Mobile Charging in Wireless-Powered Sensor Networks: Optimal Scheduling and Experimental Implementation

Fahira Sangare, *Member, IEEE*, Yong Xiao, *Senior Member, IEEE*, Dusit Niyato, *Senior Member, IEEE*, and Zhu Han, *Fellow, IEEE*

***Abstract*—Wireless radio frequency (RF) energy transfer is a promising technology to provide a reliability-guaranteed power supply for wireless sensor networks. In this paper, we consider a special wireless-powered sensor network consisting of a mobile energy station that can travel through a pre-planned path to charge wireless-powered sensors located in the considered area. We develop a hardware platform using off-the-shelf RF energy transfer hardware equipment to evaluate the practical performance of wireless sensor networks powered by RF energy transfer. We establish an empirical model based on our developed platform and use the empirical model to jointly optimize path planning and mobile charge scheduling for wireless-powered sensor networks. We derive the optimal policy for the mobile energy station to optimize its decisions about the path that it will travel and the subset of sensors to charge during each time period. Numerical results show that our derived policy significantly improves the performance of wireless sensor networks in different practical scenarios.**

***Index Terms*—Wireless power transfer, sensor networks, Markov decision process, mobile charging.**

I. Introduction

A wireless sensor network (WSN) is a special network system consisting of autonomous sensors spatially distributed in a given area to sense and collect the information of interest. It has been widely applied in area monitoring [1], healthcare monitoring [2], environmental sensing [3], industrial monitoring [4], etc. Most existing WSNs rely on the energy pre-stored in batteries to support the required service. How to develop simple and energy efficient sensors that can support data sensing and communication as long as possible is one of the most important challenges.

Recently, energy harvesting has been considered as one of the ideal solutions for WSNs due to its potential to provide perpetual energy sources for electronic devices [5]–[8]. However, energy harvested from external sources can suffer from uncertainty and fluctuation and cannot always provide reliably guaranteed energy supply for most of WSNs. For example, in solar and wind energy harvesting systems, the amount of energy is determined by the duration and strength of solar radiation or wind, which are generally time-varying and difficult to predict [9]. To solve this problem, various energy and data transmission scheduling algorithms have been proposed. More specifically, the transmit packet scheduling problem was studied for a single-user energy harvesting communication system with prefect information in [10] where the transmitter can store an infinite amount of energy and know the future changes of the energy harvesting process. An off-line data packet transmission scheduling algorithm was also proposed and proved to minimize the total transmission delay. This result has been further extended into the stochastic environment in which the transmitter cannot perfectly know the future energy harvesting process but knows only the stochastic features of the energy harvesting process [11]–[13]. For example, the power allocation problem was studied for wireless networks with energy harvesting constraints in [6], [14]. In [8], the cases that the transmitter cannot know the statistics of the future energy harvesting process were considered. A Bayesian reinforcement learning approach was proposed for the transmitter to sequentially learn the statistic parameters from past experience. In [15], the authors put forward an adaptively directional wireless power transfer scheme where the wireless energy station can adjust the energy beamforming strategy according to the locations of the sensors. In [16], the authors investigated the location-dependent power harvesting rates in multiple RF energy stations to charge the sensors in a wireless sensor network. The key challenges of designing wireless powered cellular networks were discussed in [17]. A detailed review of RF energy harvesting technologies applied to wireless networks is given in [18].

There has been a surge of research interests in wireless energy transfer (WET)-based wireless sensor networks in which the sensors can be supported by energy wirelessly supplied by dedicated energy sources mostly through inductive coupling, magnetic resonance coupling, and radio frequency (RF) energy transfer technologies [19]–[22]. Since the energy wirelessly transferred from dedicated sources is not subject to weather or seasonal constraints, WET has the potential to fundamentally solve the energy problems and provide a permanent energy source for future generation wireless sensor networks. RF wireless power transfer-based hardware has been evaluated and tested in many existing works. For example, in [23], the data relaying path selection

F. Sangare and Z. Han are with the Department of Electrical and Computer Engineering at University of Houston, TX, USA (e-mails: fahira@gmail.com and zhan2@uh.edu).

Y. Xiao is with the Department of Electrical and Computer Engineering at the University of Arizona (e-mail: xyong.2012@gmail.com).

D. Niyato is with the School of Computer Engineering at Nanyang Technological University, Singapore (e-mail: dniyato@ntu.edu.sg).

problem was evaluated using the Powercast RF power transfer systems. An optimization framework was developed to determine the optimal charging and transmission cycle for the sensor network. In [24], the scenario of a mobile charging vehicle periodically traveling inside the sensor network and charging each sensor node's battery wirelessly was considered. An optimization framework with the objective of maximizing the ratio of the wireless charging vehicle (WCV) vacation time over the cycle time was proposed. A two-dimensional directional water-filling algorithm was proposed in [25] to optimally control the flow of harvested energy in both time (from past to future) and among users (from energy-transferring to energy-receiving). It showed that the proposed algorithm achieves the boundary of the capacity region of the two-way channel. In [26], the authors consider the dynamic sensing and transmission behaviors of sensors by providing a novel charging paradigm and proposing efficient sensor charging algorithms. A multi-functional mobile entity called SenCar was employed in [27], which serves not only as a mobile data collector that roams over the field to gather data via short-range communication but also as an energy transporter that charges static sensors on its migration tour via wireless energy transmissions. The authors in [28] studied the scenario of a mobile charging vehicle periodically traveling inside the sensor network and charging each sensor node's battery wirelessly. In [29], a novel Energy Synchronized Mobile Charging (ESync) protocol was proposed to simultaneously reduce both of charger travel distance and the charging delay of sensors. In [30], the authors proposed a circuit model for renewable energy cycle and corresponding RF charging time, and derived the node lifetime expressions. In [31], the authors considered a wireless sensor network with rechargeable sensors deployed in a random sensing environment. The MDP is used to find out the optimal recharge policy. In contrast, we derive an empirical model by establishing a real hardware platform using off-the-shelf RF energy transfer hardware equipment, and then apply the derived empirical model to optimize the charging path of a robotic vehicle installed with a RF energy power transmitter.

In this paper, we consider the RF energy transfer-based wireless sensor networks in which each sensor is installed with an antenna or antenna-array that can convert RF signals into electrical energy. RF energy transfer has proven to be a suitable method for powering multiple devices through low power and long distance transfer [19], [32]–[37]. More specifically, in [32], field experiments for charging sensor nodes with RF energy transfer were conducted with Powercast RF energy harvesting kit. These equipment are commercially available RF-based wireless transfer power products [38]. A charger was continuously sending out 903-927MHz frequency RF signals which were then transformed to DC voltage to charge some sensor nodes. It was shown that recharging efficiency could be improved by adjusting three parameters: number of nodes being recharged simultaneously, distance between nodes, and distance between the nodes and the charger, to measure the average received power. The authors then formulated an optimization problem to determine the optimal node deployment and routing arrangement. They proved that the problem is NP-complete and proposed several heuristic algorithms as solutions.

Based on the same technology, a mobile robot was used for carrying a similar wireless charger to charge a WSN [39]. A wireless charging problem that the energy station was trying to solve was formulated, and two heuristic charging algorithms to address the issue were presented. Prototype experiments for a small-scale network were conducted, and the cases for a large-scale network simulated. Both experimental and simulation results showed that the proposed algorithms could prolong network lifetime. However, the low power transfer efficiency was shown to be the bottleneck of the network lifetime. In [40], Unmanned Aerial Vehicles (UAVs) were employed as an alternative to wireless charging vehicles to carry the charger in harsh terrains. UAVs were intended to carry a wireless power charger, select and fly to the sensor clusters, recharge the sensors within the selected cluster, and bring back the sensed data. The goal was to find the optimal matching pairs for sensor clusters and UAVs to obtain the maximum data delivery rate from sensor clusters to the sink. Through simulations, they demonstrated that the matching process of the greedy algorithm with descending order preference achieves the optimal solution. The focus was thus on maximizing data collection utility, not on extending the lifetime of the sensor network. In [41], [42], the authors studied the problem of how to place multiple wireless energy transmitters in a wireless sensor networks to ensure all the sensor nodes can receive sufficient energy for data transmission. In [43], [44], the authors considered the WET system with a mobile charging station installed on a vehicle that can travel through a pre-planned path to charge the sensors and collect data.

Our research focuses on a special wireless-powered sensor network consisting of a set of sensors powered by the energy transferred from a Mobile Energy Station (MES) that can periodically travel through a pre-planned path to charge the sensors. We develop an RF energy transfer-based hardware platform as shown in Figure 1 to assess the practical performance of the proposed wireless-powered sensor network. In our platform, the MES consists of an off-the-shelf RF energy transmitter installed on a robotic vehicle, and each sensor consists of a directional antenna that can receive the RF energy transferred from the MES, a supercapacitor that can store the received energy and a sensing, and data transmitting module that can generate data packets and send to the fusion center. We establish an empirical model for mobile charging-enabled WSNs using our developed platform. We then focus on the joint optimization problem for path planning and mobile charging scheduling problem of the MES. In this problem, the MES can sequentially decide the path it will travel and the subset of sensors to charge at the beginning of each time period. We formulate a Markov decision process (MDP)-based framework to derive the joint optimization solution of the above problems. Numerical results are presented to show the performance improvement that can be achieved by our

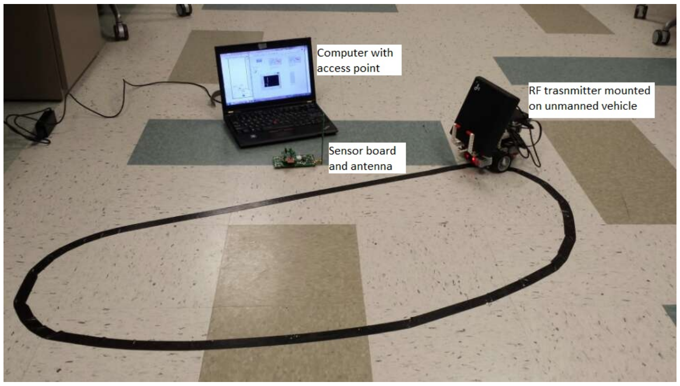


Fig. 1. Our developed hardware platform for RF energy transfer-based wireless sensor networks.

proposed approach.

We summarize the main contribution of this paper as follows:

1) We establish an empirical model for RF wireless power transfer using the data collected from the hardware prototype built using the off-the-shelf RF power transfer hardware.
2) We formulate the path selection problem for wireless sensor networks with mobile charging station as an MDP and then apply our established model to calculate the MDP parameters.
3) We derive an optimal policy for the mobile energy station to sequentially decide the optimal path and the subset of sensors to charge.
4) We present numerical results to verify the performance of our proposed policy.

The rest of this paper is organized as follows. The system model and problem formulation are presented in Section II. We describe the hardware setup and empirical model in Section III. The joint optimization solution for path planning and mobile charging scheduling is derived in Section IV. Numerical results are presented in Section V, and the paper is concluded in Section VI.

II. System Model and Problem Formulation

A. System Model

We consider a WET-based sensor network consisting of a set of K sensors denoted as $\mathcal{S} = \{s_1, s_2, \ldots, s_K\}$ randomly located in the service area. Each sensor can monitor the information of interest, and a sequence of data packets will be generated and transmitted to a fusion center. Let $\mathcal{Q}_{s_k}$ be the set of possible data packets that can be generated by the kth sensor. We assume that the data generated by each sensor s_k follows the Poisson distribution with a known parameter λ_{s_k}. In particular, let $u_{k,t}$ be the number of data packets sent by sensor s_k at the beginning of time slot t, we have $u_{s_k,t} \sim \text{Pois}\left(\lambda_{s_k}\right)$. Let $w_{s_k,t}$ be the amount of energy that will be consumed by sensor s_k to transmit $u_{s_k,t}$ data packets. We assume there exits a one-to-one mapping function $Y(\cdot)$ from $u_{s_k,t}$ to $w_{s_k,t}$. Specifically, we can write $w_{s_k,t} = Y\left(u_{s_k,t}\right)$ and $u_{s_k,t} = Y^{-1}\left(w_{s_k,t}\right)$.

Different from the traditional sensor networks in which the energy consumed for data transmission of each sensor is limited by the energy pre-stored in the battery, the lifetime of each sensor in a WET-based sensor network can be further extended by power wirelessly transferred from an energy station. In this paper, we study the wireless-powered sensor network with mobile charging in which an MES periodically starts from a charging base and travels through a pre-planned path to wirelessly charge a set of sensors before returning to the charging base. We assume that there is a minimum unit of energy, denoted as $\underline{b}$, that can be consumed by each sensor to send each data packet. Each sensor s_k is installed with an energy storage device that can store up to $\bar{b}_k$ units of energy. We focus on the wireless-powered sensor networks with causal constraints. This means that each sensor cannot use the energy that can only be received in the future, i.e., we can hence write the energy level of the energy storage device at sensor s_k at the beginning of time slot t as

$$b_{s_k,t} = \min\left\{\bar{b}_{s_k}, \left(b_{s_k,t-1} + v_{s_k,t} - w_{s_k,t}\right)^+\right\} \tag{1}$$

where $v_{s_k,t}$ is the amount of energy that can be received by s_k from the MES and $(\cdot)^+ = \max\{0, \cdot\}$. We also write the set of possible stored energy levels for sensor s_k as $\mathcal{B}_k = \{\underline{b}, 2\underline{b}, \ldots, \bar{b}_k\underline{b}\}$. Planing the optimal path that can travel and visit all the sensors with the shortest distance is an NP-hard problem [45]. Also in many practical situations, the number of paths that are feasible for traveling by the MES can be limited by various practical conditions. We assume the number of paths that can be traveled by the MES is finite and use $\mathcal{P}$ to denote the set of feasible paths that can be traveled by the MES during each period of time. Let p_t be the path chosen by the MES to travel in time slot t, i.e., we have $p_t \in \mathcal{P}$.

We assume the MES can only choose one path at each time period and cannot change its path before returning to the charging base. This can be from the fact that the computation and decision are performed and made at the charging base which has a complete information about the network. It is known that the wireless energy transfer efficiency deteriorates significantly with the increase of the distance between the MES and the energy receiving sensor. Therefore, the MES will only start sending energy to sensor s_k when it arrives at the closest location in its chosen path.

Without loss of generality, we assume the closest location of each sensor in each specific path is unique and use $\text{Dis}\left(k, p_t\right)$ to denote the distance between sensor s_k and the location that is closest to s_k in path p_t. At the beginning of time period t, the MES will jointly decide a specific path and choose a subset of sensors denoted as $\mathcal{S}_t \subseteq \mathcal{S}$ to charge before leaving the charging base. The MES will then sequentially stop at each location that is closest to each of the selected sensors in the chosen path for wireless charging. The MES will only leave for the next location when the current sensor has been fully charged. We assume the energy sent by the MES to each specific sensor cannot be received by other sensors.

B. Problem Formulation

Let $\phi\left(p_t\right)$ be the time duration for the MES to travel through path p_t for $p_t \in \mathcal{P}$. Let $\psi\left(s_k, p_t, b_{s_k,t}, u_{s_k,t}\right)$ be the time

TABLE I
LIST OF NOTATIONS

Symbol	Definition
$\mathcal{S}$	Set of sensors
Q_k	Set of possible numbers of data packets that arrived at the kth sensor
$q_{k,t}$	Number of data packets arrived at sensor k at the beginning of time period k
$\bar{b}_k$	Maximum number of energy units that can be stored at sensor k
$\mathcal{B}_k$	Energy that can be harvested by T in time period t
p_t	Path chosen by MES to travel during time period t
$\text{Dis}\left(S_k, p_t\right)$	Distance between sensor k and the location of the point that is closest to sensor k in path p_t
$\mathcal{S}_t$	Subset of sensors that are chosen by MES to charge during the tth time period
$\bar{\tau}$	Length of each time period
Ξ	Set of states of wireless-power sensor networks

duration for the MES to stop at the location closest to s_k and charge sensor s_k until its energy storage device is fully charged. The total time duration spent on the tth trip of the MES is given by

$$T_t\left(p_t, \mathcal{S}_t, \boldsymbol{b}_t, \boldsymbol{u}_t\right) = \phi\left(p_t\right) + \sum_{s_k \in \mathcal{S}_t} \psi\left(s_k, p_t, b_{s_k,t}, u_{s_k,t}\right). \quad (2)$$

We assume the maximum amount of time for the MES to travel is bounded by $\bar{\tau}$ and the mobile charging process is repeated every $\bar{\tau}$ time period. Specifically, if the time spent by the MES on charging sensors is less than $\bar{\tau}$, the MES will wait at the charging base and start the next trip at the end of $\bar{\tau}$ time period. On the other hand, if the total time duration for the MES spent on traveling over the selected path and charging all the sensors exceeds $\bar{\tau}$, the MES will only charge a subset of sensors and will return to the base within time duration of $\bar{\tau}$.

The MES tries to ensure that all sensors keep sending their data packets to the fusion center with the lowest average data loss measured by the expected number of data packets that will be dropped by all the sensors due to insufficient energy. We can write the data loss at time slot t as,

$$L_t\left(p_t, \mathcal{S}_t, \boldsymbol{b}_t, \boldsymbol{u}_t\right) = \sum_{s_k \in \mathcal{S}} \left(u_{s_k,t} - Y^{-1}\left(b_{s_k,t} + \mathbf{1}\left(s_k \in \mathcal{S}_t\right) v_{s_k,t}\right)\right)^+ \quad (3)$$

where $\mathbf{1}(\cdot)$ is the indicator function. We write the average payoff of the MES during the tth time period as

$$\varpi_t\left(p_t, \mathcal{S}_t, \boldsymbol{b}_t, \boldsymbol{u}_t\right) = \frac{1}{\bar{\tau}} L_t\left(p_t, \mathcal{S}_t, \boldsymbol{b}_t, \boldsymbol{u}_t\right). \quad (4)$$

The objective for the MES is to minimize the long-term discounted data loss for wireless-powered sensor networks, i.e., we have

$$\mathbb{E}\left(\lim_{t\to\infty} \sum_{l=0}^{t} \gamma^l \varpi_l\left(p_t, \mathcal{S}_t, \boldsymbol{b}_t, \boldsymbol{u}_t\right)\right), \quad (5)$$

where γ is the discount factor for $0 < \gamma < 1$.

III. Hardware Setup and Empirical Models

A. Hardware Setup

We implement a hardware platform to evaluate the practical performance of wireless mobile charging systems. The hardware selected for the experiments are the P1110-EVB evaluation board with components from the P2110-EVAL-01 Lifetime Power Energy Harvesting Development Kit for Wireless Sensors. The P1110-EVB contains the P1110 Powerharvester for use in charging batteries or supercapacitors.

The P2110-EVAL-01 contains a 3-watt, 915MHz RF energy transmitter with integrated 8dBi antenna, an evaluation board, a dipole (omni-directional) and a patch (directional) antenna, an access point, and a wireless sensor board to measure temperature, humidity and light. The wireless sensor boards are powered by the P2110 Powerharvester Receiver, which converts RF energy into DC power. The communication frequency from the sensor board to the access point is 2.4GHz on the Wi-Fi protocol. The kit is designed and configured for low power operation; its firmware is pre-installed for out-of-the-box operation.

1) Hardware Modification: The evaluation board P2110-EVB of the kit is not adequate for our intended experiments as it does not convert RF signals directly into an output voltage that can be used to supply power to the sensors. Instead, its Powerharvester receiver (P2110) converts RF energy to DC voltage stored in an external storage capacitor, referred to as a charge capacitor. When a threshold voltage on the charge capacitor is achieved, the P2110 boosts the voltage to a set output level and enables the power supply release. This output power supply (V_{cc}) remains steady at 3.3V as long as the voltage across the charge capacitor (V_{cap}) remains above a limit value. Once the RF transmitter is turned off after charging, V_{cap} starts to drop and the amount of time that it can remain above the lower threshold depends on the capacitance value. Due to the small value of V_{cap} (1.24V), the low gap between V_{cap} and the lower threshold, and the difficulty to balance between a brief charge period and a long hold time of V_{cc}, the P2110-EVB is not suitable to achieve optimal results.

Therefore, we replaced the P2110-EVB with a P1110-EVB board. In this board, a Powerharvester receiver (P1110) provides power management directly to a battery or storage capacitor, without any need of an external charge capacitor. When a threshold voltage V_{cc} (3.3V) on the storage capacitor is achieved, the P1110 chip automatically disables charging. The V_{cc} voltage is used as a power supply to the sensor board. The value of the storage capacitor will determine the amount and duration of energy available from the output and the length of the charge time. It should have a leakage current, which is the current at 72 hours required to keep the capacitor charged at the rated voltage, as small as possible. Higher leakage currents will result in using more of the harvested energy to replace the capacity lost due to leakage rather than replenishing the capacity [46].

A supercapacitor is an ideal choice for a storage capacitor. Supercapacitors, also referred to as Electrochemical

Capacitors or Double Layer Capacitors, are not only an excellent compromise between electronic or dielectric capacitors such as ceramic and tantalum and rechargeable batteries, but are also suitable technology for providing a unique combination of characteristics, particularly very high energy, power and capacitance densities. They exhibit much longer lifetime than batteries, can accept and deliver charge much faster, tolerate many more charge and discharge cycles, and have minimal environmental impact [47].

For this purpose, we decided to install a 5F Power storage supercapacitor of $13m\Omega$ internal resistance, 25VA leakage current, with a surge voltage of 5.5V. The antenna selected to mount on the P1110-EVB board is the patch antenna from the development kit. It is a vertically polarized directional antenna with 120-degree reception pattern with a higher gain (6.1dBi) than the dipole antenna's 1.0dBi. In order to find the minimum charging time, we vary the distance between the RF transmitter mounted on the unmanned vehicle and the sensor board to achieve the lower the separation distance, the faster the charging time. 18cm is found to be the optimal distance, since the RF transmitter automatically shuts off at shorter distance, to limit RF radiation exposure. Once the target charge voltage is reached, the RF transmitter is disabled and moved to power another board. The supercapacitor voltage V_{cc} used to power the board then starts to drop at a slow rate. As long as it remains above 2.45V, the sensor boards can still communicate with the access point. Before the lower threshold is reached, the unmanned vehicle is moved again to recharge the sensor board.

2) Firmware Customization: The sensor board of the P2110-EVAL-1 kit comes with a preloaded firmware written in C language and requires Microchip's MPLAB development environment and C30 Compiler. A Microchip PIC24F16KA102 is used to demonstrate the capabilities of the Powerharvester to supply uninterrupted power. Once the supply voltage V_{cc} is above a certain value, the Microchip turns on, reads the sensors data and via an MRF24J40MA RF Transceiver Module, and sends them to an access point. The default firmware settings include a Reset signal that turns off V_{cc} for a few milliseconds after the data packets are transmitted. The voltage V_{cap}, used by the P2110 to create the supply voltage, then drops suddenly until it reaches a lower value of 1.02V. Then it automatically charges back so that a similar transmission cycle is repeated. These settings assume an RF transmitter continuously turned on as described earlier. Similarly, with a P1110 evaluation board, V_{cc} would be disabled by the reset signal.

Our objective is to keep the communication between the sensors and the access point alive as long as possible so as to allow the charging vehicle to travel to other sensor nodes. Hence, keeping V_{cc} for a duration longer than that of the default firmware settings is essential. The first modification we implemented is to remove the reset signal so that the P1110 output voltage is not turned off once V_{cc} reaches its 3.3V target. This is achieved by changing sections of the source code. The second modification is to position the Microchip and RF Transmitter Module to sleep mode after

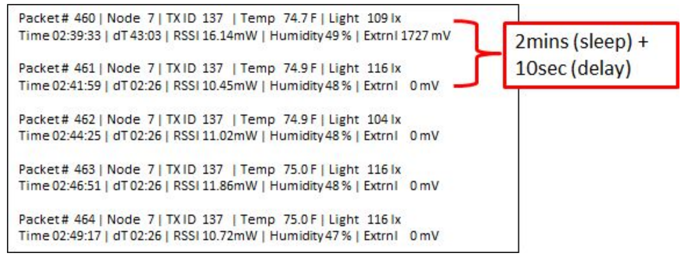


Fig. 2. Packet data received by the fusion center.

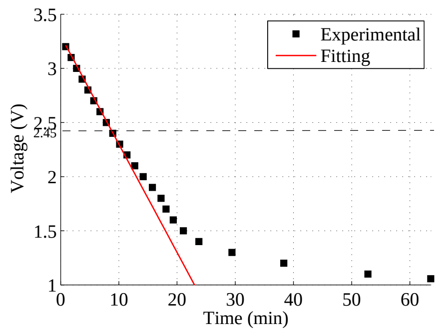
the sensing data packets are sent to the access point, thus saving power and extending V_{cc} above the minimum value as long as possible. Also, prior to entering sleep mode, all I/Os of the microprocessor are set as output and peripherals disabled so as to further lower the current consumption during sleep mode. Figure 2 shows an example of packets received by the access point two minutes apart (a microprocessor was put to sleep for two minutes after sending its packet data). It also includes the default 10 second delay between each packet, which is embedded in the source code.

B. Empirical Models

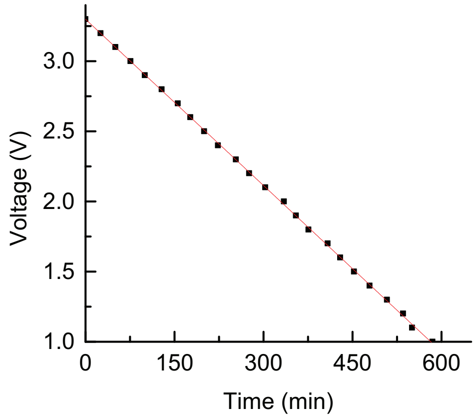
As mentioned previously, the performance of the wireless mobile charging system can be affected by many practical conditions and limitations such as the efficiency of wireless power transfer, energy consumption of data processing and transmission units in the sensor, energy storage loss, feasible paths and stopping sites that can be applied for the MES, and the maximum traveling time constraints of the MES, etc. In the rest of this section, we present empirical models for wireless discharging and charging processes developed based on our proposed wireless mobile charging platform.

1) Empirical Model for Discharging: In wireless-powered sensor networks, each sensor needs to transmit its sensing results to the fusion center with the energy available at its supercapacitor. Each sensor consists of multiple units and circuits including CPU, data collection and transmission units each of which can only be activated when it has sufficient energy supply form the supercapacitor. For example, data transmission unit in each sensor can only be activated when the voltage of the supercapacitor is above 2.45V. In other words, the discharging rate of each sensor will depend on the current energy level of the supercapacitor.

The above observation is verified in our experimental data presented in Figure 3(a) where we measure the voltage of the supercapacitor for one of the sensors under different time slots. We can observe that the voltage decreasing rate of the supercapacitor decreases significantly when the voltage of the supercapacitor becomes less than 2.45V. This means that the data transmission unit of each sensor consumes the highest amount of energy. Motivated by this observation, we modify the firmware of the sensors and allow the data transmission unit to be able to switch off according to the energy availability and the data buffer level of each sensor. More specifically, we develop two operation modes for each wireless-powered



(a) Active Mode



(b) Sleep Mode

Fig. 3. Experiment results for discharging rate under different modes.

sensor in our platform: active mode and sleep mode. Once the stored data packets reach the maximum capacity of the buffer and the supercapacitor has enough energy to support data transmission, the sensor can operate in active mode and start transmitting data packets to the fusion center.

We observe that the discharging rates for both active mode and sleep mode can be fitted into linear functions as illustrated in Figure 3. Note that since each sensor can only operate in active mode when the voltage of the supercapacitor is above 2.45V, we only use the experimental data that is above 2.45V to fit the linear function in Figure 3(a). From Figure 3, we can obtain the following discharging function for each sensor.

$$\Delta V_k(\Delta t) = \begin{cases} -\Delta t \cdot 0.1, & \text{in Active Mode,} \\ -\Delta t \cdot 0.00395, & \text{in Sleep Mode.} \end{cases} \quad (6)$$

2) Empirical Models for Wireless Power Transfer: It is known that the efficiency of wireless power transfer depends strongly on the transfer distance. The relation between transmit power, received power and the wireless power transfer distance is commonly characterized by Friis' free space propagation model given by

$$w_{k,t} = \frac{G_T G_R \nu^2}{(4\pi d)^2} w_{M,t}, \quad (7)$$

where $w_{M,t}$ is the transmit power of the MSE, $w_{k,t}$ is the power received by sensor s_k, G_T and G_R are the antenna gains of the MES and sensor s_k, respectively, d is the power transfer distance between the MES and the sensor, and ν is the power transfer signal wavelength [48]. It is known that

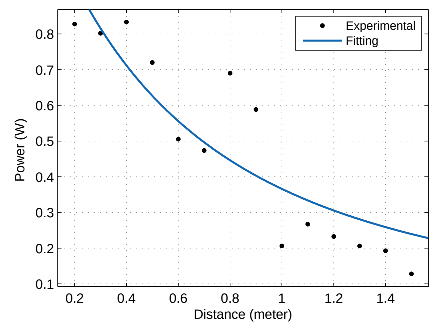


Fig. 5. Wireless power transfer efficiency under different distances.

for short distance transmission, the above equation has to be further adjusted to include the polarization loss and the effects of power rectification and conversion. The short-distance Friis' free space propagation model can then be rewritten as [41]

$$w_{k,t} = \frac{\chi}{(d+c)^2} w_{M,t}, \quad (8)$$

where $\chi = \frac{G_T G_R \nu^2}{(4\pi)^2}$ and $w_{M,t} = 3W$ and c is the compensation factor for the short-distance Friis' equation.

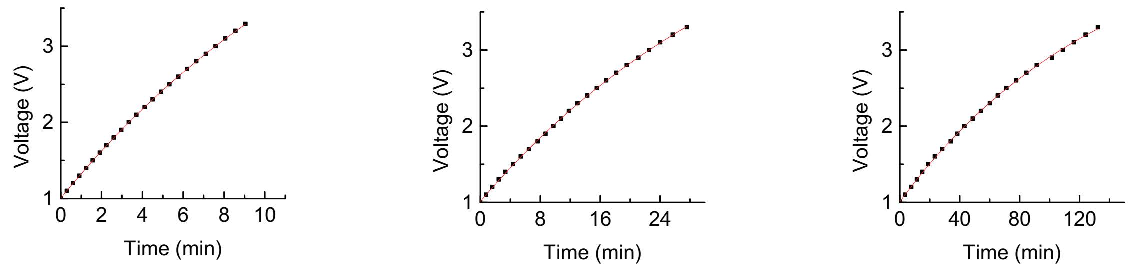
To verify (8) in a practical RF WET system, we measure the relation between the transmit and receiver powers using our hardware platform. As mentioned in Section III, the off-the-shelf wireless energy transmitter installed at the MES contains a directional antenna with transmit gain G_T =8dBi. The wireless power transfer frequency is 915MHz with average wavelength of 0.328 m. Each sensor board has also an antenna with receive gain $G_R = 6.1$dBi. We measure the instantaneous voltage of the supercapacitor and calculate the power received by each sensor k by

$$w_{k,t} = \frac{\kappa}{2\Delta t}\left(\left(V_{k,t} + \Delta V_{k,t}(\Delta t)\right)^2 - \tilde{V}_k^2\right), \quad (9)$$

where $\tilde{V}_k$ is the voltage of the supercapacitor of sensor s_k at the beginning of time period t before charging at the beginning of time period t. V_k is the observed voltage after Δt duration of charging, and $\Delta V_{k,t}(\Delta t)$ is the voltage reduction caused by the energy consumption for data collection and transmission in time interval Δt. $\kappa = 5F$ is the capacitance of the supercapacitor.

Due to the limited capacitance of the supercapacitor installed at each sensor, the maximum energy that can be received by each sensor in our hardware platform is limited. To study the relation between the received energy and the charging time and distance in a more general setting, we fit our experimental voltage data for each sensor under different charging time into a more general function. We observe that all our experimental data can fit the exponential function with standard errors less than or equal to 0.1. The relation between the observed voltages and the charging time in different charging distances is presented in Figure 4. We have the following observations from Figure 4: 1) the charging rate for each sensor under each given charging distance is closely related to the initial voltage before charging. This is because, as mentioned previously, different

This is the author's version of an article that has been published in this journal. Changes were made to this version by the publisher prior to publication.
The final version of record is available at http://dx.doi.org/10.1109/TVT.2017.2668990



(a) 20cm (b) 70cm (c) 140cm

Fig. 4. Wireless charging rates with different charging distances.

units installed at each sensor such as the CPU, the data collection and transmission units, etc., consume different energy under different amounts of energy supply. With more energy being received by each sensor, energy consumption of each sensor will also increase which results in the decrease of the charging rate. 2) the charging time increases significantly with the distance between MES and sensors. In other words, the MES should only start to transmit wireless energy when it arrives at the closest location to each sensor. We fit the average value of our measured data in Figure 5 into the Friis' equation in (8) and obtain $\chi = 1.644$ and $c = 1.112$.

In the rest of this paper, we apply our empirical models to optimize the path planning and charge scheduling for an MES.

IV. Joint Optimization for Path Planning and Mobile Charge Scheduling

Let us next consider mobile charging for wireless-powered sensor networks with multiple sensors.

A. State Estimation

We formulate the joint path planning and mobile charging scheduling problem as an MDP with infinite horizon which consists of the following elements:

- *State space* $\Xi = \boldsymbol{\mathcal{B}} \times \boldsymbol{\mathcal{Q}}$: is a finite set of all the possible energy levels of the supercapacitors for the sensors in each time slot. We write the state in time slot t as $\xi_t = \langle b_t, u_t \rangle \in \Xi$ for all t.
- *Action space* $\mathcal{A} = \mathcal{P} \times \bigcup_{\mathcal{S}' \subseteq \mathcal{S}} \mathcal{S}'$: is a finite set of all the possible paths and subsets of sensors that can be chosen by the MES at the beginning of each time period. We write the action decided by the MES in time period t as $a_t = \langle p_t, \mathcal{S}_t \rangle \in \mathcal{A}$ for all t.
- *State transition function* $\mathcal{T} : \Xi \times \mathcal{A} \times \Xi \to [0,1]$: specifies the probability distribution that, starting at state ξ_t and taking action a_t, the state ends in ξ_{t+1}. Let us now describe how to estimate the state transition function from the statistics of the environment. From (1), it can be observed that the energy level of each sensor at the beginning of time slot t is determined by the energy level, energy consumption and the received energy in the previous time slot. We can then write the probability of this state transition as follows:

$$\begin{aligned}
&\Pr\left(\xi_{t+1} | \xi_t, a_t\right) = \Pr\left(b_{t+1} | b_t, p_t, \mathcal{S}_t\right) \\
&\quad = \Pi_{s_k \in \mathcal{S}_{t+1}} \Pr\left(b_{s_k,t+1} = \bar{b}_{s_k} - w_{s_k,t}\right) \\
&\qquad \Pi_{s'_k \in \mathcal{S} \setminus \mathcal{S}_{t+1}} \Pr\left(b_{s'_k,t+1} = b_{s'_k,t} - w_{s'_k,t}\right) \\
&\quad = \Pi_{s_k \in \mathcal{S}_{t+1}} \Pr\left(u_{s_k,t} = Y^{-1}\left(\bar{b}_{s_k} - b_{s_k,t+1}\right)\right) \\
&\qquad \Pi_{s'_k \in \mathcal{S} \setminus \mathcal{S}_{t+1}} \Pr\left(u_{s'_k,t} = Y^{-1}\left(b_{s'_k,t} - b_{s'_k,t+1}\right)\right)
\end{aligned} \tag{10}$$

where $u_{s_k,t} \sim \text{Pois}\left(\lambda_{s_k}\right)$.

B. Sequential Path Planning and Charge Scheduling

To minimize the long-term data loss, the MES needs to evaluate both the current and future data loss that will result from each of possible actions. We define the value function $U\left(\xi_t, a_t\right)$ as the sum of the current and future discounted data loss when the current state and action are given by ξ_t and a_t, respectively. Suppose the current state is given by ξ_t. We can write the current expected payoff ϖ_t when the transmitter decides to take action a_t in the current time slot as follows:

$$\bar{\varpi}_t = \sum_{\xi_t \in \Xi} \Pr\left(\xi_t | \xi_{t-1}, a_{t-1}\right) \varpi_t\left(a_t, \xi_t\right), \tag{11}$$

where $\varpi_t\left(a_t, \xi_t\right)$ is defined in (4).

The MES should also be able to estimate the future expected data loss using the state transition function. We can hence write $U\left(\xi, a\right)$ as follows:

$$\begin{aligned}
U(\xi_t, a_t) &= \bar{\varpi}_t \\
&+ \gamma \sum_{s_{t+1} \in \mathcal{S}} \Pr\left(\xi_{t+1} | s_t, a_t\right) U^*(\xi_{t+1}, a_{t+1}).
\end{aligned} \tag{12}$$

We can write the optimal value function for the MES under state ξ_t as follows:

$$U^*(\xi_t) = \min_{a_t \in \mathcal{A}} U(\xi_t, a_t). \tag{13}$$

Therefore, the optimal policy π^* is given by

$$a_t^* = \arg\min_{a_t \in \mathcal{A}} U(\xi_t, a_t). \tag{14}$$

(14) means that the MES should always choose action a_t^* when the current state is given by ξ_t.

Following the same line as in [49], we can conclude that the policy in (14) is optimal in the sense that it maximizes the long-term discounted performance of the entire wireless sensor network. In addition, our proposed MDP-based model

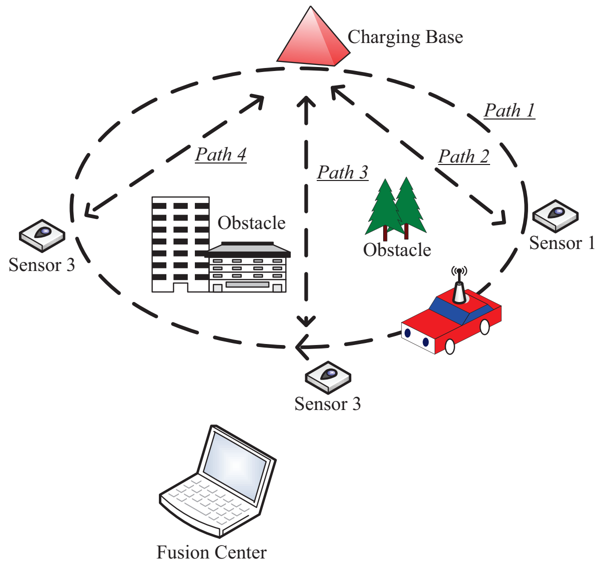


Fig. 6. Simulation setup for wireless-powered sensor networks with three sensors and one MSE.

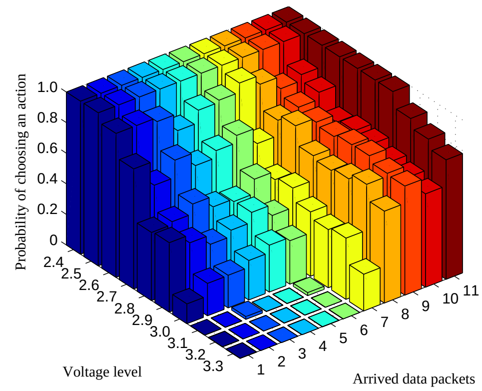


Fig. 7. Probability for MES to choose path 2 and charge sensor 1 under different states when the duration of each time period is 10 min.

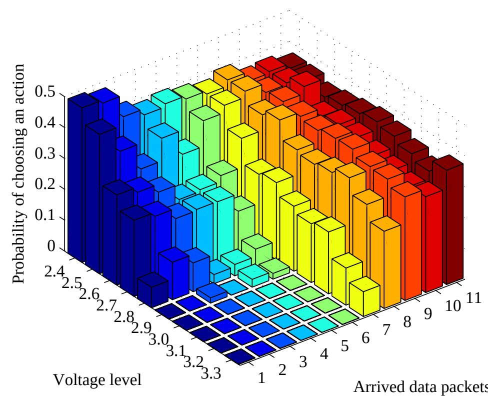


Fig. 8. Probability for MES to choose path 1 and charge sensors 1 and 2 under different states when the duration of each time period is 20 min.

is very general and can be applied into many other situations with different choice of critical variables such as wireless channels and traffic loads. It is known that the solution of the MDP-based algorithm has exponential complexity with respect to the number of states which in our algorithm include the number of battery levels and transmit data packets. Fortunately, the main calculation in our hardware platform is done by the charging station which should have equipped with high computing power infrastructure and the calculated optimal path will be informed to the MES when it arrives the charging station. In our setting, the charging station consists of a laptop computer and therefore the solution can be calculated even when the computation complexity is high.

V. Numerical Results

In this section, we evaluate the performance of the proposed joint optimization algorithm using our hardware platform. We setup an experiment with three sensor boards and one MES consisting of a powercast RF energy transmitter mounted on a robotic vehicle shown in Figure 6. We consider four possible paths for MES to charge the sensors including one circled path that can visit each sensor with the shortest distance of 18cm and three paths each of which will visit one of the sensors back and forth in a straight line. In this paper, we assume the set of paths that can be used by the MES to travel and charge sensors are pre-calculated according to the maps or existing geographic features of the area of consideration. This assumption is reasonable in many practical systems because most of the blockage such as building, trees etc. as illustrated in Figure 6, can be regarded as fixed and will not change with time. Allowing the MES to learn the geographic features and only travel through the selected path without any blockage will increase the efficiency of the mobile charging system and further increase the lifetime of the sensor networks. We set the travel time for the circled path at 5 mins and each of other paths at 2 mins. A sequence of data packets is randomly generated by each sensor at the beginning of each time period.

As mentioned previously, how to choose the path for travel and scheduling a proper subset of sensors to charge by MES directly affect the performance of wireless powered sensor networks. Our proposed joint optimization algorithm allows the MES to sequentially choose the path and charging sensors according to the state of the system. In Figure 7, we assume that the voltage and arrived data packets of sensors 2 and 3 can be regarded as fixed and analyze the probability for the MES to choose path 2 and charge sensor 1 under different voltage and arrived data packets of sensor 1. We consider data loss as the main performance criteria for our prototype because as observed in [1] and [2] that one of the main objectives for many existing wireless sensor networks is to sense the environmental data and report to the monitor station for further analysis. It is therefore very important to ensure low data loss for the wireless sensor network especially when abnormal/emergency environmental

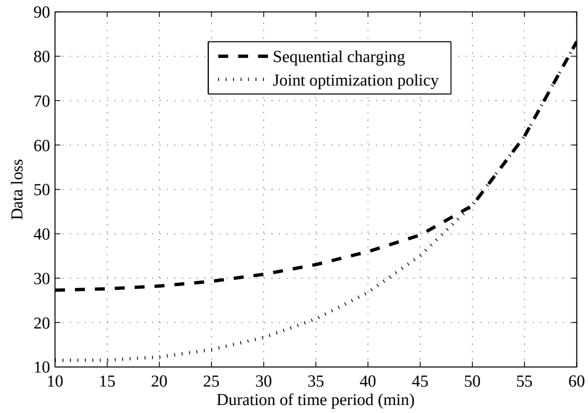


Fig. 9. Comparison of data loss using joint optimization policy and sequential charging according to duration of time period.

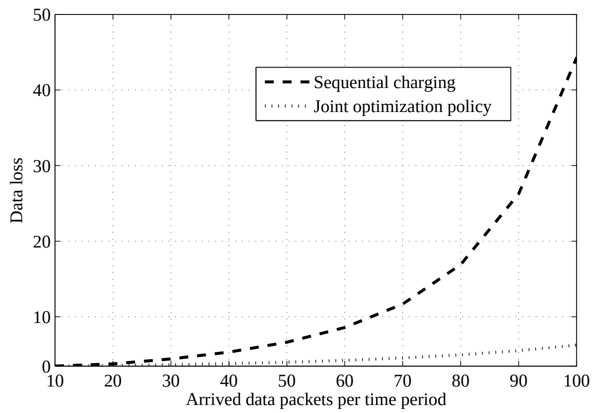


Fig. 10. Comparison of data loss using joint optimization policy and sequential charging according to arrival of data packets.

situations were observed by some sensors.

We observe that the MES will not charge sensor 1 when it believes that the energy stored at sensor 1 is sufficient to support the data transmission. However, when the voltage of the supercapacitor of sensor 1 decreases, the probability for the MES to choose sensor 1 for mobile charging will increase. If sensor 1 cannot send any data packets due to insufficient energy, the MES will always choose path 2 to charge sensor 1. Note that in our setting, the MES can only estimate the exact energy level of each sensor when it charges the sensor. Otherwise, it will use the known probability distribution of the data arrival process to estimate the energy level of each sensor. This explains why in some system states as shown in Figure 7, the probability for the MES to charge sensor 1 can also be positive when the energy of sensor 1 is enough to send all the arrived data packets during the current time period. It is known that the size of the action space is affected by the duration of each time period, i.e., the MES cannot charge all the sensors if the required time duration to charge all the sensors plus the travel time exceeds the duration of each time period.

In Figure 8, we consider the case that the duration of each time period is given by 20mins. In this case, it is possible for the MES to be able to charge two or more sensors. We observe that the MES will not charge sensor 1 but choose path 1 to charge other two sensors if it believes that sensor 1 has enough energy to send its arrived data packets. However, if the supercapacitor of sensor 1 does not have enough energy to support the data transmission, the MES will choose sensor 1 and any of the other sensors to charge. Note that in our setting, the main cost for the MES to choose path 1 compared to choose other paths is that choosing path 1 will result in more travel time during each time period. Our model does not take into consideration other costs of the MES when it chooses different paths such as the energy or other resource consumption, cost of the maintenance after each trip, etc. In other words, if the duration of each time period allows charging two or more sensors, the MES will be unlikely to choose paths 2, 3 and 4 to only charge one sensor. How to integrate these costs functions into our hardware platform will be our future works.

From the empirical models established in Section III, we can observe that due to the energy consumption and discharging of each sensor, the performance of wireless-powered sensor networks is closely related to the duration of each time period. In other words, the longer the duration of each time slot, the more data loss for the sensors due to the insufficient energy supply. In Figure 9, we compare the data loss of our proposed joint optimization policy with the sequential charging approach in which the MES equally divide the duration of each time period into three equal length intervals during each of which it will charge one sensor. We observe that our proposed joint optimization approach significantly improves the performance of the sensor network when the duration of each time period is small. When the duration of time period becomes long enough for the MES to charge all the sensors before returning back to the base, the performance of our joint optimization approach will be equal to that of sequential charging. This means that our proposed joint optimization approach is more suitable for the data loss sensitive wireless-powered sensor networks in which only limited data loss can be tolerated.

It can be observed from our empirical model established in Section III that the data transmission is the most energy consuming process for wireless-powered sensor networks. Therefore, in Figure 10, we compare the data loss of the sensor network under different data arrival rates. We observe that when the number of arrived data packets is few for all the sensors, both sequential charging and the joint optimization policy proposed in Section IV can provide sufficient energy supply for WSNs. However, when the number of arrived data packets increases, the data loss achieved by the sequentially charging will become significantly larger than that of our proposed joint optimization policy. In addition, the percentage of the lost data will not significantly increase with the total number of arrived data packets in the joint optimization policy. In other words, our proposed joint optimization policy is more efficient when it is applied in the sensor networks with high sensing data traffics.

Note that, in some practical situations, the energy level of the battery can be affected by various specific environmental and operational parameters and therefore characterizing the relationship between the overall battery life under various practical applications is also important. For example, in some emergency scenarios, the sensors may operate in the active mode for most of the time which will significantly reduce the battery life. While, in normal time, the sensors can operate in the sleep mode to reduce the energy consumption. In other words, the operation time of the sensors will be different for different applications and specific requirements. In this paper, we only present the simulation results to characterize the relationship between charging time and the received energy as well as that between discharging time and the remaining energy for the battery of the receiver in either active or sleep modes. The practical battery life of the sensors can be directly calculated from the numerical results presented in this paper.

VI. Conclusion

In this paper, we studied a wireless-powered sensor network consisting of an MES installed with RF energy transmitter. The MES could travel through a pre-planned path to charge multiple sensors in a given area. We developed a prototype with off-the-shelf RF energy transfer hardware equipment to verify the practical performance of RF energy transfer-based wireless sensor networks. We established an empirical model and used the established model to jointly optimize the path planning and mobile charge scheduling for the wireless-powered sensor network. We derived an optimal policy for the MES to sequentially optimize the planned path and the subset of sensors to charge during each time period. We also presented numerical results to show the performance improvement that can be achieved by our derived policy.

References

[1] T. P. Lambrou and C. G. Panayiotou, "Collaborative area monitoring using wireless sensor networks with stationary and mobile nodes," *EURASIP Journal on Advances in Signal Processing*, vol. 2009, p. 7, Apr. 2009.

[2] V. Peiris, "Highly integrated wireless sensing for body area network applications," *SPIE Newsroom*, vol. 10, no. 2.1201312, p. 00512, Dec. 2013.

[3] P. Corke, T. Wark, R. Jurdak, W. Hu, P. Valencia, and D. Moore, "Environmental wireless sensor networks," *Proceedings of the IEEE*, vol. 98, no. 11, pp. 1903–1917, Nov. 2010.

[4] A. A. Kumar Somappa, K. Øvsthus, and L. M. Kristensen, "An industrial perspective on wireless sensor networks: a survey of requirements, protocols, and challenges," *Communications Surveys & Tutorials, IEEE*, vol. 16, no. 3, pp. 1391–1412, Aug. 2014.

[5] Y. Xiao, D. Niyato, Z. Han, and L. DaSilva, "Dynamic energy trading for energy harvesting communication networks: A stochastic energy trading game," *IEEE Journal on Selected Areas in Communications*, vol. 33, 2015, Avaliable at http://dx.doi.org/10.1109/JSAC.2015.2481204.

[6] Y. Xiao, D. Niyato, Z. Han, and L. A. DaSilva, "Opportunistic relay selection for cooperative energy harvesting communication networks," in *IEEE Global Communications Conference (GLOBECOM)*, San Diego, CA, Dec. 2015.

[7] Y. Xiao, Z. Han, and L. A. DaSilva, "Opportunistic relay selection for cooperative energy harvesting communication networks," in *IEEE Global Communications Conference (GLOBECOM)*, Austin, TX, Dec. 2014.

[8] Y. Xiao, Z. Han, D. Niyato, and C. Yuen, "Opportunistic relay selection for cooperative energy harvesting communication networks," in *IEEE International Conference on Communications (ICC)*, London, UK, Jun. 2015.

[9] S. Guo, C. Wang, and Y. Yang, "Joint mobile data gathering and energy provisioning in wireless rechargeable sensor networks," *IEEE Transactions on Mobile Computing*, vol. 13, no. 12, pp. 2836–2852, Feb. 2014.

[10] J. Yang and S. Ulukus, "Optimal packet scheduling in an energy harvesting communication system," *IEEE Trans. Commun.*, vol. 60, no. 1, pp. 220–230, Jan. 2012.

[11] X. Lu, D. Niyato, P. Wang, D. I. Kim, and Z. Han, "Wireless charger networking for mobile devices: fundamentals, standards, and applications," *IEEE Wireless Communications*, vol. 22, no. 2, pp. 126–135, Apr. 2015.

[12] D. T. Hoang, D. Niyato, P. Wang, and D. I. Kim, "Performance optimization for cooperative multiuser cognitive radio networks with rf energy harvesting capability," *IEEE Trans. Wireless Commun.*, vol. 14, no. 7, pp. 3614–3629, Jul. 2015.

[13] A. Aprem, C. Murthy, and N. Mehta, "Transmit power control policies for energy harvesting sensors with retransmissions," *IEEE Journal of Selected Topics in Signal Processing*, vol. 7, no. 5, pp. 895–906, Oct. 2013.

[14] A. Sinha and P. Chaporkar, "Optimal power allocation for a renewable energy source," in *IEEE National Conference on Communications*, Kharagpur, India, Feb. 2012.

[15] Z. Wang, L. Duan, and R. Zhang, "Adaptively directional wireless power transfer for large-scale sensor networks," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 5, pp. 1785–1800, May 2016.

[16] M. Y. Naderi, K. R. Chowdhury, and S. Basagni, "Wireless sensor networks with RF energy harvesting: Energy models and analysis," in *IEEE Wireless Communications and Networking Conference (WCNC)*, New Orleans, LA, Mar. 2015, pp. 1494–1499.

[17] H. Tabassum, E. Hossain, A. Ogundipe, and D. I. Kim, "Wireless-powered cellular networks: Key challenges and solution techniques," *IEEE Communications Magazine*, vol. 53, no. 6, pp. 63–71, Jun. 2015.

[18] L. Xiao, P. Wang, D. Niyato, D. Kim, and Z. Han, "Wireless networks with RF energy harvesting: A contemporary survey," *IEEE Communications Surveys Tutorials*, vol. 17, pp. 757–789, May 2015.

[19] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljačić, "Wireless power transfer via strongly coupled magnetic resonances," *Science*, vol. 317, no. 5834, pp. 83–86, Jul. 2007.

[20] B. Cannon, J. Hoburg, D. Stancil, and S. Goldstein, "Magnetic resonant coupling as a potential means for wireless power transfer to multiple small receivers," *IEEE Trans. Power Electronics*, vol. 24, no. 7, pp. 1819–1825, Jul. 2009.

[21] A. Sample, D. Meyer, and J. Smith, "Analysis, experimental results, and range adaptation of magnetically coupled resonators for wireless power transfer," *IEEE Trans. Industrial Electronics*, vol. 58, no. 2, pp. 544–554, Feb. 2011.

[22] T. Imura, H. Okabe, and Y. Hori, "Basic experimental study on helical antennas of wireless power transfer for electric vehicles by using magnetic resonant couplings," in *IEEE Vehicle Power and Propulsion Conference (VPPC)*, Dearborn, MI, Sept. 2009, pp. 936–940.

[23] R. Doost, K. R. Chowdhury, and M. Di Felice, "Routing and link layer protocol design for sensor networks with wireless energy transfer," in *IEEE Global telecommunications conference (GLOBECOM)*, Miami, FL, 2010.

[24] Y. Shi, L. Xie, Y. T. Hou, and H. D. Sherali, "On renewable sensor networks with wireless energy transfer," in *2011 Proceedings IEEE INFOCOM*, Shanghai, China, Apr. 2011.

[25] B. Gurakan, O. Ozel, J. Yang, and S. Ulukus, "Energy cooperation in energy harvesting communications," *IEEE Trans. Commun.*, vol. 61, no. 12, pp. 4884–4898, Dec. 2013.

[26] X. Ren, W. Liang, and W. Xu, "Maximizing charging throughput in rechargeable sensor networks," in *IEEE International Conference on Computer Communication and Networks (ICCCN)*, Shanghai, China, Aug. 2014.

[27] M. Zhao, J. Li, and Y. Yang, "A framework of joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks," *IEEE Transactions on Mobile Computing*, vol. 13, no. 12, pp. 2689–2705, Dec. 2014.

[28] L. Xie, Y. Shi, Y. T. Hou, and H. D. Sherali, "Making sensor networks immortal: An energy-renewal approach with wireless power transfer," *IEEE/ACM Transactions on Networking (ToN)*, vol. 20, no. 6, pp. 1748–1761, Dec. 2012.

[29] L. Fu, L. He, P. Cheng, Y. Gu, J. Pan, and J. Chen, "Esync: Energy synchronized mobile charging in rechargeable wireless sensor networks," *IEEE Transactions on Vehicular Technology*.

[30] D. Mishra and S. De, "Effects of practical rechargeability constraints on perpetual RF harvesting sensor network operation," *IEEE Access*, vol. 4, pp. 750–765, Mar. 2016.
[31] S. Misra, R. R. Rout, T. R. V. Krishna, P. M. K. Manilal, and M. S. Obaidat, "Markov decision process-based analysis of rechargeable nodes in wireless sensor networks," in *Proceedings of the 2010 Spring Simulation Multiconference*, vol. 97, San Diego, CA, Apr. 2010.
[32] B. Tong, Z. Li, G. Wang, and W. Zhang, "How wireless power charging technology affects sensor network deployment and routing," in *IEEE International Conference on Distributed Computing Systems (ICDCS)*, Genoa, Italy, Jun. 2010, pp. 438–447.
[33] L. Xie, Y. Shi, Y. T. Hou, and A. Lou, "Wireless power transfer and applications to sensor networks," *IEEE Wireless Communications*, vol. 20, no. 4, pp. 140–145, Aug. 2013.
[34] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 1989–2001, May 2013.
[35] X. Zhou, R. Zhang, and C. K. Ho, "Wireless information and power transfer: architecture design and rate-energy tradeoff," *IEEE Trans. Commun.*, vol. 61, no. 11, pp. 4754–4767, Oct. 2013.
[36] J. Jadidian and D. Katabi, "Magnetic MIMO: How to charge your phone in your pocket," in *ACM MobiCom*, Maui, HI, Sep. 2014.
[37] F. Sangare, A. Arab, M. Pan, L. Qian, S. Khator, and Z. Han, "RF energy harvesting for WSNs via dynamic control of unmanned vehicle charging," *IEEE Wireless Comunications and Networking Conference (WCNC)*, New orleans, LA, Mar. 2015.
[38] Powercast, "RF energy harvesting and wireless power for low-power applications," 2011. [Online]. Available: www.powercastco.com
[39] Y. Peng, Z. Li, W. Zhang, and D. Qiao, "Prolonging sensor network lifetime through wireless charging," in *IEEE Real-Time Systems Symposium (RTSS)*, San Diego, CA, Nov. 2010, pp. 129–139.
[40] Y. Pang, Y. Zhang, Y. Gu, M. Pan, Z. Han, and P. Li, "Efficient data collection for wireless rechargeable sensor clusters in harsh terrains using UAVs," in *IEEE Global Communications Conference (GLOBECOM)*, Austin, TX, Dec. 2014, pp. 234–239.
[41] S. He, J. Chen, F. Jiang, D. K. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *IEEE Trans. Mobile Computing*, vol. 12, no. 10, pp. 1931–1942, Oct. 2013.
[42] H. Dai, L. Jiang, X. Wu, D. Yau, G. Chen, and S. Tang, "Near optimal charging and scheduling scheme for stochastic event capture with rechargeable sensors," in *IEEE International Conference on Mobile Ad-Hoc and Sensor Systems (MASS)*, Oct Hangzhou, China, Oct. 2013, pp. 10–18.
[43] L. Xie, Y. Shi, Y. Hou, W. Lou, H. Sherali, H. Zhou, and S. Midkiff, "A mobile platform for wireless charging and data collection in sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 8, pp. 1521–1533, Aug. 2015.
[44] L. Fu, P. Cheng, Y. Gu, J. Chen, and T. He, "Minimizing charging delay in wireless rechargeable sensor networks," in *IEEE INFOCOM*, Apr. 2013, pp. 2922–2930.
[45] M. M. Flood, "The traveling-salesman problem," *Operations Research*, vol. 4, no. 1, pp. 61–75, Feb. 1956.
[46] F. Sangare and Z. Han, *RF Energy Harvesting Networks: Existing Techniques and Hardware Technology*. To appear in Wireless Energy Harvesting for Future Wireless Communications, Springer-Verlag, 2016.
[47] K. Kadirvel and B. Chan, "Fundamentals of energy storage in energy harvesting applications," 2012. [Online]. Available: www.low-powerdesign.com
[48] J. A. Shaw, "Radiometry and the friis transmission equation," *American Journal of Physics*, vol. 81, no. 1, pp. 33–37, Jan. 2013.
[49] A. Bensoussan, *Stochastic control of partially observable systems*. Cambridge University Press Cambridge, 1992.

Fahira Sangare (M'10) received the B.E degree in electrical, electronics and information engineering from Nagaoka University of Technology, Japan in 2005 and the M.E.E. in electrical engineering from the University of Houston, Texas in 2013. From 2005 to 2016, he was an R&D engineer for Schlumberger, the worlds largest oilfield service company, in various countries (Japan, USA, Canada and Mexico).

He is currently pursuing a PhD in electrical engineering at the University of Houston. His research interests include wireless energy harvesting, wireless rechargeable sensor networks, mathematical optimization, and embedded software design.

Yong Xiao (S'09-M'13-SM'15) received his B.S. degree in electrical engineering from China University of Geosciences, Wuhan, China in 2002, M.Sc. degree in telecommunication from Hong Kong University of Science and Technology in 2006, and his Ph. D degree in electrical and electronic engineering from Nanyang Technological University, Singapore in 2012. Currently, he is a research assistant professor in the Department of Electrical and Computer Engineering at the University of Arizona. He is also the center manager of the NSF BWAC Center at the University of Arizona. Before he joins the University of Arizona, he worked as Postdoc Research Fellow at Nanyang Technological University, Trinity College Dublin, Massachusetts Institute of Technology and University of Houston. His research interests include machine learning, game theory and their applications in wireless networks. He is an IEEE senior member.

Dusit Niyato (M'09-SM'15) is currently an Assistant Professor in the School of Computer Engineering, at the Nanyang Technological University, Singapore. He obtained his Bachelor of Engineering in Computer Engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand. He received his Ph.D. in Electrical and Computer Engineering from the University of Manitoba, Canada. His research interests are in the areas of radio resource management in cognitive radio networks and broadband wireless access networks. Dr. Niyato has several research awards to his credit, which include the 7th IEEE Communications Society (ComSoc) Asia Pacific (AP) Young Researcher Award, the IEEE Wireless Communications and Networking Conference (WCNC) 2012 Best Paper Award, the IEEE Communications Conference (ICC) 2011 Best Paper Award, and the 2011 IEEE Communications Society Fred W. Ellersick Prize paper award. Currently he serves as an Editor for the IEEE Transactions on Wireless Communications and an Editor for the IEEE Wireless Communications Letters.

Zhu Han (S'01-M'04-SM'09-F'14) received the B.S. degree in electronic engineering from Tsinghua University, in 1997, and the M.S. and Ph.D. degrees in electrical engineering from the University of Maryland, College Park, in 1999 and 2003, respectively.

From 2000 to 2002, he was an R&D Engineer of JDSU, Germantown, Maryland. From 2003 to 2006, he was a Research Associate at the University of Maryland. From 2006 to 2008, he was an assistant professor in Boise State University, Idaho. Currently, he is a Professor in Electrical and Computer Engineering Department as well as Computer Science Department at the University of Houston, Texas. His research interests include wireless resource allocation and management, wireless communications and networking, game theory, wireless multimedia, security, and smart grid communication. Dr. Han received an NSF Career Award in 2010, the Fred W. Ellersick Prize of the IEEE Communication Society in 2011, the EURASIP Best Paper Award for the Journal on Advances in Signal Processing in 2015, several best paper awards in IEEE conferences, and is currently an IEEE Communications Society Distinguished Lecturer.