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

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# Outline

- **Introduction**
- **Joint mobile energy replenishment and data gathering (J-MERDG)**
  – Background of our work
  – System architecture and timing of operation
  – Anchor point selection
  – Optimal mobile data gathering scheme
- **Numerical results**
- **Conclusion**

# 1. Introduction

## Wireless sensor networks (WSNs)

- Applications
  - Military: battle field surveillance
  - Environment: water pollutions
  - Industry/agriculture: machine health, soil moisture
  - Daily life: health status, smart home

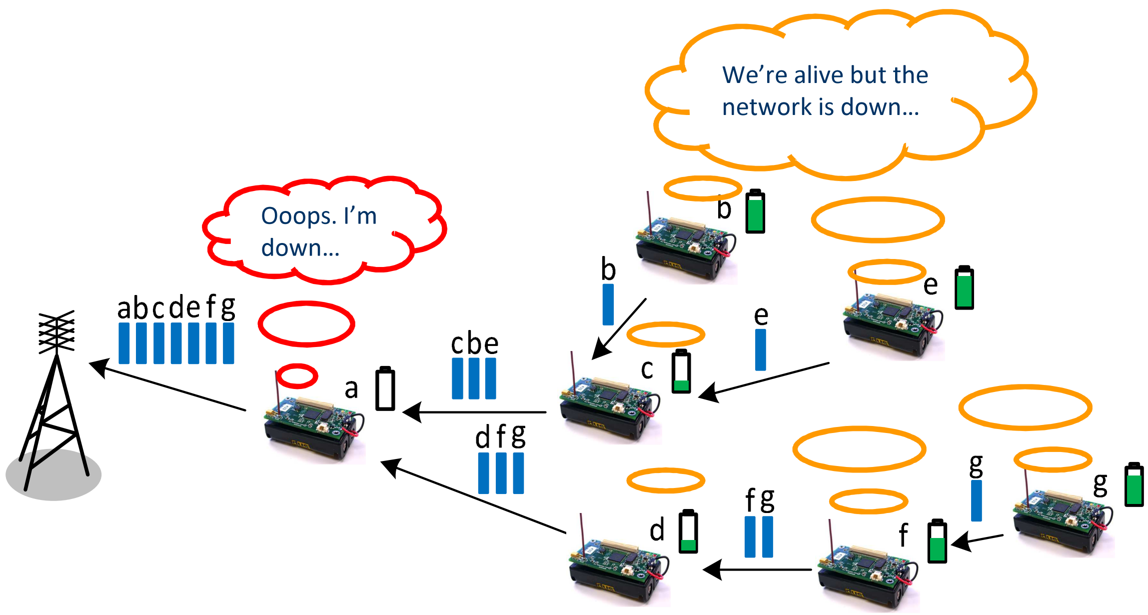





- **Main tasks of sensors**
  - Surveillance: temperature, humidity, sound, atmospheric pressure
  - Data gathering: aggregate data from scattered sensors to data sink

# Energy constraint in wireless sensor networks

- Limited energy supply: batteries
  - Energy consumption: sensing + wireless communications
    - Wireless communications is the major consumer
  - The closer to the data sink, the faster to deplete energy

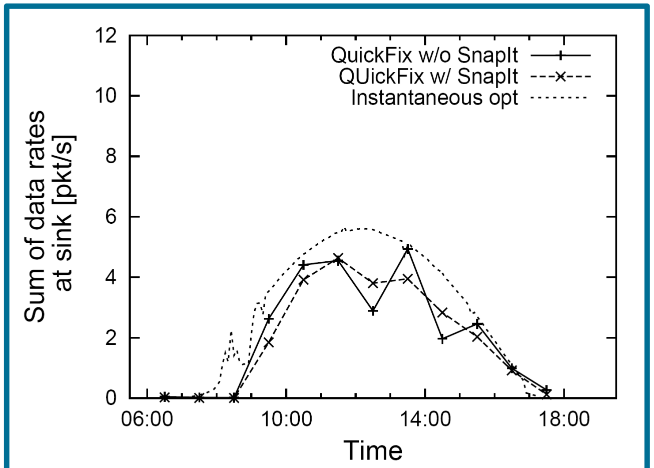


# Renewable energy supply to prolong network lifetime

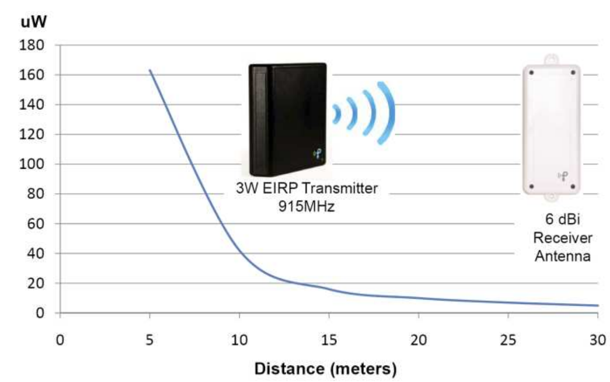
– Energy harvesting
  - Solar, wind, thermal energy, …

  - Sensitive to the ambient environment dynamics
    – Solar harvesting: $\pi_r = I \times \eta_p \times \rho_e \times A$

– Electromagnetic radiation based wireless transfer
  - Low efficiency: $P_{Rx} \propto \frac{P_{Tx}}{R^3}$
  - Even with directional antennas



Sum of data rates at sink



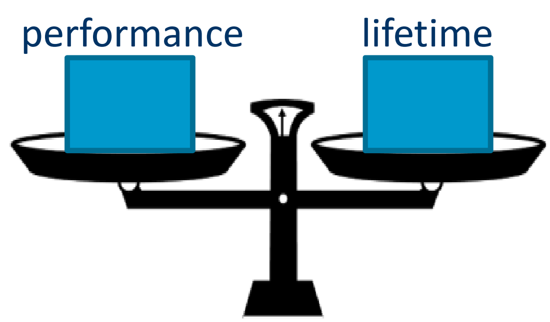
Available Power Before Conversion (Estimated)

# Challenges in designing a WSN

- Network performance:
  - How well can it serve?
    - High network utility
    - Low data latency


- Network lifetime:
  - How long can it serve?
    - The sensor nodes deplete their energy could make the network disconnected
    - Replacement of the dead sensor nodes is challenging & costly


- Performance v.s. lifetime



# 2. Joint mobile energy replenishment and data gathering (J-MERDG)

- High efficiency wireless power recharge
  - Wireless power transfer via magnetic resonance

60W over 2m @40% (MIT)

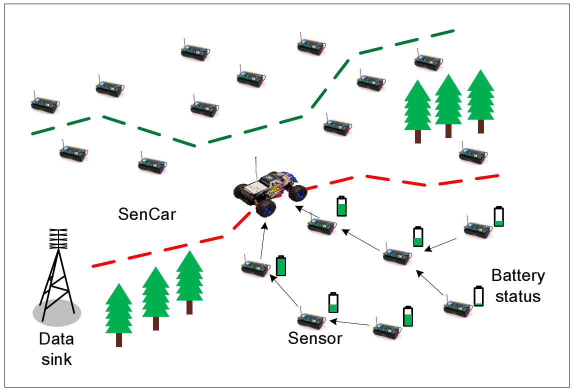
3.3kW over 18 cm @90% (WiTricity)

60W over 2-3 ft @75% (Intel)

  - New battery material for ultra-fast charging
    - Charging rate ~400C
      - Fully charge a 2200mAh battery in seconds!

# Mobile data gathering

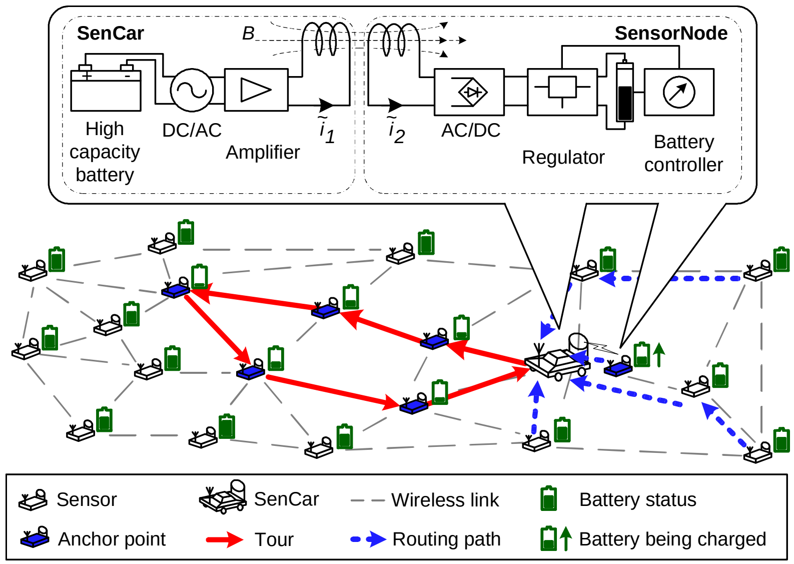
- Mobile data gathering (MDG)
  - One or multiple vehicles (*SenCars*)
  - SenCar sojourns at specified locations (*anchor points*) for data collection and node recharging
  - Sensors upload data to SenCar when it arrives




- **Characteristic and advantages of mobile data gathering**
  - Greatly save energy at sensors
    - SenCar fully or partially takes over the routing burden from sensors
  - Short-range communications between sensors and SenCars
    - Single-hop or limited multi-hop routing for data uploading
  - Work well for both connected and disconnected networks
    - SenCar plays as a “bridge” to link sub-networks

# System architecture (J-MERDG)

- Wireless charging of the sensor nodes




Architecture of joint mobile energy replenishment and data gathering (J-MERDG).

Alternating current fed to transmitter coil

↓

Alternating magnetic field generated around the transmitter coil

↓

Alternating current induced in the receiver coil

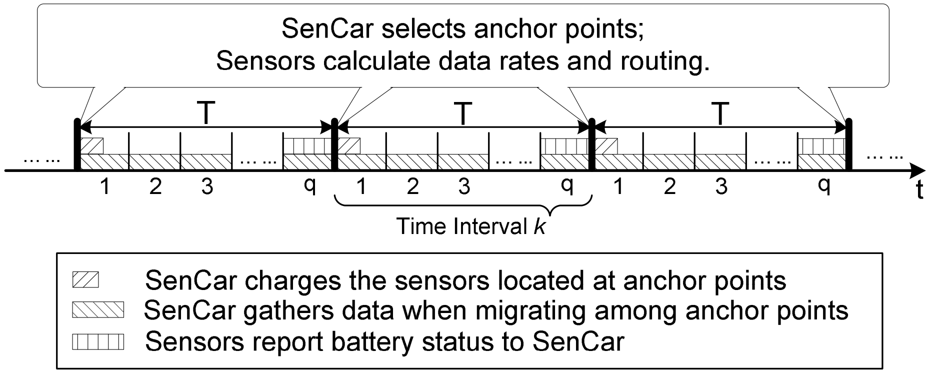
↓

Alternating current regulated and charges the battery

# Timing of operation (J-MERDG)

## In each time interval

- Select a subset of sensors and consider the locations of selected sensors as anchor points
  - ***Q: How to select sensors?***
- SenCar visits anchor points to charge the located sensors
- At each anchor point, SenCar gathers data from nearby sensors via multi-hop routing
  - ***Q: How to achieve satisfactory performance for data gathering?***

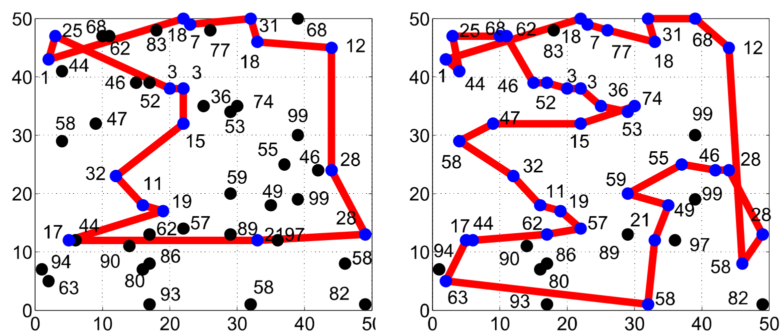



Timing of joint mobile energy replenishment and data gathering (JMERDG).

# Anchor point selection algorithm

Find sensors with urgent need of energy replenishment as many as possible with given L.

- Sort sensors in the increasing order of battery energy
- Iteratively reduce number of sensors to half each time by considering TSP length among the elements



(a) $L = 200m.$ (b) $L = 300m.$

An example of anchor point selection result.

ANCHOR POINT SELECTION ALGORITHM FOR TIME INTERVAL *k*

// $S$ is the set of sensors, $B_e^{(k-1)}$ is the set of energy states of sensors at the end of time interval $k-1$, and $L$ is the tour length bound.

**Input:** $S = \{1, 2, \ldots, N\}$, $B_e^{(k-1)} = \{\breve{b}_i^{(k-1)} \mid i \in S\}$, and $L$

**Output:** Anchor point list $A^{e(k)}$ for time interval

Sort the battery states in $B_e^{(k-1)}$ in an increasing order and record the result in another set $B'$;

Map $S$ to another set $S'$ by rearranging the sensors in the sequence corresponding to their respective battery states in $B'$;

$u \leftarrow 1$; $v \leftarrow |S'|$; $m \leftarrow 0$; $p \leftarrow 0$;

**while** *true* **do**

  **if** $u > v$

    $p \leftarrow v$; break;

  **end if**

  $m = \left\lfloor \frac{1}{2}(u+v) \right\rfloor$;

  // We use $S'(m)$ to represent the $m_{th}$ element in $S'$

  $A^{(k)} \leftarrow \{S'(1), S'(2), \ldots, S'(m)\}$;

  Find an approximate shortest tour among the anchor points in $A^{(k)}$ and let $TSP(A^{(k)})$ denote its length;

  **case**

    $TSP(A^{(k)}) < L$ : $u \leftarrow m+1$;

    $TSP(A^{(k)}) = L$ : $p \leftarrow m$; break;

    $TSP(A^{(k)}) > L$ : $v \leftarrow m-1$;

  **end case**

**end while**

$A^{(k)} \leftarrow \{S'(1), S'(2), \ldots, S'(p)\}$;

Find an approximate shortest tour among the anchor points in $A^{(k)}$

# Optimal mobile data gathering scheme (MDG)

- Important notations (for a particular time interval *k*)

$U_i(\cdot)$ : data utility function, strictly concave, increasing, twice-differentiable with respect to the amount of data uploaded from sensor i

$f_{ij,a}^{(k)}$ : flow rate on link (i,j) destined to SenCar at anchor point a

$r_{i,a}^{(k)}$ : data rate of sensor i when SenCar sojourns at anchor point a

- MDG formulation: over variables **r** and **f**

$$MDG: \max_{r^{(k)}, f^{(k)}} \sum_{i\in S} U_i\left(\sum_{a\in \mathrm{A}^{(k)}} r_{i,a}^{(k)} q\tau^{(k)}\right) \quad (1)$$

subject to

$$r_{i,a}^{(k)} + \sum_{j\in C_{i,a}^{(k)}} f_{ji,a}^{(k)} = \sum_{j\in P_{i,a}^{(k)}} f_{ji,a}^{(k)} \quad \forall i\in S, \forall a\in A^{(k)} \quad (2)$$

$$q\tau^{(k)} \sum_{a\in \mathrm{A}^{(k)}} \sum_{j\in P_{i,a}^{(k)}} f_{ij,a}^{(k)} e_{ij} \le \sigma b_i^{(k)} \quad \forall i\in S \quad (3)$$

$$r_{i,a}^{(k)} \in R^+, \quad f_{ij,a}^{(k)} \in \Pi_a^{(k)}, \quad \forall i\in S, \quad \forall j\in P_{i,a}^{(k)}, \quad \forall a\in A^{(k)} \quad (4)$$

where

$$b_i^{(k)} = \begin{cases} B_i & i\in \mathrm{A}^{(k)} \\ \breve{b}_i^{(k-1)} & otherwise \end{cases} \quad \text{and} \quad \tau^{(k)} = \frac{T - q\mathrm{TSP}\left(\mathrm{A}^{(k)}\right)/v_s}{q\cdot|\mathrm{A}^{(k)}|} \quad (5)$$

Network utility: aggregate of all data utility of all sensors

Flow conservation constraint

Energy constraint

Up-to-date energy of the sensors (the selected recharging sensor has full battery energy)

# MDG: solution

- MDG lacks of strict concavity
- Proximal approximation based algorithm
- Iterative steps in proximal approximation
  - Add a quadratic term $-\frac{1}{2c}\|\mathbf{r}^{(k)}-\mathbf{x}^{(k)}\|_2^2 = -\frac{1}{2c}\sum_{i\in S}\sum_{a\in A^{(k)}}\left(r_{i,a}^{(k)}-x_{i,a}^{(k)}\right)^2$
    - $\mathbf{x}$ is an additional vector and c is a positive constant
  - In iteration t

Step 1: Fix $x_{i,a}^{(k)} = x_{i,a}^{(k)}[t]$ for all $i \in S$ and $a \in A^{(k)}$ and solve the following problem to obtain the optimal $r_{i,a}^{(k)}[t]$ and $f_{ij,a}^{(k)}[t]$.

$$\max_{\mathbf{r}^{(k)},\mathbf{f}^{(k)}} \sum_{i\in S} U_i\left(\sum_{a\in A^{(k)}} r_{i,a}^{(k)} q\tau^{(k)}\right) - \frac{1}{2c}\|\mathbf{r}^{(k)}-\mathbf{x}^{(k)}\|_2^2 \qquad (5)$$

subject to constraints (2), (3) and (4).

Step 2: Set $x_{i,a}^{(k)}[t+1] = r_{i,a}^{(k)}[t]$ for all $i \in S$ and $a \in A^{(k)}$.

- Distributed implementation developed based on dual decomposition

# MDG: solution (cont.)

- Solving problem

$$\max_{\mathbf{r}^{(k)},\mathbf{f}^{(k)}} \sum_{i\in \mathrm{S}} U_i\left(\sum_{a\in \mathrm{A}^{(k)}} r_{i,a}^{(k)} q\tau^{(k)}\right) - \frac{1}{2c}\| \mathbf{r}^{(k)} - \mathbf{x}^{(k)}\|_2^2$$

subject to constraints (2), (3) and (4).

$$\min_{\boldsymbol{\lambda}^{(k)} \pm 0} g(\lambda) = \min_{\lambda^{(k)}} \max_{\mathbf{r}^{(k)},\mathbf{f}^{(k)}} L(\mathbf{r}^{(k)},\mathbf{f}^{(k)},\boldsymbol{\lambda}^{(k)})$$

***Dual decomposition***

**Sub-Prob1**: Rate Control

$$U_i\left(\sum_a r_{i,a}^{(k)} q\tau^{(k)}\right) - \frac{1}{2c}\sum_a (r_{i,a}^{(k)} - x_{i,a}^{(k)})^2 - \sum_a \lambda_{i,a}^{(k)} r_{i,a}^{(k)}$$

Under the Karush-Kuhn-Tucker (KKT) conditions, it can be solved with complexity $O(|\mathrm{A}^{(k)}|\log(|\mathrm{A}^{(k)}|))$ .

**Sub-Prob2**: Joint Scheduling and Routing

max $\sum_i \sum_a \sum_j (\lambda_{i,a}^{(k)} - \lambda_{j,a}^{(k)}) f_{ij,a}^{(k)}$

s.t. $q\tau^{(k)} \cdot \sum_a \sum_j f_{ij,a}^{(k)} e_{ij} < \sigma b_i^{(k)}, \forall i \in \mathrm{S}$

$f_{ij,a}^{(k)} \in \Pi_a^{(k)}, \forall i \in \mathrm{S}, \forall j \in \mathrm{P}_{i,a}^{(k)}, \forall a \in \mathrm{A}^{(k)}$

Scheduling: maximum weighted matching

Routing: greedy allocation

**r** **λ** **f**

$$\lambda_{i,a}^{(k)}[n+1] = \left[\lambda_{i,a}^{(k)}[n] + \theta[n]\left(r_{i,a}^{(k)}[n] + \sum_j f_{ji,a}^{(k)}[n] - \sum_j f_{ij,a}^{(k)}[n]\right)\right]^+$$

**Sub-gradient Projection**

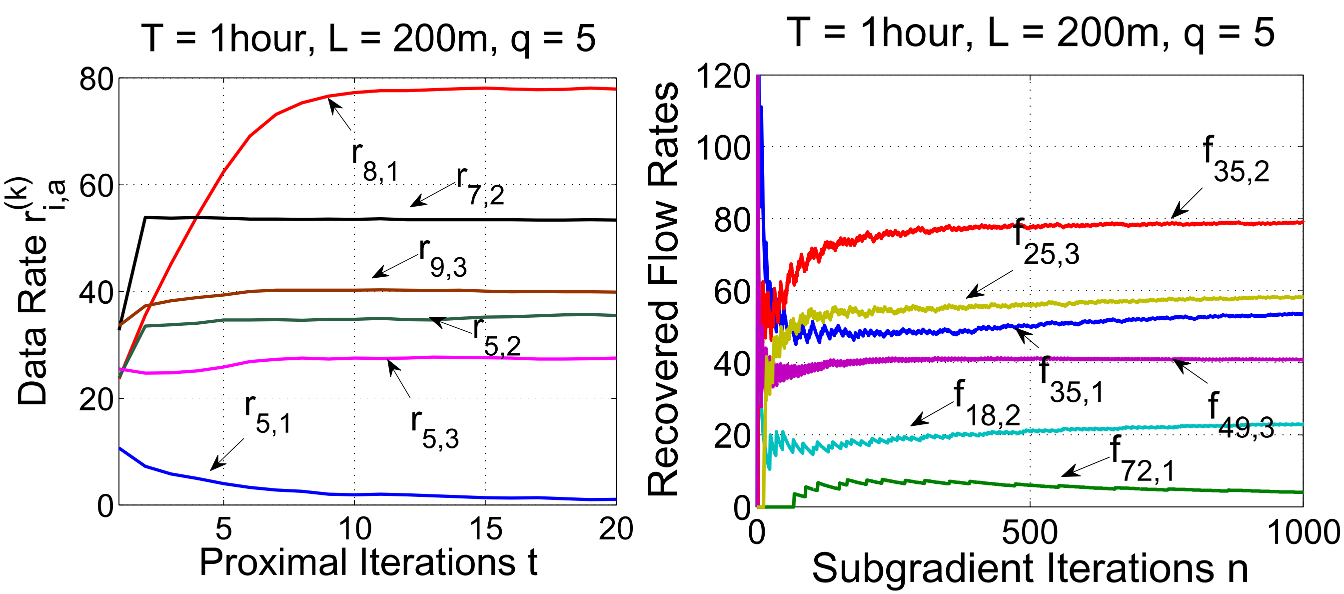
# 3. Numerical results

- Network setup
  - 100m × 100m area
  - 10 wireless rechargeable sensors
  - Utility function $U_i(\cdot) = w_i \log(\sum_a r_{i,a}^{(k)} q\tau + 1)$
  - 1 hour for each time interval length *T*
  - 5 migration tours in each time interval.
- Parameter settings

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $B_i$ | 2100mAh | $e_{ij}$ | 0.3mJ/Kbit |
| $w_i$ | 100 | $e_{i\Lambda_i}$ | 0.02J/Kbit |
| $\theta(n)$ | $\frac{1}{1+10n}$ | $L$ | 200m |
| $v_s$ | 1m/s | $\sigma$ | 0.9 |

# Convergence of Proximal Approximation Based Algorithm

- Convergence of proximal approximation based algorithm
  - Data rates: stable after 10 iterations
  - Recovered flow rates: differences within 5% of their optimal values after 500 iterations

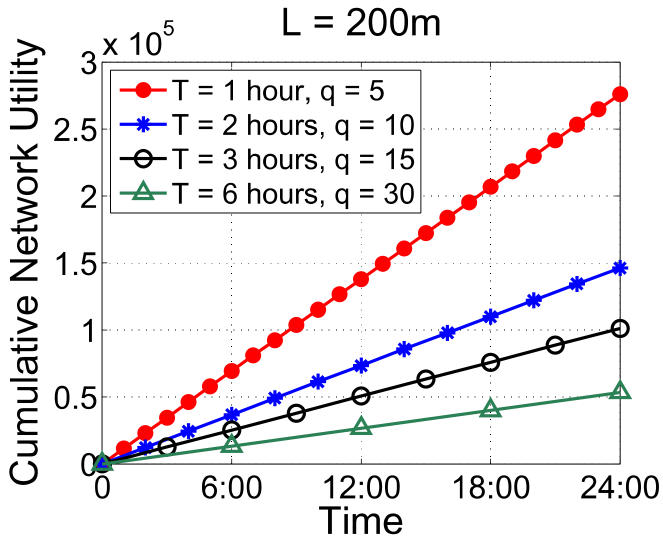



(a) Evolution of data rates versus proximal iterations t.

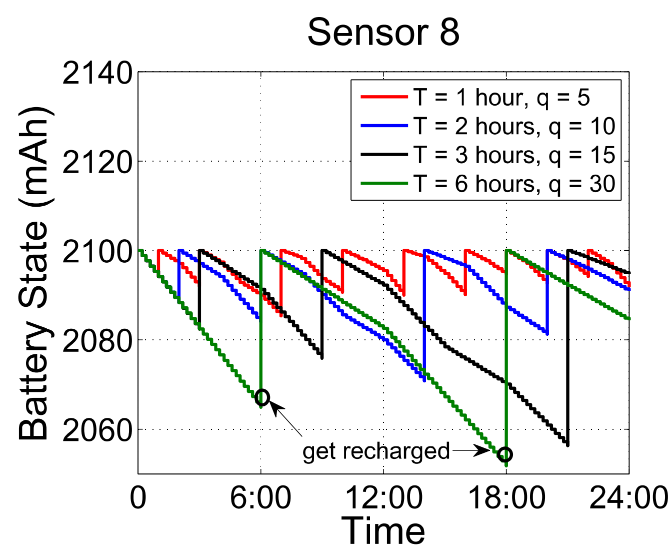
(b) Evolution of recovered flow rates versus subgradient iterations n.

# Performance of J-MERDG

- High network utility & perpetual network operations
  - Higher cumulative network utility can be obtained in the cases with a smaller T.
  - More chances for energy replenishment under a smaller *T.*
    - 9 times (*T = 1 hour) v.s. twice (T = 6 hours).*



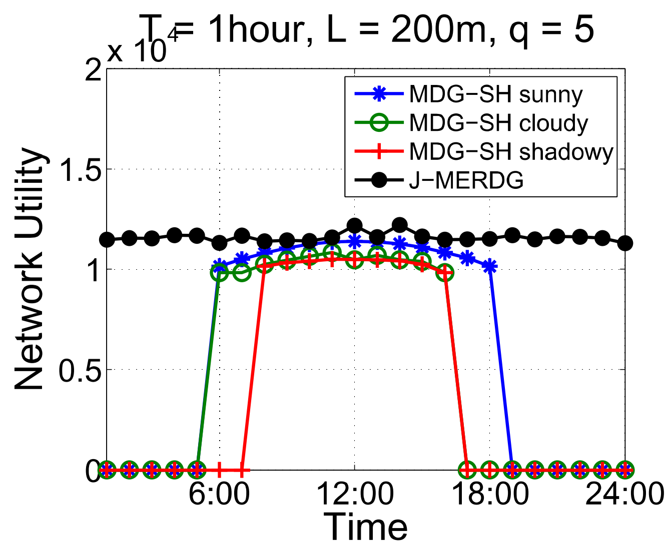

(a) Cumulative network utility.



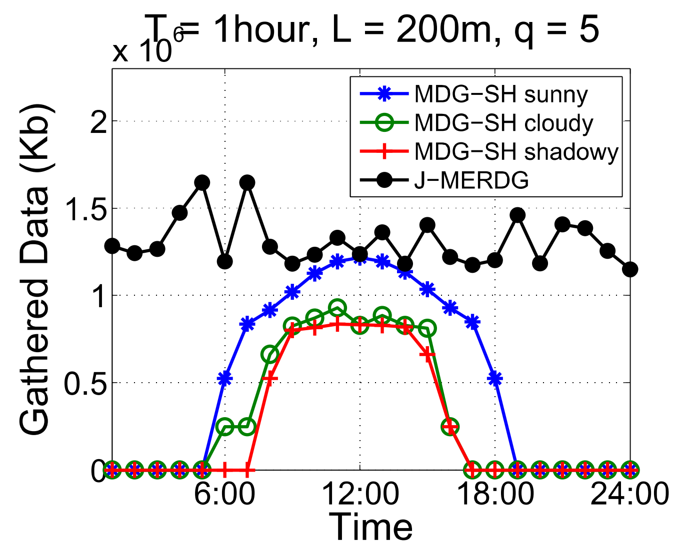

(b) Battery states of sensor 8.

# J-MERDG vs. mobile data gathering in solar harvesting system (MDG-SH)

- High network utility: 48%, 59% and 66% higher than MDG-SH in sunny, cloudy and shadowy days, respectively.
- Stable performance both during daytime and night time.




(a) Network utility.




(b) Amount of gathered data in a tour.

- Solar irradiance data from National Renewable Energy Laboratory.
- $\pi_r = I \times 0.06 \times 1369 mm^2$

# 4. Conclusion

- Joint design of energy replenishment and data gathering (J-MERDG) by exploiting mobility: the first work.
- Anchor points selection algorithm: balance between the energy replenishing range and data gathering latency.
- Flow-level network utility maximization model. We propose a proximal approximation based algorithm to obtain the system-wide optimum by adjusting data rates, link scheduling and flow routing in a distributed manner.
- Extensive numerical results: perpetual operations of the network AND significant network utility enhancement (outperforms solar harvesting system by 48%).

**Thank you!**