#### New challenges that wireless recharging oppose in WSNs

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### Studying the Feasibility of Energy Harvesting in a Mobile Sensor Network, Deborah Estrin et al., 2003

#### Studying the Feasibility of Energy Harvesting in a Mobile Sensor Network

Mohammad Rahimi, Hardik Shah, Gaurav S. Sukhatme, John Heideman, Deborah Estrin

University of Los Angeles

This paper appears in: IEEE International Conference on Robotics and Automation(IRCA), 2003

### Studying the Feasibility of Energy Harvesting in a Mobile Sensor Network, Deborah Estrin et al., 2003

- The paper feasibility of extending the lifetime of a wireless sensor network by exploiting mobility
- A small percentage of network nodes are autonomously mobile
  - they search for energy
  - recharge their batteries
  - and deliver energy to immobile, energy-depleted nodes
- At any instant of time the amount of energy consumed at node i is  $E(i,t) = \int_{t_0}^{t} [P_p(i,t) P_c(i,t)] dt$
- The network energy is the summation of the individual node energies across the network  $E(t) = \int_{t_0}^t (\sum_i [P_p(i,t) P_c(i,t)]) dt$
- A node is **self-contained** if  $E(i,t) > 0 \forall t > 0$  while a network is **self-contained** if  $E(t) E_{overhead} > 0 \forall t > 0$  where  $E_{overhead}$  is the overhead of the energy harvesting algorithm

### Studying the Feasibility of Energy Harvesting in a Mobile Sensor Network, Deborah Estrin et al., 2003

- The longest **profitable distance** a mobile robot can move is  $L = \frac{(E_{max} E_{payload})}{(2 \times E_{mov})}$
- $E_{mov}$  is the energy a mobile robot consumes(per unit distance)
- The network is devided into service zones(cells) of area ACA (total networks area is A)
- Then the number of serving robots should be: Number of Serving Robots  $\geq (\frac{A}{ACA}) \times (\frac{P_c}{P_p}) \times (ECA \times \Delta)$
- ullet  $\Delta$  is the density of static nodes
- $\frac{A}{ACA}$  is the number of cells
- $\frac{P_c}{P_p}$  is the rate of power consumption



#### Joint Mobile Energy Replenishment and Data Gathering in Wireless Rechargeable Sensor Networks

Miao Zhao, Ji Li and Yuanyuan Yang

Department of Electrical and Computer Engineering, Stony Brook University

This paper appears in: 23rd International Teletraffic Congress (ITC), 2011

#### Basic Idea

- In this paper a joint design of energy replenishment and data gathering by exploiting mobility is investigated
- A multi-functional mobile entity, called SenCar, is employed, which is equipped with a powerful transceiver and high capacity battery
- The SenCar will periodically choose a subset of sensors to visit
- While migrating among these sensors
  - it delivers energy to the visited sensors by utilizing wireless energy transmissions
  - collects data from nearby sensors via short-range communication



#### Basic Idea

- ullet On the model the **time is divided** into fixed time intervals of length  ${\cal T}$
- At the beginning of each time interval, the SenCar decides which sensors(anchor points) to be charged in this interval
- Along each tour, the SenCar would sojourn at each anchor point to gather data from nearby sensors via multi-hop communication
- It is assumed that the SenCar sojourns for the **same time** at every anchor point in a tour
- During the last tour in a time interval, each sensor will report its up-to-date battery status to the SenCar
- This information will be used for the **anchor point selection** at the beginning of next time interval

#### Basic Idea

- The solution follows a two step approach:
  - Anchor Point Selection: The SenCar selects the anchor points for the current time interval
    - finds which sensors are to be recharged and where the SenCar will sojourn for data gathering
    - 2 and how the SenCar moves over the field
  - Optimal Mobile Data Gathering Scheme
    - each sensor self determines how to transmit data to the SenCar when it arrives

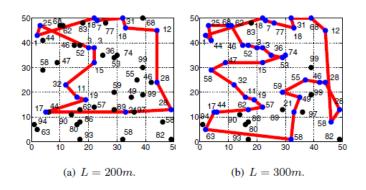
#### Anchor Point Selection

- The selection of anchor points falls into following two aspects
  - the senors located at the selected anchor points should be those with most urgent needs of energy supplement
  - the **length** of each migration tour, which implies the data gathering **latency**, is expected to be **short**

#### **Anchor Point Selection**

- Although more anchor points should be selected such that more sensors can timely get recharged, this would adversely prolong the migration tour
  - there is an inherent tradeoff between the number of sensors to be recharged and data gathering latency
- The algorithm sorts the sensors with their battery energy in a list S' of increasing order
- The algorithm first inspects the shortest migration tour among the upper half of the list
  - The migration tour can be found by an approximate solution to TSP
  - If the migration tour length equals the bound L, then the target sensor has been found
    - Otherwise, recursively the upper half of the latest list is chosen to further search an approximate tour of length L
- Similar to binary search





- (a) 34% of the sensors with the battery energy lower than or equal to 32 are charged
- (b) 78% of the sensors with the battery energy lower than or equal to 77 are charged but with increased latency

#### Optimal Mobile Data Gathering Scheme

- The remaining work is how to gather the data from sensors when the SenCar migrates among the anchor points
- The mobile data gathering problem is formulated into a utility maximization problem based on a flow-level network model
- The authors propose an optimization-based distributed algorithm for it

#### Problem Formulation

- Sensor i generates data for the SenCar at a data rate of  $r_{i,a}^{(k)}$  when the SenCar moves to anchor point  $a \in A^{(k)}$
- A utility function U<sub>i</sub>(·) is used to characterize the impact of the data from a sensor
- $U_i(\cdot)$  is defined as a <u>strictly concave</u>, increasing and <u>twice-differentiable</u> function with respect to the total amount of data gathered from sensor i in the current time interval

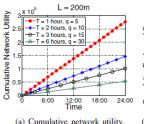
#### Problem Formulation

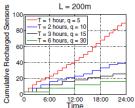
 The network utility is defined as the aggregation utility while maintaining the perpetual operation of the network

The mobile data gathering problem for time interval k can be formulated as follows:

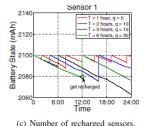
$$\begin{aligned} & \text{MDG:} \quad \max_{\mathbf{r}^{(k)},\mathbf{r}^{(k)}} \quad \sum_{i \in \mathcal{S}} U_i \left( \sum_{a \in \mathcal{A}^{(k)}} r_{i,a}^{(k)} q \tau^{(k)} \right) \\ & \text{Subject to} \\ & r_{i,a}^{(k)} + \sum_{j \in \mathcal{C}_{i,a}^{(k)}} f_{ji,a}^{(k)} = \sum_{j \in \mathcal{P}_{i,a}^{(k)}} f_{ij,a}^{(k)}, \forall i \in \mathcal{S}, \forall a \in \mathcal{A}^{(k)} \\ & q \tau^{(k)} \sum_{a \in \mathcal{A}^{(k)}} \sum_{j \in \mathcal{P}_{i,a}^{(k)}} f_{ij,a}^{(k)} e_{ij} < \sigma b_i^{(k)}, \forall i \in \mathcal{S} \\ & r_{i,a}^{(k)} \in R^+, f_{ij,a}^{(k)} \in \Pi_a^{(k)}, \forall i \in \mathcal{S}, \forall j \in \mathcal{P}_{i,a}^{(k)}, \forall a \in \mathcal{A}^{(k)} \\ & \text{where} \\ & b_i^{(k)} = \left\{ \begin{array}{cc} B_i, & \text{if } i \in \mathcal{A}^{(k)} \\ \check{b}_i^{(k-1)} & \text{otherwise} \end{array} \right. \text{and } \tau^{(k)} = \frac{T - q \text{TSP}(\mathcal{A}^{(k)}) / v_s}{q |\mathcal{A}^{(k)}|} \end{aligned}$$

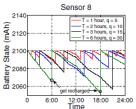
#### Simulation Results





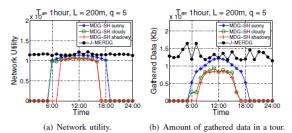
- (a) Cumulative network utility.
- (b) Amount of gathered data in a tour.





(d) Sensor battery states.

#### Simulation Results



When using solar energy the recharging rate can be derived as follows:  $\pi_r = Rad_s \times \eta_\rho \times \rho_e \times A$ 

- Rads represents the solar irradiance
- $\eta_{\rho}$  is the efficiency of the solar panel to convert solar irradiance to electrical power
- ullet  $\rho_e$  is the electrical regulating and charging efficiency
- A is the size of solar panel



#### Qi-Ferry: Energy-Constrained Wireless Charging in Wireless Sensor Networks

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Department of Computer and Information Sciences, University of Delaware, U.S.A.

This paper appears in: IEEE Wireless Communications and Networking Conference (WCNC), 2012



#### Introduction

- In the model both
  - the movement of a Qi-Ferry (QiF)
  - the wireless charging of sensor nodes
- share the same pool of battery energy
- this assumption results in a clear tradeoff between
  - how many sensors a QiF could charge
  - how far it could travel
- QiF departs from an energy station, moves from one tour stop to another, wirelessly charges all the sensors visited, and returns to the energy station
  - In a valid tour QiF returns to the energy station with nonnegative residual energy



#### Model assumptions

- Let e(T) denote a QiFs energy consumption in tour T, then
- $e(T) = \alpha \cdot L_T + \beta \cdot C_T$  where
  - L is QiFs traveling distance
  - $\bullet$   $\alpha$  is the corresponding propulsion force assumed to be a constant
  - $\bullet$   $\beta$  is the energy consumed to charge every sensor assumed to be a constant value
  - C<sub>T</sub> is the number of wirelessly-charged sensors
- The energy usage for tour T is a linear function of the tours length and coverage.



#### Problem Formulation

- Let G = (V, E) be a complete graph in an Euclidean space, with vertex set  $V = d \cup Z$ 
  - where d is the depot
  - Z denotes a set of sensors that may be covered within a QiFs wireless charging threshold r
    - $Z1 \subseteq Z$  is the subset of sensors that must be wirelessly charged
- Let the non-negative cost function c(i,j) equal the Euclidean distance between two positions i and j in the same Euclidean space where G resides.
- Let *e*<sub>0</sub> be the full battery capacity of a QiF which is fully charged at the beginning of a charging tour.



#### Problem Formulation

The goal of QiFP is to find a charging tour  $T = t_1, t_2, \dots, t_{|T|}$ , such that:

- **1** Each tour stop  $t_i \in T$  is different, with the depot as both the start and the end of the tour, i.e.,  $t_1 = t_{(|T|+1)} = d$
- ② A non-depot tour stop could be any geometric position to cover a sensor for wireless energy transfer  $T \setminus \{d\}, \exists z_k \in Z$  such that  $t_i$  can cover  $z_k$  within the covering threshold r
- **③** All vertices in  $Z_1$  are wirelessly charged during tour T, i.e.,  $\forall z_k \in Z_1, \exists t_i \in T$  such that  $c(t_i, z_k) \leq r$ .
- **1** The QiF's energy usage satisfies the upper bound  $e_0$ , i.e.,  $e(T) \le e_0$
- **5** The number of sensors in set Z covered along tour  $T(C_T)$  is maximized-cover-objective

#### **Problem Properties**

- The authors show that the problem is NP-hard by reducing it to the TSP
- In order to achieve shorter tour length, tour stops are not necessarily confined to the exact sensor locations
- A length-objective QiFP without energy-constraint is defined:
  - **Given** a set V of vertices such that there is a corresponding set K (|K| = |V|) of circles centered at each vertex  $i \in V$  with radius  $r_i \ge 0$ , where these circles may overlap arbitrarily with one another
  - Find a minimum-length tour consisting of tour stops and tour links that "touches" every circle in K

#### Heuristic Tour Planning Algorithms

- Metaheuristic of Particle Swarm Optimization (PSO) is first employed for the length-objective QiFP without energy constraint
- Then this PSO-based heuristic algorithm is used iteratively to compute the best tour subject to the given energy constraint
  - That is, the tour that fits as many as possible nodes
- In the |V|-dimensional search space, the position of a particle  $x = (x_1, x_2, \dots, x_{|V|})$  represents a set of selected tour stops
  - $x_i$  inside or on the boundary of circle  $K_i$ ,  $1 \le i \le |V|$

#### Heuristic Tour Planning Algorithms

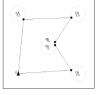
- The optimization fitness value of each particle is the length of the TSP tour over the corresponding tour stops.
  - In each iteration, every particle adjusts its "velocity"  $\bar{v}$  to move stochastically towards the locally and globally best positions as follows:

$$\begin{cases} \vec{v}(t+1) = \omega \vec{v} + R_1(c)(\vec{p}(t) - \vec{x}(t)) + R_2(c)(\vec{g}(t) - \vec{x}(t)) \\ \vec{x}(t+1) = \vec{x}(t) + \vec{v}(t+1) \end{cases}$$

- $\vec{v}(t), \vec{x}(t)$  are the particles velocity and position at iteration t
- $\vec{p}(t)$  denotes the local best up to t
- $\vec{g}(t)$  denotes the global best up to t
- ullet  $\omega$  is the inertial weight
- $R_i(c)$  is a random number uniformly distributed within [0, c]
- Disc, circle or arc are used for the search space
  - Disk usually generates the best tour in length due to the complete search space, and often converges faster



#### Performance Evaluation







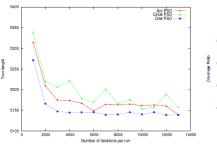


(a) sparse deployement

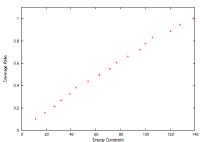
- (b) dense deployement
- QiFP heuristic tour is 19% shorter than the CSP optimal tour in (a)
- but only 0.6% shorter in (b)



#### Performance Evaluation



(a) As expected disk-pso converges faster offering the best solution



(b) Coverage vs energy constraint for a sample 90-node network

#### Prolonging Sensor Network Lifetime Through Wireless Charging

Yang Peng, Zi Li, Wensheng Zhang and Daji Qiao

Virginia Polytechnic Institute and State University, USA

This paper appears in: Real-Time Systems Symposium (RTSS), 2010

#### Introduction

- The paper studies the recharging problem in WSNs
- The proposed system has three main compnents:
  - a mobile charger (MC)
  - a network of sensor nodes equipped with wireless power receivers
  - an energy station
    - it monitors the energy status of the network
    - it directs the MC to charge sensor nodes



#### How the system works

- Sensor nodes perform application tasks and periodically report the data to the sink piggybacked with:
  - voltage readings of their own batteries and estimated lifetime
- only the energy information of the k shortest-lifetime nodes is forwarded
- the sink runs a charging algorithm and then sends the charging plan to the MC
- MC starts charging a selected set of sensor nodes sequentially according to the plane
  - when the MC receives a new command, it adjusts accordingly

#### Problem Formulation

- Let G = (V, E) represents the topology of a static sensor network
- All sensor nodes have the same battery capacity  $E_s$
- Let  $e_i$  and  $c \cdot r_i$  denote a sensor's residual energy and energy consumption rate, respectively
- Let MC's battery capacity be  $E_c$
- MC consumes  $\lambda_c$  power in order to charge a sensor
  - the sensor receives  $\eta \cdot \lambda_c$  power
    - $\bullet$   $\eta$  is the charging efficiency
- The MC's power consumption for its movement is  $\lambda_m$
- The goal is to find an optimal charging sequence for the MC.
  - $S = \langle (n_1, c \cdot t_1) \rangle, \ldots, \langle (n_{|S|}, c \cdot t_{|S|}) \rangle$ 
    - $\langle n_i, c \cdot t_i \rangle$  represents that node  $n_i$  is charged in the j-th step for a period of  $c \cdot t_i$  time
- such that the network lifetime is maximized

#### Heuristic Algorithms

- The authors show that the problem is NP-hard by reducing it from TSP
- Thus, they propose Greedy and GreedyPlus heuristic algorithms

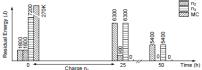
#### Greedy Algorithm

- Let  $\langle (n_1, l_1) \rangle, \dots, \langle (n_{|k|}, l_{|k|}) \rangle$  be the k-shortest lifetimes sorted
  - Clearly  $I_1$  is the network lifetime if there is no charging
- The algorithm tries to extend the lifetime from  $l_1$  to  $l_2$ 
  - If there is a feasible sequence moves on from  $l_i$  to  $l_{i+1}$

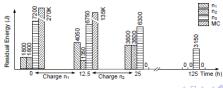


#### Greedy Algorithm

- The algorithm is greedy because once the MC starts charging a sensor node, it keeps charging the node for as long time as possible
- An example:



• A better example (GreedyPlus) would be:



#### Simulation

- The routing uses metric  $C_i = T \cdot r_i \cdot u^{1 \frac{e_i}{E_s}}$ 
  - *u* is a system parameter
    - when u=1 the metric is reduced to minimum energy (ME) metric
    - when u > 1 it is reduced to energy-aware (EA) metric
  - e<sub>i</sub> is node i's residual energy
  - $T \cdot r_i$  is the sum of energy consumption for packet transmission/reception at node i
- $\eta = 1.5\% 6\%$  similar to powercast technology
- aggregation number, k = 5



#### Effects of the number of sinks

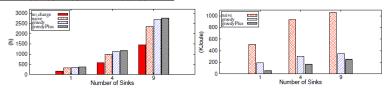


Figure: Lifetime & energy consumed by MC movement

 Energy consumption becomes more even as the number of sinks increases

#### Effects of system parameter k

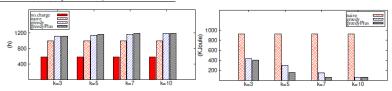


Figure: Lifetime & energy consumed by MC movement

Lifetime does not increase linearly or significantly as k increases

#### Effects of the routing algorithm

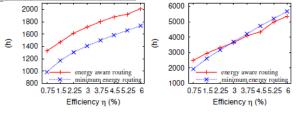


Figure: (a)  $E_c = 2000 \text{KJ}$ , (b)  $E_c = 20000 \text{KJ}$ 

- When *ME* routing is used, bottleneck nodes appear
  - When  $E_c$  or  $\eta$  is small, they use up their energy before they get recharged
- When EA routing is used, energy consumption rates are more even
  - When  $E_c$  or  $\eta$  is small, EA routing extends lifetime in comparison to ME

### Making Sensor Networks Immortal: An Energy-Renewal Approach with Wireless Power Transfer, 2012

# Making Sensor Networks Immortal: An Energy-Renewal Approach with Wireless Power Transfer

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This paper appears in: IEEE/ACM Transactions on Networking, 2012

### Making Sensor Networks Immortal: An Energy-Renewal Approach with Wireless Power Transfer, 2012

#### Introduction

- Recent advances in magnetic resonant coupling shows that sensors can be recharged efficiently
- In this paper, the authors exploit this new wireless energy transfer technology
- They investigate whether it is a scalable technology to address energy issue in a WSN
- They consider a wireless charging vehicle(WCV) which travels periodically inside the network and charges sensors
  - Upon completing each trip WCV returns to its home service station
  - It takes a "vacation" (battery replace) and starts again
- The central idea in single-node charging is that the amount of energy being charged to a node is equal to the amount of energy that the node expends in a cycle

#### The Model

- The authors partition the network into a two-dimensional plane
- Each sensor node has a battery capacity of  $E_{max}$  and is fully charged initially
- $\bullet$   $E_{min}$  is the minimum energy at a sensor node battery
  - Network lifetime is the time until the energy level of any sensor node in the network falls below E<sub>min</sub>
- The **cycle time** of traveling path  $D_p$  can be written as
  - - $sum_{k \in Q} \tau_k$  is the total amount of time the WCV spends to charge each sensor
    - $au_p = rac{D_p}{V}$  is the time spent for traveling over the path
- **Energy consumption rate** at sensor node *i* which includes both energy transmission and reception is

$$p_i = \rho \sum_{k \in N}^{k \neq i} f_{ki} + \sum_{j \in N}^{j \neq i} C_{ij} f_{ij} + C_{iB} f_{iB}$$
,  $\rho$  is the data rate

#### Problem Formulation

• Given the distance  $D_{\pi_I \pi_{I+1}}$  between the *Ith* and (I+1)th cell the arrival time of the WCV at cell K in the first cycle is

$$\alpha_{\pi_k} = \sum_{l=0}^{k-1} \frac{D_{\pi_l \pi_{l+1}}}{V} + \sum_{l=1}^{k-1} \tau_{\pi_l}$$

- To have  $e_i(t) \ge E_{min}$  for all  $t \ge 0$  it is sufficient to have:  $e_i(m\tau + \alpha_k) = e_i(m\tau) - \alpha_k \cdot p_i \ge E_{min}$
- For the first round we must have:  $E_{max} \alpha_k \cdot \geq E_{min}$
- For all other rounds( $m \ge 1$ ):

$$E_{min} \leq e_i(m\tau + \alpha_k) = e_i(m\tau) - \alpha_k \cdot p_i \leq \cdots \leq E_{max} - (\tau - \tau_k) \cdot p_i$$

- $2 \mathbf{E}_{\mathsf{max}} (\tau \tau_{\mathsf{k}}) \cdot \mathsf{p_i} \ge \mathbf{E}_{\mathsf{min}}$
- **3**  $\tau \cdot \mathbf{p_i} \mathbf{U_i} \cdot \tau_k \geq \mathbf{0}$  (The amount of energy being charged must be  $\geq$  to the amount of energy consumed during the cycle)

The authors prove that these conditions ((1), (2), (3)) are not only necessery but also sufficient conditions

### Summarizing Optimization Problem

$$max \frac{\tau_{vac}}{\tau}$$

$$s.t.$$

$$\tau = \tau_p + \tau_{vac} + \sum_{k \in Q} \tau_k$$

$$\sum_{k \in N}^{k \neq i} f_{ki} + R_i = \sum_{j \in N}^{j \neq i} f_{ij} + f_{iB}$$

$$p_i = \rho \sum_{k \in N}^{k \neq i} f_{ki} + \sum_{j \in N}^{j \neq i} C_{ij} f_{ij} + C_{iB} f_{iB}$$

$$E_{max} - (\tau - \tau_k) \cdot p_i \ge E_{min}$$

$$\tau \cdot p_i - U_i \cdot \tau_k \ge 0$$

- Time intervals  $\tau$ ,  $tau_p$ ,  $\tau_{vac}$  and  $\tau_k$ , flow rates  $f_{ij}$  and  $f_{iB}$  and power consumption  $p_i$  are optimization variables
- $R_i, \rho, C_{i,i}, C_{i,b}, U_i, E_{max}$  and  $E_{min}$  are constants
- This problem is a **nonlinear program** (NLP) with nonlinear objective  $\left(\frac{\tau_{vac}}{\tau}\right)$  and non linear terms  $\left(\tau \cdot p_i\right)$  and  $t_k \cdot p_i$  in the two last constrains
- It is known that NLP is NP-hard in general

### Summarizing Optimization Problem

- To solve the optimazation problem the authors do the following:
  - They reform to an nonlinear program(NLP) with bilinear terms.
  - They convert the NLP to a mixed integer linear program(MILP) which can be solved by an off-the-self solver suck as CPLEX
    - They discretize the variables using binary variables. This converts problem OPT to a 0-1 mixed-integer non linear program (MINLP)
    - 2 By exploiting the special structures of the 0-1 MINLP they employ a powerful technique called Reformulation Linearization Technique to eliminate all bilinear terms
    - 3 Subsequently the have a 0-1 MILP and they show that the new 0-1 MILP and the 0-1 MINLP have zero performance gap
    - This MILP has special ordered sets(SOS) which can be efficiently solved by CPLEX solver
    - They quantify performance gap(due to discretization) and

#### **Theorem**

In an optimal solution with the maximal  $\frac{\tau_{\rm vac}}{\tau}$  the WCV must move along the shortest Hamiltonian cycle that connects the service station and the centers of cells.

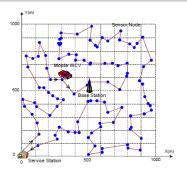


Figure: An optimal traveling path for the WCV for the 100-node sensor network

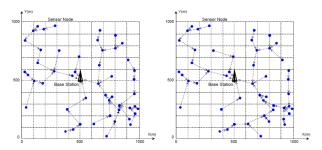


Figure: Left data routing according to the approximated solution and right minimal energy routing

## J-RoC: a Joint Routing and Charging Scheme to Prolong Sensor Network Lifetime

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This paper appears in: IEEE International Conference on Network

Protocols (ICNP), 2011

#### **Preliminaries**

- The system is composed by three main components
  - a network of sensor nodes
  - a mobile charger (MC)
  - a base station (BS) that monitors the energy status of the network and **directs** the MC to charge sensor nodes
- Every  $T_c$  time, the BS determines a charging schedule (i.e., charging time  $I_i$  for each sensor node i) for the next  $T_c$  interval
- The schedule is decided based on the following information reported by each node: energy consumption rate, residual energy level, data packet generation rate, set of parents on the energy-minimum paths to the sink and the qualities of links to each parent
- The interaction interval  $(T_c)$  can be configured to be **much** larger than the sensor data report interval

#### **Preliminaries**

- The Collection Tree Protocol (CTP) is used as the routing protocol in J-RoC to report sensory data and nodal status to the BS
  - It creates recursively an MST according to the expected number of transmissions needed to send a packet successfully(ETX) over a link
- In J-RoC, each sensor node embeds two types of routing costs in CTP beacons
  - Routing cost over a charging-aware path which is used by J-RoC
  - Routing cost over the energy minimum path which is used by the charging-aware path

### Routing Cost

• Energy minimum routing cost:  $C'_i = \min_{j \in N_i} \{C'_j + ETX_{i,j,y}\}$ 

#### Routing Cost

- Charging-aware routing cost:  $C_i' = \min_{j \in N_i} \{C_j' + u^{1 \frac{e_{i,j,t}}{E_s}}\}$  (1) where  $\hat{e}_{i,j,t} = e_{i,t} + (I_i \phi_{i,t})\Lambda_c \eta t_r \cdot c_{i,\hat{\rho}_{i,t},t} \cdot \frac{ETX_{i,j,t}}{ETX_{i,\hat{\rho}_{i,t},t}}$ 
  - $\phi_{i,t}$  denotes how long node i has been charged in the current  $T_c$
  - ullet  $t_r$  represents the remaining time in current  $T_c$  interval
  - $\hat{p}_{i,t}$  denotes the parent of node i on the charging-aware path at time t
  - The term  $c_{i,\hat{p}_{i,t},t} \cdot \frac{ETX_{i,j,t}}{ETX_{i,\hat{p}_{i,t},t}}$  estimates the **nodal energy** consumption rate if i switches its parent from  $\hat{p}_{i,t}$  to j
- A well known energy balanced routing metric is  $C_i^{'} = \min_{j \in N_i} \{C_j^{'} + u^{1 \frac{e_{i,t}}{E_s}}\}$  but may be **inefficient** when charging aware routing is used

### Charging Scheduling Algorithm

- The charging scheduling algorithm works in two phases
  - 1 It selects a set of sensor nodes that should be charged in the next  $T_c$  interval (Charging Energy Allocation)
  - it determines a sequence in which the sensor nodes are charged so that the movement time is minimized (<u>Charging</u> <u>Sequence Determination</u>)

### Charging Energy Allocation

- To maximize the network lifetime is to maximize:  $\min_{i} \left\{ \frac{e_{i,t}}{\widehat{c}_{i,t} \rho_{i} \cdot \Lambda_{c} \cdot \eta} \right\}$ 
  - $\rho_i$  is the percentage of charging energy that is allocated to sensor i,  $0 \le \rho_i \le 1$  and  $\sum_i \rho_i \le 1$
  - $\hat{c}_{i,t}$  is the future nodal energy consumption rate
- A binary search method is used to solve the optimization problem

### Charging Energy Allocation

- $\hat{C}_{i,t}$  is computed as follows:  $\hat{c}_{i,t} = \alpha c_{i,t}^{'} + (1-\alpha)c_{i,t}$ 
  - ullet  $c_{i,t}$  is the actual energy consumption rate of node i
  - $c_{i,t}^{'}$  is the energy consumption of node i if **all** sensor nodes use **energy-minimum** paths
  - ullet  $\alpha$  is the charging guiding coefficient

#### Explanation:

- For a sensor network without energy charging, the energy-balanced routing is favored to extend the network lifetime
- The strategy, however, has a side-effect:
  - packets may be routed through less energy efficient paths to the sink
- Energy-balanced routing consumes more energy compared to energy-minimum routing

### Charging Energy Allocation

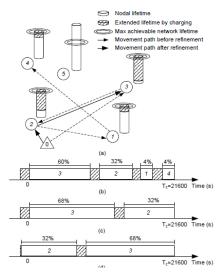
- In a WRSN, the MC is able to charge the energy bottleneck nodes
- Therefore, energy-minimum paths should be employed more often
- ullet The value of the charging guiding coefficient lpha is related to two factors
  - the relative **charging capability** of the MC  $(\frac{\Lambda_c \cdot \eta}{\sum_i c_{i,t}})$ 
    - $\bullet$  If it high enough then larger  $\alpha$  values are favorable since MC is capable of charging sensors along the energy minimum-paths
  - routing factor u as defined in routing cost metrics
- Thus  $\alpha = 1 u^{-\frac{\Lambda_c \cdot \eta}{\sum_i c_{i,t}}}$ 
  - When u>1, the stronger is the relative charging capability, the larger is  $\alpha$  and the more weight is given to energy minimum paths

### Charging Sequence Determination

- It is important to determine a charging sequence to implement the allocation with **as little movement as possible** 

  - The i value of the maximum lifetime node is iteratively merged to that of the minimum lifetime node until the the battery ceiling of the minimum lifetime node is reached
    - battery ceiling:  $r_i \cdot T_e > \frac{E_s e_{i,t}}{\Lambda_c \eta}$
    - $\Lambda_c \eta$ : amount of energy that can be charged per unit time ( $T_c$ )
  - VRPTW solver, which solves the vehicle routing problem with time window, is called to rearrange the visiting sequence to further reduce the movement time





#### Performance Upper Bound

- Assuming that
  - generation rate  $r_{i,t}$  is does not change during network lifetime
  - MC's movement delay is ignored
  - link qualities are perfect
- an optimal solution can be obtained by the following LP formulation

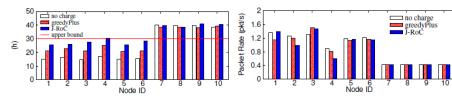
s.t.: 
$$\begin{aligned} \max \quad T, \\ T*r_i + \sum_{j \in N_i} f_{j,i} &= \sum_{j \in N_i} f_{i,j}, \\ T*\sum_i r_i &= \sum_{j \in N_{BS}} f_{j,BS}, \\ e_{tx}*\sum_{j \in N_i} f_{i,j} + e_{rx}*\sum_{j \in N_i} f_{j,i} \leq E_s + a_i * \Lambda_c * \eta, \\ \sum_i a_i \leq T, \\ f_{i,j}, a_i \geq 0. \end{aligned}$$

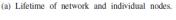
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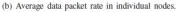
The authors evaluated the proposed J-RoC scheme in a prototype system

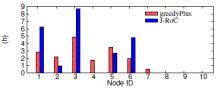
- The BS was a PC which had a stable power
- Sensors where 10 teloB sensor nodes
- A Powercast wireless power charger was used which was installed on an Acroname Garcia robot which worked as the MC
  - The MC communicates with the PC with 802.11b protocol
  - Energy charging was carried out int 903-927MHz band
  - The power consumption is 3W when the MC is charging

### Experimental Results



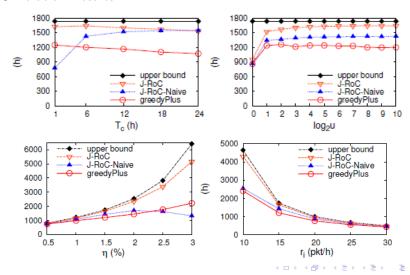




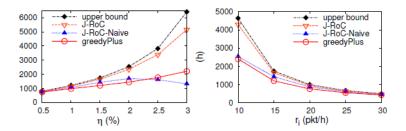


(c) Distribution of charging time among sensor nodes.

#### Simulation Results



#### Simulation Results



Obviously, as the moving speed of the MC increases, less time is wasted on the movement and more energy can be replenished into the network