Nanjing University of Posts and Telecommunications

An Approximation for Routing Planning, Mobile Charging, and Energy Sharing for Sensing Devices

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Abstract

使用无线充电车(WCV)为传感器提供能量已经被广泛探索。然而，由于充电范围非常有限，WCV往往需要移动到靠近传感器的位置充电，这将导致额外的时间和能量开销。并且位于难以进入区域的传感器将无法及时得到能量供应。因此，有必要为传感器网络设计一个有效的充电和能量共享方案，以提高充电质量。本文主要研究移动充电与传感器能量共享的联合优化问题(JOIN-ME)，这是一个NP-hard问题。为了应对这一挑战，我们首先将JOIN-ME转换为具有一般约束的子模最大化问题。随后，我们提出了路由规划、移动充电和设备能量共享(RMES)算法，其近似比为1/8(1–1/e)。最后，在不同的尺度和约束条件下，我们进行了实验，以展示RMES与现有基线算法相比的优越性能。

1. Introduction

将路径规划与能量共享相结合是解决移动充电问题的一种可行方案。WCV只访问选定的传感器对其充电，而被充电的传感器可以通过单跳或多跳的方式与其他传感器共享能量。这种方法为WCV提供了节能和省时的路线，甚至可以通过辅助设备成功地为难以访问的传感器充电。

本文贡献：

1）将JOIN-ME问题表示为具有一般约束的子模最大化问题。

2）设计了一种近似算法，称为Routing planning, Mobile charging and Energy sharing for Sensing devices(RMES)算法，近似比为1/8(1−1/e)

3）模拟实验来评估RMES。通过改变WCV电池容量和传感器数量来评估RMES问题的性能。

Fig. 1. Mobile charging with energy sharing in WRSN

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2. CHARGING MODEL AND PROBLEM FORMULATION

A. Charging Model Description

We consider a WRSN consisting of n rechargeable sensors, a WCV, and a base station. The WCV is the energy supplier for all sensors in the network, whether directly or indirectly. We assume that the WCV visits several sensors periodically to maintain the normal operation of the sensor network. The WCV starts from the base station for each tour and visits several sensors. The sensors not visited by the WCV gain energy from the sensors charged by WCV. Finally, the WCV finishes this charging tour and goes back to the base station.

Consider a set of sensors $S = \{s_1, s_2, \cdots, s_n\}$, which distribute in a 2D $d \times d$ plane. The sensors have diverse energy demands $E = \{e_1, e_2, \cdots, e_n\}$.

Fig. 1. Mobile charging with energy sharing in WRSN

2. CHARGING MODEL AND PROBLEM FORMULATION

a) **WCV charging:** A subset of sensors are directly charged by the WCV. Denote the direct energy gain from the WCV as $E_c = \{x_1, x_2, \cdots, x_n\}$, where x_i is the energy gain of sensor s_i from WCV and the charging set is $X = \{s_i \mid x_i > 0\}$. Since a long time of charging may cause the sensor to overheat, we assume that every sensor can only be charged by the WCV with a limited energy $E_{\max}$.

We also assume that the WCV has a limited energy $C_{\max}$, and the cost of the WCV is a constraint for the WRSN. There are two energy costs for WCV charging: the travelling energy cost and the charging energy cost. For travelling energy cost, we can denote that $\alpha L(T)$, where α is the energy cost for the WCV travel a unit distance, and $L(T)$ is the distance for the WCV to visit all the charging points of T. For charging energy cost, we can denote that $\sum_{i=1}^{n} x_i/\eta_i = \sum_{i=1}^{n} T_i e_{\min}/\eta_i$, where η_i is the charging efficiency of the WCV for sensor s_i. We can get the total energy cost of WCV charging as follows:

$$C(\mathbf{T}) = \alpha L(\mathbf{T}) + \sum_{i=1}^{n} T_i e_{\min}/\eta_i. \quad (1)$$

$e_{\min}$：离散化后的最小单位电量

b) **Energy sharing:** Network connections between sensors are common because data transmission and aggregation between sensors are needed. These networks can also be reused as energy transmission networks. Inherently, energy loss is inevitable during sharing and is closely related to practical factors such as distance and the transmission cable. We use η_{ij} to denote the energy efficiency from sensor s_i to sensor s_j. If s_i cannot directly charge s_j, then $\eta_{ij} = 0$. In our study, we define η_{ij} decreasing linearly:

$$\eta_{ij} = \begin{cases} \max\{1 - pd_{ij}, 0\} & \text{if } s_i \text{ can charge } s_j, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where p is the energy loss coefficient, and d_{ij} is the distance between s_i and s_j. This energy efficiency definition is only a simple example of sharing efficiency definition, and our algorithm can be extended to more complex cases.

Notice that the energy sharing process can be a multi-hop process. η_{ij} may not be the max energy efficiency from s_i to s_j, because probably there is a sensor s_k between s_i and s_j, and $\eta_{ik}\eta_{kj} > \eta_{ij}$. We use $\eta_{ij}^{\max}$ to denote the max energy efficiency from s_i to s_j.

Suppose the energy transmitted from sensor s_i to sensor s_j is x_{ij}, then the energy received by sensor s_j is $x_{ij}\eta_{ij}^{\max}$. We use E_s to denote the energy sharing vector, i.e., $E_s = \{x_{ij} | i, j = 1, 2, \cdots, n\}$.

After the WCV charging and energy sharing, the sensor s_i gain $x_i = T_i e_{\min}$ from WCV, $\sum_{j=1}^{n} x_{ji}\eta_{ji}^{\max}$ from energy sharing, and gives $\sum_{j=1}^{n} x_{ij}$ to other sensors. Then we get the residual energy $\hat{e_i}$ of sensor s_i as:

$$\hat{e_i} = x_i + \sum_{j=1}^{n} x_{ji}\eta_{ji}^{\max} - \sum_{j=1}^{n} x_{ij}. \tag{3}$$

2. CHARGING MODEL AND PROBLEM FORMULATION

B. Problem Formulation

In order to improve the overall availability and coverage, we define the energy utility U_i for sensor s_i as follows:

Definition 1 (Energy utility U_i for a sensor)**.** *The energy utility U_i for sensor s_i is defined as*

$$U_i = \min\{\hat{e}_i/e_i, 1\}, \tag{4}$$

where we compare the ratio of the sensor's residual energy $\hat{e}_i$ and its energy requirement e_i with 1, and the smaller of the two is taken as the utility value.

Summing up the energy utility of all sensors, we get the total energy utility U, which is closely related to the energy gain of the WCV charging choice $\mathbf{T}$ and energy sharing E_s:

$$U(\mathbf{T}, E_s) = \sum_{i=1}^{n} U_i = \sum_{i=1}^{n} \min\{\hat{e}_i/e_i, 1\}. \tag{5}$$

Here, We want to maximize the total utility $U(\mathbf{T}, E_s)$ and formulate the problem as follows:

Definition 2 (JOIN-ME problem)**.** *Given a set of sensors S and a WCV with total energy cosr limit $C_{\max}$, Our goal is to choose the best charging choice $\mathbf{T}$ and energy sharing E_s to maximize the total energy utility U. Consequently, we can formulate the problem of Joint OptimIzatioN of Mobile charging and Energy sharing of sensors (JOIN-ME) as follows:*

$$\begin{aligned}
\max \quad & U(\mathbf{T}, E_s); & & \\
\textit{s.t.} \quad & C(\mathbf{T}) \le C_{max}, & X \subseteq S; & \\
& \hat{e}_i \ge 0, & i = 1, 2, \cdots, n; & \qquad (6)\\
& x_i \le E_{max}, & i = 1, 2, \cdots, n; & \\
& x_{ij} \ge 0 & i, j = 1, 2, \cdots, n; &
\end{aligned}$$

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2. CHARGING MODEL AND PROBLEM FORMULATION

Theorem 1. *The JOIN-ME problem is NP-hard.*

Proof: The hardness proof is based on the NP-hard *Charging Reward Maximization problem* in [17] where a mobile charger moves and charges sensors in WRSNs such that the sum of charging rewards from all charged sensors, which is proportional to the amount of energy charged, is maximized without violation of charger energy capacity. With all sharing energy variables $x_{ij}\,(i,j=1,2,\cdots,n)$ set to 0, our problem can be directly reduced from the above problem. Therefore, we conclude that JOIN-ME is NP-hard. ∎

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3. RMES ALGORITHM

RMES算法分为能量共享和充电车充电两个阶段。能量共享阶段需要确定传感器之间能源的最佳分配。充电阶段需要为WCV设计一个充电策略，使得网络能量增益最大化，同时最小化充电成本。

A. *Energy Sharing Strategy*

In the energy sharing phase of RMES, we assume that the WCV has already chosen a charging choice $\mathbf{T}$ and a subset X of sensors to charge. Then we solve the energy sharing problem to obtain the appropriate energy sharing vector E_s. We first generate the maximum energy efficiency matrix $\eta_{ij}^{\max}$ and then solve the energy sharing problem according to the idea of a greedy algorithm.

转化为全源最短路问题

Algorithm 1: Greedy Energy Sharing Algorithm

Input: Sensor set S,
$E_c = \{T_1 e_{\min}, T_2 e_{\min}, \cdots, T_n e_{\min}\}$.
Output: Matrix variables of sharing energy E_s.

```
/* Generate maximum energy efficiency
   matrix η_ij^max.                                  */
Get all-pairs shortest-path matrix D_ij^max by Johnson
  algorithm for edge weight −log(η_ij);
η_ij^max ← exp(−D_ij^max);
/* Solve energy sharing problem.                     */
Set x_ij ← 0 and ê_i ← x_i for i, j = 1, 2, ···, n;
k_ij ← η_ij^max e_i/e_j for all i, j;
Sort K = {k_ij} non-increasingly;
for k_ij ∈ K do
    if ê_j < e_j and k_ij > 1 then
        x_ij ← min{ (e_j − ê_j)/η_ij^max , ê_i };
        ê_i ← ê_i − x_ij; ê_j ← ê_j + x_ij η_ij^max;
return E_S = {x_ij | i, j = 1, 2, ···, n}.
```

3. RMES ALGORITHM

A. *Energy Sharing Strategy*

Then we solve the energy sharing problem, which is shown in Lines 2 to 6 of Algorithm 1. We first assume that s_i transmits x_{ij} amount of energy to s_j. The original part of x_{ij} in energy ratio before sharing is x_{ij}/e_i and after sharing it turns into $(\eta_{ij}^{\max} x_{ij})/e_j$ since s_j receives $\eta_{ij}^{\max}$ amount of energy. In order to increase energy ratio, we have $(\eta_{ij}^{\max} x_{ij})/e_j > x_{ij}/e_i$, and we get $\frac{\eta_{ij} e_i}{e_j} > 1$. If energy on s_j is no less than its demand e_j, it means s_j obtains enough energy either from WCV or sensors ahead of s_i in X, s_i will not share energy with s_j.

$$U(\mathbf{T}, E_s) = \sum_{i=1}^{n} U_i = \sum_{i=1}^{n} \min\{\hat{e}_i/e_i, 1\}. \qquad (5)$$

Algorithm 1: Greedy Energy Sharing Algorithm

Input: Sensor set S,
$E_c = \{T_1 e_{\min}, T_2 e_{\min}, \cdots, T_n e_{\min}\}$.
Output: Matrix variables of sharing energy E_s.

/* Generate maximum energy efficiency matrix $\eta_{ij}^{\max}$. */
1 Get all-pairs shortest-path matrix $D_{ij}^{\max}$ by Johnson algorithm for edge weight $-\log(\eta_{ij})$;
2 $\eta_{ij}^{\max} \leftarrow \exp(-D_{ij}^{\max})$;
/* Solve energy sharing problem. */
3 Set $x_{ij} \leftarrow 0$ and $\hat{e}_i \leftarrow x_i$ for $i, j = 1, 2, \cdots, n$;
4 $k_{ij} \leftarrow \eta_{ij}^{\max} e_i / e_j$ for all i, j;
5 Sort $K = \{k_{ij}\}$ non-increasingly;
6 **for** $k_{ij} \in K$ **do**
7   **if** $\hat{e}_j < e_j$ **and** $k_ij > 1$ **then**
8         $x_{ij} \leftarrow \min\left\{\frac{e_j - \hat{e}_j}{\eta_{ij}^{\max}}, \hat{e}_i\right\}$;
9         $\hat{e}_i \leftarrow \hat{e}_i - x_{ij}$; $\hat{e}_j \leftarrow \hat{e}_j + x_{ij}\eta_{ij}^{\max}$;
10 **return** $E_S = \{x_{ij} | i, j = 1, 2, \cdots, n\}$.

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3. RMES ALGORITHM

B. Energy Allocation Strategy

Algorithm 2: Cost-Efficient Algorithm

Input: Sensor set S with related properties, max charging energy $E_{\max}$, discretization factor n_T.

Output: Charging choice vector $\mathbf{T}$, energy sharing matrix E_s.

1 $\mathbb{T}^{\text{choice}} \leftarrow \{\mathbf{t}_{i,t}^{\text{choice}} | i = 1, 2, \cdots, n; t = 1, 2, \cdots, n_T\}$;
2 Set T to a zero vector, E_s to a zero matrix;
3 **while** $\mathbb{T}^{choice}$ *is not empty* **do**
4   **for** $\forall \mathbf{t}_{i,t}^{choice} \in \mathbb{T}^{choice}$ **do**
5     $\mathbf{T}'(i,t) \leftarrow \mathbf{T}$; $\mathbf{T}'_i(i,t) \leftarrow t$;
6   Get according energy sharing matrix $E'_s(i,t)$ by Algorithm 1 of choice $\mathbf{T}'$;
7     $\Delta U(i,t) \leftarrow U(\mathbf{T}'(i,t), E'_s(i,t)) - U(\mathbf{T}, E_s)$;
8     $\Delta C(i,t) \leftarrow C(\mathbf{T}'(i,t)) - C(\mathbf{T})$;
9   **if** $C(\mathbf{T}'(i,t)) \leq C_{\max}$ *or* $\Delta U(i,t) = 0$ **then**
10       $\mathbb{T}^{\text{choice}} \leftarrow \mathbb{T}^{\text{choice}} \backslash \mathbf{t}_{i,t}^{\text{choice}}$
11   $\mathbf{t}_{i,t}^{\text{choice}} \leftarrow \arg\max_{\mathbf{t}_{i,t}^{\text{choice}}} \dfrac{\Delta U(i,t)}{\Delta C(i,t)}$ for $\forall \mathbf{t}_{i,t}^{\text{choice}} \in \mathbb{T}^{\text{choice}}$;
12   Set $T \leftarrow T'(i,t)$ and $E_s \leftarrow E'_s(i,t)$;
13   $\mathbb{T}^{\text{choice}} \leftarrow \mathbb{T}^{\text{choice}} \backslash \{\mathbf{t}_{i,j}^{\text{choice}}, j = 1 \cdots t\}$;

寻找最优的充电策略T和能量共享方案Es，使整个网络的充电效用最大化。

输入：传感器集合S，传感器最大充电量Emax，电量离散化系数nT

输出：充电策略T，能量共享方案Es

- **Rule 1:** The cost of WCV exceeds $C_{\max}$ for update choice vector T' or the marginal energy utility of WCV is zero for update energy sharing matrix E'_s when using the charging choice $\mathbf{t}_{i,t}^{\text{choice}}$ to update T and E_s. (Line 9)
- **Rule 2:** If charging choice $\mathbf{t}_{i,t}^{\text{choice}}$ is chosen in the previous iteration, then the charging choice $\mathbf{t}_{i,j}^{\text{choice}}(j = 1 \cdots t)$ is removed from $\mathbb{T}^{\text{choice}}$. In other words, if sensor s_i is charged t units of energy $e_{\min}$, then we do not consider charging less energy to sensor s_i in further iterations. (Line 13)

4. THEORETICAL ANALYSIS

A. Analysis for Energy Sharing Strategy Property

Definition 3 (Nonnegativity, monotonicity, and submodularity). *Let $\mathbf{T}_C$ be the full charge strategy, i.e., $\mathbf{T}_C = \{n_T, \cdots, n_T\}$. The $\mathcal{U}(\mathbf{T})$ is nonnegative, monotone, and submodular for T if and only if:*

- ***Nonnegativity***:$\mathcal{U}(\mathbf{T}) \geq 0$ *for* $\forall \mathbf{T} \subseteq \mathbf{T}_C$.
- ***Monotonicity***: $\mathcal{U}(\mathbf{T} \cup e^i_{\min}) \geq \mathcal{U}(\mathbf{T})$ *for* $\forall \mathbf{T} \subset \mathbf{T}_C$ *and* $\forall i$.
- ***Submodularity***: $\mathcal{U}(\mathbf{T}_1 + e^i_{\min}) - \mathcal{U}(\mathbf{T}_1) \geq \mathcal{U}(\mathbf{T}_2 + e^i_{\min}) - \mathcal{U}(\mathbf{T}_2)$ *for* $\forall \mathbf{T}_1 \subseteq \mathbf{T}_2 \subset \mathbf{T}_C$ *and* $\forall i$.

Lemma 1. *Energy utility $\mathcal{U}(\mathbf{T})$ is nonnegative, monotone, and submodular for T.*

The nonnegativity is proved from the definition of the energy utility function. To prove monotonicity, we decompose the energy utility into two parts, sharing and base, and show that adding energy to any charging choice will increase both of these parts, leading to an overall increase in the energy utility. Finally, to prove submodularity, we use a greedy sharing strategy and show that adding energy to a smaller charging choice will always have a greater marginal effect than adding energy to a larger charging choice.

$$U(\mathbf{T}, E_s) = \sum_{i=1}^{n} U_i = \sum_{i=1}^{n} \min\{\hat{e}_i/e_i, 1\}. \qquad (5)$$

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4. THEORETICAL ANALYSIS

B. Analysis for Charging Discretization

To deal with continuous charging, we adopt a charging energy discretization mechanism. In this subsection, we give the gap between our solution to the optimal continuous one.

Lemma 2. *When the energy capacity of the mobile charger satisfies that $C_{\max} > \alpha n \times 2\sqrt{2}d$, the optimal energy utility after charging energy discretization achieves at least $1/2$ of the optimal energy utility in the continuous case.*

Proof: As the mobile charger has more than $2\sqrt{2}nc_1a$ amount of energy, then it can visit all sensors at least once when traveling in the $a*a$ square plain. We use U^* denote the continuous optimal solution where any sensor can be charged any amount of energy to maximize the overall coverage utility. Given any minimum amount of energy charged to a sensor as e_{min}, we can achieve a discrete solution U_r by rounding U^*. For example, for any sensor s_i to be charged e_i amount of energy in U^*, we round it by charging only $\left\lfloor \frac{e_i}{e_{min}} \right\rfloor e_{min}$ and thus construct this discrete solution U_r. Apparently due to $\left\lfloor \frac{e_i}{e_{min}} \right\rfloor e_{min} \leq e_i$, U_r is a feasible discrete solution.

Moveover, the sufficient energy of the mobile charger can maintain that each sensor can be charged e_{min} amount of energy. Then we consider this kind of feasible discrete solution which can be denoted by U_e. Naturally, the value of the sum of the two discrete solutions is larger than the value of the optimal solution and we have

$$U^* \leq U_r + U_e. \tag{15}$$

If we use U_c^* to denote the optimal discrete solution based on the e_{min} amount of energy, apparently we have the following two relations as

$$U_r \leq U_c^*, U_e \leq U_c^*$$

and derive $U_r + U_e \leq 2U_c^*$. Combining Equation 15, we have the result $U^* \leq 2U_c^*$. ■

4. THEORETICAL ANALYSIS

C. Analysis for Energy Sharing Strategy Gap

In this subsection, we analyze the gap between our greedy energy sharing strategy and the optimal sharing strategy. According to the previous analysis, we have $U(X) = U(T, E_s)$. Let P' be our greedy sharing strategy and P^* be the optimal, and energy utility under P' be $U(T, E'_s)$ and energy utility under P^* be $U(T, E^*_s)$.

Lemma 3. *For any selected sensor set X with their charging energy, the overall utility achieved by our greedy sharing strategy P' in $U(T, E'_s)$ can achieve at least $1/2$ of the optimal energy utility in $U(T, E^*_s)$ under optimal sharing strategy P^*.*

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D. Approximation Ratio Analysis

Theorem 2. *If energy capacity of mobile charger satisfies that* $B > \alpha n \times 2\sqrt{2}d$, *the proposed algorithm achieves* $\frac{1}{8}(1-1/e)$ *approximation ratio.*

Proof: In Lemma 1, we prove that utility sharing function is nonnegative, monotone, and submodular. Hence, we transform the joint optimization problem into a submodular maximization problem with a general routing constraint. Thus, referring to [18], our Cost-Efficient algorithm, where the nearest-neighbor rule is applied to calculate the traveling cost, would achieve $\frac{1}{2}(1-1/e)$ bi-criterion approximation ratio with a slightly relaxed budget constraint. The quality of the approximated cost function $C(\mathbf{T})$ in Equation (1) has a significant impact on the relaxed degree.

Furthermore, we prove the $1/2$ gap between discrete and continuous solutions in Lemma 2, and the $1/2$ approximation ratio of our greedy energy sharing strategy compared with the optimal in Lemma 3. Hence, combine all bounds above and we can obtain $\frac{1}{8}(1-1/e)$ approximation ratio of our solution. Besides, proof of the time complexity of our algorithm is omitted here due to the space limit. ■

5. EXPERIMENTS AND RESULTS

Although no algorithm is completely compatible with the JOIN-ME problem, some works are similar to ours. We select the following algorithms for comparison:

a) **Utility Greedy:** This algorithm is similar to our algorithm, but it only considers the energy utility of the sensors. It is a greedy algorithm that iteratively selects the sensor with the highest energy utility $\Delta U(i,t)$ and assigns it to the WCV.

b) **Clustering Method:** This algorithm is a clustering algorithm that divides the sensors into several clusters. Many studies have shown that the clustering method can achieve a good result [4], [20]–[22]. We use the DBSCAN algorithm to cluster the sensors [23]. The sensor with the highest energy need is selected to charge to match our capability-sharing strategy. To calculate how much energy the WCV should charge, we give every cluster a weight w_i according to the energy need of the cluster:

$$w_{\text{cluster i}} = \frac{\sum_{j \in \text{cluster}} e_j / \eta_{\text{charged sensor},j}}{\eta_{\text{charged sensor}}}. \quad (8)$$

Then we calculate the energy for the WCV to visit all the sensors need to chargeC_{travel}, and allocate the rest of the energy to the sensors according to the weight w_i:

$$x_{\text{charged sensor}} = (C_{\max} - C_{\text{travel}}) \frac{w_{\text{cluster}} \eta_{\text{charged sensor}}}{\sum_{i \in \text{cluster}} w_i}. \quad (9)$$

对比实验设置

Utility Greedy：与本文算法相似，但它只考虑传感器的充电效用。它是一种贪婪算法，迭代地为WCV选择能量效用增量ΔU(i, t)最高的充电操作。

Clustering Method：该算法是一种聚类算法，通过使用DBSCAN算法对传感器进行聚类。对每个簇都选择能量需求最高的传感器进行充电。为了计算WCV应该分配多少能量，算法根据每个簇的能量需求占总能量需求的比重计算权重wi:

$$w_{\text{cluster i}} = \frac{\sum_{j \in \text{cluster}} e_j / \eta_{\text{charged sensor},j}}{\eta_{\text{charged sensor}}}. \quad (8)$$

然后，计算WCV访问所有待充电传感器的所需的移动能量消耗Ctravel，并根据权重wi将剩余能量分配给传感器:

$$x_{\text{charged sensor}} = (C_{\max} - C_{\text{travel}}) \frac{w_{\text{cluster}} \eta_{\text{charged sensor}}}{\sum_{i \in \text{cluster}} w_i}. \quad (9)$$

5. EXPERIMENTS AND RESULTS

*c) **TSP Only:*** In some studies, the energy sharing is not considered [24], [25]. The TSP only means the sharing efficiency is 0 and all other parameters are the same as our RMES algorithm.

*d) **One Hop:*** In this algorithm, we set the maximum energy sharing efficiency $\eta_{\max}$ as:

$$\eta_{i,j}^{\max} = \eta_{i,j} \quad \forall i, j, \tag{10}$$

and all other parameters are the same as RMES. This algorithm is intermediate between TSP Only and RMES.

TSP Only： 不考虑能量共享，其他参数与RMES算法相同。

One Hop： 只考虑传传感器间的直接能量传输。将最大能量共享效率ηmax设为:

$$\eta_{i,j}^{\max} = \eta_{i,j} \quad \forall i, j, \tag{10}$$

其他参数均与RMES相同。该算法介于TSP Only和RMES之间。

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5. EXPERIMENTS AND RESULTS

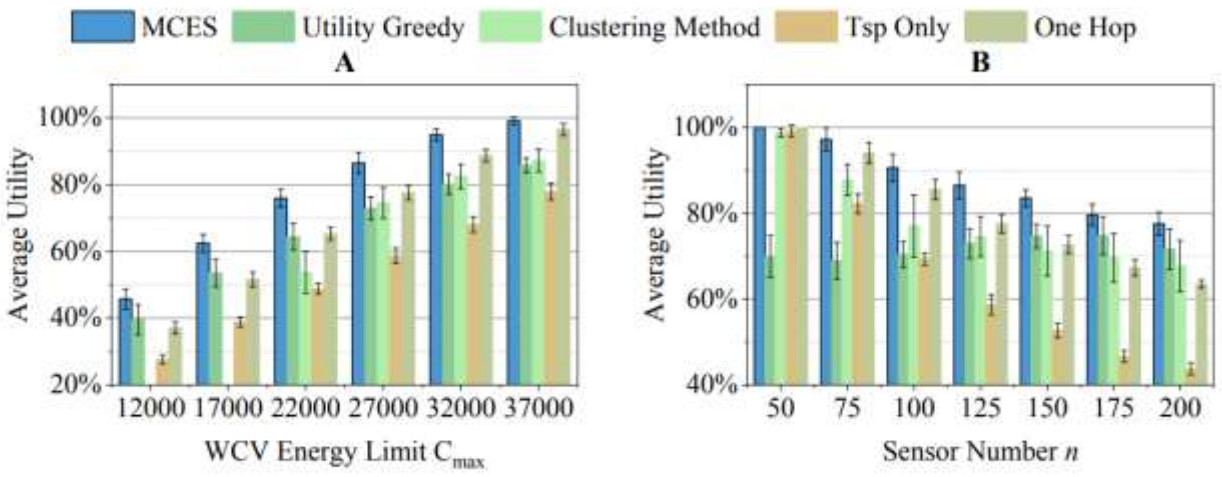

Fig. 2. The average energy utility under different map settings and algorithms. In subfigure (A), we change the WCV energy limit $C_{\max}$ from 12000 to 37000; In subfigure (B), we change the sensor number n from 50 to 200. Each situation is repeated 10 times with different random seeds.

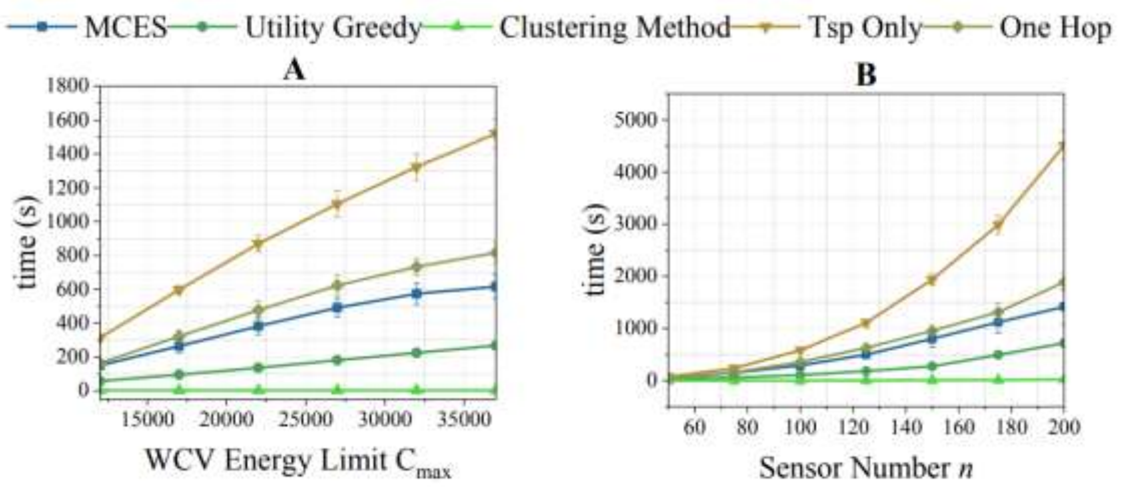

Fig. 3. The time for a single solution. In subfigure (A), we change the WCV energy limit $C_{\max}$ from 12000 to 37000; In subfigure (B), we change the sensor number n from 50 to 200. Each situation is repeated 10 times with different random seeds.

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谢谢！