IJIBC 22-4-10

# Energy-efficient charging of sensors for UAV-aided wireless sensor network

Shakila Rahman, Shathee Akter and Seokhoon Yoon\*

M.Sc. Student, Department of Electrical, Electronic, and Computer Engineering, University of Ulsan, Ulsan, Korea Ph.D. Candidate, Department of Electrical, Electronic, and Computer Engineering, University of Ulsan, Ulsan, Korea Professor, Department of Electrical, Electronic, and Computer Engineering, University of Ulsan, Ulsan, Korea <u>shakila.rahman1119@gmail.com</u>, <u>erittrashathee@gmail.com</u>, and <u>seokhoonyoon@ulsan.ac.kr</u>

## Abstract

Lack of sufficient battery capacity is one of the most important challenges impeding the development of wireless sensor networks (WSNs). Recent innovations in the areas of wireless energy transfer and rechargeable batteries have made it possible to advance WSNs. Therefore, in this article, we propose an energy-efficient charging of sensors in a WSN scenario. First, we have formulated the problem as an integer linear programming (ILP) problem. Then a utility function-based greedy algorithm named UGreedy/UF1 is proposed for solving the problem. Finally, the performance of UGreedy/UF1 is analyzed along with other baseline algorithms: UGreedy/UF2, 2-opt TSP, and Greedy TSP. The simulation results show that UGreedy/UF1 performs better than others both in terms of the deadline missing ratio of sensors and the total energy consumption of UAVs.

**Keywords:** Wireless sensor networks (WSNs), unmanned aerial vehicle (UAV), traveling salesman problem (TSP), greedy algorithm.

# **1. Introduction**

Over the past few decades, wireless sensor networks (WSNs) have been frequently employed in a variety of areas, such as disaster relief, military operations, households, smart cities, and agriculture. In typical WSN applications, the data are usually collected from sensors using a multi-hop forwarding scheme. However, this may result in an energy hole problem since sensors near the sink will consume more energy than the sensors far away from the sink to relay the data. Therefore, we have considered charging the sensors in the network by employing multiple unmanned aerial vehicles (UAVs) since UAVs are flexible, easy to deploy, and can reach remote places to charge the sensors.

There have been several studies that consider charging the sensors using UAVs in the WSN areas [1]-[5]. The authors in [1] focused on charging energy-constrained devices using UAVs. They aimed at increasing the total energy of UAVs while charging devices. [2] used the charging unmanned aerial vehicles (CUAVs) to charge

Corresponding Author: seokhoonyoon@ulsan.ac.kr

Tel: +82-52-259-1403, Fax: +82-52-259-1687

Manuscript Received: September. 5, 2022 / Revised: September. 9, 2022 / Accepted: September. 11, 2022

Professor, Department of Electrical, Electronic, and Computer Engineering, University of Ulsan, Korea

sensor nodes in a WSN area, considering the traveling energy consumption reduction while increasing the efficiency of charging. The network lifespan increase in a charging situation was the main topic of the study [3]. UAVs can be used to recharge sensor networks, which may be one way to extend network lifetime. This article assesses that strategy, identifying the benefits it offers and under what circumstances. In [4], the authors studied that mobile chargers can be utilized to send energy to sensor nodes using UAVs with large-capacity batteries. They created a mathematical model that can minimize dead nodes in the WSN and maximize energy efficiency during charging. Moreover [5] also focused on sensor node charging issues using wireless charging drones or UAVs. They have developed their model with a single drone with a limited range and a number of wireless charging pads (pads) placed throughout the network to charge the drone when it can't make it to the next stop. However, they did not consider the UAVs' path as a Hamiltonian path and did not consider the UAV battery constraint and deadline constraint of the sensors into account.

Therefore, this paper studies the total energy consumption minimization of UAVs in a charging scenario while planning the trajectories for multiple UAVs, along with the battery constraints of UAVs and the deadline constraint of sensors. In the proposed approach each UAV path is a TSP tour, where each UAV starts and ends its journey to the sink and recharges the UAV battery from the sink while charging the sensor nodes in its traveling path. An algorithm UGreedy/UF1 is proposed to find the UAV trajectories, which outperforms other comparing algorithms.

The paper's organization is given as follows: The system model and problem formulation are described in section 2. After that, the algorithm is described in section 3 with pseudo-code. Finally, the performance evaluation and conclusion are presented in sections 4 and 5, respectively.

### 2. System model and Problem formulation

In this section, the proposed system model and problem formulation are presented in detail. The proposed energy-efficient charging scheme is illustrated in Figure 1. Assuming a square area with N sensors and a sink, where sensors are randomly allocated to the area and the positions of the sensors are known. Sensors have a limited battery capacity, which means the network can only remain operational for a limited amount of time. To keep the sensors from completely draining out their battery and the network alive, a set of UAVs  $U = \{1, 2, ..., P\}$  is appointed to charge the groups of sensor nodes periodically. The sensors in the environment are grouped into P number of groups according to the number of

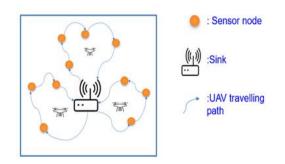


Figure 1. System model

UAVs, and a UAV is assigned to each group to charge the sensors. Let us consider, a deadline  $D_i$  for each sensor, and each UAV needs to visit the sensor *i* within the given deadline  $D_i$ . Here, for each sensor the

deadline is the expected time when the sensor's battery capacity is expected to finish. Furthermore, we consider that the UAV battery will be fully charged at the beginning of the tour and the battery capacity of UAV p is  $Q_p$ . In this work, the total energy consumption by UAV  $p(p \in U) E_{uav}^p$ , is calculated as follows:

$$E_{uav}^p = E_t^p + E_c^p + E_h^p \tag{1}$$

where  $E_t^p$ ,  $E_c^p$ , and  $E_h^p$  represent the energy utilized by the UAV while traveling, while charging the sensors and while hovering, respectively.

The objective of this work is to find the paths for multiple UAVs with minimum energy consumption of UAV while ensuring that the total energy consumption of UAV p cannot exceed the battery capacity  $Q_p$ . Assume a graph  $V = \{0, 1, 2, ..., N\}$ , where 0 represents the sink and rest of the elements are sensor nodes. The UAV will start its' journey to charge the sensors from sink node 0 and ends the journey to the sink. Let  $x_{ii}^p$  be a decision variable, and that is,

$$x_{ij}^{p} = \begin{cases} 1, if \ UAV \ visit \ sensor \ j \ right \ after \ visiting \ the \ sensor \ i. \ i, j \ \in V, p \in U \\ 0, & Otherwise \end{cases}$$
(2)

Let us denote  $A_p$ ,  $B_p$  and  $C_p$  as the power supplied by UAV p while traveling, charging, and hovering, respectively. Moreover, the total traveling time of a UAV from the sensor i to j is denoted by  $t_{ij}$ , the time spend for charging of a UAV is represented by  $t_i$  and  $h_i$  denote the time spends by a UAV when it hovers. So, equation (1) can be rewritten as,

$$E_{uav}^{p} = \sum_{p=1}^{p} \sum_{i=1}^{N} \sum_{j=1}^{N} (A_{p}t_{ij} + B_{p}t_{i}) x_{ij}^{p} + C_{p}h_{i}$$
(3)

Here  $t_{ij}$  is calculated by,  $t_{ij} = \frac{a_{ij}}{v}$ .  $d_{ij}$  is the Euclidean travel distance from node *i* to *j*, and *v* is the velocity of the UAV. As deadline  $D_i$ , is the expected time when the battery capacity of sensor *i* will finish, which can be calculated by,  $D_i = \frac{R_i}{P_i}$ . Here,  $P_i$  is the energy consumed by a sensor in per second and  $R_i$  is the remaining energy of sensor *i* before UAV start it's tour. Now the problem can be formulated as,

$$minimize \ \sum_{p=1}^{P} \sum_{i=1}^{N} \sum_{j=1}^{N} \left( A_p \frac{d_{ij}}{v} + B_p t_i \right) x_{ij}^p + C_p h_i \tag{4}$$

subject to 
$$\sum_{j=1, j \neq i}^{N} \sum_{p=1}^{P} x_{ij}^{p} = 1, i \in V \setminus \{0\}$$
 (5)

$$\sum_{i=1, i \neq j}^{N} \sum_{p=1}^{P} x_{ij}^{p} = 1, \ j \in V \setminus \{0\}$$
(6)

$$\sum_{p=1}^{P} \sum_{i=1}^{N} \sum_{j=1}^{N} \left( A_p \frac{d_{ij}}{v} + B_p t_i \right) x_{ij}^p + C_p h_i \le Q_p \tag{7}$$

$$u_0^p = 1, i \in V \setminus \{0\}, p \in V \tag{8}$$

$$2 \le u_i^p \le N, \forall_i \in V \setminus \{0\}$$
(9)

$$u_j^p \ge u_i^p + 1 - n\left(1 - x_{ij}^p\right), i \ge 0, j \ge 1, i \ne j, x_{ij}^p \in \{0, 1\}$$
<sup>(10)</sup>

$$\sum_{i'=1}^{\binom{p}{l'=j}-1} \left[ \frac{d_{i^*j^*}}{v_p} + t_{i^*} \Big|_{i^* \mid u_{i^*}^p = i', j^* \mid u_{j^*}^p = i'+1} \right] \le D_j$$
(11)

$$\forall_j \in V \setminus 0, \forall_p \in U, i^*, j^* \in V \setminus 0 \tag{12}$$

The objective function of this work is represented in the equation (4). Equation (5) and (6) are the outgoing and incoming constraint, which ensure that every sensor except sink is visited exactly once by only one UAV. The equation (7) is the UAV energy consumption constraint, which limit the UAV energy consumption. Constraints (8), (9), and (10) represent the sub tour elimination constraint. The sub tour elimination constraints and the deadline constraints (11) and (12) together ensure that UAV will come to the sensor j before its deadline  $D_j$ .

## 3. Algorithm

In this section, we have explained a utility function-based greedy algorithm named UGreedy/UF1 that has been used to plan the UAV's path according to our system model. In UGreedy/UF1, at each step the path with the highest utility value is chosen. At first, we will explain the utility function (UF1) and then the UGreedy/UF1 algorithm is explained along with the proposed utility function.

UF1: The utility function used in the UGreedy/UF1 is represented by,

$$Z(i,j) = \frac{1}{\left(\alpha \times \frac{d_{ij}}{x}\right) + \left((1-\alpha) \times \frac{D_j}{y}\right)}$$
(13)

Here  $\alpha$  is a co-efficient value with the range [0-1],  $d_{ij}$  is the traveling distance from sensor *i* to *j*,  $D_j$  is the given deadline value of sensor *j*,  $x = \max_{j \in V \neq \{i\}} (d_{ij})$  is the maximum traveling distance between any two sensor *i* and *j* among all distances between any two sensors, and  $y = \max_{j \in V} (D_j)$  is the maximum deadline value among all sensors in *V*.

A utility function based greedy approach (UGreedy/UF1): The pseudo-code of the UGreedy/UF1 algorithm

Algorithm 1 UGreedy/UF1 Input: Set of sensors V for p groups Output: Set of tours T for p UAVs 1: Initialization 2: Apply k-means algorithm to V and made p groups for p UAVs 3: for  $p \in U$  do  $T_p \leftarrow \{0\}, k = 0$ 4: while  $V_p \neq 0$  do 5:  $j \leftarrow \operatorname{argmax} Z(k, j); k \neq j$ 6:  $j \in V_p$  $T_p \leftarrow T_p \cup \{j\}$ 7:  $V_p \leftarrow V_p \setminus \{j\}$ 8: while all constraints are feasible do 9: k = j10: end while 11: 12:Calculate  $E_p$  using the equation (3) and deadline missing ratio end while 13:14: Set of tours T that contains the maximum utility value and total energy consumed by all UAVs with a deadline missing ratio 15: end for

is presented in algorithm 1. At first, sensors are grouped into p using the K-means algorithm [6] in line 2. For

each UAV p, the next visiting sensor is selected in lines 3-6 based on the utility function. Then, add the sensor j with the highest utility value in the UAV trajectory  $T_p$  in line 7. After that, the visited sensor j is removed from the set of unvisited sensors  $V_p$  in line 8 and j is updated to the current visiting node k in line 10 when all constraints are feasible. The total energy consumption and deadline missing ratio for each UAV p is calculated in line 12. Finally, the set of optimal tours of UAVs is found in line 14 with maximum utility value and total energy consumption of all UAVs with a deadline missing ratio r.

## 4. Performance Evaluation

In this section, the performances of our proposed algorithm UGreedy/UF1 is compared with other baseline algorithms in different scenarios. The simulation parameters are presented below, where the default values are presented in bold fonts: the experimental area is considered as the area of  $7 \times 7 \ km^2$ , where the number of sensors are 8,10,12,14,16, and the number of UAVs are 2,4,6,8,10. We have used different velocity (km/h) for the UAVs, such as 10, 20, 30, 40 and 50. Each UAV consume 3500 watts [7], 10 watts [7] and 4375 watts [7] power while traveling, charging and hovering, respectively. The UAV battery capacity or residual energy is 12000 KJ [8] and the initial power of sensors is 10800 watts [9]. The value of remaining energy of sensors changes within a range [a,b], where a is fixed, i.e., 1620 Joules, and b varies from 1620J to 2160J, 2700J, 3240J, 3780J and 4320J. In this work, the deadline of a sensor is the sensor's remaining time to function in the network. Therefore, the lower deadline value is 3 minutes, where the upper range of the deadline changes as 6, 9, **12**, 15 and 18 minutes, which is calculated using the sensor's remaining energy and power. Each UAV spends 2 seconds to charge the sensor nodes. The co-efficient value for the proposed UGreedy/UF1 is considered from range 0 to 1.

#### Description of compared algorithms:

*UGreedy/UF2*: The UGreedy/UF2 is similar to UGreedy/UF1. The only difference is in their utility function. The utility function (UF2) used in UGreedy/UF2 is presented as,

$$W(i,j) = \frac{1}{t_{ij} + D_j} \tag{14}$$

where  $t_{ij}$  is the traveling time from sensor *i* to *j* and  $D_j$  is the deadline of the sensor *j*.

*Greedy TSP:* The Greedy TSP is similar to both UGreedy/UF1 and UGreedy/UF2. The only difference is that while calculating the utility value, the Greedy TSP only considers the distances between sensors.

2-opt TSP: The 2-opt TSP algorithm [10] is applied to each group of sensors, aiming at obtaining the total energy consumption with a deadline missing ratio. In this case, the sensors are grouped using the K-means algorithm.

#### Result analysis:

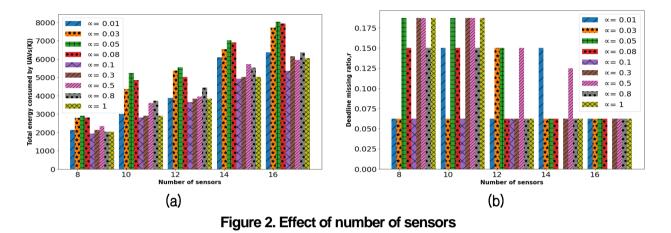
Optimal co-efficient value ( $\alpha$ ) selection for the proposed UGreedy/UF1: The performance of UGreedy/UF1 varies for different co-efficient values of  $\alpha$ . Thus, to have the optimal value of  $\alpha$ , we have evaluated the UGreedy/UF1 over different values of  $\alpha$  ranging from 0 to 1.

In Figure 2(a), with the increasing number of sensors, the total energy consumption for all UAVs also increases. However, among all the scenarios, the  $\alpha = 0.1$  shows better results. For example, in the case of 16 sensors and the value of  $\alpha = 0.1$ , the UGreedy/UF1 uses 15.73%, 30.56%, 33.38%, 32.57%, 12.99%, 10.07%, 15.73%, 11.55% less energy than the value of  $\alpha$  is 0.01, 0.03, 0.05, 0.08, 0.3, 0.5, 0.8, and 1, respectively.

Figure 2(b) shows how the value of  $\alpha$  affects the deadline missing ratio r for different numbers of

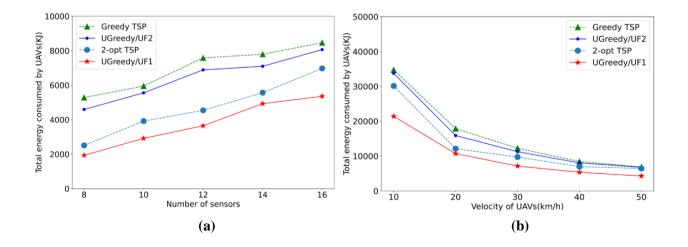
sensors. In all cases, the value of  $\alpha = 0.1$  shows better performances. For instance, when the value of the sensor is 8, the deadline missing ratio is 0.0625, 0.0625, 0.1875, 0.15, 0.0625, 0.1875, 0.1875, 0.15 and 0.1875, when the  $\alpha$  value is 0.01, 0.03, 0.05, 0.08, 0.3, 0.5, 0.8 and 1, respectively. Moreover, when the number of sensors is 14 and 16, the deadline missing ratio is zero in case of  $\alpha = 0.1$ .

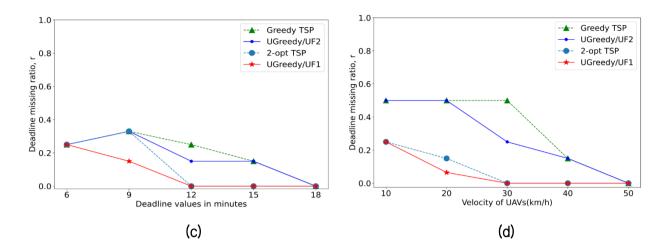
Thus,  $\alpha = 0.1$  can be chosen as the optimal co-efficient value in between 0 to 1 range, for UGreedy/UF1 algorithm.



*Performance of different algorithms:* In this section, the performance of UGreedy/UF1 with an optimal value of  $\alpha = 0.1$  is compared with other comparing algorithms: UGreedy/UF2, Greedy TSP, and 2-opt TSP.

Figure 3(a) shows that with the increasing number of sensors, the total energy consumed by UAVs increases, and the UGreedy/UF1 performs better in all cases. For instance, when the number of sensors is 16, the UGreedy/UF1 consumes 23.19%, 33.55%, and 36.69% less energy than the 2-opt TSP, UGreedy/UF2, and Greedy TSP, respectively.





# Figure 3. Performance of different algorithms. (a) effects of number of sensors on total energy consumed by UAVs, (b) effects of UAV velocities on total energy consumed by UAVs, (c) effects of deadline values on deadline missing ratio, and (d) effects of UAV velocities on deadline missing ratio.

In Figure 3(b), at the increasing number of UAV velocities, the total energy consumption of UAVs decreases, and in all cases, the proposed UGreedy/UF1 performs better than others. Moreover, the slope in Figure 3(b) becomes moderate after when the UAV velocity is 30 km/h. Before that, the slope is more acute.

Figure 3(c) shows the effects of different ranges of deadline on the deadline missing ratio. Here, we have considered the deadline value for each sensor in a range. The lower deadline value is 3 minutes which is fixed, and the higher deadline values varies such as 6, 9, 12, 15, and 18 minutes, respectively. In all cases, our proposed UGreedy/UF1 performs better than other algorithms. For example, when the sensor's deadline range is 3 to 9 minutes Ugreedy/UF1 shows better results than all other algorithm variants.

In Figure 3(d), the effects of UAV velocity on the deadline missing ratio are shown. The UGreedy/UF1 shows better results compared to others in all cases. For example, when the velocity is 20, the deadline missing ratio is 0.065, 0.15, 0.50, and 0.50 for UGreedy/UF1, 2-opt TSP, UGreedy/UF2, and Greedy TSP, respectively.

## 5. Conclusion

In this paper, we have studied UAVs near optimal path planning in a WSN scenario aiming at minimizing the total energy consumption of UAVs under the UAV's battery constraint and sensor's deadline constraint. In the considered energy-efficient charging scheme, each UAV tour is a TSP tour. Each UAV will finish its tour before its battery drains out, which is the UAV battery constraint. While visiting the sensors, the UAV reaches each sensor node within a given deadline to charge it. An integer linear optimization problem is formulated, and a utility function-based greedy algorithm named UGreedy/UF1 is proposed to solve the problem. The UGreedy/UF1 is designed based on the utility function UF1, where, at each step, the highest utility value is selected. The performance of the UGreedy/UF1 algorithm is compared with other baseline algorithms, i.e., UGreedy/UF2, Greedy TSP, and 2-opt TSP, where UGreedy/UF1 outperforms others in all cases.

For future work, we intend to extend the work within an obstacle contained system. Hence, any kind of obstacle is a threat to UAV path planning. Moreover, the proposed study is performed using a greedy based

method. We also plan to analyze the system's performance with a genetic algorithm-based approach or a reinforcement learning based approach.

# Acknowledgement

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) by the Ministry of Education under Grant 2021R111A3051364.

# References

- Su, Chunxia, et al., "UAV-assisted wireless charging for energy-constrained IoT devices using dynamic matching", The Journal of The Institute of Internet, IEEE Internet of Things Journal, Vol. 7, Issue. 6, June 2020. DOI: https://doi.org/ 10.1109/JIOT.2020.2968346
- [2] Li, Songyang, et al., "Improving charging performance for wireless rechargeable sensor networks based on charging uavs: a joint optimization approach", 2020 IEEE Symposium on Computers and Communications (ISCC), pp. 1-7, July 07-10, 2020.
   DOI: https://doi.org/ 10.1109/ISCC50000.2020.9219670
- Basha, Elizabeth, et al., "UAV recharging opportunities and policies for sensor networks", International Journal of Distributed Sensor Networks, August 11, 2015.
   DOI: https://doi.org/10.1155/2015/824260
- Yang, Longan, et al, "An Efficient Charging Algorithm for UAV-aided Wireless Sensor Networks", 2020 IEEE 6th International Conference on Computer and Communications (ICCC), pp. 834-838, 2020.
   DOI: https://doi.org/ 10.1109/ICCC51575.2020.9345142
- [5] Chen, Jingjing, Chang Wu Yu, and Wen Ouyang, "Efficient wireless charging pad deployment in wireless rechargeable sensor networks", IEEE Access, Vol. 8, pp. 39056-39077, 2020.
   DOI: https://doi.org/10.1109/ACCESS.2020.2975635
- [6] Peng, Wei, and David J. Edwards, "K-means like minimum mean distance algorithm for wireless sensor networks", 2010 2nd International Conference on Computer Engineering and Technology, Vol. 1, 2010.
   DOI: https://doi.org/ 10.1109/ICCET.2010.5486264
- [7] Wu, Pengfei, et al., "Trajectory Optimization for UAVs' Efficient Charging in Wireless Rechargeable Sensor Networks", IEEE Transactions on Vehicular Technology, Vol. 69, Issue. 4, pp. 4207-4220, 2020. DOI: https://doi.org/ 10.1109/TVT.2020.2969220
- [8] Thibbotuwawa, Amila, et al., "Planning deliveries with UAV routing under weather forecast and energy consumption constraints", IFAC-PapersOnLine, Vol. 52, Issue. 13, pp. 820-825, 2019. DOI: https://doi.org/ 10.1016/j.ifacol.2019.11.231
- [9] Jia, Jie, et al., "Joint power charging and routing in wireless rechargeable sensor networks", Sensors, Vol. 17, Issue. 10, 2017.
   DOI: https://doi.org/ 10.3390/s17102290
- [10] Zhou, Yongquan, et al., "A discrete invasive weed optimization algorithm for solving traveling salesman problem", Neurocomputing, Vol. 151, pp. 1227-1236, March 2015.
   DOI: https://doi.org/ 10.1016/j.neucom.2014.01.078