STONY BROOK UNIVERSITY

CEAS Technical Report 834

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

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March 31, 2011

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Abstract—**Recent studies have shown that environmental energy harvesting technologies have the potential to provide perpetual operation to rechargeable sensor networks. However, due to the large variations of the ambient energy source, such networks could only support low-rate data services and their performance is influenced by numerous unpredictable environmental factors. In order to bridge this gap to yield high and controllable recharge rates, we import the novel wireless power transmission technology to rechargeable sensor networks. We propose that by combining traditional mobile data sink whose role is data collection with wireless energy replenishment would suffice our needs to offer short-time high rate data service and refill sensor's battery energy at the same time. In this paper, a new network architecture based on wireless energy replenishment is presented. We establish an analytical model to show the potential using probabilistic sensor activation and mobile energy replenishment could improve the system performance and elongate network lifetime. Second, we introduce three protocols (1) static activation on sensors (2) linear adaptation activation with prioritized recharge (3) battery-aware activation with selective recharge. Finally, we compare these protocols by extensive simulations and show that a smart design of sensor activation with effective control of mobile energy replenishment can provide significant performance improvement and elongate the lifetime of the network by over ten times even in the worst case.**

Index Terms—**Wireless power charging, rechargeable sensor networks, mobile energy replenishment**

I. INTRODUCTION

Recent studies of energy harvesting in wireless sensor networks have shown that by capturing renewable energy resources from the environment, it is possible to extend the lifetime of a sensor network to indefinitely long operation. A majority of the previous research considered using solar power, a renewable energy source and its availability depends on a variety of environmental factors. Clouds, fog, air pollution and building obstructions could attenuate the power arrives at the solar panel. Due to large intra-day variations and unavailability of sunlight during the night, network protocols aim to support solar power harvesting have to suppress sensor energy consumption in order to maintain energy neutral operations [11],[12]. A great portion of energy from the daytime surplus (if there is any) has to be reserved for the nighttime operations [6]. For example, if the sensor's task is monitoring a field for certain targets or events, we would expect very low performance once there is a shortage of the sunlight. Therefore, environmental energy harvesting techniques could only provide low-rate data services and the network performance is significantly influenced by unknown environmental factors.

In this paper, we propose a novel approach using wireless power transmission to recharge sensors. Our work is inspired by the recent breakthroughs in wireless energy transfer. 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 just a few years, wireless power device has gone from lab prototype to commercial products. Haier has published a completely wireless HDTV which has a remote power source [9]. For low-power circuit devices such as phones, cameras and media players, wireless power consortium [10] has just 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 be implemented in sensor networks. In this paper, we use a multi-functional mobile actuator (denoted "SenCar" for convenience), which is equipped with high-capacity rechargeable batteries, a resonant coil and a DC/AC converter. Once SenCar moves into the proximity of a sensor node, it first converts power in the battery using DC/AC converter to induce a magnetic field around the transmitting coil on the SenCar. Then the sensor nodes tuned its frequency to resonate with the transmitter coil and converts the received energy to DC current through an AC/DC converter. In addition to acting as a mobile energy transporter, SenCar can jointly perform the task as data sink to collect sensed data while charging sensors. A key advantage of this approach to merging recharge and data collection together over conventional environmental energy harvesting is the SenCar can move very closely to sensors to provide high recharge rate as well as short time high-rate data transmission without worrying about sensor energy depletion. Unlike in environmental energy harvesting the recharge rate depends on various uncontrollable non-human factors, in our wireless recharge framework, the availability of energy only depends on the mobile behavior of the SenCar. Furthermore, we can implement complicated algorithms on the SenCar which we assume having considerably larger computation, storage and battery capacity than the sensor nodes. Hence, 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.

The objective of our work is to design mobility pattern and energy replenishment algorithms on the SenCar and corresponding sensor activation schemes so that good network performance can be achieved while maintaining perpetual operation of the network. To provide a criteria to measure network performance, we assume the sensing mission is to observe a target traversing the sensor field. Sensors need to be active to accurately detect the target. If a sensor node consumes too much energy and mandatorily tunes into sleep mode to conserve energy, it might miss the target thereby degrade the overall surveillance performance. Thus, designing robust and distributed sensor activation algorithms which takes the random behavior of the target and the mobility pattern of SenCar into account is critical to the detection performance. On the other hand, SenCar's mobility and energy supply determine the lifetime of the network which would implicitly impact on the overall detection performance. For the ease of analysis, we establish a completely discrete model in which time is equally slotted and sensors are placed uniformly on a two dimensional grid. SenCar will follow certain mobility patterns on the grid to recharge sensors. In the meanwhile, the target node performs a symmetric random walk on the grid and the objective is to detect and delineate the trajectory of the target as accurate as possible.

The rest of this paper is organized as follows. Section 2 summarizes the previous work. In Section 3, we introduce our system architecture and establish an analytical model to untangle the relationships between key parameters in our system. Based on the analytical model, in Section 4, we present three protocols with their results evaluated in Section 5. Finally, Section 6 concludes this paper.

II. Related Work

Environmental energy harvesting in sensor networks has been intensively studied recently. A distributed framework is proposed in [5] so that sensors could adaptively learn the energy environment and exploit energy resources efficiently to increase network lifetime. In [11] and [7], several adaptive duty cycling algorithms were presented which can adjust sensor duty cycle according to the available energy and maintain energy neutral operations under the variability of environmental energy profile. Two dynamic active time scheduling schemes are introduced for a solar energy harvesting network in [6]. Their protocols take the probabilistic nature of energy income and expenditure into consideration and show great improvement to extend network lifetime. Deploying redundancy in a rechargeable sensor network is exploited in [8], in which dynamic node activation schemes are proposed to maximize the system performance. However, the aforementioned literatures are based on the framework of environmental energy harvesting. Due to the fact that the availability of ambient energy resources is unpredictable and harvested energy is usually not enough compared to sensor energy consumption, node deployment redundancy and complicated energy management algorithms on sensor node are the two main approaches to extend network lifetime in an environmental energy harvesting network. In a wireless rechargeable network, energy profile becomes completely different from an environmental energy harvesting network that we could design algorithms on how to selectively recharge sensors instead of increasing deployment redundancy to improve network performance. On the other hand, we could also alleviate some of the computational burden on sensors through a mobile actuator. Thus, the design of such protocols is a new challenge in a wireless rechargeable network. The possibility of using wireless power charging in a rechargeable sensor network is envisioned in [3]. Field experiments with equipment from Powercast [4] are conducted and revisions of node deployment and routing to conventional non-rechargeable sensor network are proposed. In this paper, we present a new network architecture with combining the role of data collection and wireless recharge through a mobile actuator(data sink equipped with wireless charging circuits) and subsequently propose several protocols that coordinate sensors with SenCar to extend the lifetime of the network.

III. System Architecture and Analytical Model

In this section, we present the system architecture of our wireless rechargeable sensor network and an analytical model to estimate the detection performance under different activation probabilities.

A. System Architecture

We now describe the system architecture of our work. Fig. 1 gives a pictorial view of our network. Sensors have three

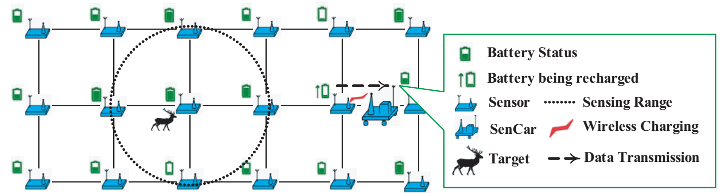

Fig. 1. System architecture of the wireless rechargeable sensor network.

major components: processor unit, multi-channel radio, sensing unit and an independent wireless energy charging component. Sensor nodes are placed uniformly on a virtual grid. A target node moves on the grid following a symmetric random walk. It can represent any event of interest such as hostile vehicles or monitored herd in the habitat. Time is equally slotted. We assume the target node has constant speed. In each time slot, sensors either choose to work or sleep following a predetermined probability. In the sleeping mode, major power consumers such as sensor components and radio channel are turned off. And we assume some spatial overlaps of the sensing range. That is each sensor covers its four neighboring nodes in the sensing range. In other words, for a target in a specific intersection, only one of the five sensors needs to be active to successfully detect the target. SenCar also moves on the grid following some mobility patterns to recharge sensors and collect data. The simplest mobility pattern is the SenCar selects a random position to start and follows a symmetric random walk. More complicated mobility patterns depend on sensor's battery energy will be presented in the subsection. When the battery energy of a sensor falls below a threshold, sensors mandatorily tune into sleep mode to reduce energy consumption and wait for recharge. In this paper, we assume sensors do not communicate with each other and they only exchange information with the SenCar. Though we realize that this discrete system model cannot accurately describe the real scenario, it at least gives us some insight into this new design of rechargeable sensor network.

1) Energy Consumption: Let E_i denote the energy consumption of the network at i-th slot. E_w and E_s are the energy consumption in a slot while the sensor is working and sleeping, respectively. N is the total number of sensors and A_i is the number of sensors working in i-th slot. Thus the energy consumption in i-th slot is,

$$E_i = E_w A_i + E_s(N - A_i) \tag{1}$$

Though power consumption depends on various system parameters such as transmission power, sensing range, battery leakage and certain non-linear battery effects, the utilization of SenCar could help alleviate major fluctuations due to transmission. Because SenCar can recharge sensors at high efficiency at very short distance, and the instantaneous recharge rate is much higher than the power consumption rate, we can ignore the power consumption fluctuation due to transmission and simply consider both E_w and E_s as average values.

2) SenCar Mobility and Recharge with Priority: SenCar's mobility pattern is critical to the lifetime of the sensor network. If a mobility algorithm leads to a dead loop in the field, there is no chance for most of the sensors to be recharged on time. Our goal is to design a totally randomized mobile scheme which would avoid the SenCar being locked in a trail and make mobility decisions at run-time. On the other hand, it is also important for the SenCar to move more aggressively to the sensor nodes having lower battery energy. Otherwise, a node failure will not only degrade the surveillance performance but also create a blind region and fragment the network. Thus, we propose a probabilistic-based mobility model in which after the SenCar finishes recharging the node at its current position, it requests battery information from four neighboring nodes, store or update their battery information in local memory. Once a neighboring node is in sleep mode and does not respond, the SenCar will use the previous stored battery information. Assume the SenCar finishes recharging sensor at location (i, j) and it uses its four neighboring battery energy to calculate the next slot moving probability.

$$p_{(i,j+1)} = \frac{1}{1 + \frac{b_{(i,j+1)}}{b_{(i-1,j)}} + \frac{b_{(i,j+1)}}{b_{(i,j-1)}} + \frac{b_{(i,j+1)}}{b_{(i+1,j)}}} \tag{2}$$

$$p_{(i-1,j)} = p_{(i,j+1)} \frac{b_{(i,j+1)}}{b_{(i-1,j)}} \tag{3}$$

$$p_{(i,j-1)} = p_{(i,j+1)} \frac{b_{(i,j+1)}}{b_{(i,j-1)}} \tag{4}$$

$$p_{(i+1,j)} = p_{(i,j+1)} \frac{b_{(i,j+1)}}{b_{(i+1,j)}} \tag{5}$$

Equations (2) - (5) represent probabilities to move to sensor locations at $(i, j+1)$, $(i-1, j)$, $(i, j-1)$ and $(i+1, j)$ respectively. $b(i, j)$ is the battery energy of sensor at location (i, j). In this mobility model with taking consideration of sensor's energy, SenCar would have a higher probability to move to the direction in which sensor has a lower battery energy. Once the four neighboring nodes have the same battery energy, this scheme converges to a symmetric random walk. By using this mobility model, we correlate sensor's energy level with the energy transporter's mobile behavior in hope that SenCar would take higher priority to recharge those nodes consume more power to avoid node failure.

3) Target Model: We introduce a target node for the purpose to evaluate our proposed algorithms. Despite in specific application targets exhibit certain deterministic mobile behaviors, we use a simple 2-dimensional symmetric random walk model which allows us to generalize various real target traces. Thus, the target node at coordinate (i, j) has transition probability 1/4 to each direction.

4) Sleep Threshold: To prevent sensors from depleting their battery energy, we impose a mandatory sleep threshold on sensors. If a sensor's battery level falls below this value, it tunes into sleep mode and waits for the SenCar. Obviously, the choice of this value is critical to the performance and lifetime of the network. That is, if the sleep threshold is too large, a large portion of sensors are falling into unnecessary sleep. While this value is too small, the network is vulnerable to node failure.

B. Analytical Model

The detection performance of our wireless rechargeable sensor network basically depends on two important parameters: sensor activation probability and SenCar recharge rate. In this subsection, we establish an analytical model to derive the relationship between activation probability, recharge rates and detection performance.

We assume the SenCar follows a symmetric random walk to recharge sensors and compared to active mode, energy consumption at sleeping mode is negligible. All commonly used symbols and notations are listed in Table I.

TABLE I
NOTATIONS USED IN ANALYTICAL MODEL AND SIMULATIONS

Notations in Analytical Model	
X_n	A discrete-time Markov chain
S	State Space of the Markov chain represents the node battery energy
N	The number of sensor nodes on the grid
$p_{i,j}$	The transition probability $p\{X_{n+1} = j \| X_n = i\} \forall i, j \in S$
p_r	Probability a sensor node is recharged in a time slot
p	Probability a sensor node is active in a time slot
L	Sleeping threshold of the system
C	Battery capacity of a sensor
R	Recharged energy in a time slot
Notations in Simulation	
E_i	Sensor's residual energy in i-th time slot
U	Upper threshold 2/3 of the total battery capacity
a_i	Activation probability in i-th time slot
Δ_d	Linearly decreasing steps
Δ_i	Linearly increasing steps
T_w	Number of time slots sensor can work using the residual energy
T_d	Number of time slots till next arrival of SenCar
K	$\lceil R/E_w \rceil$
$A[]$	An array stores K previous visited sensor node locations
L_1,L_2	Two battery energy benchmarks to adopt different recharge rates
R_1,R_2	Two recharge rates: $R_1 < R < R_2$

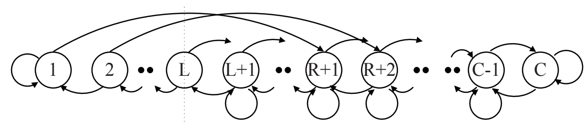

Fig. 2. Sensor energy state transition diagram.

The state of the Markov chain is the energy of a sensor node and we assume unit energy consumption in the active mode. 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 [14].

$$p_r = \frac{1}{N} \tag{6}$$

We next write the state transition probabilities, for $i \in [1, C]$,

$$p_{1,1} = 1 - p_r, \qquad i = 1 \tag{7}$$

$$p_{i,i-1} = \begin{cases} p(1-p_r), & i > L \\ 1 - p_r, & 2 \le i \le L \end{cases} \tag{8}$$

$$p_{i,i} = (1-p)(1-p_r), \qquad i > L \tag{9}$$

$$p_{i,i+R} = p_r, \qquad i + R \le C \tag{10}$$

$$p_{i,C} = p_r, \qquad i + R > C \tag{11}$$

This model resembles a *Geom/Geom/m/N* queueing system and we are interested in the stationary probabilities that a sensor node is in sleeping mode, which is $\sum_{i=1}^{L} \pi_i$, π_i is the stationary probability of state i. An advantage of this simple analytical model is that we can compute π_i iteratively and then normalize equilibrium state probabilities. The complete procedure is shown in [15]. The equilibrium sleeping probability p_s and target detection rate p_d can be calculated once we obtain stationary probabilities.

$$p_s = \sum_{i=1}^{L} \pi_i \tag{12}$$

$$p_d = 1 - p_s^5 \tag{13}$$

We analyze a 100-node sensor network using this model. Fig. 3(a) is the detection probability given sensor activation probability

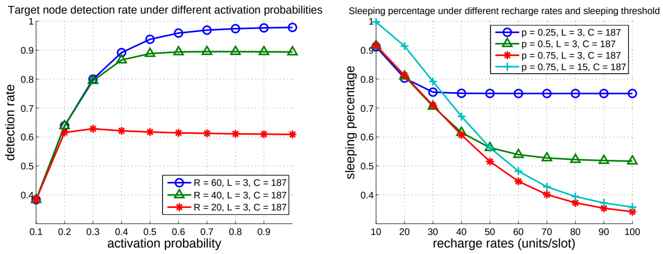

Fig. 3. Detection rate and sleeping probability of a 100-node sensor network. (a) Detection rate under different sensor activation probabilities. (b) Sleeping probability under different recharging rates and sleeping thresholds.

from [0.1,1]. Intuitively, under the same recharging rate, detection performance increases with sensor activation probability as sensors are more active, the chance of detecting the target node is higher. However, it reaches a limit and further increase activation probability does not increase detection rate anymore(at low recharge rates further increasing activation probability would degrade performance). On the other hand, in Fig. 3(b), our goal is to minimize the sleeping probability and at the same time ensure that few sensor has battery failure. Likewise, we can see that sleeping probability decreases with a higher recharge rate. Increasing the sleeping threshold from 3 to 15 would have prevented node failure but degrade network performance. Our analytical model suggests that unlike in an environmental energy harvesting network which requires certain deployment redundancy to bridge the gap between low harvesting rate and high consumption rate, we could improve system performance by increasing recharge power. Furthermore, it indicates that using a static activation probability would not be energy-efficient so that simply increasing recharge rate would not increase system performance after the detection rate reaches a limit. In addition to sensors which could adaptively tune their activation probability, SenCar could also use different recharge rates according to sensor having different battery energy to prevent sensor from being put to mandatory sleep. Thus, we need to develop several distributed activation algorithms combining with mobile energy replenishment which collectively adapt to the scenario of various recharge rates, achieve better detection performance, minimize node failure and elongate network lifetime. In other words, at different recharge rates, sensors should be able to smartly tune the activation probability to maximize the use of obtained energy.

IV. Sensor Activation and Mobile Energy Replenishment Algorithms

In the previous section, the analytical results suggest that static activation approach is not robust enough to generate good performance even given ample energy resources. Another drawback is the lack of adaptation and prediction to random target behavior. Thus, we propose two adaptive algorithms in this section.

A. Static Probability Sensor Activation and Random Walk Recharge(SRR)

This basic algorithm offers a benchmark to evaluate proposed schemes. Sensors follow a static probability p = 0.5 to work and sleep randomly and SenCar performs a symmetric random walk in the field to recharge sensors irrespective to their battery energy.

B. Linear Adaptation and Prioritized Recharge(LAPR)

This algorithm originates from the idea that sensor nodes work longer should have less chance to consume energy in the next time slot and those sleep longer should have more chance for surveillance. It can be done by decreasing activation probability and increasing activation probability in the next time slot respectively. SenCar should also have a higher priority to recharge nodes with lower energy. When a sensor detects a threat in its sensing range, it checks to see if its residual battery energy is larger than the mandatory sleep threshold. If it is true, the sensor maintains active for the next time slot. Each time the battery energy is refilled by the SenCar, sensor resets the activation probability to a value proportional to the ratio of the current recharge rate and battery capacity. We also define a threshold to be 2/3 of the total battery capacity that if a sensor's energy is above this threshold, it remains active at all time whereas energy drops below this threshold, it follows the aforementioned linear adaptation strategy. Table II shows the pseudocode of the algorithm. Due to the probabilistic nature of our system, extending successive surveillance time improves the detection performance while a threat is present. By adjusting activation probability, it could reach an equilibrium around a probability value. In this algorithm, SenCar follows the mobility pattern with prioritized recharge of those sensors having lower energy. Incorporating prioritized recharge with sensor's adaptation, our goal to drive the SenCar to recharge those sensors having lower battery energy is achieved and this algorithm further renders merits to reduce unnecessary energy consumption as mentioned in Fig.3(a) the key is to find a probability value p that generates good performance at lowest energy cost.

TABLE II
Linear Adaptation and Prioritized Recharge

Get p_i and E_i from the memory
  if $E_i > U$ p_{i+1} = 1
  elseif $L \leq E_i \leq U$
    if the sensor is working p_{i+1} = p_i - Δ_d
    else the sensor is sleeping p_{i+1} = p_i + Δ_i
    endif
  elseif $E_i < L$ p_{i+1} = 0
  endif
if a sensor detects the target node AND $E_i \geq L$
Keep this sensor on for next time slot, store p_i in the memory
endif
After sensor gets recharged by the SenCar: Reset activation probabilities to $p_i = R/C$.

C. Battery-aware Sensor Activation and K-step Selective Recharge(BSR)

A drawback of the previous algorithm is that it is possible the algorithm would reduce the activation probability to a very small value and diminish the chance of detecting the target and it is also possible for SenCar to move to (i, j) where it has visited in the previous k steps. Since the algorithm on sensors should be as straightforward as possible given their limited computation power and battery capacity, it is more desirable to implement complicated algorithms on the SenCar. In the previous linear adaptation scheme, sensor's operation is not directly connected with its residual battery energy. Thus, we further propose a battery-aware activation scheme combined with SenCar's k-step selective recharge.

In each time slot, sensors calculate the time duration they can work from their residual energy and estimate the duration till next arrival of the SenCar using historical data. Sensors log the timestamp of every visit of the SenCar and average over the past k interarrival time of the SenCar to form an estimation of

TABLE III
BATTERY-AWARE ACTIVATION AND K-STEP SELECTIVE RECHARGE

Sensor Activation:
Get E_i from the memory, then calculate
T_w = round(E_i/E_w)
  if $E_i \geq L$
  $T_d = \sum_{j=i-k+1}^{i} T_{d(j)}/k$
  $p_{i+1} = T_w/(T_w + T_d)$
  else
  p_{i+1} = 0
  endif
if a sensor detects the target node AND $E_i \geq L$
Keep this sensor on for next time slot, store p_i in the memory
endif
  if $E_i \leq L_1$ recharge at rate R_1
  elseif $L_1 < E_i \leq L_2$ recharge at rate R
  elseif $E_i > L_2$ recharge at rate R_2
  endif
 SenCar Mobility:
 Get current location coordinates (i, j)
 Search for four neighboring nodes $(i+1, j)$, $(i-1, j)$, $(i, j+1)$, $(i, j-1)$ in $A[]$
   if node(s) existed in $A[]$
   exclude them from next step direction calculation
   elseif search returns null
   use four neighbor's battery energy to calculate next step probability
   endif
 Obtain next step movement decision (i', j') and update $A[]$:
 Duplicate $A_d[] = A[]$ before update $A[]$
 $A[1] = (i', j')$, $A[2] = A_d[1]$, ...,
 $A[x] = A_d[x-1]$, x from 2 to K.

the next arrival. SenCar follows a k-step mobility model. That is, it remembers the k previous nodes visited(recharged) and excludes those nodes from the destination selection in the next time slot. In this way, SenCar will prioritize to recharge those nodes have not been visited in the previous k steps, where k depends on the ratio of average recharge and discharge energy. Note that a key advantage of this algorithm over conventional environmental energy harvesting is that energy supply becomes controllable and we could design algorithms to satisfy sensor's energy demands. To make recharge adaptive to sensors having different energy levels, we can adopt different recharge rates which is to increase recharge rate to sensors near energy depletion and decrease recharge rate to sensors with high energy level. The detail of this combined approach is shown in Table III.

V. SIMULATION RESULTS

To compare the proposed schemes, we develop a simulation environment in Matlab. Our focus is to compare detection performance of the three approaches under different energy resources. In addition, we also demonstrate battery-aware activation with k-step selective recharge algorithm is able to achieve great improvement to avoid sensor battery failure thereby having the potential to extend the network lifetime towards perpetual operations. In order to emulate the real scenario, we use linear functions to approximate the wireless charging efficiency similar to the efficiency curve in [13]. In this way, increasing recharge rates would incur a higher energy cost. Table IV has listed all the simulation parameters.

A. Target Detection

The main objective of the sensor network is to detect the presence of the target node at a specific location in each time slot. As we can see from the previous analysis, the detection performance is greatly influenced by how many sensors are in active mode. A sensor node could go to sleep mode either because of

TABLE IV
SIMULATION PARAMETERS

Parameters	Value
Number of sensor nodes N	100
Sensing range	30m
Grid Distance	25m
Sleep threshold L	24 (units)
Battery capacity C	1500 (units)
Recharge rate R	[0,750] (units/slot)
Energy Consumption rate E_w	8 (units/slot)
Energy Consumption rate while sleeping E_s	0.5 (units/slot)
Simulation time	50000 time slots
SRR	
Activation probability p	0.5
LAPR	
Upper threshold U	1000 (units)
Step changeΔ_d	0.01
Step changeΔ_i	0.005
BSR	
Energy benchmark L_1	R
Energy benchmark L_2	$2R$
Recharge Rate R_1	$2R$
Recharge Rate R_2	$R/2$

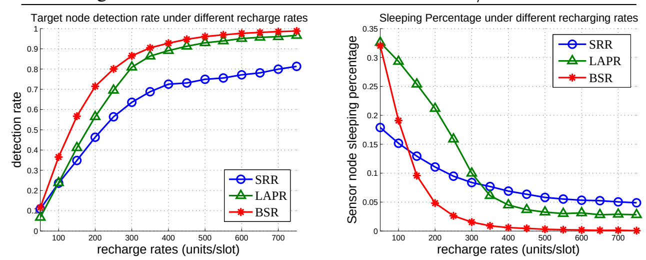

Fig. 4. Detection rate and sleeping percentage. (a) Target node detection rate under different recharge rates. (b) Sleeping percentage under different recharge rates.

its battery goes below the sleep threshold or it complies with the probabilistic decision. Fig. 4 shows the detection rate and sleeping percentage under different recharge rates. The battery-aware activation with SenCar's k-step selective recharge(BSR) outperforms the other two algorithms. For example, if 80% of target detection is satisfied, BSR achieves this level under a recharge rate at only 250 units/slot compared to the static activation approach at 700 units/slot. It is also worth mentioning that LAPR is also capable of achieving 80% detection rate at a recharge rate 300 units/slot which also surpass the static approach by saving 42% of energy. On the other hand, Fig. 4(b) shows the average percentage of sensor nodes to the whole network that are in sleeping mode. We can see as the recharge rate increases, BSR drops sharply and reaches to a sleeping percentage closed to 0 at 400 units/slot whereas static approach stays around 5% even given recharge rate at 700 units/slot. Notice that for low energy income, BSR and LAPR are able to put more sensor nodes into sleeping mode to avoid node failure. It means by incorporating a more complicated SenCar recharge model with battery-aware activation, sensors are able to utilize the available power more efficiently to minimize the sleeping percentage when resources are abundant.

B. Energy Consumption

In contrast to energy management of an environmental energy harvesting network in which the goal is to maximize the utilization of the harvested energy to maintain good detection performance, our concern in a wireless rechargeable sensor network is the average energy consumption spent on each detected target as well as residual battery energy in each time slot. First, since the

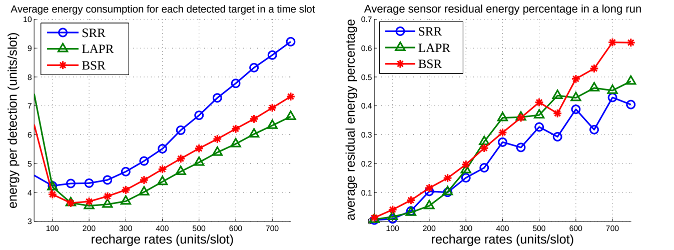

Fig. 5. Average node energy consumption per target detection and sensor residual energy in a long run (a) Average energy consumption for each detected target in a time slot (b) Average sensor residual energy percentage in a long run.

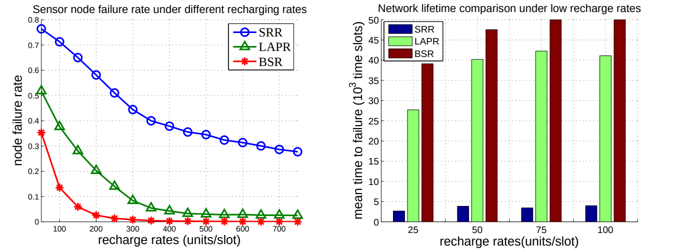

Fig. 6. Node failure rate and network lifetime. (a) Sensor node failure rate under different recharging rates. (b) Network lifetime comparison under low recharge rates from 25 to 100 (units/slot).

efficiency of wireless charging is around 40%-70% [1],[2],[13], even though by increasing the recharge rate would have benefited network performance, the energy wasted in transmission would be proportional to the transmitting power. Second, the charging efficiency would decrease as we increase power at the transmitter [13]. Hence, the energy consumption should not be too large as it is a hidden prerequisite for our system. On the other hand, sensor's residual energy in each time slot is critical to the lifetime of the network. Because in the current design, a SenCar serves a field of sensors, inadequate recharge would cause (single) node failure and jeopardize the operation of the whole network.

Fig. 5(a) is the average energy consumption per detection of each node in a time slot. The proposed revisions to the original static algorithm are more energy-efficient in the sense that they consume less energy on each successful detection of the target. Fig. 5(b) shows the average residual energy when the energy profile of the network reaches an equilibrium. The focal point is at scarce energy resources(small recharge rates), which scheme is able to provide the most average residual energy thus the chance of node failure can be significantly lowered. Our result shows BSR has surpassed SRR with higher energy reserves.

C. Node Failure and Network Lifetime

In addition to attain better detection performance, another objective of our proposed algorithms is to prevent sensor node from running out of battery and extend the lifetime of the network. In the experiment, we define the time until the appearance of the first sensor battery failure as the lifetime of the network. Fig. 6(a) is a comparison of the failure rate under different recharge rates. Similar to the previously shown percentage of sleeping node, BSR achieves less than 5% failure rate at a recharge rate of 200 units/slot whereas it takes nearly 2 times of energy cost for LAPR. Note that SRR still has 30% node failure given enough energy supply. This is due to the fact that recharging sensors with a random walk does not prioritize nodes near energy depletion. In order to demonstrate the robustness of the proposed algorithms, we measure the lifetime of the network under especially low energy income to check which algorithm could have the potential to extend the lifetime of the network towards perpetual operations. Fig. 6(b) shows the simulation result at very low recharge rates from 25 to 100 units/slot. Even in the worst case, BSR and LAPR have shown great strength to prevent node failure and they extend the lifetime around more than 10 times compared to the original SRR approach.

VI. Conclusions

In this paper we proposed an architecture based on the novel wireless charging techniques for rechargeable sensor networks and several possible energy management schemes in this framework. We demonstrate through an analytical model that using a static probability activation is not efficient and implementing mobile energy replenishing algorithm on the SenCar could give us more leverage to improve performance. Two comprehensive algorithms that yield better detection performance as well as lower node failure rate are proposed. A key advantage of our system is the energy income is independent of environmental factors which potentially indicates this architecture is able to extend the lifetime of sensor network towards perpetual operations. As our focus in this paper is from the sensor energy perspective, a direction for the future research is how to combine data collection to the SenCar to achieve optimal data throughput and at the same time keep all the sensors alive. Another direction of future research would be to discover using multiple SenCars and the coordination among them to provide a scalable service.

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