Impact of Mobility on Energy Provisioning in Wireless Rechargeable Sensor Networks

Haipeng Dai*, Lijie Xu*, Xiaobing Wu*, Chao Dong† and Guihai Chen*‡
*State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing, Jiangsu 210023, CHINA
†Institute of Communications Engineering, Nanjing, Jiangsu 210007, CHINA
‡Shanghai Key Laboratory of Scalable Computing and Systems, Shanghai Jiao Tong University, Shanghai 200240, CHINA
Emails: {dhpphd2003, ljxu83, dch999}@gmail.com, {wuxb, gchen}@nju.edu.cn

***Abstract*—One fundamental question in Wireless Rechargeable Sensor Networks (WRSNs) is the energy provisioning problem, i.e., how to deploy energy sources in a network to ensure that the nodes can harvest sufficient energy for continuous operation. Though the potential mobility of nodes has been exploited to reduce the number of sources necessary in energy provisioning problem in existing literature, the non-negligible impacts of the constraints of node speed and battery capacity on energy provisioning are completely overlooked, in order to simplify the analysis.**

In this paper, we propose a new metric — Quality of Energy Provisioning (QoEP) — to characterize the expected portion of time that a mobile node can sustain normal operation in WRSNs, which factors in the constraints of node speed and battery capacity. To avoid confining the analysis to a specific mobility model, we study spatial distribution instead. We investigate the upper and lower bounds of QoEP in one-dimensional case with one single source and multiple sources respectively. For single source case, we prove the tight lower bound and upper bound of QoEP. Extending the results to multiple sources, we obtain tight lower bound and relaxed upper bound in normal cases, together with tight upper bound for one special case. Moreover, we give the tight lower bounds in both 2D and 3D cases. Finally, we perform extensive simulations to verify our findings. Simulation results show that our bounds perfectly hold, and outperform the former works.

I. Introduction

Wireless Sensor Networks (WSNs) are mainly powered by small batteries, and the limited energy supply constrains the lifetime of WSNs. Recently, the emergence of wireless power charging technology [1] has shed light on the power supply problem in WSNs. By using the wireless charging technology, we can create a controllable and perpetual energy source to provide wireless power from a distance. Despite the fact that many schemes [2] [3] [4] have been proposed to make use of wireless charging, little literature focuses on the issues with mobile nodes. The role of mobility in Wireless Rechargeable Sensor Networks (WRSNs) has been largely overlooked, whereas a number of studies have illustrated that mobility enhances the capacity [5], increases the connectivity [6], and brings coverage improvement [7] in WSNs.

Nevertheless, He *et al.* [8] investigated the energy provisioning problem in a WRSN built from the industrial Wireless Identification and Sensing Platform (WISP) [9]. Specifically, one of their studied problems, which is called the path (energy) provisioning problem, refers to how to deploy readers in a network to ensure that mobile tags can harvest sufficient energy for continuous operation. They proposed the necessary requirement for path provisioning, that is, the average recharge rate during the tag's movement should be no smaller than the power consumption of the tag in the long run. However, this condition may not really guarantee sustainable operation for tags due to constraints of node speed and battery capacity, which are totally ignored in the literature. For example, recharge energy loss will happen if a tag travels into a power-rich area with fully charged battery, which would eventually result in energy shortage and operation suspension in power-deficient areas. This observation shows that battery capacity limits the performance of energy provisioning.

To evaluate the performance of energy provisioning for mobile nodes, we propose a new metric, namely Quality of Energy Provisioning (QoEP), which is defined as the expected portion of time that a node can sustain normal operation. It captures the characteristics of energy provisioning performance even when node works in an intermittent mode. In this paper, our work is mainly focused on the upper and lower bounds of QoEP based on node spatial distribution. Theoretical results provide insights into how to effectively deploy energy sources to meet requirements for energy provisioning performance in applications, while factoring in constraints of node speed and battery capacity.

II. Problem Statement

A. Network Model

In this paper, we use a wireless recharge infrastructure which is much similar to [8]. That is, a WRSN consists of a single or multiple static sources and a set of mobile nodes (e.g., they are worn by human users for activity monitoring) in a region of interest. Sources are responsible for recharging the nodes via wireless. Nodes harvest wireless energy and store it in their batteries for normal operations like sensing and logging data. One objective proposed by [8] is to keep nodes' sustainable operation to avoid any information loss, which is referred to as energy provisioning problem. This wireless recharge infrastructure is generic and can be reused for diverse types of different applications. For example, it can be applied to WRSNs built on equipments from Powercast [10], involving power transmitters and rechargeable sensor nodes.

We further propose some assumptions about node mobility and its energy consumption as follows. (i) At any time, a node can move at an arbitrary speed which is no more than v^{max}; (ii) the node's power consumption for working, such as sensing and logging data, is constant and independent of its motion, which can be denoted as p_s; and (iii) each node has a battery capacity of E_π, and its power leakage of battery can be neglected. Moreover, a node keeps working with a nonzero residual energy till depletion, and then it suspends its work. As long as the node absorbs any amount of energy, it resumes work immediately. The energy cost for switching on or off can be ignored. Though the third assumption is somewhat unrealistic, it makes the problem much easier to solve. We will take into account practical concerns in future work.

B. Recharging Model

A critical factor impacting energy provisioning is the wireless recharge model. In this paper, we adopt the practical models assumed by [8]. In particular, the receive power p_r of RF signal at the location which is d m away from the source can be expressed as $p_r = \frac{\tau}{(d+\beta)^2}$, where both τ and β are constants independent of d. In addition, the additivity of the transmission power of multiple sources has been verified by realistic experiments for multiple sources, and the impact of mobility on recharge power can be safely neglected.

C. Concept of Quality of Energy Provisioning

Before formally stating the problem in this paper, we introduce the following definitions in advance.

Definition 2.1: Instantaneous Quality of Energy Provisioning (IQoEP) of node at time t is defined as follows:

$$IQoEP(t) = \begin{cases} \frac{p_r(t)}{p_s}, & E_{re}(t) = 0 \ and \ p_r(t) < p_s \\ 1, & otherwise \end{cases} \tag{1}$$

where $p_r(t)$ and $E_{re}(t)$ respectively denote the received cumulative recharge power and residual energy at time t.

Recall that p_s is the nodes power consumption for working. The above equation is derived from the third assumption.

Definition 2.2: The Quality of Energy Provisioning (QoEP) in the region Ω is defined as the expected portion of time in the long run that a node can sustain normal operation. That is:

$$QoEP = \lim_{t\to\infty} \frac{1}{t - t_0} \int_{t'=t_0}^{t} IQoEP(t')dt'. \tag{2}$$

We note that this concise form of QoEP not only simplifies our following analysis, but also captures the characteristics of energy provisioning performance, even when node works in an intermittent mode. In addition, QoEP also serves as a metric that helps to evaluate the efficiency of deployment of energy sources, while factoring in constraints of node speed and battery capacity.

Definition 2.3: The Quality of Energy Provisioning at Location x (LQoEP) is defined as the expected proportion of cumulative time that a mobile node can sustain normal operation to that node spent at x.

$$LQoEP(x) = \lim_{t\to\infty} \frac{\int_{t'=t_0}^{t} IQoEP(t')I(t',x)dt'}{\int_{t'=t_0}^{t} I(t',x)dt'} \tag{3}$$

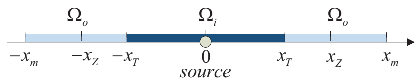


Fig. 1. Illustrations of Single Source in One Dimensional Case

where $I(t',x)$ is an indicator function which equals to 1 when node appears at location x at time t', or 0 otherwise.

With $LQoEP(x)$, Equation (2) can be rewritten as:

$$\begin{aligned} QoEP &= \lim_{t\to\infty} \frac{1}{t-t_0} \int_{t'=t_0}^{t} IQoEP(t')dt' \\ &= \lim_{t\to\infty} \frac{1}{t-t_0} \int_{\Omega} \int_{t'=t_0}^{t} IQoEP(t')I(t',x)dt'dx \\ &= \lim_{t\to\infty} \int_{\Omega} LQoEP(x) \frac{\int_{t'=t_0}^{t} I(t',x)dt'}{t-t_0} dx \\ &= \int_{\Omega} LQoEP(x) f_{dis}(x)dx. \end{aligned} \tag{4}$$

D. Problem Statement

Intuitively, there exist infinite mobility models obeying the same spatial distribution $f_{dis}(x)$. Denote P the set of all those qualified mobility models, we define the lower bound of $QoEP$ with respect to spatial distribution $f_{dis}(x)$ by $QoEP_{min}$, which is no more than any $QoEP$ of mobility model in P. Similarly, we define the upper bound of $QoEP$ by $QoEP_{max}$. In this paper, we prefer to investigate the problems based on spatial distribution rather than a specific mobility model in that the former is more general, practical and tractable [11]. After all, our quality of energy provisioning problems, with respect to single source and multiple sources respectively, can be formally proposed as follows.

Quality of Energy Provisioning Problem for Single Source (Multiple Sources): Assume that there is a single source (multiple sources) and a set of nodes in a region Ω. Given nodes' spatial distribution $f_{dis}(x)$, maximum speed v^{max} and battery capacity E_π, the quality of energy provisioning problem for single source (multiple sources) is to determine $QoEP_{min}$ and $QoEP_{max}$, as there are potentially infinite mobility models obey the same spatial distribution $f_{dis}(x)$.

We emphasize that our work is not confined to 1D case, as many useful results are also found in 2D and 3D cases.

III. Single Source Case

In this section, we investigate the QoEP in one dimensional case with a single source, as a preliminary study.

Assume that the source is placed at the origin while the node's movement is confined to a finite line segment $[-x_m, x_m]$. For simplicity, suppose the node spatial distribution $f_{dis}(x)$ is symmetric. Then we are able to obtain exact QoEPs in some special cases.

Theorem 3.1: Given a source placed at the origin, a node moves on a line $[-x_m,\ x_m]$ according to some mobility model which results in a node spatial distribution $f_{dis}(x)$. Then $QoEP = 2\int_{x=0}^{x_m} \frac{p_r(x)}{p_s} f_{dis}(x)dx$ for $p_r(0) < p_s$, and $QoEP = 1$ for $p_r(x_m) \geq p_s$.

Proof: If $p_r(x_m) \geq p_s$, then a node can sustain normal working anywhere and anytime. Hence $QoEP = \int_\Omega LQoEP(x)f_{dis}(x)dx = 1$ according to (4). If $p_r(0) < p_s$, it indicates that any location in the area Ω cannot provide sufficient recharge power for normal working. Then the node shall exhaust all its initial energy in a finite period of time, which can be ignored in a rather long period. Then $QoEP = \int_{\Omega} LQoEP(x)f_{dis}(x)dx = 2\int_{x=0}^{x_m} \frac{p_r(x)}{p_s} f_{dis}(x)dx$. ■

Except for these two special cases, we can only estimate the lower and upper bounds of QoEP.

A. Lower Bound Analysis

As Figure 1 shows, the whole area is divided into two regions, Ω_i and Ω_o by x_T and $-x_T$, such that nodes in region Ω_i are guaranteed to receive a power no less than than p_s, while that in Ω_o are not. Hence we have $p_r(x_T) = p_s$, and $x_T = \sqrt{\frac{\tau}{p_s}} - \beta$.

Theorem 3.2: Under the condition that $p_r(0) \geq p_s$ and $p_r(x_m) < p_s$, the lower bound of QoEP with single source in one dimensional case is:

$$QoEP_{min} = 2\left(\int_{x=0}^{x_T} f_{dis}(x)dx + \int_{x=x_T}^{x_m} f_{dis}(x)\frac{p_r(x)}{p_s}dx\right) \quad (5)$$

and it is tight.

Proof: First, given a mobility model $\mathscr{M}_1$, we can construct a new one $\mathscr{M}_1'$, by slowing down the speed at any time with a constant factor c. Apparently $\mathscr{M}_1'$ obeys the same spatial distribution, $f_{dis}(x)$, followed by $\mathscr{M}_1$. As illustrated in Figure 1, for any node starting from x_T to region Ω_o following mobility model $\mathscr{M}_1'$, x_Z is the furthest location it can reach with nonzero residual energy. This situation occurs only when the node starts with a fully charged energy state, and maintains a constant speed cv^{max} before it reaches x_Z. Hence we have:

$$E_\pi - \int_{x_T}^{x_Z} \frac{(p_s - p_r(x))}{cv^{max}}dx = 0. \quad (6)$$

Then we calculate the QoEP of $\mathscr{M}_1'$ as follows:

$$\begin{aligned} QoEP =& \int_{\Omega} LQoEP(x)f_{dis}(x)dx \\ =& 2\left(\int_{x=0}^{x_T} f_{dis}(x)dx + \int_{x=x_T}^{x_Z} LQoEP(x)f_{dis}(x)dx \right. \\ &\left. + \int_{x=x_Z}^{x_m} f_{dis}(x)\frac{p_r(x)}{p_s}dx\right) \\ \geq& 2\left(\int_{x=0}^{x_T} f_{dis}(x)dx + \int_{x=x_T}^{x_m} f_{dis}(x)\frac{p_r(x)}{p_s}dx\right). \end{aligned} \quad (7)$$

Note that $LQoEP(x) \geq \frac{p_r(x)}{p_s}$ for $x \in [x_T, x_Z]$ due to the potential nonzero residual energy of the node. Then the right side of inequality (8) is indeed a lower bound. Next we continue to prove its tightness. Given an arbitrarily small value ε, we have:

$$\begin{aligned} QoEP - QoEP_{min} =& 2\left(\int_{x=x_T}^{x_Z} (LQoEP(x) - \frac{p_r(x)}{p_s})f_{dis}(x)dx\right. \\ \leq& 2\int_{x=x_T}^{x_Z} 1 \cdot f_{dis}(x)dx \\ \leq& 2c_1(x_Z - x_T) \end{aligned} \quad (8)$$

where $c_1 = max_{x\in\Omega_o} f_{dis}(x)$. Let $x_Z = min\{x_m, x_T + \varepsilon/2c_1\}$, then $2c_1(x_Z - x_T) \leq \varepsilon$. Then we substitute it into Equation (6) and obtain:

$$c = \frac{1}{E_\pi v^{max}} \int_{x_T}^{min\{x_m, x_T+\varepsilon/2c_1\}} (p_s - p_r(x))dx. \quad (9)$$

Apparently, we have $QoEP - QoEP_{min} \leq \varepsilon$ for c given by (9). Hence the tightness of the lower bound is proved. ■

B. Upper Bound Analysis

Due to symmetry of the topology, we only need to consider subregion $[0, x_m]$, and still use Ω_i and Ω_o to denote the area $[0, x_T]$ and $[x_T, x_m]$ respectively as long as no confusion can arise. Next we'll first propose some new conceptions to facilitate our further study. Then we derive a loose upper bound as well as a tight upper bound of QoEP.

B.1 Related Conceptions

First of all, we associate location $x \in \Omega_o$ with the *expected battery energy consumption rate*, i.e., the average consumption of nodal battery energy in terms of time at x:

$$\begin{aligned} \lambda_c(x) =& \lim_{t\to\infty} \frac{t_1(x)}{t - t_0} \cdot 0 + \lim_{t\to\infty} \frac{t(x) - t_1(x)}{t - t_0}(p_s - p_r(x)) \\ \leq& \lim_{t\to\infty} \frac{t(x)}{t - t_0}(p_s - p_r(x)) \quad (p_s - p_r(x) > 0) \\ =& f_{dis}(x)(p_s - p_r(x)) = \lambda_c^{max}(x) \end{aligned} \quad (10)$$

where $t_1(x)(\geq 0)$ is the cumulative time the node stays at location x when its residual energy is 0. Accordingly, the expected battery energy consumption rate $\Lambda_c(\Omega')$ for some subregion $\Omega' \subseteq \Omega$ can be written as:

$$\Lambda_c(\Omega') = \int_{\Omega'} \lambda_c(x)dx \leq \Lambda_c^{max}(\Omega') = \int_{\Omega'} \lambda_c^{max}(x)dx. \quad (11)$$

Similarly, the *expected battery energy harvest rate* for location $x \in \Omega_i$ is defined by:

$$\begin{aligned} \lambda_h(x) =& \lim_{t\to\infty} \frac{t_2(x)}{t - t_0} \cdot 0 + \lim_{t\to\infty} \frac{t(x) - t_2(x)}{t - t_0}(p_r(x) - p_s) \\ \leq& f_{dis}(x)(p_r(x) - p_s) = \lambda_h^{max}(x) \end{aligned} \quad (12)$$

where $t_2(x)(\geq 0)$ is the cumulative time the node stays at location x when it is fully recharged. And $\Lambda_h(\Omega')$ for some subregion $\Omega' \subseteq \Omega_i$:

$$\Lambda_h(\Omega') = \int_{\Omega'} \lambda_h(x)dx \leq \Lambda_h^{max}(\Omega') = \int_{\Omega'} \lambda_h^{max}(x)dx. \quad (13)$$

Lemma 3.1: $\Lambda_c(\Omega_o) = \Lambda_h(\Omega_i)$.

Proof: Its complete proof is available in [11]. ■

B.2 Analysis for A Loose Upperbound

In this section, we give a loose upperbound for QoEP. Actually, $\Lambda_c(\Omega_o)$ plays an important role in QoEP, as the following theorem states.

Theorem 3.3: Under the condition that $p_r(0) \geq p_s$ and $p_r(x_m) < p_s$, QoEP in single source case is given by:

$$QoEP = QoEP_{min} + \frac{2\Lambda_c(\Omega_o)}{p_s}. \quad (14)$$

Proof: Its complete proof is available in [11]. ■

Besides, we continue to define *energy providing ability* of location x as the average energy a node brings into the area $[x, x_m](x_T \leq x \leq x_m)$:

$$p_{ep}(x) = \lim_{t\to\infty} \frac{1}{t - t_0}(\Sigma_{m=1}^{M(t)}(E_{re}^{i,m}(x) - E_{re}^{o,m}(x))) \quad (15)$$

where $E_{re}^{i,m}(x)$ (or $E_{re}^{o,m}(x)$) is the residual energy of a node upon its m_{th} traveling across location x to region $[x, x_m]$ (or $[0, x]$) during time interval $[t_0, t]$, and $M(t)$ is the number of times of the node's crossing to different direction (actually at most 1 difference exists here and it can be ignored when $M(t) \to \infty$ as $t \to \infty$).

Denote by $\Omega^{\geq x}$ the region $[x, x_m]$. Based on the principle of energy conservation, the providing energy from location x

must be fully converted to the battery energy consumed in region $\Omega^{\geq x}$.

Lemma 3.2: $p_{ep}(x) = \Lambda_c(\Omega^{\geq x})$ $(x \in \Omega_o)$.

Further we have a related lemma as follows.

Lemma 3.3: For any location $x \in \Omega_o$, its energy providing ability $p_{ep}(x)$ is subject to:

$$p_{ep}(x) \leq max\{0, \frac{1}{2} f_{dis}(x) v^{max} (E_\pi - \int_{y=x_T}^{x} \frac{(p_s - p_r(y))}{v^{max}} dy)\}. \tag{16}$$

Proof: Its complete proof is available in [11]. ■

For convenience, we refer to the maximum value of $p_{ep}(x)$ as $p_{ep}^{max}(x)$.

Lemma 3.4: For any $x \in \Omega_o$ $(x_T \leq x < x_m)$:

$$\Lambda_c(\Omega_o) = \Lambda_c(\Omega_o - \Omega^{\geq x}) + p_{ep}(x) \tag{17}$$

and:

$$\Lambda_c(\Omega_o) \leq \Lambda_c^{max}(\Omega_o - \Omega^{\geq x}) + \tilde{p}_{ep}^{max}(x) \tag{18}$$

where:

$$\tilde{p}_{ep}^{max}(x) = max\{0, \frac{1}{2} f_{dis}(x) v^{max} (E_\pi - 2 \int_{y=x_T}^{x} \frac{(p_s - p_r(y))}{v^{max}} dy)\}. \tag{19}$$

Proof: Its complete proof is available in [11]. ■

Let $x = x_T$ in Lemma 3.2 and Lemma 3.3, and combine them with Theorem 3.2, 3.3, we can obtain a relaxed upper bound of QoEP.

Theorem 3.4: Under the condition that $p_r(0) \geq p_s$ and $p_r(x_m) < p_s$, QoEP is subject to:

$$QoEP \leq QoEP_{min} + \frac{f_{dis}(x_T) v^{max} E_\pi}{p_s} \tag{20}$$

The right side of the inequality can be used as a loose upper bound of QoEP in some scenarios.

B.2 Analysis for A Tight Upperbound

We employ a novel technique to pursue the tight upperbound of QoEP by making an analogy between node's movement and flow. However, due to space limit, we can only offer the main result of the tight upperbound as follows.

Theorem 3.5: Under the condition that $p_r(0) \geq p_s$ and $p_r(x_m) < p_s$, the upper bound of QoEP with single source in one dimensional case is:

$$QoEP_{max} = QoEP_{min} + 2\frac{min\{\Lambda_c^{opt}(\Omega_o), \Lambda_h^{opt}(\Omega_i)\}}{p_s} \tag{21}$$

where $\Lambda_c^{opt}(\Omega_o)$ and $\Lambda_h^{opt}(\Omega_i)$ are the maximum expected battery energy consumption rate for region Ω_o and the maximum expected battery energy harvest rate for region Ω_i respectively. It is a tight bound.

As we can see, the most critical issue regarding the tight bound is how to compute $\Lambda_c^{opt}(\Omega_o)$ and $\Lambda_h^{opt}(\Omega_i)$. Actually, we develop effective algorithms to address this issue. We omit it here to save space and refer the reader to [11] for details.

IV. Multiple Sources Case

In this section, we attempt to extend the results to multiple sources case.

For this case, we assume that there are totally N randomly deployed one-dimensional sources networks, as is illustrated in Figure 2. The whole area is partitioned into multiple regions which can be classified into two types according to whether

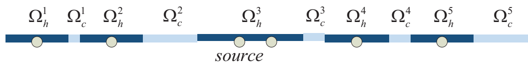


Fig. 2. Illustration of Multiple Randomly Deployed Sources

nodes within this region can receive a power no less than p_s, as depicted in dark color and light color blocks respectively. We denote them as Ω_h^p $(p = 1, 2, 3, \ldots, P)$ and Ω_c^q $(q = 1, 2, 3, \ldots, Q)$ respectively.

Theorem 4.1: Given N sources in region Ω, the tight lower bound of QoEP in one dimensional case is:

$$QoEP_{min} = \sum_{p=1}^{P} \int_{\Omega_h^p} f_{dis}(x)dx + \sum_{q=1}^{Q} \int_{\Omega_c^q} f_{dis}(x) \frac{p_r(x)}{p_s} dx \tag{22}$$

where Ω_h^p $(p = 1, 2, 3, \ldots, P)$ are regions that can receive a power no less than p_s while Ω_c^q $(q = 1, 2, 3, \ldots, Q)$ are regions not, $p_r(x)$ is the cumulative recharge power node receives at x.

Its proof is very similar to Theorem 3.2, so we omit it here to save space. In fact, we can further extend the result to 2D and 3D cases.

Theorem 4.2: Given N sources in region Ω, the tight lower bounds of QoEP in 2D and 3D cases are:

$$QoEP_{min} = \int_{\Omega} f_{dis}(x, y) J(\frac{p_r(x, y)}{p_s}) dxdy \tag{23}$$

and:

$$QoEP_{min} = \int_{\Omega} f_{dis}(x, y, z) J(\frac{p_r(x, y, z)}{p_s}) dxdydz \tag{24}$$

respectively, where $J(x) = x$ for $0 \leq x \leq 1$ and 1 for $x > 1$.

Proof: We are concerned with 2D case first. Suppose that the whole region interest Ω can be divided into two subregions, i.e., region Ω_c wherein the received power $p_r(x, y)$ is no less than p_s and Ω_h wherein $p_r(x, y)$ is not. In addition, we define an expansion region Ω_e wherein node can probably enjoy a nonzero battery energy. That is, for any point e in Ω_e, there exists a path p originated from some point s on boundary of Ω_h to e, followed by a node which starts with a fully recharged battery at s and ends with nonzero residual battery energy, while its speed is no more than v^{max}. Then we have:

$$\begin{aligned} QoEP &= \int_{\Omega_h} f_{dis}(x, y)dxdy + \int_{\Omega_c - \Omega_e} \frac{p_r(x, y)}{p_s} f_{dis}(x, y)dxdy \\ &\quad + \int_{\Omega_e} QoEP(x, y) f_{dis}(x, y)dxdy \\ &\geq \int_{\Omega_h} f_{dis}(x, y)dxdy + \int_{\Omega_c} \frac{p_r(x, y)}{p_s} f_{dis}(x, y)dxdy \\ &= \int_{\Omega} f_{dis}(x, y) J(\frac{p_r(x, y)}{p_s}) dxdy. \end{aligned} \tag{25}$$

Since $QoEP(x, y) \geq \frac{p_r(x,y)}{p_s}$ for point $x \in \Omega_e$ It shows that $QoEP_{min}$ is indeed a lower bound. Next we continue to prove its tightness. Similar to proof of Theorem 3.2, we can construct a new mobility model $\mathscr{M}_1'$, by slowing down the speed at any time with a constant factor c based on an arbitrary mobility model $\mathscr{M}_1$. Apparently $\mathscr{M}_1$ and $\mathscr{M}_1'$ obey the same spatial distribution $f_{dis}(x, y)$. Then its QoEP is subject to:

$$\begin{aligned} &QoEP - QoEP_{min} \\ &= \int_{\Omega_e} (QoEP(x, y) - \frac{p_r(x, y)}{p_s}) f_{dis}(x, y)dxdy \\ &\leq c_1 \int_{\Omega_e} 1dxdy = c_1 |\Omega_e| \end{aligned} \tag{26}$$

where $c_1 = max_{(x,y) \in \Omega_c} f_{dis}(x, y)$. On the other side, it is obvious that $|\Omega_e|$ decreases monotonically with a decrease

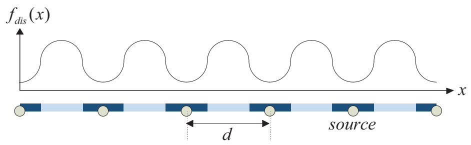


Fig. 3. Illustration of Multiple Equidistantly Deployed Sources and Symmetric Spatial Distribution of Node

node maximum speed cv^{max} as long as $|\Omega_e| \leq |\Omega_c|$, and $|\Omega_e| = 0$ for $cv^{max} = 0$ ($c = 0$). For this reason, given an arbitrarily small value ε, there must exist an c such that $|\Omega_e| = min\{\varepsilon/c_1, |\Omega_c|\}$ based on the properties of continuous function. Consequently, we have:

$$QoEP - QoEP_{min} = c_1|\Omega_e| \leq \varepsilon \tag{27}$$

The result follows. The analysis is the same for 3D case, so we omit it to save space. ■

Nevertheless, the calculation of upper bound in multiple case turns to be much more complicated. For example, suppose that the optimal expected battery energy consumption rate for region Ω_c^2 in Figure 2 is $\Lambda_c^{opt+}(\Omega_c^2)$ in its left side and $\Lambda_c^{opt-}(\Omega_c^2)$ in its right side, which are obtained by launching main flows from the left end point and the right end point into Ω_c^2. Then we claim that $\Lambda_c(\Omega_c^2) \leq min\{\Lambda_c^{opt+}(\Omega_c^2) + \Lambda_c^{opt-}(\Omega_c^2), \Lambda_c^{max}(\Omega_c^2)\}$. If one of its end point lies on the boundary of Ω, we set the expected battery energy consumption rate on the corresponding side to 0. For instance, we set $\Lambda_c^{opt-}(\Omega_c^5) = 0$ for region Ω_c^5.

By similar analysis, we can conjecture that $\Lambda_h(\Omega_h^p)$ for region Ω_h^p is subject to: $\Lambda_h(\Omega_h^p) \leq min\{\Lambda_h^{opt+}(\Omega_h^p) + \Lambda_h^{opt-}(\Omega_h^p)\ , \Lambda_h^{max}(\Omega_h^p)\}$.

Theorem 4.3: Given N sources in region Ω, the QoEP in one dimensional case is subject to:

$$QoEP \leq QoEP_{min} + min\{\sum_{p=1}^{P} \Lambda_h^{opt}(\Omega_h^p) + \sum_{q=1}^{Q} \Lambda_c^{opt}(\Omega_c^q)\} \tag{28}$$

where $\Lambda_h^{opt}(\Omega_h^p) = min\{\Lambda_h^{opt+}(\Omega_h^p) + \Lambda_h^{opt-}(\Omega_h^p), \Lambda_h^{max}(\Omega_h^p)\}$ and $\Lambda_c^{opt}(\Omega_c^q) = min\{\Lambda_c^{opt+}(\Omega_c^q) + \Lambda_c^{opt-}(\Omega_c^q), \Lambda_c^{max}(\Omega_c^q)\}$.

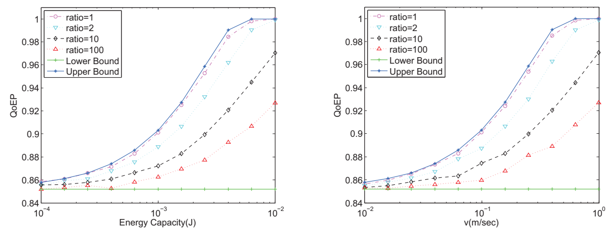
Note that the right side of Inequality (28) is not a tight bound for QoEP. Furthermore, suppose sources are equidistantly distributed with interval distance d, and $f_{dis}(x)$ are identical for subregions partitioned by sources and symmetric, as Figure 3 illustrates. By excluding the recharge power from other sources outside, we can decompose the problem and consider only a subregion, and ultimately transformed it into that in one source case. By doing so, we can obtain its tight upper bound via solution proposed in the previous section.

V. Simulation Results

In this section, we present simulation results to verify our findings, with two issues considered. Unless otherwise specified, we use the following default parameter settings: $\tau = 4.328 \times 10^{-4} W \cdot m^2$, $\beta = 0.2316m$ and $p_s = 1 \times 10^{-3} W$. In addition, we define ratio as v^{max}/v^{min}, which can take values of 1, 2, 10 and 100 during the simulations.

A. Single Source Case

We first evaluate our theoretical results under random waypoint mobility model (RWMM) [12] for single source case. We set $x_m = 1$ and fix the pause time to 0, which means nodes keeps moving throughout the simulation process. Accordingly we have $x_T = 0.4257$. The spatial distribution of RWMM is illustrated in Figure 6. Comparison of the simulation data points on the dotted curve with the theoretical data points on the solid curve shows they are in good agreement.



(a) QoEP Vs. Battery Capacity ($v^{max} = 0.1$)

(b) QoEP Vs. Maximum Speed ($E_\pi = 0.001$)

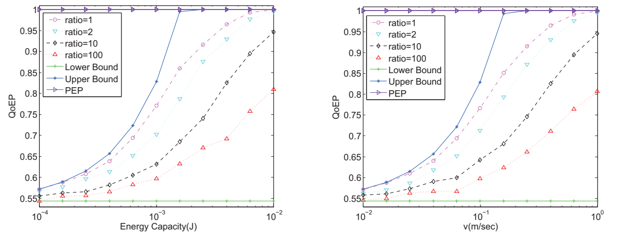
Fig. 4. Simulation Results of Random Waypoint Mobility Model in Single Source Case

As shown in Figure 4(a), if E_π decreases to 0, the simulation results of QoEP approach to the lower bound 0.8519. The ratio in Figure 4(a) refers to v^{max}/v^{min} while v^{max} keeps constant and equals to 0.1. Note that the speed of a node for each movement is randomly selected from $[v^{min}, v^{max}]$. Though QoEPs increase monotonically with E_π for RWMMs of different ratios, they are always bounded by the upper and lower bounds. Moreover, the RWMM of ratio=1, which implies that the node moves with an invariable speed v^{max}, yields an QoEP very close to the upper bound. This is largely due to the overall random destination selection policy that makes the node incline to move globally, thus speeds up the energy exchange. Likewise, the QoEPs also increase monotonically with the varying maximum speed v^{max}, given that $E_\pi = 0.001$ as Figure 4(b) exhibits.

B. Multiple Sources Case

For multiple sources case, we are concerned with the random walk mobility model when sources are equidistantly distributed with distance interval d. Due to uniform node spatial distribution of this mobility model and symmetry of the sources, we can consider only a subregion $[-d/2, d/2]$ with a reference source placed at the origin. As a result, the mobility model can be equivalently viewd as the random walk with reflection mobility model (RWRMM) in [13], where each movement occurs in a constant distance traveled l (we set $l = 0.4\ d$ in this simulation), at the end of which a new direction and speed are randomly selected. If node reaches boundary, it “bounces” off the border and continues along this new direction. It can be proved that RWRMM follows uniform distribution.

To evaluate the performance of our work, we compare it with that of path energy provisioning in [8]. Specifically, we adapt the solution of path energy provisioning to one-dimensional case, by applying the following equation to determine the distance d between adjacent sources: $\frac{1}{d}\int_{r=0}^{d}[\frac{\tau}{(r+\beta)^2} + \frac{\tau}{(d-r+\beta)^2}]dr = p_s$. Solving this equation we obtain $d = \frac{2\tau}{\beta p_s} - \beta$. In fact, this is exactly the maximum distance to guarantee path energy provisioning, as [8] indicates.



(a) QoEP Vs. Energy Capacity ($v^{max} = 1$)

(b) QoEP Vs. Maximum Speed ($E_\pi = 0.01$)

Fig. 5. Simulation Results of Random Walk Mobility Model in Multiple Sources Case

In Figure 5(a) and 5(b), we can see that the QoEP always equals to 1 for path energy provisioning, which is referred to as PEP in these figures, as we set $d = \frac{2\tau}{\beta p_s} - \beta = 3.5059$. In contrast, the simulated results, and even the upper bounds, are much smaller than 1, especially when energy capacity or maximum speed is low. Next, we vary p_s and compute the maximum distance which guarantees $QoEP = 1$ for lower and upper bounds as well as path energy provisioning. It can be seen from Figure 7 that the distance for upper bound increases as E_π or v^{max} increases. However, it is always smaller than that of path energy provisioning. We conclude that our proposed upper and lower bounds are more realistic than path energy provisioning as it factors in both node speed and energy capacity.

After all, the results of lower bound and upper bound can be used to estimate the distance in sources deployment. More importantly, our solution can meet the requirements of those applications with a given QoEP threshold (not necessarily equal to 1). In this sense, our solution is also more flexible compared with path energy provisioning.

VI. Related Work

In this section, we briefly review related work on wireless energy transfer technology in WSNs and energy provisioning problem. Tong *et al.* [14] investigated the impact of wireless charging technology on sensor network deployment and routing arrangement. The authors in [2] and [3] used a wireless charging vehicle (WCV) or a mobile charger (MC) to periodically travel inside the sensor network and charge each static sensor node's battery via wireless, and studied the optimization problem about routing and charging. In [4], a mobile charger was used to serve not only as an energy transporter that charges static sensors, but also as a data collector. Zhang *et al.* [15] proposed a scheme employed multiple energy-constrained MCs to collaboratively charge a linear WSN. MCs are allowed to charge each other. Their goal is to maximize the energy efficiency of charging.

All the schemes mentioned above aim to mobilize a charger to charge static sensor nodes. In contrast, He *et al.* [8] proposed the only scheme to the energy provisioning problem, where static or mobile nodes are charged by stationary chargers.

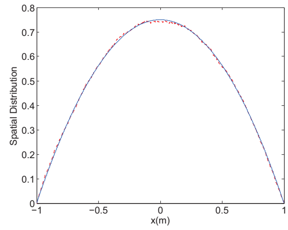


Fig. 6. Spatial Distribution of RWMM

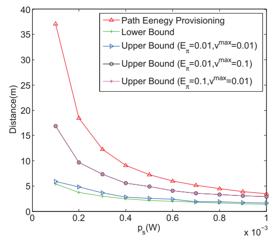


Fig. 7. Illustration of Distance Comparison of Sources Deployment

VII. Conclusion

In this paper, we have studied the impact of mobility on energy provisioning in WRSNs, especially in one-dimensional cases. Our work mainly focuses on the upper and lower bounds of QoEP in both single source and multiple sources. The theoretical results show that the lower bounds in two cases have nothing to do with node speed and battery capacity. Our results also provide fundamental insights into the sources deployment in WRSNs. Numerical results are offered to demonstrate the effectiveness of our solutions.

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