JOINT CHARGING, ROUTING, AND POWER ALLOCATIONS FOR RWSNS

JOINT CHARGING, ROUTING, AND POWER ALLOCATIONS FOR RECHARGEABLE WIRELESS SENSOR NETWORKS

BY

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Lay Abstract

In a wireless sensor network (WSN), sensor nodes monitor the physical environment and forward the collected data to a data sink for further processing. Sensors are battery powered and, therefore, prolonging the lifetime of their batteries is critically important. In a rechargeable WSN (RWSN), prolonging the battery lifetime of sensors is achieved through reducing communication energy and recharging the batteries periodically. Reducing the communication energy consumption is done through choosing the best forwarding sensors (i.e., routing) for data collected by each sensor and deciding the transmission power of each sensor (i.e., power allocation). Recharging the batteries is achieved through harvesting energy from external sources. In this thesis, we consider a RWSN that uses wireless power transfer as the energy harvesting technology and jointly optimizes charging and communications in order to minimize the power consumption of the RWSN.

Abstract

Prolonging the battery lifetime of sensors has been one of the most important issues in wireless sensor networks (WSNs). With the development of Wireless Power Transfer (WPT) technology, sensors can be recharged and possibly have infinite lifetime. One common approach to achieving this is having a wireless charging vehicle (WCV) move in the system coverage area and charge sensors nearby when it stops. The duration that the WCV stays at each charging location, the amount of traffic that each sensor carries, and the transmission power of individual sensors are closely related, and their joint optimization affects not only the data transmissions in the WSN but also energy consumption of the system. This problem is formulated as a mixed integer and non-convex optimization problem. Different from existing work that either solves similar problems using genetic algorithms or considers charging sensors based on clusters, we consider the optimum charging time for each sensor, and solve the joint communication and charging problem optimally. Numerical results demonstrate that our solution can significantly reduce the average power consumption of the system, compared to the cluster-based charging solution.

To my son

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Notation and Abbreviations

Notation

f_0	Resonant frequency
L	Effective inductance
C	Effective capacitance
ω	Resonant angular frequency between coupling devices
κ	Coupling coefficient
α	Path-loss exponent
D	Charging distance
R_c	Charging range
μ	Charging efficiency
U_{mi}	Charging efficiency from anchor location m to sensor i
I	Number of sensor nodes

t_{tot}	Charging cycle duration
t_{path}	WCV travel time
t_m^a	Dwelling time of WCV at m th anchor location
t_{mi}	Charging time WCV for sensor i at m th anchor location
t_0	Vacation time of WCV
τ_{ij}	Transmission time from sensor i to sensor j in one charging cycle
E_i	Total amount of energy charged to sensor i in one charging cycle
$E_{\max}$	Maximum battery capacity of a sensor
$E_{\min}$	Minimum battery energy of a sensor
R_i	Data generation rate of sensor node i
f_{ij}	Data transmission rate from sensor i to sensor j in one charging cycle
$f_{\max}$	Maximum data transmission rate
p_{ij}	Transmission power from sensor i to sensor j
$p_{\max}$	Maximum transmission power of a sensor
p_{path}	Power consumption of the WCV when traveling
P_c	Power consumption of the WCV charging
P_{avg}	Average power consumption of a RWSN
p_{noise}	Noise power

ρ_i	Energy consumed for sensor i to receive each bit of data
g_{ij}	Channel gain between sensors i and j

Abbreviations

RWSN	Rechargeable Wireless Sensor Network
WSN	Wireless Sensor Network
WPT	Wireless Power Transfer
RF	Radio Frequency
WCV	Wireless Charging Vehicle
GA	Genetic Algorithm
RABC	Restart Artificial Bee Colony
TSP	Travelling Salesman Problem
GP	Geometric Programming
SCA	Successive Convex Approximation
SNR	Signal-to-Noise Ratio

Chapter 1

Introduction

In a Wireless Sensor Network (WSN), sensor devices distributed in a given geographical area are used to sense the physical measurements, such as temperature, humidity, pressure, etc. and send the data to the data sink or sinks [21]. As a network, some sensors are also responsible for relaying data for other sensors. With the increasingly wide applications of WSNs, such as environmental monitoring, military surveillance, and industry automation [27], the battery energy problem of the sensors has become an important issue [20]. As the sensors are battery powered, the lifetime of the battery of a sensor is often the lifetime of the sensor in many cases [19] [8]. This is especially true in harsh environments or areas where humans cannot easily reach [6], such as in nuclear stations [13], since it is practically impossible to replace the "dead" sensors.

Using energy harvesting techniques to power WSNs helps prolong the battery lifetime of sensor nodes [12]. This kind of energy harvesting techniques utilizes energy collecting equipment, e.g., solar panels [25] or wind turbines [10], to absorb ambient energy from natural sources, and stores the collected energy into an energy storage device (e.g., a battery). Extensive research work has been done to improve the natural energy harvesting efficiency and resolve the mismatch between the amounts of harvested and demanded energy, e.g., [24][23][1]. However, the amount of harvested energy using this type of techniques is sensitive to the environment, e.g., the amount of sunshine time, and the device used for collecting energy often has much larger size than the sensor itself. This can cause difficulties in sensor deployment in practical applications [33].

Sensor batteries can also be charged through wireless power transfer (WPT). Compared with harvesting energy from the natural sources, WPT provides a more stable and reliable approach to charge batteries in the near fields. As an alternative to harvesting energy from natural sources, WPT is a technology that is able to transfer power between two copper coils [15]. Recently, the new WPT technology has attracted researchers and engineers to investigate different algorithms to improve the lifetime and energy consumption of WSNs or even to keep the WSNs always alive.

1.1 Wireless Power Transfer

The history of WPT can be dated back to 1914 when Nikola Tesla created his patent to transfer power wirelessly in the United State [28]. However, it did not work as expected due to unexpected electrical fields when transferring energy between the transmitter and the receiver. In the early 1990s, a new wireless power supply system was designed by Albert and Hans-Christopher by having a rotatable transformer transfer energy to a robot at a frequency of around 25 kHz [7]. The charging efficiency for this technique is 95% at 100 μm of charging distance. Installing the entire energy transfer system is not feasible in WSNs due to the short charging distance and the size of the transformer.

A patent for contactless battery charger with wireless control link was published in 2001 [9], where an inductive coupler is used to transfer energy from its primary side (i.e., the energy source) to the secondary side (i.e., devices being charged). In addition to charging devices on the secondary side, this system also provides a control signal that can be used to improve the charging efficiency. Although the charging efficiency dropped to 60%, the charging distance can reach 3 mm, which is much longer than that in [7]. However, the charging distance is still relatively short in the ecosystem of WSNs.

A radio frequency (RF) radiation method was invented in 2006 that uses a converter circuit to convert energy in a range of RF frequencies and charges batteries [29]. Compared to the previous methods, this technique adds an additional feature that allows simultaneous wireless information and power transfer. Due to the nature of RF signal transmissions, the charging distance is longer than in the previous methods, but the overall charging efficiency is much lower, e.g., below 1% [4], especially when the radiation is omnidirectional. In addition, it requires the direct line of sight between the charging and charged devices.

In 2007, a theory of midrange power transfer was proposed in [11], which proves that strongly coupled resonant coils can be used to transfer power with high efficiency. With strongly coupled resonant, the high coherent coupling rate at the surface of the resonator results in highly efficient wireless energy transfer [2]. Setting up WPT in such a way is a prominent technology that can be used in extending the lifetime of WSNs, because it can be operated in an omnidirectional way without the line of sight requirement. Based on this theory, a breakthrough WPT technology was proposed in [15] that uses strongly coupled magnetic resonances to transfer power wirelessly and efficiently. This WPT technique is suitable for daily applications, because the magnetic fields do not interact with common materials. The same technique can also be used to transfer energy from a single source to multiple devices [16].

1.1.1 One-to-one Wireless Power Transfer

As shown in figure 1.1, the one-to-one WPT system consists of one sender and one receiver, which are made by strongly coupled magnetic copper coils, and the coils are resonant [15]. The main reason for using resonance in this WPT system is that it helps improve the energy transfer efficiency significantly compared with the scenario using non-resonant materials. Let f_0 be the resonant frequency at which the WPT system is operating, then [15]

$$f_0 = \frac{1}{2\pi(LC)^{\frac{1}{2}}}, \tag{1.1.1}$$

where L and C, respectively are the effective inductance and effective capacitance for each coil. The sender circuit is a cooper loop which is supplied by an AC power source. In order to maximize the WPT efficiency, the input frequency must be within the range of 1 MHz to 50 MHz. In the experiment performed in [15], the frequency is set to be 9.9 MHz. The receiver circuit is also a loop of wire with a load attached to it. The coupling coefficient is given by

$$\kappa = \frac{\omega M}{2(LC)^{\frac{1}{2}}} \tag{1.1.2}$$

where ω is the resonant angular frequency and M is the effective mutual inductance between the coupling devices. The efficiency of WPT decreases as the charging distance increases. Curve fitting is used in [15] to find the relationship between the charging efficiency and charging distance as follows:

$$\mu = \begin{cases} -0.0958D^2 - 0.0377D + 1.0, & \text{if } D \leq R_c \\ 0, & \text{otherwise,} \end{cases} \tag{1.1.3}$$

where μ is the charging efficiency, D is the charging distance, and $R_c \approx 3.04$ m is the maximum charging range. Notice that $\mu \in [0, 1]$. As special cases, $\mu = 1$ when $D = 0$; and $\mu = 0$ when $D > R_c$.

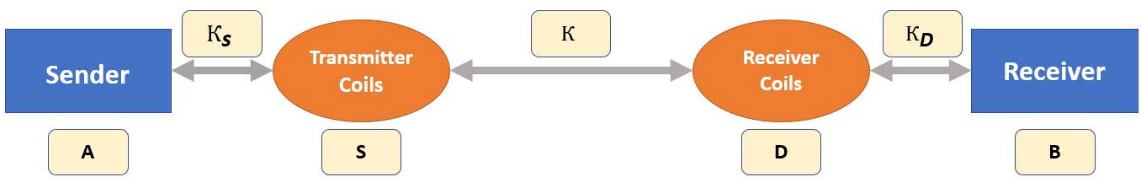

Figure 1.1: One-to-one WPT system [15]: A and B, respectively, represent the the driving circuit (sender circuit) and device circuit (receiver circuit), S and D, respectively, are the sender and receiver coil, and κ_S and κ_D, respectively, are the A-S and B-D coupling coefficients.

1.1.2 One-to-multiple Wireless Power Transfer

Similar to one-to-one charging, one-to-multiple charging uses the same base theory that the source should be strongly coupled with the receivers [16]. The overall efficiency is determined by the ratio of the total power delivered to all the loads over the power fed into the system. The overall power transfer efficiency in one-to-multiple charging is higher than that in one-to-one charging [16]. In order to achieve the optimal efficiency, the entire system needs to be tuned into the same frequency, which is the resonant frequency. Each resonant device must apply smaller loop-and-capacitor technique to match the predefined resonant frequency. Besides tuning the coils to couple with the sender at the resonant frequency, the location of the receivers is also an important factor for strong coupling [16].

In the experiment reported in [16], 25 watts of power was supplied to each receiving device over a 2 meter distance. The results also show that the measured overall efficiency is higher than the efficiency of the one-to-one charging by at least 10%. Similar to the one-to-one charging, the measured efficiency in the one-to-multiple charging also decreases with the charging distance, and the difference between the one-to-multiple and one-to-one charging efficiency becomes more significant as the charging distance increases.

1.2 Rechargeable Wireless Sensor Networks

The above mentioned WPT technology is a promising way to extend the lifetime of WSNs. Compared to other existing charging options, this method is less affected by the surrounding environment. However, since the geographical coverage of a WSN is usually much larger than the charging range of the WPT, the charger should be moved to different locations of the network coverage area. This can be achieved by having a vehicle carry the charger, and the charger together with the vehicle is referred to as a wireless charging vehicle (WCV) [3, 31, 26, 33, 34]. In this case, the WCV should periodically recharge itself, and this is usually done at a fixed home station. The WCV moves along a certain charging trajectory, stops at a number of charging locations (also referred to as anchor locations) to charge the sensors within the charging range, and returns to the home station before it runs out of energy. A full charging cycle includes the travel time during which the WCV is moving along the path, multiple charging intervals during which the charger stops at individual anchor locations, and the time when the charger is at the home station to recharge itself or at "rest".

Given the moving trajectory of the WCV, [31] has proved that, if the network flow follows a periodical cycle, the charging behaviour is also periodical, i.e., charging can be done periodically. The concept of "charging cycle" has been used in other work, e.g., [26, 3]. Within each charging cycle, the energy consumption of the system includes that for driving the charging vehicle and for charging the sensors. The former is directly related to the length of the moving trajectory, while the latter is determined by the communication loads of the sensors, which is further related to flow routing in the WSN.

The WPT technology makes is possible to keep the sensors in a WSN recharged. In this scenario, it is important to ensure that the battery energy of the sensors is always sufficient for the communication requirements. Meanwhile, the energy consumed by the WCV should be minimized. The charging decisions are also related to the data sensing rate, data flow routing, transmission power and rate of the sensors in the WSNs. This is the problem studied in this thesis.

1.3 Organization of The Thesis

The rest of the thesis is organized as follows. Section 2 summarizes the related work on charging decisions in rechargeble WSNs. Section 3 describes the system model that our research work is based on and formulates the problem of optimum charging, flow routing, power and rate allocations. A special case with all sensors in the charging rang of the same anchor node charged with the same amount of time is solved in Section 4. Section 5 solves the optimum charging problem for the general case when individual sensors may be charged with a different amount of time. Section 6 presents the simulation results to demonstrate performance of the proposed charging solutions. Finally, the conclusions are drawn in Section 7.

Chapter 2

Literature Review

This chapter first introduces related work on joint charging and traffic routing in RWSNs, based on which the motivations and main contributions of the thesis work are summarized.

2.1 One-to-one Charging

In the one-to-one charging, the charger is usually moved to be as close to the sensor to be charged as possible in order to maximize the charging efficiency. Since the charger has to visit individual sensors one by one, the energy consumed for the WCV to travel can be significant. In order to minimize the travel energy, the shortest charging trajectory should be followed. It is proved in [26] that the shortest path is a Hamiltonian cycle, which is in general not unique.

The charging performance is closely related to other aspects in a WSN. Specifically, the amount of energy charged to each sensor should be sufficient for the sensor to carry all the data communications, which is further related to data routing in the network. By taking these factors into consideration, an optimization problem is formulated in [26] for a single WCV to charge all sensors in a WSN while maximizing the fraction of the vacation time in a charging cycle. When solving the problem, the quadratic terms are approximated by piece-wise linear terms, which results a near-optimal solution.

Due to the high complexity of the system, methods based on the genetic algorithm (GA) have been used to solve the joint charging and routing problem. In [34], a similar system as in [26] is studied, and the objective is to minimize the total cycle time of the WCV. The problem is divided into several relatively independent sub-problems. First, the shortest travel path is calculated based on the traveling salesman problem. Given the charging trajectory, minimizing the total cycle time is equivalent to minimizing the total charging time, which is further equivalent to minimizing the total consumed energy of the sensors. The optimal communication flow routing is then found by using a restart artificial bee colony (RABC) method in order to minimize the total energy consumption of the sensors.

In the previous work, the WCV should charge all the sensors before it can return to the home station for recharging itself. The one-to-one charging scheme in [33] allows the WCV to charge only a portion of the sensor nodes in each charging cycle. The work completely decouples the routing and charging problems. First, communication flow routing is performed with an objective of minimizing the total power consumption of all sensor nodes without considering the charging conditions. After this, an algorithm is designed to group the sensors so that the WCV charges only one group of the sensors during each charging cycle. The objective of the grouping is to minimize the traveling distance of the WCV. Similar decoupling methods are also used in [17] and [32] to solve the charging problem in RWSNs.

In [3] the optimum charging problem in RWSNs is formulated as a multi-objective problem, which considers maximizing fairness in terms of energy consumption of the sensors, maximizing routing efficiency, and maximizing vacation time of the WCV over a charging cycle. Reinforcement leaning is used to train the sensor nodes for self-organizing data relaying routes in order to achieve fair energy consumption. An algorithm is designed to find the optimal path for the WCV based on the residue energy of the sensors. The energy consumption for driving the WCV to travel along the charging path is ignored in this formulation.

When the geographical area of the WSN is wide or the number of sensors is large, the charging problem may become infeasible since the amount of energy charged to the WCV in one charging cycle may be insufficient for it to charge all the sensors and travel back to the home station. For this reason, reference [14] considers having multiple WCVs in a RWSN. This brings more flexibility in charging the sensors but increases the complexity in optimizing the overall energy efficiency of the system. An enhanced k-mean clustering algorithm is used to separate the sensors into clusters, each of which is charged by one WCV, and the charging trajectory of the WCV is determined based on the locations of the sensors to be charged. Meanwhile, the work also minimizes the percentage of energy spent by the WCVs for traveling over the total energy consumption of the system.

2.2 One-to-multiple Charging

Instead of charging the sensors one after another, multiple sensors can be charged simultaneously. This not only improves the charging efficiency but also helps reduce the travel distance of the WCV and reduce the energy consumption of the WCV.

Sensors within the charging range of a given anchor location can be considered as a cluster or bundle and charged at the same time. Given the charging range (or maximum charging distance) of the WCV, finding the optimum charging bundles is equivalent to finding the optimum anchor locations of the WCV. It is proved in [30] that the optimum bundling and optimum trajectory problems are both NP-hard. Therefore, some simplifications are often needed to achieve practical solutions. The problem of minimizing the total energy consumption in a densely deployed RWSN is considered in [30]. Two steps are used to solve the problem. The first step is to assign all sensors into the smallest number of bundles, since a smaller number of bundles in general means a shorter charging tour. The second step is to minimize the energy of both charging the sensors and driving the WCV to travel. The effect of the data flow routing on the overall energy consumption and charging efficiency is not considered in this work.

In [18], sensors are first clustered based on distances, and the genetic algorithm is then used to find the best charging location (anchor point) for each cluster in order to minimize the cycle duration. Once the anchor nodes are found, the entire trajectory of the WCV can be found based on Travelling Salesman Problem (TSP), and the total cycle time is also known.

The work in [31] is to minimize the WCN energy consumption while taking into consideration the flow routing problem in the WSN. The problem is translated into two problems, one is to maximize the vacancy time of the WCV in a charging cycle, while keeping the sensors charged to satisfying the communication requirements; and another is to decide the anchor locations, since it is directly related to which sensors can be charged at each location and how long a charging cycle should last.

2.3 Joint Charging Trajectory and Data Flow

In RWSNs, charging-related parameters are strongly coupled with traffic flow routing, since the latter affects the amount of energy needed by individual sensors. Therefore, the charger trajectory and flow routing problems are often jointly studied, which leads to some complicated optimization problems, e.g., [31, 26, 3, 33, 34].

In one-to-one charging, the optimum amount of charging time for each sensor is to ensure that the amount of energy charged to the sensor is equal to the amount of consumed energy during each charging cycle [26, 33]. In one-to-multiple charging, the charging duration at a given anchor location is determined by the energy needed by all the sensor nodes charged in the same location and the relative distances of the sensors to the anchor location. Therefore, the joint optimization of charging time and flow routing in the one-to-multiple charging case is much more complicated than in the one-to-one case. For this reason, existing work tried to decouple charging and routing, e.g., [33, 34], which simplifies the solution at a price of reduced performance.

Furthermore, existing work that studies joint traffic routing and charging time/path problems assumes that the transmission power of a sensor node is a function of the transmission distance. In a practical system, sensor nodes should adapt their transmission power and the data transmission rates based on the channel conditions, and this consideration affects the charging solution.

In addition, in one-to-multiple charging, the charger outputs power to all the sensors to be charged from a given anchor location for the same amount of time. This normally results in overcharging some sensor nodes and wasting the energy of the charger in order to satisfy the energy requirements of the sensors that have longer distance to the anchor nodes or/and higher communication loads.

2.4 Overview of the Thesis Work

In this thesis, the joint charging and flow routing problem for RWSNs is studied. The main differences of this work and the previous work are summarized below together with the main contributions of this thesis.

- Instead of considering constant data transmission rate for each sensor for the entire duration of a charging cycle, sensors adapt their transmission rates, time, and power based on their channel conditions.

- Instead of considering the same amount of charging time to all the sensors within the charging range of a given anchor location, we consider that individual sensors can be charged for a different amount of time based on their charging distances and communication requirements. This helps greatly to save the energy consumption of the charger.

- An optimization problem is formulated that jointly considers the communication and charging parameters, where the former includes transmission power, data rate, and transmission time of each sensor, and the latter includes the duration of a charging cycle, the amount of time at each charging location, and the amount of charging time for each sensor. The objective is to minimize the average power consumption of the system, while satisfying the communication energy requirements of the sensors and keeping the sensors always alive.

- A special case of the optimization is solved by assuming that all sensors within the charging duration of a given anchor node are charged with the same amount of time.

- The general case of the optimization problem is non-convex, which is then transformed and decomposed into an outer sub-problem and an inner sub-problem. The outer sub-problem includes a single continuous variable, which is the charging cycle duration. Given the cycle duration, the inner sub-problem is transferred into a mixed integer and convex programming and solved using commercial software such as MATLAB. The outer problem is then solved through binary search.

- Extensive simulation results show that our solution outperforms the existing one-to-one and one-to-multiple charging solutions.

Chapter 3

System Model and Problem Formulations

In this chapter, we first describe the system model that this research is based on. Different constraints related to wireless charging in a RWSN are defined, based on which an optimization problem is formulated at the end with an objective of minimizing the average power consumption of the wireless charging system.

3.1 System model

We consider a WSN that consists of I sensor nodes, indexed by $i = 1, 2, \ldots, I$. The sensor nodes are distributed in a certain geographical area. All the data collected by the sensor nodes should be transmitted directly or forwarded through other sensor nodes to a sink node.

The sensor nodes are periodically charged by a wireless charging vehicle (WCV), which includes a charger carried by a vehicle. Within the coverage area of the WSN, there are M charging locations, referred to as anchor locations, where the WCV can stop and charge the sensors nearby. The anchor locations are indexed by $m = 1, 2, \ldots, M$. We consider that the anchor locations are along a predefined path within the coverage area of the WSN. Finding the optimum trajectory is mainly to find the shortest path in order to minimize the energy consumed for the WCV to travel within a charging cycle. The problem is relatively independent of the traffic conditions and has been studied in [26, 18].

Define t_{tot} as the duration of one charging cycle that includes 1) t_{path}, which is the time needed for the WCV to travel along the entire charging path without stopping; 2) t^a_m, $m = 1, 2, \ldots, M$, which is the amount of time that the WCV stays at the mth anchor location; and 3) t_0, which is the time that the WCV stays in its home location for either recharging itself or being idle, and it is also referred to as vacation time. Note that the charger does not charge any sensors when it is traveling or at vacation. We have

$$t_{tot} = t_0 + t_{path} + \sum_{m=1}^{M} t^a_m. \tag{3.1.1}$$

The power consumption of the WCV is different during the three types of time intervals. We assume that the power consumption of the WCV is approximately zero when it is not moving nor charging. Let p_{path} be the power consumption of the WCV when it is moving (and not charging), and P_c be the power consumption of the WCV when it is charging (and not moving) a given sensor node. At a given anchor location, the MCV may charge multiple sensors within its charging range. Let D_{mi} be the distance between the ith sensor node and the mth anchor location, then the charging efficiency μ_{mi} can be calculated from (1.1.3).

At a given anchor location m, let t_{mi} be the amount of time that the ith sensor is charged for. We then have

$$t_{mi} \leq t_m^a \tag{3.1.2}$$

for all $i = 1, 2, \ldots, I$.

Each sensor may be located in the charging range of multiple anchor locations and charged multiple times in a charging cycle. Let E_i be the total amount of energy charged to sensor i in one charging cycle. We have the following relationship

$$E_i \leq P_c \sum_{m=1}^{M} \mu_{mi} t_{mi}. \tag{3.1.3}$$

Each sensor node has a maximum battery capacity $E_{\max}$ and should maintain a minimum energy level $E_{\min}$ to keep its battery alive in the network (3.1.4). Therefore, the amount of energy that can be charged to a sensor node is limited by $E_{\max} - E_{\min}$. That is,

$$E_i \leq E_{\max} - E_{\min}. \tag{3.1.4}$$

Given this, the average power consumption of the WSN is given as

$$P_{avg} = \frac{P_c \sum_{m=1}^{M} \sum_{i=1}^{I} t_{mi} + p_{path} t_{path}}{t_{tot}} \tag{3.1.5}$$

where the numerator on the right-hand side is the total energy consumption of the WCV during one charging cycle with the first term equal to the total energy consumed for charging and the second term equal to the total energy consumed for traveling.

For sensor node i, let R_i represent the data generation rate of its locally sensed data. The sensors form a meshed topology for routing the sensed data to the sink. We use τ_{ij} to represent the amount of transmission time from sensor i to sensor j during one charging cycle, and f_{ij} to represent the physical data transmission rate from node i to node j during this time period. All the sensors transmit data to the data sink. For the sensors that are not within the communication range of the data sink, another sensor nearby may act as a relay to help transmit the data to the sink. Overall, the WSN can be considered as having a mesh topology. The following flow balance equation then should hold for each node i,

$$\sum_{k=1,k\neq i}^{I} \tau_{ki} f_{ki} + R_i t_{tot} \leq \sum_{j=1,j\neq i}^{I} \tau_{ij} f_{ij} \tag{3.1.6}$$

for all $i = 1, 2, \ldots, I$.

For each sensor, its power or energy consumption consists of three sources, sensing local data, receiving from other sensors, and transmitting to other sensors. Let $p_{ij} \in [0, p_{\max}]$ be the power consumption of sensor i when it is transmitting to sensor j with $p_{\max}$ the maximum transmission power of sensor node i, ρ_i be the energy consumed per received bit when it is receiving from another sensor, and η_i the energy consumed by sensing each bit of data. The total energy consumption of sensor i during one charging cycle is given by

$$\rho_i \sum_{k=1,k\neq i}^{I} \tau_{ki} f_{ki} + \sum_{j=1,j\neq i}^{I} \tau_{ij} p_{ij} + \eta_i R_i t_{tot} \leq E_i, \tag{3.1.7}$$

for all $i = 1, 2, \ldots, I$. On the left-hand side of (3.1.7), the first term represents the energy consumption of receiving data, the second term is the energy cost for transmitting data, and the third term is the sensing energy consumption during one charging cycle.

We use the Shannon's formula to model the relationship between the physical transmission rate and transmission power of a sensor. That is, for each sensor node i,

$$f_{ij} \leq B \log_2 \left(1 + \frac{p_{ij} g_{ij}}{p_{noise}} \right), \tag{3.1.8}$$

where B is the bandwidth of the wireless channel, p_{noise} is the noise power, and g_{ij} is the channel gain between nodes i and j.

3.2 Problem Formulation

We assume that in the initial setup, all the sensor nodes are charged with full battery capacity $E_{\max}$. The objective is to minimize P_{avg} by finding the optimum t_m^a, t_{mi}, f_{ij}, p_{ij}, and t_{tot}, while allowing all the sensed data transmitted to the sink, given R_i and D_{mi} for all $i, j = 1, 2, \ldots, I$ and $m = 1, 2, \ldots, M$. Define $\mathbf{t}^a = [t_m^a, \forall m = 1, 2, \ldots, M]$, $\mathbf{t} = [t_{mi}, \forall m = 1, 2, \ldots, M, i = 1, 2, \ldots, I]$, $\mathbf{p} = [p_{ij}, \forall i, j = 1, 2, \ldots, I]$, $\boldsymbol{\tau} = [\tau_{ij}, \forall i, j = 1, 2, \ldots, I]$, and $\mathbf{f} = [f_{ij}, \forall i, j = 1, 2, \ldots, I]$. As a special case, when

$i = j$, $f_{ij} = p_{ij} = \tau_{ij} = 0$. The optimization problem is given as

$$\text{OPT.1} \min_{\mathbf{t}^a, \mathbf{t}, \mathbf{p}, \boldsymbol{\tau}, \mathbf{f}, t_{tot}} P_{avg} = \frac{P_c \sum_{m=1}^{M} \sum_{i=1}^{I} t_{mi} + p_{path} t_{path}}{t_{tot}} \tag{3.2.1}$$

$$\text{s.t.} \sum_{k=1, k \neq i}^{I} \tau_{ki} f_{ki} + R_i t_{tot} \leq \sum_{j=1, j \neq i}^{I} \tau_{ij} f_{ij},\ i = 1, 2, \ldots, I \tag{3.2.2}$$

$$\rho_i \sum_{k=1, k \neq i}^{I} \tau_{ki} f_{ki} + \sum_{j=1, j \neq i}^{I} \tau_{ij} p_{ij} + \eta_i R_i t_{tot} \leq E_i,\ i = 1, 2, \ldots, I \tag{3.2.3}$$

$$f_{ij} \leq B \log_2 \left(1 + \frac{p_{ij} g_{ij}}{p_{noise}} \right),\ i, j = 1, 2, \ldots, I \tag{3.2.4}$$

$$E_i \leq P_c \sum_{m=1}^{M} \mu_{mi} t_{mi},\ i = 1, 2, \ldots, I \tag{3.2.5}$$

$$E_i \leq E_{\max} - E_{\min},\ i = 1, 2, \ldots, I \tag{3.2.6}$$

$$t_{mi} \leq t_m^a,\ i = 1, 2, \ldots, I,\ m = 1, 2, \ldots, M \tag{3.2.7}$$

$$\sum_{m=1}^{M} t_m^a + t_{path} < t_{tot} \tag{3.2.8}$$

$$f_{ij} > 0,\ i, j = 1, 2, \ldots, I \tag{3.2.9}$$

$$0 \leq p_{ij} \leq p_{\max},\ i, j = 1, 2, \ldots, I \tag{3.2.10}$$

$$0 \leq \tau_{ij} \leq t_{tot},\ i, j = 1, 2, \ldots, I \tag{3.2.11}$$

Constraint (3.2.8) is equivalent to (3.1.1) since t_0 is non-negative.

Chapter 4

Equal Time Charging and Proposed Solution

In this chapter we consider a special case when $t_{mi} = t_m^a$ for all i with $\mu_{mi} > 0$ and $t_{mi} = 0$ otherwise. That is, all sensors within the charging range of the anchor node m are charged with the same amount of time. With this, the problem OPT.1 formulated in Chapter 3 can be transformed into a geometric programming (GP) problem and solved optimally using commercial software, such as matlab. However, this approach requires high computation complexity because Successive Convex Approximation (SCA) [22] is needed in order to transform the posynomials in the constraint functions into monomials to fit the general format of the GP. The complexity becomes prohibitively high when the number of sensor nodes is large. A heuristic algorithm with lower complexity is then proposed to solve the problem by decomposing the problem into two sub-problems. The first sub-problem finds the optimal power consumption for each sensor, and the second sub-problem finds the required charging time at each anchor location.

4.1 Equal time charging problem

Define a set of binary variables B_{mi}'s as

$$B_{mi} = \begin{cases} 1, & \text{if } \mu_{mi} > 0; \\ 0, & \text{otherwise} \end{cases} \tag{4.1.1}$$

then problem OPT.1 in Chapter 3 is reduced to

$$\text{OPT.2} \min_{\mathbf{t}^a, \mathbf{p}, \boldsymbol{\tau}, \mathbf{f}, t_{tot}} P_{avg} = \frac{P_c \sum_{i=1}^{I} B_{mi} \sum_{m=1}^{M} t_m^a + p_{path} t_{path}}{t_{tot}} \tag{4.1.2}$$

$$\text{s.t.} \sum_{k=1, k\neq i}^{I} \tau_{ki} f_{ki} + R_i t_{tot} \leq \sum_{j=1, j\neq i}^{I} \tau_{ij} f_{ij}, \ i = 1, 2, \ldots, I \tag{4.1.3}$$

$$\rho_i \sum_{k=1, k\neq i}^{I} \tau_{ki} f_{ki} + \sum_{j=1, j\neq i}^{I} \tau_{ij} p_{ij} + \eta_i R_i t_{tot} \leq E_i, \ i = 1, 2, \ldots, I \tag{4.1.4}$$

$$f_{ij} \leq B \log_2 \left(1 + \frac{p_{ij} g_{ij}}{p_{noise}}\right), \ i, j = 1, 2, \ldots, I \tag{4.1.5}$$

$$E_i \leq P_c \sum_{m=1}^{M} \mu_{mi} t_m^a, \ i = 1, 2, \ldots, I \tag{4.1.6}$$

$$E_i \leq E_{\max} - E_{\min}, \ i = 1, 2, \ldots, I \tag{4.1.7}$$

$$\sum_{m=1}^{M} t_m^a + t_{path} < t_{tot} \tag{4.1.8}$$

$$f_{ij} > 0, \ i, j = 1, 2, \ldots, I \tag{4.1.9}$$

$$0 \leq p_{ij} \leq p_{\max}, \ i, j = 1, 2, \ldots, I \tag{4.1.10}$$

$$0 \leq \tau_{ij} \leq t_{tot}, \ i, j = 1, 2, \ldots, I \tag{4.1.11}$$

All the constraints except (4.1.5) are linear. Therefore, we first consider constraint (4.1.5), which includes a logarithm function that is difficult to handle. When the signal-to-noise ratio (SNR) of the link from sensor i to sensor j is sufficiently high, i.e., $\frac{p_{ij}g_{ij}}{p_{noise}} \gg 1$, we have

$$B\log_2\left(1+\frac{p_{ij}g_{ij}}{p_{noise}}\right) \approx B\log_2\left(\frac{p_{ij}g_{ij}}{p_{noise}}\right) = \frac{1}{\ln 2}\ln\left(\frac{p_{ij}g_{ij}}{p_{noise}}\right). \tag{4.1.12}$$

The high SNR assumption holds in a practical system in order to support a reasonably high data transmission rate between the two sensors.

Next, consider two large numbers $u \gg 1$ and $a \gg 1$ with $u^{1/a} \approx 1$, we have $u^{1/a} > 1$ and $u^{1/a} - 1 \approx 0$. In this case,

$$\ln u^{1/a} = \ln[1 + (u^{1/a} - 1)] \approx u^{1/a} - 1. \tag{4.1.13}$$

Therefore

$$\ln(u) \approx a(u^{1/a} - 1). \tag{4.1.14}$$

Thus, (4.1.12) can be further approximated as

$$B\log_2\left(1+\frac{p_{ij}g_{ij}}{p_{noise}}\right) \approx \frac{Ba}{\ln 2}\left[\left(\frac{p_{ij}g_{ij}}{p_{noise}}\right)^{1/a} - 1\right] \geq f_{ij}. \tag{4.1.15}$$

We then consider the objective function (4.1.2), which is equivalent to minimizing p_{avg} with the following constraint

$$\frac{P_c\sum_{i=1}^{I} B_{mi}\sum_{m=1}^{M} t_m^a + p_{path}t_{path}}{t_{tot}} \leq P_{avg}, \tag{4.1.16}$$

and can be further rewritten as

$$\frac{P_c \sum_{i=1}^{I} B_{mi} \sum_{m=1}^{M} t_m^a + p_{path} t_{path}}{P_{avg} t_{tot}} \leq 1. \tag{4.1.17}$$

It can be further simplified by substituting all the t_{tot}'s with $t_{path} + \sum_m t_m$ assuming the sensor communication time is less than the total charging and traveling time.

Problem OPT.2 is then transformed to the following problem:

$$\text{OPT.3} \quad \min_{\mathbf{t}^a, \mathbf{p}, \boldsymbol{\tau}, \mathbf{f}} P_{avg} \tag{4.1.18}$$

$$\text{s.t.} \frac{P_c \sum_{i=1}^{I} B_{mi} \sum_{m=1}^{M} t_m^a + p_{path} t_{path}}{P_{avg} t_{tot}} \leq 1 \tag{4.1.19}$$

$$\frac{\sum_{k=1,k\neq i}^{I} f_{ki}\tau_{ki} + R_i(t_{path} + \sum_{m=1}^{M} t_m^a)}{\sum_{j=1,j\neq i}^{I} \tau_{ij} f_{ij}} \leq 1, \; i = 1, 2, \ldots, I \tag{4.1.20}$$

$$\left(\frac{p_{ij} g_{ij}}{p_{noise}}\right)^{-1/a} \left(\frac{\ln 2}{Ba} f_{ij} + 1\right) \leq 1, \; i, j = 1, 2, \ldots, I \tag{4.1.21}$$

$$\frac{\tau_{ij}}{t_{path} + \sum_{m=1}^{M} t_m^a} \leq 1, \; i, j = 1, 2, \ldots, I \tag{4.1.22}$$

$$\frac{\rho_i \sum_{k=1,k\neq i}^{I} \tau_{ki} f_{ki} + \sum_{j=1,j\neq i}^{I} \tau_{ij} p_{ij} + \eta_i(t_{path} + \sum_{m=1}^{M} t_m^a) R_i}{\sum_{m=1}^{M} t_m^a U_{mi}} \leq 1, \quad i = 1, 2, \ldots, I \tag{4.1.23}$$

$$\frac{E_{\min} + \rho_i \sum_{k=1,k\neq i}^{I} \tau_{ki} f_{ki} + \sum_{j=1,j\neq i}^{I} \tau_{ij} p_{ij_t} + \eta_i(t_{path} + \sum_{m=1}^{M} t_m) R_i}{E_{\max}} \leq 1, \quad i = 1, 2, \ldots, I \tag{4.1.24}$$

$$0 \leq \frac{p_{ij}}{p_{\max}} \leq 1, \; i, j = 1, 2, \ldots, I \tag{4.1.25}$$

$$f_{ij} > 0, \; i, j = 1, 2, \ldots, I \tag{4.1.26}$$

$$\tau_{ij} \geq 0, \; \forall i, j = 1, 2, \ldots, I \tag{4.1.27}$$

where constraint (4.1.23) is obtained by combining (4.1.4) and (4.1.6), and constraint (4.1.24) is obtained by combining (4.1.4) and (4.1.7).

With this, left-hand side of all the constraints are posynomials except (4.1.20), (4.1.22), and (4.1.23). To solve this problem, we apply SCA and transform the polynomials in the denominator on the LHS of these constraints into a monomial so that the LHS of each of these constraints become a posynomial. The GP problem is then solved using the commercial software such as MATLAB.

The SCA is an iterative method and the basic method is given as follows. Given a polynomial

$$g(x) = \sum_{k=1}^{K} a_k x^k. \tag{4.1.28}$$

Let $x^{(j)}$ be the feasible solution in the jth iteration. $g(x)$ can be approximated as

$$g(x) \approx \widetilde{g}(x)|_{x=x^{(j)}} \triangleq \prod_{k=0}^{K} \left(\frac{a_k x^k}{\alpha_k} \right)^{\alpha_k} |_{x=x^{(j)}} \tag{4.1.29}$$

where

$$\alpha_k = \frac{a_k x^k}{g(x)} \tag{4.1.30}$$

Although OPT.3 can be solved using commercial software such as matlab, solving the problem is time consuming due to the high computational load caused by SCA. In the next section, we design a heuristic method that can solve the problem approximately with much lower complexity.

4.2 Heuristic Algorithm

The optimization problem OPT.2 consists of two sets of constraints, one set for communications and the other set for charging. Our basic idea of designing the heuristic method is to separate OPT.2 into a communication-based problem and a charging-based problem. In the communication-based problem, the following optimization problem is formulated that uses the constraints (4.1.3)-(4.1.5) and (4.1.9)-(4.1.11) in OPT.2:

$$\text{OPT.4} \min_{\mathbf{p},\boldsymbol{\tau},\mathbf{f}} \quad \sum_{i=1}^{I} P_i \tag{4.2.1}$$

$$\text{s.t.} \sum_{k,k\neq i} f_{ki}\tau'_{ki} + R_i \leq \sum_{j,j\neq i} f_{ij}\tau'_{ij}, \ i = 1, 2, \ldots, I \tag{4.2.2}$$

$$P_i = \rho_i \sum_{k,k\neq i} f_{ki}\tau'_{ki} + \sum_{j,j\neq i} p_{ij} + \eta_i R_i, \ i = 1, 2, \ldots, I \tag{4.2.3}$$

$$f_{ij} \leq B \log_2 \left(1 + \frac{p_{ij} g_{ij}}{p_{noise}}\right), \ \ i, j = 1, 2, \ldots, I \tag{4.2.4}$$

$$f_{ij} > 0, \ \ i, j = 1, 2, \ldots, I \tag{4.2.5}$$

$$0 \leq p_{ij} \leq p_{\max}, \ i, j = 1, 2, \ldots, I \tag{4.2.6}$$

$$0 \leq \tau'_{ij} \leq 1, \ i, j = 1, 2, \ldots, I \tag{4.2.7}$$

where P_i is the power consumption of sensor i, and $\tau'_{ij} = \frac{\tau_{ij}}{t_{tot}}$ for all $i, j = 1, 2, \ldots, I$. Problem OPT.4 does not take into consideration any effects caused by charging. The objective of minimizing the total power consumption of all the sensors in the problem is a heuristic way toward reducing the power consumption of the entire system. Problem OPT.4 can be transformed into a GP problem and solved using the same method as solving OPT.2. Since the size of OPT.4 is usually much smaller than that of OPT.2, solving it is much less time consuming.

In problem OPT.4, the objective function (4.2.1) minimizes the total power consumption of all the sensor nodes. This objective treats all the sensors equally without considering their charging conditions. As a more practical consideration, the power consumption of individual sensors should be related to their charging conditions. More specifically, sensors with poor charging conditions should carry less communication loads and consume less average power. Since larger u_{mi} represents a better charging condition of sensor i with respect to the anchor location m, we define a charging weight w_i for sensor i as $w_i = \sum_{m=1}^{M} 1/U_{mi}$ and modify OPT.4 as

$$\text{OPT.5} \quad \min_{p_{ij_t}, f_{ij}, \tau'_{ij}, P} \quad \sum_i w_i P_i \tag{4.2.8}$$

$$\text{s.t.} \sum_{k,k\neq i} f_{ki}\tau'_{ki} + R_i \leq \sum_{j,j\neq i} f_{ij}\tau'_{ij},\ i = 1, 2, \ldots, I \tag{4.2.9}$$

$$P_i = \rho_i \sum_{k,k\neq i} f_{ki}\tau'_{ki} + \sum_{j,j\neq i} p_{ij} + \eta_i R_i,\ i = 1, 2, \ldots, I \tag{4.2.10}$$

$$f_{ij} \leq B \log_2 \left(1 + \frac{p_{ij} g_{ij}}{p_{noise}}\right),\ \ \forall i, j = 1, 2, \ldots, I \tag{4.2.11}$$

$$f_{ij} > 0,\ i, j = 1, 2, \ldots, I \tag{4.2.12}$$

$$0 \leq p_{ij} \leq p_{\max},\ i, j = 1, 2, \ldots, I \tag{4.2.13}$$

$$0 \leq \tau'_{ij} \leq 1,\ i, j = 1, 2, \ldots, I \tag{4.2.14}$$

In this case, sensors with poor charging conditions are given larger weights in (4.2.8) so that OPT.5 will result in smaller power for the sensors.

After OPT.4 or OPT.5 is solved, the transmission power for each sensor is obtained, based on which the charging time can be found by solving the following problem:

$$\text{OPT.6} \quad \min_{\mathbf{t}^a, t_0, t_{tot}} P_{avg} = \frac{P_c \sum_{i=1}^{I} B_{mi} \sum_{m=1}^{M} t_m^a + t_{path} p_{path}}{t_{tot}} \tag{4.2.15}$$

$$\text{s.t. } P_i(\sum_{m=1}^{M} t_m^a + t_{path} + t_0) \leq \sum_{m=1}^{M} U_{mi} t_m^a, \ i = 1, 2, \ldots, I \tag{4.2.16}$$

$$P_i(\sum_{m=1}^{M} t_m^a + t_{path} + t_0) \leq E_{\max} - E_{\min}, \ i = 1, 2, \ldots, I \tag{4.2.17}$$

$$0 \leq t_m^a \leq t_{tot}, \ m = 1, 2, \ldots, M \tag{4.2.18}$$

$$0 \leq t_0 \leq t_{tot}. \tag{4.2.19}$$

In OPT.6, only t_0 and t_m^a's are unknown. This is a linear-fractional programming problem and can be transformed into a linear programming problem.

The general format of a linear-fractional programming problem is given as

$$\min \frac{c^T x + d}{e^T x + f} \tag{4.2.20}$$

$$\text{s.t. } Gx \leq h \tag{4.2.21}$$

$$Ax = b \tag{4.2.22}$$

For problem OPT.6, we have

$$x = [t_1^a \ t_2^a \ ... \ t_M^a \ t_0]^T \tag{4.2.23}$$

$$c = [P_c \ P_c \ ... \ P_c \ 0]^T, \tag{4.2.24}$$

$$d = t_{path} p_{path}, \tag{4.2.25}$$

$$e = [1 \ 1 \ ... \ 1]^T, \tag{4.2.26}$$

$$f = t_{path} \tag{4.2.27}$$

$$G = \begin{pmatrix} Pe^T - U_0 \\ Pe^T \end{pmatrix} \tag{4.2.28}$$

$$h = \begin{pmatrix} -p_{path} t_{path} \\ E_{\max} - E_{\min} - p_{path} t_{path} \end{pmatrix} \tag{4.2.29}$$

$$A = 0 \tag{4.2.30}$$

$$b = 0. \tag{4.2.31}$$

In (4.2.28)

$$P = [P_1 \ P_2 \ ... \ P_I]^T, \tag{4.2.32}$$

$$U_0 = \begin{pmatrix} U^T | 0 \end{pmatrix} \tag{4.2.33}$$

and $U = [U_{mi}, m = 1, 2, \ldots, M, i = 1, 2, \ldots, I]$ is a $M \times I$ matrix.

When $e^T x + f > 0$, the problem can be transformed into a linear programming problem as follows [5]

$$\text{OPT.7} \ \min_{y,z} \ c^T y + dz \tag{4.2.34}$$

$$\text{s.t.} \ Gy - hz \preceq 0 \tag{4.2.35}$$

$$Ay - bz = 0 \tag{4.2.36}$$

$$e^T y + fz = 1 \tag{4.2.37}$$

$$z \geq 0 \tag{4.2.38}$$

where

$$y = \frac{x}{e^T x + f} \tag{4.2.39}$$

$$z = \frac{1}{e^T x + f}. \tag{4.2.40}$$

Chapter 5

Unequal Charging Time and Proposed Solution

In this chapter, we solve the general case for problem OPT.1 formulated in Chapter 3. Problem OPT.1 is not convex. To solve it, we first decompose it into an outer problem and an inner problem, where the outer problem is to solve the charging cycle length when all the other variables are known and the inner problem is to solve all the variables except the charging cycle length. Next, we prove a theorem that helps greatly simplify the inner problem, which is then transformed into a mixed linear and convex problem and can be solved using commercial software such as matlab.

5.1 Decomposition

To solve OPT.1, we divide all the variables in this system into two sets with one set related to charging and another set related to communications. The charging-related variables include t_m^a's, t_{mi}'s, and E_i's, the communication related variables include

f_{ij}'s, p_{ij}'s, τ_{ij}'s, and E_i's. Note that E_i's are the variables that connect the charging-related variables and the communication-related variables, while all other variables belong to either the charging-set or the communication-set but not both. From the communication point of view, a sufficient power should be supplied to each sensor in order to satisfy the need for data sensing and communications. Meanwhile, the supplied power is dependent on the charging distance and time of each sensor at each anchor location.

Problem OPT.1 is not convex and should be reformulated in order to find the optimum solution efficiently. First, we decompose OPT.1 into two sub-problems, an outer problem for solving t_{tot} and an inner problem to solve the remaining variables when t_{tot} is given. That is,

$$\begin{aligned} \text{OPT.1d} \quad & \max_{t_{tot}} \min_{\mathbf{t}^a, \mathbf{t}, \mathbf{p}, \boldsymbol{\tau}, \mathbf{f}} \frac{P_c \sum_{m=1}^{M} \sum_{i=1}^{I} t_{mi} + p_{path} t_{path}}{t_{tot}} \\ & (3.2.2) - (3.2.11). \end{aligned} \tag{5.1.1}$$

If the inner problem can be solved, a binary searching method can be used to solve the outer problem and find the optimum t_{tot}. For the inner problem, since t_{tot}, P_c, p_{path}, and t_{path} in the objective function are all given, the objective function is equivalent to minimizing $\sum_{m=1}^{M} \sum_{i=1}^{I} t_{mi}$.

Therefore, the remaining part of this chapter is to solve the a reduced version of the inner problem as follows:

$$\begin{aligned} \text{OPT.8} \quad & \min_{\mathbf{t}, \mathbf{p}, \boldsymbol{\tau}, \mathbf{f}} \sum_{m=1}^{M} \sum_{i=1}^{I} t_{mi} \\ \text{s.t.} \quad & (3.2.2) - (3.2.11) \end{aligned} \tag{5.1.2}$$

5.2 Theorem

Theorem 1 *In problem OPT.8, given any feasible charging time t_{mi}'s, the optimum τ_{ij} is either 0 or t_{tot}, for all $i, j = 1, 2, \ldots, I$.*

Proof: Based on (3.1.3), when t_{mi}'s are given, the upper bound of E_i is given for all i's. The objective in OPT.8 is not affected by the communication parameters, namely τ_{ij}'s, f_{ij}'s, and p_{ij}'s, as long as the problem is feasible. This statement is true when t_{mi}'s are optimum. In this case, one feasible solution to the communication parameters is to minimize the total energy consumption of all sensor nodes.

Based on (3.2.4), the relationship between transmission power and data rate for a given sensor does not depend on any parameters related to other sensors.

Consider sensor i, its total energy consumption given in the left-hand side of (3.2.3) can be divided into three types:

- $E_{i,s} = \eta_i R_i t_{tot}$ is the energy consumption for sensing local data, and is determined once t_{tot} is given;

- $E_{ki,r} = \rho_i \tau_{ki} f_{ki}$, for all $k \neq i$, is the energy consumed for receiving from node k; and

- $E_{ij,t} = \tau_{ij} p_{ij} = \tau_{ij} \frac{2^{f_{ij}/B} p_{noise}}{g_{ij}}$, for all $j \neq i$, is the energy consumed for transmitting to node j.

For each link from sensors i to j, given the amount of data to be transmitted, p_{ij} increases exponentially and τ_{ij} decreases proportionally with f_{ij}. This means that, $E_{ij,t}$ is minimized when f_{ij} is minimized and τ_{ij} is maximized, while keeping $f_{ij}\tau_{ij}$ equal to the amount of data to be delivered in one charging cycle. Note that adjusting f_{ij} does not affect the receiving energy consumed by sensor j.

The above argument is true for any feasible t_{mi}'s, and therefore, true for the optimum t_{mi}'s. Since the maximum τ_{ij} is t_{tot}, we have proved theorem 1.

5.3 Reduced inner problem

Theorem 1 helps reduce the complexity in solving OPT.8. Define a set of binary variables A_{ij} with $A_{ij} = 1$ indicating that sensor i forwards some or all its traffic to sensor j and $A_{ij} = 0$ otherwise. Define $\mathbf{A} = [A_{ij}, \forall i, j = 1, 2, \ldots, I]$. We can remove τ_{ij}'s from the optimization problem, and problem OPT.8 is then reduced to

$$\text{OPT.9} \min_{\mathbf{t},\mathbf{p},\mathbf{f},\mathbf{A}} \sum_{m=1}^{M} \sum_{i=1}^{I} t_{mi} \tag{5.3.1}$$

$$\text{s.t.} \sum_{k=1,k\neq i}^{I} A_{ki} f_{ki} - \sum_{j=1,j\neq i}^{I} A_{ij} f_{ij} \leq -R_i, \ i = 1, 2, \ldots, I \tag{5.3.2}$$

$$\rho_i \sum_{k=1,k\neq i}^{I} A_{ki} f_{ki} + \sum_{j=1,j\neq i}^{I} A_{ij} p_{ij} + \eta_i R_i \leq E_i / t_{tot}, \ i = 1, 2, \ldots, I \tag{5.3.3}$$

$$p_{ij} \geq \frac{\left(2^{\frac{f_{ij}}{B}} - 1\right) p_{noise}}{g_{ij}}, \ \forall i, j = 1, 2, \ldots, I \tag{5.3.4}$$

$$(3.2.5) - (3.2.11)$$

where the relationship between p_{ij} and f_{ij} in (3.2.4) is replaced with the equivalent convex format in (5.3.4).

In OPT.9, constraints (5.3.2) and (5.3.3) include products of the binary variables and continuous variables. The product format can be linearized by defining $Y_{ij} = A_{ij} f_{ij}$ and $Z_{ij} = A_{ij} p_{ij}$ for all $i, j = 1, 2, \ldots, I$ and having additional constraints. The equivalent problem OPT.10 is given below, followed by the explanations.

$$\text{OPT.10} \quad \min_{\mathbf{t},\mathbf{p},\mathbf{f},\mathbf{A},\mathbf{Y},\mathbf{Z}} \sum_{m=1}^{M}\sum_{i=1}^{I} t_{mi} \tag{5.3.5}$$

$$\text{s.t.} \sum_{k=1,k\neq i}^{I} Y_{ki} - \sum_{j=1,j\neq i}^{I} Y_{ij} \leq -R_i, \quad i = 1, 2, \ldots, I \tag{5.3.6}$$

$$\rho_i \sum_{k,k\neq i} Y_{ki} + \sum_{j,j\neq i} Z_{ij} + \eta_i R_i \leq E_i/t_{tot}, \; i = 1, 2, \ldots, I \tag{5.3.7}$$

$$f_{ij} - (1 - A_{ij}) f_{\max} \leq Y_{ij} \leq A_{ij} f_{\max}, \; i, j = 1, 2, \ldots, I \tag{5.3.8}$$

$$0 \leq Y_{ij} \leq f_{ij}, \quad i, j = 1, 2, \ldots, I \tag{5.3.9}$$

$$p_{ij} - (1 - A_{ij}) p_{\max} \leq Z_{ij} \leq A_{ij} p_{\max}, \; i, j = 1, 2, \ldots, I \tag{5.3.10}$$

$$0 \leq Z_{ij} \leq p_{ij}, \; i, j = 1, 2, \ldots, I \tag{5.3.11}$$

$$(5.3.4), (3.2.5) - (3.2.11)$$

where $f_{\max}$ is any number larger than the maximum value that f_{ij} may take. With (5.3.8)-(5.3.9), $Y_{ij} = f_{ij}$ when $A_{ij} = 1$, and $Y_{ij} = 0$ when $A_{ij} = 0$. Similarly, with (5.3.10)-(5.3.11), $Z_{ij} = p_{ij}$ when $A_{ij} = 1$, and $Z_{ij} = 0$ when $A_{ij} = 0$. Problem OPT.10 is a mixed integer and convex programming problem and can be solved using commercial software such as matlab.

Chapter 6

Simulation Setup and Results

In this chapter, we provide the simulation setup and corresponding simulation results based on the original and alternative problem formulation introduced in Chapter 4 and Chapter 5. The simulation setup and corresponding results are separated in to two sections below. In the first section, the setup and result are presented for the original formulation. In addition, the alternative simulation results are discussed in the second section.

6.1 Simulation Setup

In this section, We consider a RWSN that consists of I sensors uniformly distributed in a circular geographical service area of radius $2R_c$ and the sink node is located at the center of this area with a coordinate $(0, 0)$. A WCV follows a circular path that is centered at (0,0) and has a radius of R_c. There are 6 anchor locations equally distanced along the circular charging path. The sensor locations are uniformly distributed within charging range of all the anchor locations.

Table 6.1: Default parameters

Parameter	Value
Number of anchor locations M	6
Number of sensor nodes I	10
Local data sensing rate R_i	1 Mbps
WCV travel time t_{path}	60 s
WCV charging range R_c	2.7 m
WCV power when moving p_{path}	10 W
WCV power when charging P_c	5 W
Sensor receiving energy ρ	50 nJ/bit
Sensing energy η	25 nJ/bit
Sensor transmission power limit p_{max}	1 W
Bandwidth B	1MHz
Noise power p_{noise}	0.5 nW
Full battery capacity $E_{\max}$	10.8 kJ
Minimum energy level $E_{\min}$	$5\%E_{\max}$
Normalized link gain κ	1
Pathloss exponent α	2.5

We use pathloss-based link gains with $g_{ij} = \kappa l_{ij}^{-\alpha}$, where κ is a normalized constant and α is the pathloss exponent depending on the propagation environment. Default parameters are listed in Table 6.1.

6.2 Results with Equal Time Charging

In this section, we discuss the simulation results based on the equal time charging. That is, the results in this section assume that all sensors within the charging range of a given anchor location are charged with an equal amount of time when the WCV is at the anchor location. Fig. 6.1 - 6.3 show the simulation results. Three different solutions are compared: the "Optimal solution" is based on OPT.3 and solved using SCP and GP as described in Chapter 4, "heuristic with equal weight" is based on solving OPT.5 and OPT.6, and "heuristic with unequal weights" is based on solving OPT.5w and OPT.6.

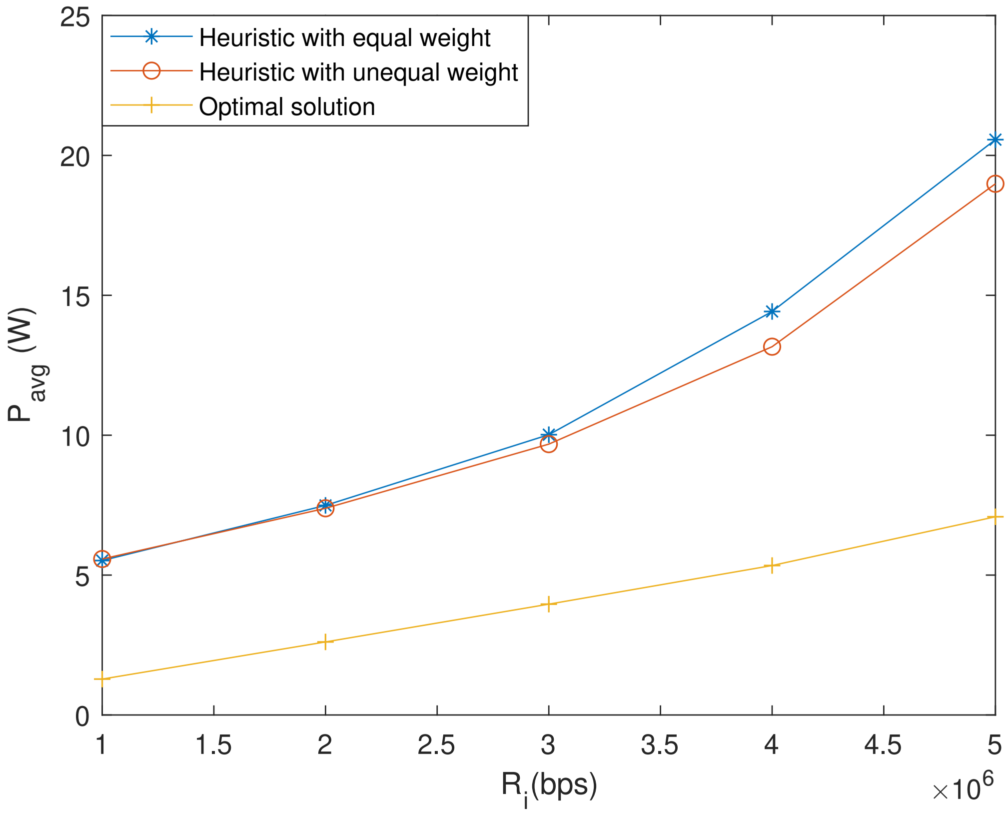

Figure 6.1: Average power consumption versus sensing data rate for equal time charging

Fig. 6.1 shows the average power consumption as the data sensing rate of individual sensors increases. The average power consumption increases exponentially as the data rate increases. The optimum solution achieves much lower power consumption, which is at the price of significantly higher computation complexity. For the proposed heuristic solutions, the weighted solution helps reduce the average power consumption, compared with the equal weight solution. However, such improvement is not obvious due to the decoupling between the charging and communication problems in the heuristic solution.

Fig. 6.2 presents the average power consumption versus charging power P_c. Based on the results, we can state that the charging power does not affect the average power consumption of the system in an obvious way. However, as mentioned earlier, P_c must be sufficiently large in order to make the system to be feasible because it directly affects the minimum amount of energy that a sensor can be charged in a given time interval.

Fig. 6.3 shows that average power consumption increases as the number of sensors in the network increases. Furthermore, the gap between the heuristic and the optimum solutions increases with the number of sensors. By decoupling the charging and communication variables, the heuristic solutions cause more performance drop when there are more sensors in the network.

6.3 Results with Unequal Time Charging

The results in this section are obtained by solving OPT.1 using the method proposed in chapter 5. Figs. 6.4 - 6.6 show the results. Two charging methods, "sensor-based charging" and "cluster-based charging", are simulated. The "sensor-based charging" results are obtained by solving OPT.1 directly using the method proposed in chapter 5. The "cluster-based charging" results are obtained by solving the same outer and inner problems in chapter 5 except that in the inner problem $t_{mi} = t_m^a$ for all $i = 1, 2, \ldots, I$ and $D_{mi} < R_c$. Note that the "cluster-based charging" does not result in the same results as the "equal time charging" in the previous section, because the inner problem in chapter 5 assumes that the charging time of all sensors in a cluster

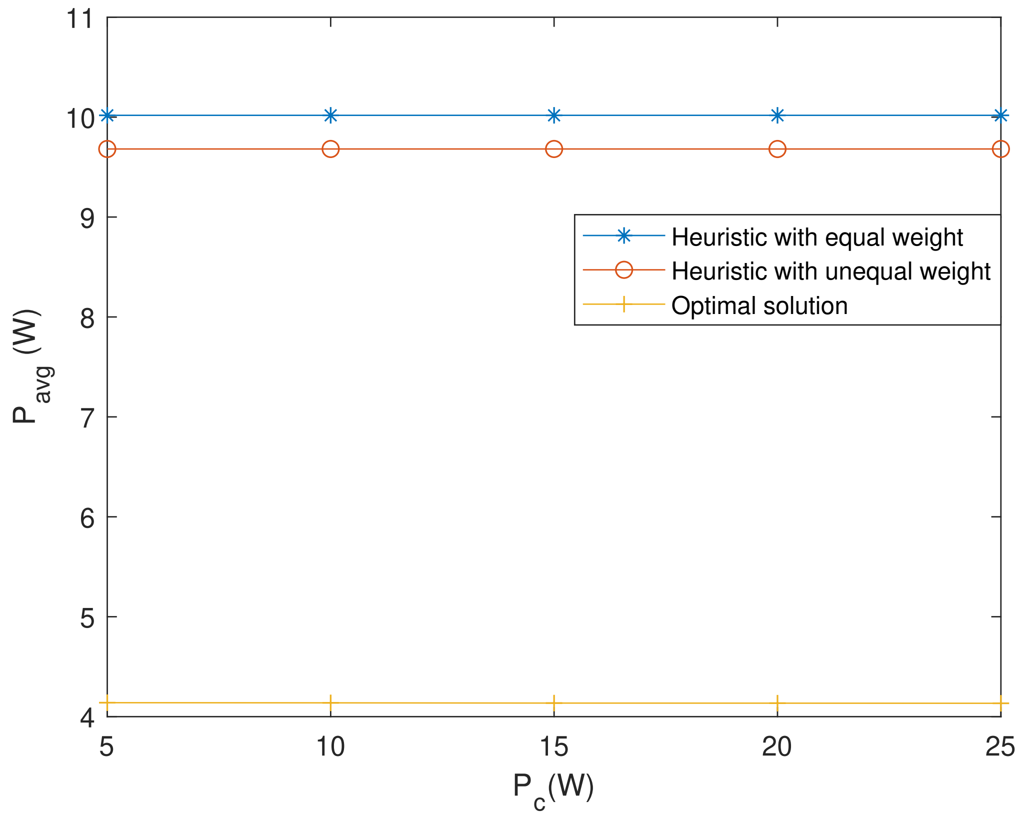

Figure 6.2: Equal time charging, average power consumption versus charging power

are either t_{tot} or 0. This in general is not the optimum, given that all sensors in a cluster are charged with an equal amount of time.

Fig. 6.4 shows the optimum average power consumption as the data sensing rate of individual sensors increases. The figure shows that as the data rate increases, the average power consumption increases linearly. Notice that the relationship between transmission power and data rate of individual sensors is exponential. However, the overall power consumption of a RWSN only increases linearly with the average data rate of individual sensors. This is due to the effect of one-to-multiple charging. Meanwhile, the figure also shows that the average power consumption using the proposed

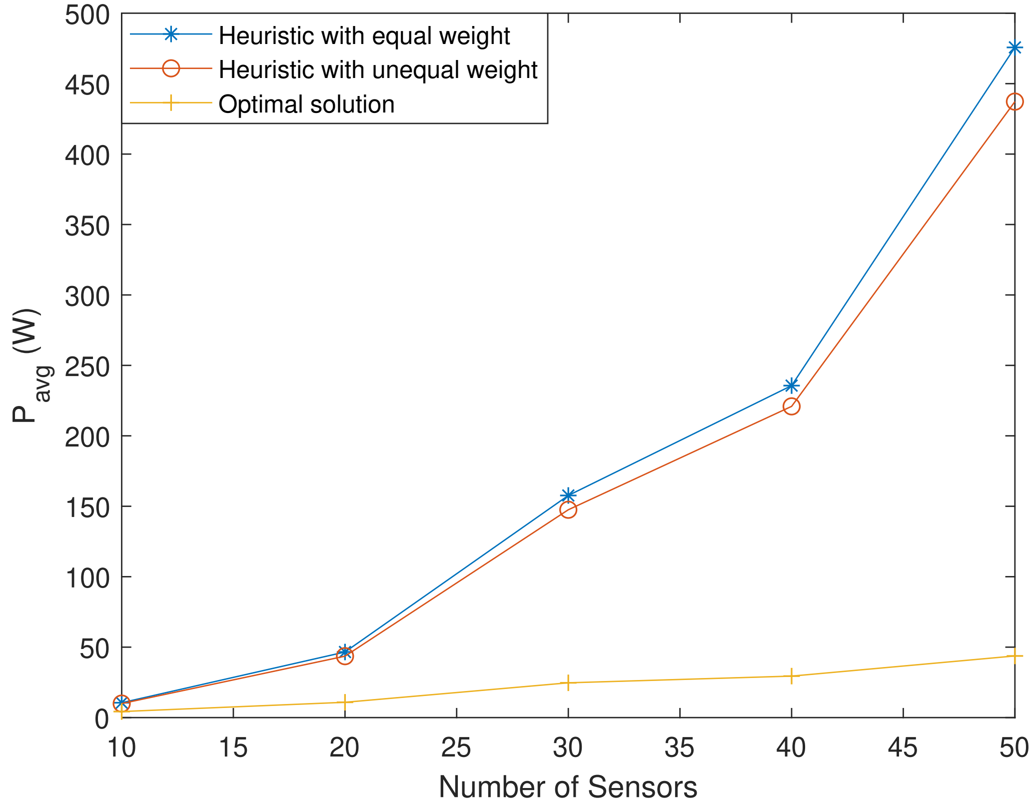

Figure 6.3: Equal time charging, average power consumption versus number of sensors

sensor-based charging solution is significantly lower than that using the cluster-based charging solution, since the sensor-based solution provides more flexibility for the charger to output power based on the charging efficiency to individual sensor nodes.

Fig. 6.5 shows the average power consumption of the system as P_c changes. It is seen that the average power consumption is not affected much by P_c. Provided P_c is sufficiently large to keep the optimization problem feasible, the average power consumption is determined mainly by the communication load of the network, so that amount of energy charged to each sensor is sufficient for it to complete required data

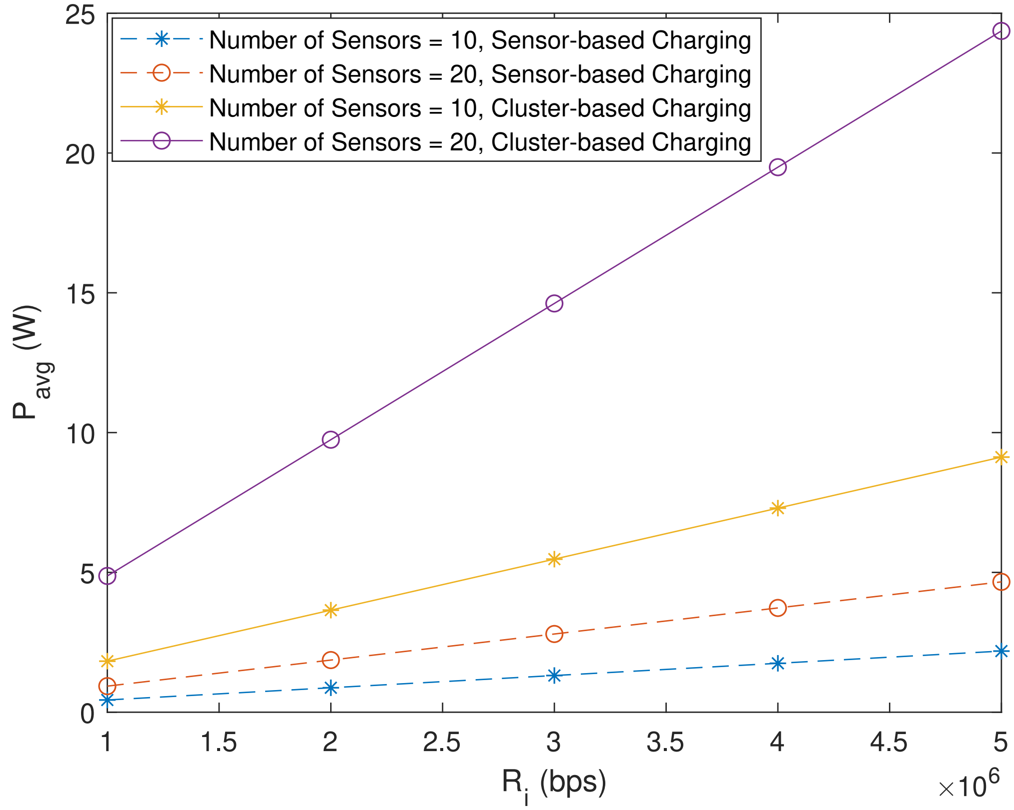

Figure 6.4: Sensor-based charging, average power consumption versus sensing data rate

sensing, transmissions and receiving.

Fig. 6.6 shows that as the number of sensor nodes increases, the average power consumption increases. This is due to the higher traffic load of the WSN that requires more total energy for data sensing and transmissions. The figure also shows that using the proposed solution can significantly reduce the average power consumption of the system, compared to using the cluster-based charging; and the increase of the average power is much slower using the sensor-based charging solution as the number of sensors increases.

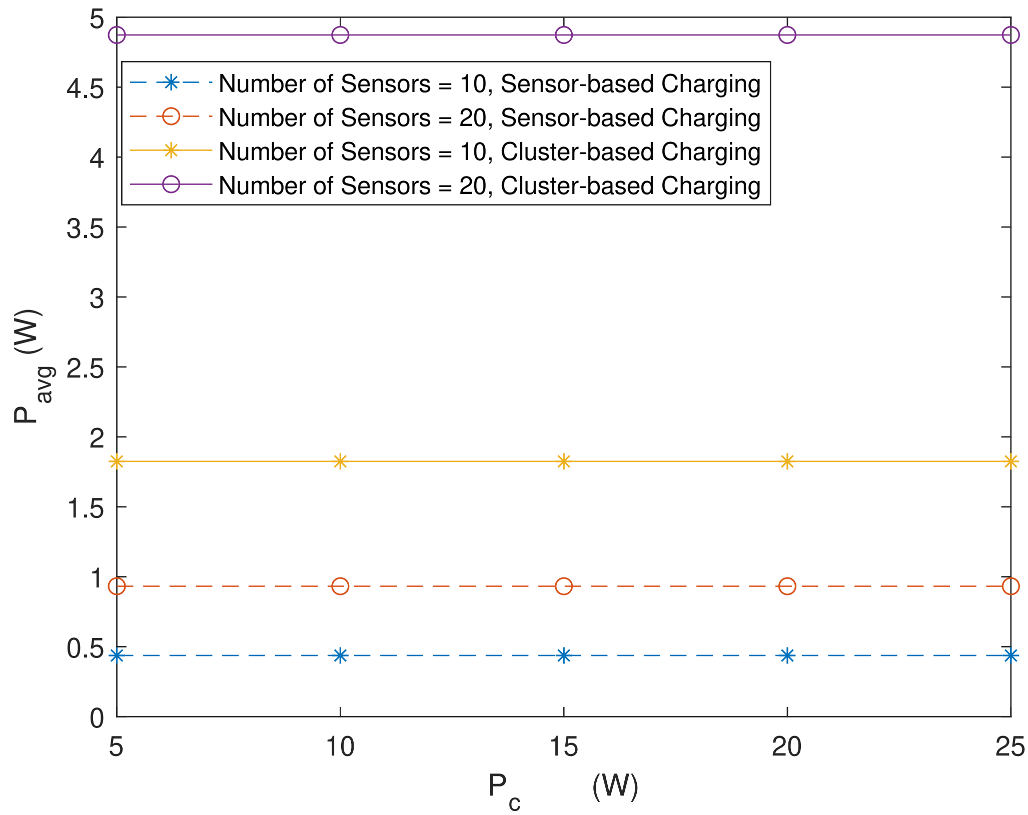

Figure 6.5: Sensor-based charging, average power consumption versus charging power

6.4 Comparison between Equal and Unequal Time Charging

Finally, figs. 6.7-6.9 compare the average power consumption between equal and unequal time charging. The results show that the solution of unequal time charging helps greatly reduce the average power consumption of the system, and such an effect is especially significant when the sensing data rate is high or number of sensor nodes is large.

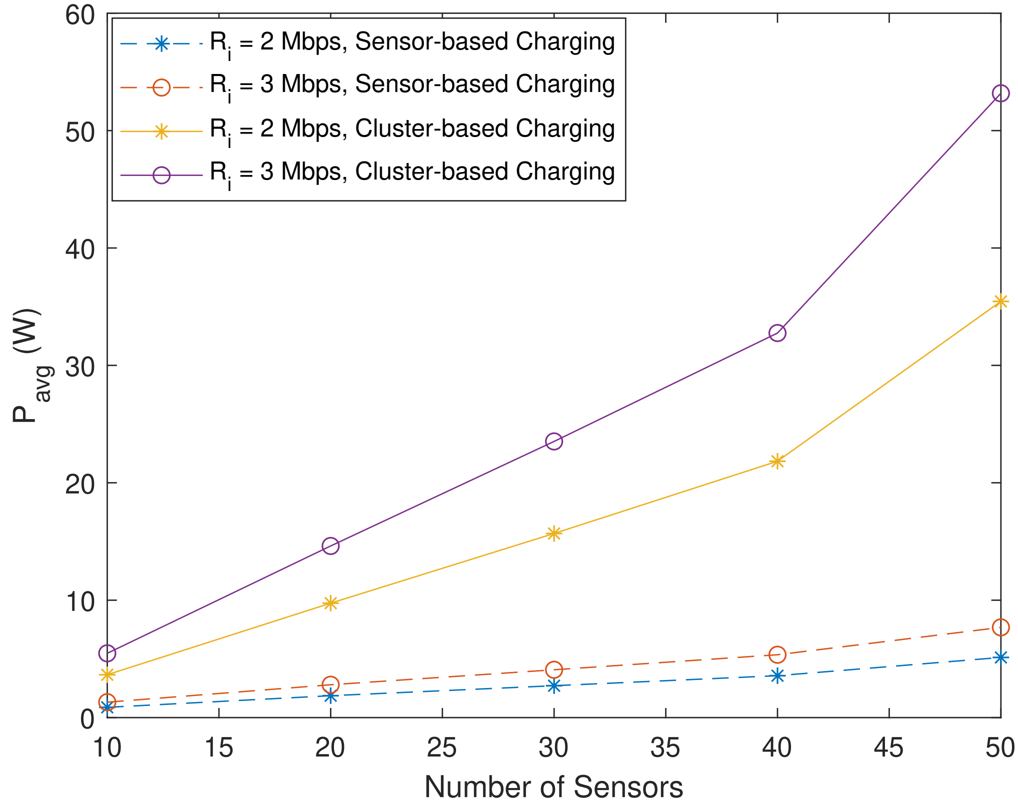

Figure 6.6: Sensor-based charging, average power consumption versus number of sensors

It should be clarified that the "equal time charging" and the "cluster-based charging" are based on the same assumption that all sensors within the charging range of the same anchor location are charged with the same amount of time. However, they use different methods to solve the charging time and therefore result in different performance.

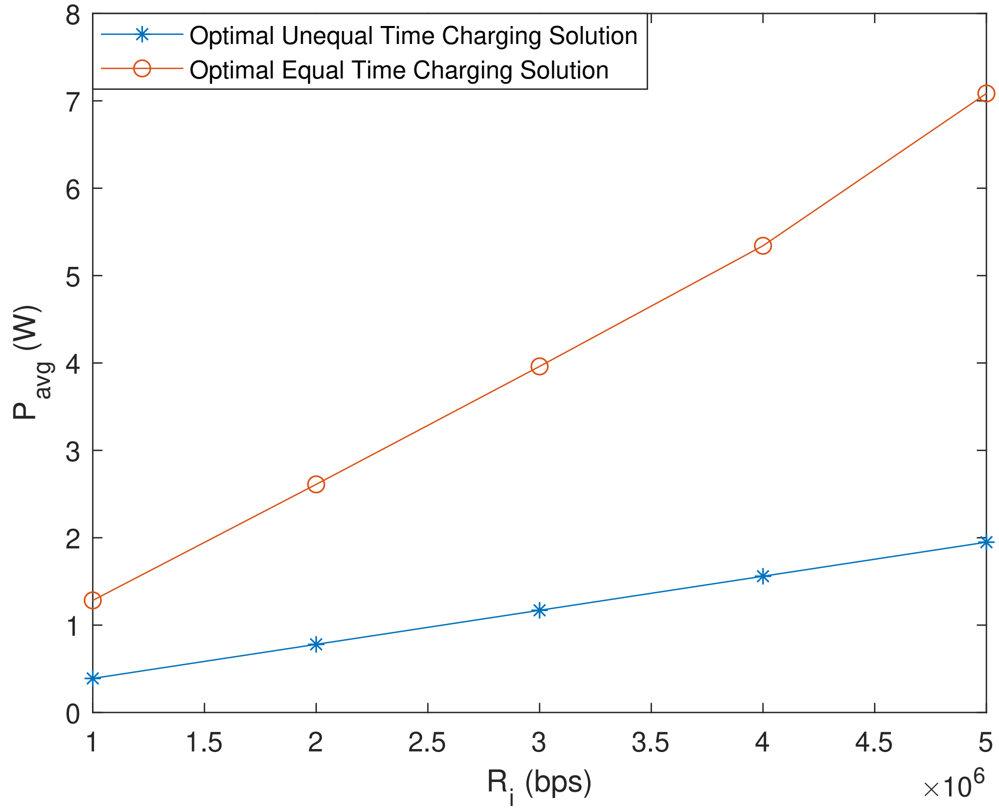

Figure 6.7: Equal vs. unequal charging, average power consumption versus sensing data rate

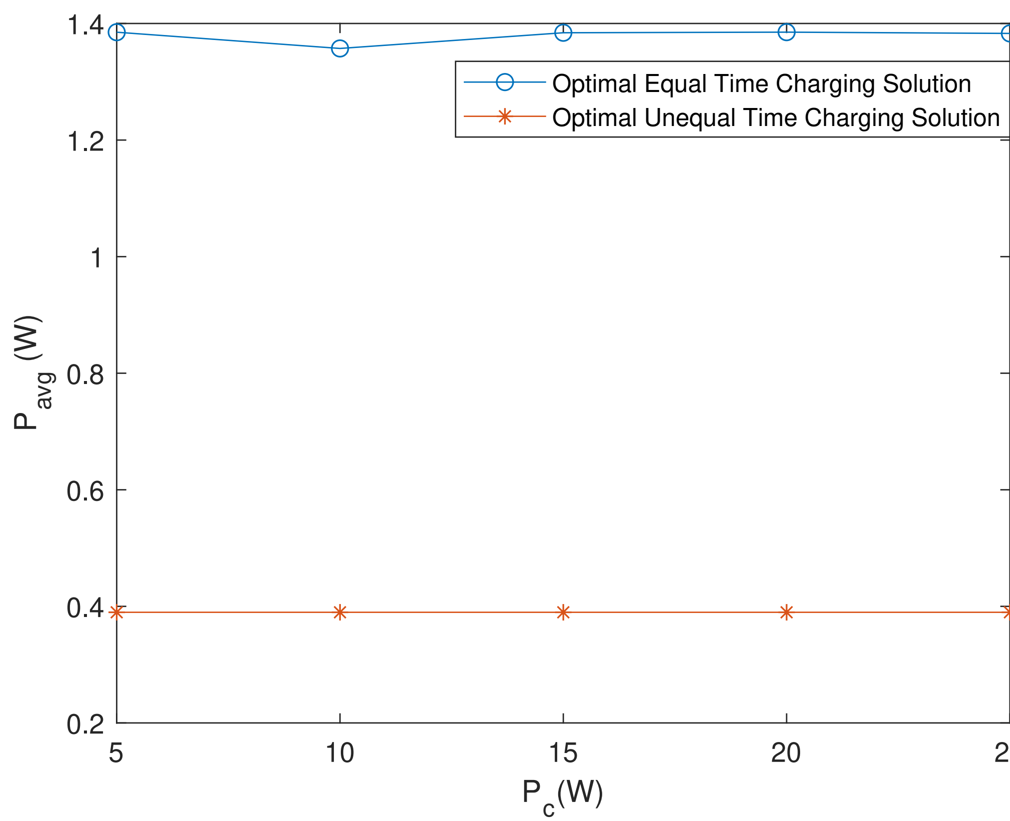

Figure 6.8: Equal vs. unequal charging, average power consumption versus charging power

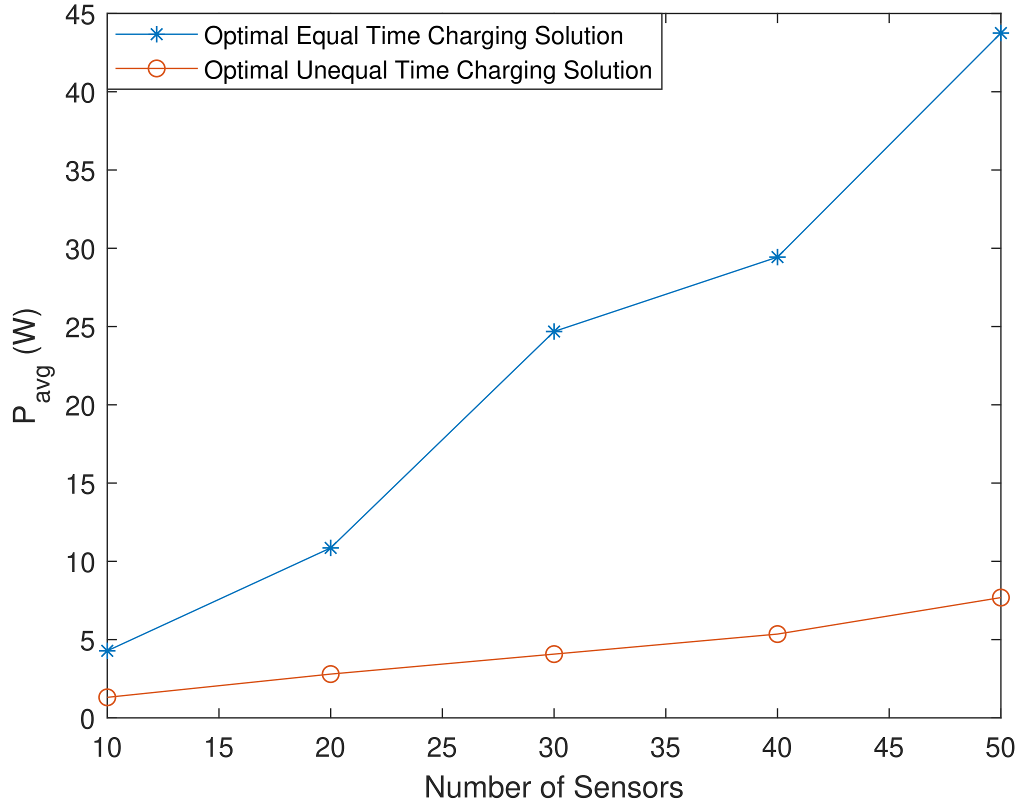

Figure 6.9: Equal vs. unequal charging, average power consumption versus number of sensors

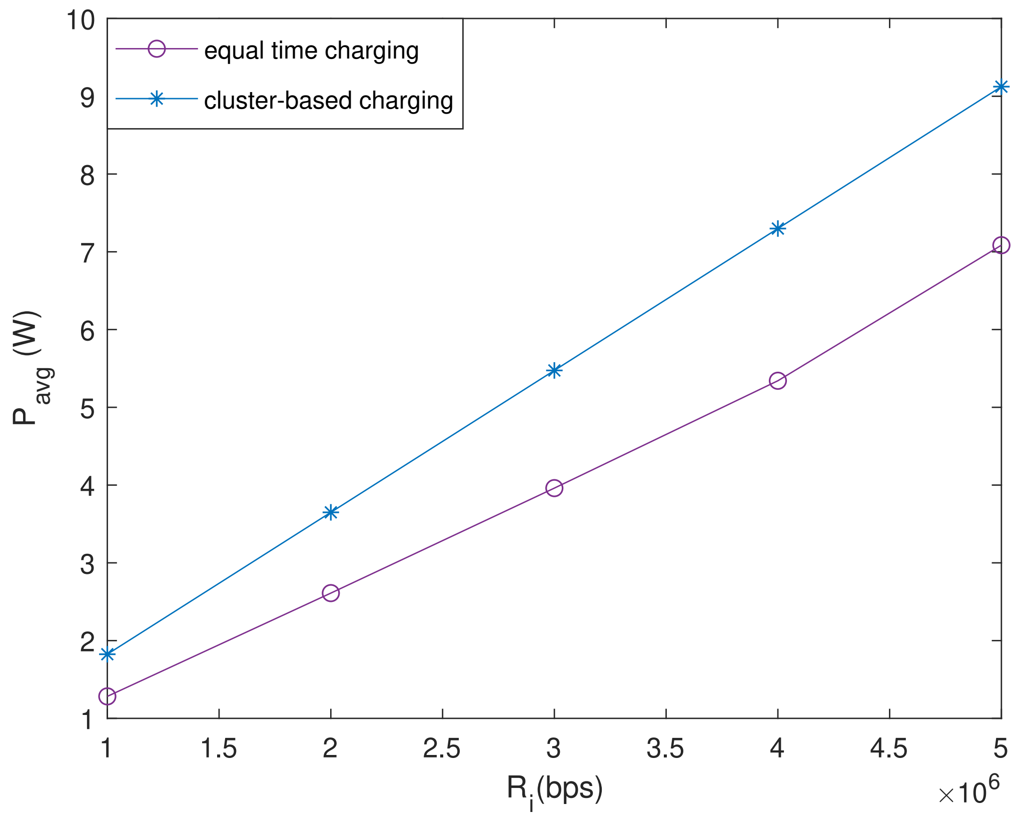

Figure 6.10: Equal vs. cluster charging, average power consumption versus sensing data rate

Chapter 7

Conclusions and Future Work

7.1 Conclusions

In this thesis, we have studied the joint optimization of charging time, flow routing, and transmission rate, time, and power allocations in a RWSN. The system includes a wireless charging vehicle that travels along a given trajectory and stops at predefined anchor locations to charge the sensors with its charging range. The objective is to minimize the average power consumption of the system while satisfying the sensing rate and communication requirements of the network. The problem has been formulated as a non-convex optimization problem. A special case is first solved by considering that all sensors within the charging range of a given anchor location are charged with the same amount of time. The general problem is then solved by considering that the charging time of individual sensors may be different, even when they are charged from the same anchor location. Different decomposition methods are used to solve the problem. Our numerical results have shown that compared to the cluster-based charging, the proposed sensor-based charging solution can significantly reduce the average power consumption of the system. The cluster-based charging assigns the same charging time to all sensors in one cluster, which makes it difficult to take advantage of the different charging conditions of the sensors and results in much higher power consumption.

7.2 Future Work

Our solutions assume that the communications of different sensors use orthogonal channels. When this is not the case, co-channel interference is an important factor that affects the data transmission rate, time and transmission power, which further affects the energy consumption of sensors and their required charging time. In addition, the system studied in this work considers only one WCV. When the traffic load of the sensor network is high, the system may become infeasible, since the amount of charged energy to the WCV may be insufficient for it to charge all sensors and return to the home station. In this case, multiple WCVs can be used to jointly charge the sensors. How to coordinate the charging time of the WCVs for each sensor is another issue that should be studied in order to optimize the average power consumption of the multi-WCV RWSN.

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