Stochastic Mobile Energy Replenishment and Adaptive Sensor Activation for Perpetual Wireless Rechargeable Sensor Networks

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***Abstract*—Recent studies have shown that environmental energy harvesting technologies have the potential to provide perpetual operation to wireless sensor networks. However, due to the large variations of the ambient energy source, such networks could only support low-rate data services and the performance is affected by many unpredictable environmental factors. To deliver energy to sensor nodes reliably, in this paper, we apply the novel wireless power transmission technology to rechargeable sensor networks by introducing a mobile actuator to replenish sensor energy wirelessly. We first establish an analytical model based on stochastic wireless energy replenishment to obtain a variety of performance metrics. Then based on the theoretical results, we further propose battery-aware mobile energy replenishment scheme and present two heuristic algorithms: (1) linear adaptation sensor activation with prioritized recharge; and (2) battery-aware activation with selective recharge. We validate the theoretical results and evaluate the performance of the proposed algorithms through extensive simulations. The results demonstrate that a good design of sensor activation with effective control of mobile energy replenishment can provide substantial performance improvement.**

***Index Terms*—Wireless sensor network, wireless charging, mobile energy replenishing, stochastic modeling, sensor activation, target detection.**

I. Introduction

Wireless energy transmission technique [1], [2] is a game-changing technology for providing energy to sensor networks. Compared to energy harvesting networks [3], [4] where the energy supply is opportunistic and not always available, it can deliver energy to sensor nodes reliably without wires or plugs. In [1] and [2] it has been demonstrated that using self-resonant coils in a strongly coupled regime, the efficiency of nonradioactive power transmission of 60 watts over 2 meters is 40%. This technology has been gaining tremendous attention from the industry and in only a few years, wireless power device has gone from lab prototype to commercial products. For example, Haier has published a completely wireless HDTV which has a remote power source [5]. Wireless power consortium [6] has released low-power standard “Qi” that opts to provide interoperability among products from different vendors. As nonradioactive wireless charging becomes more and more popular, it can also find its applications in rechargeable sensor networks.

In this paper, we employ a mobile actuator (called “SenCar”) for simultaneous energy replenishment and data collection. Sensors can be recharged wirelessly by the SenCar and we call such a network *wireless rechargeable sensor network*. As envisioned in [7], [8], a key advantage of wireless recharge over the conventional environmental energy harvesting is that the SenCar can move very closely to sensors to provide high recharge rate. A joint optimization of data collection and energy replenishment is considered in [7]. A set of sensors with energy below a threshold is chosen as the anchor points and a mobile vehicle sojourns at these locations for energy replenishment and data collection. An optimization problem to find the shortest path for energy replenishment is studied in [8]. However, in [7], [8], the decisions to recharge which sensors and in which order are predetermined. Since recharging a commercial off-the-shelf battery requires nontrivial (e.g., 30-80 min) time [9], a recharging tour consists of several tens of sensor nodes may take even days to finish and during this time energy on sensor node may change dramatically and the pre-computed optimal solution is no longer valid. On the other hand, since data is aggregated in a multi-hop fashion at the SenCar, nodes near the location of the SenCar have higher traffic load thereby consume more energy. Thus, the SenCar would move to recharge nodes in the vicinity and it finishes recharging a node, a new decision should be made according to the real-time energy information. Based on these observations, we present a new analytical model that the SenCar makes stochastic recharge decisions in real-time and further propose several dynamic algorithms to manage energy expenditure on sensors and replenishment from the mobile actuator to extend network lifetime. Thus, in this paper, we will focus on the issue of how SenCar should recharge sensors and how to adaptively activate sensors to achieve high and energy efficient system performance.

In particular, the objective of this work is to provide stochastic analysis of wireless energy replenishment and propose battery-aware energy replenishment strategies with corresponding sensor activation schemes so good network performance can be achieved while maintaining long lifetime operation of the network. We first establish a stochastic model in which the SenCar follows a two dimensional random walk and give theoretical results on the percentage of sensors that are inactive and having battery failure. Based on the theoretical results, we further propose two battery-aware energy replenishment strategies with their relevant sensor activation algorithms. To quantitatively evaluate the network performance, we introduce a typical sensing mission which is to observe a target traversing the field. Sensors need to be active to accurately detect the target. We show through extensive simulation that the proposed algorithm provides improved network performance with higher target detection rate and longer network lifetime. Our study also reveals that in order to fully utilize the structure and wireless charging capabilities of the system, we can run more complex algorithms on the SenCar to alleviate the computational burden on sensors, thus significantly improve the system performance.

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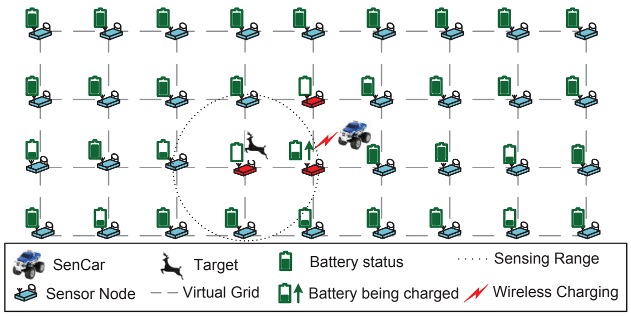


Fig. 1. System architecture of the wireless rechargeable sensor network.

The main contributions of our work can be summarized as follows. First, we propose a network architecture in which the SenCar follows a two-dimensional symmetric random walk to recharge sensors in real-time. Based on this random environment, we provide analytical solutions to various system metrics in the network and validate the correctness of theoretical results through simulations. Second, we use the insights obtained from the analytical model to further improve system performance by developing new battery-aware mobility scheme for the SenCar which retains the randomness of the system as well as prioritizes the recharge of low-energy sensor nodes. Based on this new paradigm, we propose two adaptive algorithms on sensors and SenCar for probabilistic activation and energy replenishment, respectively. Third, we conduct extensive simulations and demonstrate the robustness of the proposed algorithms for improving target detection, reducing battery failure and prolonging network lifetime.

II. System Architecture and Preliminaries

In this section, we introduce a fully discrete model that allows us to have insights of system performance. Fig. 1 gives a pictorial view of our network. In such a wireless rechargeable sensor network, each sensor has four major components: processor unit, multi-channel radio, sensing unit and an independent wireless energy charging unit. For analytical tractability, we consider sensor nodes placed regularly on a virtual grid. Time is equally slotted. At the beginning of each time slot, sensors choose to work with probability p and sleep with probability $1-p$. In the sleeping mode, major energy consumers such as sensing components and radio channel are turned off. SenCar moves on the grid following a two-dimensional symmetric random walk to recharge sensors at a constant rate. We introduce a target node for the purpose of evaluating the performance of the network. Despite in specific applications, targets exhibit certain deterministic mobile behaviors, for generality, we use a two-dimensional symmetric random walk model to characterize the target movement, which would allow us to generalize it to various real target traces. Next, we describe some more detailed assumptions in our system.

1) Energy Consumption: Let E denote the energy consumption of the network in each time slot. In this system, E could be either E_w or E_s, which are the energy consumption while the sensor is working or sleeping, respectively.

TABLE I
List of Notations

N	Total number of sensor nodes in the field.
S	State Space of Markov chain representing sensor battery energy.
$P_{i,j}$	Transition probability $P\{X_{n+1}=j\|X_n=i\}\forall i,j\in S$.
r	Probability a sensor node gets recharged in a time slot.
p	Probability a sensor node is working in a time slot.
π_L	Steady state probability sensors in mandatory sleep.
L	Sleeping threshold of a sensor.
M	Battery capacity of a sensor.
R	Energy refilled in a time slot.
E_w	Energy consumed in a time slot while working.
E_s	Energy consumed in a time slot while sleeping.

2) Sleep Threshold: To prevent sensors from depleting their battery energy, we impose a mandatory *sleep threshold*, L, on sensors. If a sensor's battery energy falls below this value, it turns into sleep mode and waits for the SenCar to recharge.

3) Recharge Rate: In our system, SenCar adopts a constant recharge rate in each time slot to refill a portion of the total battery capacity determined by the recharge rate and time. A natural question may arise here: Why not refill every sensor to its full battery capacity? The main reason is that normal battery such as NiMH battery for sensors takes 30 - 80 min to get fully charged [9]. However, during this time other sensor nodes in the field may have depleted their battery energy. Thus, refilling each battery to full capacity is prohibitive in such a system.

III. Analytical Model and Theoretical Analysis

In this section, we establish a stochastic model to analyze the energy status of sensor nodes and obtain theoretical results on energy performance of the system. The energy performance of a sensor network generally depends on two important factors: energy income and expenditure. In our network, energy income is determined by the recharge rate of the SenCar and how often the SenCar can visit each sensor node; energy expenditure is governed by sensor activation probability at the beginning of each time slot. In more detail, two parameters would have an impact on energy income which are the network size N and amount of energy refilled in a time slot R. Similarly, four parameters, sleep threshold L, sensor activation probability p, energy consumption while working E_w and sleeping E_s, would affect energy expenditure in each time slot. Next, we establish an analytical model to untangle the relationship between activation probability, recharge rate and network size, and derive a quantitative estimation to major performance metrics which are: inactive sensor percentage and sensor failure rate. Notations used in the analytical model are listed in Table I.

A. Stochastic Energy Replenishment Model

We assume that the SenCar follows a symmetric random walk and recharges R units energy in a time slot. Compared to the active mode, energy consumption at sleeping mode is negligible. We can model the wireless recharge process by a Markov chain with the state representing the energy level of a sensor node. In our model, if a node gets recharged it can

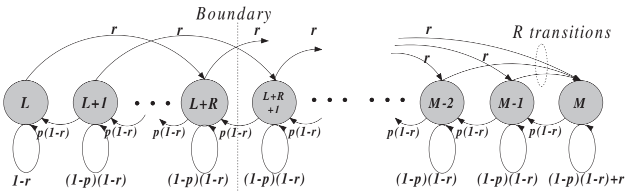


Fig. 2. Sensor energy state transition diagram.

transfer from state i to state $i+R$ in one step and if a node works in a time slot, it consumes the amount of E_w units of energy and results its energy state transferring from i to $i-1$. The state transition diagram is shown in Fig 2. Since the SenCar performs a symmetric random walk, the probability for each sensor to be recharged in a time slot is equiprobable. That is, the expected number of time slots for a sensor to get recharged is equal to the network size, N. We have $r = \frac{1}{N}$. The elements of transition matrix $\mathbf{P}$ for this Markov Chain are given by

$$P_{i,j} = \begin{cases} (1-p)(1-r), & j = i \\ r, & j = \min(i+R, M) \\ p(1-r), & j = i-1 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

for $i = L, \ldots, M$. Moreover, we have $P_{L,L} = 1 - r$ and $P_{M,M} = (1-p)(1-r) + r$. Note that the initial state of this Markov chain equals the energy level of sleep threshold L.

B. System Metrics

To find performance metrics $P_{\bar{a}}$ and P_f, which are inactive sensors percentage and sensor failure rate respectively, in our model, we need to first obtain the steady state probability that a sensor node is in mandatory sleep, denoted as π_L. To calculate π_L, we need to find the steady state probabilities of all the states which can be obtained by eigen decomposition of transition matrix $\mathbf{P}$. In our Markovian model, the amount of energy refilled R in a time slot is an input variable, where $2 \le R \le M$. It is difficult to perform eigen analysis given that R is changing and the computation complexity grows with the size of matrix $\mathbf{P}$. Fortunately, we can exploit the particular structure of this Markov chain which forms an R-th order linear recurrence equation to derive π_L. Thus, we can derive a closed form solution for π_L for the case $R = 2$ and obtain π_L for $R > 2$ using a recursive algorithm. To obtain steady state probabilities, we write equilibrium equations by making the flow across the vertical boundary between i and $i-1$ balanced.

$$\sum_{j=i-R}^{i-1} (r\pi_j) = \pi_i(1-r)p, \qquad i = L+1, L+2, \ldots, M$$

Let $\alpha = \frac{r}{(1-r)p}$. For $R = 2$, the general form of π_i can be derived as in [10]

$$\pi_i = -(\alpha\pi_{L+1} - \pi_{L+2}) \sum_{k=0}^{i-L-2} \alpha^k \binom{k}{i-L-k-2} + \pi_{L+1} \sum_{k=0}^{i-L-1} \alpha^k \binom{k}{i-L-k-1}$$

$$= \alpha\pi_L \sum_{k=0}^{i-L-2} \alpha^k \left[\binom{k}{i-L-k-2} + \binom{k}{i-L-k-1} \right] + \alpha^{i-L}\pi_L$$

$$= \alpha\pi_L \sum_{k=0}^{i-L-2} \alpha^k \binom{k+1}{i-L-k-1} + \alpha^{i-L}\pi_L$$

for $L+1 \le i \le M$. Applying constraint $\sum_{i=L}^{M} = 1$ yields

$$\pi_L = \frac{1}{\sum_{i=L+1}^{M} (\alpha \sum_{k=0}^{i-L-2} \alpha^k \binom{k+1}{i-L-k-1} + \alpha^{i-L}) + 1} \quad (2)$$

In general, deriving steady state probabilities for the case that recharge energy is R times greater than energy consumption is to solve the following R-th order linear recurrence equation

$$\pi_i = \alpha(\pi_{i-1} + \pi_{i-2} + \cdots + \pi_{i-R}) \qquad i \ge R \quad (3)$$

If the characteristic equation of Eq. (3)

$$t_i - \alpha t_{i-1} - \alpha t_{i-2} - \cdots - \alpha t_{i-R} = 0 \qquad i \ge R$$

has R distinct roots $t_1, t_2, \ldots, t_R$, then sequence π_n is a solution to Eq. (3) if and only if

$$\pi_n = \alpha_1 t_1^n + \alpha_2 t_2^n + \cdots + \alpha_R t_R^n \quad (4)$$

for $n = 0, 1, \ldots$, where $\alpha_1, \alpha_2, \ldots, \alpha_R$ are constants.

It is very difficult to obtain a closed-form solution for the general R. However, by exploiting the special structure of the Markov chain, given an arbitrary R, we could sequentially solve it using a recursive algorithm shown in Algorithm 1. Note that this Markov chain can be seen to have the structure of Type A non-product form as referred to in [11]. The key of this algorithm is that for each transition there is only one unknown external probability entering the known subsets of probabilities. The algorithm first sets the value of π_L to 1 then computes the fraction of subsequent steady state probabilities iteratively, sums up all the unnormalized values from π_L to π_M and finally normalizes to the equilibrium state probabilities.

Algorithm 1 Recursive Algorithm for Calculating π_i

Initialization: $i = L$, P_i = 1, q = 0, j = 1
P_i is the unnormalized state probability
while $i \le M$ **do**
    while $j \le R$ **do**
        if $i - j \ge 1$ **then**
            $q \leftarrow q + P_{i-j}$
        end if
        $j \leftarrow j + 1$
    end while
    $P_i \leftarrow (q \cdot r)/(1-r)$
    Reset $q \leftarrow 0$
    $i \leftarrow i + 1$
end while
Normalization $\pi_i = P_i / \sum_{i=L}^{M} P_i$
Return π_i

After obtaining π_L, the percentage of sensor nodes that are inactive after the network achieves an equilibrium can be estimated by

$$P_{\bar{a}} = (1-\pi_L)(1-p) + \pi_L = 1 - p + \pi_L p \quad (5)$$

The percentage of sensors below the sleep threshold that would ultimately fail is

$$P_f = (1-r)^{LE_w/E_s}\pi_L \quad (6)$$

The derivation of $P_{\bar{a}}$ and P_f can help network administrator plan the network at the initial stage. Once the experimental parameters and the application specifics from the sensors have been determined (e.g., network size N, battery capacity M, sensor sleeping threshold L, activation probability p, sensor energy consumption while working and sleeping E_w and E_s, energy refilled in a time slot R), we can easily obtain the percentage of inactive nodes and failure rate of the network. Therefore, our analytical model can provide great insights to the feasibility of a network plan. As will be seen later, we also validate the correctness of the theoretical results using simulations.

IV. Sensor Activation and Mobile Energy Replenishment Algorithms

There were two problems in the analytical model. First, the SenCar follows a random walk mobility model regardless of energy states of sensors. Second, the static sensor activation may result in high failure rate. Thus, in this section we further develop two adaptive algorithms: linear adaptation with prioritized recharge (LAPR) and battery-aware sensor activation with k-step selective recharge (BSR). Here, k is the number of time slots sensors can work using recharged energy. BSR is more complex in its energy replenishment components on the SenCar. We want to show that through more sophisticated algorithm design on the SenCar, network performance can be further improved. In contrast to the two dimensional grid topology used in our analytical model, both algorithms are designed based on random sensor deployment to meet the requirements of real applications. In order to offer a benchmark to evaluate the proposed algorithms, we use a static probability sensor activation and random walk recharge (SRR) as the basic scheme. In SRR, sensors follow a static probability p = 0.5 to work and sleep randomly in each time slot and SenCar performs a symmetric random walk on the grid to recharge sensors at a constant rate.

A. Linear Adaptation and Prioritized Recharge Algorithm (LAPR)

The limitation of SRR is that sensors are lack of adaption to their battery energy and SenCar recharges sensors regardless of their different energy states. To tackle this problem, we propose the linear adaptation and prioritized recharge algorithm on sensors and SenCar, respectively. In our algorithm, the probability to work in the $(i+1)$-th slot p_{i+1} is reduced by Δ_d if a node works in current time slot i. By the same token, the probability to work in the $(i+1)$-th slot p_{i+1} is increased by Δ_i if a node sleeps in current time slot i. When a sensor detects the target in its sensing range and its energy is more than the mandatory sleep threshold L, it maintains active for the next time slot. Each time the battery energy is refilled by the SenCar, the sensor resets the activation probability to a value proportional to the ratio of the current recharge energy R to the full battery capacity M.

On the energy transporter's side, SenCar should have a higher priority to recharge nodes with lower energy based on the energy level in real-time. Symmetric random walk used in SRR suffers from slow field exploration at the contingency of sensor battery failure. In other words, the SenCar might blindly move to a position where the surrounding sensors' average energy level is high but miss the position where the average energy level is low and some sensor batteries are nearly depleted. To avoid this situation, we revise the symmetric random walk model by proposing *battery-aware mobility* for the SenCar. When the SenCar finishes recharging nodes around its current position, it sends a message to request battery information from nodes within the distance of the next movement, stores or updates their battery information in local memory. If a node is in sleep mode and does not respond, the SenCar will use the previously stored battery information. Suppose that the SenCar finishes recharging sensors around intersection point (i,j) and it uses the mean value of battery energy in four directions to calculate the next slot moving probability. Let b_1, b_2, b_3 and b_4 represent the average battery energy of sensors in the area to the directions of intersection points $(i,j-1)$, $(i-1,j)$, $(i+1,j)$ and $(i,j+1)$, respectively. $P(i,j)$ is the transition probability that the SenCar is at position (i,j) in the next time slot. We have

$$P(i,j+1) = \frac{b_1b_2b_3}{b_1b_2b_3 + b_1b_4b_3 + b_2b_3b_4 + b_1b_2b_4} \quad (7)$$

$$P(i-1,j) = \frac{b_1b_3b_4}{b_1b_2b_3 + b_1b_4b_3 + b_2b_3b_4 + b_1b_2b_4} \quad (8)$$

$$P(i,j-1) = \frac{b_2b_3b_4}{b_1b_2b_3 + b_1b_4b_3 + b_2b_3b_4 + b_1b_2b_4} \quad (9)$$

$$P(i+1,j) = \frac{b_1b_2b_4}{b_1b_2b_3 + b_1b_4b_3 + b_2b_3b_4 + b_1b_2b_4} \quad (10)$$

Note that when the average energy in four directions are all equal, this scheme reduces to a symmetric random walk as that used in SRR and previous assumptions. Advantages of using this battery-aware mobility scheme are that we do not lose connections to the previous analysis and also retain the randomness of the moving decision, while correlating sensor's energy with SenCar's mobile behavior. In general, this strategy can be considered as a variation of symmetric random walk. Algorithm 2 shows the pseudocode of the scheme.

B. Battery-aware Sensor Activation and k-Step Selective Recharge Algorithm (BSR)

In the LAPR algorithm, it is possible that the algorithm would reduce the activation probability to a very small value, which could significantly lower the probability of detecting the target, and it is also possible for SenCar to move to a position (i,j) where it has visited in the previous l steps, $l < k$ and $k = \frac{R}{E_w}$. Due to these reasons, we further propose a battery-aware activation scheme combined with SenCar's

Algorithm 2 Linear Adaptation and Prioritized Recharge (LAPR)

Sensor Activation: Get p_i and E_i from the memory.
if $L \leq E_i$ **then**
  if sensor is working **then**
    $p_{i+1} \leftarrow p_i - \Delta_d$.
  else
    $p_{i+1} \leftarrow p_i + \Delta_i$.
  end if
else
  $p_{i+1} \leftarrow 0$.
end if
if sensor detects target AND $E_i \geq L$ **then**
  Remain active for the next time slot, store p_i in the memory.
end if
After sensor gets recharged by the SenCar: Reset activation probabilities: $p_i \leftarrow R/M$.
SenCar Mobility: Get current position coordinates (i, j).
Calculate transition probability $P(i+x, j+y)$ using Eq. (7) - (10) ($[x, y]$ from [0,1], [0,-1], [1,0] and [-1,0]).

k-step selective recharge. A k-step selective recharge is a variation of the battery-aware mobility scheme in LAPR except the difference illustrated below.

In this algorithm, sensors calculate the activation probability p_{i+1} in the next time slot based on its residual energy E_i at the i-th slot and battery capacity M, which is p_{i+1} = E_i/M. On the other hand, SenCar follows a k-step mobility model. That is, it remembers the k previous nodes recharged and excludes those nodes from the destination selection (moving probability calculation) in the next time slot by maintaining a list $A[\,]$ with size k. In this way, SenCar will prioritize to recharge those nodes that have not been recharged in the previous k steps. The detail of this combined approach is shown in Algorithm 3.

Algorithm 3 Battery-aware Activation and k-Step Selective Recharge (BSR)

Sensor Activation: Get E_i from the memory.
if $E_i \geq L$ **then**
  $p_{i+1} \leftarrow E_i/M$
else
  $p_{i+1} \leftarrow 0$
end if
if sensor detects target AND $E_i \geq L$ **then**
  Remain active for the next time slot, store p_i in the memory
end if
SenCar Mobility and Recharge: Get current position coordinates (i, j) and list $A[\,]$.
if node l existed in list $A[\,]$ **then**
  Exclude l from next step probability calculation
else
  Calculate transition probability $P(i+x, j+y)$ using Eq. (7) - (10) ($[x, y]$ from [0,1], [0,-1], [1,0] and [-1,0])
end if
After recharge node j, add j at the end of list $A[\,]$, remove first element in list $A[\,]$.

TABLE II
SIMULATION PARAMETERS

Parameters	Value	Parameters	Value
M	2000 (units)	N	200
R	[50,1000] (units/s)	L	20 (units)
E_w	10 (units/s)	E_s	1 (unit/s)
Δ_d(in LAPR)	0.005	Δ_i(in LAPR)	0.005
Sensing range	25(m)	Field area	500 $\times 500(m^2)$
SenCar speed	2 (m/s)	Target speed	3-10 (m/s)
Simulation time	50000(s)	p (in SRR)	0.5

V. SIMULATION RESULTS

In this section, we validate the analytical model introduced in Section III and evaluate the performance of the proposed algorithms through Matlab simulations.

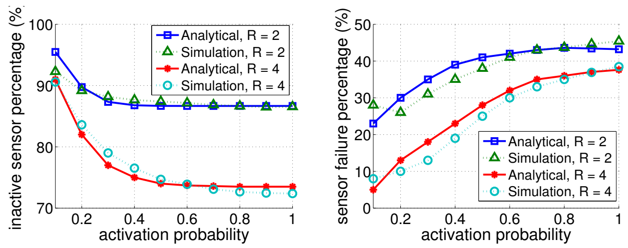
In the simulation evaluation of our proposed algorithms, we consider a field size of $500 \times 500m^2$ with 200 sensor nodes randomly deployed. The target node follows a Random Waypoint Mobility with the speed uniformly distributed from 3 to 10 m/s. SenCar moves on the virtual grid at a constant speed of 2 m/s. To the best of our knowledge, this is the first work that considers stochastic energy replenishment using wireless power transfer. Thus, we will compare the two proposed algorithms with the basic scheme, SRR. Table II has listed all the simulation parameters. We will first validate our analytical model through simulations and then evaluate target detection probability, node sleeping percentage, failure rate and network lifetime.

A. Validation of Analytical Model

To validate theoretical results and compare with simulations, we implement our analytical model on a 4×4 grid with 16 sensor nodes and set battery capacity M = 50. Though a large L could offer a buffer zone to prevent battery failure, many sensors could be sent into unnecessary sleep. Therefore, we set the sleep threshold L to be 5% of total battery capacity M. We have applied our theoretical results to R = 2 and 4 (recharge rates 20 and 40 units/s), respectively, in the simulation with the same environment. First, we observe the activation probability p's impact on system performance with $0.1 \leq p \leq 1$. Fig. 3 shows the percentage of inactive sensors and failure rate obtained from Eq. (5) and Eq. (6) versus simulation results. In general, our theoretical results matches with simulations except some small inaccuracies. Those imperfections are mainly caused by the fact that energy consumption in the sleeping mode is ignored in the analytical model. Once the energy consumption while working, E_w, is much higher than energy consumption while sleeping, E_s, the difference between the theoretical results and simulations could be narrowed. Nevertheless, the purpose of the analytical model which serves to illustrate the quantitative relationships remains intact despite the minor imperfections. By utilizing our theoretical analysis, network administrator can make reasonable estimations for the feasibility of a network plan.

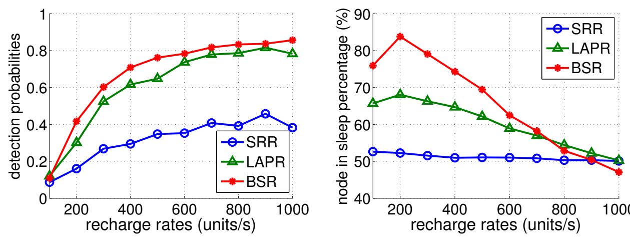
B. Target Detection

In this subsection, we evaluate the proposed algorithms LAPR and BSR through extensive simulations and compare



(a) (b)

Fig. 3. Theoretical vs. simulation results (a) Inactive sensor percentage. (b) Sensor failure percentage.



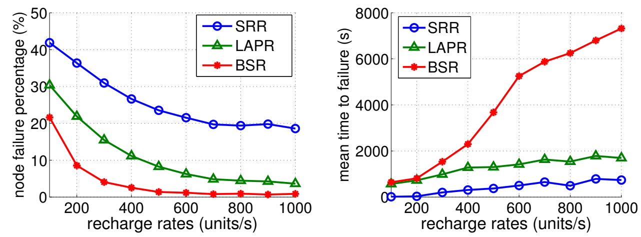
(a) (b)

Fig. 4. Network performance (a) Target node detection probability. (b) Percentage of node in sleep.

their performance in terms of target detection probability and percentage of node in sleep with the basic scheme SRR. Fig. 4 shows the target detection probability and node sleep percentage under different recharge rates. We can see that battery-aware activation with SenCar's k-step selective recharge (BSR) algorithm outperforms other two algorithms. SRR reaches a limit around 40% detection probability, whereas LAPR and BSR are able to push the detection probability over 80% in Fig. 4(a). Fig. 4(b) shows the average percentage of sensor nodes to the whole network that are in sleeping mode. We can see that as the recharge rate increases, the sleep percentage of BSR drops faster than LAPR, which means that the BSR approach could adaptively wake up more sensors given sufficient energy resources. It means that by incorporating a more complex recharge scheme on SenCar, sensors can utilize the available energy more efficiently when resources are abundant.

C. Node Failure and Network Lifetime

In addition to attaining better detection performance, another objective of the proposed algorithms is to prevent sensor nodes from running out of battery and extend network lifetime towards perpetual operations. Fig. 5(a) is a comparison of the failure rate under different recharge rates. We can observe that BSR and LAPR can achieve less than 5% node failure, whereas SRR will ultimately result in 18% node failed even given sufficient energy supply. This is due to the fact that recharging sensors with a random walk does not prioritize nodes near energy depletion, however, BSR and LAPR algorithms are benefited from the priority in selecting those sensors prone to fail. Fig. 5(b) shows the average network lifetime under different recharge rates. We can see that LAPR and BSR have extended network lifetime over two times than SRR even at low recharge rates. We can also observe that



(a) (b)

Fig. 5. Network performance (a) Sensor node failure percentage. (b) Network lifetime comparison.

when the recharge energy is sufficient, the average network lifetime under BSR increases much faster than LAPR.

VI. Conclusions

In this paper we have proposed an architecture for wireless rechargeable sensor networks based on the novel wireless charging technique and given two energy management algorithms under this architecture. We first established an analytical model to derive theoretical results on system metrics. Based on the indication that using a static probability activation is not energy efficient, we then proposed two comprehensive algorithms for sensor activation and energy replenishment, which yield significant performance improvement when we add complexities on the SenCar. We believe this work could spark many future venues for research on energy efficiency in wireless networks from a different perspective other than energy harvesting networks.

VII. Acknowledgements

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