RF-Powered Internet of Things

A Dissertation Presented

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To my parents, Masoumeh and Gholamali,
for their endless love, encouragement, and support
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Abstract of the Dissertation

RF-Powered Internet of Things

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Wireless charging through directed radio frequency (RF) waves and ambient RF energy sources is an attractive solution to power small wireless devices. RF-based wireless charging can potentially realize battery-less sensor networks and eliminate the need for external power cables or periodic battery replacements. However, the coexistence of data communication and energy comes at the cost of new challenges, which this research tackles holistically through a combination of system level design, experimentation, analysis and protocol formulation.

First, a stochastic tool for analyzing nodal residual energy and lifetime distribution is proposed. Our analytical framework models an energy harvesting sensor as a stochastic semi-Markov process and introduces a new analysis technique, called energy transient analysis. The framework returns, with fine granularity, the energy consumed during various protocol-related functions, as well as the incoming energy via harvesting. As a second contribution, the opportunities and challenges of RF energy harvesting are identified through extensive practical testing. This study lays out essential network design guidelines for separating energy transmitter (ET) operations and those of the RF energy harvesting nodes in the spatio-temporal and frequency domains. It also examines the energy interference among concurrent RF waves that may result in destructive combinations of the net signal energy if the ETs are randomly placed. To verify the experimental findings, a set of closed form equations for omni-directional ETs is developed that accurately captures the locations where the ET action is cumulative. Next, a medium access control called RF-MAC is designed for ET and sensor coordination that jointly selects energy transmitters and their frequencies based on the collective impact on charging time and energy interference, sets the maximum energy charging threshold, requests and grants energy, and decides the access priority of both data and energy.

Finally, a planning and network resource management framework for powering small form factor sensor node called HYDRA is introduced that uses distributed ad hoc beamforming-capable ETs and leverages cognitive ambient energy harvesting from cellular and TV spectrum bands.
HYDRA proposes a new strategy for supplying energy called energy-in-advance transfer (EIA) which provides nodes in advance with the energy they will need for current and future operations. In the planning phase, it determines the locations of ETs that jointly maximizes energy from ambient sources and minimizes the number of ETs to reduce costs and overhead. In the resource management phase, through novel mathematical formulations for optimal radiating power levels and phases of the ETs, HYDRA determines the spatial scheduling of the energy beams mapping ET operations to changing network requirements and available ambient energy, while minimizing the energy expenditures of ETs.

The results of this work can all be integrated to address real-world wireless powered systems, such as the design of the next generation RF-powered Internet of Things (IoT).
Chapter 1

Introduction

Wireless Sensor Networks (WSNs) are a fundamental building block of the Internet of Things (IoT) and a key enabler for cyber physical and pervasive computing systems. However, sensor nodes are typically battery-powered, and their limited energy affects protocol design, sacrificing throughput, bandwidth usage, and reliability to the need for extended network lifetime through judicious use of energy. Since it is often difficult, if not impossible, to access the sensor nodes and replace their batteries, most research efforts have focused on intelligent duty cycling and energy saving techniques at all layers of the protocol stack. Recent developments in energy harvesting technology from ambient sources promise to alleviate some of these concerns. Among sources of energy, electromagnetic waves carry energy in the form of electric and magnetic fields, which can be converted (with some losses) and stored as energy at the receiving front-end, and used to power the processing and communication circuits of the nodes of a wireless sensor network (WSN). The ability of transferring energy via contact-less radio frequency (RF) will ensure the sensor nodes to remain operational for long times, without the need of costly battery replacement efforts.

1.1 Research Challenges

Sensor nodes powered by rechargeable batteries would replenish through energy scavenged from controlled or ambient sources. Such a charging paradigm extends the network lifetime by reducing the charge drawn from the battery, prevents disruptions owing to battery replacement, and ensures environmentally friendly operation. However, as the residual energy at the node is time varying, and is subject to a variety of other factors, it is a challenge for the network designer to formulate closed form expressions that indicate future energy levels and lifetime of a EHWSN node.
CHAPTER 1. INTRODUCTION

Moreover, current prototypes of RF transfer have limited charging range (few meters) and efficiency (40 to 60%). This imposes the concurrent and coordinated use of multiple ETs to power an entire WSN. While multiple ETs are needed to ensure high energy transfer rates, they introduce interference among RF waves from different ETs, leading to significant and various constructive and destructive combinations over the network deployment area. Being able to compute the energy harvestable at a given point in space is a non-trivial task, as it depends on the relative locations of active ETs, path loss information, and on the different distances from the ETs and a receiver at that point.

The integration of data and energy communications also results into several challenges at the protocol level such as: (i) how and when should the energy transfer occur, (ii) its priority over, and the resulting impact on the process of data communication, (iii) the challenges in aggregating the charging action of multiple transmitters, and (iv) impact of the choice of frequency. Thus, the act of energy transfer becomes a complex medium access problem, which must embrace a cross-disciplinary approach incorporating wave propagation effects and device characteristics, apart from the classical link layer problem of achieving fairness in accessing the channel.

While ambient energy harvesting has the advantage of scavenging existing pervasive radiation without any need of dedicated transmitter, its power density is subject to the surrounding environments, schedule followed by the base stations and mobile users, underlying dynamic channel characteristics, the line of sight, and distance to the ambient sources. Moreover, the wireless power transfer can be carefully controlled through dedicated ETs, though this needs distributed coordination among multiple ETs, energy load distribution, adaptive power control and scheduling of energy transmissions based on the dynamic traffic and energy requirements of the sensor nodes for effective energy transfer.

In this dissertation in order to address these problems we propose a set of analytical frameworks, communication protocols, and resource allocation algorithms along comprehensive simulations and experimental studies.

1.2 Organization and Contributions of the Thesis

Chapter 2 explores the opportunities and challenges of energy harvesting wireless sensor networks (EHWSNs), explaining why the design of protocol stacks for traditional WSNs has to be radically revisited. It describes the architecture of a EHWSN node, and especially that of its energy subsystem and presents the various forms of energy that are available and ways for harvesting them.
CHAPTER 1. INTRODUCTION

Models for predicting availability of energy as well as task allocation, MAC and routing protocols are discussed.

Chapter 3 introduces a stochastic tool called SAVE, Stochastic Analysis and aVailability of Energy, for the analysis of the residual energy and the lifetime distribution of nodes. It models the energy harvesting wireless sensor node as a stochastic semi-Markov process and introduce a new analysis technique, called energy transient analysis, for the computation of the net consumed energy distribution. The amount of consumed and harvested energy in each state of a node are modeled as random variables, depending on discharging and recharging rates and on the holding time distribution of that state. SAVE captures a wide umbrella of input factors through its kernel, including channel characteristics, different energy sources and harvesting policies, link layer parameters (e.g., error control and duty cycling) and data traffic generation models.

Chapter 4 proposes a medium access control for integrated data and energy transfer. It addresses the problems of the joint selection of energy transmitters and their frequencies based on the collective impact on charging time and energy interference, setting the maximum energy charging threshold, requesting and granting energy, and energy-aware access priority. It optimizes energy delivery to sensor nodes, while minimizing disruption to data communication. The grouping of the ETs into two sets with varying transmission frequencies, and the minimal control overhead are both geared to keep the hardware requirements simple, and the protocol easier to implement. Both simulation and experimental testbed results provide the performance of this protocol in terms of the average harvested energy and average network throughput.

Chapter 5 studies the omnidirectional RF-powered wireless sensor network and propose analytical models to capture the behavior and energy interference in such networks. In particular, it first provides the experimental study to quantify the rate of charging, packet loss due to interference, and suitable ranges for charging and data communication of the ETs. It explores how the placement and relative distances of multiple ETs affect the charging process, demonstrating constructive and destructive energy aggregation at the sensor nodes. In addition, it investigates the impact of the separation in frequency between data and energy transmissions, as well as among multiple concurrent energy transmissions, and demonstrates how separating the energy and data transfer gives rise to black (high loss), gray (moderate loss), and white (low loss) regions with respect to packet errors. Then it shows safe frequency separation for concurrent data and energy transmission and measures the impact of energy cancellation on the amount of harvested power. Finally, chapter 5 introduces closed form expressions of the energy harvestable at any point in the deployment space of the WSN capturing low-power data communications, RF energy harvesting circuit, and interference among
energy signals.

Chapter 6 proposes a planning and resource management framework for jointly harvesting RF energy from directional beams and ambient sources. It first introduces a mathematical model for the task of optimal ET placement that jointly optimizes direct and ambient energy harvesting. Furthermore, it formulates strategies for dynamically adjusting the transmission power and phase of the ETs and for determining the spatial scheduling of the energy beams, mapping ET energy provisioning to the changing demands of the nodes while considering available ambient energy and minimizing the energy expenditures of ETs. To this end, it formalizes the necessary traffic and energy models for the nodes based on the volume of transferred data. Moreover, it proposes a new strategy for supplying energy called energy-in-advance transfer that provides nodes with the energy they will need for current and future operations, while minimizing the power from the ETs. It leverages the hardware-centric properties of typical RF harvesting circuits and strict convexity of harvested power as a function of input power. Then the potential and benefits of cognitive ambient RF energy harvesting are demonstrated through a set of experiments conducted in Boston subway stations for digital TV, and the 3G, GSM, and LTE bands. Finally, the proposed models, algorithms, and framework are evaluated through comprehensive network simulations.

Chapter 7 draws the main conclusions of this thesis and outline future research directions.
Chapter 2

Energy Harvesting Wireless Sensor Networks

2.1 Introduction

Wireless Sensor Networks (WSNs) have played a major role in the research field of multi-hop wireless networks as enablers of applications ranging from environmental and structural monitoring to border security and human health control. Research within this field has covered a wide spectrum of topics, leading to advances in node hardware, protocol stack design, localization and tracking techniques and energy management [2].

Research on WSNs has been driven (and somewhat limited) by a common focus: Energy efficiency. Nodes of a WSN are typically powered by batteries. Once their energy is depleted, the node is “dead.” Only in very particular applications batteries can be replaced or recharged. However, even when this is possible, the replacement/recharging operation is slow and expensive, and decreases network performance. Different techniques have therefore been proposed to slow down the depletion of battery energy, which include power control and the use of duty cycle-based operation. The latter technique exploits the low power modes of wireless transceivers, whose components can be switched off for energy saving. When the node is in a low power (or “sleep”) mode its consumption is significantly lower than when the transceiver is on. However, when asleep the node cannot transmit or receive packets. The duty cycle expresses the ratio between the time when the node is on and the sum of the times when the node is on and asleep. Adopting protocols that operate at very low duty cycles is the leading type of solution for enabling long lasting WSNs [3]. However, this approach
CHAPTER 2. ENERGY HARVESTING WIRELESS SENSOR NETWORKS

suffers from two main drawbacks. 1) There is an inherent tradeoff between energy efficiency (i.e., low duty cycling) and data latency, and 2) battery operated WSNs fail to provide the needed answer to the requirements of many emerging applications that demand network lifetimes of decades or more. Battery leakage depletes batteries within a few years even if they are seldom used [4, 5]. For these reasons recent research on long-lasting WSNs is taking a different approach, proposing energy harvesters combined with the use of rechargeable batteries and super capacitors (for energy storage) as the key enabler to “perpetual” WSN operations.

Energy Harvesting-based WSNs (EHWSNs) are the result of endowing WSN nodes with the capability of extracting energy from the surrounding environment. Energy harvesting can exploit different sources of energy, such as solar power, wind, mechanical vibrations, temperature variations, magnetic fields, etc. Continuously providing energy, and storing it for future use, energy harvesting subsystems enable WSN nodes to last potentially for ever.

This chapter explores the opportunities and challenges of EHWSNs, explaining why the design of protocol stacks for traditional WSNs has to be radically revisited. We start by describing the architecture of a EHWSN node, and especially that of its energy subsystem (Section 2.2). We then present the various forms of energy that are available and ways for harvesting them (Section 2.3). Models for predicting availability of wind and solar energy are described in Section 2.4. We then survey task allocation, MAC and routing protocols proposed so far for EHWSNs in Section 2.5. Conclusions are drawn in Section 6.6.

2.2 Node platforms

EHWSNs are composed of individual nodes that in addition to sensing and wireless communications are capable of extracting energy from multiple sources and converting it into usable electrical power. In this section we describe in details the architecture of a wireless sensor node with energy harvesting capabilities, including models for the harvesting hardware and for batteries.

2.2.1 Architecture of a Sensor Node with Harvesting Capabilities

An EHWSN platform typically consists of one or more energy harvesting boards (the harvesters) attached to the wireless sensor node (Figure 2.1). The harvesting board uses one or more energy harvesting techniques and is responsible for capturing and converting the external energy into electrical power and for storing it.
Figure 2.1: System architecture of a wireless node with energy harvesters.

The system architecture of a wireless sensor node includes the following components: 1) The energy harvester(s), in charge of converting external ambient or human-generated energy to electricity; 2) a power management module, that collects electrical energy from the harvester and either stores it or delivers it to the other system components for immediate usage; 3) energy storage, for conserving the harvested energy for future usage; 4) a microcontroller, for communication control and other functions; 5) a radio transceiver, for transmitting and receiving information; 6) sensory equipment, for sensing; 7) an A/D converter to digitize the analog signal generated by the sensors and makes it available to the microcontroller for further processing, and 8) memory to store sensed information, application-related data, and code.

In the next section we focus on the energy harvesting components (the energy subsystem) of a EHWSN node, describing abstractions that have been proposed for modeling them.

2.2.2 Harvesting Hardware Models

The general architecture of the energy subsystem of a wireless sensor node with energy harvesting capabilities is shown in Figure 2.2.

The energy subsystem includes one or multiple harvesters that convert energy available from the environment to electrical energy. The energy obtained by the harvester may be used to directly supply energy to the node or it may be stored for later use. Although in some application it is possible to directly power the sensor node using the harvested energy (Harvest-use architecture [6]), in general this is not a viable solution: The energy source needs to be available when the device is operational, which can be an unrealistic assumption.

A more reasonable architecture enables the node to directly use the harvested energy, but also includes a storage component that acts as an energy buffer for the system, with the main purpose
of accumulating and preserving the harvested energy. When the harvesting rate is greater than the current usage, the buffer component can store excess energy for later use (e.g., when harvesting opportunities do not exist), thus supporting variations in the power level emitted by the environmental source.

The two alternatives commonly used for energy storage are secondary rechargeable batteries and supercapacitors (also known as ultracapacitors). Supercapacitors are similar to regular capacitors, but they offer very high capacitance in a small size. They offer several advantages with respect to rechargeable batteries [7]. First of all, supercapacitors can be recharged and discharged virtually an unlimited number of times, while typical lifetimes of an electrochemical battery is less than 1000 cycles [4]. Second, they can be charged using simple charging circuits, thus reducing system complexity, and do not need full-charge nor deep-discharge protection circuits. They also have higher charging and discharging efficiency than electrochemical batteries [7]. Finally, due to high power density, they can be charged quickly. Another additional benefit is the reduction of environmental issues related to battery disposal. The major limitations of ultracapacitors are the lower energy density and the higher self-discharge with respect to electrochemical batteries. They also experience linear discharge, which makes them unable to deliver the full charge. However, the leakage effect can be compensated quite well in case of solar energy harvesting, due to the periodic and unlimited nature of this power source [8]. Thanks to this characteristics, many platforms with harvesting capabilities use supercapacitors as energy storage, either by themselves [9][10] or in combination with batteries [11][12][13]. Other systems, instead, focus on platforms using only rechargeable batteries [14][15][16].
Real energy storage devices, such as supercapacitors and rechargeable batteries, deviate from ideal energy buffers in a number of ways: They have a finite size $B_{Max}$ and can hold a finite amount of energy; they have a charging efficiency $\eta_c < 1$ and a discharging efficiency $\eta_d < 1$, i.e., some energy is lost while charging and discharging the buffer, and they suffer from leakage and self-discharge, i.e., some stored energy is lost even if the buffer is not in use. Leakage and self-discharge are phenomena that affect both batteries and supercapacitors. All batteries suffer from self-discharge: A cell that simply sits on the shelf, without any connection between the electrodes, experiences a reduction in its stored charge due to internal chemical reactions, at a rate depending on the cell chemistry and the temperature. A similar phenomenon affects electrochemical supercapacitors in charged state. They suffer gradual loss of energy and reduction of the inter-plate voltage.

Considering leakage current is important while dealing with energy harvesting systems, especially if the application scenario requires the harvested energy to be stored for long periods of time. In general, if the energy source is sporadic or if it is only able to provide a small amount of energy, the portion of the harvested energy lost due to leakage may be significant. The leakage is of particular relevance for supercapacitors, because their energy density is about one order of magnitude lower than that of an electrochemical battery, but they suffer from considerably higher self-discharge. A supercapacitor leakage is strongly variable and depends on several factors, including the capacitance value of the supercapacitor, the amount of energy stored, the operating temperature, the charge duration, etc. For this reason, the leakage pattern of a particular supercapacitor must often be determined experimentally [12, 17, 18, 7]. Additionally, the leakage current varies with time: It is considerably higher immediately after the supercapacitor has been charged, then it decreases to a plateau.

Several models for the leakage from a charged supercapacitor have been proposed in the literature, modeling the leakage as a constant current [19], or as an exponential function of the current supercapacitor voltage [20], or by using a polynomial approximation of its empirical leakage pattern [18], or, finally, by using a piecewise linear approximation of its empirical leakage pattern [7]. Another aspect to consider in the supercapacitors vs. battery comparison is that in many application scenarios it is not possible to use the full energy stored in the supercapacitor. The voltage of a supercapacitor drops from full voltage to zero linearly, without the flat curve that is typical of most electrochemical batteries. The fraction of the charge available to the sensor node depends on the voltage requirements of the platform. For example, a Telos B mote requires a minimal voltage ranging from 1.8 V to 2.1 V. When the supercapacitor voltage drops below this threshold, its residual
energy can no longer be used to power the node. This aspect may be partially mitigated by using a DC-DC converter to increase the voltage range, at the cost of introducing inefficiencies and an additional source of power consumption.

In order to reduce the energy lost through buffer inefficiencies, many platforms allow the node to directly use the energy harvested. In particular, if the current energy consumption is greater or equal than the energy currently harvested, then the node can use the harvested energy for its operations. This is the most efficient way of using the environmental energy, because it is used directly and there is no energy loss. Otherwise, if the amount of energy harvested is greater than the current energy consumption, some energy is directly used to sustain the node operations, while excess energy is stored in the buffer for later use.

### 2.2.3 Battery Models

Many existing network simulators provide very simple battery models. Batteries are seen as ideal energy storage devices and are modeled as containers of finite capacity, containing a certain amount of energy units. Executing a network operation, e.g., sending or receiving a packet, uses a certain amount of energy units, depending on the energy cost of the operation. Real batteries, however, operate differently. As mentioned earlier, all batteries suffer from self-discharge. Even a cell that is not being used experience a charge reduction caused by internal chemical activity. Batteries also have charge and discharge efficiency strictly $< 1$, i.e., some energy is lost when charging and discharging the battery. Additionally, batteries have some non-linear properties [4, 21, 22]. These are: Rate-dependent capacity, i.e., the delivered capacity of a battery decreases, in a non-linear way, as the discharge rate increases; temperature effect, in that the operating temperature affects the battery discharge behavior and directly impact the rate of self-discharge; recovery effect, for which the lifetime and the delivered capacity of a battery increases if discharge and idle periods alternate (pulse discharge). Furthermore, rechargeable batteries experience a reduction of their capacity at each recharge cycle, and their voltage depends on the charging level of the battery and varies during discharge. These characteristics should be taken into account when dimensioning and simulating energy harvesting systems, because they can easily lead to wrong estimations of the battery lifetime. For example, if the harvesting subsystem uses a rechargeable battery to store the energy harvested from the environment, it is important to consider that the reduction in capacity experienced by the battery at each recharge cycle is likely to reduce both its delivered capacity and its lifetime.

Many types of battery models have been proposed recently in the literature [22]. These
include: **Physical models** that simulate the physical processes that take place into an electrochemical battery. These models are usually very accurate, but have high computational complexity and require high configuration effort [23, 24]. **Empirical models** that approximate the discharge behavior of a battery with simple equations. They are generally the least accurate. However, they require low computational resources and configuration effort [25, 26]. **Abstract models** that emulate battery behavior by using simplified equivalent representation, such as stochastic system [27], electrical-circuit models [28, 29], and discrete-time VHDL specification [30], and **mixed models** that use both a high-level representation of a battery (simpler than a real battery) and analytical expressions based on low-level analysis and physical laws [31].

### 2.3 Techniques of Energy Harvesting

Figure 2.3 shows the variety of energy types that can be harvested. In this section we provide their brief description and relevant references.

**Mechanical energy harvesting** indicates the process of converting mechanical energy into electricity by using vibrations, mechanical stress and pressure, strain from the surface of the sensor, high-pressure motors, waste rotational movements, fluid, and force. The principle behind mechanical energy harvesting is to convert the energy of the displacements and oscillations of a spring-mounted mass component inside the harvester into electrical energy [32, 33]. Mechanical energy harvesting can be: **Piezoelectric, electrostatic** and **electromagnetic**.
Piezoelectric energy harvesting is based on the piezoelectric effect for which mechanical energy from pressure, force or vibrations is transformed into electrical power by straining a piezoelectric material. The technology of a piezoelectric harvester is usually based on a cantilever structure with a seismic mass attached into a piezoelectric beam that has contacts on both sides of the piezoelectric material [33]. In particular, strains in the piezoelectric material produce charge separation across the harvester, creating an electric field, and hence voltage, proportional to the stress generated [34, 35]. Voltage varies depending on the strain and time, and an irregular AC signal is produced. Piezoelectric energy conversion has the advantage that it generates the desired voltage directly, without need for a separate voltage source. However, piezoelectric materials are breakable and can suffer from charge leakage [36, 37, 33]. Examples of piezoelectric energy harvesters can be found in [38, 39, 40, 41, 42] and references therein.

The principle of electrostatic energy harvesting is based on changing the capacitance of a vibration dependent variable capacitor [43, 44]. In order to harvest the mechanical energy a variable capacitor is created by opposing two plates, one fixed and one moving, and is initially charged. When vibrations separate the plates, mechanical energy is transformed into electrical energy from the capacitance change. This kind of harvesters can be incorporated into microelectronic-devices due to their integrated circuit-compatible nature [45]. However, an additional voltage source is required to initially charge the capacitor [37]. Recent efforts to prototype sensor-size electrostatic energy harvesters can be found in [46, 47].

Electromagnetic energy harvesting is based on Faraday’s law of electromagnetic induction. An electromagnetic harvester uses an inductive spring mass system for converting mechanical energy to electrical. It induces voltage by moving a mass of magnetic material through a magnetic field created by a stationary magnet. Specifically, vibration of the magnet attached to the spring inside a coil changes the flux and produces an induced voltage [43, 33, 34]. The advantages of this method include the absence of mechanical contact between parts and of a separate voltage source, which improves the reliability and reduce the mechanical damping in this type of harvesters [36, 44]. However, it is difficult to integrate them in sensor nodes because of the large size of electromagnetic materials [36]. Some examples of electromagnetic energy harvesting systems are presented in [48, 49].

Photovoltaic energy harvesting is the process of converting incoming photons from sources such as solar or artificial light into electricity. Photovoltaic energy can be harnessed by using photovoltaic (PV) cells. These consist of two different types of semiconducting materials called n-type and p-type. An electrical field is formed in the area of contact between these two materials, called the P-N junction. Upon exposure to light a photovoltaic cell releases electrons. Photovoltaic energy conversion is a
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traditional, mature, and commercially established energy-harvesting technology. It provides higher power output levels compared to other energy harvesting techniques and is suitable for larger-scale energy harvesting systems. However, its generated power and the system efficiency strongly depend on the availability of light and on environmental conditions. For example, in outdoor environment power densities up to $100\,\text{mW/cm}^2$ are available, while indoor power levels are between 100 to $1000\,\mu\text{W/cm}^2$ [6, 50]. Other factors, including the materials used for the photovoltaic cell, affect the efficiency and level of power produced by photovoltaic energy harvesters [36, 16]. Some recent prototypes of photovoltaic harvesters are described in [51, 52, 53, 54]. Known implementations of solar energy harvesting sensor nodes include Fleck [55], Enviromote [56], Trio [11], Everlast [10], and Solar Biscuit [57].

**Thermal energy harvesting** is implemented by thermoelectric energy harvesting and pyroelectric energy harvesting.

*Thermoelectric energy harvesting* is the process of creating electric energy from temperature difference (thermal gradients) using thermoelectric power generators (TEGs). The core element of a TEG is a thermopile formed by arrays of two dissimilar conductors, i.e., a p-type and n-type semiconductor (thermocouple), placed between a hot and a cold plate and connected in series. A thermoelectric harvester scavenges the energy based on the Seebeck effect, which states that electrical voltage is produced when two dissimilar metals joined at two junctions are kept at different temperatures [58]. This is because the metals respond differently to the temperature difference, creating heat flow through the thermoelectric generator. This produces a voltage difference that is proportional to the temperature difference between the hot and cold plates. The thermal energy is converted into electrical power when a thermal gradient is created. Energy is harvested as long as the temperature difference is maintained.

*Pyroelectric energy harvesting* is the process of generating voltage by heating or cooling pyroelectric materials. These materials do not need a temperature gradient similar to a thermocouple. Instead, they need time-varying temperature changes. Changes in temperature modify the locations of the atoms in the crystal structure of the pyroelectric material, which produces voltage. To keep generating power, the whole crystal should be continuously subject to temperature change. Otherwise, the produced pyroelectric voltage gradually disappears due to leakage current [59].

Pyroelectric energy harvesting achieves greater efficiency compared to thermoelectric harvesting. It supports harvesting from high temperature sources, and is much easier to get to work using limited surface heat exchange. On the other hand, thermoelectric energy harvesting provides higher harvested energy levels. The maximum efficiency of thermal energy harvesting is limited by
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the Carnot cycle [43]. Because of the various sizes of thermal harvesters, they can be placed on the human body, on structures and equipment. Some example of this kind of harvesters for WSN nodes are described in [60, 61].

**Wireless energy harvesting** techniques can be categorized into two main categories: RF energy harvesting and resonant energy harvesting.

*RF energy harvesting* is the process of converting electromagnetic waves into electricity by a rectifying antenna, or *rectenna*. Energy can be harvested from either ambient RF power from sources such as radio and television broadcasting, cellphones, WiFi communications and microwaves, or from EM signals generated at a specific wavelength. Although there is a large number of potential ambient RF power, the energy of existing EM waves are extremely low because energy rapidly decreases as the signal spreads farther from the source. Therefore, in order to scavenge RF energy efficiently from existing ambient waves, the harvester must remain close to the RF source. Another possible solution is to use a dedicated RF transmitter to generate more powerful EM signals merely for the purpose of powering sensor nodes. Such RF energy harvesting is able to efficiently delivers powers from micro-watts to few milliwatts, depending on the distance between the RF transmitter and the harvester.

*Resonant energy harvesting*, also called resonant inductive coupling, is the process of transferring and harvesting electrical energy between two coils, which are highly resonant at the same frequency. Specifically, an external inductive transformer device, coupled to a primary coil, can send power through the air to a device equipped with a secondary coil. The primary coil produces a time-varying magnetic flux that crosses the secondary coil, inducing a voltage. In general, there are two possible implementations of resonant inductive coupling: Weak inductive coupling and strong inductive coupling. In the first case, the distance between the coils must be very small (few centimeters). However, if the receiving coil is properly tuned to match the external powered coil, a “strong coupling” between electromagnetic resonant devices can be established and powering is possible over longer distances. Note that since the primary and secondary coil are not physically connected, resonant inductive coupling is considered a wireless energy harvesting technique. Some recent implementations of wireless energy harvesting techniques for WSNs can be found in [62, 63, 64].

**Wind energy harvesting** is the process of converting air flow (e.g., wind) energy into electrical energy. A properly sized wind turbine is used to exploit linear motion coming from wind for generating electrical energy. Miniature wind turbines exists that are capable of producing enough energy to power WSN nodes [65]. However, efficient design of small-scale wind energy harvesting...
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is still an ongoing research, challenged by very low flow rates, fluctuations in wind strength, the unpredictability of flow sources, etc. Furthermore, even though the performance of large-scale wind turbines is highly efficient, small-scale wind turbines show inferior efficiency due to the relatively high viscous drag on the blades at low Reynolds numbers [66, 32]. Recent examples of wind energy harvesting systems designed for WSNs include [65, 67, 68, 69].

Biochemical energy harvesting is the process of converting oxygen and endogenous substances into electricity via electrochemical reactions [70, 71]. In particular, biofuel cells acting as active enzymes and catalysts can be used to harvest the biochemical energy in biofluid into electrical energy. Human body fluids include many kinds of substances that have harvesting potential [72]. Among these, glucose is the most common used fuel source. It theoretically releases 24 free electrons per molecule when oxidized into carbon dioxide and water. Even though biochemical energy harvesting can be superior to other energy harvesting techniques in terms of continuous power output and biocompatibility [70], its performance depends on the type and availability of fuel cells. Advantages and disadvantages of using enzymatic fuel cells for energy production are described in [73]. Research efforts such as [74, 70, 71] are examples of recent proposed prototypes that use biochemical energy harvesting to power microelectronic devices.

Acoustic energy harvesting is the process of converting high and continuous acoustic waves from the environment into electrical energy by using an acoustic transducer or resonator. The harvestable acoustic emissions can be in the form of longitudinal, transverse, bending, and hydrostatic waves ranging from very low to high frequencies [75]. Typically, acoustic energy harvesting is used where local long term power is not available, as in the case of remote or isolated locations, or where cabling and electrical commutations are difficult to use such as inside sealed or rotating systems [76, 75]. However, the efficiency of harvested acoustic power is low and such energy can only be harvested in very noisy environments. Harvestable energy from acoustic waves theoretically yields 0.96μW/cm³ [77], which is much lower than what is achievable by other energy harvesting techniques. As such, limited research has been performed to investigate this type of harvesters. Examples of acoustic energy harvesting systems can be found in [78, 79].

All previously described harvesting techniques can be combined and concurrently used on a single platform (hybrid energy harvesting).
2.4 Prediction Models

Practical use of energy harvesting technologies needs to deal with the variable behavior of the energy sources, which impose the amount and the rate of the harvested energy over time. In case of predictable, non controllable power sources, such as the solar one, energy prediction methods can be used to forecast the source availability and estimate the expected energy intake [19]. Such a predictor can alleviate the problem of the harvested power being neither constant nor continuous, allowing the system to take critical decisions about the utilization of the available energy. In this section, we give an overview of the different energy predictors proposed in the literature for two popular forms of energy harvesters, namely, solar and wind harvesters.

**EWMA.** Kansal et al. [19] propose a solar energy prediction model based on an Exponentially Weighted Moving-Average (EWMA) filter [80]. This method is based on the assumption that the energy available at a given time of the day is similar to that available at the same time of previous days. Time is discretized into $N$ time slots of fixed length (usually 30 minutes each). The amount of energy available in previous days is maintained as a weighted average where the contribution of older data is exponentially decreasing. More formally, the EWMA model predicts that in time slot $n$ the amount of energy $\mu_n^{(d)} = \alpha \cdot x_n + (1 - \alpha) \cdot \mu_n^{(d-1)}$ will be available for harvesting, where $x_n$ is the amount of energy harvested by the end of the $n$th slot; $\mu_n^{(d-1)}$ is the average over the previous $d - 1$ days of the energy harvested in their $n$th slot, and $\alpha$ is a weighting factor, $0 \leq \alpha \leq 1$. EWMA exploits the diurnal solar energy cycle and adapts to seasonal variations. The prediction results very accurate in presence of scarce weather variability. However, when weather conditions are frequently changing (e.g., a mix of sunny and cloudy days in a row) EWMA does not adapt well to the variations in the solar energy profile.

**WCMA.** The prediction method Weather-Conditioned Moving Average, or WCMA for short, has been proposed by Piorno et at. [81] for addressing the shortcomings of EWMA. Similarly to EWMA, WCMA takes into account energy harvested in the previous days. However, it also consider the weather conditions of the current and of the previous days. Specifically, WCMA stores a matrix $E$ of size $D \times N$, where $D$ is the number of days considered and $N$ is the number of time slots per day. The entry $E_{d,n}$ stores the energy harvested in day $d$ at time slot $n$. Energy in the current day is kept in a vector $C$ of size $N$. In addition, WCMA keeps a vector $M$ of size $N$ whose $n$th entry $M_n$ stores the average energy observed during time slot $n$ in the last $D$ days:
\[ M_n = \frac{1}{D} \cdot \sum_{i=1}^{D} E_{d-i,n} \]

At the end of each day, \( M \) is updated with the energy just observed, overwriting the date of the previous day. The amount of energy \( P_{n+1} \) predicted by WCMA for the next time slot \( n + 1 \) of the current day is computed as \( \alpha \cdot C_n + (1 - \alpha) \cdot M_{n+1} \cdot \text{GAP}_K \), where \( C_n \) is the amount of energy observed during time slot \( n \) of the current day; \( M_{n+1} \) is the average of the energy harvested during time slot \( n + 1 \) over the last \( D \) days; \( \text{GAP}_K \) is a weighting factor providing an indication of the changing weather conditions during time slot \( n \) of the current day with respect to the previous \( D \) days, and \( \alpha \) is a weighting factor, \( 0 \leq \alpha \leq 1 \). In case of frequently changing weather conditions, WCMA is shown to obtain average prediction errors almost 20% smaller than EWMA.

An enhanced version of WCMA has been presented by Bergonzini et al. \[82\]. The authors noticed that the prediction error of WCMA shows characteristics peaks at sunrise and at sunset, especially for values of \( \alpha > 0.5 \). This is due to the fact that WCMA considers the value observed in the previous slot for energy predictions. Since at sunrise and sunset the solar conditions changes significantly, this leads to higher prediction errors. In order to address the issue, the authors propose to use a feedback mechanism, called *phase displacement regulator*, providing a sensible decrease of the WCMA prediction error.

**ETH predictor.** Moser et al. \[83\] of Zurich ETH propose a prediction method based on a weighted sum of historical data. The ETH prediction algorithm assumes solar power to be periodic on a daily basis. As in previous approaches time is partitioned into time slots of fixed length \( T \) (in practice lasting from a few minutes to an hour). During time slot \( t \) the energy generated by the power source is denoted as \( E_S(t) \). The ETH estimator unit receives in input the amount of energy harvested \( E_S(t) \) for all times \( t \geq 1 \) and outputs \( N \) future energy predictions. The prediction intervals are all of equal length \( L \), multiple of \( T \). The overall prediction horizon is \( H = N \cdot L \). At each time slot \( t \) predictions about future energy availability \( P_S(t,k) \) are computed for the next \( N \) prediction intervals as \( P_S(t,k) = P_S(t + kL), \quad 0 \leq k \leq N \). The prediction algorithm combines information about the energy harvested during the current time interval with the energy availability obtained in the past. Similar to EWMA the contribution of older data is exponentially decreasing.

The solution proposed by Noh and Kang \[84\] is similar to previous approaches. They use the EWMA equation to keep track of the solar energy profile observed in the past. In order to account for short-term varying weather conditions, they introduce a scaling factor \( \varphi_n \) to adjust future energy expectations. This factor is computed as: \( \varphi_n = \frac{x_{n-1}}{\mu_{n-1}} \), where \( x_{n-1} \) is the amount of energy harvested
by the end of slot \( n - 1 \), and \( \mu_{n-1} \) is the prediction of the amount of energy harvestable during slot \( n - 1 \) according to the EWMA. Thus, \( \varphi_n \) expresses the ratio between the actual harvested energy at time slot \( n \) and the energy predicted for the same time slot. This scaling factor is then used to adjust future predictions.

**Pro-Energy (PROfile energy prediction model)** is an energy prediction model based on using past energy observations for both solar and wind-based EHWSNs. The main idea of Pro-Energy is to use harvested profiles representing the energy available during different types of “typical” days. For example, days may be classified into sunny, cloudy or rainy and a characteristic profile may be associated to each of these types. Each day is discretized into a certain number \( N \) of time slots. Predictions are performed once per slot. The energy harvested in the current day is stored in a vector \( C \) of length \( N \). A pool of energy profiles observed in the past is also maintained in a \( D \times N \) matrix \( E \). These profiles represent the energy obtained during a given number \( D \) of typical days. Once per time slot Pro-Energy estimates the expected energy availability during the next time slot by looking at the stored profile that is the most similar to the current day. The similarity of two different profiles is computed as the Euclidean distance between their two vectors, taking into account the first \( t \) elements of the vectors, where \( t \) is the current time slot. The value predicted for the next time slot is then computed based on the value for that slot from the stored profile, possibly scaled by a factor that depends on the current weather conditions.

Pro-Energy maintains a pool of \( D \) typical profiles, each ideally representative of a different weather condition. In order to adapt predictions to changing seasonal patterns, this pool has to be periodically updated. To this aim, at the end of each day Pro-Energy checks if the current profile, i.e., the one just observed, significantly differs from other profiles. In so, an old profile is discarded and the current profile is stored in \( E \). Statistics about profile usage are maintained, so that the profile discarded from the pool is one that has been stored for a long time or that has been used infrequently. Figure 2.4 shows an example of application of the Pro-Energy algorithm over 4 days of solar predictions. During the initial time slots of October 23rd (day 1), the first stored profile is selected among the typical ones, as it is the most similar to the portion of the current day observed so far. As the day goes on, the shape of the profile changes according to the new observations. Two further different profiles are used for predictions during days 2 and 3. Then, on the fourth day, the first profile is selected again as the most similar to the current observations. Pro-Energy performance compares favorably with respect to previous solutions. For instance, because of the use of energy profiles of typical days, Pro-Energy is able to sensibly decrease prediction errors even in cases with a variable mix of sunny and cloudy days, a case where EWMA instead exhibits poor performance.
We conclude this section by mentioning an approach for energy predictions at medium-length timescales. Sharma et al. [85] explore a system for solar and wind powered sensor nodes that derives energy harvesting predictions based on weather forecast. The method is based on the claim that at medium-length timescales (3 hour to 3 days) using weather forecasting data provides greater accuracy than energy predictions based on past observation. The reason they give for the scarce performance of “traditional” predictors is the fact that weather patterns are not consistent in many regions of the United States. They thus formulate a model for solar panels and wind turbines that is able to convert weather forecast data into energy harvesting predictions. The effectiveness of the proposed method is measured by comparing the performance of their solution to that of simple energy predictors based on past observations. A comparison with the predictors cited here is not presented.

2.5 Protocols for EHWSNs

In this section we describe protocols for EHWSNs focusing specifically on those from research areas that have received greater attention, namely, allocation of tasks to the sensors, and MAC and routing solutions.

2.5.1 Task Allocation

Many applications for energy harvesting sensor networks, such as structural health monitoring, disaster recovery and health monitoring, require real-time reliable network protocols and efficient task scheduling. In such networks, it is important to dynamically schedule node and network
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tasks based on remaining energy and current energy intake, as well as predictions about future energy availability.

In this section, we first provide a classifications of tasks based on their type and characteristics, and then we present an overview of task scheduling algorithms.

Tasks can be categorized as follows:

1. **Periodic vs. Aperiodic.** Depending on their arrival patterns over time, tasks are divided into periodic and aperiodic. Periodic tasks arrive regularly and their inter-arrival time is fixed. Aperiodic tasks, also called on-demand, have arbitrary arrival patterns.

2. **Preemptive vs. Non-preemptive.** A preemptive active task may be preempted at any time, while a non-preemptive task cannot be paused or stopped at any time during its execution.

3. **Dependent vs. Independent.** A task is defined to be independent if its execution does not depend on the running or on the completion of other tasks. A dependent task cannot run until some other tasks have completed their executions.

4. **Multi-version tasks.** Multi-version tasks have multiple versions, each with different characteristics in terms of time, energy requirements and priority.

5. **Node vs. Network tasks.** Each EHWSN node can schedule two kind of tasks: Node and network tasks. Tasks such as sensing, computing, and communication can be considered node tasks. Examples of network tasks are routing, leader election, cooperative communication, etc. Due to different characteristics of node and network tasks, they need different scheduling and energy budgeting algorithms.

Each task is characterized by:

- **Execution time.** The amount of time during which a task is running on the CPU.

- **Deadline:** The time by which the task should be completed. If the task deadline passes before completing the task, a deadline violation occurs.

- **Power requirement:** The amount of energy required by a task to be successfully completed. This may include the energy necessary to perform sensing, computation, and communication activities.
• **Reward.** Each task $T$ may be associated with a value or reward $r$ indicating its importance. Rewards can be a function of a task priority [86, 87, 88, 89], invocation frequency [90], utility [91], or any other metric. An instance of task $i$, $T_i$, contributes $r_i$ units to the total system reward only if it completes by its deadline. The reward (priority) of each tasks may change over time.

• **Running speed:** The speed of the task currently executing. Running speed can be adjusted by employing Dynamic Voltage and Frequency Selection (DVFS) techniques, which lower the operating frequency of the processor (CPU speed) and reduce its energy consumption [86]. As the processor changes its operational frequency and voltage, the task execution speed varies accordingly. Adjusting task speed is desirable because it allows a node to adapt the execution speed of a task based on the energy source availability.

Task scheduling protocols for EHWSNs can be categorized depending on the type of tasks they schedule. At the highest level, task scheduling solutions can be divided into protocols that schedule node tasks and protocols that schedule network tasks.

*Scheduling protocols for node tasks.* The **Lazy Scheduling algorithm** (LSA) [92] is one of the earliest work in EHWSN task scheduling. Tasks are dynamically scheduled depending on future energy availability, the capacity of the energy storage, the residual energy, and the maximum power consumption of the sensor node. In particular, LSA aims at keeping the energy storage level as high as possible and starts executing a task $T$ at time $t$ only if the following conditions are met: $T$ is ready for execution; $T$ has the earliest deadline among those of tasks that are ready; the sensor node will not run out of energy if it executes $T$ to completion (at its maximum power), and $T$ will not miss its deadline if the node starts executing it at time $t$. LSA introduces the concept of energy variability characterization curve (EVCC), which captures the dynamics of the energy source. This concept is used to determine the schedulability of a set of tasks. More specifically, the LSA uses an offline schedulability test that, given the EVCC of the energy source, the capacity of the energy storage, and the maximum power requirement of a running task, determines whether all the deadlines of a given set of tasks can be met or not. LSA suffers several drawbacks. For instance, in realistic application a task actual energy consumption does not depend on the worst case energy demand, but rather on factors including the sensor operational state and the circuitry used to perform the task. Furthermore, LSA does not consider dependency among tasks. Finally, the performance of LSA is highly dependent on the accuracy of predicted available energy, which is challenging and, as mentioned, prone to errors.
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The STAM-STFU protocol by Audet et al. \[93\] combines the operation of two scheduling algorithms, namely, Smooth to Average Method (STAM) and Smooth to Full Utilization (STFU), for scheduling a set of tasks offline, with the aim of reducing the total task deadline violations. STAM-STFU handles energy uncertainty and deadline constraints without relying on any energy prediction model. STAM-STFU introduces the concept of virtual tasks to smooth out the energy consumption in the long run. Each real (physical) task has a corresponding virtual task that has the same arrival time, but equal or longer duration, and equal or smaller energy demand. Virtual tasks are distributed over a longer execution time than their real counterparts, but each consumes the same amount of energy as its corresponding real task. A scheduling for virtual tasks that meets the deadline constraints will not violate the deadline of any real task. STAM-STFU smooths out real task consumption to approximately the average power required by all tasks and then schedules them by using the Earliest Deadline First algorithm. Simulation results show that STAM-STFU performs better than non-energy-aware static scheduling algorithms. It is also shown that its performance is similar to LSA that, with the additional benefit of not requiring a prediction model. It is important to note that STAM-STFU is only suitable for offline scheduling, which requires that tasks and their deadlines are known in advance.

The goal of the multi-version scheduling algorithm \[90\] is to execute the most important and valuable periodic tasks while meeting all the timing and energy constraints. Each task is assumed to have multiple versions, each with different characteristics and reward. “Easier” versions of a task execute faster, require less energy, and produce less accurate and valuable results. This static (offline) scheduling solution determines the best task versions and their execution speeds that maximize rewards. Selection is based on worst case scenario assumptions, i.e., the worst-case task execution times, worst-case number of speed changes, minimum harvesting rate, and worst-case battery discharging rates, are assumed and known in advance. However, a system does not always consume or harvest energy as in the worst-case, and often time the selection of tasks is not optimal. To obviate to this problem, the authors propose dynamic algorithms according to which the node periodically check the current energy storage and accordingly reschedule the tasks.

In \[94\] EL Ghor et al. describe an on-line scheduling algorithm, called EDeg (Earliest Deadline with energy guarantee), a variant of the Earliest Deadline First algorithm. EDeg maintains energy neutrality by making sure that before a task is started sufficient energy is in storage for all future occurring tasks. This protocol assumes that future task arrival times are known. Task execution is delayed until recharging has produced enough energy to meet the task deadline. When the stored energy drops below a threshold EDeg stops the current tasks and starts recharging the battery up
to a level that support task completion. Thus, tasks never run in absence of enough energy. The requirement to know in advance the arrival times, the deadlines, and the energy demands of the tasks, seriously limits the applicability of this algorithm in real-life application scenarios.

Steck et al. [91] present a task utility scheduling protocol with two main goals: First, given a certain level of utility, determine the expected execution time and energy consumption of a set of tasks. Second, given a time constraint, find the maximum achievable utility for the set of tasks. This algorithm schedules the tasks by balancing task utility and execution time subject to an energy constraint aimed to ensure the energy neutrality of the system. The relationship among the tasks is assumed to be known and modeled by a Directed Acyclic Graph (DAG). In addition, the task execution times, past energy harvesting information, tasks qualities, and utility relationships are given in advance. For most applications, the utility is modeled as accuracy and as a function of the task priority. A task with higher priority is executed with the higher utility.

In [95], an energy-aware DVFS (EA-DVFS) scheduling algorithm is proposed that dynamically matches its schedules to the stored energy and harvestable energy in the future. Specifically, tasks are executed at full speed if the stored energy is sufficient. Execution speed is slowed down when the stored energy is not sufficient. This work has been extended further in [87] by the adaptive scheduling and DVFS algorithm (AS-DVFS). AS-DVFS adaptively tunes the operation voltage and frequency of a node processor whenever possible while maintaining the time and energy constraints. The goal of AS-DVFS is to reach a system-wide energy efficiency by scheduling and running the tasks at the lowest possible speed and allocating the workload to the processor as evenly as possible. Moreover, it decouples the timing and energy constraints, addressing them separately. A harvesting-aware DVFS (HA-DVFS) algorithm is proposed in [86] to further improve the system performance and energy efficiency of EA-DVFS and AS-DVFS. In particular, the main goals of HA-DVFS are to keep the running speed of the tasks always at the lowest possible value and avoid wasting harvested energy. Based on the prediction of the energy harvesting rate in the near future, HA-DVFS schedules the tasks and tunes the speed and workload of the system to avoid energy overflow. Three different time series prediction techniques, namely regression analysis, moving average, and exponential smoothing, are used for predicting the harvested energy. Similar to AS-DVFS, HA-DVFS decouples the energy constraints and timing constraints to reduce the complexity of scheduling algorithm.

Another DVFS-based task scheduling algorithm is presented in [88]. The basic DVFS ideas are combined with a linear regression model. The model is used to associate the number of tasks and their complexity to the execution time, energy consumption, and data accuracy. The main objectives of this protocol are maximizing system performance given the current energy availability,
increasing the efficiency of energy utilization, and improving task accuracy. The protocol is deemed specifically suitable for structural health monitoring applications, since the events generated by this kind of applications concern mostly periodic tasks instead of sporadic externally triggered events.

*Scheduling protocols for network tasks.* Task allocation at the network level concerns matching the sensing resources of a WSN to appropriate tasks (missions), which may come to the network dynamically. This is a non trivial task, because a given node may offer support to different missions with different levels of accuracy and fit (*utility*). Missions may vary in importance (*profit*) and amount of resources they require (*demand*). They may also appear in the network at any time and may have different duration. The goal of a sensor-missions assignment algorithm is to assign available nodes to appropriate missions, maximizing the profit received by the network for mission execution. Although solutions for WSNs with battery-operated nodes have been proposed for this problem [96, 97, 98, 99], until recently [100] no attention has been given to networks whose nodes have energy harvesting capabilities. For these networks, new paradigms for mission assignments are needed, which take into account that nodes currently having little or no energy left might have enough in the future to carry out new missions. These solutions should also consider that energy availability is time-dependent and that energy storage is limited in size and time (due to leakage) so that energy usage should be carefully planned to minimize waste of energy.

*EN-MASSE* [100] is a decentralized heuristic for sensor-mission assignment in energy-harvesting wireless sensor networks, which effectively takes into account the characteristics of an energy harvesting system to decide which node should be assigned to a particular mission at a given time. It is able to handle hybrid storage systems consisting of multiple energy storage devices (supercapacitor and battery) and to adapt its behavior according to the current and expected energy availability of the node, while maximizing the efficient usage of the energy harvested. EN-MASSE has been designed for sensing task assignment. Each mission arrives in the network at a specific geographic location $l_i$. In EN-MASSE the sensor node closest to $l_i$ is selected as the *mission leader* and coordinates the process of assigning nodes to the mission. The communication protocol described in [97, 98] is selected for exchanging information between the mission leader and the nearby nodes. Each time a new mission arrives in the network, the leader advertises mission information, including mission location, profit and demand, to its two-hop neighbors, starting the *bidding phase* for the mission. During this bidding phase, each node receiving the mission advertisement message sent by the leader, autonomously decides whether to bid for participating to the mission or not. Such a decision is taken accordingly to the bidding scheme used by the node. EN-MASSE uses an energy prediction model to estimate the energy a node will receive from the ambient source and to classify
missions. Different predictors, such as the ones described in Section 2.4, may be used in combination with EN-MASSE.

2.5.2 Harvesting-aware Communication Protocols: MAC and Routing

Harvesting capabilities have changed the design objectives of communication protocols for EHWSNs from energy conservation to opportunistic optimization of the use of the harvested energy. This fundamental change calls for novel communication protocols. The aim of this section is to explore the solutions proposed so far for EHWSN medium access control (MAC) and routing.

MAC protocols. We describe exemplary MAC protocols for EHWSNs, which include ODMAC [101], EA-MAC [102, 103], MTTP [104], and PP-MAC [105].

**ODMAC** [101] is an on demand MAC protocol for EHWSNs. It is based on three basic ideas: Minimizing wasting energy by moving the idle listening time from the receiver to the transmitter; adapt the duty cycle of the node to operate in the energy neutral operation (ENO) state, and reducing the end-to-end delay by employing an opportunistic forwarding scheme. In ODMAC, transmission scheduling is accomplished by having available receivers broadcasting a beacon packet periodically. Nodes wishing to transmit listen to the channel, waiting for a beacon. Upon receiving a beacon, the transmitter attempts packet transmission to the source of the beacon. Setting the beacon period imposes a trade-off between energy consumption and end-to-end latency: When the beacon period is short, more energy is consumed for transmitting beacons. Longer beacon periods result in higher energy conservation. Figure 2.5 shows the operation mechanism of the ODMAC protocol. ODMAC supports a dynamic duty cycle mode, in which the sensing period and the beacon periods of each node is periodically adjusted according to the current power harvesting rate. To this end, a battery level threshold is selected and periodically compared the current battery level to determine if the duty cycle should be increased or decreased. ODMAC also includes the concept of opportunistic forwarding, in which, instead of waiting for a specific beacon, each frame is forwarded to the sender of the first beacon received as long as it is included in a list of potential forwarders. In ODMAC it is assumed that charging (harvesting) is independent of sensor node operations and thus a sensor can harvest available energy during all operational states, i.e., irrespective of whether it is sleeping, listening, transmitting, etc. ODMAC is not suitable to be used in lossy environment, as it does not acknowledge and retransmits packets.

**EA-MAC** [102, 103] is a MAC protocol proposed for EHWSNs with RF energy transfer. EA-MAC uses the node energy harvesting status as a control variable to tune the node duty cycles and
back-off times. To this end, two adaptive methods, energy adaptive duty cycle and energy adaptive contention algorithm, are proposed to manage the node duty cycle and back-off time depending on the harvested power rate. EA-MAC is similar to the unslotted CSMA/CA algorithm in IEEE 802.15.4 [106], but its sleep duration, back-off times, and state transitions are controlled by the average amount of harvestable energy. When a node harvested energy level is equal to the energy required to transmit a packet, the node transitions from sleep state to active state. Then it follows a CSMA/CA scheme to transmit the packet. If the channel is idle during the clear channel assessment (CCA) period, the node transmits a data packet. If the channel is busy, the node decides to either perform the random backoff procedure or terminate the CSMA/CA algorithm. The number of backoff slots depends on the current energy harvesting rate. Analytical models for the throughput and fairness of EA-MAC are provided and validated by simulations [103]. Similar to ODMAC, EA-MAC assumes the sensor node can harvest energy in any operational states. EA-MAC does not consider some important application requirements, such as end-to-end delay, and provides no mechanism to optimize network performance and lifetime. In addition, EA-MAC suffers form the hidden terminal problem, which results in increased collisions. Finally, its performance is not compared to any other protocol, such as slotted or unslotted CSMA/CA.

The Probabilistic polling (PP-MAC) protocol [105] is a polling-based MAC mechanism that leverages the energy characteristics of EHWSNs to enhance the performance of traditional polling schemes in terms of throughput, fairness and scalability. PP-MAC is similar to the polling protocol described in [107]: The sink broadcasts a polling packet and the polled sensor responds
with a packet transmission (single-hop topology). Instead of carrying the ID of a specific sensor, the polling packet contains a contention probability that the receiving sensor nodes use to decide whether to transmit their packet or not. The contention probability is computed based on current energy harvesting rate, number of nodes, and packet collisions. The probabilistic polling protocol increases the contention probability gradually when no sensor responds to the polling packet. It decreases it whenever there is a collision between two or more sensor nodes. As a result, and based on an additive-increase multiplicative-decrease (AIMD) mechanism, the contention probability is decreased when more nodes are added to the EHWSN, and increased when nodes fail or are removed from the network. Moreover, in case of increase/decrease of the average energy harvesting rates, the contention probability is decreased/increased accordingly. PP-MAC uses the charge-and-spend harvesting strategy in which it first accumulates enough energy and then goes to the receive state to listen and receive the polling packet. Nodes return back to charging state either when their energy falls below the energy required to transmit a data packet or after transmitting their packet. Energy is assumed to be harvested only while in charging state. Analytical formulas and analysis of the throughput performance of PP-MAC is presented and validated by simulations. PP-MAC does not support multi-hop EHWSNs.

The multi-tier probabilistic polling (MTPP) protocol [104] extends probabilistic polling à la PP-MAC to multi-hop data delivery in EHWSNs with no energy storage, i.e., whose operations are powered solely by energy currently harvested (charge-and-spend harvesting policy). The polling packets generated by the sink are sent to the immediate neighbors of the sink, and these nodes forward them to nodes in following tiers, in a “wave-expanding” fashion (Figure 2.6).
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data packets are broadcast and relayed, respectively, from tier to tier until they reach their destination. As the number of tiers increases, the overhead of polling packets and packet collisions also increase, imposing higher latencies. Analytical models for energy consumption, energy harvesting, energy storage, and interference as well as the delivery probability are presented in [108] and validated by numerical analysis.

A comparative summary of the characteristics of these presented MAC protocol is presented in Table 2.1.

<table>
<thead>
<tr>
<th>MAC Protocol</th>
<th>ODMAC</th>
<th>EA-MAC</th>
<th>PP-MAC</th>
<th>MTTP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topology</td>
<td>Multi-hop</td>
<td>Single-hop</td>
<td>Single-hop</td>
<td>Multi-hop</td>
</tr>
<tr>
<td>Harvesting policy</td>
<td>Store</td>
<td>Store</td>
<td>Charge-and-spend</td>
<td>Charge-and-spend</td>
</tr>
<tr>
<td>Harvesting technology</td>
<td>Generic</td>
<td>RF energy transfer</td>
<td>Solar</td>
<td>Solar</td>
</tr>
<tr>
<td>Latency</td>
<td>Increases with traffic</td>
<td>Fair</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Channel access type</td>
<td>CSMA/CA</td>
<td>CSMA/CA</td>
<td>Polling</td>
<td>Polling</td>
</tr>
<tr>
<td>Scalability</td>
<td>Good</td>
<td>Weak</td>
<td>Good</td>
<td>Good</td>
</tr>
<tr>
<td>Communication patterns</td>
<td>All</td>
<td>Convergecast</td>
<td>Convergecast</td>
<td>Convergecast &amp; Broadcast</td>
</tr>
<tr>
<td>Performance evaluation</td>
<td>OPNET simulations</td>
<td>OPNET simulations</td>
<td>Real-measurements &amp; QualNet</td>
<td>Real-testbed</td>
</tr>
<tr>
<td>Use of control packets</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Adaptivity to changes</td>
<td>Fair</td>
<td>Good</td>
<td>Good</td>
<td>Good</td>
</tr>
</tbody>
</table>

Table 2.1: Comparison of MAC protocols for EHWSNs.

Routing protocols. Energy-efficient routing has been widely explored for battery operated WSNs. EHWSNs exhibit unique characteristics and among their man objective there is not only extending the network lifetime, but also the maximization of the workload that the network can sustain, given the source-dependent energy availability of the nodes [109]. This is the rationale behind protocols for routing in EHWSNs that we present in this section.

**HESS.** In [110], Pais et al. propose a routing protocol termed HESS for hybrid energy storage systems combining a supercapacitor with a rechargeable battery. Their approach is to favor routes that use more energy from supercapacitors and that go through nodes with higher harvesting rates. Their work stems from the fact that a rechargeable battery can only sustain a limited amount of recharge cycles before its capacity falls below 80% of its original capacity. The authors propose a cost-benefit function that reflects the cost and revenue of choosing a specific node as a relay for a packet. Such a function considers several factors, including the relay hop count, its residual battery and supercapacitor energy, the energy it harvested previously, the remaining cycles of its battery and its queue occupancy. Nodes with higher residual energy, harvesting rate and remaining battery cycles are preferred as relays, while choosing nodes with higher hop count or lower transmission queue...
availability is less desirable. These cost/benefit factors are combined together, opportunely weighted, in order to account for both desirable and undesirable parameters. The overall goal of HESS is to minimize the cost of each end-to-end transmission. A simulation-based performance evaluation shows that HESS provides an average 10% increase of network residual energy with respect to the Energy Aware Routing (EAR) protocol [111], without compromising the data packet delivery ratio.

DEHAR (Distributed Energy Harvesting Aware Routing Algorithm, Jakobsen et al. [112]) is an adaptive and distributed routing for EHWSNs that calculates the shortest paths to the sink based on hop count and the energy availability of the nodes. To add energy-harvesting awareness to the algorithm, a local penalty is assigned to each node. This penalty, dynamically updated, is inversely proportional to the fraction of energy available to the node. When the energy buffer of the node is fully charged, this penalty should ideally be zero, while it should tend to infinity when the node has depleted its energy. When a change in the local penalty of a node occurs, it advertises it to its immediate neighbors. For each node, the local penalty is combined with distance from the sink to define the node energy distance, which is used by other nodes when choosing a potential relay. The energy distance of a node may become a local minimum if the penalty of a node neighbor is changed due to variations in its energy availability. To solve this problem, distributed penalties are introduced. Each time a node receives an energy update from a neighbor, it checks if it has become a local minimum. If this is the case, it increases its distributed distance penalty and advertises it to its immediate neighbors. Distributed and local penalty of a node are finally merged in a total penalty that is distributed to neighbor nodes.

EHOR: Energy Harvesting Opportunistic Routing (Eu et al. [113]) is an opportunistic routing protocol for EHWSNs powered solely by energy harvesters (no batteries). Nodes of EHWSNs powered only by harvested energy are normally awake for a short period of time, then they shut down to recharge. To determine the best active relays in its neighborhood, a node partitions potential relays in groups, or regions, based on their distance from the sink and on the residual energy of the nodes in the region. After receiving a data packet, the potential relay that is the closest to the sink rebroadcasts it. Each node in the network follows a charging cycle consisting of a charging phase, during which the power consumption is minimal and the node waits to be recharged by the harvested energy, a receive phase, to which the node switch when it is fully charged, and an optional transmit phase. Simulation results show that EHOR achieves good performance and outperforms traditional opportunistic routing protocols. EHOR, however, assumes that the network topology is linear, i.e., that nodes are uniformly deployed over a given interval and does not work in 2D topologies.

Noh and Yoon introduce D-APOLLO (Duty cycle-based Adaptive toPOLogical KR aLgO-
a harvesting-aware geographic routing protocol. Their approach aims at maximizing the utilization of the harvested energy and reduce latency by dynamically and periodically adapt the duty-cycle and the knowledge range (KR) of each node. The knowledge range of each node is the topological extent of the information that it collects. Dimensioning the KR involves a trade-off between the optimality of the path produced by the routing algorithm and the energy needed to collect and maintain a larger quantity of information about a node neighbors. The duty cycle of the nodes and their knowledge range are usually fixed in battery-operated WSNs. D-APOLLO, instead, periodically tries to find the duty cycle and the knowledge range that maximize utilization of the harvested energy based on the expected harvesting power rate, the residual energy of the node and the predicted energy consumption.

The Energy-opportunistic Weighted Minimum Energy (E-WME, Lin et al. [115]) calculates the shortest path to the sink based on a cost function metric that considers the residual energy of the node, its battery capacity, it harvesting power rate and the energy required for receiving and transmitting packets. The cost of each node is an exponential function of the nodal residual energy, a linear function of the transmit and receive energies, and an inversely linear function of the harvesting power rate. The authors show that as an online protocol E-WME has an asymptotically optimal competitive ratio and that it can lead in practice to significant improvements in the performance of EHWSNs with respect to other harvesting-unaware routing protocols.

Bogliolo et al. present a modified version of the Ford-Fulkerson algorithm to determine the maximum energetically-sustainable workload of an EHWSN [116]. Their Randomized Max-Flow (R-MF) protocol, and its enhancement Randomized Minimum Path Recovery Time (R-MPRT) [109], select the edge over which to route the packet with probability proportional to the maximum flow through that edge. More specifically, in R-MF and R-MPRT the cost $C_{u,v}$ of routing a packet through a link $(u, v)$ is expressed as

$$C_{u,v} = \frac{p_u}{e_{u,v}^{\text{routing}}},$$

where $p_u$ is the harvesting power rate of node $u$, and $e_{u,v}^{\text{routing}}$ is the energy needed to process or generate a packet at node $u$ and to transmit it to node $v$ through the link $(u, v)$.

Hasenfratz et al. analyze and compare three state-of-the-art routing protocols for EHWSNs: R-MF, E-WME and R-MPRT [117]. In their work, they show the influence of various real-life settings on their performance, namely, 1) the usage of a low-power MAC protocol instead of an ideal one; 2) the effect of considering a realistic wireless channel, and 3) the influence of the
They also propose a modified version of the R-MPRT algorithm, which is able to outperform R-MPRT in scenarios where little energy is harvested from the environment. More precisely, they suggest to modify Equation (2.1) as follows:

\[ C_{u,v} = \frac{E_u}{e_{u,v}^{\text{routing}}} \]  

(2.2)

where \( E_u \) is the amount of energy available at node \( u \), and \( e_{u,v}^{\text{routing}} \) is the energy needed to process or generate a packet at node \( u \) and transmit it to node \( v \) through the link \((u, v)\).

In [118], Zeng et al. propose two geographic routing algorithms, called GREES-L and GREES-M, which take into account energy harvesting conditions and link quality. Each node is required to maintain its one-hop neighbor information including the neighbors location, residual energy, energy harvesting rate, energy consuming rate, and wireless link quality. While forwarding a packet towards its destination, the nodes in the network try to balance the energy consumption across their neighbors, by minimizing a cost function combining the information they maintain. Such cost function is defined based on two factors, namely, the geographical advance per packet transmission and the energy availability of the receiving node. The difference between GREES-L and GREES-M is in the way they combine the two factors: GREES-L uses a linear combination of them, while GREES-M multiplies them. GREES-L and GREES-M only consider as potential relay neighbor nodes that provide positive advancement towards the sink, which is typical of greedy geographic forwarding. GREES-L and GREES-M have been shown to be more energy efficient than the corresponding residual-energy-based protocols via simulations.

There are two important quality metrics to take into account while comparing energy harvesting techniques. First is the power density and the second is conversion efficiency. The power density is the rate of harvested energy per unit volume, area, or mass. The common metrics of power density include: watts per square centimeter and watts per cubic centimeter. The other important property of energy harvesting is the conversion efficiency, which is defined as the ratio of the harvested electrical power to the harvestable input power. Note that energy conversion efficiency is a dimensionless number between 0 to 100%. Table 2.2 compares the power density and conversion efficiency of different energy harvesting techniques.

2.6 Final Remarks

This chapter covers the fundamental aspects of EHWSNs, ranging from the architecture of a EHWSN node and of its energy subsystem to protocols for task allocation, MAC and rout-
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<table>
<thead>
<tr>
<th>Energy harvesting technique</th>
<th>Power density</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Photovoltaic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoors (direct sun)</td>
<td>15 mW/cm²</td>
<td>Highest: 32 ± 1.5%</td>
</tr>
<tr>
<td>Outdoors (cloudy day)</td>
<td>0.15 mW/cm²</td>
<td>Typical: 25 ± 1.5%</td>
</tr>
<tr>
<td>Indoors</td>
<td>&lt;10 µW/cm³</td>
<td></td>
</tr>
<tr>
<td>Thermoelectric</td>
<td></td>
<td>±0.1%</td>
</tr>
<tr>
<td>Human</td>
<td>30 µW/cm²</td>
<td>±3%</td>
</tr>
<tr>
<td>Industrial</td>
<td>1 – 10 µW/cm³</td>
<td>±3%</td>
</tr>
<tr>
<td>Pyroelectric</td>
<td>8.64 µW/cm²</td>
<td>3.5%</td>
</tr>
<tr>
<td>at temperature rate 8.5°C/s</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Piezoelectric</td>
<td>250 µW/cm³</td>
<td></td>
</tr>
<tr>
<td>330 µW/cm³ (shoe inserts)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electromagnetic</td>
<td></td>
<td>a</td>
</tr>
<tr>
<td>Human motion</td>
<td>1 – 4 µW/cm³</td>
<td></td>
</tr>
<tr>
<td>Industrial</td>
<td>306 µW/cm³</td>
<td></td>
</tr>
<tr>
<td>Electrostatic</td>
<td>50 – 100 µW/cm³</td>
<td></td>
</tr>
<tr>
<td>RF</td>
<td></td>
<td>a</td>
</tr>
<tr>
<td>GSM 900/1800 MHz</td>
<td>0.1 µW/cm²</td>
<td>50%</td>
</tr>
<tr>
<td>WiFi 2.4 GHz</td>
<td>0.01 µW/cm²</td>
<td></td>
</tr>
<tr>
<td>Wind</td>
<td>380 µW/cm³ at speed 5 m/s</td>
<td>5%</td>
</tr>
<tr>
<td>Acoustic Noise</td>
<td>0.96 µW/cm³ at 100 dB</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.003 µW/cm³ at 75 dB</td>
<td></td>
</tr>
</tbody>
</table>

* Max power and the efficiency are source dependent.
* Excluding the transmission efficiency.
* Noise power densities are theoretical values.

Table 2.2: Comparison of power density and efficiency of different energy harvesting techniques

ing, passing through models for predicting energy availability. With the advancement on energy harvesting techniques, and the development of small factor harvester for many different energy sources, EHWSNs are poised to become the technology of choice for the host of applications that require network functionalities for years or even decades. Through the definition of new hardware and communication protocols specifically tailored to the fundamentally different models of energy availability, new applications can also be conceived that rely on “perennial” functionalities from networks that are truly self-sustaining and with low environmental impact.
Chapter 3

Reliability Modeling of Energy Harvesting Sensor Nodes

3.1 Introduction

Energy harvesting wireless sensor networks (EHWSNs) are made up of wireless sensor nodes powered by rechargeable batteries that are replenished through energy scavenged from renewable or ambient sources. Such a charging paradigm extends the network lifetime by reducing the charge drawn from the battery, prevents disruptions owing to battery replacement, and ensures environmentally friendly operation. However, as the residual energy at the node is time varying, and is subject to a variety of other factors, it is a challenge for the network designer to formulate closed form expressions that indicate future energy levels and lifetime of a EHWSN node. The analytical framework proposed in this chapter, called Stochastic Analysis and aVailability of Energy (SAVE), takes the first step towards this direction.

Recent research on analyzing the lifetime and energy consumption in “classical,” battery-limited WSNs has been presented in [129, 130, 131] (average analysis) and [132, 133] (distribution analysis). However, the key consideration of re-charging the energy reserve is not considered in these works. Seyedi et al. present a Markov-based model for energy harvesting nodes in a body sensor network [134]. The work provides an an analysis of the probability of event loss due to energy depletion. Moreover, Ventura and Chowdhury present MAKERS, a Markov based model for one or multiple-sources energy harvesting nodes in WSNs [135]. This work provides analytical model for predicting the probability of a sensor running out of energy with very low computational complexity.
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In addition, it can model energy harvesting sensors equipped with multiple energy harvesting boards. Sus et al. present DTMC for environmentally powered sensor nodes for assessing statistical properties such as the probability of achieving a given operation time and the expected downtime \[136\]. While re-charging is considered, these models are examples of average analysis, where only the long term, average behavior of the nodes is ascertained, and do not consider the stochastic nature of energy availability.

SAVE is a general analytical framework that provides a stochastic tool for the analysis of the residual energy and the lifetime distribution of EHWSN nodes. We model the energy harvesting wireless sensor node (harvesting node, from now on) as a stochastic semi-Markov process and introduce a new analysis technique, called energy transient analysis, for the computation of the net consumed energy distribution. The amount of consumed and harvested energy in each state of a node are modeled as random variables, depending on discharging and recharging rates and on the holding time distribution of that state. The main contributions of this chapter include the following: 

(i) We introduce SAVE for node residual energy and lifetime predictions at any time, based on the distributions of harvested energy, net-consumed energy (by processing, wireless re/transmissions, and sleep-awake cycles), and node lifetime. 

(ii) We show that SAVE is not limited to exponential or fixed holding time distributions in each Markov state. The operational states can have general and arbitrary holding time distributions, resulting in a more accurate and flexible analytical framework. 

(iii) We present a new technique called energy transient analysis serving as a tool for deriving the energy distributions based on the semi-Markov process of a harvesting node. This technique is harvesting technology- and harvesting node-independent, thus being applicable in a wide variety of practical settings.

3.2 The SAVE Analytical Framework

We consider nodes equipped with one or multiple energy harvesting modules, working under different energy sources, each with their independent charging and discharging rates. SAVE models a harvesting sensor node as a semi-Markov process (SMP) in which each state corresponds to a node operational mode. A SMP is a type of stochastic process whose states change as in a Markov chain, but where the permanence in a particular state happens for a random amount of the time (called holding time), following a given distribution. The holding time depends on the current state and on the next state to be visited. In a SMP, each state is associated with one or more reward variables called reward rates. In the case of SAVE, every state \(i\) has two reward rates: Power discharging
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(battery consumption) rate \( d_i \) and power recharging (energy replenishment) rate \( r_i \). The discharging rate depends on the node hardware specifications and on the node operation of that state. The power recharging rate depends on the renewable energy source.

With \( X_h = \{X(t) : t \geq 0\} \) we represents the SMP of the harvesting node \( h \) with sample states \( S = \{1, 2, \ldots, M\} \), \( M \) being the number of a harvesting node operational states. The random variable \( X(t) \) indicates the state of the system at time \( t \). The Markov renewal process \( Z = \{(Z_n, T_n); n \geq 0\} \) is connected to the SMP \( X_h \) as follows:

\[
X(t) = Z_n, \ T_n \leq t < T_{n+1},
\]

where \( n \) is the number of state transitions that has taken place by time \( t \), \( Z_n \in S \) is the state after the \( n^{th} \) transition and \( T_n \) is the time of the \( n^{th} \) transition. The state transition probability \( P_{ij} \), which governs the change from state \( i \) to state \( j \), is defined as follows:

\[
P_{ij} = Pr\{X(T_1) = j | X(0) = i\}.
\]

Accordingly, \( P = [p_{ij}] \) is the transition probability matrix. The kernel of the semi-Markov process is independent of the number \( n \geq 0 \) of transitions, and it is defined as:

\[
K(i, j, t) = Pr(Z_{n+1} = j, T_{n+1} - T_n \leq t | Z_n = i),
\]

or, equivalently:

\[
K(i, j, t) = P_{ij}Q_{ij}(t).
\]

In the latter equation \( Q_{ij}(t) \) denotes the holding time distribution of state \( i \), after a transition from state \( i \) to state \( j \) has occurred. More specifically:

\[
Q_{ij}(t) = Pr(T_{n+1} - T_n \leq t | Z_{n+1} = j, Z_n = i).
\]

The state transition probabilities and holding time distributions depend on the specific network and protocol parameters.

The matrix \( K(t) = [K(i, j, t)] \) is the kernel matrix of the harvesting node and stores information on the harvesting node operations. This is the information we need for computing the energy and node lifetime distributions. In other words, the stochastic nature of the harvesting node is captured by the kernel of its SMP. The distribution of the holding time in a particular state \( i \) is obtained from the kernel matrix of the SMP as follows:
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\[ Q_i(t) = \sum_{j \in S} K(i, j, t). \]

Fig. 3.1 shows two generic states of the SMP representing a harvesting node. The time-varying behavior of a harvesting node from state \( i \) to state \( j \) is expressed by the transition probability \( P_{ij} \) and the holding time distribution \( Q_{ij}(t) \), while the power discharging and recharging rates capturing the consumed and harvested energies.

![Figure 3.1: A harvesting node as a semi-Markov process.](image)

3.2.1 Residual Energy Distribution

The amount of residual energy at a harvesting nodes over time plays a key role in fundamental network functions, such as its connectivity, coverage and lifetime. In this section, we derive the distribution of the energy available at a harvesting node at a given time \( T \).

The amount of energy consumed in state \( i \) is a random variable \( E_i \) that depends on the discharging rate \( d_i \) and on the probability distribution of the holding time in that state. Similarly, the amount of harvested energy in state \( i \) is a random variable \( H_i \) that depends on the recharging rate \( r_i \) and the holding time distribution. The energy consumption distribution in state \( i \) when a transition from state \( i \) to state \( j \) occurs, is as follows:

\[ E_{ij}(e) = Pr(E_i \leq e|Z_{n+1} = j, Z_n = i). \]

For example, if the discharging rate in state \( i \) is \( d_i \) and \( Q_{ij}(t) \) is the holding time distribution before the harvesting node moves into state \( j \), the energy consumption distribution \( E_{ij}(e) \) is:

\[ E_{ij}(e) = Q_{ij}\left(\frac{e}{d_i}\right). \]
Similarly, the energy harvesting distribution in state $i$ when SMP moved from state $i$ to $j$ is:

$$H_{ij}(e) = Pr(H_i \leq e | Z_{n+1} = j, Z_n = i).$$

The unconditional energy consumption and harvesting distributions in state $i$ when a transitions form state $i$ to state $j$ occurs are:

$$E(i, j, e) = Pr(Z_{n+1} = j, E_i \leq e | Z_n = i) = P_{ij} E_{ij}(e)$$

and:

$$H(i, j, e) = Pr(Z_{n+1} = j, H_i \leq e | Z_n = i) = P_{ij} H_{ij}(e),$$

Clearly, considering the discharging and recharging rates, both of the two last distributions could be computed based on the kernel of the semi-Markov process. The distribution of energy consumption and harvesting in state $i$ are finally obtained as follows:

$$E(i, e) = \sum_{j \in S} E(i, j, e)$$

and

$$H(i, e) = \sum_{j \in S} H(i, j, e).$$

We now describe a new energy transient analysis technique for computing the distributions of the consumed and of the harvested energy. We assume that the harvesting node starts in state $i$ and after time $T$ is in state $k$. Throughout time $T$ the node might have transitioned through different sequences of states (paths in the SMP). However, independently of the followed path, for each state $m$ in the path the harvesting node consumes a random amount of energy $E_m$ and harvests a random amount of energy $H_m$. Both random values $E_m$ and $H_m$ depend on the state holding time probability distribution, and on the discharging and recharging rates associated to state $m$. Therefore, the total amount of energy consumed and harvested over a path of $N$ states from state $i$ to state $k$ during time $T$ can be obtained as the sum of $N$ independent random variables:

$$E_{ik}(T) = E_i + E_{i+1} + \ldots + E_m + \ldots + E_k,$$

and

$$H_{ik}(T) = H_i + H_{i+1} + \ldots + H_m + \ldots + H_k,$$

where $k = N + i - 1$. The probability density function (pdf) $f_{ik}^e(e, T)$ of $E_{ik}$ is defined such that:

$$Pr(e_1 \leq E_{ik} \leq e_2) = \int_{e_1}^{e_2} f_{ik}^e(e, T).$$
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The pdf $f_{ik}^h(e, T)$ of $H_{ik}$ is defined similarly. Recall that the pdf of the sum of $N$ independent random variables is the $N$-fold convolution of their pdfs. Therefore, in order to determine the joint conditional pdf of energy consumption (conditioned with respect to time $T$ and initial state $i$) it is necessary to convolve the energy consumption pdfs of the states, $\frac{dE_{ik}(e)}{de}$, over all possible paths starting from state $i$ and finishing in state $k$ throughout time $T$. To this end, we calculate the Laplace transform of the convolutions over all possible paths with different state holding times. This is done through the following theorem.

**Theorem 1** For any given time $T$, the Laplace transform $L_{ik}^e(s, T)$ of $f_{ik}^e(e, T)$ with respect to $e$, is the solution of the following equation:

$$L_{ik}^e(s, T) = e^{-sd_i T} (1 - E(i, d_i T)) + \sum_m \int_0^{T d_i} e^{-se} L_{mk}^e(s, T - \frac{e}{d_i}) dE(i, m, e),$$

where $m$ ranges over all states in the SMP $X$, and $d_i$ is the discharging rate in state $i$.

**Proof 1** Let $E$ be a random variable with cumulative distribution function (CDF) $F(e)$. The Laplace-Stieltjes transform (LST) of $F$ is defined as follows:

$$E(e^{-se}; E \leq e | Z_0 = i) = \int_0^\infty e^{-se} dF(e).$$

The Laplace transform of $f_{ik}^e(e, T)$ is as follows:

$$L_{ik}^e(s, T) = E(e^{-sE_{ik}(T)}; E_{ik}(T) \leq e | Z_0 = i),$$

where the random variable $E_{ik}(T)$ shows the total amount of consumed energy during time $T$ starting from state $i$. Conditioning on the initial state energy consumption $E_i$ we have:

$$E(e^{-sE_{ik}(T)}; E_{ik}(T) \leq e | E_i = c, Z_0 = i) = \begin{cases} e^{-sd_i T} & c \geq d_i T, \\ e^{-sc} \sum_m L_{mk}^e(s, T - \frac{c}{d_i}) & c < d_i T. \end{cases}$$

Now, unconditioning with respect to $E_i$, we obtain:
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\[ L_{ik}^e(s, T) = \int_0^{T_{di}} e^{-se} \sum_m L_{mk}^e(s, T - \frac{e}{d_i}) dE(i, m, e) + e^{-sd_i T} (1 - E(i, d_i T)) = \sum_m \int_0^{T_{di}} e^{-se} L_{mk}^e(s, T - \frac{e}{d_i}) dE(i, m, e) + e^{-sd_i T} (1 - E(i, d_i T)). \]

Similarly, \( L_{ik}^h(s, T) \) is calculated as follows:

\[ L_{ik}^h(s, T) = \sum_r \int_0^{T_{ri}} e^{-sr_i T} \sum_m L_{mk}^h(s, T - \frac{e}{r_i}) dH(i, m, e) + e^{-sr_i T} (1 - H(i, r_i T)), \]

where \( r_i \) is the recharging rate in state \( i \). The energy available at the harvesting node at time \( T \) is defined as the residual battery energy taking into account the net consumed energy until time \( T \). The net consumed energy includes both consumed and harvested energies. Since the consumption process is stochastically independent of the harvesting process, we can derive the Laplace transform of the net consumed energy during time \( T \) as

\[ L_i(s, T) = L_{ik}^e(s, T) L_{ik}^h(s, T), \]

Thus, the pdf \( f(e, T) \) of the net consumed energy \( e \) consumed through time \( T \) can be calculated by numerically inverting the Laplace transform \( L_i(s, T) \). Then, the CDF \( E(e, T) \) is found by \( \int_0^e f(e, T) de \). Note that such distribution depends on the initial state \( i \), which in this work is assumed to be always the sleep state. Finally, the distribution of the energy available to harvesting node, residual energy, after time \( T \) is given by:

\[ P^A(e, T) = E(E_0 - e, T). \]

(3.1)

which depends on the overall net consumed energy distribution \( E(e, T) \) and the initial energy of the primary battery \( E_0 \). The set of transitions from one specific state (e.g., sleep state) to the next visit to that state construct a harvesting node operational cycle. As a special case, the energy
distributions regarding the number of cycles can be found based on the steady-state probabilities of the SMP, \( \pi_i \), and the average time spent in each state, \( \mu_j \). In particular, the average length of one cycle is equal to \( \sum_j \pi_j \mu_j \), and accordingly one can compute the Laplace transform of the net consumed energy and its equivalence residual energy for different number of cycles.

3.2.2 Node Lifetime Distribution

In this section, considering the sensor semi-Markov model \( X(t) \), we characterize the harvesting node lifetime distribution as a function of time (or number of cycles). Let \( g \) be the power consumption reward function which for any time \( t \) over the operation of the sensor defined as:

\[
g(X(t)) = d_i \geq 0, \text{ if } X(t) = i,
\]

where \( g(X(t)) \) indicates the power consumption per unit time in the state \( i \) (at time \( t \)). Similarly, we consider \( f \) to be the charging reward function as:

\[
f(X(t)) = r_i \geq 0, \text{ if } X(t) = i,
\]

\( r_i \) represents the energy recharging rate of the harvesting sensor in state \( i \). We define the net consumed energy \( E(t) \) as a random variable which takes into consideration both accumulated charging and discharging energies of a harvesting sensor node in time as follows:

\[
E(t) = \int_0^t [g(X(\tau)) - f(X(\tau))]d\tau = \int_0^t [d_{X(\tau)} - r_{X(\tau)}]d\tau = \int_0^t e_{X(\tau)}d\tau.
\]

where \( e_i \) indicates the combined reward rate in state \( i \) when \( X(t) = i \) and \( E(t) \) is a stochastic process based on \( X(\tau) \) for \( 0 < \tau < t \). The harvesting sensor node lifetime can be defined as a random variable \( T \) representing the time to accumulate a combined reward requirement equal to a random variable \( w \) which represents the initial energy of the sensor's battery (\( w = E_0 \)):

\[
T(w) = \min\{t \geq 0 : E(t) = w\},
\]

Moreover, node lifetime \( T \) is the time instant at which the overall (net) consumed energy by the sensor node reaches the value \( w \) for the first time. Given that the initial state is \( i \), the probability that harvesting node consumes more accumulated energy than \( w \) during sensor operation time \( t \) is:

\[
Pr(E(t) > w | X(0) = i),
\]
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Table 3.1: Parameters of SAVE Framework for the case study

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_0$</td>
<td>Initial energy of the on-board battery</td>
</tr>
<tr>
<td>$G$</td>
<td>Maximum number of retransmissions</td>
</tr>
<tr>
<td>$BER$</td>
<td>Channel bit error rate</td>
</tr>
<tr>
<td>$P_e$</td>
<td>Packet error rate</td>
</tr>
<tr>
<td>$P_{B}$</td>
<td>Channel busy probability</td>
</tr>
<tr>
<td>$K$</td>
<td>Maximum number of backoff occurrences</td>
</tr>
<tr>
<td>$T_s$</td>
<td>Sleeping period</td>
</tr>
<tr>
<td>$T_w$</td>
<td>Wakeup period</td>
</tr>
<tr>
<td>$\lambda^e$</td>
<td>Average event arrival rate</td>
</tr>
<tr>
<td>$S_p$</td>
<td>Data packet size</td>
</tr>
<tr>
<td>$S_M$</td>
<td>Data message size</td>
</tr>
<tr>
<td>$S_H$</td>
<td>Packet header size</td>
</tr>
<tr>
<td>$R_{tx}$</td>
<td>Channel transmission rate</td>
</tr>
<tr>
<td>$\bar{t}_{ch}$</td>
<td>Average charging time</td>
</tr>
<tr>
<td>$P_{sc}$</td>
<td>Charging probability</td>
</tr>
<tr>
<td>$B$</td>
<td>Average processing time per event</td>
</tr>
<tr>
<td>$P_I$</td>
<td>Event of interest probability</td>
</tr>
</tbody>
</table>

which is exactly the probability that the lifetime of the harvesting node is shorter than $t$. Correspondingly, the conditional node lifetime distribution which is the probability distribution that the sensor node achieves the desired lifetime $t$, when $i$ is the given initial state, would be as:

$$Pr(T(w) \leq t | X(0) = i) = Pr(E(t) > E_0 | X(0) = i),$$

3.3 Framework Analysis: A Case Study

In section II, we described a general analysis framework for any arbitrary state diagram that defined the operation of an energy harvesting sensor. In this section, we take a specific example of a sleep-awake duty cycled sensor that harvests energy with an exponential charging time, and uses a CSMA-based MAC protocol with ARQ for error recovery at the link layer. A detailed description of the variables used is given in Table I.
3.3.1 Semi-Markov Chain Overview

The functions of the harvesting sensor node is modeled as a semi-Markov chain consisting of (i) charging (C), (ii) sleeping (S), (iii) listening (L), (iv) processing (P), and (v) transmitting (T) operational states, which are represented in Fig. 3.2 with their corresponding abbreviations in the parenthesis. The operation of the sensor for this example scenario is described in the following, assuming the above states:

3.3.1.1 Energy Harvesting Policy

The initial energy of the primary battery is \( E_0 \). During its reduced activity sleep time (i.e., in state S), the sensor may either transition into deep sleep and charge (i.e., enter state C) with the probability \( P_{sc} \), which is equal to a given charging probability, for an exponentially distributed time with the mean value of \( t_{ch} \), or continue in its current state with probability \( 1 - P_{sc} \) for a fixed sleeping period \( T_s \). Note that while our framework supports any arbitrary harvesting policy, for the purpose of tractability, we assume here an exponential charging time. After completing the sleeping period \( T_s \), the node switches to the listening state (i.e., state L) and starts sensing the environment.

3.3.1.2 Event Processing

The node returns back to the sleeping state when no event is detected, or else it processes the detected events in the processing state (i.e., state P) to find out if any of them are the events of interest. The processing time per event follows an exponential distribution with mean \( B \), though our
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general model supports arbitrary distributions. Consequently, the processing time of \( R \) events has \( R \)-stage Erlang distribution.

3.3.1.3 MAC Protocol

After completion of the processing stage, if any desired event is detected, the node switches to the transmitting state (i.e., state \( T \)) with probability \( P_{pt} \), which is derived later in Section III-B. If the sensor node finds the channel idle during its initial carrier sensing, it begins transmitting. But if the channel is busy with probability \( P_B \), the node defers its transmission for a random amount of time. It waits in the idle mode, and probes the wireless channel again after that time. A maximum number of \( K \) backoff occurrences for each packet is assumed. Moreover, the path loss wireless channel is modeled with a two-state discrete Markov chain known as Gilbert model in which \( P_e \) indicates the average packet error probability and is computed based on the wireless channel bit error rate. Finally, an ARQ error control mechanism with \( G \) maximum number of packet retransmissions is considered.

3.3.2 Constructing the SMP Kernel

In this section, we construct the kernel matrix of our example. In particular, each kernel has two elements: probability transition matrix (\( P \)) and holding time distribution matrix (\( Q \)). Next, we derive the transition probabilities and holding time distributions of our SMP described in Figure 3.2. Note that the matrix elements for non-existent transition paths in SMP are zero.

\[
P = \begin{pmatrix}
P_{ss} & P_{sc} & P_{sl} & \cdots & P_{st} \\
P_{cs} & P_{cc} & P_{cl} & \cdots & P_{ct} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
P_{ps} & P_{pc} & P_{pl} & \cdots & P_{pt} \\
P_{ts} & P_{tc} & P_{tl} & \cdots & P_{ts}
\end{pmatrix}
\]

\[
Q = \begin{pmatrix}
Q_{ss}(t) & Q_{sc}(t) & Q_{sl}(t) & \cdots & Q_{st}(t) \\
Q_{cs}(t) & Q_{cc}(t) & Q_{cl}(t) & \cdots & Q_{ct}(t) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
Q_{ps}(t) & Q_{pc}(t) & Q_{pl}(t) & \cdots & Q_{pt}(t) \\
Q_{ts}(t) & Q_{tc}(t) & Q_{tl}(t) & \cdots & Q_{tt}(t)
\end{pmatrix}
\]
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The holding time distributions of sleeping state is $Q_{sl}(t) = U(t - T_s)$ and $Q_{sc}(t) = 0$, here $U$ is the unit step function. Furthermore, the holding time in charging state has exponential distribution $Q_{cl}(t) = 1 - e^{-t/T_{ch}}$. Since the event arrivals occur during the awake period follow a Poisson process with average rate $\lambda^e$, the transition probabilities of listening state are $P_{ls} = e^{-\lambda^e T_w}$ and $P_{lp} = 1 - e^{-\lambda^e T_w}$, and staying time distribution is $Q_{ls}(t) = Q_{lp}(t) = U(t - T_w)$.

Assuming $N^l_E$ is the number of received events during listening time, then the probability that $n$ events are detected and the average number of sensed events are:

$$f^l_e(n) = Pr(N^l_E = n) = \frac{(\lambda^e T_w)^n e^{-\lambda^e T_w}}{n!},$$

$$E[N^l_E] = \lambda^e T_w.$$  

Additionally, when $n$ events are detected during the listening time, the total summation of the exponential processing time approaches the $n$-stage Erlang distribution with density function $f_{Erlang}(n, B, t)$ with the cumulative distribution $H_{Erlang}(n, B, t)$. The probability that the processing state reveals no event of interest is equal to transition probability $P_{ps}$, and is calculated by:

$$P_{ps} = \sum_{n=0}^{\infty} f^l_e(n) (1 - P_I)^n.$$  

Here, $P_I$ is the probability of a single event being of interest. We approximate $P_{ps} = (1 - P_I)^{E[N^l_E]}$ with the average number of detected events, without a significant loss of precision. Similarly, the distribution of the holding time at the processing state can be computed by using the $k$-stage Erlang distribution, with the average value $E[N^l_E]$ as follows:

$$Q_{ps}(t) = Q_{pt}(t) = H_{Erlang}([E[N^l_E]], B, t).$$

Let $N^T_E$ indicate the number of events of interest detected after processing, having the average value equal to $\lambda^e T_w P_I$. Thus, the probability of detecting $i$ events of interest is:

$$g^l_e(i) = Pr(N^T_E = i) = \sum_{n=0}^{\infty} f^l_e(n) \binom{n}{i} (P_I)^i (1 - P_I)^{n-i},$$

Considering the average number of desired events, this probability is approximated by:

$$g^l_e(i) = Pr(N^T_E = i) = \left(\frac{\lambda^e T_w}{i}\right) (P_I)^i (1 - P_I)^{\lambda^e T_w - i}. \quad (3.2)$$
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The transition probability from transmitting state to sleeping state is equal to one. Furthermore, the staying time at the transmitting state is related to the back-off time, packet transmission time, wireless channel error probability, and maximum allowable number of retransmissions. Accordingly, we first compute the holding time distribution of transmitting one packet and then extend it to the total number of packets sent in the burst (i.e., in state T of the current cycle).

Let $T^P_T$ be holding time for one packet transmission in the state $T$. Then $T^P_T$ and its pdf $f^p_t(t)$ can be represented as follows:

$$T^P_T = T_{\text{backoff}} + T_{\text{Tx}},$$

$$f^p_t(t) = f_{\text{backoff}}(t) * f_{\text{Tx}}(t),$$

(3.3)

where * represents a convolution operation. Accordingly, to compute the $f^p_t(t)$, we need to find the probability density of back-off time as well as the probability density of a packet transmission time. Clearly, as the transmission time of a packet $T_{\text{packet}}$ is a constant value, $f_{\text{Tx}}(t)$ is:

$$f_{\text{Tx}}(t) = \delta(t - T_{\text{packet}}),$$

(3.4)

$$T_{\text{packet}} = \frac{S_{\text{packet}} + S_{\text{header}}}{R_{\text{tx}}},$$

which based on the convolution property of delta function results in $f^p_t(t) = f_{\text{backoff}}(t - T_{\text{packet}})$.

Next, assume $X_i'$ is a random variable that indicates the backoff time of $i' + 1$-th attempt and $Y_{i'}$ is random variable of the total (sum) backoff time for $i' + 1$ backoff attempts. The probability density function of $Y_{i'}$ can be calculated based on the pdf of $X_i'$ as shown:

$$f_{Y_{m}}(t) = f_{X_0}(t) * f_{X_1}(t) * \ldots * f_{X_m}(t),$$

$$f_{Y_{m}}(t) = f_Y(m,t) = f_{X_m}(t) * f_Y(m-1,t).$$

where:

$$f_{X_i}(t) = U(0, 2^{i+1}) = \begin{cases} 
1 & 0 \leq t \leq 2^{i+1}, \\
0 & t > 2^{i+1} or t < 0.
\end{cases}$$

Consequently, the probability density function of total back-off time for one packet transmission would be determined as follows:

$$f_{\text{backoff}}(t) = f_{Y_0}(t)P_0 + f_{Y_1}(t)P_1 + \ldots \ldots + f_{Y_{K-1}}(t)P_{K-1} + f_{Y_K}(t)P_K,$$

(3.5)
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\[ P_i = \begin{cases} 
(P_B)^i(1 - P_B) & 0 \leq i \leq K - 1, \\
(P_B)^i & i = K.
\end{cases} \]

where \( P_B \) is the probability that the sensed channel is busy before transmission and where \( K \) is the maximum number of allowable back-offs. Then the pdf of holding time in state \( T \) for one packet transmission (Equation 3) can be computed based on the equations 4 and 5.

The above analysis considers a single packet transmission. However, the wireless channel introduces an average packet error rate \( P_e \) and ARQ error recovery permits \( G \) number of packet retransmissions. Moreover, for each detected event of interest, the sensor node packs its sensed information into a data message and transmits to the base station. Therefore, there are a number of packets sent per desired event, depending on the size of packet and data message, that is calculated as

\[ \alpha = \left\lceil \frac{S_M}{S_P} \right\rceil, \]

where \( S_M \) and \( S_P \) represent the sizes of the data message and packet, respectively. Accordingly, next we extend this analysis for the case of multiple packet transmissions that result from wireless channel errors and the message.

The expected number of transmissions for one packet \( E[\gamma] \) until it is successfully transmitted or dropped is computed as follows:

\[ f_\gamma(i) = \begin{cases} 
(P_e)^{i-1}(1 - P_e) & 1 \leq i < G, \\
(P_e)^i & i = G.
\end{cases} \]

\[ E[\gamma] = \sum_{i=1}^{G} (i)f_\gamma(i) = \sum_{i=1}^{G-1} [i(P_e)^{i-1}(1 - P_e)] + G(P_e)^G = \frac{1 - (P_e)^G}{1 - P_e}. \]  

(3.6)

where \( \gamma \) is a random variable of the number of transmissions per packet. The average number \( E[N^T] \) of total transmitted packets \( N^T \) (also considering retransmissions) in the state \( T \) in the current cycle is:

\[ E[N^T] = (\alpha) E[\gamma] E[N^T_E]. \]

The probability density function of the holding time of the transmitting state can be derived by using equations 2, 3, and 6 as follows:

\[ f_{ts}(t) = \sum_{j=1}^{\infty} \eta_e(\left\lfloor \frac{j}{\alpha} \right\rfloor) G_t(jE[\gamma], t), \]
Figure 3.3: Probability density functions of net consumed energy for different operational cycles n=10 and n=30.

\[ G_t(n, t) = f^P_t(t) \ast G_t(n - 1, t), \]

which is also approximated by \( f_{ts}(t) = G_t(E[N^T], t) \). Then, the holding time distribution at state \( T \) is computed from the density function by integrating \( f_{ts}(t) \) from 0 to \( t \).

### 3.4 Performance Evaluation

In this section, we present the simulation and analytical results of the energy and lifetime distributions evaluated through MATLAB. The packet data size is 140 bytes, with the data and header sizes being \( S_p = 128 \) bytes and \( S_h = 12 \) bytes, respectively. The data message size \( S_M \) is set to 1 kbyte. The event arrival rate is \( \lambda_e = 0.15 \). The wireless channel bit error rate (BER) is \( 10^{-3} \), and channel busy probability is set to \( P_B = 0.2 \). The packets are transmitted with a rate 250 Kbps and the maximum number of retransmissions \( G = 3 \). Also, a CSMA-based MAC with maximum five allowable backoff occurrences is employed. The sleeping and wakeup periods are simulated with \( T_s = 0.2s \) and \( T_w = 1.8s \), respectively. For the harvesting parameters, the charging probability is equal to 0.3 and the average charging time is set as 2s, \( \overline{t_{ch}} = 2 \). Each packet or event would be
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Figure 3.4: Distribution of node lifetime with $E_0 = 10$ Joules.

processed for an average of 0.2s, while the probability of the event being of interest is 0.8. The energy consumption rates are set based on the Imote2 sensor mote [129]. More specifically, the discharging rates for sleeping, listening, processing, and transmitting are set to 1.8, 88, 237, 273 mW, respectively, and recharging rate is set to 50mW. The simulations are performed 200 times for each node with different random number seeds. Fig. 5.3(a) shows the simulation and Fig. 5.3(b) presents the corresponding analytical results of net consumed energy after 10 and 30 cycles. It is shown that in both of simulation and analytical analysis, the density of net consumed energy is converging to an asymptotic Normal distribution. Moreover, comparing the density functions of simulation and analytical results in Fig. 5.3, the accuracy of the analysis in predicting the probability of net consumed energy can be observed. Clearly, by knowing the net consumed and initial energy, the residual energy is determined by using Equation 1. However, due to space limitations, here, we have presented only the net consumed energy distributions. It noteworthy that since the number of simulation runs are always finite, the histogram (pdf) of net consumed energy is computed by employing discretization and bins.

Since the node lifetime is defined as the time until the residual energy drops below a minimum energy requirement, the initial energy of the on-board primary battery directly affects the distribution of lifetime. Fig. 3.4 depicts results for node lifetime, analysis and simulation, with $E_0 = 10$ Joules. We observe an accurate match between the simulated results for node lifetime and the analytical model derived in this chapter.
3.5 Final Remarks

In this chapter, we proposed a generic framework for analysis of energy and lifetime distributions in energy harvesting sensor nodes. The behavior of a harvesting sensor node is modeled by a semi-Markov model, in which the discharging and recharging rates are assumed as the semi-Markov state reward rates. The node lifetime is calculated through the energy transient analysis approach. Finally, the simulation and analytical results for net consumed energy and node lifetime distributions reveal a close match thereby verifying the correctness of our approach.
Chapter 4

Medium Access Control for Integrated Data and Energy Transfer

4.1 Introduction

Wireless sensor networks (WSNs) are being increasingly used in a wide variety of applications including industrial and infrastructure monitoring, smart home, smart grid, medical systems, and so on. One of the main challenges and performance bottleneck in these systems is the limited lifetime of the sensor nodes due. Recent advances in the area of wireless energy transfer allow sensors to recharge during network operation, thereby extending their lifetimes and minimizing application downtime. Our recent research on powering Mica2 sensor motes by harvesting the energy contained in radio frequency (RF) electromagnetic waves in [1] indicated the potential for large scale deployment of this technology. However, at the protocol level, this form of in-band energy replenishment is fraught with several challenges on: (i) how and when should the energy transfer occur, (ii) its priority over, and the resulting impact on the process of data communication, (iii) the challenges in aggregating the charging action of multiple transmitters, and (iv) impact of the choice of frequency. Thus, the act of energy transfer becomes a complex medium access problem, which must embrace a cross-disciplinary approach incorporating wave propagation effects and device characteristics, apart from the classical link layer problem of achieving fairness in accessing the channel. We focus on in-band transmission since multiple separate frequencies for data and energy transfer increases the complexity of the sensors, brings in numerous antennas and transceiver related hardware requirements, and imposes additional spectrum availability needs. This chapter
is concerned with the design of a CSMA/CA based MAC protocol for such RF energy harvesting sensors, inspired by experimental evaluations on our testbed.

Our MAC protocol that works with RF energy harvesting, called as RF-MAC, allows a node to broadcast its request for energy (RFE) packet containing its ID, and then waits to hear from the energy transmitters (ETs) in the neighborhood. These responses from ETs are called cleared for energy (CFE) pulses, which are simple, time-separated energy beacons. These pulses maybe transmitted by more than one ET concurrently as overlapping CFEs need not be distinguished. Rather, the concurrent emission of the CFEs increases the received energy level at the sensor, and this indicates a higher number of potential transmitters from the energy requesting sensor. The responding ETs are then classified into two sets, based on rough estimates of their separation distance from the energy requesting node to minimize the impact of destructive interference as much as possible. Each set of ETs is assigned a slightly different peak transmission frequency (separated by only few KHz, hence, still called in-band as the channel separation is typically 5 MHz for 802.11) so that each set of ETs contributes constructively to the level of RF energy received at the node.

While we retain the essential concepts of the CSMA/CA mechanism for the data access mechanism \cite{137}, there are several points of departure from the classical implementation. We separately select and dynamically vary the slot time, the inter-frame spacing, and the contention window size for both energy transfer and data communication.

The core contributions of our work can be summarized as follows:

- We experimentally identify the operating constraints of the RF energy transferring MAC protocol using actual wireless energy harvesting circuits interfaced with Mica2 motes. We demonstrate how two slightly separated energy transfer frequencies can be assigned to ETs to improve the constructive interference of their collective action.

- We design a MAC protocol to balance the needs of efficient wireless energy delivery and data exchange. We bridge these dissimilar concepts by establishing the importance of a node in the data communication, which in turn quantifies how much should the node charge.

- We analytically establish optimality conditions for the energy transfer, and create a strongly coupled protocol that operates on link layer metrics with the awareness of both the underlying hardware and fundamental limits of RF energy harvesting.

The rest of this chapter is organized as follows: In Section 4.2 we give the related work. The key design challenges are described in Section 4.3 with experimental studies. A brief overview of
our RF-MAC protocol in given in Section 4.4, with a comprehensive detailed description in Section 4.5. The simulation and experimental results are presented in Sections 4.6 and 4.7, respectively. Finally, Section 4.8 concludes our work.

4.2 Related Works

MAC protocols that aim for energy conservation have been extensively explored in the recent past, with a comprehensive classification and survey on this topic presented in [105, 138, 139, 140].

4.2.1 General Energy Harvesting Sensor Networks

In [101], the authors propose an on-demand medium access protocol (Fafoutis.Dragoni:11) based on three basic ideas: minimizing wasting energy by moving the idle listening time from the receiver to the transmitter; adapting the duty cycle of the node to operate in the energy neutral operation (ENO) state (i.e. energy used by the system is less than the energy harvested from the environment), and reducing the end-to-end delay by employing an opportunistic forwarding scheme. In [105], a polling-based medium access mechanism (PP-MAC) is described for single-hop sensor networks, which uses the charge-and-spend paradigm for harvesting strategy. In [141], we model a CSMA-based MAC protocol with an ARQ error control mechanism for energy harvesting sensor networks through an analytical framework leveraging stochastic semi-markov models. However, all of the above protocols assume no impact of the energy harvesting process on data communication.

4.2.2 Sensor Networks with Wireless Energy Transfer

Specific to the scenario of RF energy transfer, an energy-adaptive MAC protocol (EA-MAC) is proposed in [142], which adopts a duty-cycle based on the proportion of harvested energy. However, this protocol requires a strict centralized base station control and relies on out-of-band RF power transfer. In [108], conventional MAC protocols, such as the classical TDMA and variants of ALOHA are evaluated assuming out-of-band RF transfer.

In [143], the authors present multiple concepts for multi-hop wireless energy transfer (such as store and forward vs. directly single hop transfer) and derive the efficiency of each method using magnetically coupled resonators for wireless power transfer demonstrated in [144]. However, this
non-radiative transfer is shown to work up to 2 m and requires perfectly aligned coils of 25 cm radius among the source and receiver nodes.

RFID technology comes closest to the energy transferring paradigm, where a tag operates using the incident RF power emitted by the transmitter [145]. The Token-MAC protocol for RFID systems in [146] enables fair access to the medium for all tags requiring neither a-priori knowledge of the tags nor synchronization. However, there are limitations in directly porting these approaches to networking scenarios, since RFID is unable to generate enough energy to run the local processing tasks on a typical node.

Some preliminary work on the energy transmitter grouping strategy appeared in [147], which has been integrated in the current RF-MAC protocol design.

4.3 Design Challenges and Preliminary Experiments

In this section we describe the key challenges for RF-MAC that concern specific characteristics of RF harvesting sensor networks, including (i) energy interference between emitted energy waves that results in wireless charging cancellation, (ii) optimal frequency and distance separation between ETs, (iii) energy charging time, (iv) requesting and granting energy, and (v) data vs. energy channel access.

4.3.1 Energy Interference and Cancellation

When more than one ET transmits power in-band, the concurrent emitted energy waves can combine either constructively or destructively, leading to variations in the amount of harvestable power and a possible energy cancellation. In the case of constructive interference (in-phase), the received power of the resulting wave at the RF energy harvester is greater than that of either of the individual energy waves. Conversely, in the case of destructive interference (out-phase), the net received power is less than that of the individual energy waves. This raises the question of which sets of ETs must be concurrently allowed to transmit by the MAC protocol, which we answer below.

An example network architecture, with stationary, omnidirectional ETs $x$, $y$, and $z$, is shown in Figure 4.1. The sensor $S1$ can be charged either through a unilateral action of any of the ETs, or through a coordinated transmission of multiple ETs. However, the joint action can only be beneficial if the arriving waves at sensor $S1$ are aligned in phase. Hence, ETs $x$ and $z$ may together transmit, both being at a multiple of the signal wavelength $\lambda$ away (which translates in a phase
CHAPTER 4. MEDIUM ACCESS CONTROL FOR INTEGRATED DATA AND ENERGY TRANSFER

Figure 4.1: Example network architecture with energy transmitters ($x$, $y$, $z$) and RF harvesting sensors ($S_1$, $S_2$). The energy transmitters can cancel emitted energy waves of each others (a). Phase difference effect on the received signal power at 915 MHz (b).

difference that results in ‘constructive’ interference). While the sensor can also be charged by ET $y$, combining the action of $y$ with either of the others diminishes the performance (owing to $y$ causing ‘destructive’ interference with respect to $x$ and $z$).

To characterize the constructive and destructive effect of the ETs, we our experimental setup involved two such 0 dBm continuous wave transmitters, each placed 2.5 m on either side of the receiver. Two Agilent N5181 MXG RF signal generators, each connected to a 50 $\Omega$ omnidirectional antenna tuned to the 915 MHz ISM band, were used to generate the RF energy signal. We fixed the phase of one signal generator and varied the phase of another, while keeping their locations fixed (note that keeping the transmission phase fixed and varying their distance as a function of the signal wavelength will have the same effect on the received signal phase). The fall in the signal strength, shown in Figure 4.1b was dramatic when the ETs operated in phase opposition ($-54$ dBm) compared to in-phase operation ($-36$ dBm). These results show the importance of considering such energy interferences when controlling the medium access in wireless-powered sensor networks.

Our observations motivate the design goal for our MAC protocol to ensure that the maximum energy transfer occurs by minimizing this cancellation effect, especially, in a shared medium where $N$ energy transmitters may transmit on the channel at the same time.
4.3.2 Optimal Frequency and Distance Separation

We next find the optimal frequency separation of the continuous wave ETs and their respective distances from the energy requesting sensor. Our RF-MAC protocol will use these results in setting the transmission frequency and activating only those ETs that result in out-phase energy transfer. Our approach here is to group the ETs together into two sets. All ETs in a given set transmit at the same center frequency. The two transmission frequencies corresponding to the two groups are only slightly separated (the complete spectrum of an ET spans only a few KHz). We describe next how to classify the ETs into separate groups using phase mismatch, such that their cumulative spectrum spread is still contained within the bandwidth of the energy harvesting (EH) circuit of the sensor node.

4.3.2.1 Optimal phase mismatch

We first perform a set of experiments to determine how much of the phase mismatch between two ETs is actually harmful. If the ETs are not completely $\pi$ radians separated in phase, then some of them may even be allowed to transmit together. The resultant increase in the raw emitted power in these cases compensates for the loss owing to the slight mismatch. Figure 4.2a shows the effect of phase difference $\Delta\phi$ between two energy transmitters on the received signal power at 433 MHz and 915 MHz. The experimental setup is the same as for Fig. 1(b). Here, the phase difference is varied from $[0, \pi]$ radians. A phase difference of 0 or $2\pi$ for the received signal (the emitted signals being in-phase), corresponds to a linear distance of one wavelength between the two transmitters. Thus, depending upon the actual distance $L$ between the ET $x$ and receiver node, we represent $\phi_x = \frac{L}{\lambda} \cdot 2\pi$. Here, $\lambda$ is the wavelength of the transmitted radiation. From Figure 4.2a, we observe that for small phase difference, i.e., for $\Delta\phi \leq \frac{\pi}{2}$, the resultant signal strength is not significantly lowered (i.e., the fall is only about $1 - 2$ dBm). This determines the optimal phase separation that is an important parameter in the protocol level design. Accordingly, all those ETs that are separated by $\Delta\phi \leq \frac{\pi}{2}$ can be grouped under one category (and center its transmissions at frequency $f_1$, say). Similarly, ETs that are separated by $\frac{\pi}{2} \leq \Delta\phi \leq \pi$ fall in the second category (and use frequency $f_2$ as the center transmission). We call this method as the two-tone energy transfer.

4.3.2.2 Optimal distance separation

In Figure 4.2b, using the experimental results and the relationship between the phase and distance, all the ETs separated by a multiple of the wavelength from each other, i.e., $L = m\lambda$,
Figure 4.2: Effect of energy waves phase difference on the received signal power at different frequencies. The power of resulting wave drops significantly after $\pi/2$ phase separation (a). The scheme for two-tone wireless energy transfer (b).

$m = 1, 2, \ldots$ can transmit on $f_1$, while the others separated by $L = (m + 1/2)\lambda$ can transmit on frequency $f_2$. As there are two active transmission tones present concurrently during transmission, each of these are separated in the frequency domain, one on each side of the center response point of the harvesting circuit. Both these tones must be completely encompassed by the response of the harvesting circuit at the receiver side.

We can potentially group the ETs into more than two categories. However, it can be observed from Figure 2(a) that increasing the number of groups, results in a smaller phase difference between ETs. This results in insignificant constructive effect (i.e. about 2 dBm) on the received signal power. For example, if three groups of ETs are to be employed, the decision region will be $\lambda/3$ and the received signal power is only slightly affected by $\pi/3$ phase mismatch. On the other hand, increasing the number of groups will increases the chance of more destructive interference, especially for EH circuit with narrow bandwidths. More groups also increase hardware complexity and energy transfer delay, which are described later in Section 4.5.1. Also, it noteworthy that the 99% occupied bandwidth of the currently used Powercaster ET is relatively small, approximately 63 kHz, thereby allowing us to accommodate the entire transmission spectrum of the ET within the 900 MHz frequency response curve of the EH circuit we designed in [1].
4.3.3 Energy Charging Time

As ETs transmit at comparatively higher energy levels in the same band (34 dBm using Powercaster transmitter [126] in our testbed, compared to −20 dBm for the Mica2), a much larger area is rendered unusable for data communication. For example in Figure 4.1a, even if $S_2$ is situated at a considerable distance away from ET $x$, it will still fall within its interference band (shown by the area with dotted lines) and unable to receive data. Thus, the sensor nodes need to balance between the communication and charging times so that (i) prevent extend durations of communication outage and (ii) allocate charging durations per energy request based on the traffic load to adaptively sync the energy harvesting and consumption demands. Accordingly, the effective duration for which charging is allowed plays an important role in the performance and design of a new MAC protocol.

4.3.4 Requesting and Granting Energy

In a network with multiple ETs, the process of requesting energy by the sensor nodes and granting energy by the ETs require a timely coordination and cooperation. The MAC protocol must decide (i) when and how a sensor should actually request energy from neighboring ETs, (ii) when the ETs should start transferring energy, (iii) how ETs know about suitable charging duration and the choice of frequency need to be addressed.

4.3.5 Data vs. Energy Channel Access

At the time the sensor node sends the RFE, the residual energy of the requesting node is very low. Thus, the medium access control should give higher priority to energy requests over data in the channel access. This design issue is not incorporated into the classical MAC protocols, and needs to be carefully considered in the design of RF-MAC. Note that issues such as when, how long, and how frequently ETs access to the channel are determined by charging time and energy requesting and granting process.

4.4 RF-MAC Protocol Overview

At a high level, the medium access control mechanism in the RF-MAC protocol is organized into three components - (i) joint ET-spectrum selection, (ii) adaptive charging threshold selection, and (iii) energy-aware access priority. We now give an overview the RF-MAC protocol, and in the next section, we describe its detailed operation.
Figure 4.3: Example scenario for overview of RF-MAC protocol with three RF energy harvesting sensor nodes.

- **Joint ET-spectrum Selection:** In this phase, the energy requesting node issues its request for energy (RFE) packet. The ETs that receive this request independently separate themselves into two groups slightly separated in the center frequency, but still contained within the transmission band. The ETs use the signal strength of the RFE to estimate their (rough) individual distances to the requesting sensor to identify in which group they belong (see Section 4.3.2) and reply with a cleared for energy (CFE) pulse. Depending upon which group of ETs supplies higher level of energy, the requesting sensor solves an optimization framework to assign center frequencies to these two groups. This technique incorporates consideration of the (i) the destructive effect (i.e. energy cancellation) of concurrent energy transmissions, and (ii) the spectrum response of the EH circuit, which is an important physical layer characteristic.

- **Adaptive Charging Threshold:** In this phase, the energy requesting sensor node determines its upper charging level threshold and the charging duration, based on its local network conditions. This threshold is unique for a given node, and is derived from the ratio of its own data communication activity to that observed in its neighborhood. The charging duration determines how long the data communication should be disrupted.

- **Energy-aware Access Priority:** This phase has two main functionalities. First, it gives higher priority to the energy request packets than the data packets for accessing the channel by defining different durations for the slot time for data and energy access. The slot time is the fundamental time unit for channel access and exponential back off calculations in CSMA/CA. Second, it adapts the sensor’s back-off duration based on its residual energy. Thus, the sensor with higher residual energy has a higher access priority for data communication.
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Figure 4.4: Five stages of joint ET-spectrum selection component in RF-MAC protocol.

4.4.1 Example Operation of RF-MAC

As an example, in Figure 4.3, three sensors $S_1$, $S_2$, and $S_3$ have residual voltages of 2.6, 2.3, and 3.0 V, respectively. Since the voltage of $S_2$ is reached a pre-set threshold, 2.3 V, this node sends out the RFE packet requesting for immediate charging. RF-MAC, through the access priority mechanism (Section 4.5.3), ensures that $S_2$ wins the channel access for energy transfer earlier than $S_1$ and $S_3$ that have data packets to deliver. At this time, $S_1$ and $S_3$ are forced to freeze their backoff timers and get into charging mode, as data communication is infeasible. Once RFE packet is received by the ETs, they reply back with the CFE, which is a short energy pulse.

Node $S_2$ identifies the two sets of ETs by measuring the received power of CFEs and determines their associative optimal energy transfer frequencies (Section 4.5.1). How much should $S_2$ charge depends upon the adaptive charging threshold selection (Section 4.5.2). The node $S_2$ then sends out an ACK packet to the ETs in which it includes the optimal frequencies as well as the charging duration. Finally, when nodes $S_1$ and $S_3$ compete for data transfer, access priority ensures their respective backoff windows are a function of the residual energy (Section 4.5.3). Assuming that $S_1$ has higher residual energy, it will likely get the data communication opportunity first, followed by $S_3$. The latter freezes the countdown timer in this duration, and resumes the remaining countdown as soon as the channel is next available.

The details of the above three phases and the complete RF-MAC protocol description is given in the next section.
4.5 Detailed RF-MAC Protocol Description

4.5.1 Joint ET-spectrum Selection

As shown in Figure 4.4, the specific stages considered during the joint ET-spectrum selection are (i) requesting for energy, (ii) grouping ETs based on destructive interference, (iii) computing harvestable power, (iv) spectrum selection optimization, and (v) spectrum confirmation.

4.5.1.1 Requesting for energy

The sensor node broadcasts the RFE packet, requesting for energy, when its voltage falls under a pre-set threshold (~ 2.3 V, as minimum operating voltage of the Mica2 is 1.8 V). The RFE contains the requesting sensor node’s ID, transmitted at constant signal strength. This RFE can be sent when the channel is free, i.e., when there is no ongoing data transfer or energy charging operation and the channel lies idle for the DIFS_{energy} duration (calculation of this channel sensing duration is described later in Section 4.5.3). The ETs that receive this packet estimate roughly their distances from the node, based upon the received signal strength (RSS). In the following, we define that the distance measurement only needs to determine a band in which the ET lies, and not its exact location.
4.5.1.2 Grouping ETs based on destructive interference

Recall from Section 4.3, the distance between the ET and the sensor node directly results in a phase difference of the incoming wireless signals at the node. The ETs that identify themselves to lie in the band \([m\lambda - \frac{\lambda}{4}, m\lambda + \frac{\lambda}{4}]\), are grouped together, where \(m = \{1, 2, \ldots\}\). We call this as Group I. Similarly, the other ETs in the range \([(m + 1/2)\lambda - \frac{\lambda}{4}, (m + 1/2)\lambda + \frac{\lambda}{4}]\) fall in the second group, called Group II. Thus, on receiving the RFE, each ET knows which concentric band it lies in centered around the requesting node, and the group in which it belongs. Figure 4.5a shows a sample scenario. The shaded region depicts the ETs 4 and 5 that lie in the band of \(\lambda\), i.e., in Group I. This region extends up to \(\frac{\lambda}{4}\) on either side of the central bold line that lies at an exact distance of \(\lambda\) with the requesting node placed at the center. Since we do not precisely require the ET to calculate the distance from the requesting node, but only need to determine if it lies within a concentric band-region, our approach is more robust to RSS fluctuations. Of course, using a dedicated localization scheme or GPS hardware considerably eases this constraint, though adding to the implementation cost and power requirement.

The ETs that hear the RFE reply back with a single and constant energy pulse. Each concentric band has the choice of one of two time slots in which this pulse may be emitted, beginning from the instant of completion of the RFE, as shown in Figure 4.5b. Referring again to the band structure in Figure 4.5a, the first slot is allocated for CFE pulses sent by energy transmitter of Group I (note: all Group I bands are shown shaded). Similarly, CFE pulses from energy transmitters of Group II are sent during the second slot, i.e. ETs 1, 2 and 3 collectively lie in the second concentric (Group II) band and simultaneously transmit their pulses in the second slot.

4.5.1.3 Computing harvestable power

The node that sent the initial RFE estimates the total energy that it will receive based on the signal strength of the CFE pulses in the slot number in which they were received. This arrangement of using the pulses allows the ETs to be simple in design, and removes the concern of collisions. Unlike classical data communication, it is not important for the node to know which ET will transmit energy. Rather, its energy calculations are based on how much energy is contributed by the two groups of ETs separately. We define this cumulative energy as \(E_{RX}^{Group\ I}\) and \(E_{RX}^{Group\ II}\), respectively, which are calculated by the RFE issuing node from the received pulses. Each slot time is 10\(\mu\)s in our work, allowing a very fast response time. The purpose of differentiating the energy contribution from the two groups is useful in the next stage, where an optimization function returns the center
4.5.1.4 Spectrum selection optimization

Let Group I ETs be centered at frequency $f_1$, and Group II ETs be centered at frequency $f_2$ so that they can concurrently transfer energy without destructively affecting each other. How to select these frequencies $f_1$ and $f_2$ is explained next, which takes into account two important physical layer characteristics of the energy transfer. The first is the spectrum response of the energy harvesting circuit that is connected to the sensor nodes, shown by the envelope $H(f)$ in the frequency domain in Figure 4.2b. The physical bandwidth of energy harvesting circuit is denoted by $BW_{EH}$. The power spectral density (PSD) of the two groups of ETs is the other concern, represented by $S_1(f)$ and $S_2(f)$, respectively, for Group I and Group II. The sensor node observes these shapes from the incoming pulses from the ETs. Thus, the bandwidth $2\varepsilon$ of the transmission spectrum (centered at $f_1$ and $f_2$) must be selected in such a way there is a minimum overlap between their individual spectra, and yet contained within the envelope of $H(f)$. We use the following optimization if the transmission spectrum of the ETs occupies a bandwidth of $2\varepsilon$.

The aim of the optimization formulation is to maximize the energy transfer $E_{RX}^{Max} = E_{RX}^{Group\ I} + E_{RX}^{Group\ II}$, which at a given frequency point is the product of the power spectral density and the circuit frequency response. Thus, the useful components that need to be maximized are the first two terms of (4.2), which give the constructive energy contribution of the ETs of the two groups.

\[
\text{Given : } S_1(f), S_2(f), BW_{EH}, H(f) \\
\text{To find : } f_1, f_2, \gamma \tag{4.1}
\]

\[
\text{To Maximize : } \\
E_{RX}^{Max} = \int_{f_1-\varepsilon}^{f_1+\varepsilon} S_1(f)H(f)\,df + \int_{f_2-\varepsilon}^{f_2+\varepsilon} S_2(f)H(f)\,df \\
- \underbrace{\left( \int_{f_2-\varepsilon}^{\gamma} S_2(f)H(f)\,df + \int_{\gamma}^{f_1+\varepsilon} S_1(f)H(f)\,df \right)}_{\text{destructive interference}} \tag{4.2}
\]

\[
\text{Subject to : } \\
|f_2 - f_1| < BW_{EH} \tag{4.3} \\
\left| \frac{d(S_1(f)H(f))}{df} \right|_{f=\gamma} < 0 \tag{4.4} \\
\left| \frac{d(S_2(f)H(f))}{df} \right|_{f=\gamma} > 0 \tag{4.5}
\]
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The first constraint is to ensure that both frequency groups are contained within the bandwidth of the energy harvesting circuit. The constraints 4.4 and 4.5 ensure that the spectrum shapes of the Group I and Group II ETs do not overlap completely. We assign \( f_1 \) to the left of \( f_2 \) on the frequency scale (see Figure 4.2b). At the point of the intersection of the PSD curves \( S_1(f) \) and \( S_2(f) \), which we call the cross-over point \( \gamma \), the slope of the curves must be positive and negative, respectively. This is calculated by differentiating the respective PSD plots at \( \gamma \), to ensure that one of them increases (positive slope) while the other falls (negative slope). A problem is said to have an optimal substructure if an optimal solution can be constructed efficiently from optimal solutions to its sub-problems. We claim as follows that our proposed optimization also exhibits the optimal substructure property.

**Lemma 1**: Given the power spectral density \( S_1(f) \) and \( S_2(f) \), the total energy transfer \( (E_{RX}^{Max}) \) under the RF energy harvesting circuit’s frequency response \( H(f) \) is maximum.

\[
E_{RX}^{Max} = \int_{f_1-\epsilon}^{f_1+\epsilon} S_1(f)H(f)df + \int_{f_2-\epsilon}^{f_2+\epsilon} S_2(f)H(f)df - \{ \int_{f_2-\epsilon}^{\gamma} S_2(f)H(f)df + \int_{\gamma}^{f_1+\epsilon} S_1(f)H(f)df \}
\]

is maximum then

\[
\int_{f_1-\epsilon}^{f_1+\epsilon} S_1(f)H(f)df - \int_{f_2-\epsilon}^{\gamma} S_2(f)H(f)df \text{ and}
\]

\[
\int_{f_2-\epsilon}^{f_2+\epsilon} S_2(f)H(f)df - \int_{\gamma}^{f_1+\epsilon} S_1(f)H(f)df
\]

are maximum as well.

**Proof**: Let (1) - (3) give the area under the curve represented by X and (2) - (4), similarly, return the area of Y, then (1) + (2) - \{ (3) + (4) \} has the total area of X+Y. Assume we find \( \alpha \) such that \( \alpha = (1) - (3) + \epsilon \); \( \epsilon > 0 \) then the total area = (1) + (2) - \{ (3) + (4) \} + \epsilon = X + Y + \epsilon > X + Y. This contradicts the supposition that (1) + (2) - \{ (3) + (4) \} is maximum. (1) - (4) can be proved in a similar fashion.
4.5.1.5 Spectrum confirmation

With the resulting dual-frequency wireless energy transfer, both groups of ETs can be simultaneously active. The final part of this stage involves letting the ETs know that they are cleared for energy transmission through an Acknowledgement (ACK) packet. This packet provides the ETs the center point for the frequencies $f_1$ and $f_2$, according to the results of optimization. The ETs know which group they belong to internally, based on the RSS-based band structure shown in Figure 4.5a. Additionally, the ACK carries an estimated charging time $T$ based on a target voltage level of the capacitor (calculated in Section 4.5.2). This upper limit on the charging voltage is decided by the node’s relative activity in the neighborhood.

After a short SIFS wait period following the ACK (using shorter slot times, for energy, compared to those used for data communication), the ETs begin their transmission. In case of loss of the RFE due to packet collision or bad channel conditions, the contention windows are re-set to the minimum width, thereby initiating an immediate subsequent retry. The idea here is that (i) time is critical when a node has extremely low voltage and (ii) nodes will require energy recharging opportunities much less than the data communication opportunities [148]. Hence, the number of energy request packets will be less than data packets and there will not be frequent collision related losses of the RFE arising from the shorter contention window.

From our preliminary experimental results, we recall that increasing the number of groups to more than two has negligible constructive effect on the received signal power (see Section 4.3.2.2). In addition to this, we find that introducing an additional frequency group, say Group III with PSD $S_3(f)$, increases the chance of more destructive interference, and in the optimization formula the destructive interference term increases from 2 terms (all overlapping areas of $S_1(f)$ and $S_2(f)$) to at least 4 terms (all overlapping areas of $S_1(f)$, $S_2(f)$, $S_3(f)$). Furthermore, as the number of groups increases the number of slot times for CFE pulses and computing the harvestable power also increases. Clearly, this results in additional delay in granting energy to the sensor nodes. Finally, more than two groups of energy transmitters mean tighter location detection requirement and hence most likely more expensive hardware.

4.5.2 Adaptive Charging Threshold

As our energy transfer is in-band, each node needs to decide the charging time that may possibly result in a reduced level of energy replenishment. Our proposed method defines this upper charging level based on the level of participation in data communication activity for that node.
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with respect to its neighbors. Each node maintains a moving average of the time spent by itself in transmitting and receiving data packets to the total time the channel is used or sensed as busy. Many nodes, hence, will never charge to their maximum capacity, and thereby, they sacrifice their charging opportunity for the larger good of the network performance. The node’s importance index (IDX) is shown in (4.6), where $Tx$ represents the number of data packets that originate from it and $Rx$ denotes the number of packets destined for the node. Data transfer activity, overhead by the node, that neither originate nor end at it are expressed through Channel busy time. The upper charging voltage $V_{\text{threshold}}^{\text{max}}$ is calculated from (4.7).

$$\text{IDX} = \frac{Tx + Rx}{Tx + Rx + \text{Channel busy time}}$$

(4.6)

$$V_{\text{threshold}}^{\text{max}} = \text{IDX} \times (V_{\text{max}} - V_{\text{min}}) + V_{\text{min}}$$

(4.7)

The charging time $T$ that the node includes in the ACK is calculated as follows, using the standard definitions of energy stored in the capacitor, (4.7) and the trigger voltage $V_{\text{threshold}}^{\text{min}}$ under which the RFE is set out by the node.

$$T = \frac{1}{2} C \{(V_{\text{threshold}}^{\text{max}})^2 - (V_{\text{threshold}}^{\text{min}})^2\} \frac{2\text{Slot energy}}{E_{\text{Max}}^{\text{RX}}}$$

(4.8)

Here, the received energy during the CFE pulses is obtained from two successive time slots, each of duration $\text{Slot energy}$.

4.5.3 Energy-aware Access Priority

This channel access determining feature of the RF-MAC manifests in two ways: The first is prioritizing between energy transfer and data communication, and secondly, identifying which nodes within the network should send out the data packets first by winning the channel.

4.5.3.1 Energy transfer prioritization

The residual energy of the requesting node is below a threshold $V_{\text{threshold}}^{\text{min}}$ when it sends the RFE, and hence, it should have higher priority in channel access. This is ensured by separately defining the DIFS duration for energy and data. Consequently, the specially formulated energy request DIFS duration ($\text{DIFS}_{\text{energy}}$) is shorter than DIFS for data exchange ($\text{DIFS}_{\text{data}}$), achieved by assigning a shorter slot time for energy request, while data exchange is provisioned with a longer slot time. Hence, we use the slot time of $10\mu$s for energy request and $20\mu$s for data communication as defined in the 802.11 standard [137]. Since DIFS is defined as $\text{SIFS} + 2\text{Slot time}_{\text{energy}}$, we
derive 25 $\mu$s for $\text{DIFS}_{\text{energy}}$ and 50 $\mu$s for $\text{DIFS}_{\text{data}}$. With the shorter DIFS duration and slot time, RF-MAC prioritizes the energy request over data exchange. Note that DIFS and SIFS are defined acronyms in 802.11 standard [137]. The time calculations for the protocol are given in Table I.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>slot time</td>
<td>10$\mu$s (energy), 20$\mu$s (data)</td>
</tr>
<tr>
<td>$\text{CW}_{\text{min}}$</td>
<td>32</td>
</tr>
<tr>
<td>$\text{CW}_{\text{max}}$</td>
<td>1024</td>
</tr>
<tr>
<td>$\text{DIFS}_{\text{energy}}$</td>
<td>$\text{SIFS}<em>{\text{energy}} + 2\text{Slot time}</em>{\text{energy}} = 25 \mu s$</td>
</tr>
<tr>
<td>$\text{DIFS}_{\text{data}}$</td>
<td>$\text{SIFS}<em>{\text{data}} + 2\text{Slot time}</em>{\text{data}} = 50 \mu s$</td>
</tr>
<tr>
<td>$\text{SIFS}$</td>
<td>5 $\mu$s (energy), 10 $\mu$s (data)</td>
</tr>
</tbody>
</table>

Table 4.1: Parameters used in RF-MAC

4.5.3.2 Data transfer prioritization

In the data exchange phase, the sensor contends for a channel using the CSMA/CA mechanism defined in 802.11 [137], i.e., it senses the channel for the DIFS duration before attempting a transmission. Consequently, sensors with higher energy harvesting rate, owing to their position or channel characteristics between the ETs and themselves, will have shorter charging durations. They will be able to participate timely for data communication, without interruptions and packet drops for frequent replenishment of energy, all of which contribute to the energy usage. We assign sensors with higher residual energy level a correspondingly higher priority to transmit. [149] proves analytically that this method results in an asymptotically optimal network lifetime. We design RF-MAC in such a way that the sensor’s backoff duration is influenced by its residual energy, i.e., the node with higher residual energy experiences a shorter backoff duration than the node with lower residual energy. An example of the adaptive backoff mechanism for data exchange is described in (4.9). The contention window for data exchange ($\text{CW}_{\text{data}}$) is randomly selected from the range between the minimum $\text{CW}$ and node’s current $\text{CW}$, $[\text{CW}_{\text{min}}, \text{CW}_{\text{current}}]$. We set the contention window of 32 for $\text{CW}_{\text{min}}$ in this work. Further, (4.9) shows how the effective slot time is a scaled value based on the residual energy. The capacitor voltage is used for scaling, where it is limited at the high end by the rated voltage of the capacitor $V_{\text{max}}$ (note this is different from the upper charging threshold in
Figure 4.6: Energy-aware data exchange process in RF-MAC protocol with three transmitter nodes $S_1$, $S_2$, and $S_4$ and the receiver node $S_3$.

Equation (4.7), current voltage $V_{\text{current}}$, and the $V_{\text{threshold}}$ that signals a critical point if the sensor needs to be kept in operation.

\[
\text{Backoff} = \text{DIFS}_{\text{data}} + CW_{\text{data}} \times \left\{ \text{Slot}_{\text{energy}} + \frac{(V_{\text{max}} - V_{\text{current}})(\text{Slot}_{\text{data}} - \text{Slot}_{\text{energy}})}{V_{\text{max}} - V_{\text{threshold}}} \right\}
\]

(4.9)

The overall process of data exchange is explained using Figure 4.6. Sensors $S_1$, $S_2$, and $S_4$ all have packets to transmit to sensor $S_3$ at the start (indicated by the arrow on the time axis). They each sense the channel for DIFS$_{\text{data}}$. Intuitively from (4.9), sensor $S_2$ with the residual energy of 3.0 V, should experience the shortest backup duration, as opposed to $S_1$ and $S_4$. However, this does not imply that the nodes with higher residual energy will always have a shorter back off duration, as the random selection of the backoff slots within the window does contribute to the overall backoff time. This selection of the window $[CW_{\text{min}}, CW_{\text{current}}]$ is independent of node’s residual energy.

### 4.6 Simulation Results

In this section, we evaluate the performance of our RF-MAC protocol using the ns-2 network simulator, with experimental results presented in the next section. We demonstrate the performance improvement with respect to the following metrics: (i) number of energy transmitters, (ii) number of data flows, (iii) numbers of nodes, and (iv) packet size. The primary performance metrics are the average network throughput and the average harvested energy. In particular, the first
metric shows the average per-node throughput of the sensor network, and the second metric gives the average energy harvested per-node that is found by recording and averaging the harvested power by nodes during the simulation.

The simulation parameters are set as follows. The EH circuit parameters are from [1]. We model the ETs on the Powercaster transmitter [126], which radiates continuous waves at 3 W. The operational characteristics of the sensor, such as energy spent on transmission, reception, idle listening, channel bandwidth, etc. are from Mica2 specifications [150]. Unless specifically stated, 250 sensor nodes and 100 ETs are deployed uniformly at random in 50 x 50 m² grid. Traffic loads are generated by constant bit rate (CBR) flows. Nodes have a full buffer and all data packets are 50 bytes in size. The sender/receiver pairs are chosen randomly, and the intermediate relaying nodes do not aggregate or compress data. Additional parameters used in the simulation are presented in Table I.

We compare three different protocols: 1) RF-MAC-opt, 2) RF-MAC-no-opt, and 3) modified unslotted CSMA. RF-MAC-opt is the full-featured RF-MAC, including the joint spectrum-ET selection, adaptive charging threshold, and energy-aware channel access priority mechanisms, as discussed in Section 4.4. The RF-MAC without the optimization (named RF-MAC-no-opt) has all components of RF-MAC other than joint spectrum-ET selection component. In particular, it does not assign different frequencies to the ETs and makes no attempt to identify and classify ETs based on their phase mismatch. We evaluate the RF-MAC-opt against RF-MAC-no-opt in order to investigate the effectiveness of the joint spectrum-ET selection feature incorporated in our RF-MAC protocol, especially in avoiding energy interference and improving the network performance. Finally, the modified CSMA is adapted from [105], which provides the baseline for our performance evaluations. To have a fair baseline comparison, the modified CSMA (in which each sensor node may issue the RFEs and receive the CFEs) is compared against both RF-MAC-opt and RF-MAC-no-opt. In the modified CSMA, there is no attempt made to calculate the optimal charging time, and it has none of the features of the RF-MAC protocol. Once an RFE is sent out, the node charges to its maximum capacity and does not take into consideration the impact on data traffic, energy cancellation, and the residual level of the sensor nodes. Data points in each graph represent the mean of twenty scenarios and the corresponding 95% confidence intervals are plotted as error bars in the figures.
4.6.1 Impact of the Number of ETs

In the first set of experiments, we investigate the effect of the number of ETs for different MAC protocols. Figure 4.7 shows the effect of the ET density on the average harvested energy of two RF-MAC variants. The ET density, defined as the average number of ETs located within the radio range of a sensor node, varies from 1 to 12. It is clear that both RF-MAC variants dominate over the modified CSMA. As shown in Figure 4.7, RF-MAC-opt delivers monotonically increasing average harvested energy with increasing the number of ET density. The benefit of frequency optimization greatly improves the performance as it maximizes the energy transfer by separating two transmission spectrum and ensuring the highest level of energy delivery. Without this optimization, ETs enter the charging process and do not take into account the possibility of destructive interference, resulting in sub-optimal energy transfer.

The average network throughput is shown in Figure 4.8 and the trend is observed to be very similar to the average harvested energy plot. Both variants of RF-MAC yield higher average network throughput as ET density increases. However, the throughput of RF-MAC-opt is significantly higher than RF-MAC-no-opt, with a 62% increase on average. Both the average harvested energy and average network throughput of modified CSMA are the lowest among protocols under study. This is because modified CSMA does not have the adaptive charging features included in the RF-MAC protocol. In this case, RF-MAC-opt yields over 100% and 300% more than the modified CSMA in terms of the average harvested energy and average throughput, respectively.
4.6.2 Impact of Multiple Flows

The effect of multiple simultaneous flows in the sensor network is investigated next, with random selection of source and destination nodes, while the number of flows is varied from 1 to 6. Again, we observe the behavior of RF-MAC on two energy and throughput metrics, when nodes experience different levels of channel usage and traffic loads. Figure 4.9 shows a smooth and monotonic increase in the average harvested energy of RF-MAC-opt as the number of flows increases. Even though the RF-MAC-no-opt exhibits a similar pattern, the increase is not as smooth as one with the frequency optimization. Evidently, the amount of average harvested energy yield could be almost 150% less than RF-MAC-opt. Figure 4.10 depicts the average network throughput of RF-MAC with various numbers of data flows. Interestingly, the average network throughput of both RF-MAC variants gracefully drops as the number of data flow increases. This reduction in the throughput is a result of more nodes sending out RFEs as they deplete their energy faster with increasing number of data flows. Consequently, the network spends more time in the charging state and less time spent in the data exchange state. However, RF-MAC-opt yields higher average network throughput, approximately 20% more in this case. Again, both variants of RF-MAC largely outperform the modified CSMA. Especially, RF-MAC-opt yields approximately 112% increase in terms of throughput.
4.6.3 Impact of the Number of Sensor Nodes

We investigate how RF-MAC protocol behaves when the number of sensor nodes in the topology changes. We randomly deploy various numbers of sensor nodes in the topology, ranging from 60 to 240. The average harvested energy is shown in Figure 4.11 wherein the performance of RF-MAC-opt smoothly drops and tends to stabilize when 120 sensor nodes or more are present. On the other hand, RF-MAC-no-opt yields a similar pattern to the modified CSMA, a rather constant average harvested energy with fluctuations around the mean trend. Again, RF-MAC-opt offers higher average harvested energy when compared to RF-MAC-no-opt. Figure 4.12 depicts the average network throughput of RF-MAC with different numbers of sensor nodes. Similar to the earlier case with the average harvested energy, both RF-MAC variants experience the reduction in average network throughput even RF-MAC-opt displays marginally higher throughput. Moreover, the modified CSMA performs significantly lower than RF-MAC-opt and RF-MAC-no-opt in both harvested energy and network throughput.

4.6.4 Impact of Packet Size

The packet size is varied from 30 to 90 bytes with an increment of 20 bytes, while other parameters are kept to their default settings. The impact of packet size on the average harvested energy of RF-MAC is shown in Figure 4.13. It is clear that the average harvested energy of RF-MAC-opt is monotonically increasing with an increasing packet size, and offers up to 25% gain over...
RF-MAC-no-opt at the packet size of 90 bytes. On the other hand, the average harvested energy of RF-MAC-no-opt tends to stabilize for packet sizes larger than 50 bytes. The average network throughput of RF-MAC is shown in Figure 4.14. Both RF-MAC variants offer an increase in average network throughput with increasing packet size. Again, the RF-MAC-opt outperforms, in terms of the average network throughput, its non-optimized variant and the modified CSMA throughout the study range.

4.7 Experimental Study

Our testbed consists of 4 parts, signal generators (Agilent N5181 MXG RF signal generators), RF switches, RF amplifiers of 3W EIRP (to emulate two ETs), and three wireless sensors. We implemented the RF-MAC protocol in Mica2 motes equipped with Chipcon CC1000 radios and connected to our in-house fabricated RF energy harvester [1] operating at 915MHz shown in Figure 4.15. The sender motes are programmed to continuously transmit 30 Byte packets to the sink. We use the following setup to build the two ETs for the transmission of wireless RF power, whose schematic is shown in Figure 4.16. The signal generators produce two energy waves with bandwidth 63 kHz (similar to Powercaster transmitter [126]) that are slightly shifted, corresponding to the frequencies \( f_1 \) and \( f_2 \) obtained in frequency assignment optimization earlier. These frequencies for our energy harvesting setup are found as \( f_1 = 915 \text{ MHz} \) and \( f_2 = 916 \text{ MHz} \). This assures that transmission of the ETs and the sensor motes are in-band and mechanisms such as data vs. energy
channel access can be verified correctly through the experiments. The ET controller sends appropriate interrupt signal to the RF switch upon receiving the ACK packet from the energy requesting node. We also programmed Mica2 mote to function as an ET controller by using three interrupt pins of the mote’s expansion connector based on the MPR/MIB User’s Manual[150]. Specifically, INT0 is used to disable and enable the RF switch, INT1 is used to select output frequency $f_1$, and INT2 is used for selecting output frequency $f_2$. Accordingly, the RF switch passes the selected input signal to the RF amplifier which then transmits with output power 3W EIRP. Note that in the testbed both ET1 and ET2 have the same configurations, with the interior working of one of them expanded for brevity.

In order to verify the benefit of RF-MAC variants (two-tone and single-tone energy transfer) over the modified CSMA, the RF harvester is fixed at the location $0\lambda$, ET1 is fixed in location $3\lambda$ away from the harvester, while the location of ET2 is varied between location $0\lambda$ to $3\lambda$. We evaluate the testbed under three different scenarios as follows:

- Both ET1 and ET2 adopt RF-MAC with two-tone energy transfer ($f_1$ at 915 MHz and $f_2$ at 916 MHz).
- Both ET1 and ET2 adopt RF-MAC with single-tone energy transfer (only one group is transmitted on $f_1$ at 915 MHz).
- Both ET1 and ET2 adopt the modified CSMA that does not employ frequency assignment optimization.

Figure 4.11: Effect of the number of nodes on the average harvested energy.
The average charging time and the network throughput of the testbed under various MAC protocols are shown in Figures 4.17 and 4.18. Each point in the experimental results represents an average of ten independent experiments for 95% confidence interval with 5% precision. It is clear that the RF-MAC with two-tone energy transfer not only yields the highest average network throughput and the lowest charging time but also it experiences minimal fluctuations. On the other hand, the modified CSMA gives the highest charging time and the lowest network throughput when ET2 is not located at the position that results in in-phase combination of energy waves at the harvester. The RF-MAC protocol prevents destructive effect by out-of-phase combination of energy waves, and consequently achieves higher average network throughput. Moreover, the RF-MAC with two-tone energy transfer provides additional improvements in the receiving power when compared to single-tone energy transfer since both ET1 and ET2 can operate simultaneously. There exists a region where destructive effect is less pronounced, i.e., when ET2 is varied from location $0\lambda$ to $1\lambda$. This is because the power provided by ET2 is much higher when compared to the one provided by ET1. ET2 power and phase simply dominates the behavioral outcome. However, it can be observed that the destructive effect is more pronounced when ETs are distanced equally, i.e. ET2 at $2.5\lambda$ or $3.5\lambda$ when ET1 is at $3\lambda$. 

Figure 4.12: Effect of the number of nodes on the average network throughput.
4.8 Final Remarks

In this chapter, we proposed the RF-MAC protocol that specifically addresses the problems of joint selection of energy transmitters and their frequencies based on the collective impact on charging time and energy interference, setting the maximum energy charging threshold, requesting and granting energy, and energy-aware access priority. The grouping of the ETs into two sets with varying transmission frequencies, and the minimal control overhead are both geared to keep the hardware requirements simple, and the protocol easier to implement. Our protocol delves on the important issue of how to determine the energy vs. data communication tradeoff, especially as one occurs as the cost of the other. Finally, simulation and testbed results reveal that RF-MAC largely outperforms the modified CSMA in both average harvested energy and average network throughput.
Figure 4.14: Effect of the packet size on the average network throughput.

Figure 4.15: Our fabricated RF energy harvester powers Mica2 mote by converting the received RF power to electrical energy.
Figure 4.16: Schematic of our experimental setup for transmission of wireless RF power.

Figure 4.17: Effect of ET2 position on the average harvested energy.

Figure 4.18: Effect of ET2 position on the average network throughput.
Chapter 5

Omnidirectional RF-Powered Wireless Sensor Network

5.1 Introduction

In this chapter, we study the omnidirectional RF-powered wireless sensor network and propose analytical models to capture the behavior and energy interference in such networks. In particular, we investigate the possibility and effects of concurrent data and energy transfer in the first section. It follows with an experimental section to show how practically low-power data communications can survive the presence of high-power energy signals. The last section introduces an analytical framework to calculate the received and harvestable power from multiple wireless chargers at each point of space taking into account low-power data communications, RF energy harvesting circuit, and interference among energy signals.

5.2 Concurrent Data and Wireless Energy Transfer

Wireless Sensor Networks (WSNs) are a fundamental building block of the Internet of Things (IoT) and a key enabler for cyber physical and pervasive computing systems. However, sensor nodes are typically battery-powered, and their limited energy affects protocol design, sacrificing throughput, bandwidth usage, and reliability to the need for extended network lifetime through judicious use of energy. Since it is often difficult, if not impossible, to access the sensor nodes and replace their batteries, most research efforts have focused on intelligent duty cycling and energy
saving techniques at all layers of the protocol stack. Recent developments in energy harvesting technology from ambient sources promise to alleviate some of these concerns [138].

This section explores the scenario where radio frequency (RF)-based technology is used to charge the sensors through dedicated energy transmitters (ETs). However, the high broadcast power of the ETs, emitting energy waves up to 3 Watts, introduces additional interference in data communication. Through detailed experimentation, this section aims at quantifying the impact of selecting network parameters relevant to RF energy transfer and data communication on the coexistence of ETs and sensor nodes. In particular, we are interested in determining values of those parameters that enable fruitful coexistence, considering the challenges imposed by the low transmission power of the sensor nodes (e.g., the output power of 802.15.4 devices, which is typically as low as 0 dBm) and the high-power energy waves (possibly above 30 dBm), causing interference and significant packet loss.

Our experiments involve both the physical layer and the link layer by measuring the received signal strength, packet reception rate, and the amount of harvested power under carefully-designed scenarios with single and multiple ETs. Previous empirical studies in WSNs focused on complex, non-ideal behavior of low-power wireless links [151, 152], concurrent data transmissions [153], and the coexistence between WSNs and WiFi [154, 155], microwave ovens [156] and the smart grid [157]. To the best of our knowledge, this work provides the first study on interference and coexistence issues in RF energy-powered WSNs. In so doing, we identify the boundary conditions that allow nodes equipped with RF energy harvesters to transfer data with high throughput and with limited interference from transmitting ETs.

The key contributions of our work include the following.

- We investigate the effect of data transmissions and energy transfer in the same frequency band, quantifying the impact of long-range interference of energy transmitters, and the energy charging range required to effectively recharge nodes.

- We show the interference between RF energy transmitters and wireless nodes when they occur simultaneously as a function of the separation of frequency of use. We also identify safe frequency separation for concurrent data and energy transmission.

- We demonstrate the destructive interference effect of multiple energy transmissions on the same frequency, and measure the impact of energy cancellation on the amount of harvested power.
CHAPTER 5. OMNIDIRECTIONAL RF-POWERED WIRELESS SENSOR NETWORK

- We show the viability and efficiency of multi-frequency band RF energy harvesting for RF energy circuits with a wide frequency response range.

The rest of this part is organized as follows. In Section 5.3.1 we describe our experimental setup. Section 5.2.2 presents results on determining viable ranges for coexistent WSNs and ETs. Results on concurrent data and energy transmissions are discussed in Section 5.2.3. Results concerning concurrent energy transmissions from multiple ETs are illustrated in Section 5.2.4 and 5.2.5.

5.2.1 Experimental Setup

We selected a controlled environment with four plain walls and no other intermediate reflective objects to limit time-varying changes in the wireless channel due to multi-path fading and shadowing. We use a pair of Mica2 motes equipped with Chipcon CC1000 radios [158] operating at 915 MHz for the sensor nodes with a default RF (data) transmission power of 0 dBm. The receiver sensitivity is –98 dBm. Motes use a 38.4 Kbps data rate with Manchester encoding and a non-coherent FSK modulation scheme. For the RF frequency-tunable ET, we use an Agilent N5181 MXG RF signal generator [159] connected to an amplifier with a 50 Ω omnidirectional antenna in the 902–928 MHz band. Our setup also deploys commercially available P2110 RF energy harvesters from Powercast Co. [160], connected to the motes. The Agilent E5061B vector network analyzer is used to measure the strength of interfering signals caused by the ETs. The motes and ETs are placed on a flat table, 0.5 m from the floor. The sender and receiver nodes are placed one meter from each other, and they are equidistant from the ET. We use a total of 360 packet transmission epochs to estimate the packet reception rate (PRR) with a precision of 1.2% for each particular combination of energy transmission frequency and distance between the ET and the motes.

5.2.2 Ranges for Coexistent WSNs and ETs

In this section we determine ET ranges that affect mote charging and data communications. We are concerned about data communication among motes, as well as communications between motes and the ETs, for energy requests, control packet exchange and to relay traffic. More precisely, we are interested in determining: $C_1$: The charging range within which a mote can harvest RF energy and recharge its batteries. $C_2$: The data communication range within which a mote can communicate with the ET. However, motes in the circular area determined by $C_2 - C_1$ cannot be charged. $C_3$: The interference range. Motes in the circular area determined by $C_3 - C_2$ cannot be charged or communicate with the ET. Motes within the $C_3$ range experience interference from the ET energy...
transmission and therefore data communications among them is affected when the ET is charging the
motes. These ranges are depicted in Fig. 5.1.

In the rest of this section we introduce the RF wireless charging model, and perform
experiments to determine the maximum ranges for charging, communication and interference.

5.2.2.1 RF wireless charging model

According to Friis’ free space model, the amount of RF power received by the energy
harvesting circuit of the mote decreases with the square of the distance between the transmitter
and the receiver. As a consequence, the available power and charging rate decreases for increasing
distances between the ET and a mote. This means that after a certain distance, there would not be
enough input power for the energy harvesting circuit to charge the node. Moreover, the incident
RF radiation on the energy harvesting antenna is converted to a DC voltage using the RF energy
harvester. The total RF-to-DC conversion efficiency of a node, which is defined as the ratio of output
DC power to the incident RF power, depends on the design of the energy harvesting circuit and on
the received RF power. The output voltage from the harvester (i.e., the available DC power after
conversion) is then either stored in an energy storage component or delivered to the sensor node for
immediate usage. Based on the Friis’ free space model, the following formula provides a first-order
estimate of the amount of power that may be harvested:

\[ P_r = \eta G_{ET} G_r \left( \frac{\lambda}{4\pi D} \right)^2 P_{ET}, \]  

(5.1)

where \( P_{ET} \) is the output power of the ET, \( \eta \) is the RF-to-DC conversion efficiency, \( G_{ET} \) is the
antenna gain of the ET, and \( G_r \) is the antenna gain of the RF energy harvester. Also, \( D \) indicates the
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Figure 5.2: Charging ranges: experiments vs. theory.

Figure 5.3: (a) Communication ranges for different data transmit powers. (a) Energy transmission interference for different ET powers. (c) RSS for concurrent data and energy transfer at the same frequency.

We perform experiments to determine the maximum charging range and demonstrate the accuracy of Equation (5.1). We use the Powercast P2110 evaluation board. The average wavelength of the energy signals transmitted at $f_c = 915$ MHz is 0.328 m, and the energy transmitter and RF energy harvesting circuit have antenna gains of 1 dBi and 6.1 dBi, respectively. The harvested energy is stored in a capacitor with capacitance rating $C = 100$ mF. We set the energy transmitter output power to 3, 2, and 1 Watts. The Federal Communications Commission (FCC) in the US limits the output power of radios using unlicensed frequency bands to 4 Watts effective isotropic radiated power.
power (EIRP), and, accordingly, the ETs usually send power at maximum level of 3 Watts. We vary the distance between the antennas of the harvester and that of the ET from 0.5 to 7 m, in increments of 0.5 m. At each location, we measure the wireless charging duration $\Delta T$ starting from an initial voltage $V_1 = 1.8$ V, as minimum operating voltage of the Mica2, to $V_2 = 3.3$ V, as the maximum voltage of the capacitor, and calculate the harvested power using the relation: $C(V_2^2 - V_1^2)/2\Delta T$.

Fig. 5.2 shows curves for the experimental and theoretical results (Equation (5.1)) on the average harvested power as a function of the distance between the ET and the mote for three different transmit power settings. The theoretical and experimental curves are remarkably close. It can be observed that the measured harvested power significantly depends on the charging distance as well as on the ET transmission power. Furthermore, it is shown that when the mote is far away from the ET, the harvested RF power is negligible, and after a threshold the sensor node cannot effectively harvest any amount of useful energy. As depicted in Fig. 5.2 at the highest transmit power (3 Watts) the measured maximum charging range $C_1$ is about 5 m. The charging ranges for energy powers of 2 and 1 Watts are 3 and 1.5 m, respectively. The RF-to-DC conversion efficiency ($\eta$) in Equation (5.1), which depends on the received input RF power at a given location, is obtained from the Powercast P2110 harvester data-sheet [160].

5.2.2.3 Communication range

The data communication range between the mote and the ET and among sensor motes in an RF-powered WSN may be influenced by several factors such as the data transmission power, the sensitivity of the receiver node, the gain and efficiency of the antennas, and the transmission rate. To quantify the communication range, we assume the ET uses the same RF transceiver chip as the motes. We plot packet reception rate for different combinations of data transmission power and the separation distance between the sender and the receiver when the ETs are turned off. Specifically, we vary the straight line distance between two Mica2 motes and obtain PRR measurements at transmission power levels of 5, 0, −5, and −10 dBm, as shown in Fig. 5.3a. We observe that for each data transmit power, when the distance increases beyond a threshold, the packet reception rate decreases dramatically. We consider the threshold at which the percentage of received packets drops below 85% as an estimate of the communication range. Accordingly, from Fig. 5.3a we observe that the maximum communication ranges $C_2$ are approximately 75 m, 50 m, 20 m, and 12 m for data transmit powers of 5, 0, −5, and −10 dBm, respectively. It can be observed that the measured communication ranges are relatively longer than the charging ranges.
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<table>
<thead>
<tr>
<th>ET Power</th>
<th>Charging Range ((C_1))</th>
<th>Interference Range ((C_3))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Watts</td>
<td>1.5 m</td>
<td>160 m</td>
</tr>
<tr>
<td>2 Watts</td>
<td>3 m</td>
<td>230 m</td>
</tr>
<tr>
<td>3 Watts</td>
<td>5 m</td>
<td>275 m</td>
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</table>

<table>
<thead>
<tr>
<th>Data Power</th>
<th>Communication Range ((C_2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>+5 dBm</td>
<td>75 m</td>
</tr>
<tr>
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<td>50 m</td>
</tr>
<tr>
<td>-5 dBm</td>
<td>20 m</td>
</tr>
<tr>
<td>-10 dBm</td>
<td>12 m</td>
</tr>
</tbody>
</table>

Table 5.1: Summary of measured coexistence ranges in wireless-powered sensor network.

5.2.2.4 Interference range

We investigate the interference range \(C_3\) of the ETs and how different energy transmission powers affect it. To this end, we use a pair of communicating Mica2 motes and vary the distance between the receiver mote and the ET under different output power levels. In particular, at each location, we measure the PRR over 360 packet transmission epochs for each of the three energy transmission values. From Fig. 5.3b, we observe that for each transmit power there is a threshold distance at which the percentage of correctly received packets reaches zero. When the distance increases beyond that threshold, the percentage of received packets starts to increase gradually. This threshold is the interference range \(C_3\). We observe that the interference ranges are significantly larger than both of the communication and the charging ranges obtained from Fig. 5.2 and 5.3a. We see in Fig. 5.3b that the maximum interference range is 160 m, 230 m, and 275 m when the ET transmits at 1, 2 and 3 Watts, respectively. Table 5.1 compares all the measured ranges for charging, communication, and interference.

5.2.3 Concurrent Data and Energy Transmissions

In this section, we investigate how high power energy transfer affects concurrent low power data transmissions among motes. We perform two different sets of experiments depending on whether energy and data transmissions happen at the same or at different frequencies.
5.2.3.1 Transmissions at the same frequency

We set the distance between the receiver mote and the ET to 5 m, the value of the maximum charging range. Packets are transmitted back to back from the sender to the receiver mote. The ET transfers power at 915 MHz, with an output power of 3 Watts. The ET is switched on at 30 s from the start of the experiment, turned off at 50 s, turned on again at 100 s and finally turned off at 140 s. The experiment terminated after 180 s. The level of interference in a channel is determined by measuring the received signal strength (RSS) values in the receiver, with the measured ambient noise having a standard deviation of less than 1 dBm.

Fig. 5.3c shows that without interference, the sender node has reliable communication with the destination. However, when the ET is turned on, the received power at the receiver mote increases noticeably from −50 dBm (data plus noise floor) to −6 dBm (joint data, noise, and interference). This leads to no packet reception during the transmission of energy signals.

5.2.3.2 Transmissions at different frequencies

The long interference ranges of ETs motivates us to investigate how PRR is affected by energy waves at frequencies different than those used for data communication. Interference may still occur because the transmission power of high radiative energy signals may leak into the data communication channel. This leakage power is a function of the separation between two channels used for energy and data transmission.

For this investigation we set the operating frequency for data communications to 915 MHz, and we vary the energy transfer frequency from 911 MHz to 919 MHz, while the power output of the
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ET is set to 3 Watts. For each frequency, we change the distance between the ET and the receiver mote from 1 m to 5 m (the maximum charging range), and measure the average PRR over all ranges. Note that these short ET ranges represent the worst case of interference, and as the ET distance increases, the packet reception rate improves. In Fig. 5.4 the bars indicate the average PRR over all ET ranges, and the error bars show the maximum and minimum PRRs among all distances as the frequency of energy transfer varies.

The results reveal the interference patterns between the ET and the mote when concurrent energy and data transmission happens at different frequencies, regardless of their distance. We find that the energy spectrum can be divided into three different areas: The one characterized by severe interference, the one by moderate packet reception, and the one with no packet loss. Table 5.2 summarizes these frequency areas. From Fig. 5.4 it can be observed that any energy transmission from 914.400 MHz to 915.800 MHz results in corruption of all data packets. In fact, the sensor data channel is still affected by the leakage power of energy signals transmitting on these frequencies, which results in 0% PRR. However, there are two spectral ranges, namely, from 913 MHz to 914 MHz and from 916 MHz to 917 MHz, where the average PRR is between 40% to 90%. This means that when the ET transfers energy over these frequency ranges, data transmissions will not always be successful, though at some frequencies high PRR is achieved. Fig. 5.4 shows that any energy transmission at frequencies less than 913 MHz or larger than 917 MHz does not affect the PRR significantly. We observe that the average PRR in this case is always ≥ 90%.

Based on our experiments, we are able to determine a safe frequency separation distance \( \Delta f(e, d) \) between energy and data signals such that if energy transmission and data transmission happen concurrently at frequencies that are separated more than \( \Delta f(e, d) \), data transmission occurs without considerable interference.

In our testbed we find that the value of \( \Delta f(e, d) \) is 2 MHz. Knowing this value can be useful for designing communication protocols for RF-powered sensor networks to guarantee concurrent data and energy transmissions over different frequencies without packet losses. Finally, Fig. 5.5 shows the 95% confidence interval of the average PRR for all selected distances between the ET and the receiving mote.

5.2.4 Concurrent Energy Transmissions: Same Frequency

In this section we study the feasibility and the effects of energy transmissions from multiple ETs operating at the same frequency. We first investigate the constructive and destructive interference
of concurrent energy transmissions and determine the energy cancellation range for concurrently transmitting ETs.

A sensor node can be charged either through a unilateral energy transfer of one ET, or through the coordinated transmission of multiple ETs. When a node requests energy from neighboring ETs, other nodes within the ET charging range also benefit from the energy transmission and can be recharged. In the case of multiple ETs, concurrent energy transmissions can only be beneficial if the arriving energy waves at the node are aligned in phase [16]. More specifically, the multiple energy waves can combine constructively or destructively according to their relative phases or path lengths between the energy transmitters and the receiver node, leading to variations in the amount of harvestable power. In constructive interference (in-phase), the received power of the resulting wave at the RF energy harvester is greater than that of either of the individual energy waves. In the case of destructive interference (out-phase), the net received power is less than that of the individual energy
Figure 5.6: Multiple energy transmitters at the same frequency cancel transferred energy in destructive areas and aggregate energy in constructive areas.

waves. Constructive and destructive interference depend on the relative distance from the ETs and the receiving nodes. Therefore, there will be areas where energy combines constructively and areas where energy waves cancel each other.

Fig. 5.6 depicts examples of constructive and destructive areas when two and three ETs transmit at the same frequency. These areas map out the way in which the phase difference between the energy waves varies in space. Here, the middle of the black circles represents crests of energy waves and the middle of the white circles represents the troughs. The energy waves interfere and cancel each other to some degree in the destructive areas (wedges of white) and strengthen each other within the constructive areas (wedges of dark). The patterns of constructive and destructive areas depend on the number and the separation of energy transmitters. As the number of ETs increases, it becomes quite involved to accurately estimate the power intensity distribution, and the pattern of the constructive and destructive areas.

Next, we perform a set of experiments to better understand and illustrate the effects of destructive and constructive interference. We consider two energy transmitters, ET1 and ET2, with the same configuration used for the charging range measurements in Section 5.2.2.2. The ETs transfer energy at 915 MHz (i.e., $\lambda = 0.328$ m) each with an output power of 3 Watts. The ET and RF energy harvesting circuits have antenna gains of 1 dBi and 6.1 dBi, respectively, and the capacitor storage of the receiver node is $C = 100$ mF. We measure the total harvested power while varying the distances between energy transmitters and the receiver, which leads to the different phase separations of the arriving energy waves. In particular, we fix the path length between ET1 and the receiver mote at distances of 1, 2, and 3 meters, and at each location we vary the distance between ET2 and the antennas of the RF harvester from 0.5 to 6 meters. We repeat each experiment 10 times, and for each we record the wireless recharge duration and calculate the total harvested power (see Section 5.2.2.2).

Fig. 5.7 compares our measurement results for different distances of ET1 and ET2. It can
be observed that destructive interference from one ET strongly affects the energy transmitted by another ET, and at distances, all transmitted energy waves could be canceled totally. This results in very low or no harvested power even when all ETs are transferring energy with high power. Also, this figure shows that there are distances in which the energy signals arrive constructively and the total measured harvested power in this case can be as much as four times the power of a single energy wave if the two energy transmitters have the same path length. Moreover, it is shown that the total measured harvested power oscillates between constructive and destructive values as the ET moves from one location to another.

From Fig. 5.7, we see that the interference from multiple energy transmissions depends on both the distance of the ETs from each other and the path length of each ET from the receiver mote. As the path length of the ET increases, the intensity of interference decreases, and after a threshold distance the destructive interference becomes negligible. On the other hand, comparing Fig. 5.7 (a), (b), and (c), we can see that the energy interference is more significant when the ETs are
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closer to the receiver. For example, the energy interference is higher when ET1 is 2 m away from
the mote compared to when it is 3 m away. It is lower compared to when ET1 is 1 m away. Thus,
interestingly, even though the ETs that are closer to the receiver provide higher levels of energy, they
can result in higher levels of energy cancellation. This shows the importance of energy interference
in the design of network protocols for RF-powered WSNs with multiple ETs.

The destructive and constructive interference of two incident energy waves are less pro-
nounced when the power of one wave dominates the other, or when the power of both waves are very
low. Let $R_1$ and $R_2$ denote the distances of ET1 and ET2 from the receiver mote, respectively. Based
on our experimental results, we define the energy cancellation range as the minimum path length
difference of the two ETs $\Delta R_{\text{min}}$ with respect to the ET closer to the receiver and such that for all
values of $R_1$ and $R_2$ for which $|R_2 - R_1| \geq \Delta R_{\text{min}}$ the joint energy interference has negligible
effect on the amount of the total harvested power. The energy cancellation range could be useful in
the design of routing protocols, for managing energy cancellation effects, and for channel assignment
algorithms. The energy cancellation range is determined as follows. From Fig. 5.7 we see that when
the first ET is located at distance 1 meter from the receiver, the effect of constructive and destructive
energy interference in terms of fluctuations in the harvested power would be significant till ET2 is 2
m from the receiver. The energy interference decreases as the distance between ETs and the receiver
increases, and the interference becomes negligible when ET2 is 5 m away. Accordingly, the energy
cancellation range when ET1 is 1 m away from the receiver is found to be 4 meters. Similarly, the
energy cancellation range when ET1 is 2 and 3 meters away is be found to be 0 m, when ET2 is 2
m away, and 1.5 m when ET2 is 1.5 m away, respectively.

5.2.5 Concurrent Energy Transmissions: Multi-Frequency

In this section, we show the feasibility and efficiency of RF energy harvesting at multiple
frequencies (multi-band RF harvesting).

Fig. 5.8a and 5.8b show the harvesting efficiency of the P2110 and P1110 energy har-
vesters [160] over the full ISM frequency range for 902 MHz to 928 MHz, for various ET-to-harvester
distances. These results are obtained from the powercast RF harvester data-sheets as well as the pow-
ercast wireless charging calculator [160] that contains the RF-to-DC conversion efficiency at different
frequencies and input powers. We can see that the efficiency of RF energy harvesting depends on the
input power, which is a function of the distance between the ET and the RF harvester. Moreover,
both pictures in Fig. 5.8 show that the design of the harvesting circuit has a significant impact on the
efficiency of harvesting. Specifically, the P2110 powerharvester outperforms the P1110 harvesting board over long charging distances, while the P1110 harvesting board has better performance over short charging distances. Most important, at each distance the RF energy harvesting circuit provides almost the same performance and efficiency over a range of frequencies. As the bandwidth of the energy signal is relatively small (i.e., 99% of the occupied bandwidth is approximately 63 kHz [161]), our results demonstrate that if the RF harvester is optimized for a frequency range transferring energy at different frequencies will not decrease the amount of harvested power when using multiple ETs, independent of the distance between the energy transmitters and the receivers. Consequently, the RF harvester can simultaneously and effectively harvest RF power over a range of different frequencies within the bandwidth of its harvesting circuit.
5.3 Surviving Wireless Energy Interference

Recent advancements in energy harvesting and wireless energy transfer through radio frequency (RF) waves have opened up new possibilities for powering the nodes of a wireless sensor network (WSN) wirelessly. This not only extends the network lifetime, but also obviates the problem of retrieving sensors and physically replacing batteries. The RF energy harvesting sensors convert the energy contained in incident electromagnetic radiation emitted by wireless energy transmitters (ETs) into stored electrical charge within a capacitor or re-chargeable battery. This limited stored energy can then be used for sensing, processing and communication. However, the high power of RF waves emitted from ETs interfere with low-power data communications among sensor nodes. This leads to interference and packet loss. The objective of this experimental study is to quantify this loss under various placements of ETs, including choice of frequencies and separation distances.

Motivation. The Federal Communications Commission (FCC) permits up to 4 Watts effective isotropic radiated power (EIRP) for wireless energy transfer. Most Commercial Off-The-Shelf (COTS) ETs (e.g., Powercaster [160]) generate 3 Watts energy waves. These high levels of radiation are much higher than those of typical sensors, such as the MicaZ, whose maximum transmission power is limited to 1mW. Thus, the adverse impact of continuous RF energy transfer on sensor communication should be quantified. One approach could be using duty-cycle based energy and data transfer, resulting in controlled and pre-decided trade-offs between data throughput and energy harvesting levels [138]. At the hardware level, the state-of-the-art RF energy harvesting circuits can operate over a range of frequencies [162, 163]. Thus, if the ET frequencies can be separated from data frequencies then the packet losses caused by simultaneous data and energy transfer may be minimized.

Previous empirical studies in WSNs have focused on understanding the coexistence between WSNs and WiFi [154, 155], microwave ovens [156], and smart grids [157]. There are also experimental studies on concurrent data transmissions on low-power wireless links [152, 151]. However, none of them have studied the interference issues in WSNs with wireless energy transfer. Moreover, the power difference between interfered signals (i.e. high power energy signal and low-power data) in RF-harvesting sensor networks is much higher than those in the previous studies, which necessitates to study the adjacent-channel interference of energy signals on low-power data communications in practice. To fill these gaps, this study is looking to find what are the observable impacts of energy interference, how to survive such interference, and leverage the interference level at each node for reliable data and energy transfer.

Experimental methodology. We conduct a series of experiments at indoor and outdoor locations to
study the effects of (i) RF energy interference on data communication, (ii) the benefits of energy transfer when spread over different frequencies (i.e., under various separation levels of energy and data frequencies), and (iii) the location of ETs on packet delivery. We present the distributions of energy interference measured by sensor nodes for different energy frequencies. Our experiments involve both statistical and time-trace measurements of packet reception rates, as well as the received interferer power under carefully-designed conditions. We use Mica2 motes and RF frequency-tunable ETs. To the best of our knowledge, this is the first empirical study on RF energy harvesting sensor networks.

**Summary of findings.** Our measurements indicate the presence of hard separation thresholds in the frequency domain that guarantee successful data packet reception among sensor nodes when ETs are transferring energy. This threshold changes with indoor/outdoor locations and separation distance of the ETs from the sensors. We identify three regions based on the separation of the energy and data transfer channels on the frequency scale, which we name as *black*, *gray*, and *white*, with high, moderate and low packet error rates, respectively. For example, the packet reception rate (PRR) when the ET transfers energy in the *gray* region can vary significantly with high temporal fluctuations. Also, sensors do not receive any packets in the *black* frequency region. However, wireless energy transfer at any *white* band of frequencies result in higher than 90% PRR. We find differing behavior in indoor and outdoor environments. For example, when RF transfer is done in the *gray* frequencies with increasing ET distance outdoor, the PRR improves monotonically. However, in indoor spaces, as ET increases, PRR has fluctuations due to signal reflections. On the contrary, when ET transfers at *white* frequencies, the PRR is almost the same in both indoor and outdoor experiments, regardless of ET locations. Finally, we find the interferer power at the sensor node that can be used to detect the frequency regions and set the appropriate energy transfer frequencies of ETs.

The rest of the part is organized as follows. In Section 5.3.1 we describe our experimental methodology. Section 5.3.2 presents measurement results on packet reception performance, including the effect of multifrequency wireless energy transfer and the placement of the ET. Results on the distribution of received energy interference are discussed in Section 5.3.3. Section 5.3.4 presents the temporal variability of the energy interferer power.
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5.3.1 Experimental Platform and Methodology

5.3.1.1 Hardware and software

We use Mica2 motes as the data communicating and energy harvesting nodes. Each mote is equipped with CC1000 radio operating at 915 MHz with a default RF transmission power of 0 dBm. The receiving sensitivity is $-98$ dBm. The CC1000 radio supports the measurements of the received signal strength (RSSI). We link the P2110 RF energy harvesters from Powercast Co. [160] to the mote. The RF frequency-tunable wireless ET is an Agilent N5181 MXG RF signal generator connected to an amplifier with a 50 Ω omnidirectional antenna and 3 W output power in the 902–928 MHz band. This configurable ET setup lets us change the frequency of wireless energy transfer precisely.

5.3.1.2 Measurement Metrics

We use interference power and PRR as the measurement metrics. The PRR is the fraction of packets that are received within a time window over the total transmitted packets. We use a total of 360 packet transmission epochs to estimate the PRR with a precision of 1.2% for each particular combination of energy transmission frequency and distance between the ET and the motes. For each ET energy frequency, the motes take 600 RSSI samples at the rate of 10 samples/sec over the data channel (i.e., 915 MHz) that is important in a node’s point of view. Six hundred RSSI samples are enough to collect meaningful measurements about the level of energy interference on the data channel.

5.3.1.3 Locations

We conduct our experiments in indoor and outdoor environments. For the indoor environment we select a space with four plain walls and no other intermediate reflective objects to limit time-varying changes in the wireless channel due to multi-path fading and shadowing. The second set of measurements are conducted in an open-space outdoor, with no structural obstructions. Each experiment involves three nodes: The sender, the receiver, and the wireless ET. The motes and ET are placed on a flat table, 0.5 m from the floor. The sender and receiver nodes are placed one meter from each other, and they are equidistant from the ET. The locations of the sender and receiver sensor nodes are fixed, but we vary the frequency and distance of the ET and measure the packet reception rate and the relative interference experienced by the sensor motes.
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Figure 5.9: Effects of varying wireless ET frequencies on PRR (a) indoor and (b) outdoor.

Figure 5.10: Effects of ET distance on the PRR at gray, white, and black energy frequencies (a) indoor and (b) outdoor.

5.3.2 Packet Reception Rate

When the strength of data signal is sufficiently above the noise and interference data packets can be successfully received and decoded. However, as the transmission power of the RF waves is significantly higher and because the power contained in the energy signal may leak into adjacent data communication channel, interference and packet losses may occur if this transfer occurs at different frequencies.

- **PRR and frequency.** Figures 5.9a and 5.9b present the average PRR as a function of varying ET frequencies indoor and outdoor, respectively. The data communication frequency is centered at 915 MHz. The experiments show that three distinct regions occur: In the middle region of the graph,
there is the band of black frequencies, in which none of the packets that are transferred between sensor motes are successfully received. In these black frequencies, the power of energy signals that leaks into the data channel is high enough to completely block all data communications. We observe that the actual frequency range of black region depends on the distance of ET from the receiver (Fig. 5.9). More specifically, the spread of the black frequency region for the ET with distance of 1m is 2 MHz; for the ET with distance 3m is 1.2 MHz. Similarly, for the ET with distance 5m it is 0.8 MHz. Fig. 5.9 shows that even when the ET is 5m away from the mote, which is the maximum effective charging range in our testbed, there are still energy frequencies with 100% packet loss. Thus, an appropriate separation of energy and data channels must be chosen in the design of protocols for such RF powered nodes.

On the extreme ends of the plots there are two frequency regions where the PRR is always uniformly high. We call these regions white areas, where the sensor motes experience correct reception even in the presence of concurrent wireless energy transfer from the ET. We observed that the white range for indoor environment includes all energy frequencies higher than 917.600 MHz and lower than 912.200 MHz (Fig. 5.9a). As shown in Fig. 5.9b, the white outdoor range includes those frequencies that are higher than 917.800 MHz and lower than 912 MHz. ET placement does not appear to affect the extent of the white region. These results further show that frequency separation is a better approach for sensor survival of energy interference and to boost network throughput, compared to duty-cycle based approaches.

Finally, we observe that both indoor and outdoor there are frequency ranges where the PRR is rather unstable. These energy frequency regions are the gray areas. In these, the motes experience variations in PRR ranging from 50% to 90%. While the high power of energy transfer at gray frequencies still leaks into the data channel, the energy interference has a power that is nearly the one of the data signal at the receiver. The pattern of fluctuations depends on the environment and on the form of energy signal. Interestingly, we observed that outdoor the patterns of fluctuations are symmetric for different ET distances. Indoor, however, even when multi-path fading and shadowing are limited, the reflections due to the walls resulted in different constructive and destructive interference levels at the receiver. As a consequence, for indoor environments we observe asymmetric variations of packet reception with varying ET distances. Furthermore, our measurements show that the spread of the gray region in both indoor and outdoor depends on the location of ETs. In particular, as the distance of ET increases, the width of the gray region also increases: When the ET is 1m away, the gray region is the narrowest; when the ET is 5m away, it is the widest.
PRR and distance. Fig. 5.10 compares the PRR for five different ET distances for a mix of gray, black, and white frequency regions, both indoor and outdoor. First, we observe that the energy frequency of 915.6 MHz is within the black area when the ET is 1, 2, and 3 m away from the motes. As the distance increases (4 and 5 m), this frequency moves to the gray area. This observation highlights the importance of ET location in RF transfer frequencies assignment. We also observed that the indoor PRR at the gray frequencies does not improve monotonically for increasing distances of the ET. This is because of small reflections of energy signals. For example, at the gray frequency of 913.600 MHz, the PRR is lower when ET is 3 m away that when it is 2 m away. Outdoor, instead, packet reception improves monotonically with increasing distances of the ET.

Overall, our experimental study reveals that the existence and width of the three regions has important implications for RF energy harvesting-based WSNs. In particular, we have observed that the frequency of energy and data signals need to be separated beyond a threshold that depends on the distance of the ET from the nodes to allow packets to be received successfully. The naming for white, gray, and the white areas is inspired from earlier works observing similar behaviors for classical sensor networks [9], which are concerned only on inter-nodal spatial distance. In this work, the demonstrated areas refer to frequency domain in RF energy harvesting sensor networks.

5.3.3 Energy Interference

In traditional WSNs, the RSSI provides an indication of connectivity, aids access points selection, and is used to determine error-prone wireless links. However, it is not immediately obvious
how the interferer power measured by the sensor nodes could be used to determine the energy frequency regions and preferred power transfer frequencies in RF harvesting WSNs. In this section, we aim at studying how knowing the distributions of the energy interference strength can be used by a node to detect in which region (white, gray or black) is the node, and the appropriate energy transfer channels it can use.

- **RSSI distributions with frequency.** Figures 5.11 and 5.12 illustrate the impact of different energy frequency regions on the distribution of the received interferer power indoor and outdoor, respectively. The y-axis corresponds to the RSSI values in dBm measured by the CC1000 radio of the Mica2 mote. The distance between the ET and the motes is 1 m. We also present the signal strength distribution of the ambient noise and of the data signal both indoor and outdoor, measured in absence of energy transfer. The rightmost distribution shows the RSSI of data signal (around $-49\, \text{dBm}$), and the leftmost one shows the measured ambient signal distribution (between $-93\, \text{dBm}$ and $-89\, \text{dBm}$) indoor. The outdoor noise is between $91\, \text{dBm}$ and $-75\, \text{dBm}$. Figures 5.11 and 5.12 show that the RSSI of the recorded energy can be clustered into three classes corresponding to three different frequency areas. We observe a correlation between the frequency separation of energy and data and the clusters. However, within each cluster this correlation does not necessarily hold. The RSSI distributions of black regions are close to each other and can be clustered with the data signal, while the distributions of white region can be clustered with the ambient noise. The cluster for the gray region is in the middle. We notice that the gray area exhibits a wider range of RSSI than that of the other two regions.

The range of the interferer signal strength for the gray region vary from $-87\, \text{dBm}$ to
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<table>
<thead>
<tr>
<th>ET Frequency</th>
<th>Outdoor</th>
<th>Indoor</th>
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<td>914,200</td>
<td>-61.602</td>
<td>0.001</td>
</tr>
<tr>
<td>913,600</td>
<td>-79.864</td>
<td>0.010</td>
</tr>
<tr>
<td>912,600</td>
<td>-85.364</td>
<td>0.009</td>
</tr>
<tr>
<td>912,200</td>
<td>-79.472</td>
<td>0.022</td>
</tr>
<tr>
<td>911,800</td>
<td>-87.617</td>
<td>0.011</td>
</tr>
</tbody>
</table>

Table 5.3: Map of energy interference power and associated PRR.

–65 dBm indoor, and from –84 dBm to –64 dBm outdoor. In this region, the RSSI samples are normally distributed and can be categorized into three groups: High, medium, and low. The first group includes ET frequencies such as 916.200 MHz that exhibits higher RSSI, and hence lower packet reception rates. The second group contains frequencies such as 913.600 MHz indoor and as 912.200 MHz outdoor showing slightly lower RSSI. Finally, the third group in the gray area corresponds to ET frequencies with negligible energy interference.

The recorded RSSI at each energy transfer frequency within the gray area have different variances. Some ET frequencies can cause higher variations of RSSI (i.e., 912.200 MHz outdoor), while frequencies like 913.600 MHz have low RSSI variations. Comparing the two figures, we find that the RSSI values in the gray area exhibits markedly different patterns indoor and outdoor. For example, the indoor ET frequency 912.600 MHz has higher interferer power compared to 917.600 MHz. These power values are lower outdoor. It is shown that the black frequency range (rightmost point of the plots) shows a large spike of received power both indoor and outdoor, but the interference patterns remain the same. The RSSI distributions reveal that the energy interference at the white frequencies in both indoor and outdoor environments are negligible. This confirms the high values of PRR shown in Section 5.3.2.
Figure 5.13: Effects of different ET distances on distributions of energy interference for (a) indoor gray region, (b) outdoor gray region, and (c) outdoor white region.

Table 5.3 summarizes the energy interference power and associated PRR for different ET frequencies from all regions in both indoor and outdoor environments, and strongly suggests that the measurement of energy interference within the sensor node can be used as a good estimate to detect energy areas and appropriate energy frequencies in RF harvesting sensor networks.

- **RSSI and distance.** We investigate the relationship between the distance among ET and motes, and the RSSI at the receiving mote. We plot the received interferer power for varying distances and energy frequency regions both indoor and outdoor. Due to space limitations, we show results for the gray frequency (913.600 MHz) indoor (Fig. 5.13a) and outdoor, and for the white frequency (911.800 MHz) regions outdoor only (Fig. 5.13b).

In Figure 5.13a, we see that the interference may increase with increasing ET distance. Specifically, the measured RSSI for ET located at distance 1m is about -76 dBm, however, the RSSI increases to about -74 dBm at distance 3m. This occurs because of reflections in the indoor setup, and confirms the asymmetric PRR variations over different ET distances. In outdoor environment, the received interferer power decreases as the distance of ET increases. In particular, Figure 5.13b shows that the measured power is about -80 dBm for ET distance 1m, and it decreases to about -84 dBm and -87 dBm for ET distances 3m and 5m, respectively. Thus, the distribution of energy interference at the white frequency region has very few changes with the location of the ET. Our measurements indicate that both gray and white frequencies have normal interference distributions over all ET distances.
5.3.4 Temporal Change in Energy Interference

In this section, we examine how the energy interference varies with time for indoor and outdoor environments.

Figure 5.14 shows the received energy interferer power for the three colored frequency regions at different ET distances of 1m, 3m, and 5m. The energy interference when ET transfers at the gray frequency region shows significant variations over time in the outdoor environment. On the other hand, the indoor scenario that caused noticeable variations in RSSI compared to the ambient noise, exhibits comparatively less temporal variation. The high temporal variation results indicate not only sensor nodes experience variable PRR over different gray frequencies, but also the fact that nodes experience time varying energy interference at each frequency. In addition, these results suggest to continuously measure the energy interferer power at gray frequencies since the RSSI can vary significantly over time. Figures 5.14c and 5.14d show the temporal variations in the white
region, which is comparatively less than those in the gray region. The interference caused by energy transfer in the black frequency band caused no variations in the measured RSSI. Interestingly, in all the plots, we find that the variation of the interferer power decreases as the distance between ET and the sensor node increases.

### 5.4 Energy Models and Analysis

Electromagnetic waves carry energy in the form of electric and magnetic fields, which can be converted (with some losses) and stored as energy at the receiving front-end, and used to power the processing and communication circuits of the nodes of a wireless sensor network (WSN). The ability of transferring energy via contact-less radio frequency (RF) will ensure the sensor nodes to remain operational for long times, without the need of costly battery replacement efforts [138]. Current prototypes of RF transfer, however, have limited charging range (few meters) and efficiency (40 to 60%). This imposes the concurrent and coordinated use of multiple ETs to power an entire WSN [164].

While multiple ETs are needed to ensure high energy transfer rates, they introduce interference among RF waves from different ETs, leading to significant and various constructive and destructive combinations over the network deployment area. Being able to compute the energy harvestable at a given point in space is a non-trivial task, as it depends on the relative locations of active ETs, path loss information, and on the different distances from the ETs and a receiver at that point. However, estimating the harvestable energy is a key first step in network planning and protocol design for long-lived WSNs. For example, at the link layer, sensors placed in regions that will receive energy at low transfer rates should have lower duty cycles. At the network layer, routes can be pre-computed to pass through regions with high energy transfers. Task assignment, at the application layer can also be facilitate by knowing how much energy will be available at a node at a certain time. Deriving closed form expressions of the energy harvestable at any point in the deployment space of the WSN is the main aim and contribution of this section.

Our approach starts from considering the path-loss models between one transmitter and one receiver, such as the one expressed by the Friis transmission equation [165] [166] estimating the received power between two nodes. We then incorporate in these models results from array factor calculation in an N-element antenna array and phased array [167] [168] [169] used to estimate the cumulative contribution of all the isotropic radiating elements at any far-field point. Hardware design factors, such as the diode operational parameters used in voltage multiplier sections of the...
energy harvesting circuit and RF-to-DC conversion efficiency, are integrated in our communication-centric analytical models. The resulting closed matrix form expressions give an estimate of the harvestable energy from multiple wireless ETs at any point, explicitly considering the unique features of constructive and destructive combination of RF waves. Our analytical approach first concentrates on the case of two and \( N \) ETs in the plane, and then generalizes the results to \( N \) ETs in 3D. Through our derived models we analyze and determine optimal distributions of power outage, energy interference, and harvested voltage and power over the whole WSN. Our analysis shows that the received power from multiple ETs over the entire network and the network energy interference caused by concurrent RF energy transfer has Log-Normal distributions. In addition, the harvested voltage over the whole WSN has Raleigh distribution due to use of either diodes or transistors, which are typically used in energy harvesting circuits, and to their input power-voltage curves.

The rest of part is organized as follows. In Section 5.4.1 we determine the harvestable energy in the plane. Section 5.4.2 extends generalize our findings to 3D spaces. In Section 5.4.3 we study the impact of wireless energy interference from multiple ETs over the entire WSN, and present the observed distributions of energy-related metrics.

5.4.1 2D RF Energy Model

In this section we develop analytical expressions for the total harvestable energy from two ETs at any given location in the plane. We then extend these expressions to the case of \( N \) ETs in the plane. The ETs and sensors are assumed to be equipped with omnidirectional dipole antennas, and ETs transfer RF waves with the same initial phase. The RF waves carry energy in the form of the electric field. Computation of the intensity of harvestable power from two ETs starts with computing the sum of their electric fields at any given location. The electric field \( E \) from an ET measured by a receiver device at distance \( R \) is:

\[
E = \sqrt{Z_0S}e^{-jkR} = \sqrt{Z_0S}e^{-j\left(\frac{2\pi}{\lambda}\right)R},
\]

where \( Z_0 \) is a physical constant indicates the wave-impedance of a plane wave in free space [170]. Moreover, \( S \) is the power spatial density at distance \( R \) (i.e., the power per unit area), and \( k \) is the wavenumber of the energy wave (i.e., the magnitude of the energy wave vector). The term \( kR \) indicates the phase shift of the transmitted energy signal at distance \( R \). Here, \( S = \frac{G_tP_t}{4\pi R^2} \), where \( G_t \) is the transmitter gain and \( P_t \) is the output power of the ET. Fig. 5.15 shows a scenario with two ETs.
Figure 5.15: Two ETs transferring power on the same frequency to a receiver node at distance $R_1$ and $R_2$.

The total electric field $E_T$ at the receiver when both ETs are transmitting energy is merely the superposition of their individual electric fields:

$$E_T = E_1 + E_2 = \sqrt{Z_0 S_1} e^{-j k R_1} + \sqrt{Z_0 S_2} e^{-j k R_2},$$

where the first term is the electric field from $ET_1$ and the second term is the electric field from $ET_2$. The magnitude of the field can be expressed as:

$$|E_T| = \sqrt{|E_1|^2 + |E_2|^2 + 2 |E_1||E_2| \cos(k(R_2 - R_1))}.$$

Therefore, the density of the total transferred power at the receiver is:

$$S_T = \frac{|E_T|^2}{Z_0} = S_1 + S_2 + 2 \sqrt{S_1 S_2} \cos(k \Delta r),$$

where $\Delta r = |R_1 - R_2|$ is the difference of the distances between the two ETs and the receiver. Since an ET is an isotropic radiator (an EM source radiating the same power in all directions), the expression for the magnitude of $E$ can be expanded as follows:

$$S_T = \frac{G_1 P_1}{4\pi R_1^2} + \frac{G_2 P_2}{4\pi R_2^2} + \frac{2}{4\pi} \sqrt{\frac{P_1 P_2 G_1 G_2}{R_1^2 R_2^2}} \cos(k \Delta r),$$

where $P_1$ and $P_2$ are the transmission powers and $G_1$ and $G_2$ are the transmission gains of $ET_1$ and $ET_2$, respectively.

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The aperture of the antenna of the receiver determines how well it can harvest power from an incoming EM wave. The total available power at an isotropic receiving antenna with an effective area $A$ is given by:

$$P_r = S_T A = S_T G_r \left( \frac{\lambda^2}{4\pi} \right),$$

where $G_r$ is the gain of the RF harvester antenna. The total received power from two ETs would be as follows:

$$P_r = G_1 P_1 G_r \left( \frac{\lambda}{4\pi R_1} \right)^2 + G_2 P_2 G_r \left( \frac{\lambda}{4\pi R_2} \right)^2 + 2 \left( \frac{\lambda}{4\pi R_1 R_2} \right)^2 G_r \sqrt{G_1 G_2 \sqrt{P_1 P_2 \cos(k \Delta r)}}. $$

If two energy transmitters have the same antenna gain (i.e., $G_t$) and transmission power (i.e., $P_t$), then the total received energy at the receiver node simplifies to:

$$P_r = P_t G_t G_r \left( \frac{\lambda}{4\pi} \right)^2 \left( \frac{1}{R_1^2} + \frac{1}{R_2^2} + \frac{2 \cos(k \Delta r)}{R_1 R_2} \right).$$

According to the RF wireless charging model, the amount of harvested power by the RF energy harvesting receiver would be

$$P_H = \eta P_r,$$

where $\eta$ is the RF-to-DC conversion efficiency. This formula captures both destructive and constructive interferences at any given location by considering the path lengths as well as the path differences between the ETs and the receiver. The harvested voltage could be found by $V_H = F(P_r)$ where the function $F$ relates input power to harvested voltage and depends on the energy harvesting circuit \[1\].

Similarly, we can obtain the total received power from $N$ ETs as follows:
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\[
P_r^T = G_r \left( \frac{\lambda}{4\pi} \right)^2 \left[ \sum_{i=1}^{N} \frac{P_i G_i}{R_i^2} + \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{\sqrt{G_i G_j P_i P_j}}{R_i R_j} \cos(k(\Delta r_{ij})) \right],
\]

where \( P_i \) and \( G_i \) are the transmission power and the transmission gain of \( ET_i \), respectively, and \( G_r \) is the gain of the receiver antenna. If all ETs have the same antenna gain and transmission powers, then the total received energy at the receiver node simplifies to:

\[
P_r^T = P_t G_t G_r \left( \frac{\lambda}{4\pi} \right)^2 \left[ \sum_{i=1}^{N} \frac{1}{R_i^2} + \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{\cos(k(\Delta r_{ij}))}{R_i R_j} \right],
\]

which in matrix form can be written as follows:

\[
P_r^T = (P \cdot corr) \cdot (R^{-1})
\]

where \( P \) is a constant row vector with size \( N \) defined as \( (P_t G_t G_r \left( \frac{\lambda}{4\pi} \right)^2) \cdot 1^T \), the \( N \times N \) correlation matrix \( corr \) is shown in Equation (5.2), and the distance matrix \( R^{-1} \) is:

\[
R^{-1} = \begin{bmatrix}
1/R_1 \\
1/R_2 \\
\vdots \\
1/R_n
\end{bmatrix}
\]

5.4.2 3D RF Energy Model

In practice and for most applications of energy harvesting sensor network such as healthcare, structural health monitoring, smart home, etc we need to deal with three-dimensions, where the heights of ETs and sensor nodes are not necessary the same. Accordingly, in this section we first explain the coordinate system for computing transmitted power from an ET, and then we derive the analytical model of harvestable energy for three-dimensional case of a sensor network with \( N \) wireless energy transmitters.

Fig. 5.16 shows the geometrical parameters for finding the electric field of \( ET_n \) with respect to the phase reference at origin. We assume the receiver is located at a given point \( M, (r,\phi,\theta) \), and it is a far-field point in regard to all energy transmitters. Here, \( \rho_n \) is the vector from the
Figure 5.16: Geometrical parameters of an $ET_n$ transferring wireless energy to a receiver at far-field point M.

origin to the $ET_n$ (ET vector); $\vec{r}$ is the vector from origin to the observation point (energy transfer direction vector), and $\vec{R}_n$ is the distance vector from the ET to the receiver. Moreover, using spherical coordinates, $x = r \sin(\theta) \cos(\phi)$, $y = r \sin(\theta) \sin(\phi)$, and $z = r \cos(\theta)$, respectively. For $ET_n$, the electric field at a far-field point, M, can be expressed as

$$E_n = \sqrt{Z_0 S_n e^{-jk|\vec{R}_n|}} = \sqrt{Z_0 S_n e^{-j\gamma_n}}$$

where $k = \frac{2\pi}{\lambda}$ is the wave number, and $\gamma_n$ is the phase shift of emitted energy signal from $ET_n$ at the receiver with respect to the origin, and $S_n$ is the power density of transmitted signal at point M and would be computed as

$$S_n = \frac{G_n P_n}{4\pi|\vec{R}_n|^2} \sin^2(\theta)$$

where $G_n$ is the gain of $ET_n$ assuming its antenna is oriented to $\hat{z}$ direction and $P_n$ is the transmission power. Using spherical coordinates, $R_n$ for a far-field point M (i.e. $r \gg \rho_n$) can be approximated as follows:

$$\vec{R}_n = \vec{r} - \vec{\rho}_n$$
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Figure 5.17: (a) Received power samples over the WSN space with 40 ETs. (b) Log-Normal distributions of the network wide received power from multiple ETs. (c) Power outage probability based on CDF of the received power from multiple ETs.

\[ |\vec{R}_n| = |\vec{r}| - |\rho_n| \cos(\phi - \phi_n) \]

Thus, the electric field of ET\textsubscript{n} at the receiver located in point M would be found as

\[ E_n = \sin(\theta) \sqrt{\frac{Z_0 G_n P_n}{4\pi R^2_n}} \left( e^{-jkR_n} e^{jk\rho_n \sin(\theta) \cos(\phi - \phi_n)} \right) \]

We assume the location of N energy transmitters are given by \( \rho_1, \rho_2, \rho_3, \ldots, \rho_N \). We need to find the received and harvestable power at point M, determined by \((r, \phi, \theta)\). Similar to the 2D case, the total electric field strength at the receiver, when N ETs are transmitting simultaneously, is the superposition of individual received electric fields. Hence, the density of total transferred power at the receiver can be calculated as follows,

\[ S_T = \frac{|ET|^2}{Z_0} = \frac{1}{Z_0} \left[ \sum_{n=1}^{N} |E_n|^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} (|E_i| |E_j| \cos(\gamma_i - \gamma_j)) \right], \]

where the relative phase difference of EM waves from ET\textsubscript{i} and ET\textsubscript{j} is found as:
\[ P_T^r = \sin^2(\theta) P_t G_t G_r \left( \frac{\lambda}{4\pi} \right)^2 \left[ \sum_{i=1}^{N} \frac{1}{(r - \rho_i \sin(\theta) \cos(\phi - \phi_i))^2} \right. \\
+ \sum_{i=1}^{N} \sum_{j=1}^{N} \cos(\gamma_i - \gamma_j) \left( r - \rho_i \sin(\theta) \cos(\phi - \phi_i) \right) \left( r - \rho_j \sin(\theta) \cos(\phi - \phi_j) \right) \left( r - \rho_i \sin(\theta) \cos(\phi - \phi_i) \right) \right], \quad (5.2) \]

\[ \gamma_i - \gamma_j = k (R_i - R_j) = - k \sin(\theta) \left( \rho_i - \cos(\phi - \phi_i) \right) \\
- \left( \rho_j - \cos(\phi - \phi_j) \right). \]

Thus, the available power at point M would be:

\[ P_T^r = G_r \frac{\lambda^2}{4\pi} S_T = G_r \frac{\lambda^2}{4\pi} \left[ \sum_{i=1}^{N} S_i + \sum_{i=1}^{N} \sum_{j=1}^{N} (\sqrt{S_i S_j} \cos(\gamma_i - \gamma_j)) \right], \]

where \( P_i, P_j, \) and \( G_r \) are the transmission power of \( ET_i \), the transmission power of \( ET_j \), and the receiver gain, respectively. If ETs have the same antenna and transmission powers, then the available power at the receiver node can be simplified to

\[ P_T^r = \sin^2(\theta) P_t G_t G_r \left( \frac{\lambda}{4\pi} \right)^2 \left[ \sum_{i=1}^{N} \frac{1}{R_i^2} + \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{\cos(\gamma_i - \gamma_j)}{R_i R_j} \right], \]

which is equal to Equation (5.2). This can be written in matrix form as: \( P_T^r = (P)(corr)(R^{-1}) \) where the distance matrix \( R^{-1} \) is \([1/R_1, 1/R_2, \ldots, 1/R_n] \), the row vector \( P \) is equal to \( \left( \sin^2(\theta) P_t G_t G_r (\frac{\lambda}{4\pi})^2 \right) \cdot 1^T \), and the correlation matrix \( corr \) would be:

\[ corr(i, j) = \cos(\gamma_i - \gamma_j)/R_i \]
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Finally, the amount of harvested power by the RF energy harvesting receiver would be:

\[ P_H = \eta P_T^e \]

where \( \eta \) is the RF-to-DC conversion efficiency. Also, the harvested voltage could be found by \( V_H = F(P_T^e) \) where function \( F \), similar to 2D case, depends on the energy harvesting circuit.

5.4.3 Analysis and Simulation Results

In this section, we analyze the performance of wireless energy transfer over a sensor network with multiple ETs. A variable number of ETs is randomly deployed in a 50 \times 50 m^2 grid. Each ET transfers RF energy at center frequency 915 MHz with Effective Isotropic Radiated Power (EIRP) equal to 4 W, which is the maximum transmission power allowed by the Federal Communications Commission (FCC) for omni-directional energy transfer. The transmission parameters of all ETs are assumed to be identical. The parameters of the energy harvesting receiver are set according to our dual-stage energy harvester \([1]\) with linear antenna gain of 6 dBi. The energy transfer of multiple ETs has been analyzed over the whole WSN. In particular, each time we have computed the received and harvested power in all points (samples) in the WSN deployment space, and accordingly found the network distributions of multiple wireless energy transfer. To this end, all sample points from the mesh grid range \([0, 50]\) are selected with interval 0.1. We assume two energy transfer scenarios. In the first scenario all ETs transmit omni-directional RF power at the same frequency, while in the second scenario (i.e., FDMA-like) each ET transmits power at a different frequency. This latter scenario is used as the base case for multiple energy transfer without interference. We focus our analysis on studying network-wide performance of concurrent wireless energy transfer in terms of power outage probability, energy interference, and harvested power and voltage.

5.4.3.1 Power outage probability

First, we investigate the power outage probability in sensor network when ETs are transmitting omni-directional RF signals. The power outage probability is defined as the probability that the received power from multiple ETs at a destination in the network be less than a given threshold. Fig. 5.17a shows the received power over different samples in a network with 40 ETs. We see that the constructive and destructive interference of energy waves lead to different values of received energy at each destination. Figures 5.18 depict that the PDF and CDF distributions of received power for different number of ETs, namely, 10, 20, 30 and 40. Fig. 5.17b shows that the received power
Figure 5.18: (a) Comparison of received power with energy interference and without interference. (b) Energy interference samples over the sensor network with 40 ETs. (c) Log-Normal distributions of energy interference for multiple ETs.

over the network has Log-Normal distribution (Gaussian distribution in a logarithmic scale such as dBm). Also, Fig. 5.17c indicates the effects of increasing ETs on the received power over the network. Interestingly, the probability that the received power from multiple ETs becomes larger than 0 dBm is 20% for 10 ETs, 40% for 20 ETs, 60% for 30 ETs, and 70% for 40 ETs. In addition, Fig. 5.17c represents the outage probability when multiple ETs transmitting at the same frequency. For example, when the minimum desired energy to power a sensor node is set to $-5$ dBm, then the power outage probability is 50% for 10 ETs, 30% for 20 ETs, 15% for 30 ETs, and 10% for 40 ETs. Furthermore, the outage probability does not exhibit linear dependency with the number of ETs. Particularly, as the number of ETs increases, the rate at which the energy received changes does not increase at the same rate.

5.4.3.2 Energy interference

Next, we study the distributions of energy interference due to concurrent energy transfer from multiple ETs. To this end, we use FDMA transfer scheme as the base case for our comparisons, in which ETs transmit power at different frequencies and there is no interference between simultaneous energy waves. The difference between the received energy from ETs in the same band and ETs transmitting with FDMA scheme is considered as the energy interference. Fig. 5.18a compares the received power over the network with 40 ETs. It is shown that the received power in the multi-energy transfer at the same frequency could be at times greater, and at other times, smaller than FDMA. In fact, at some points over network, we see higher energy while other points receive less energy than
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Figure 5.19: (a) Dual-stage distributions of the harvested power (dBm) over the sensor network with different number of ETs. (b) Rayleigh distributions of the harvested voltage over the network. (c) CDFs of the harvested voltage over the network.

Furthermore, Fig. 5.18-b shows interference in a network with 40 ETs. We see that energy interference varies over the networks from locations with very high interference to ones with near zero interference. Finally, Fig. 5.18-c depicts the distribution of energy interference for different number of ETs 10, 20, 30, and 40. Interestingly, it is shown that energy interference over network has Log-Normal distribution (Gaussian distribution in dBm scale).

5.4.3.3 Harvested voltage and power

We next investigate the distributions of the harvested power and voltage over the sensor network. As shown in our previous work [1], regardless of the type of energy harvesting circuit, the output voltage vs. input power (dBm) plot has an exponential curve due to use of either diodes or transistors in voltage multiplier sections of the energy harvesting circuit. Moreover, the efficiency curve (i.e. output power in dBm vs. input power in dBm) has polynomial distribution. In this section, without loss of generality we emulate a dual-stage circuit which adaptively switches in low-power and high-power regions based on our energy harvesting circuit prototype presented in [1].

Figures 5.19-a and 5.19-b show the PDF of the harvested power and harvested voltage over the whole sensor network for 10, 20, 30, and 40 ETs. Importantly, it is shown that harvested voltage over network has Rayleigh distribution, and harvested power clearly shows a dual-stage behavior in its distribution. Fig. 5.19-c shows the CDF of harvested voltage in the network. We see that the probability that the harvested voltage is less than 5V is 50% for 10 ETs, 25% for 20 ETs, 20% for 30
ETs, and 15\% for 40 ETs. Finally, Fig. 5.20 shows the harvested voltage map for 3 and 5 randomly deployed ETs, when the dual-stage harvesting circuit is used. The circles, which also have the highest harvested voltages, indicate the location of actual ETs. This figure depicts the randomness of energy patterns over the network, and shows as the number of ETs increases the randomness of energy patterns increases too. It can be observed even in points close to ETs such as (14, 10) in Fig. 5.20-a and (33, 20) in Fig. 5.20-b voltage drops due to the destructive interference, while instead there are points at distance of ETs where show high harvested voltage owing to the constructive interference.

5.5 Final Remarks

In the chapter, first we have presented an experimental investigation of concurrent energy and data transmissions in RF-powered WSNs. Our experiments have quantified the wireless charging, communication, and interference ranges for coexistent WSNs and wireless energy transmitters. We have shown the severe effect of high power energy waves on data communication and the energy cancellation of concurrent energy transmissions. We have demonstrated that frequency separation and multi-band RF harvesting are promising for enabling coexistence and improving general network performance and energy harvesting throughput.

Then we presented an experimental study to understand the effect of RF energy transfer from an energy transmitter on low-power data communications, as those of WSNs. Our results confirm that multifrequency energy transfer is crucial for surviving energy interference and improving
the PRR. We discovered three distinguishable regions in the frequency domain, each of which results in different levels and pattern of interference. Finally, we showed that local energy interference measurements at a sensor node can provide a good estimate for detecting the energy frequency regions where the node is, thus guiding the selection of ET frequencies for a desirable PRR.

Finally, we derived closed matrix form expressions for the total harvestable power at any location in a WSN with multiple ETs by capturing the spatial correlation between ETs and their constructive and destructive energy interferences. We provided the formulas for plane and 3D WSN deployments. We analyzed the wireless energy over the network and presented the distributions of the received power, energy interference, and harvested voltage. Our results show that the received power from multiple ETs over the network and the network energy interference have Log-Normal distributions. We further observed that the harvested voltage over the network has a Rayleigh distribution.
Chapter 6

Energy Harvesting from Direct RF Beamforming and Ambient Sources

6.1 Introduction

Wireless charging through radio frequency (RF) waves and ambient RF energy sources is an attractive solution for powering small form factor sensors, such as those used for implementing the Internet of Things. RF-based charging could potentially realize energy neutral or even battery-less operations, thus eliminating the need for expensive powering of the nodes or periodic battery replacement. The main goal of this chapter is to devise a holistic framework, called HYDRA for _Harvesting energy from Direct RF and Ambient sources_, for the deployment of dedicated ETs that transfer RF energy on-demand to sensors using beamforming, while also considering the available ambient RF energy. The typical scenarios we consider in this chapter concerns networked sensor systems, where each node is capable of harvesting energy from various cellular and TV spectrum bands such as GSM/EDGE, WCDMA/HSPA, LTE, and digital TV, as well as from dedicated ETs. Like the mythical multi-headed hydra, our proposed framework can activate one of many possible front-ends, each optimized for a specific band, and switch to a different selection when the energy harvesting capability is reduced. The main design features of HYDRA are:

6.1.1 Using Beamforming vs. Omnidirectional Radiation

Omnidirectional energy transmission is relatively simple to implement [171]. However, it has many limitations: First of all, the net energy available at a specific location is a mere fraction
of the total radiated energy, which is further reduced by path loss and circuit-related conversion losses. This requires the positioning of omnidirectional ETs very close to the sensors to be recharged. Through in field experiments, we observed charging distances as short as 5m for ETs radiating at 3W [172]. As a consequence, to support even the most basic network operations, a high number of ETs must be deployed. Moreover, multiple ETs with omnidirectional energy radiation may result in energy cancellation due to the random destructive combination of signals that may happen at certain locations. Finally, high power energy signals interfere with the low power data communications of wireless networked systems, causing significant packet losses [172, 173]. Directional energy beamforming provides a suitable design choice that allows energy transfer over longer distances and mitigates unintended interference with data transmissions. In our design of HYDRA, we ensure that beams combine constructively at desired location by appropriate selection of power and phases, by optimizing the ET placement, and by carefully balancing the energy load among the ETs.

### 6.1.2 A “cognitive” Approach to Ambient Energy Harvesting

The feasibility of RF ambient energy harvesting was demonstrated by a recently conducted city-wide RF spectral survey for GSM1800, GSM900, 3G and DTV bands [174, 175]. Data from some 270 London Underground station indicated that the level of harvestable energy was sufficient for powering low power devices. This survey revealed that the signal with the highest strength was from GSM1800 (57%) of all the measurement sites, followed by GSM900 (27%), 3G (11%), and finally DTV (6%). This motivates us to formulate an energy harvesting strategy that is cognizant
of the strength of the available signal at a given location. Our experiments show a 30% increase in harvested energy through this ‘cognitive’ approach, when compared to always harvesting from the best performing band on average (i.e., static selection of GSM1800). Further, HYDRA integrates this cognitive approach with determining the appropriate transmission power of ETs that must be added to RF ambient harvesting for completing the energy budget. For instance, when the same amount of received energy is harvested, ambient harvesting used and the power of that ET is decreased, with beneficial effects on cost and interference.

6.1.3 Dynamic and Anticipatory Energy Scheduling

Sensors nodes have spatially and temporally varying energy needs, based on their geographic location, participation in data forwarding, application specific requirements and on the network topology. HYDRA uses current traffic rates and information on the energy level of each node to schedule the duration and transfer power from ET beams and that from ambient source that are adequate to support current node operations. Furthermore, anticipating application-specific traffic demands (based in node-initiated “energy reports”), HYDRA is capable of directing ETs to provide power and charging times that are adequate to support future node operations.

The contributions of this chapter are summarized as follows.

- We devise a mathematical model for ET placement that jointly optimizes direct and ambient energy harvesting by first estimating the aggregate beamforming power, considering their constructive and destructive combination. This is a function of the distances between ETs and sensor nodes, of antenna gains at either ends, of the frequency and phase of the transmission, and of the transmission power of the ETs.

- We formulate strategies for dynamically adjusting the transmission power and phase of the ETs and for determining the spatial scheduling of the energy beams, mapping ET energy provisioning to the changing traffic and energy demands of the nodes while considering available ambient energy and minimizing the energy expenditures of ETs.

- We introduce a new strategy for supplying energy called energy-in-advance transfer. Through this strategy HYDRA provides nodes with the energy they will need for current and future operations, while minimizing the power from the ETs. We achieve this by showing that the harvested power is a strictly convex function of the input power, and leverage hardware-centric properties of typical harvesting circuits.
We demonstrate the potential and benefits of multi-band cognitive ambient RF energy harvesting through a set of experimental measurements conducted at Boston subway station exits.

The rest of the chapter is organized as follows. Section 6.2 describes the HYDRA architecture and provides an birds-eye overview of the framework. In Section 6.3 we delve deeper into the HYDRA building blocks including ET placement optimization, energy duty-cycling, and adaptive resource allocation. Our models and algorithms are evaluated via ns-2-based simulations in Section 6.4. Section 6.5 describes related works. Finally, Section 6.6 concludes our chapter.

6.2 Architecture and System Operation

We first explain the HYDRA network architecture, followed by an overview of its operation using its functional blocks.

6.2.1 Architecture Description

As shown in Fig. 6.1 HYDRA is composed of (i) RF energy harvesting equipped sensor nodes, (ii) multiple ETs, and (iii) ambient sources such as TV or cellular base stations.

- **Sensors with RF Harvesting**: Recent advancements in RF harvesting technology has enabled harvesters to run highly optimized sensors with efficiency up to 40% at signal strengths as low as −25 dBm [174]. Other efforts have shown functioning Mica2 sensors in the 915 MHz ISM band using incident RF signals above −6 dBm [176], and in the digital TV band around 614 MHz [177]. We assume that the RF harvesting circuit in the sensor is tunable to any one of allowed frequencies in the cellular, TV bands (for ambient sources) and ISM band (for ETs) for the following reasons: While wideband harvesting captures power across a range of spectrum, it provides very low efficiency [178] as the impedance matching between antenna and the voltage rectifier circuit becomes difficult to sustain over the entire frequency range [179]. Multi-band harvesting is able to capture power efficiently from different bands at once [179] by having one dedicated circuit per band. However, the required array of harvesting circuits poses scalability and cost questions, results in losses due to summation of out-of-phase received powers from multiple frequency bands, and increases the cumulative leakage current from the increasing number of diodes [180]. In light of these circuit-level challenges, we advocate and assume the design of the tunable narrowband band RF harvester [181],
as it allows selection of a specific band of interest and provides highly efficient and sharp rectification of signals from a single source with the highest power.

- **ETs**: The ETs use pre-decided transmission spectrum in the ISM band. They transmit single-tone sine waves, but are able to control both the power and their phase of the signal at the time of emitting the signals. Additionally, the ETs use beamforming with directional smart antenna to focus the radiated energy, but are bound by Federal Communications Commission (FCC) rules on the maximum allowed radiation (see FCC part 15 ISM-UNI [182]). By suitably modifying the energy signals sent from \( N \) ETs, HYDRA creates energy beams in the direction of a target sensor, which gives a gain improvement factor \( N^2 \) in terms of the received power, when compared to the transmission of a single ET [183]. While the FCC limits the EIRP of the omni-directional antenna, including transmitted power and gains that the antenna provides, to 4 Watts, it relaxes EIRP limitations for directional smart antenna by permitting significantly higher EIRPs. For example, in the case of omni directional antenna, for adding each 3 dBi to antenna gain, FCC requires 3 dBm subtraction from transmission power. However, in the case of directional antennas, it requires only 1 dBm subtraction for each 3 dBi increase in antenna gain [182]. The reason for accepting higher EIRPs is that the higher gain antennas are more directive and reduces the possibility of RF interference with other devices.

- **Ambient RF Sources**: We assume two main sources of RF ambient power: cellular and broadcast TV signals. The RF energy level from TV broadcasts at a given location is available from sites like [184] or spectrum databases, which can be communicated to the sensors directly by a centralized BS or ETs that have such querying capability. The GSM/EDGE and LTE base stations are the cellular ambient sources. The specific signal level in each of the respective downlink bands is assumed to be known a priori via carrier-provided coverage maps, or can also be collected in the field via capable ETs that have cellular modem technology.

### 6.2.2 System Operation Overview

Fig. 6.2 depicts the functional blocks of HYDRA system, which are explained in more detail in Sec. 6.3. The placement information from the sensor nodes, the TV channel activity from the spectrum databases, as well as cellular coverage maps, are together fed to the **ET Placement Optimization** stage, where the ET topology is decided. The optimization also takes into consideration the offered traffic loads of the sensors and tries to distribute the load among the ETs, while leveraging the ambient power as much as possible.
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Figure 6.2: Functional blocks for HYDRA.

The second functional stage sets the Integrated Energy and Data Duty-cycling parameters for the network with distinct data \( (D_{intv}) \) and energy \( (E_{intv}) \) transmitting durations. Sensors operate based on the network-wide data duty-cycle \( D_{intv} \). Here, we leverage the non-linear response of the energy harvesting circuit where high signal spikes, but for short duration, results in greater RF-to-DC conversion efficiency than lower signal received level for longer durations, even if the product of received signal power and time of harvesting remains constant [185]. Thus, from a performance viewpoint, we explicitly insert multiple short charging pulses instead of a lengthy transmission duration. The rest of each energy duty-cycle is used by the tunable harvester for the cognitive ambient RF harvesting.

Finally, the Adaptive Resource Allocation block schedules the power levels, phases, sequences, and durations of energy beams based on the changing energy demands of sensor nodes and the ambient environment. The sensors inform ETs about updates in their energy requirement and traffic rate via an energy packet that contains current voltage level, local traffic rate, ambient harvesting rate, and event detection flag (see Sec. 6.3-B), which triggers a proportional response in energy transmission level and duration for the next cycle. The important variables used in the description of HYDRA are summarized in table 6.1 which will be used in the subsequent analysis.

6.3 HYDRA Functional Blocks

In this section, we delve deeper into each functional blocks of HYDRA as follows: Sec. III-A) ET placement optimization, Sec. III-B) integrated data and energy duty-cycling, and Sec. III-C) adaptive resource allocation.
6.3.1 ET Placement Optimization

**Problem Definition:** We consider a scenario where a set $S$ of sensor nodes $S_1, ..., S_M$ are randomly deployed in an area. Each node is equipped with a tunable RF harvester that is capable of harvesting energy beams in the ISM band $f_{ET}$ and ambient signals in range $f_1 \leq f_{cog} \leq f_C$. There is a set $E$ of energy transmitters $ET_1, ..., ET_N$ that provides controlled energy beamforming to the nodes. The location of each sensor node is known to the ETs. As shown in Fig. 6.3, the RF-powered sensor network operates in two separate duty-cycle planes: data ($D_{intrv}$) and energy ($E_{intrv}$), where $N_e = D_{intrv}/E_{intrv}$. Each data duty cycle of a sensor node $D_{intrv}$ is divided into three main periods: i) sensing $T_s$, ii) scheduling $T_{sch}$, and iii) communication and sleep $T_{data/sleep}$ (see traffic model in Section III-B).

![Figure 6.3: Model of data and energy duty-cycle planes. RF energy harvesting follows $E_{intrv}$ duty-cycling and data communications have the offered traffic rate $\bar{T}_{dc}$ over $D_{intrv}$.](image)

We first optimize ET locations assuming an average offered traffic load of $\bar{T}_{dc}$ over $D_{intrv}$ for any given sensor, and the expected required energy to operate and communicate is $\bar{E}_{dc}$. Note the sensor-specific energy requirements may be subsequently communicated to the ETs during network operation, which will then determine their transmission schedules, transmission power etc. Within each energy duration $E_{intrv}$, ETs cooperatively transfer energy beams $B_1, B_2, ..., B_M$ to sensors $S_1, S_2, ..., S_M$ for duration $D(1), D(2), D(3), ..., D(M)$, respectively. ETs transmit with power
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\( P_{ET} \) and the delivered energy depends on the distance and signal phase between ETs and each receiver. We assume the average cognitive ambient harvesting rate \( P_{amb}^H(i) \) corresponding to the best performing spectrum for a given node \( S_i \). The charging operation in \( D_{intrv} \) is a sequence of \( N_e \) energy duty-cycles in each of which the ETs transfer energy to a number of sensors, and node \( S_i \) harvests from the transmitted beam \( B_i \) for duration \( D(i) \) and then receives ambient power \( P_{amb}^H(i) \) for duration \( E_{intrv} - D(i) \). Thus, the total amount of required energy \( \bar{E}_{dc} \) delivered to a sensor node over a complete cycle is cumulative over both these sources. The ET placement goal is defined as follows:

Given \(|S|\) nodes and their locations, given \(|E|\) ETs and their transfer power, given the data duty-cycle and its offered traffic load, determine the optimal number and locations of ETs, energy duty-cycle, transfer phase and duration to satisfy the following objectives: i) ensuring minimum energy coverage over sensor network to support offered traffic load; ii) maximizing the leverage of ambient power, so beams can be allocated more effectively along the ambient signals; iii) balancing the load of energy transfer among ETs in regard to the location of sensor nodes.

- **Analytical Model of Energy Beams:** In a network with multiple ETs, the RF waves can combine constructively and destructively over the space based on the initial transmission phase and relative distance of participating ETs. Due to this complexity, the amount of received power from multiple ETs is not a simple superposition of the individual values, but the summation of received signals in phasor form. In this section, we discuss the analytical energy model for the total received beam power from ETs. This allows us to solve the ET placement and resource allocation optimization problems.

Fig. 6.1 shows an example of a sensor network with multiple ETs. The received signal on channel \( f_{ET} \) at a given point \( A, (x_r, y_r) \), from ET \( i \), located at \( (x_i, y_i) \), can be written as:

\[
S^i_r = \sqrt{P_r(i)}e^{-j(\phi(i)+K'R(i))}
\]  

(6.1)

where \( P_r(i) \) is instantaneous received power from ET \( i \), \( \phi(i) \) is the initial transmission phase of ET, \( K' = \frac{2\pi}{\lambda} \) is the wave number of the energy wave (i.e., the magnitude of the energy wave vector), \( R(i) = [(x_r - x_i)^2 + (y_r - y_i)^2]^{\frac{1}{2}} \) is the Euclidean distance from ET \( i \) to the receiver. The term \( K'R \) indicates the phase shift of the transmitted energy signal at the receiver. We assume a free space path loss model for the received power which results in

\[
S^i_r = \sqrt{G_r G^i_t P_t(i) \left( \frac{\lambda}{4\pi R(i)} \right)} e^{-j(\phi(i)+K'R(i))}
\]  

(6.2)
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Here, $G_i$ and $G_r$ are the transmit and receiving antenna gains, and $P_{iT}$ is the transmit power of ET $i$. The received power at a receiver due to $N$ ETs, i.e., $P_r^T$, can be computed by summing signals $| \sum_{m=1}^{N} S_r^m |^2$. Hence,

$$P_r^T = G_r \left( \frac{\lambda}{4\pi} \right)^2 \left[ \sum_{i=1}^{N} \frac{P_{iT}^i G_i^i}{R(i)^2} + \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \sqrt{G_i^i G_j^j P_{iT}^i P_{iT}^j} \frac{1}{R(i)R(j)} \cos(K' \Delta R_{ij} + \Delta \phi_{ij}) \right]$$

(6.3)

where $\Delta \phi_{ij} = \phi(i) - \phi(j)$ is difference between the transmission phases of ET $i$ and ET $j$, and $\Delta R_{ij} = R(i) - R(j)$ is the difference between distances of ET $i$ and $j$ from the receiver [186]. It noteworthy that optimal phases could result in constructive energy beams. Finally, the total harvested power at the receiver would be

$$P_H^T = \eta(P_T^r)P_r^T$$

(6.4)

where $\eta$ is the RF-to-DC conversion efficiency function, and a function of the received input power.

- **Formulation of the Optimal ET Placement Problem:**

Based on the above discussion, we present a mathematical formulation for optimal placement of ETs as follows:

Given $D_{intrv}, T_{dc}, M, P_{ET}, P_{amb}^H$

To find $N, E_{intrv}, R, \phi, D$

Minimize $\sum_{i=1}^{M} D(i) / E_{intrv}, N$

Maximize $\sum_{i=1}^{M} P_{amb}^H(i) \ast (E_{intrv} - D(i))$

Subject to $D_{intrv} / E_{intrv} (P_{et}^H(i, C_{ET}) \ast D(i) + P_{amb}^H(i) \ast (E_{intrv} - D(i))) \geq \bar{E}_{dc} \quad i = 1, \ldots, M.$

$D(1) + D(2) + \ldots + D(M) \leq E_{intrv}$

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The inputs in our problem formulation are the offered traffic load, data duty-cycle, sensors and their locations, transmission power of ETs, and average ambient power harvesting rate at each node from the best performing spectrum. In the initial ET placement step we assume all ETs have the same transmit power, but in the Integrated Energy and Data Duty-cycling phase (Sec. III-B) we find optimal power for each ET. We observe that the optimal parameters to be found are (i) the locations, $R$, (ii) number of ETs, $N$, (iii) duration of energy duty-cycle, $E_{intrv}$, (iv) the transmission phase for each ET, $\phi$, and (v) the duration of beams for each sensor target, $D$. The first objective is to minimize the number of ETs and also energy beam durations in order to reduce the deployment cost. In addition, we want to make sure the optimal ET locations maximize the leverage of ambient power while minimizing the use of controlled energy, so during operation (ETs are fixed but traffic varies) energy beams can be allocated more effectively along the ambient signals. The first constraint accommodates the energy coverage requirement, such that all nodes receive enough power to support communication of the expected traffic load $\bar{T}_{dc}$ within each data interval. Here, $C_{ET}$ is the set of ETs parameters including $N$, $R$, $P_{ET}$, $G_t$, and transfer frequency $f_{ET}$. Consequently, $P_{et}^H(i, C_{ET})$ indicates the harvesting rate of energy beam from ETs with configuration $C_{ET}$ at node $S_i$ with harvester antenna gain $G_r$, and is based on the energy harvester hardware. The second constraint limits the total duration of all energy beams that sequentially transfer to M sensors to not exceed $E_{intrv}$. The solution that adheres to this set of constraints and objectives also balances the load of energy transfer among ETs with regards to the location of sensor nodes and the available ambient power.

6.3.2 Integrated Energy and Data Duty-cycling

We assume ETs can change their energy beams (i.e., power, phase, duration) based on the available cognitive ambient power and the required energy of the node which is a function of the data traffic and sensing.

- **Traffic Model:** Sensors periodically collect and report data from the physical environment. The data reporting frequency might be either static or dynamic. In this chapter, we assume that over each cycle-interval $D_{intrv}$, the node $S_i$ senses the environment and records the sensed data for subsequent reporting with rate $r_s^i$. In case of event detection, each node $S_i$ reports data with a higher frequency $r_e^i$, after detecting certain pre-defined network events that are dynamic. The local generated traffic rate at sensor $S_i$ during operation can be: $r_s^i$, $r_e^i$, and $r_s^i + r_e^i$ depending on events and network dynamics. A node first senses/monitors the environment for $T_s$, then exchanges
communication schedules with the downstream nodes for new traffic over $T_{sch}$, and finally, sleeps and communicates data with other nodes over $T_{data/sleep}$. We adopt a reservation mechanism from [187], that allows a sensor to transmit a small setup control frame at the start of $T_{sch}$ period, which in turn travels across multiple hops and schedules the upcoming data delivery along the forwarding path. During the $T_{data/sleep}$ period, nodes go to sleep except for those that have communication tasks that set up by control frames. Note that a node can wake up multiple times over a $T_{data/sleep}$ if it has received multiple control frames.

For each sensor $S_i$, $i \in M$, $r_i$ denotes the local sampling rate, $r^{rx}_i$ shows the total receiving rate, and $r^{tx}_i$ represent the total transmitting rate. Moreover, $f^o(i, j)$ is the fractional amount of node $S_i$’s total output traffic that passes through link $(i, j)$ based on routing and bandwidth allocation algorithms, and is known to node $S_i$ and ETs through the control frames traverse during $T_{sch}$. $P_i$ denotes the parent nodes and $N_i$ is the possible next hops of node $S_i$. Figure 6.4 shows a sensor network with its corresponding active routing paths that represent with a set $A$. Accordingly, given the active paths and local rate of each node, the aggregated reception rate for node $S_i$ is computed through a recursive relation as given below:

$$r^{rx}_i = \sum_{p \in P_i} (1 + e(p, i)) f^o(p, i)(r_p + r^{rx}_p),$$

(6.5)

where $P_i$ is the set of parents of $S_i$, and $e(p, i)$ is the packet error rate for link $(p, i)$.
Similarly, the aggregated transmission rate of node $S_i$ is estimated by

$$r_{tx}^i = \sum_{n \in N_i} (1 + e(i, n)) f^o(i, n)(r_{tx}^i + r_i)$$

(6.6)

where $N_i$ is the set of nodes that have node $S_i$ as the next hop. Traffic matrix $M(T)$ indicates the $r_{tx}$ and $r_{rx}$ of each sensor node on the given active paths.

- **Energy Updates:** Every $D_{update}$ time units, the rates and patterns of traffic as well as ambient harvesting rate are updated by each sensor for re-computing the ET parameters. The energy update packet has four fields: i) current voltage ($<voltage>$) ii) local traffic rate ($<rate>$) iii) ambient harvesting rate ($<cognitive ambient>$) and iv) event detection flag ($<event flag>$). The current voltage and rate fields are used by ETs to calculate the energy demands of the node. In addition, the rate and event detection flag determine the next energy demand state. If the traffic rate is lower than $T_{threshold}$ it indicates the node has moved to monitoring state. If the event detection flag is not set and updated data rate is bigger than $T_{threshold}$, this shows the node is going to report data. Finally, in the case that event detection flag is set the node will track and report the event.

- **Energy Model:** As depicted in Fig. 6.5, each sensor node $S_i$ has $N_e = \frac{D_{intrv}}{E_{intrv}}$ number of energy cycles in a single data interval to harvest the required energy for supporting the traffic rate (i.e., $r_{tx}^i + r_{rx}^i$). $D_{update}$ consists of $N_d = \frac{D_{update}}{D_{intrv}}$ data duty-cycles. Assuming ETs transmit $K$ optimal energy beams over $D_{update}$, where $K \leq N_k = \frac{D_{update}}{E_{intrv}}$, we denote the sequence of
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the transmission powers of ETs toward the sensor $S_i$ as $P_{N}^{tx}(i, 1), P_{N}^{tx}(i, 2), \ldots, P_{N}^{tx}(i, K)$, with the corresponding duration of $D(i, 1), D(i, 2), D(i, 3), \ldots, D(i, K)$, and transmission phases of $\phi_N(i, 1), \phi_N(i, 2), \ldots, \phi_N(i, K)$, respectively.

Then, the total transferred energy by $ET_N$ is given by

$$ET(N) = \sum_{i=1}^{M} \sum_{j=1}^{K} P_{N}^{tx}(i, j) D(i, j)$$ (6.7)

The total consumed energy by all $N$ ETs is $E_{ET}^T = \sum_{n=1}^{N} ET(n)$.

Here, we note that the transmission duration $D(i, j)$ is equal for all ETs due to use of beamforming. Let the sequence of the received powers from ETs at a sensor node $S_i$ be $P_{rx}(i, 1), P_{rx}(i, 2), P_{rx}(i, 3), \ldots, P_{rx}(i, K)$, and the corresponding harvested powers from ETs are $H(i, 1), H(i, 2), \ldots, H(i, K)$, where

$$H(i, j) = \eta(P_{rx}(i, j)) P_{rx}(i, j)$$ (6.8)

Here, $\eta$ is the RF-to-DC conversion efficiency of harvesting circuit, and is a function of the received input power. Note that as shown in equation 6.3, the received power $P_{rx}(i, j)$ is a function of all ETs transmitted signals. Accordingly, the vector of the received energy epochs at sensor $S_i$ over $D_{update}$ is represented by $e_1^i, e_2^i, \ldots, e_K^i$, where $e_k^i = P_{rx}(d, i)D(d, i)$.

Thus, the amount of harvested energy from directional beams of ETs is

$$E_{ET}^H(i) = \sum_{j=1}^{K} H(i, j) D(i, j) = \sum_{j=1}^{K} h_j^i$$ (6.9)

where $h_j^i$ indicates the harvested energy at node $S_i$ from received beam $e_j^i$. Furthermore, the harvested energy from cognitive ambient harvesting at sensor $S_i$ would be

$$E_{cog}^H(i) = P_{cog}^H(i)(\sum_{j=1}^{K}(E_{intrv} - D(i, j)) + (N_k - K)E_{intrv})$$ (6.10)

Here, $P_{cog}^H(i)$ is the latest cognitive ambient harvesting rate reported by the sensor $S_i$, which is the average of actual harvested powers over its update interval, through the energy update packet, and can be represented as

$$P_{cog}^H(i) = E[Max\{P_{LTE}^H(i), P_{3G}^H(i), P_{GSM}^H(i), P_{TV}^H(i)\}]$$ (6.11)

Therefore, the total harvested energy at sensor $S_i$ can be calculated by

$$E^H(i) = E_{cog}^H(i) + E_{ET}^H(i)$$ (6.12)
The energy required to support the operation of node $S_i$ over an energy state with duration $D_{update}$ can be found by

$$E_{req}(i) = E_{dc}(i) - \frac{1}{2}C(V_{min} - V(i))^2], \quad (6.13)$$

where $V(i)$ is the current voltage of sensor reported through the update packet, $V_{min}$ is the minimum given voltage, $C$ is the size of capacitor as the energy storage in the sensor node, and

$$E_{dc}(i) = N_d[P_{tx}g(r_{tx}^i) + P_{rx}g(r_{rx}^i) + P_{sense}T_s$$
$$+ P_{sleep}(T_{data/sleep} - g(r_{tx}^i) - g(r_{rx}^i)) + P_{tx}T_{ctrl}]$$

Here, $P_{tx}$, $P_{rx}$, $P_{sense}$, and $P_{sleep}$ are the power rates of data transmit, receive, sense, and sleep, respectively. Moreover, $T_{ctrl}$ is the duration of a control frame, and $g(r)$ indicates the transmission time of traffic rate $r$ based on the sensor channel bandwidth. In addition, the energy required to be provided by ETs would be

$$E_{ET}^{req}(i) = E_{req}(i) - E_{H}^E(i) \quad (6.14)$$

- **Energy-in-Advance Transfer Policy:** For $N$ ETs transferring energy pulses to a sensor node $S_i$ over $D_{update}$, the optimal transfer can be defined as the strategy that satisfies two properties: i) provide the required energy at the receiver with the least amount of transferred energy, ii) load balance ETs, which is equal to transmission completion maximization over each $D_{update}$. The optimal policy can be formulated as follows:

$$\max K, \quad 0 < K \leq N_k$$
$$\min E_{ET}(i) = \sum_{n=1}^{N} \sum_{j=1}^{K} P_{n}^{tx}(i,j)D(i,j)$$
$$\text{s.t. } E_{ET}^{H}(i) = E_{ET}^{req}(i)$$

First, we discuss the properties of the harvested power as the function of the input power, and then accordingly determine the properties of the optimal energy transfer policy through two lemmas.

The harvested power is related to input power of the RF harvesting circuit through a continues function $\eta(P_{in})$ where $P_{in}^H(P_{in}) = \eta(P_{in})P_{in}$. Let assume the optimal operating range
of the circuit at $f_{ET}$ is $[P_{in}^{min}, P_{in}^{max}]$ which depends on the design and hardware characteristics of the RF harvester. In this range, $\eta(P_{in})$ is a monotonically increasing function in $P_{in}$ such that $\eta^{min} = \eta(P_{in}^{min})$ and $\eta^{max} = \eta(P_{in}^{max})$. Consequently, the $P_{H}(P_{in})$ increases monotonically in $P_{in}$, and is continuously differentiable. The monotonicity of both $P_{H}(P_{in})/P_{in}$ and $P_{H}(P_{in})$ guarantees that $P_{H}(P_{in})$ is a strictly convex function in $P_{in}$. The strict convexity of harvested power implies for a fixed amount of transferred energy over a given time, which is a product of power and time, the amount of harvested energy increases as the received input power of beams increases and so the total duration of beams decreases. Next we determine the properties of the optimum policy in the following lemmas:

**Lemma 1:** Under the optimal energy transfer policy the amount of received energy beams at sensor $S_i$ decreases monotonically, $e_i^1 \geq e_i^2 \geq \ldots \geq e_i^K$.

**Proof:** In order to prove this lemma, we show that under optimal energy transfer policy both the power of received beams and duration of received beams at sensor $S_i$ decrease monotonically, $P_{rx}(i, 1) \geq P_{rx}(i, 2) \geq \ldots \geq P_{rx}(i, K)$, and $D(i, 1) \geq D(i, 2) \geq \ldots \geq D(i, K)$, and consequently the received energy beams monotonically decrease.

Assume that the power of received beams in optimal transfer do not decrease monotonically, i.e., that we can find two beams $P_{rx}(i, j) < P_{rx}(i, j + 1)$. The total energy received from ETs for these beams is $E_b = P_{rx}(i, j)D(i, j) + P_{rx}(i, j + 1)D(i, j + 1)$. Let define a new policy as

$$P_{rx}'(i, j) = P_{rx}(i, j + 1)$$

$$D'(i, j) = D'(i, j + 1) = \frac{P_{rx}(i, j)D(i, j) + P_{rx}(i, j + 1)D(i, j + 1)}{2P_{rx}(i, j + 1)}$$

We use these to replace the two received powers, $P_{rx}(i, j)$ and $P_{rx}(i, j + 1)$, and durations $D(i, j)$ and $D(i, j + 1)$ in the optimal transmission policy, and keep the rest the same. Here, the total received energy is the same as $E_b$. Accordingly, the harvested power of beams would be

$$H'(i, j) = H'(i, j + 1) = H(i, j + 1) = \eta(P_{rx}(i, j + 1))P_{rx}(i, j + 1)$$

Then, the total harvested energy over the duration of two beams becomes
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\[ H'(i,j)D'(i,j) + H'(i,j + 1)D'(i,j + 1) \]
\[ = H(i,j + 1)\left(\frac{P_{rx}(i,j)D(i,j) + P_{rx}(i,j + 1)D(i,j + 1)}{P_{rx}(i,j + 1)}\right) \]
\[ > \eta(P_{rx}(i,j))P_{rx}(i,j)D(i,j) \]
\[ + \eta(P_{rx}(i,j + 1))P_{rx}(i,j + 1)D(i,j + 1) \]
\[ = H(i,j)D(i,j) + H(i,j + 1)D(i,j + 1) \]

where the inequality follows from the fact that harvested power is a convex function of input received power. Therefore, the new policy harvests more energy by \( j + 1 \) beam than the optimal policy while the received energy is the same. Keeping the remaining received beam powers and durations same, the new policy will need less received energy, and consequently less transferred energy from ETs (equation 6.3) to provide the same required energy over \( D_{update} \). Thus, the original policy could not be optimal, and the optimal policy must have monotonically decreasing received powers.

Next assume that durations do not monotonically decrease, i.e., that we can find two durations so \( D(i,j) < D(i,j + 1) \). We can follow steps similar to above and show there is a new policy that harvest more energy by \( j + 1 \) beam than the original policy while the received energy becomes the same and received powers decrease monotonically. We achieve this by defining

\[ P'_{rx}(i,j) = P'_{rx}(i,j + 1) = P_{rx}(i,j) \]
\[
D'(i,j) = D'(i,j + 1) = \frac{P_{rx}(i,j)D(i,j) + P_{rx}(i,j + 1)D(i,j + 1)}{2P_{rx}(i,j)} \] (6.18)

Since under the optimal energy transfer policy both the received power and duration of beams are decreasing monotonically, their products also decrease monotonically, \( \epsilon_1^i \geq \epsilon_2^i \geq \ldots \geq \epsilon_K^i \).

\textbf{Lemma 2:} Under the optimal transfer policy, the amount of available energy from ETs at sensor \( S_i \) over each data cycle \( (D_{interv}) \) is always equal or bigger than \( E_{ET}^{req}(i)/N_d \), and so the node never run out of energy.

\textbf{Proof:} We know that there are \( N_e \) energy beams over each data cycle, \( N_d \) data cycle over an update interval, and maximum \( N_k \) beams.

Let assume in optimal transfer policy there is a data cycle \( n \) that the amount of the available energy from ETs is not enough to support the required energy. This can be written as

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which indicates \( \sum_{j=(n-1)N_e+1}^{(n)N_e} h_i^j < \frac{E_{ET}^{req}(i)}{N_d} \). From lemma 1 and the convexity of the harvested power, we know the sequence of harvested energies \( h_1^i, h_2^i, \ldots, h_{N_e}^i \) decreases monotonically. Accordingly,

\[
\sum_{j=(l)N_e+1}^{(l+1)N_e} h_i^j < \frac{E_{ET}^{req}(i)}{N_d}, \quad n \leq l < N_d
\]

\[
\sum_{j=1}^{N_k=N_dN_e} h_i^j < E_{ET}^{req}(i)
\]

This conflicts with the optimality condition of transfer policy. Therefore, the optimal policy always provides the required energy \( E_{ET}^{req}(i)/N_d \) from ETs over each data cycle.

Based on the definition and lemmas 1 and 2, we depict the optimal energy-in-advance transfer policy for a node in Fig. 6.6. It can be observed that instead of transferring power equally over each data cycle to guarantee the required energy within each update interval, the optimal transfer policy gives more power and energy in advance to maximize the harvested power with less amount of transferred energy.
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6.3.3 Adaptive Resource Allocation

Given the nodes and their location, ETs and their optimal locations, data and energy duty-cycles, the duration of update interval, and set of current local traffics, voltages, active paths, and ambient harvesting rates of the nodes, we determine the radiating power levels and phases of the ETs, and scheduling of the energy beams.

• **Formulation of the ET Resource Allocation Problem:** Without loss of generality, we assume the hardware parameters such as the minimum and maximum input powers of RF energy harvesting circuit, the minimum battery voltage, and the maximum transfer power of ET are given. The local rates, cognitive ambient harvesting rates, and voltages of all nodes are known centrally through the periodic energy update packets. In addition, the number of beams $K$ is set to $N_k$ based on the definition of optimal transfer policy and due to ET load balancing. Now we can write the formal optimization as follows:

Given
\[
M, N, D_{\text{intrv}}, E_{\text{intrv}}, D_{\text{update}}, P_{\text{cog}}, A
\]
\[
V(i), r_i \quad \forall i \in M
\]

To find
\[
P^ET_n, \phi^ET_n, \quad \forall n \in N
\]
\[
D_m, \quad \forall m \in M
\]

Minimize
\[
E^T_{ET}
\]

Subject to
\[
E^H(m) \geq E^{req}(m), \quad \forall m \in M
\]
\[
E_{\text{intrv}} = \sum_{i=1}^{M} D(i, n), \quad \forall n \in K
\]
\[
e^m_1 \geq e^m_2 \geq e^m_3 \geq \ldots \geq e^m_K, \quad \forall m \in M
\]
\[
P^\text{min}_m \leq P_{rx}(i, j) \leq P^\text{max}_m, \quad \forall i \in M, \forall j \in K
\]
\[
P^ET_n \leq P^\text{max}_{ET}, \quad \forall n \in N
\]

• The optimization determines the vectors of (i) the optimal radiation powers, (ii) the optimal phases, and (iii) optimal beam durations for all $N$ ETs. This solution ensures the optimal energy transfer to set of $M$ nodes over the update interval $D_{\text{update}}$.

• Even though ETs are the source of power, one of the optimization objectives is to minimize the total energy consumed by all the ETs (equation 6.14).
The energy transferring-related power control and scheduling strategy for the ETs needs to meet the required energy demand at each sensor node, and thus, the amount of harvested energy indicated by $E^H(m)$ (equation 6.12) should be always equal or larger than the energy demand estimated by $E^{req}(m)$ (equation 6.13) over the update interval in order to support the current traffic operation (constraint 1). The harvested energy function consists of both metrics related to ETs and also cognitive ambient harvesting. Additionally, the estimated energy demands capture metrics such as sensing energy, current voltages of nodes, and transmission and reception traffic rates computed based on set of local rates, $r_i$, and active paths, $A$, (equations 6.5 and 6.6).

The sum of all beam durations for a node over a cycle of energy transfer need to be equal with $E_{intrv}$.

From lemma 1, the optimal transfer policy follows the energy-in-advance transfer mechanism that is specified by energy constraint 3 on the received beam powers at each sensor node.

If the received power from ETs is lesser than the minimum or larger than maximum input power of the RF harvesting circuit, it results into low-efficient or close to zero energy harvesting. Constraint 4 ensures the beams are within the optimal operating range.

Finally, the last constraint is checked to ensure the instantaneous radiated power of each ET will not exceed the maximum permitted value $P_{\text{max}}^{ET}$, set based of FCC regulations.

Adaptive Resource Allocation Algorithm: On obtaining energy updates from the nodes, the ETs adaptively adjust their energy beams. This incurs calling the centralized optimization framework described before. The steps used to alter the energy beams are described in the following algorithm, if the current beam parameters do not sufficiently support the new demand of the network.

6.4 Performance Evaluation

In this section, we evaluate the performance of our HYDRA framework using the ns-2 network simulator. Our simulation results are based on the mean value of 30 different network topologies located randomly in an area of $100 \times 100$ m where the location of the base station was fixed at the top-center of map. We simulate the Two Ray Ground radio propagation model in air. The simulation parameters are set as follows. The EH circuit parameters are obtained from [176]
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**Algorithm:** Adaptive Resource Allocation

1: Receive energy update packets or $D_{update}$ ends
2: Update traffic matrix $M(T)$ based on reported local rates (equations 6.5 and 6.6)
3: Determine new energy requirements of the nodes (equation 6.13)
4: Update $P_{cog}$ based on latest reported ambient harvesting rates
5: Check if current energy beams and ambient power support new energy demands
   \[ E_H(i) \geq E_{req}(i) \forall i \in M \]
6: Based on (5), decide to continue operation with current ETs settings, or determine new optimal energy beams (run optimization)
7: Transfer the energy beams for next energy demand $D_{update}$

for energy beam harvesting at 915 MHz and from [175] for ambient energy harvesting at TV and cellular bands. We model each ET with directional antenna gain 1.0 dBi and maximum EIRP 4. The characteristics of the sensor, such as power of transmission, reception, sensing, sleeping, channel bandwidth, etc. are set based on Mica2 Mote hardware [188]. Table II presents some power and duty cycle related parameters used in the simulation.

In our simulations, sensor traffic loads are generated from a sensor node to the sink by constant bit rate (CBR) flows, and all data packets are 50 bytes in size. In particular, to simulate dynamic traffic rates and active paths, at periodic intervals over simulation time, a sensor node is randomly selected to send to the sink packets with a given input rate, $\alpha$, and the intermediate relaying nodes do not aggregate or compress data. If a node is selected to send, it is taken out from the selection pool till all nodes send the data. We model event arrival as Poisson process with inter-arrival occurrence parameter $\gamma$. The sensors report the event with a bursty traffic with packet size 200 bytes to the sink. We have organized the experiments into three parts. We start by presenting our RF ambient survey experimental results in Boston to obtain realistic power measurements to feed our simulations. We then evaluate the performance of optimal ET planning phase, and finally verify the benefits of our proposed adaptive resource allocation framework.

### 6.4.1 Ambient RF Preliminary Experiments

In order to obtain both temporal and spatial real measurements for ambient RF power, we have conducted a citywide RF spectral survey at GSM850, GSM1900, LTE730, LTE740, and DTV bands within Boston area at Massachusetts. Our ambient spectrum studies were undertaken from
outside of 40 subway stations at street level as survey points that are distributed in the city to measure the available RF power within each ambient band. We used a USRP2 device with a WBX antenna manufactured by Ettus Research LLC, and it was calibrated in the laboratory with the Agilent N9000 signal analyzer. The banded input RF power mW is calculated by summing and averaging over all received power across the band in a similar way the spectrum analyzer calculates channel power. We used our experimental results as input for simulating ambient energy harvesting in both optimal ET placement and adaptive resource allocation steps. Table III summarizes our results across all subway stations indicating the frequencies, average, maximum, median, and standard deviation for all banded power measurements. Using the complete dataset from our RF ambient survey, we calculate the percentages that each ambient channel wins the highest measured power over all locations as 46%, 5%, 13%, 16% and 3% for GSM850, GSM1900, LTE730, LTE740, and DTV, respectively. When selecting the spectrum with the highest strength in our measurements, among all candidate options at any given time, we observe about 73% improvement of the average received input power using the cognitive approach over a static band selection.

6.4.2 Optimal ET Placement Evaluation

In order to study the performance of HYDRA optimal ET placement method proposed in Section III-A, we compare HYDRA with random placed beamforming and omnidirectional energy transfer schemes. We evaluate the impact of the number of nodes, available ambient power, and ET transmission power on the optimal number of ETs that support the given offered traffic load in the network. We set the number of randomly placed sensors to 10, 20, 30, 40, and 50. The ET antenna gains are assumed unity, and the default transmission power is 3 EIRP at the planning phase. It noteworthy that in the adaptive resource management we dynamically allocate the transmit powers based on traffic rates over network operation as described in Section III-C. Furthermore, we use the average received powers from our RF survey experimental measurements as the ambient input received power $P_{amb}$ over all sensor nodes. The minimum number of ETs is set to 4.

We compare HYDRA with five schemes: i) beamforming-RPOD, ii) beamforming-RPFD, iii) omnidirectional-RPOD, iv) omnidirectional-RPFD, v) omnidirectional-RPNA. In beamforming-RPOD, the ETs are randomly placed, the duration of beams are optimized, and the sensor harvests the ambient power. However, beamforming-RPFD scheme follows a fixed beam duration that is set to $E_{intra}/M$ for all ETs. This scheme has randomly placed ETs and harvest RF ambient power too. The three omnidirectional schemes operate based on randomly placed ETs and nodes experience...
constructive and destructive energy interferences. Both omnidirectional-RPOD and omnidirectional-RPFD harvest ambient power when there is no ET transfer while in the first scheme the optimal duration for ETs to support the given traffic load is computed and in the second scheme this duration is set to a fixed number $E_{\text{intrv}}/M$. Finally, omnidirectional-RPNA includes randomly placed ETs that transfer power over duration data cycle $D_{\text{intrv}}$ without any RF ambient harvesting.

Fig. 6.7 shows the effect of increasing offered load, number of nodes, and ambient power on the optimal number of ETs in HYDAR framework. As expected, the optimal number of ETs decreased with the increasing of average ambient power here from 0.0825 mW to 0.7938 mW. From Fig. 6.7, we observe that there is a high increase in number of optimal ETs with decreasing of available ambient power in low offered load. This gap on the number of ETs between high and low ambient harvesting rates is reduced as the offered load increases. This is because the leverage and contribution of ambient power decreases in the higher offered loads. We observe the minimum number of ETs needed for a given offered load increases with the increasing the number of nodes in the network regardless of the traffic or ambient power rates. In other words, the higher number of nodes, the higher optimal ETs. This is because the higher network density decreases the beam duration for charging each sensor over an energy cycle, and thus requires more ETs to support the same offered load. From the observed values, we also see that for low offered loads up to 17 and a high ambient power.
power 0.7038 mW, the minimum number of ETs is sufficient.

We next compare HYDRA scheme with random placed beamforming and omnidirectional schemes as described before for varying offered loads. Fig. 6.8-a depicts the optimal number of ETs for the average ambient power rate 0.0362 mW and Fig. 6.8-b shows this for the ambient rate 0.0821 mW where in both figures 10 number of nodes is randomly deployed. We observe that HYDRA with optimal placement has the best performance and lower number of ETs among all other compared schemes. It is shown that beamforming outperforms omnidirectional schemes regardless of the available ambient rates and the offered loads. Interestingly, the omnidirectional schemes require significantly higher number of ETs as the traffic load increases. This gap of the optimal number of ETs between beamforming and omnidirectional methods grows significantly, where it is going in average from 10 at offered load 6 to 20 at load 10 and eventually to 50 at offered load 14.

In addition, it can be observed that schemes with optimized transfer durations are always provide better performance in both beamforming and omnidirectional cases. Finally, as seen in Fig. 6.8 the omnidirectional-RPNA which does not harvest ambient energy outperforms other omnidirectional schemes at higher offered loads. This is because even though other schemes can leverage ambient power at low loads, as traffic increases the contribution of ETs becomes more significant. Despite such performance, RPNA method transfers power over the whole $D_{intrv}$, and thus consumes much more energy than two other omnidirectional schemes, and still requires higher number of ETs in compare to HYDRA.

Fig. 6.9 evaluates the impact of ET transmission power on optimal number of ETs for increasing number of nodes and ambient powers. It can be observed as the transmission power increases the optimal number of ETs decreases regardless of available ambient power and nodes.

In addition, Fig. 6.9 shows the number of sensors has higher impact on performance at lower ET transmission powers and lower ambient powers. For example, the gap between number of ETs is high at EIRP 1.5 and decreases to 3 at EIRP 4 for $P_{amb} = 0.0821$ mW.

### 6.4.3 Adaptive Resource Allocation Evaluation

In this section, we verify the benefits of our proposed adaptive resource allocation described in Section III through extensive simulations. We study the impact of the number of sensors, the CBR input packet rate, and the event interval rate. CBR traffic packets are generated at periodic intervals 10s each time for a randomly selected source node with input packet rate $\alpha$ to send the sink over 5000s simulation time. The input packet rates have values varying from 1 to 16, and event interval
Figure 6.8: Comparing HYDRA planning with random placed beamforming and omnidirectional schemes for $N=10$ and $P_{amb}$ equals to (a) 0.0362 mW, (b) 0.0821 mW.
Figure 6.9: Optimal number of ETs is shown for varying number of ET transmission power, number of nodes, and ambient power.

rate ($\gamma$) varies from 0s to 400s. For the RF ambient harvesting simulations, we use our RF ambient survey experiments in Boston, and specifically consider the measured samples from Museum of Fine Arts (MFA) location as the input. Our performance evaluation metric is the total consumed energy by all ETs over the entire network simulation time. As formulated in Section III, the important goal of HYDRA is to adaptively guarantee the required energy for sensors with dynamic traffic while minimizing the consumed energy by all ETs.

In order to evaluate HYDRA adaptive allocation, we compare five different schemes: i) HYDRA-Full, ii) HYDRA- w/o CH, iii) HYDRA- w/o EIA, iv) static beamforming- w AH, v) static beamforming- w/o AH. HYDRA-Full is the full-featured HYDRA framework, including energy-in-advance, cognitive ambient harvesting, and adaptive beam control mechanisms, as discussed in Section III-B and III-C. The HYDRA without cognitive ambient harvesting (named HYDRA w/o CH) has all features of HYDRA other than cognitive harvesting. In particular, instead of adaptively tuning and harvesting to the best ambient performing spectrum over the time, it selects the ambient spectrum with the highest average measured power in the initial measurements as the fixed ambient band. We evaluate HYDRA- w/o CH in order to investigate the effectiveness of cognitive harvesting in our framework. On the other hand, HYDRA- w/o EIA has all features of HYDRA except the energy-in-advance mechanism that presented in Section III-B. Moreover, we compare HYDRA with static beamforming as the base case of comparisons where there is no adaptive control and
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Figure 6.10: Comparing HYDRA variants and static beamforming for varying packet input rates over entire simulation time.

allocation of energy beams, and it has none of energy-in-advance and cognitive harvesting features. The duration and power of ETs are set to the fixed values of $E_{intrv}/M$ and 3 EIRP. Here, we consider two schemes for static beamforming, namely, with ambient harvesting (i.e., w AH) and without ambient harvesting (i.e., w/o AH), where in the case of ambient harvesting the nodes harvest from a fixed ambient spectrum that had the highest average measured power. In this section, we assume for all simulated scenarios the optimal locations and numbers of ETs are determined in the deployment phase based on optimal ET placement method (Section III-A). Accordingly, the compared scenarios may have different number of ETs that support the required load.

Fig. 6.10 shows the effect of increasing input CBR packet rate on the total consumed energy by all ETs. Here, 50 sensors are randomly deployed and event interval rate is assumed to be 50s. It is clear that three HYDRA variants dominate over the static beamforming schemes. As shown in Fig. 6.10, HYDRA-full has the best performance and delivers monotonically increasing consumed ETs energy with increasing the input packet rate. The benefits of full featured HYDRA greatly reduce the required energy for supporting different packet rates in compare to other schemes. We observe the ETs total energy consumptions are increased by more than 12% and 21% on average for HYDRA without cognitive harvesting and HYDRA without energy-in-advance schemes, respectively. Both variants of HYDRA-Full yield higher ET energy consumptions as the input traffic rate increases. However, the HYDRA w/o CH provides higher performance than HYDRA w/o EIA, with a 10%
increase of total energy consumption on average. Both the static beamforming w AH and w/o AH are the lowest among transfer schemes under study and consume a considerably large amount of energy from ETs. This is because these schemes do not have the proposed features of HYDRA including adaptive beam control (i.e. power and duration) over the network operation. The HYDRA yields as high as 53\% and on average 30\% more energy efficient transfer than static beamforming over different input packet rates.

Next we investigate the effect of event rate over the ETs total consumed energy while the event interval is varied up to 400s in steps of 50s. Again, 50 sensors are randomly deployed and input packet rate is set to 6. Fig. 6.11 shows a smooth and monotonic decrease in the ETs total consumed energy for three HYDRA variants as the event interval rate increases. Interestingly, we observe the gap between performance of full featured HYDRA and its variants becomes significant at higher event interval rates. It is shown that HYDRA full, w/o CH, and w/o EIA outperform static beamforming schemes over 160\%, 45\%, 20\%, respectively, in terms of total consumed energy at event interval 400s. The static beamforming with ambient harvesting over all event intervals yields in better performance than static beamforming without harvesting and packet rates and this trend can be observed clearly in Figures 6.10 and 6.11.

Finally, we evaluate the performance of HYDRA for different increasing number of nodes. Fig. 6.12 that the total consumed energy by ETs increases for larger number of nodes. In addition,
it can be observed here the effect of event interval rate is higher than packet CBR rate, where the
energy consumption of $\alpha = 16, \gamma = 400$ is less than $\alpha = 1, \gamma = 150$.

6.5 Related Works

Wireless energy transfer for powering mobile and sensor nodes has received significant
attention in the recent years, with comprehensive classification and surveys on this topic presented
in [171, 189]. The earlier works mainly considered single antenna omni-directional energy transfer
and multi-antenna beamforming with a single transmitter/base station. However, nowadays many
communication systems are equipped with more than one transmitter, and the need for distributed
beamforming is emerging.

In [190], the authors design an adaptive energy beamforming scheme based on imperfect
CSI feedback in a point-to-point MISO system. They balance the time resource used for channel
estimation and wireless power transfer to maximize the harvested energy and also investigate the
allocation of energy resource used for power transfer. The authors in [191] and [192] investigate
energy beamforming in multi-user systems. In particular, [191] considers a TDMA-based MISO sys-
tem that is powered by a power station. They model a joint time allocation and energy beamforming
design as a non-convex programming problem to maximize the system sum-throughput. In addition,
exploits collaborative energy beamforming with distributed single-antenna transmitters. To this end, a novel signal splitting scheme is introduced at the transmitters to optimize the rate-energy tradeoff. In [194], two energy harvesting transmitters is considered in a system with optimal packet scheduling and multiple access communication. In [195], an optimal power allocation policy for a communication system with two energy harvesting transmitters over an interference channel is proposed. [196] proposes a max-min fair rate allocation and routing in energy harvesting networks for making fairness among both the nodes and the time slots. [197] introduces a framework for the cognitive spectral awareness to achieve higher spectrum utilization and fairness.

Finally, the previous works on wireless charger deployment have approached this problem in four main ways as point provisioning, path provisioning, multi-hop provisioning, and landmark provisioning with a complete survey on them can be found in [189]. However, to the best of our knowledge, none of charger placement strategies have considered the RF ambient energy and the energy interference of distributed chargers [172] on the optimal deployment problem.

6.6 Final Remarks

In this chapter, we proposed a planning and network resource management framework, called HYDRA, for RF powered-sensor networks. We deployed a joint directional energy beamforming and cognitive ambient harvesting approach that leverages an integrated energy and data duty-cycling mechanism. We devised a mathematical model for the task of ET placement that jointly optimizes the direct energy transfer and ambient energy harvesting. We also introduced an adaptive resource allocation algorithm that controls the optimal powers and phases of ETs, schedules the beams, and determines the durations of energy transmission epochs to support the required energy based on time-varying traffic in the network and available ambient powers. Our performance evaluation results shows the benefits of HYDRA in compare to different variations of static beamforming and omnidirectional schemes.
## Table 6.1: Important Symbols Used for HYDRA Description

<table>
<thead>
<tr>
<th>Symbols</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S$</td>
<td>Set of $M$ nodes (and their locations)</td>
</tr>
<tr>
<td>$E$</td>
<td>Set of the ETs</td>
</tr>
<tr>
<td>$N$</td>
<td>Optimal number of ETs</td>
</tr>
<tr>
<td>$R$</td>
<td>Set of optimal locations of the ETs</td>
</tr>
<tr>
<td>$W$</td>
<td>Set of directed links indicating possible routes in the sensor network</td>
</tr>
<tr>
<td>$D_{\text{intrv}}$</td>
<td>Duration of a data duty-cycle, in time units</td>
</tr>
<tr>
<td>$E_{\text{intrv}}$</td>
<td>Duration of an energy duty-cycle, in time units</td>
</tr>
<tr>
<td>$D_{\text{update}}$</td>
<td>Duration of update intervals, in time units</td>
</tr>
<tr>
<td>$A$</td>
<td>Set of current active paths during energy demand $D_{\text{update}}$</td>
</tr>
<tr>
<td>$P_{\text{it}}$</td>
<td>Parent nodes of sensor node $S_i$ in the set of active paths $A$</td>
</tr>
<tr>
<td>$N_{\text{it}}$</td>
<td>Possible next hops of node $S_i$ in the set of active paths $A$</td>
</tr>
<tr>
<td>$T_{\text{dc}}$</td>
<td>Offered traffic rate of a node in a data duty-cycle</td>
</tr>
<tr>
<td>$E_{\text{dc}}$</td>
<td>Required energy to supply the traffic rate $T_{\text{dc}}$</td>
</tr>
<tr>
<td>$D_{\text{update}}(i)$</td>
<td>Duration of energy beam at sensor node $S_i$, in time units, over $E_{\text{intrv}}$</td>
</tr>
<tr>
<td>$P_{\text{tx}}(i,j)$</td>
<td>Transmission power of $i$th ET at $j$th energy epoch for target node $S_m$</td>
</tr>
<tr>
<td>$P_{\text{ET}}$</td>
<td>Set of the transmission powers of $i$th ET in set $E$, in Watt</td>
</tr>
<tr>
<td>$P_{\text{H}}$</td>
<td>Set of average ambient power harvesting rates for all sensor nodes</td>
</tr>
<tr>
<td>$P_{\text{H cog}}$</td>
<td>Set of latest cognitive ambient power harvesting rates for all sensor nodes</td>
</tr>
<tr>
<td>$\Delta R_{\text{mn}}(i)$</td>
<td>Distance difference between $ET_m$ and $ET_n$ and receiver $S_i$</td>
</tr>
<tr>
<td>$\Delta \phi_{\text{mn}}(i)$</td>
<td>Transmit phase difference between $ET_m$ and $ET_n$ for a target node $S_i$</td>
</tr>
<tr>
<td>$\phi_{\text{m}(i,j)}$</td>
<td>Transmit phase of $i$th ET at $j$th energy epoch for target node $S_m$</td>
</tr>
<tr>
<td>$\phi_{\text{ET}}$</td>
<td>Set of the transmission phases of $i$th ET in set $E$</td>
</tr>
<tr>
<td>$r_{i}$</td>
<td>Total local traffic rate of node $S_i$</td>
</tr>
<tr>
<td>$r_{i}^{rx}$</td>
<td>Total receiving rate at sensor node $S_i$</td>
</tr>
<tr>
<td>$r_{i}^{tx}$</td>
<td>Total transmitting rate of sensor node $S_i$</td>
</tr>
<tr>
<td>$f_{i}^{a}(i,j)$</td>
<td>Fractional amount of node $i$’s total output traffic passes through link $(i,j)$</td>
</tr>
<tr>
<td>$e_{i}^{j}$</td>
<td>$j$th received energy epoch at sensor $S_i$</td>
</tr>
<tr>
<td>$h_{i}^{e}$</td>
<td>Harvested energy epoch from $e_{i}^{j}$</td>
</tr>
<tr>
<td>$E_{ET}$</td>
<td>Total consumed energy by all $N$ ETs over $D_{\text{update}}$</td>
</tr>
<tr>
<td>$F_{\text{tx}}(i,j)$</td>
<td>Received power of $j$th energy beam at a sensor node $S_i$ over $D_{\text{update}}$</td>
</tr>
<tr>
<td>$H(i,j)$</td>
<td>Harvested power at sensor node $S_i$ from $j$th energy epoch over $D_{\text{update}}$</td>
</tr>
<tr>
<td>$D(i,j)$</td>
<td>Duration of $j$th energy beam that is received by node $S_i$ in $D_{\text{update}}$</td>
</tr>
<tr>
<td>$E_{\text{H}}(i)$</td>
<td>Total harvested energy at sensor $S_i$ from both energy beams and ambient</td>
</tr>
<tr>
<td>$E_{\text{req}}(i)$</td>
<td>Energy required to support the operation of node $S_i$ over $D_{\text{update}}$</td>
</tr>
<tr>
<td>$\eta(P_{r}, f)$</td>
<td>RF-to-DC conversion efficiency at frequency $f$ and input power $P_{r}$</td>
</tr>
<tr>
<td>$V(i)$</td>
<td>Current voltage of node $S_i$</td>
</tr>
<tr>
<td>$V_{\text{min}}$</td>
<td>Minimum operating voltage of sensors in set $S$</td>
</tr>
</tbody>
</table>
Table 6.2: HYDRA simulation parameters in ns-2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_s$</td>
<td>50 ms</td>
<td>Data Tx Power</td>
<td>41.53 mW</td>
</tr>
<tr>
<td>$T_{sch}$</td>
<td>200 ms</td>
<td>Data Rx Power</td>
<td>30 mW</td>
</tr>
<tr>
<td>$T_{data/sleep}$</td>
<td>4250 ms</td>
<td>Sense Power</td>
<td>0.012 mW</td>
</tr>
<tr>
<td>$D_{intrv}$</td>
<td>4.5 s</td>
<td>Sleep Power</td>
<td>0.003 mW</td>
</tr>
<tr>
<td>$E_{intrv}$</td>
<td>1.5 s</td>
<td>Channel Bandwidth</td>
<td>19.2 kbps</td>
</tr>
<tr>
<td>CW</td>
<td>34 ms</td>
<td>Tx Range</td>
<td>40 m</td>
</tr>
<tr>
<td>DIFS</td>
<td>10 ms</td>
<td>CS range</td>
<td>60 m</td>
</tr>
</tbody>
</table>

Table 6.3: Summary of Boston ambient RF power measurements over 40 subway stations.

<table>
<thead>
<tr>
<th>Band</th>
<th>GSM850</th>
<th>GSM1900</th>
<th>LTE730</th>
<th>LTE740</th>
<th>DTV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequencies (MHz)</td>
<td>869-894</td>
<td>1930-1950</td>
<td>734-744</td>
<td>746-756</td>
<td>494-584</td>
</tr>
<tr>
<td>Average (mW)</td>
<td>1.8153</td>
<td>0.1335</td>
<td>1.4193</td>
<td>1.4029</td>
<td>0.0547</td>
</tr>
<tr>
<td>Maximum (mW)</td>
<td>10.3474</td>
<td>0.5226</td>
<td>13.0601</td>
<td>19.1625</td>
<td>0.3038</td>
</tr>
<tr>
<td>Median (mW)</td>
<td>0.7938</td>
<td>0.0821</td>
<td>0.2869</td>
<td>0.0825</td>
<td>0.0362</td>
</tr>
<tr>
<td>StDev</td>
<td>2.4500</td>
<td>0.1351</td>
<td>2.9876</td>
<td>3.5793</td>
<td>0.0610</td>
</tr>
</tbody>
</table>
Chapter 7

Conclusion

In this dissertation, we set out to understand the main communication and network challenges in RF-powered wireless sensor networks and proposed a set of solutions to address them using tools such as analytical modeling and performance evaluation, communication and network protocol design, prototyping and experimental studies, as well as planning and resource management. We were motivated by the critical need of supplying power and recharging the pervasive sensor devices, and significant impacts of the wireless energy charging on future of embedded devices and Internet of Things. We briefly summarize our main findings.

We proposed analytical framework for reliability analysis of energy harvesting nodes. We first modeled the behavior of a harvesting sensor node by a semi-Markov model, in which the discharging and recharging rates are assumed as the semi-Markov state reward rates. Then we calculated the node lifetime through a new proposed energy transient analysis approach. Finally, through a set of simulations, we verified the correctness of the analytical results for net consumed energy and node lifetime distributions.

We introduced the RF-MAC protocol to provide the reliable and fair energy-on-demand medium access for both data and energy in sensor networks with wireless energy harvesting. It specifically addressed the problems of joint selection of energy transmitters and their frequencies based on the collective impact on charging time and energy interference, setting the maximum energy charging threshold, requesting and granting energy, and energy-aware access priority. The grouping of the ETs into two sets with varying transmission frequencies, and the minimal control overhead are both geared to keep the hardware requirements simple, and the protocol easier to implement. Simulation and testbed results revealed that RF-MAC largely outperforms the modified CSMA in both average harvested energy and average network throughput.
We presented an experimental investigation of concurrent energy and data transmissions in RF-powered WSNs. Our experiments quantified the wireless charging, communication, and interference ranges for coexistent WSNs and wireless energy transmitters. We showed the severe effect of high power energy waves on data communication and the energy cancellation of concurrent energy transmissions. In addition, we demonstrated that frequency separation and multi-band RF harvesting are promising for enabling coexistence and improving general network performance and energy harvesting throughput. Then we presented an experimental study to understand the effect of RF energy transfer from an energy transmitter on low-power data communications, as those of WSNs. Our results confirmed that multifrequency energy transfer is crucial for surviving energy interference and improving the PRR. We discovered three distinguishable regions in the frequency domain, each of which results in different levels and pattern of interference. Finally, we showed that local energy interference measurements at a sensor node can provide a good estimate for detecting the energy frequency regions where the node is, thus guiding the selection of ET frequencies for a desirable PRR.

Moreover, we derived closed matrix form expressions for the total harvestable power at any location in a WSN with multiple ETs by capturing the spatial correlation between ETs and their constructive and destructive energy interferences. We provided the formulas for plane and 3D WSN deployments. We analyzed the wireless energy over the network and presented the distributions of the received power, energy interference, and harvested voltage. Our results showed that the received power from multiple ETs over the network and the network energy interference have Log-Normal distributions. We further observed that the harvested voltage over the network has a Rayleigh distribution.

Finally, we proposed a planning and network resource management framework, called HYDRA, for RF powered-sensor networks. We deployed a joint directional energy beam-forming and cognitive ambient harvesting approach that leverages an integrated energy and data duty-cycling mechanism. We devised a mathematical model for the task of ET placement that jointly optimizes the direct energy transfer and ambient energy harvesting. We introduced an adaptive resource allocation algorithm that controls the optimal powers and phases of ETs, schedules the beams, and determines the durations of energy transmission epochs to support the required energy based on time-varying traffic in the network and available ambient powers. Our performance evaluation results showed the benefits of HYDRA in compare to different variations of static beamforming and omnidirectional schemes.
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