increase in its ND time.

However, the directional node still finds 90% of its neighbors faster in the $k = 40$ case (fig 4-10). Also, as the interarrival time between arrivals of energy decreases, the directional transmitter performs better. It can be seen that the directional transmitter at IA = 10 performs even better than the omnidirectional transmitter that sees more frequent energy arrival at IA = 5.

Again, this better performance of the directional transmitter can be explained by the higher number of collisions in the omnidirectional case. It can be seen from figure 4-11 that as the IA increases, the number of collisions reduce. This can be explained by the fact that nodes respond less often to the finding node's ND packets due to lower frequency of energy arrival.

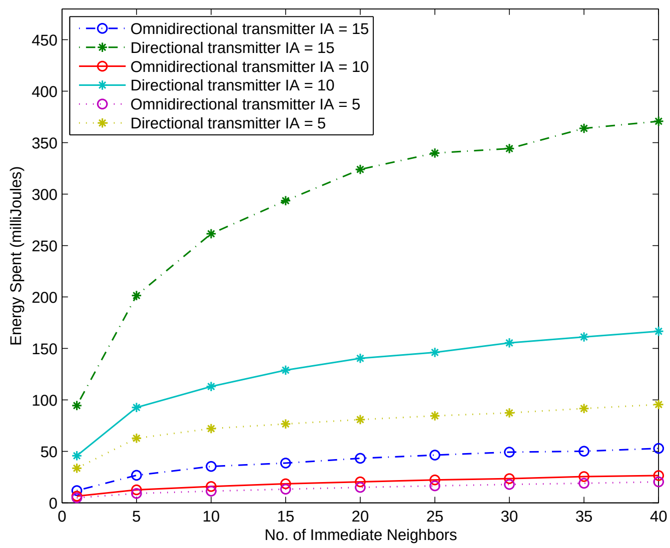


Figure 4-9: Effect of Energy Interarrival Times on ND energy

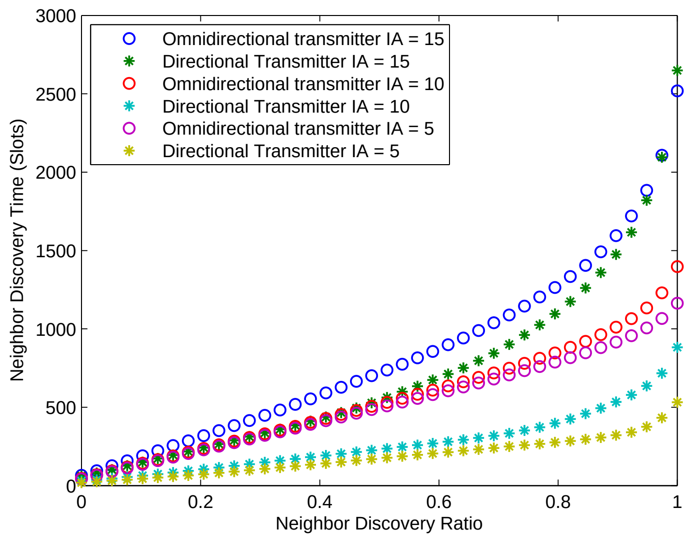


Figure 4-10: Effect of Energy Interarrival Times for $k = 40$ on ND time

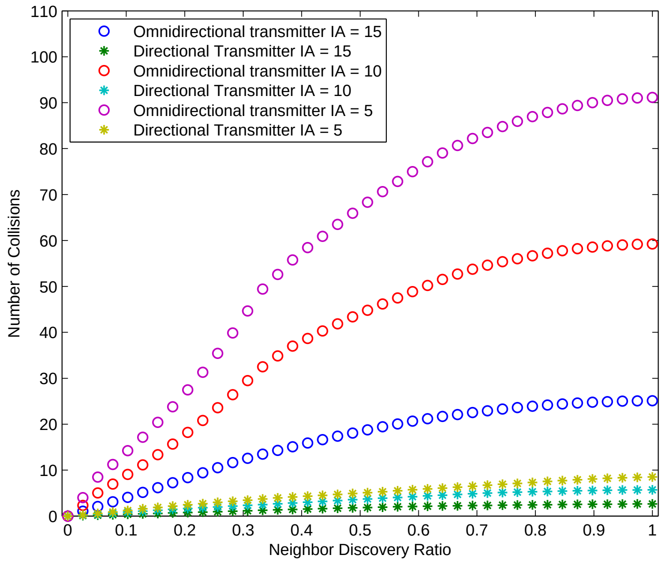


Figure 4-11: Effect of Energy Interarrival Times for $k = 40$ on ND collisions

4-1-5 Effect of Storage Capacity

As discussed earlier, we consider that the harvested energy is stored in a supercapacitor. In the discussions above, we consider a supercapacitor whose Capacitance (C) is approximately $0.7F$ such that the maximum amount of energy it can store is $E = 1/2 * C * V^2 = 3mJ$. To understand if the C of the supercapacitor has an effect on the ND time, we studied the performance for various values of C. The study was conducted entirely for the IA $= 15$ case to understand how the system behaves in the most adverse condition. For all cases that we study here, we vary C for all nodes in the network. As before, neighbor nodes operate at 20% duty cycle and the results are an average of 1000 simulation run outputs.

As can be seen from Fig. 4-12, as C increases, the ND time reduces as should be expected. Since the storage buffer can store larger amounts of energy, the effects of constantly changing input energy conditions is reduced as the supercapacitor now has a smoothing effect on these variations. Another interesting consequence of an increased C is that the difference in the ND time between the directional and omnidirectional finding node reduces. For the case where C $= 0.9F$, the directional finding node matches the performance of the omnidirectional one for low values of k and even betters it for $k = 35$.

This improvement in performance is not seen beyond a threshold C. We see in Fig. 4-13 that there is no improvement in ND time from $2.1F$ to $3.1F$ and very little improvement from 1.1 to $2.1F$. It can be seen that the value of k at which the directional transmitter performs better than the omnidirectional one reduces from $0.9F$ at $k = 35$(seen in Fig. 4-12) to 1.1F at $k = 25$ and 2.2F at $k = 20$. Such a reduction is a result of the increased collision count for the omnidirectional transmitter as seen in Fig. 4-14 at higher values

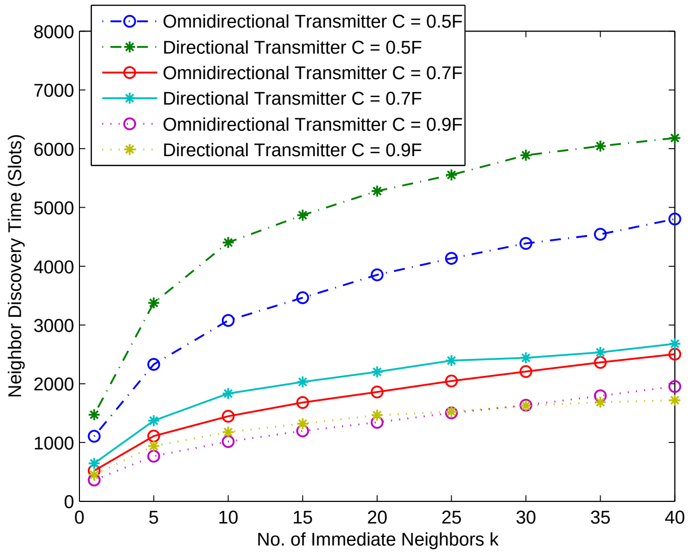


Figure 4-12: Effect of Supercapacitor Capacity on ND time

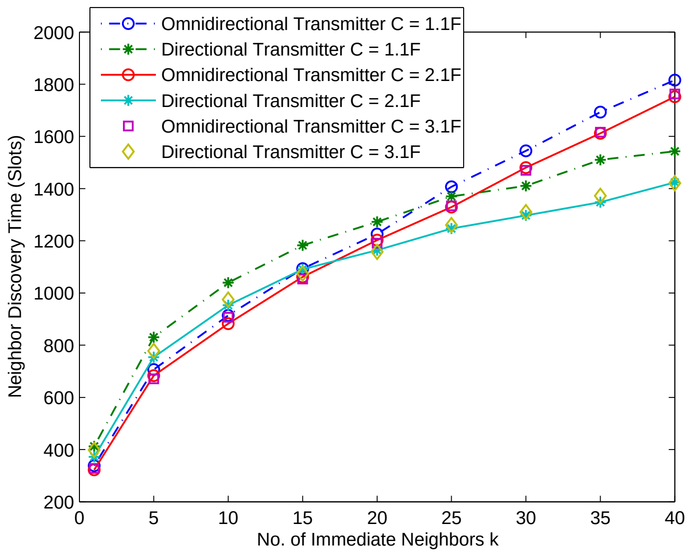


Figure 4-13: ND Time does not improve after a threshold C

of k.

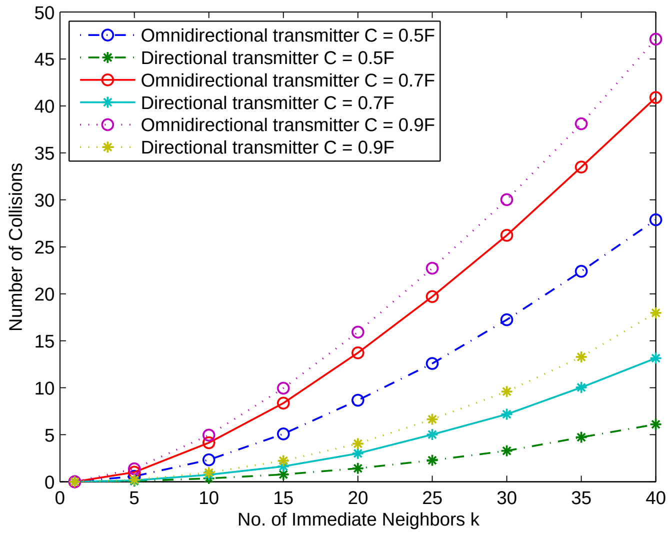


Figure 4-14: Number of Collisions for Different Values of C

We see in Fig 4-14 that the number of collisions keeps increasing as the C goes up. This can be explained by the fact that every node in the setup has a better chance of responding to ND packets when the amount of stored energy goes up. This is also supported by the ND energy seen in Fig 4-15. Larger C allows for better use of available energy.

At this point, it is important to discuss the effect of the use of the storage element. We have seen previously, the behavior of the system when there is no storage element present (through numerical results presented in Chapter 3). We saw that in the absence of a storage element, the directional transmitter performed poorly and was unable to better omnidirectional performance despite the advantage of suffering lower interference. Here, we see that for the cases where C takes values $0.5F$ and $0.7F$, the directional transmitter performs worse than the omnidirectional case, but it recovers when the value of C increases.

4-1-6 Recommendations

As we have seen, there are various parameters that have a pronounced effect on the neighbor discovery time in the two-way scheme. From these results, we can provide several recommendations on parameter settings. Here we explore some possibilities and solutions.

We have seen that every parameter setting and scheme has advantages and disadvantages to it. While a directional finding node is capable of better performance due to lesser interference, at very low energy availability, the directional antenna loses its advantage due to the larger number of ND packets and hence higher energy consumption.

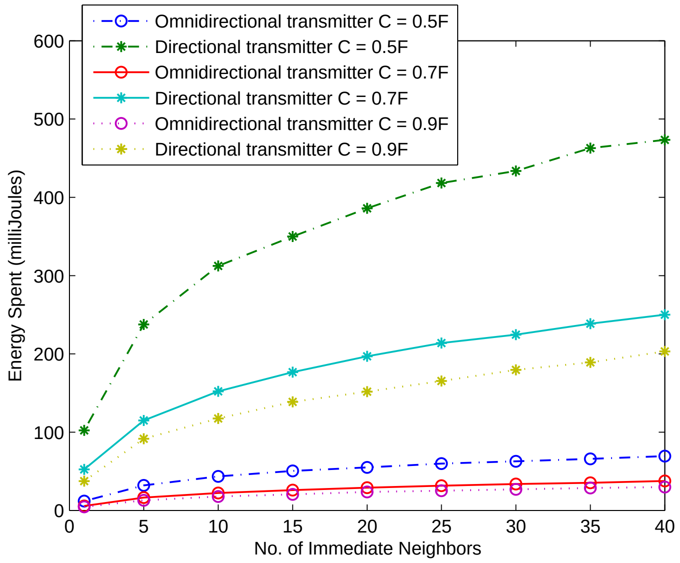


Figure 4-15: Energy Cost at Different Values of C

We initially assumed that the finding node was in some way more endowed than its neighbor nodes which is why it pro-actively took on the role of finding its neighbors. In the directional discovery case, the onus of the excess energy consumption is only on the finding node. Obviously, neighbor nodes waste lesser energy on collisions in this case. Thus the energy spent across the network is reduced and this makes such an option more profitable to a network deployed in a setting where energy availability is a major concern. Though this is at the cost of low performance, over the long run, it can be argued that this network will be able to maintain connectivity for a longer duration due to fewer number of nodes dying out due to high energy consumption in the neighbor discovery process itself. In order to increase the advantages of the directional finding node, a better scheme could be devised by choosing a wider θ such that the benefits of both lesser interference and lower number of DND packets can be enjoyed.

In adverse conditions, if even the supposedly well-endowed finding node has very low energy availability, we must distribute the burden among the other nodes. From the results we can understand that there is a threshold energy interarrival time below which it is advisable to perform directional neighbor discovery. Here our results indicate that this interarrival time is 10 time slots. But, this threshold is dependent on the transceiver chip used as the difference between energy consumed for different transmit powers varies widely among the various commercial offerings today. If there is a chip that provides lower energy requirement (than we consider here) for its lowest transmit power option, this threshold would not apply and probably would not be required any more.

Node densities are chosen in networks to provide redundancy in case of failure of nodes. However, as we have seen increased node density has an adverse effect on the performance of the ND process. Thus, there exists a trade-off between performance and redundancy that must be resolved at design time.

As mentioned earlier, energy harvesting networks copy with varying energy income by adapting duty cycles. Also the periodicity of sleep and wake up is disturbed when activities are deferred due to lack of energy. Again, while the burden falls on the finding node, the rest of the network benefits from less wastage of energy as lesser collisions are seen for low duty cycles. During the ND process, the duty cycle of neighbor nodes can be stipulated at a fixed value depending on the performance requirements of the application versus the demand of energy at the finding node to take on this burden.

Next on the subject of storage element size, we can conclude from that the effects of energy variability or infrequency would affect the directional transmitter more than the omnidirectional transmitter. This problem however, is very easily solved by the choice of an appropriate size of storage element given information on the rate of energy arrival and node density.

Finally, in this two-way discovery scheme, given a value of node density, energy interarrival time and neighbor node duty cycle, the finding node must choose the best beamwidth and storage element size to achieve the best possible performance in terms of ND time, ND energy in tradeoff with network parameters such as connectivity and node redundancy.

4-2 One-way Neighbor Discovery

Once initial neighbor discovery is complete, we assume that every node is aware of all of its immediate neighbors. Howe The finding node behaves like a simple receiver in this study. Since we propose that this scheme be used for continuous neighbor discovery, we must ensure that this method has the least possible overhead. However, as mentioned earlier the beaconing that we expect neighbor nodes to perform is multi-purpose and the overhead is not strictly for the neighbor discovery process alone. Hence we focus only on the energy spent at the finding node.

As can be seen from the fig. 4-16 the directional finding node (θ=45°) takes a longer time to discover all of its neighbors than the omnidirectional node. At longer energy interarrival times, the directional finding node performs worse as all nodes defer listening for an ND packet to a time when energy is available.

The energy consumption at the finding node is seen in fig. 4-17. At IA of 5 and 10, the energy consumption for discovery at the directional finding node is the same, whereas the required number of time slots for discovery are more for the IA = 10 condition.

For the omnidirectional finding node, the energy consumption is almost the same for all energy conditions. In terms of energy requirement, the omnidirectional case provides the best performance with little or no variation with energy condition, but its performance in terms of required number of slots does vary. Thus, we may conclude that this is due to the deferment of beaconing at the neighbor nodes due to lack of energy.

Similarly, the energy requirement at the directional node (θ=45°) is the same for energy interarrival times of 5 and 10, but a little higher for IA = 15 time slots. Oddly, when the node faces infrequent energy arrival, it must spend more energy. The reason for

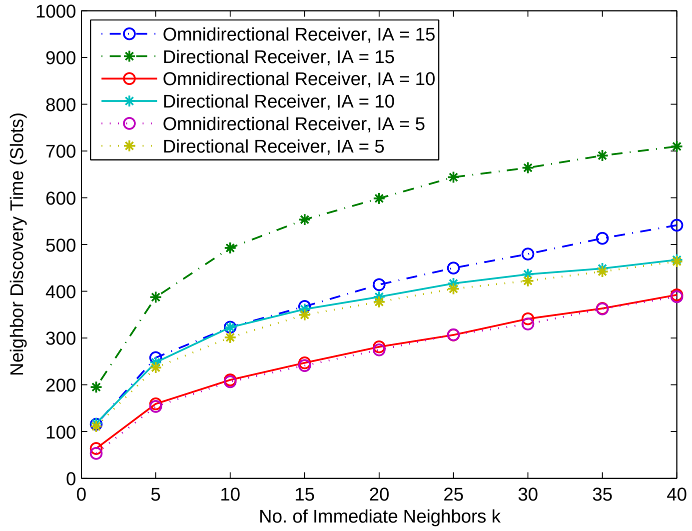


Figure 4-16: ND time for One-Way Discovery

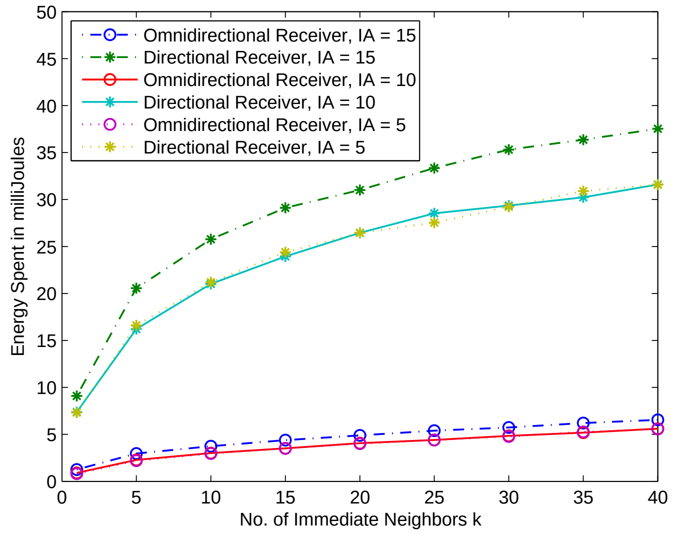


Figure 4-17: ND Energy for One-Way Discovery

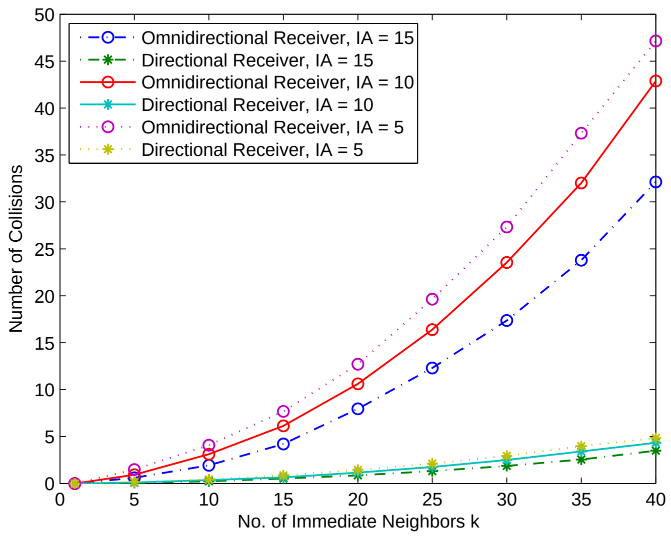


Figure 4-18: ND Collisions for One-Way Discovery

such a behavior can be explained by the rarity of energy in all nodes. This further motivates the importance of better design and choice of storage element size.

The energy requirement in all IA cases is much larger than that for omnidirectional case. This is inevitable because the directional finding node spends more energy to listen as it scans sector 1 through $\frac{2\pi}{\theta}$. Also, the probability of listening in a sector when a neighbor node transmits a beacon in that same sector is heavily reduced as the nodes no longer respond to a query, which explains the increased number of slots required for discovering all neighbor nodes in the directional case.

The advantage of the directional finding node, in the two-way case, of lower interference is lost here as nodes do not respond to a query and thus there is a lower probability of collision caused by greater variation in the instant at which beacons are transmitted. Thus, the number of collisions as seen in fig. 4-18 is much lower than that observed for the two-way neighbor discovery, even in the omnidirectional case.

In conclusion, the one-way neighbor discovery scheme can be implemented for neighbor discovery with the finding node acting as an omnidirectional receiver. At lower beamwidths, the system performance goes down and cannot be improved. The advantage of the one-way method is that the node attempting to discover its neighbors has a low energy overhead and requires lesser neighbor discovery time than the two-way scheme. However, the scheme is not ideal for initial discovery as bi-directional discovery does not occur here. It can be used for continuous neighbor discovery such that the energy overhead across the network is minimized.

Chapter 5

Energy Prediction Algorithms

5-1 Introduction

In nature, energy availability is random and highly variable. For instance, the energy from the sun depends on the time of day and the time of year at a given geographical location. Further, the topography of the deployment area defines the amount of sunlight that is available for harvesting. In a field with several deployed harvesting nodes, the energy harvested at each node is different depending on this topography and the arrangement.

In energy harvesting nodes, energy arrival can be measured when it arrives and is stored in the energy storage element. However, let us consider the following: (a) nodes have to spend energy in order to measure arriving or stored energy - performing measurements at regular intervals is thus expensive in the long run, (b) nodes must schedule their activities based on energy availability, (c) when the size of the storage element is small, it is possible that energy arrives too frequently and cannot be stored - here, the node would have to take measures to ensure that energy is not wasted. It is evident from these points that the node would benefit from a simple and accurate prediction algorithm for the purposes of rate and duty cycle adaptation.

The importance of a lightweight prediction algorithm is clear when we consider the energy requirements of running such an algorithm. While periods of plenty do occur in an energy harvesting node, it must use as little energy as possible for an essential operation such as energy prediction. In this chapter, we discuss the various features of existing energy prediction algorithms and introduce mechanisms that would enable a simple, lightweight and accurate energy prediction algorithm.

5-2 State of the Art

Several energy prediction algorithms have been proposed for application in harvesting devices. Here we summarize some of the most prominent prediction algorithms.

Time series algorithms are frequently used as prediction algorithms in various applications. The mode of operation of this family of algorithms is to extrapolate based on previously measured data. A time series prediction technique that is popular for its simplicity and ease of implementation is the Exponentially Weighted Moving Average (EWMA) [37]. In EWMA, measured samples of the quantity to be predicted are weighted according to the freshness of the data such that the most recent is weighted more than the earlier values. Thus the accuracy of the prediction algorithm depends upon the choice of the weighting factor depending on the application. EWMA with the choice of right weighting factor α is found to be fairly accurate for solar energy prediction by Kansal and others [17]. The authors present a methodology to perform energy prediction that involves a database of previous days' energy availability. While EWMA has advantages when used for energy prediction in small energy harvesting devices, it is limited as it requires prior knowledge and does allow the introduction of context. For example, EWMA does not provide room for improvements that information on seasonality and diurnal behavior for solar harvesting can provide, rather it bases its behavior entirely on past measurements. Thus, for energy harvesting sources that face sudden and instant variations may not benefit from this method.

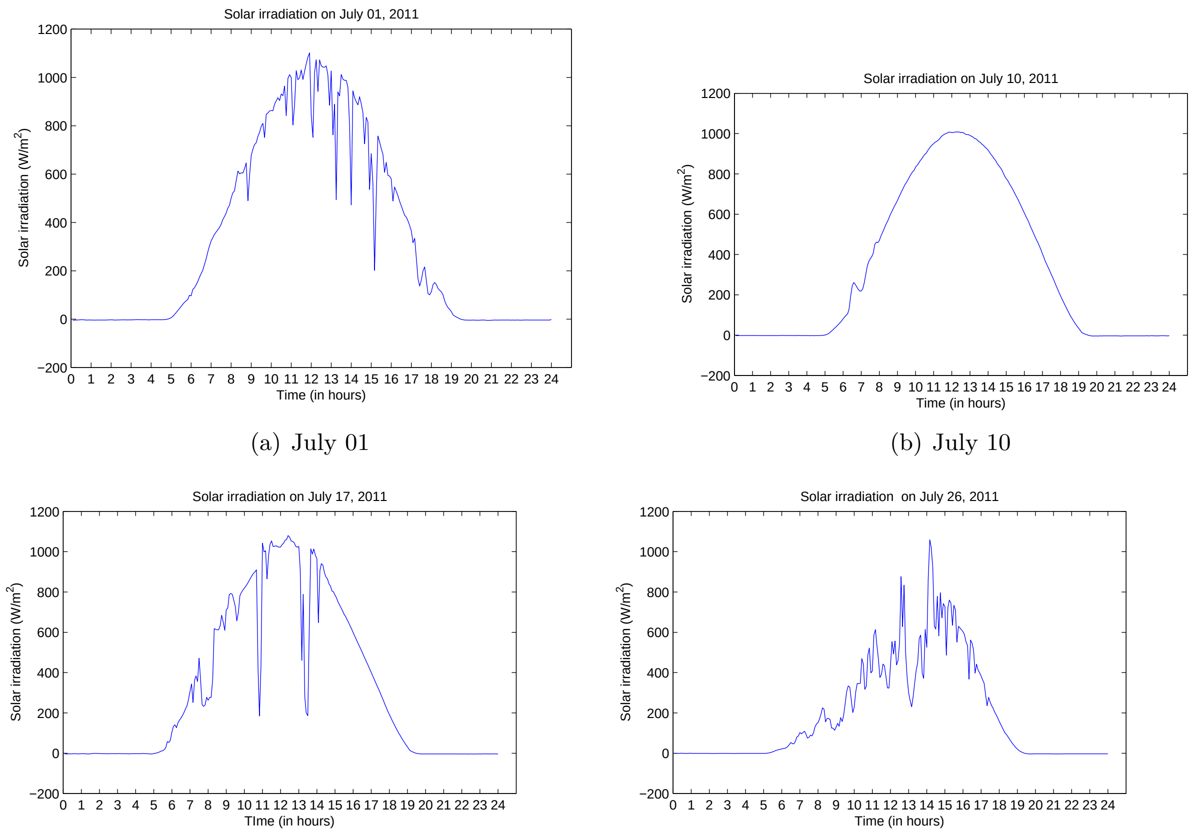
An improvement over EWMA is proposed by Piorno et al. describe a prediction algorithm for solar energy harvesting that shows a large improvement over the EWMA [38]. This algorithm, based on the EWMA, provides information on the weather and is called Weather-Conditioned Moving Average (WCMA). Here, a factor known as the "GAP" is calculated that depends on the differences between the present and previous day's solar conditions. Extending this concept, Weather-Conditioned Selective Moving Average (WCSMA) performs weighted moving average after classifying a day into a category as a sunny or cloudy day. For example, if a day is classified as sunny, the algorithm uses the data recorded for the previous sunny days to predict. The authors claim that this approach allow to account for changing lengths of day and intensity with the time of year. Again, prediction errors are seen to reduce in comparison with the EWMA [39].

Bergonzini and others describe a compound time series predictor labeled the "ETHZ predictor" [40] which splits prior knowledge into a long term average and a short term average – each of which are EWMA series with weighing factors α and β respectively. These average values are again combined to predict energy using an EWMA predictor with weight γ.

Heading away from the time series family, Bergonzini et al. also describe an error back propagation nets based prediction algorithm called the neural predictor, that uses a set of training data to define the weights of a neural network. Once the neural network has been defined for a given set of training data, it is now possible to use this network to predict given recent measurement values. However, the training process for the neural network would require continual computational effort at the node. If the training process were to be performed at design time, changes in weather at a date after deployment would no longer be possible. However, both ETHZ and neural predictors do not better the average error of WCMA.

5-3 Markov Chain Prediction Method

Natural energy sources such as the sun follow a seasonal and diurnal pattern that can be predicted according to the trend that they follow. However, weather has an impact on how much of this solar power is incident on the Earth. Thus, what would be relatively simple to forecast (just accounting for time of sunrise and sunset) is now a complex task. For instance, Fig. 5-2(b) shows irradiation on a clear day in July. However, in the same month of July, we see different patterns on different days (see Fig. 5-1). Also, over different years, the same days are bound to have different patterns (see Fig. 5-2). Given such data, we need to predict with sufficient accuracy for efficient operation of the WSN.

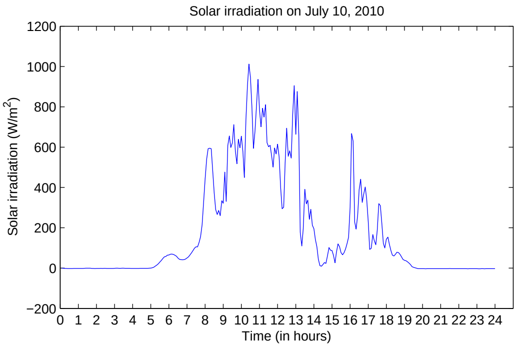


(a) July 01 (b) July 10

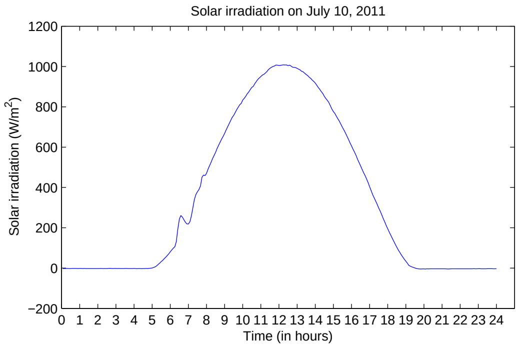
(c) July 17 (d) July 26

Figure 5-1: Solar irradiation on different days of July 2011

We have solar insolation values recorded over the period of several years at the CONFRRM project [41]. For all our calculations we take the measured values from Elizabeth City State University in New York. The parameter of interest in available data is the



(a) 2010



(b) 2011

Figure 5-2: Solar irradiation on July 10 2010 and 2011

Global Horizontal Irradiance (GHI) which is a sum of direct light and light diffused by the atmosphere, given in W/m^2. The available data provides five-minute averages for every day of the year.

From these averaged GHI values, we can observe the changes in length of day with season, the effects of weather - cloudy skies, rain and snow. In order to account for changes in length of day, we split a 12-month period into 18-day categories each with roughly 21 days with exceptions for the days of February. We shall elaborate on this choice later.

For prediction with a Markov model, we use a simple three state Markov Chain (MC) model to predict the solar irradiation. The idea of using a three state MC is to reduce the complexity of prediction algorithm as well as space complexity on the nodes, since the nodes are both memory and power constrained. The MC model is shown in Fig. 5-3.

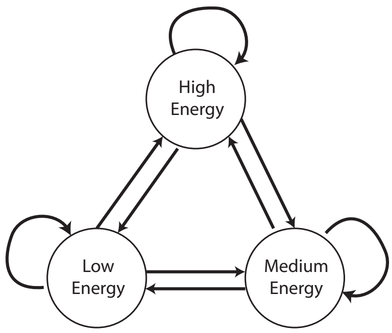


Figure 5-3: Markov Chain model for prediction

We can now train, or create transition matrices, for different months using the data from CONFRRM. We assume the base-station has all the historical data over different months and years. However, creating such a model for the whole day yields only random sequences since the time-factor of the day is lost in the MC model. Hence, we chose to divide the day into 3 and 5 parts. A division of the day into 3 parts is depicted in Fig. 5-4. With this model, the base station creates 3 (or 5) transition matrices per category. We assume no harvesting is done during nights (due to ambient light), and hence no prediction is done.

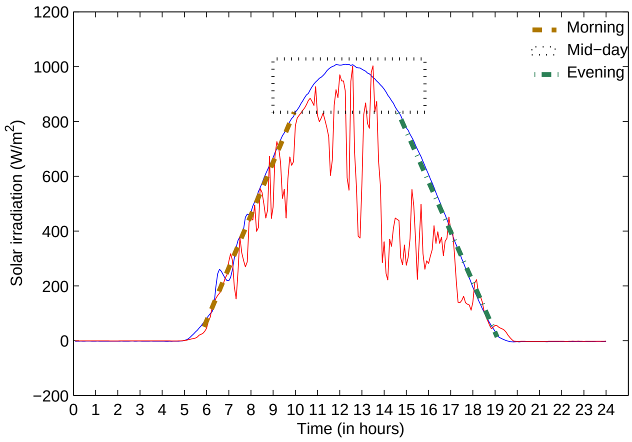


Figure 5-4: Day divided into 3 periods shown over two different days

Each morning the base-station sends a transition probability matrix to the WSN nodes. The nodes use this matrix to predict the energy over the next slot. At the same time, the energy haversted in the next slot is recorded and the transition matrix is updated. At the beginning of mid-day the updated matrices are uploaded to the base-station which updates it own matrices. Then the base-station sends in a new set of transition probability matrix for the next period of the day.

The prediction in the nodes is done by calculating the expected hitting times of the states from the current state. It is done as follows: Let τ_i be the expected time to hit state j starting in state i. Hitting time for i is 0, and for other states:

$$\begin{aligned} \tau_j &= E(time\ to\ hit\ j|start\ in\ i) \\ &= 1 + \textstyle\sum_{k \in S} p_{ik}\tau_k \end{aligned}$$

where p_{ik} is the transition probability from state i to k, and S is the set of states. Obviously, the state j with minimum τ_j is the next possible state. A threshold is used to distinguish whether the transition was to the same state or to a different one.

We show the mean prediction error obtained with this method for a day divided into 3 parts in Fig 5-5. This method gives best prediction for category 3 with mean number of prediction errors equal to 8.4. The worst is category 8 with mean prediction errors equal to 52.0952.

In Fig. 5-6, we see the worst case of prediction with total number of errors amounting upto 86. This is because of rapid changes in the irradiation during mid-day and evening periods.

When we divide the day into 5 parts, as expected, it works better than 3 divisions per day. As seen in Fig. 5-7, the average prediction error decreases. This is due to the

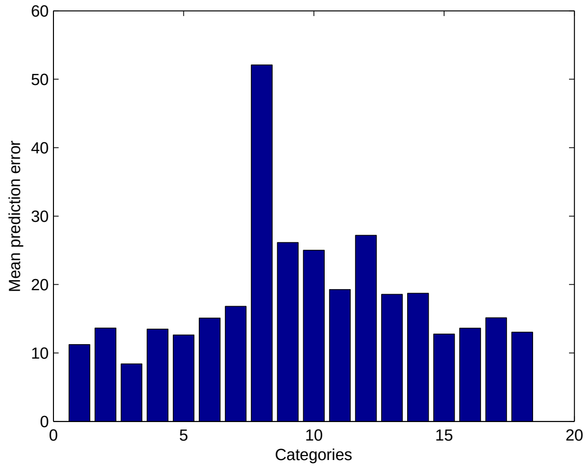


Figure 5-5: Mean prediction error for day divided into 3 parts for different categories

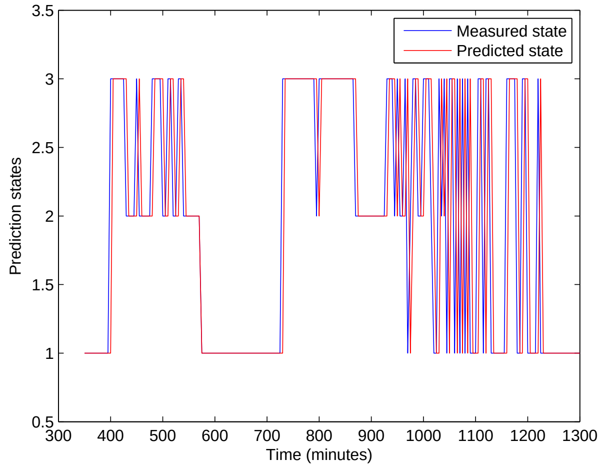


Figure 5-6: Worst day for prediction. Number of errors = 86

increased learning of small sections of the day. The worst category with highest average error is again 8 with average error equal to 24.8571. The worst day of prediction for 5 divisions is now day 21 of category 8 (see Fig. 5-8), whereas it was day 12 of category 8 for 3 divisions per day.

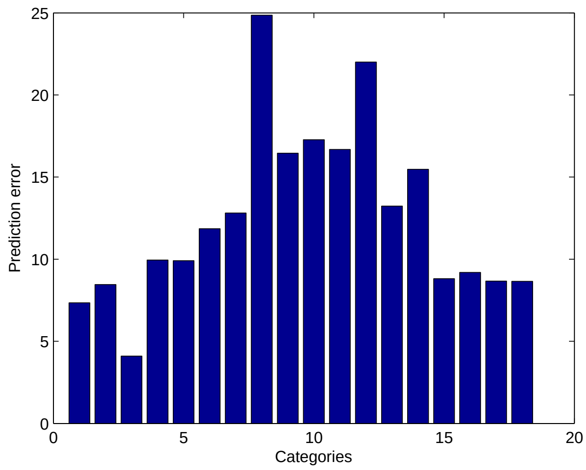


Figure 5-7: Mean prediction error for day divided into 5 parts for different categories

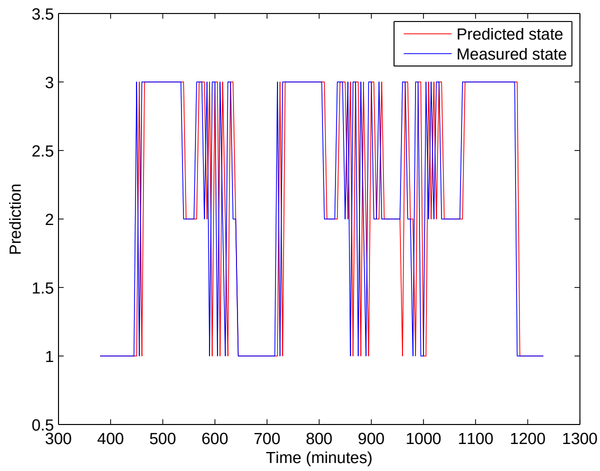


Figure 5-8: Worst day for prediction. Number of errors = 45

5-4 Curve Fitting Prediction Method

While MC method provides a simple method to predict the irradiation with some accuracy, the overheads are more. For instance, with 3 parts per day the base station needs to broadcast the transition matrices thrice a day in the network. To obtain higher accuracy, the divisions per day needs to be increased and hence the overhead in transmissions. Moreover, this method only predicts the state the node may be in. While in some cases, it may just be useful to know what state you are in, most other cases it is better to know the value of the power that will be harvested.

The new prediction algorithm needs to be simple (low complexity algorithm), low overheads, and should give us better accuracy than the MC method. Our contention is that there must be room for introducing context into a simple prediction algorithm, which is possible using a simple curve fitting exercise.

The methodology for the curve fitting prediction method is as follows. From the averaged GHI values obtained from CONFRRM, we can observe the changes in length of day with season, the effects of weather - cloudy skies, rain and snow. In order to account for changes in length of day, we split a 12-month period into 18-day categories each with roughly 21 days with exceptions for the days of February. After dividing data in this manner, we plot each data point for the whole category and fit a polynomial curve with least Root Mean Square Error (RMSE). The RMSE is used in order to measure how close a predictive model comes to the actual quantity. An example for the curve (in red) with the least possible RMSE or one which is closest to measured values, is seen in Fig 5-9, where each of the blue dots represent the five-minute average of GHI for that time of day. We plot only the duration of day which has a strictly positive value for GHI - that is daytime.

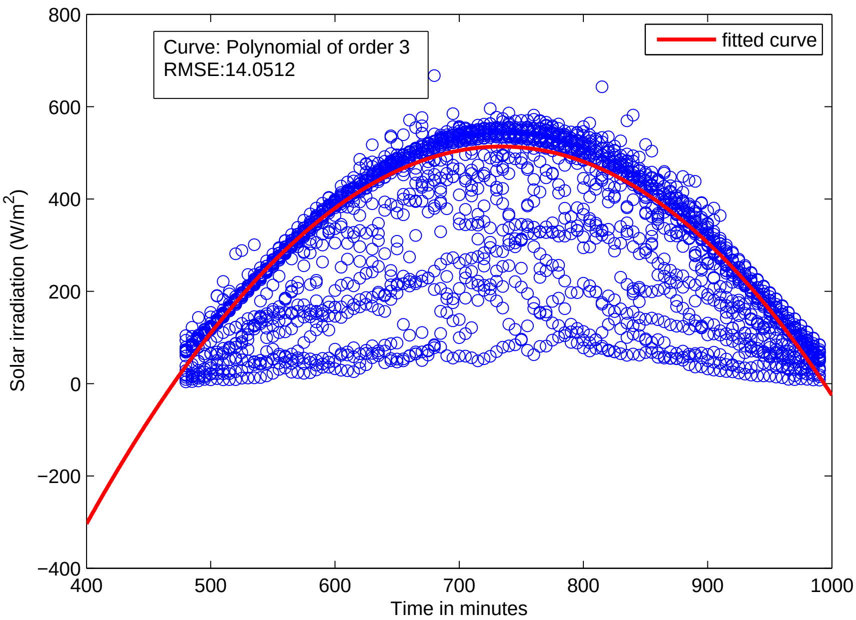


Figure 5-9: Best Curve Fitting Results for M1 - Best RMSE

In order to understand the choice to split days of the month of February, we must look at weather in New York for the year in question – 2010. Frequently, during the month of February, the North American region suffers from lack of sunlight due to blizzards and this was the case in New York in 2010. Seen in Fig 5-11 is the average RMSE values when the year is divided into 17 categories. Thus, the best fitting curve for this month shows a very large RMSE in Fig 5-10.

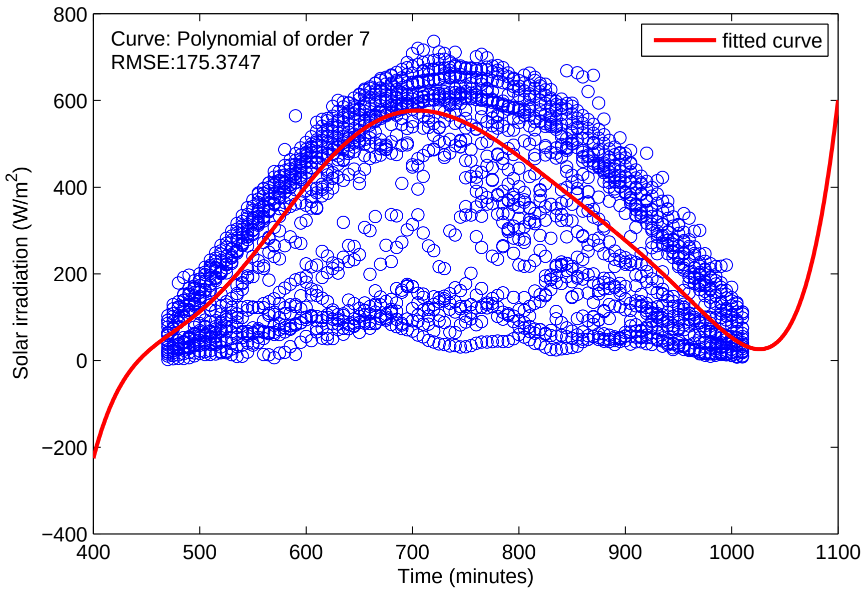


Figure 5-10: Best Curve Fitting Results for M2 - Worst RMSE

When the aberrant month, February, is split in two, we see RMSE values for 18 categories in Fig 5-12. The split has little effect on the average RMSE value, but as we stated before, the effect would be felt on fewer days of the year.

Once the curves for each of these 18 categories have been obtained, we now attempt to predict the GHI values. In order to do so, we use the polynomial representing the best fit for that category and extrapolate according to this polynomial as to what the next value must be. We predict for a given month in 2011 – of which we have measured data. Thus, we have a means to compare predicted values to measured ones. In Fig 5-13 we see the results of this prediction. As can be seen, the measured value differs imperceptibly.

However, the effectiveness of this method is seen when we examine the worst performance in Fig 5-14. This figure shows the averaged predictions for days over the category, and it can been seen, at most, the prediction is wrong for a few points and quickly recovers in situations of high variability in solar insolation. The worst day prediction, seen in Fig. 5-15, shows the predicted curve follows the measured curve very well. However due to the sudden variations in the sunlight (possibly due to cloudy/rainy weather), the prediction error is high.

Since the curve fitting method extrapolates from real measurements rather than predicting hard values, fewer resources would be required for the purpose of prediction of energy in the harvesting device. Polynomials for prediction could be programmed into nodes at design time or disseminated by a "super" node or base station during the course of the year. The latter method would ensure that the predictions stay as close

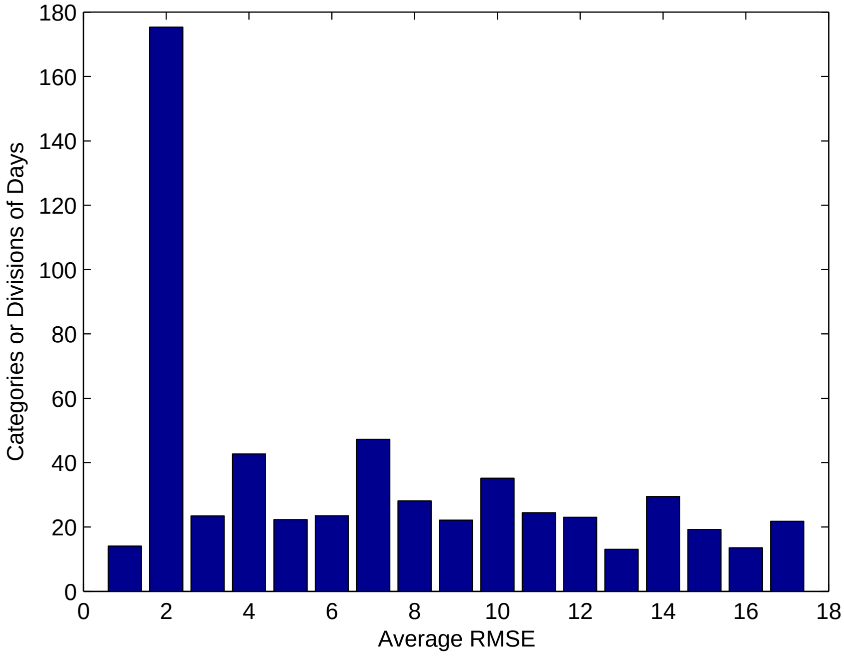


Figure 5-11: Average RMSE for 17 Categories

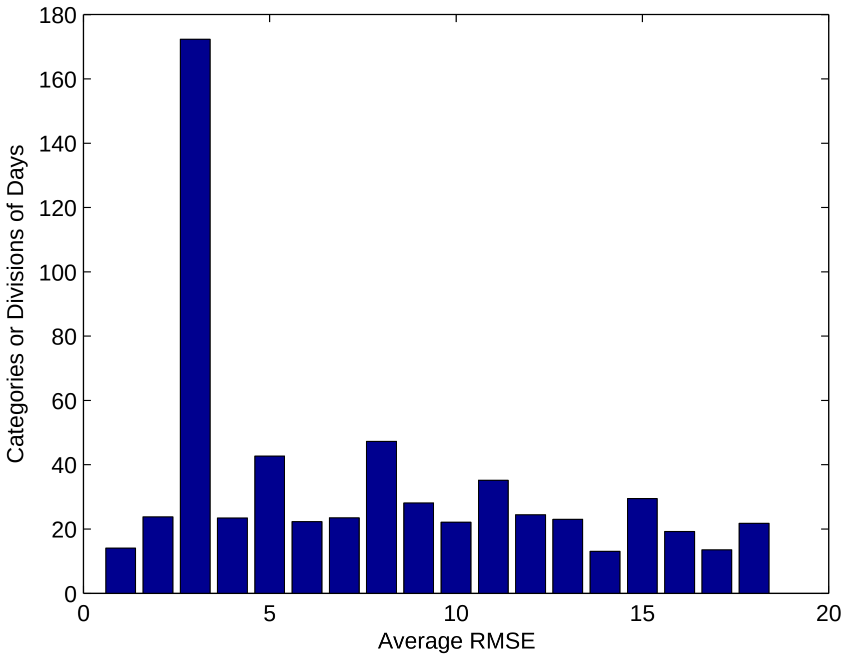


Figure 5-12: Average RMSE for 18 Categories

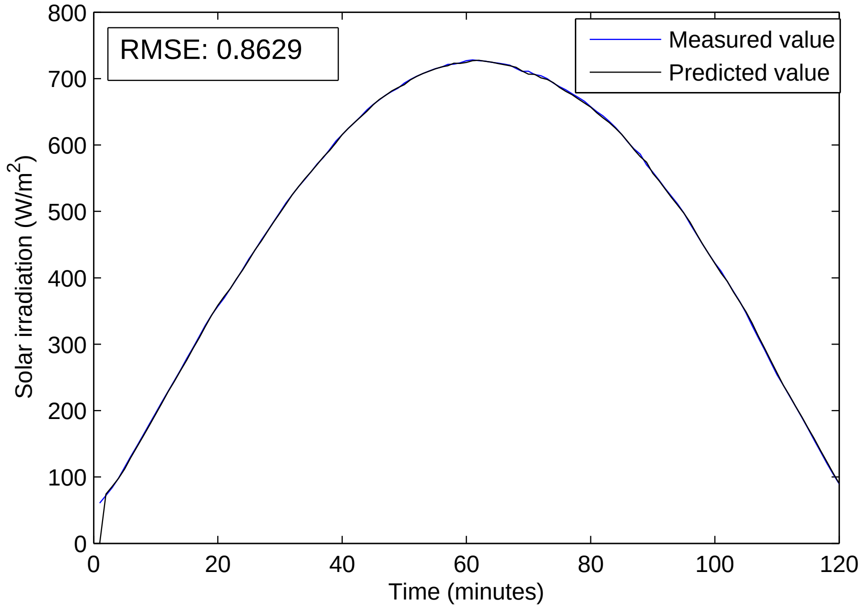


Figure 5-13: Comparison of Measured and Predicted Values - Best Case

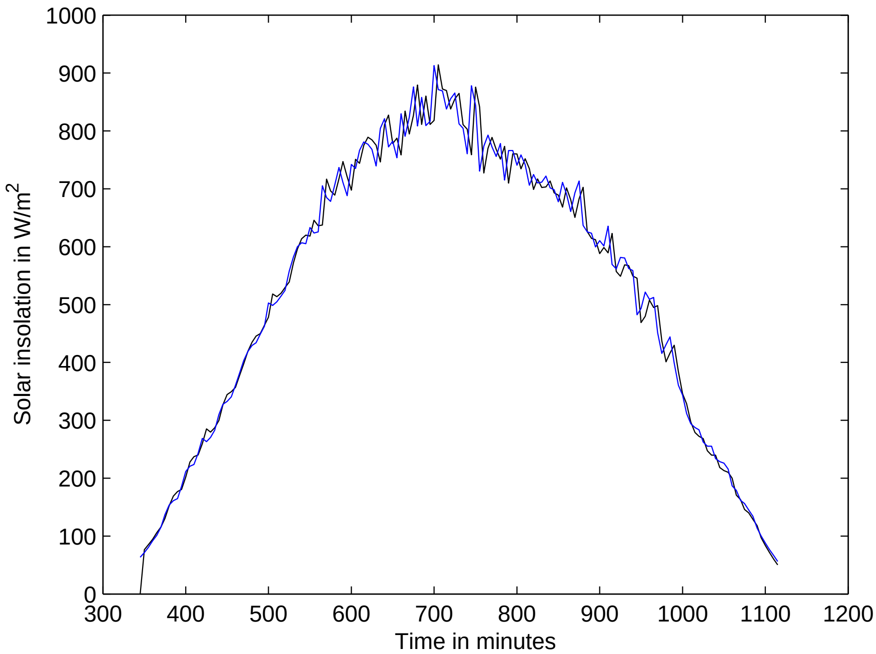


Figure 5-14: Comparison of Averaged Measured and Predicted Values - Worst Category

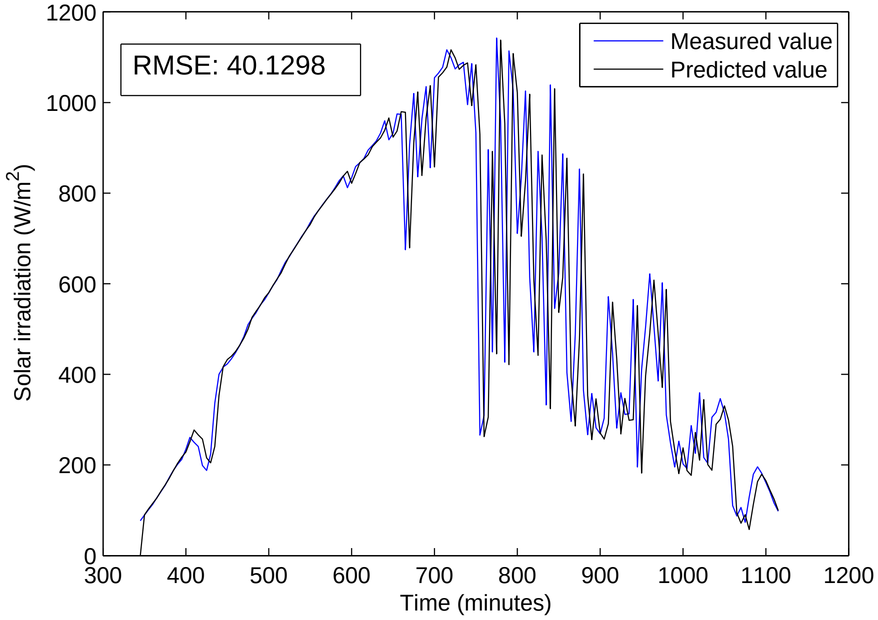


Figure 5-15: Comparison of Measured and Predicted Values - Worst Day

to current day weather as possible, while ensuring that no extra resources or manual intervention is required in the deployment.

Thus, in a nutshell, we see that curve fitting method is quite accurate, simple and has less overheads.

5-5 Integration of Prediction into Communication

Here we discuss the impact that prediction inputs would have on the ND process. With this as a starting point, we discuss how the entire communication stack could be improved for EHS.

5-5-1 Enhancing ND Process with Prediction Inputs

In our discussion on ND schemes, we have discussed the role of a special node that proactively takes on a role as a finding node. Let us take a step back and understand this assumption. The allotment of this role during design or deployment would create a hierarchy in the setup – causing our setup to become a centralized model. In reality, most deployments are required to be distributed setups. Ideally, the role of finding node should be alloted only at run time. However, the process of such a choice at runtime would depend on an election process among nodes. Such an election process would involve additional overhead in terms of message exchanges. But, more importantly, in our setup, nodes would not be aware of each other when deployed, thus the need to perform ND. Cluster node selection would assume knowledge of neighborhood or implicit discovery. Hence, we must look at other options.

A possibility is that nodes proactively offer to take on ND. If a node were to do so, it would have to possess prior knowledge that it would be able to harvest sufficient energy to perform ND for k number of nodes. Thus, the requirement is that the knowledge of future energy be accurate. Of course, the need for low overhead in gaining this knowledge in terms of energy, memory and computation must also be satisfied. We have described such a method of obtaining future information in our curve fitting prediction method.

We have provided a number of different recommendations for choice of different parameters at runtime in Section 4-1-6. We have demonstrated how parameter choices must depend on the arrival rate of energy. For example, the choice of beamwidth is to be made depending on energy arrival rate. With accurate energy predictions, the choice of beamwidth can be made for the best possible performance – in terms of ND energy, ND collisions and ND time.

In our discussions on the effects of storage element size in Section 4-1-5, we see that the impact of the storage element is that of smoothing variations in incoming energy. The impact of an energy prediction algorithm would be similar. With a good energy forecast, nodes could choose to respond to packets at a later time. In case of a dismal forecast, nodes would try to use as much energy as possible at that instant of time in order to make an attempt to complete ND process before stored energy is lost due to leakage and energy consumption by other processes. This would also constitute cooperative behavior among nodes.

5-5-2 Enhancing the Overall Communication Model

We described the impact that energy prediction inputs would have on the ND process. This discussion can be carried forward into the rest of the communication model for EH-IoTs. As we have contended before, the energy harvesting device can benefit from knowledge of energy availability at every layer of the communication model. At node level, this would translate to better scheduling of tasks according to priority. At a network level, it would correspond to greater performance because of cooperative behavior – nodes expecting energy arrival defer network operations.

Further, it can be argued that energy measurement in itself is an energy consuming activity. If a physical measurement can be supplemented by a prediction input, energy measurement would still be required, but the frequency with which it is conducted could be reduced. Thus, energy prediction would result in energy savings even before the knowledge is even used.

We have seen how ND performance can be improved by energy predictions, through better parameter choices. Similarly, through careful study of interrelation of parameters at each level, recommendations can be provided for node and network processes such medium access and routing.

In summary, energy prediction mechanisms can provide opportunity for cooperative behavior, scheduling of tasks within a node, runtime choices for various parameters that depend on energy availability.

Chapter 6

Conclusion

6-1 Summary

In this thesis, the importance of performing explicit neighbor discovery in energy harvesting wireless sensor networks was motivated. The importance of differentiating ND upon initial deployment and for continuous ND in re-entering nodes was elaborated on. With the help of an analytical model, the important parameters that would influence ND were identified as transmitter beamwidth, node density, node duty cycle and the rate of energy arrival. The exact effects of these various parameters was observed through simulations and several design recommendations were presented. Some important implications of this study are :

- With increasing number of neighbor nodes, interference increases. Thus, neighbor node density has a detrimental effect on ND performance. Choosing the right node density to tradeoff with network performance parameters is important.
- When nodes operate at low duty cycles, ND performance is lowered. However, increasing duty cycle would have the adverse effect of increased energy usage and would impact the ND performance even more. The right duty cycle must be picked keeping energy consumption in mind
- Antenna directionality offers an advantage in ND. Under certain conditions, it is advisable to use a small beamwidth of transmission to actively discover neighbor nodes.
- Energy availability has a great impact on ND performance. If energy arrives at less frequent rates ND performance worsens. The adverse effects of varying energy availability are more on directional discovery. If the variations in energy availability are smoothened with a buffer, performance is positively impacted.

- It is important to differentiate between initial and continuous ND for seamless network operation. A simple one-way scheme can perform continuous ND with relatively low overhead.

Finally, the importance of light-weight energy prediction were discussed and solutions towards the practical implementation of prediction algorithms were proposed. With the impact of an accurate energy prediction algorithm on the ND process as an example, the effect of using energy prediction to improve all round performance in the communication model for EH-IoTs was discussed.

6-2 Recommended Future Work

We see that the existence and size of the storage element has a pronounced effect on the performance of ND process. Therefore care must be taken in accurate modeling before recommendations are provided on size of storage element before a practical implementation. We mentioned that we have assumed a simple linear model for accounting for leakage that occurs in supercapacitors. In future work, a complex non-linear model that approaches the behavior of leakage current should be attempted.

With respect to the analytical energy model, it would be interesting to arrive at a definition for the PDF of buffer occupancy for an unstable queue given as an $\mathrm{M}^X/\mathrm{N}^*\mathrm{D}/1/\mathrm{K}$ system. Such a derivation would allow for an expression that would allow for accurate numerical quantification. In the absence of such a model, we are still able to provide design recommendations.

We consider nodes to form clusters that have a specially endowed super node that performs initial neighbor discovery. Although this provides us insight into the requirements for ND, in order to present a generalized solution, a model in which every node initiates ND processes of its own must be studied and understood. This homogeneous network would be an extension of the model we have studied here.

Using the example of improving ND performance with energy prediction, efforts must be made towards integrating inputs from energy prediction into every layer of the EH communication model such that network-wide cooperative schemes can be implemented. Proactive nodes can take on responsibilities in order to reduce burden on less fortunate neighbors with information from prediction algorithms. With such a scheme in place, the effects of a dynamic energy regime could be tackled effectively to the network's benefit.

Publications

1. Vijay Rao, Shruti Devasenapathy, Venkatesha Prasad, Prabhakar T V and Ignas Niemegeers, "Work-in-Progress: Prediction of Solar Energy for Infrastructure-based Wireless Sensor Networks", in *Proceedings of Fourth Extreme Conference on Communication,* ExtremeCom '12, Mar. 2012

2. "Reincarnation Over the Air: Energy Harvesting Devices and Networks", to be submitted to *IEEE Surveys and Tutorials*

3. Shruti Devasenapathy, R. Venkatesha Prasad, Vijay S. Rao and Ignas Niemegeers, "Impact of antenna directionality and energy harvesting rate on Neighbor Discovery in EH-IoTs", (submitted) to *IEEE Consumer Communications and Networking Conference*, CCNC '13

4. Shruti Devasenapathy, R. Venkatesha Prasad, Vijay S. Rao and Ignas Niemegeers,"An Analysis of Neighbor Discovery in EH-IoTs", to be submitted to ICC'13

Bibliography

[1] G. Park, T. Rosing, M. Todd, C. Farrar, and W. Hodgkiss, "Energy harvesting for structural health monitoring sensor networks," *Journal of Infrastructure Systems*, vol. 14, no. 1, pp. 64–79, 2008. [Online]. Available: http://ascelibrary.org/doi/abs/10.1061/%28ASCE%291076-0342%282008%2914%3A1%2864%29

[2] D. Mascarenas, E. Flynn, C. Farrar, G. Park, and M. Todd, "A mobile host approach for wireless powering and interrogation of structural health monitoring sensor networks," *Sensors Journal, IEEE*, vol. 9, no. 12, pp. 1719 –1726, dec. 2009.

[3] C. A. Nelson, S. R. Platt, D. Albrecht, V. Kamarajugadda, and M. Fateh, "Power harvesting for railroad track health monitoring using piezoelectric and inductive devices," pp. 69 280R–69 280R–9, 2008. [Online]. Available: +http://dx.doi.org/10.1117/12.775884

[4] T. V. Prabhakar, A. U. Nambi S.n, H. S. Jamadagni, K. Swaroop, R. V. Prasad, and I. I. Niemegeers, "A novel dtn based energy neutral transfer scheme for energy harvested wsn gateways," *SIGMETRICS Perform. Eval. Rev.*, vol. 38, no. 3, pp. 71–75, Jan. 2011. [Online]. Available: http://doi.acm.org/10.1145/1925019.1925034

[5] Turtlenet project at umass. [Online]. Available: http://prisms.cs.umass.edu/dome/turtlenet

[6] A. Hande, T. Polk, W. Walker, and D. Bhatia, "Indoor solar energy harvesting for sensor network router nodes," *Microprocessors and Microsystems*, vol. 31, no. 6, pp. 420 – 432, 2007, <ce:title>Special Issue on Sensor Systems</ce:title>. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0141933107000415

[7] W. S. Wang, T. O'Donnell, N. Wang, M. Hayes, B. O'Flynn, and C. O'Mathuna, "Design considerations of sub-mw indoor light energy harvesting for wireless

sensor systems," *J. Emerg. Technol. Comput. Syst.*, vol. 6, no. 2, pp. 6:1–6:26, Jun. 2008. [Online]. Available: http://doi.acm.org/10.1145/1773814.1773817

[8] H. Bai, M. Atiquzzaman, and D. Lilja, "Wireless sensor network for aircraft health monitoring," in *Broadband Networks, 2004. BroadNets 2004. Proceedings. First International Conference on*, oct. 2004, pp. 748 – 750.

[9] Enocean's eco 200 - energy converter for motion energy harvesting. [Online]. Available: http://www.enocean.com/en/enocean_modules/eco-200/

[10] M. A. Green, K. Emery, Y. Hishikawa, W. Warta, and E. D. Dunlop, "Solar cell efficiency tables (version 39)," *Progress in Photovoltaics: Research and Applications*, vol. 20, no. 1, pp. 12–20, 2012. [Online]. Available: http://dx.doi.org/10.1002/pip.2163

[11] S. Roundy, D. Steingart, L. Frechette, P. Wright, and J. Rabaey, "Power sources for wireless sensor networks," in *Wireless Sensor Networks*, ser. Lecture Notes in Computer Science, H. Karl, A. Wolisz, and A. Willig, Eds. Springer Berlin / Heidelberg, 2004, vol. 2920, pp. 1–17. [Online]. Available: http://dx.doi.org/10.1007/978-3-540-24606-0$_$1

[12] T. Voigt, H. Ritter, and J. Schiller, "Utilizing solar power in wireless sensor networks," in *Local Computer Networks, 2003. LCN '03. Proceedings. 28th Annual IEEE International Conference on*, oct. 2003, pp. 416 – 422.

[13] Z. A. Eu, H.-P. Tan, and W. K. G. Seah, "Design and performance analysis of mac schemes for wireless sensor networks powered by ambient energy harvesting," *Ad Hoc Netw.*, vol. 9, no. 3, pp. 300–323, May 2011. [Online]. Available: http://dx.doi.org/10.1016/j.adhoc.2010.07.014

[14] P. Dutta and D. Culler, "Practical asynchronous neighbor discovery and rendezvous for mobile sensing applications," in *Proceedings of the 6th ACM conference on Embedded network sensor systems*, ser. SenSys '08. New York, NY, USA: ACM, 2008, pp. 71–84. [Online]. Available: http://doi.acm.org/10.1145/1460412.1460420

[15] M. J. McGlynn and S. A. Borbash, "Birthday protocols for low energy deployment and flexible neighbor discovery in ad hoc wireless networks," in *Proceedings of the 2nd ACM international symposium on Mobile ad hoc networking & computing*, ser. MobiHoc '01. New York, NY, USA: ACM, 2001, pp. 137–145. [Online]. Available: http://doi.acm.org/10.1145/501431.501435

[16] V. Iyer, A. Pruteanu, and S. Dulman, "Netdetect: Neighborhood discovery in wireless networks using adaptive beacons," in *Self-Adaptive and Self-Organizing Systems (SASO), 2011 Fifth IEEE International Conference on*, Oct. 2011, pp. 31 –40.

[17] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power management in energy harvesting sensor networks," *ACM Trans. Embed. Comput. Syst.*, vol. 6, no. 4, Sep. 2007. [Online]. Available: http://doi.acm.org/10.1145/1274858.1274870

[18] C. Moser, L. Thiele, D. Brunelli, and L. Benini, "Adaptive power management in energy harvesting systems," in *Design, Automation Test in Europe Conference Exhibition, 2007. DATE '07*, April 2007, pp. 1 –6.

[19] R. Cohen and B. Kapchits, "Continuous neighbor discovery in asynchronous sensor networks," *IEEE/ACM Trans. Netw.*, vol. 19, no. 1, pp. 69–79, Feb. 2011. [Online]. Available: http://dx.doi.org/10.1109/TNET.2010.2053943

[20] R. Madan and S. Lall, "An energy-optimal algorithm for neighbor discovery in wireless sensor networks," *Mob. Netw. Appl.*, vol. 11, no. 3, pp. 317–326, Jun. 2006. [Online]. Available: http://dx.doi.org/10.1007/s11036-006-5185-x

[21] S. Vasudevan, J. Kurose, and D. Towsley, "On neighbor discovery in wireless networks with directional antennas," in *INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE*, vol. 4, March 2005, pp. 2502 – 2512 vol. 4.

[22] X. An and R. Hekmat, "Self-adaptive neighbor discovery in ad hoc networks with directional antennas," in *Mobile and Wireless Communications Summit, 2007. 16th IST*, July 2007, pp. 1 –5.

[23] X. An, R. Prasad, and I. Niemegeers, "Impact of antenna pattern and link model on directional neighbor discovery in 60 ghz networks," *Wireless Communications, IEEE Transactions on*, vol. 10, no. 5, pp. 1435 –1447, May 2011.

[24] M. Nilsson, "Spida: A direction-finding antenna for wireless sensor networks," in *Real-World Wireless Sensor Networks*, ser. Lecture Notes in Computer Science, P. Marron, T. Voigt, P. Corke, and L. Mottola, Eds. Springer Berlin / Heidelberg, 2010, vol. 6511, pp. 138–145.

[25] E. Öström, L. Mottola, and T. Voigt, "Evaluation of an electronically switched directional antenna for real-world low-power wireless networks," in *Proceedings of the 4th international conference on Real-world wireless sensor networks*, ser. REALWSN'10. Berlin, Heidelberg: Springer-Verlag, 2010, pp. 113–125. [Online]. Available: http://dl.acm.org/citation.cfm?id=1947841.1947856

[26] G. Hackmann, O. Chipara, and C. Lu, "Robust topology control for indoor wireless sensor networks," in *Proceedings of the 6th ACM conference on Embedded network sensor systems*, ser. SenSys '08. New York, NY, USA: ACM, 2008, pp. 57–70. [Online]. Available: http://doi.acm.org/10.1145/1460412.1460419

[27] W. Ye, J. Heidemann, and D. Estrin, "An energy-efficient mac protocol for wireless sensor networks," in *INFOCOM 2002. Twenty-First Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, vol. 3, 2002, pp. 1567 – 1576 vol.3.

[28] Crossbow's iris mote. [Online]. Available: http://www.dinesgroup.org/projects/images/pdf_files/iris_datasheet.pdf

[29] L. Zubieta and R. Bonert, “Characterization of double-layer capacitors for power electronics applications,” *Industry Applications, IEEE Transactions on*, vol. 36, no. 1, pp. 199 –205, Jan/Feb 2000.

[30] A. Weddell, G. Merrett, T. Kazmierski, and B. Al-Hashimi, “Accurate supercapacitor modeling for energy harvesting wireless sensor nodes,” *Circuits and Systems II: Express Briefs, IEEE Transactions on*, vol. 58, no. 12, pp. 911 –915, Dec. 2011.

[31] P. Poggi, G. Notton, M. Muselli, and A. Louche, “Stochastic study of hourly total solar radiation in corsica using a markov model,” *International Journal of Climatology*, vol. 20, no. 14, pp. 1843–1860, 2000. [Online]. Available: http://dx.doi.org/10.1002/1097-0088(20001130)20:14<1843::AID-JOC561>3.0.CO;2-O

[32] C. K. Ho, P. D. Khoa, and P. C. Ming, “Markovian models for harvested energy in wireless communications,” in *Communication Systems (ICCS), 2010 IEEE International Conference on*, Nov. 2010, pp. 311 –315.

[33] J. Lei, R. Yates, and L. Greenstein, “A generic model for optimizing single-hop transmission policy of replenishable sensors,” *Wireless Communications, IEEE Transactions on*, vol. 8, no. 2, pp. 547 –551, Feb 2009.

[34] A. Seyedi and B. Sikdar, “Modeling and analysis of energy harvesting nodes in wireless sensor networks,” in *Communication, Control, and Computing, 2008 46th Annual Allerton Conference on*, sept. 2008, pp. 67 –71.

[35] B. Medepally, N. Mehta, and C. Murthy, “Implications of energy profile and storage on energy harvesting sensor link performance,” in *Global Telecommunications Conference, 2009. GLOBECOM 2009. IEEE*, 30 2009-Dec. 4 2009, pp. 1 –6.

[36] P. V. Mieghem, *Performance Analysis of Communications Networks and Systems*. Cambridge University Press, 2006. [Online]. Available: http://dx.doi.org/10.1017/CBO9780511616488

[37] D. R. Cox, “Prediction by exponentially weighted moving averages and related methods,” *Journal of the Royal Statistical Soc. Series B*, vol. 23, pp. 414–422, 1961.

[38] J. Piorno, C. Bergonzini, D. Atienza, and T. Rosing, “Prediction and management in energy harvested wireless sensor nodes,” in *Wireless Communication, Vehicular Technology, Information Theory and Aerospace Electronic Systems Technology, 2009. Wireless VITAE 2009. 1st International Conference on*, May 2009, pp. 6 –10.

[39] Z. Jiang, X. Jin, and Y. Zhang, “A weather-condition prediction algorithm for solar-powered wireless sensor nodes,” in *Wireless Communications Networking and Mobile Computing (WiCOM), 2010 6th International Conference on*, Sept. 2010, pp. 1 –4.

[40] C. Bergonzini, D. Brunelli, and L. Benini, “Algorithms for harvested energy prediction in batteryless wireless sensor networks,” in *Advances in sensors and Interfaces, 2009. IWASI 2009. 3rd International Workshop on*, june 2009, pp. 144 –149.

[41] Project CONFRRM. [Online]. Available: http://rredc.nrel.gov/solar/new_data/confrrm/

Glossary

List of Acronyms

ND	Neighbor Discovery
OND	Omnidirectional Neighbor Discovery
DND	Directional Neighbor Discovery
RND	Reply to ND packet
IA	Interarrival Time
EH-WSN	energy harvesting wireless sensor network
EH	energy harvesting
EHS	Energy Harvesting System
C	Capacitance
EWMA	Exponentially Weighted Moving Average
WCMA	Weather-Conditioned Moving Average
WCSMA	Weather-Conditioned Selective Moving Average
GHI	Global Horizontal Irradiance
RMSE	Root Mean Square Error

List of Symbols

$_{min}$	Minimum

^{max}	Maximum
$^\circ$, [deg]	Degrees
θ	Beamwidth in Deg
F	Farad (unit of capacitance)
J	Joule (unit of energy)
m	Milli -
μ	Micro-