A Joint Optimization of Sensor Activation and Mobile Charging Scheduling in Industrial Wireless Rechargeable Sensor Networks

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Outline

- Introduction
- System Model and Problem Description
- Joint Sensor Activation and Mobile Charging Scheduling
- Simulation Results
- Conclusion

Background

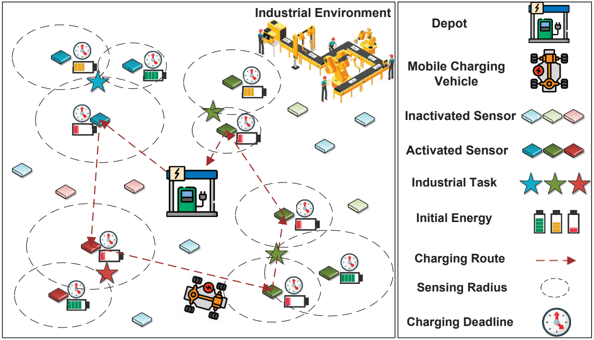
- Industrial wireless rechargeable sensor networks (IWRSNs):
  - To tackle sensor energy shortage problem in industrial wireless sensor networks (IWSNs);
  - Mobile charging vehicles (MCV) are deployed in IWRSNs to travel around and replenish energy for sensors without interconnecting wires.
- Open problems:
  - Activating optimal sensor set to execute industrial tasks while guaranteeing tasks requirements;
    - heterogeneity of industrial tasks (i.e., task requirements, locations and types, ect.) and sensors (i.e., sensing radius, types, energy consumption rate, ect.).
  - Scheduling the charging route of the MCV with charging deadlines.
    - the MCV should recharge sensors before their charging deadlines (i.e., the instant of running our their energy) with constraints of energy capacity, moving velocity and charging efficiency of the MCV.

Motivations

- The emergence of massive machine-type internet of things communications (mMTIC) [1] leads to a huge amount of energy may be consumed in sensing, computing and information exchanging in the future IWRSNs, which further involve the energy consumption of the MCV.
- These two problems (i.e., sensor set activation and MCV charging route scheduling) are tightly coupled.

[1] S. R. Pokhrel, S. Verma, S. Garg, A. K. Sharma, and J. Choi, "An efficient clustering framework for massive sensor networking in industrial internet of things," *IEEE Trans. Ind. Inform.*, 2021.

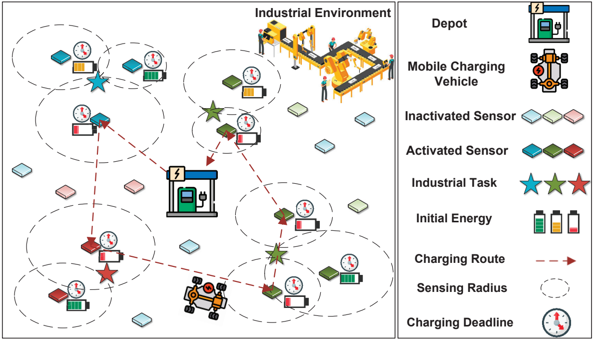
System Model



- Sensor set $\mathcal{S}$ uniformly distributed and an MCV.
- Monitoring tasks $\mathcal{Z} = \{z_j^m | \forall m \in \{1, 2, ..., M\}, \forall j \in \{1, 2, \ldots, J\}\}$.
- Each sensor's sensing radius $R_i, i \in \mathcal{S}$ is limited.
- Denote the set of sensor specialized in task type j as S_j.
- Detection probability of sensor i to task z_j^m (probabilistic sensing coverage model):

$$p_{i,z_j^m} = \begin{cases} e^{-\alpha_i \cdot dist\left(i, z_j^m\right)}, & \text{if } dist\left(i, z_j^m\right) \leq R_i, i \in \mathcal{S}_j, \\ 0, & \text{otherwise.} \end{cases}$$

System Model (Cont'd)

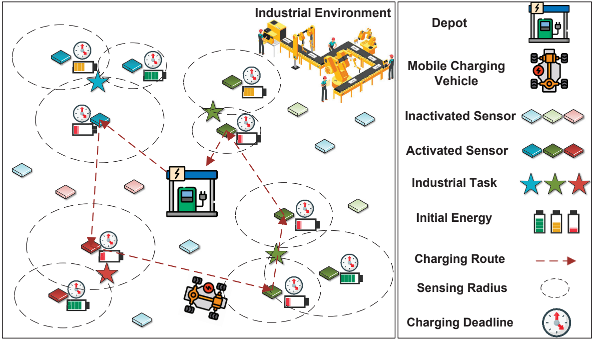


- The collaborative coverage probability of sensor set $\mathcal{H} \subseteq \mathcal{S}$ to the monitoring task z_j^m is required to be larger or equal to $P_{z_j^m}^{demand}$:

$$1 - \prod_{i \in \mathcal{H}} (1 - p_{i,z_j^m}) \geq P_{z_j^m}^{demand}.$$

- The battery capacity of each sensor $E_i^{capacity}, i \in \mathcal{S}$ and the MCV E_{MCV} are limited.

System Model (Cont'd)



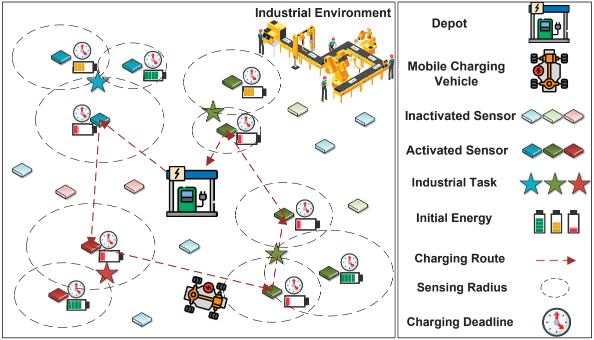
- Sensors $\mathcal{H}_0 \subseteq \mathcal{H}$ with sufficient enough initial energy $E_i^{initial}$.
- Sensors' energy demands in $\mathcal{H}_1 \subseteq \mathcal{H} \backslash \mathcal{H}_0$:

$$E_i^{demand} = T \cdot E_i^{consume} - (E_i^{initial} - E_i^{min}), \forall i \in \mathcal{H}_1.$$

- Charging deadline of sensor $i, i \in \mathcal{H}_1$:

$$ddl_i = \frac{E_i^{initial} - E_i^{min}}{E_i^{consume}}, \forall i \in \mathcal{H}_1.$$

System Model (Cont'd)



- Charging route of the MCV $\mathcal{L}^{\mathcal{H}_1} = \{\pi_0, \pi_1, \dots, \pi_g, \dots, \pi_{|\mathcal{H}_1|}, \pi_{|\mathcal{H}_1|+1}\}$.
- The time of the MCV arrive at target π_g:

$$A_{\pi_g} = A_{\pi_{g-1}} + \frac{E_{\pi_{g-1}}^{demand}}{\varepsilon} + \frac{dist\left(\pi_{g-1}, \pi_g\right)}{v}, \forall \pi_g \in \mathcal{L}^{\mathcal{H}_1}.$$

Problem Description

- The energy consumption of an IWRSN includes:
  - traveling energy consumption of the MCV: $\sum_{g=0}^{|\mathcal{H}_1|} \gamma \cdot dist\left(\pi_g, \pi_{g+1}\right)$;
  - energy consumption of all activated sensors $\mathcal{H}$: $\sum_{i \in \mathcal{H}} T \cdot E_i^{consume}$.
- The energy consumption of an IWRSN:

$$E_{total}(\mathcal{H}, \mathcal{L}^{\mathcal{H}_1}) = \sum_{g=0}^{|\mathcal{H}_1|} \gamma \cdot dist\left(\pi_g, \pi_{g+1}\right) + \sum_{i \in \mathcal{H}} T \cdot E_i^{consume}$$

Problem Description (Cont'd)

- Joint optimization of sensor activation (i.e., the optimal set of sensors $\mathcal{H}$ to activate) and mobile charging scheduling (i.e., the optimal charging route $\mathcal{L}^{\mathcal{H}_1}$) for the IWRSN:

$$[\mathcal{P}1]: \min_{\mathcal{H},\mathcal{L}^{\mathcal{H}_1}} E_{total}(\mathcal{H},\mathcal{L}^{\mathcal{H}_1})$$

$$s.t.,\ 1-\prod_{i\in\mathcal{H}}(1-p_{i,z_j^m}) \geq P_{z_j^m}^{demand}, \forall z_j^m \in \mathcal{Z}, \quad (1)$$

$$A_{\pi_g} \leq ddl_{\pi_g}, g=1,\ldots|\mathcal{H}_1|, \quad (2)$$

$$\pi_g \neq \pi_{g'}, g \neq g'; g=1,\ldots|\mathcal{H}_1|, g'=1,\ldots|\mathcal{H}_1|, \quad (3)$$

$$\sum_{g=0}^{|\mathcal{H}_1|}\gamma\cdot dist\,(\pi_g,\pi_{g+1})+\sum_{g=1}^{|\mathcal{H}_1|}E_{\pi_g}^{demand} \leq E_{MCV}, \quad (4)$$

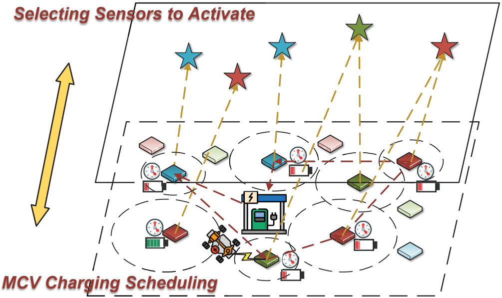
$$\pi_0=0, \pi_{|\mathcal{H}_1|+1}=0, \quad (5)$$

$$\mathcal{H} \subseteq \mathcal{S}, \quad (6)$$

$$\mathcal{H}=\mathcal{H}_0 \cup \mathcal{H}_1, \quad (7)$$

$$\mathcal{L}^{\mathcal{H}_1}=\{\pi_0,\pi_1,...,\pi_g,...,\pi_{|\mathcal{H}_1|},\pi_{|\mathcal{H}_1|+1}\}. \quad (8)$$

Hardness Analysis



- Given the charging route $\mathcal{L}^{\mathcal{H}_1}$, the upper layer sensor set selection problem:

$$\min_{\mathcal{H}} \sum_{i \in \mathcal{H}} T \cdot E_i^{consume}$$

$$s.t., \ 1 - \prod_{i \in \mathcal{H}} (1 - p_{i,z_j^m}) \geq P_{z_j^m}^{demand}, \forall z_j^m \in \mathcal{Z},$$

$$\mathcal{H} = \mathcal{H}_0 \cup \mathcal{H}_1,$$

$$\mathcal{H} \subseteq \mathcal{S}'$$

is NP-hard.

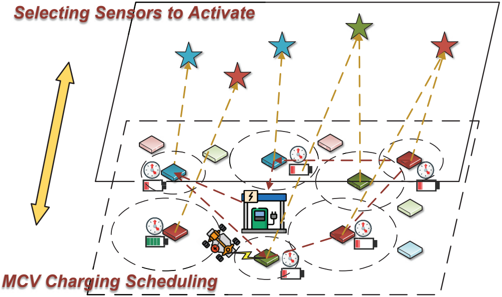
- Given the set $\mathcal{H}$, the set $\mathcal{H}_1$ can also be obtained, the lower layer mobile charging scheduling problem:

$$\min_{\mathcal{L}^{\mathcal{H}_1}} \sum_{g=0}^{|\mathcal{H}_1|} \gamma \cdot dist\left(\pi_g, \pi_{g+1}\right)$$

$$\begin{aligned}
s.t., \; & A_{\pi_g} \leq ddl_{\pi_g}, g=1, \ldots |\mathcal{H}_1|, \\
& \pi_g \neq \pi_{g'}, g \neq g'; g=1, \ldots |\mathcal{H}_1|, g'=1, \ldots |\mathcal{H}_1|, \\
& \sum_{g=0}^{|\mathcal{H}_1|} \gamma \cdot dist\left(\pi_g, \pi_{g+1}\right) + \sum_{g=1}^{|\mathcal{H}_1|} E_{\pi_g}^{demand} \leq E_{MCV}, \\
& \pi_0 = 0, \pi_{|\mathcal{H}_1|+1} = 0, \\
& \mathcal{L}^{\mathcal{H}_1} = \left\{\pi_0, \pi_1, ..., \pi_g, ..., \pi_{|\mathcal{H}_1|}, \pi_{|\mathcal{H}_1|+1}\right\}
\end{aligned}$$

is NP-hard.

Hardness Analysis (Cont'd)

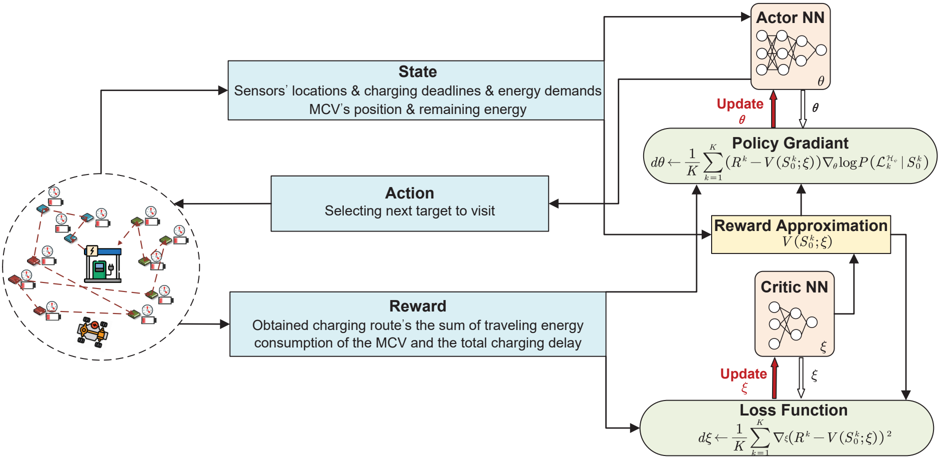


- Both the upper layer sensor selection optimization, and the lower layer charging route scheduling problem are NP-hard.
- The upper and lower layer problems are tightly coupled, and can not be addressed separately to obtain the global solution:
  - the input of the lower layer problem depends on the output of the upper layer one, while the optimization of the upper layer problem is in turn subject to the results of the lower layer one.

Joint Sensor Activation and Mobile Charging Scheduling

Integrating deep reinforcement learning (DRL) and marginal product based approximation algorithm:

- DRL algorithm for mobile charging route scheduling:



Joint Sensor Activation and Mobile Charging Scheduling

- joint sensor activation and charging scheduling algorithm (JSACS):
  1. Initialize the candidate sensor set $\mathcal{S}_{z_j^m}^{candidate} = \{i | p_{i,z_j^m} \neq 0, \forall i \in \mathcal{S}\}, \mathcal{S}^{candidate} = \sum_{z_j^m \in \mathcal{Z}} \mathcal{S}_{z_j^m}^{candidate}$ and the set of unfinished tasks $\mathcal{Z}^{unsatisfied} = \mathcal{Z}$;
  2. Adding a sensor from the candidate sensor set $\mathcal{S}^{candidate}$ with the largest marginal product into $\mathcal{H}$:
  $$\arg\max_{i \in \mathcal{S}^{candidate}} \{ \frac{(1-\prod_{i' \in \mathcal{H} \cup \{i\}}(1-p_{i',z_j^m})) - (1-\prod_{i' \in \mathcal{H}}(1-p_{i',z_j^m}))}{E_{total}\left(\mathcal{H} \cup \{i\}, \mathcal{L}^{\mathcal{H}_1 \cup h}\right) - E_{total}\left(\mathcal{H}, \mathcal{L}^{\mathcal{H}_1}\right)}, \forall z_j^m \in \mathcal{Z}\},$$
  where the charging route $\mathcal{L}^{\mathcal{H}_1}$ of the MCV are calculated by calling the trained DRL model. (If there is no charging route that meets every sensor's charging deadline or the energy consumption of the MCV exceeds the energy capacity E_{MCV}, we delete the sensor from $\mathcal{S}^{candidate}$);
  3. Updating the candidate sensor set and the set of unfinished tasks;
  4. Iterating process 2$\sim$3 until all tasks are finished.

Simulation Settings

Tabela 1: Main Simulation Parameters.

Parameter	**Value**
Sensor types	[0,1,2,3]
Task types	[0,1,2,3]
Number of sensors	800 (number of each type: 200)
Number of tasks	40 (randomly chosen over [0,1,2,3])
Area dimensions	80 m $\times$ 80 m
Sensing radius R_i	randomly chosen over [10,15,20,25] m
Energy capacity $E_i^{capacity}$	10.8 kJ
Energy consumption rate $E_i^{consume}$	0.5 J/s
Minimum energy E_i^{min}	540 J
Initial energy $E_i^{initial}$	randomly over [1080,3240] J
Intensity coefficient α_i	randomly over [0.1,0.3]
QoM demand $P_{z_j^m}^{demand}$	randomly over [0.5, 0.7]
Charging efficiency ε	15 W
Velocity v	2 m/s
Traveling energy consumption γ	20 J/m
Energy capacity of MCV E_{MCV}	128 kJ
Time duration of monitoring period T	1 hour

Simulation Settings

- Greedy Algorithm (GRE): always selecting a sensor which has maximum coverage probability and applies the earliest deadline first policy (EDF) [2] to obtain the charging route of the MCV.
- Reward-cost ratio algorithm (RC-ratio): RC-ratio is an existing algorithm [3] which selects a sensor with largest marginal product. And it use EDF to derive the charging route of the MCV.

[2] SJ. A. Stankovic, M. Spuri, K. Ramamritham, and G. C. Buttazzo, " Deadline scheduling for real-time systems: EDF and related algorithms," *Springer Science & Business Media*, 2012, vol. 460.

[3] T. Wu, P. Yang, H. Dai, C. Xiang, X. Rao, J. Huang, and T. Ma, "Joint sensor selection and energy allocation for tasks-driven mobile charging in wireless rechargeable sensor networks," *IEEE Internet Things J.*, vol. 7, no. 12, pp. 11 505–11 523, 2020.

Simulation Results

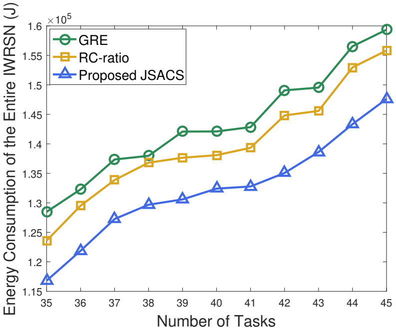


Figura 1: Comparison of energy consumption of the entire IWRSN w.r.t. number of tasks.

- The energy consumption of the entire network increases monotonically with the number of tasks because more activated sensors leads to more energy consumption in both sensors and the MCV.
- The proposed JSACS outperforms GRE and RC-ratio because it selects sensors with largest marginal product and optimized the charging route of the MCV by a well DRL model.

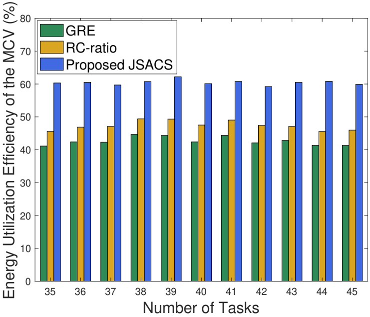


Figura 2: Comparison of energy utilization efficiency of the MCV w.r.t. number of tasks.

- It is shown that the proposed JSACS performs better than GRE and RC-ratio. The reason is that
  - the proposed JSACS consider the two-layer optimization simultaneously when selecting a sensor;
  - the objective of the trained DRL model is to minimize the traveling energy consumption of the MCV while meeting the charging deadlines of sensors.

Simulation Results (Cont'd)

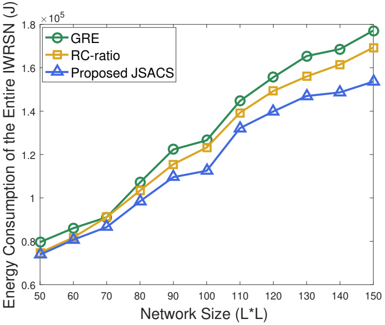


Figura 3: Comparison of energy consumption of the entire IWRSN w.r.t. network sizes.

- The energy consumption of the entire network of these three algorithms increases almost linearly with the network size. The reason is that
  - larger network size makes the sensor deployment more sparsely,and it leads to more traveling energy;
  - the distance between the sensor and its monitoring tasks larger, and the detection probabilities of sensors decrease, result in more sensors are activated.

Conclusion

- A joint optimization of sensor activation and mobile charging scheduling for IWRSNs is formulated, where the objective is to minimize the energy consumption of the entire network.
- An efficient algorithm, called joint sensor activation and charging scheduling algorithm (JSACS), is proposed integrating DRL and marginal product based approximation algorithm, which jointly optimizes the sensor activation and the MCV's charging route scheduling.
- Simulations are conducted to show the superiority of the proposed JSACS over counterparts.

Thank you

Q&A