ECTSA: An Efficient Charging Time Scheduling Algorithm for Wireless Rechargeable UAV Network

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***Abstract*—With the development of airborne equipment and integrated avionics technology, the unmanned aerial vehicle (UAV) network replaces human beings in many fields. To improve the durability of the UAV network, we propose a nondisruptive wireless rechargeable UAV network (WRUN) model, in which UAVs can be charged by wireless static chargers (WSCs) without returning back to the charging platform. Under the nondisruptive WRUN model, a baseline algorithm is proposed to solve the nondisruptive charging time schedule problem (nCTSP), in which chargers do not release energy all the time and can ensure UAVs do not run out of energy. Then to improve the energy utilization rate of WSCs, we propose an efficient charging time scheduling algorithm (ECTSA), in which the flight time and paths of UAVs are discretized and nCTSP is transformed into a linear binary integer programming (LBIP) problem to calculate the efficient charging time periods of WSCs. Finally, experiments are conducted to verify that ECTSA can improve the energy utilization of WSCs.**

***Index Terms*—UAV networks, wireless charging, UAV charging, nondisruptive charging, partial charging**

I. Introduction

At present, unmanned aerial vehicle (UAV) has been widely used in various fields to replace humans in completing some urgent and dangerous tasks [8], such as forest fire fighting and battlefield surveys. The survivability and capability of a single UAV are limited [9]. Therefore, in many scenarios, the ground base station (GS) coordinates multiple UAVs into a UAV network [10] to complete missions. However, the energy capacity of UAVs is limited and if one UAV runs out of energy, the time for the UAV network to complete the mission will increase a lot.

There have been some studies dedicated to extending the lifetime of UAVs. According to the location of replenishing energy, there are two main types: charging on the ground [12] and in the air [14]–[16]. A battery replacement platform on the ground is designed in [12] and a ground contact charging platform is used to charge UAVs [13]. However, charging on the ground requires UAVs to land first, which will incur too much turnaround time. To solve this problem, some new wireless charging methods are proposed to charge UAVs in the air [14]–[16]. Although these methods can reduce the time of landing and taking off, they still require UAVs to hover and suspend the mission they are performing until the charging is completed.

ISBN 978-3-903176-39-3©2021 IFIP

Motivations: 1) At present, UAVs need to hover and suspend the mission being performed to replenish energy, which leads to a longer time for the UAV network to complete tasks. To improve the efficiency of task execution, we introduce wireless power transmission technology (WPT) [2] to obtain a nondisruptive wireless rechargeable UAV network (WRUN) in which UAVs can be charged while flying. 2) By deploying wireless static chargers (WSCs) to charge UAVs during mission execution, the UAV network can complete long-term missions. However, WSCs continuously release energy, which will cause a lot of energy waste. To reduce the energy waste, under the premise that UAVs will not run out of energy and can complete the task successfully, we schedule WSCs to turn on and release energy only in certain time periods.

Challenges: To realize nondisruptive charging, we face the following challenges. During the flight of UAVs, the topology of WRUN changes dynamically, which leads to an infinite solution space in time and space. From the space perspective, the distance between the UAV and the WSC changes continuously during the flight, so the number of positions that UAV can be charged is infinite. Considering the time, there are countless charging time periods for the charger to turn on and charge.

To transform the infinite solution space into finite, we discretize the flight paths of UAVs in time and space simultaneously [29], [30], and formalize the nondisruptive charging time scheduling problem (nCTSP) as an optimization problem. Then two algorithms are proposed to solve nCTSP.

In summary, the main contributions of this paper are as follows:

- As far as we know, we are the first to consider the nondisruptive charging time schedule problem (nCTSP) in WRUN. By scheduling WSCs to turn on and release energy in appropriate charging time periods, the energy utilization rate is improved.
- In order to solve nCTSP, we first propose a baseline algorithm to get the charge time periods of WSCs, which can ensure the energy of UAVs will not be used up during the flight.
- To further improve the energy utilization rate of WSCs and get the efficient charging time periods, we propose an efficient charging time scheduling algorithm (ECTSA), in which the flight time and paths of UAVs are discretized

and nCTSP is transformed into a linear binary integer programming (LBIP) problem.
- Finally, experiments are conducted to verify the effectiveness of ECTSA in terms of the energy utilization of WSCs.

The rest of this paper is organized as follows: we investigate related work in Section II. Section III introduces the network model, charging model, and problem statement. Two algorithms we proposed in this paper are introduced in Section IV and Section V respectively. Experimental results and conclusions are provided in Section VI and Section VII.

II. Related Work

In this paper, to extend the lifetime of UAVs, we deploy wireless static chargers (WSCs) with wireless power transmission technology (WPT) [2] to wirelessly charge UAVs. At present, WPT is widely used in the wireless charging of rechargeable devices, and there has been a lot of works dedicated to the scheduling of wireless chargers. We introduce these works from three aspects: the charging model, charging way, and the angle of charging.

1) One-to-one and one-to-many charging: According to the number of devices that can be charged simultaneously, there are two charging models: one-to-one [5] and one-to-many [6].

In the one-to-one model, the wireless charger can only charge one device at a time. Lin et al. consider the problem of maximizing energy efficiency with a charger to charge nodes one to one in [22]. The time that the one-to-one charging model takes is long and to improve charging efficiency, one-to-many charging is proposed, in which chargers can charge multiple devices simultaneously [7]. To maximize energy efficiency, [21] schedules chargers to charge multiple nodes at the same time by optimizing the traveling path of chargers.

2) Partial and full charging: According to the amount of energy charged each time, there are two charging ways: partial charging and full charging.

In full charging, each time the charger charges the UAV to its maximum energy capacity. To improve the energy utilization, an approximate algorithm with a constant approximate ratio is proposed in [23] and a global optimization scheduling algorithm TSCA is developed in [22], in which the devices are charged fully every time.

In partial charging, the UAVs don't need to be charged to their energy capacity, so the charging takes a shorter time. But if all devices are partially charged with little energy, they will request charging again in a short time and the charger cannot respond to all requests in time, so, some devices that can't wait for charging will run out of energy. Therefore, Lin considers which devices are partially charged by a charger and how much energy is charged in [20]. To further improve charging efficiency, a multi-node time-space partial charging algorithm (MTSPC) is proposed in [21], which schedules multiple chargers simultaneously.

3) Omnidirectional and directional charging: According to the charging angle of wireless chargers, there are currently two main types of charging: omnidirectional and directional charging.

In directional charging, the wireless charger can rotate and the charging range is a sector. Considering the mobility of the device, the charging utility is maximized by rotating the angle of chargers in [24]. Lin et al. consider the charging delay of the mobile charger to reduce the energy waste in [25].

In omnidirectional charging, the charging area of chargers is a circle. Liang and Zhang focus on the minimum number of omnidirectional mobile charging vehicles that are required by WRSNs [26], [27], and Zhang proposes the Pushwait algorithm in [27]. However, neither of them combines temporal and spatial requirements in their charging decision-making process. Deng et al. do consider spatiotemporal constraints in their Decouple Spatiotemporally Coupled Constraint (DSCC) algorithm [28].

However, all these methods schedule chargers in a static network. So these scheduling methods are not applicable in WRUN. In this paper, considering the dynamic topology of the UAV network, we use omnidirectional charging to charge UAVs partially, which can improve the energy utilization of chargers while the UAVs will not run out of energy during the flight.

III. Preliminaries

In this section, we introduce the network model, charging model, and the formalization process of nCTSP. The related symbols and definitions are shown in Table I.

TABLE I: Symbols and Definitions

Symbols	**Definitions**
I	Number of UAVs
J	Number of WSCs
M	The number of time periods after segment
T	The work time of WRUN
T_m	The m-th time period after segmentation
ΔT	The length of each time period T_m
$initE_i$	Initial energy of UAV u_i
E^i_{max}	Energy capacity of UAV u_i
v^i_f	Flight speed of u_i
v^i_c	Energy consumption Rate of u_i
R	Charging radius
P_r	Received power
re^t_i	Remaining energy of u_i at time t
e_i	Energy received by u_i
R_j	Energy utilization rate of charger c_j
e	Dispersion factor
ϵ	Dispersion power error
$tr^k_{i,j}$	The k-th rechargeable time period of u_i

A. Network Model

As shown in Fig. 1, in WRUN, the ground base station (GS) plans the flight paths of UAVs with path planning algorithms [4], and WSCs are deployed in WRUN in advance [28]. GS is responsible for receiving the monitoring data returned by UAVs and scheduling WSCs to turn on and release energy at appropriate time. Here we consider that WSCs are sparse in the network, and a UAV can only receive the energy from

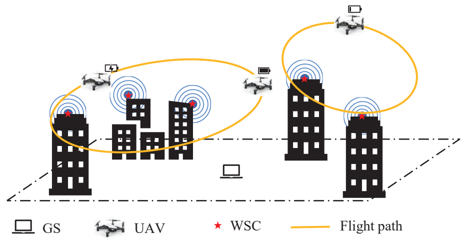


Fig. 1: The network model

one WSC in one location [19]. If a WSC is releasing energy, UAVs within the WSC's charging range can receive the energy without suspending the current missions.

B. Charging Model

This paper uses the WISP-reader charging model [18]. The power received by the UAV is calculated as below:

$$Pr(c,p) = \frac{G_s G_r \eta}{L_p}\left(\frac{\lambda}{4\pi\left(dist(c,p)+\beta\right)}\right)^2 P_0 \tag{1}$$

where $dist(c,p)$ is the Euclidean distance between the location of charger c and location p, P_0 is the source power of chargers, G_s is the source antenna gain, G_r is the receive antenna gain, L_p is polarization loss, λ is the wavelength, η is rectifier efficiency, and β is a parameter to adjust the Frris' free space equation for short-distance transmission.

In one-to-many charging model [7] and the omnidirectional charging [27], assuming the maximum charging radius of chargers is R [17], the charging range of each WSC is a circle with radius R. When there are multiple UAVs close to a WSC within R, all these UAVs can be charged simultaneously. Besides, in (1), except for the parameter $dist(c,p)$, the rest are all constants determined by the environment or device. We merge all these constants into α and simplify the model to:

$$Pr(c,p) = \begin{cases} \dfrac{\alpha}{\left(\beta + dist(c,p)\right)^2}, dist(c,p) \le R \\ \qquad\qquad 0, dist(c,p) > R \end{cases} \tag{2}$$

C. Problem Formalization

In WRUN, there are J WSCs $C = \{c_1, c_2, \cdots, c_J\}$, and I UAVs $U = \{u_1, u_2, \cdots, u_I\}$. The flight time of UAV $u_i (1 \le i \le I)$ is denoted as $flytime_i$ and the working time T of the entire UAV network is the time when UAVs complete their missions $T = max\{flytime_1, flytime_2, \cdots, flytime_I\}$.

The UAV u_i continuously consumes energy during the flight and when the remaining energy re_i^t of u_i at time t $(0 \le t \le flytime_i)$ is lower than 0, u_i will drop and the mission will fail. This paper aims to find charging time periods for WSCs to turn on and charge UAVs wirelessly, so that the UAVs can replenish energy in time while the energy utilization rate of WSCs is maximized.

We formalize this nondisruptive charging time schedule problem (nCTSP) as an optimization problem:

$$\max \sum_{j=1}^{J} R_j \tag{3}$$

subject to:

$$\begin{cases} re_i^t \; > 0 \\ re_i^t \; < E_{max}^i \end{cases} \tag{4}$$

where:

$$R_j = \frac{\sum_{i=1}^{I} \Delta E_j^i}{E_j} \tag{5}$$

In (3), R_j is the energy utilization rate of WSC c_j, which is related to E_j and ΔE_j^i. E_j is the total energy that c_j released, and ΔE_j^i is the total energy that UAV u_i received from c_j.

The constraint condition in (4) is used to ensure the UAV cannot run out of energy during flight, that is, the remaining energy re_i^t at any time is greater than 0 and less than its maximum energy capacity E_{max}^i.

IV. Baseline Algorithm

In this section, we propose a baseline algorithm to calculate the charging time periods to ensure UAVs do not run out of energy. In the baseline algorithm, WSCs do not charge all the time and only release energy when there are UAVs entering their charging ranges.

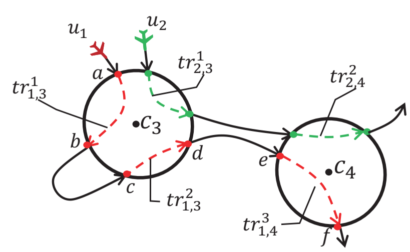


Fig. 2: The example of rechargeable time periods

As shown in Fig. 2, UAV u_1 flies to position a at time t_1 and starts to enter the charging radius of charger c_3. Then u_1 flies to position b at time t_2 when it leaves the charging radius of c_3. When u_1 flies to position c at time t_3, it enters the charging radius of c_3 again and leaves c_3 when it reaches d at time t_4. The flight time from a to b is regarded as the 1-th rechargeable time period $tr_{1,3}^1 = [t_1, t_2]$ of u_1 about charger c_3, and the flight time from c to d is the 2-th rechargeable time period $tr_{1,3}^2 = [t_3, t_4]$ of u_1 about c_3. In the same way, the rechargeable time period sets RTP_1 of u_1 and RTP_2 of u_2 can be obtained as:

$$RTP_1 = \left\{tr_{1,3}^1, tr_{1,3}^2, tr_{1,4}^3\right\}$$
$$RTP_2 = \left\{tr_{2,3}^1, tr_{2,4}^2\right\}$$

After obtaining the rechargeable time period sets of all UAVs, we can calculate the charging time period CTP_j of WSC c_j. First, we select all the rechargeable time periods of UAVs about WSC c_j, and then the union of these rechargeable time periods is regarded as the charging time period CTP_j of c_j. Taking Fig. 2 as an example, the rechargeable time periods of u_1 and u_2 about the charger c_3 are: $tr_{1,3}^1, tr_{1,3}^2, tr_{2,3}^1$, so the charging time period of charger c_3 is $CTP_3 = tr_{1,3}^1 \cup tr_{1,3}^2 \cup tr_{2,3}^1$, during which c_3 releases energy and charges UAVs.

V. ECTSA

Although in the baseline algorithm, WSCs do not charge all the time and only release energy when there are UAVs entering their charging ranges, once the number of UAVs that enter the charge range of a WSC increases, the charging time duration of the WSC will be extended greatly. Therefore, considering the energy utilization rate of WSCs, the solution of the baselin algorithm is not efficient. In this section, we introduce an efficient charging time scheduling algorithm (ECTSA), in which we transform nCTSP into a linear binary integer programming (LBIP) problem to calculate the efficient charging time periods of WSCs.

ECTSA mainly includes the following three steps:

Step 1: First, we divide the working time $[0, T]$ of WRUN into M time periods $\{T_1, T_2, \cdots, T_M\}$ to determine whether WSCs release energy in each time period $T_m (1 \leq m \leq M)$.

Step 2: Then, in order to calculate the power received by UAVs in each time period T_m, we discretize the continuous flight paths of UAVs into discrete locations to calculate the power received at each discrete location.

Step 3: Thirdly, based on the M time periods obtained by the first step and the result of path discretization in the second step, we transform nCTSP into a LBIP problem to get the efficient charge time period of WSCs.

A. Time Period Segmentation

To transform nCTSP into a LBIP problem, we first divide the work time interval $[0, T]$ of the WRUN into M time periods $T_1, T_2, \cdots, T_M$, where $T_m = [\frac{(m-1)T}{M}, \frac{mT}{M}], (1 \leq m \leq M)$ and T is the end time for completing the task of WRUN. The length of each time period T_m is denoted as $\Delta T = \frac{T}{M}$. Then we define a flag x_m^j to denote the status of each WSC c_j in each time period T_m. $x_m^j = 1$ indicates that c_j releases energy during the time period T_m, otherwise c_j will not release energy in T_m. Therefore, the problem of calculating the charging time periods of WSCs is transformed into a LBIP problem of calculating the value of x_m^j.

B. Path Discretization

After time period segmentation, we need to calculate the energy received by UAVs in each time period T_m.

From (2), during the flight of UAVs, the position of UAVs changes continuously, so the charging power received by the UAVs from each WSC changes continuously. In order to calculate the received power of UAVs during the flight and realize nondisruptive charging, we discretize the continuous flight paths into discrete locations and calculate the charging power of UAVs at each discrete location.

With the discretization method introduced in [17], the partial flight paths of UAVs within the maximum charging radius R can be discretized according to the received power of UAVs.

As shown in Fig. 3, regarding the charging circle of charger c_j as a Smallest Enclosing Space (SES) [17], and then we divide the SES into D concentric circles. The d-th circle of WSC c_j is C_j^d with radius $R_j^d (1 \leq d \leq D)$. So, the charging circle of c_j is divided into D rings: $ring_j^1, ring_j^2, ..., ring_j^D$.

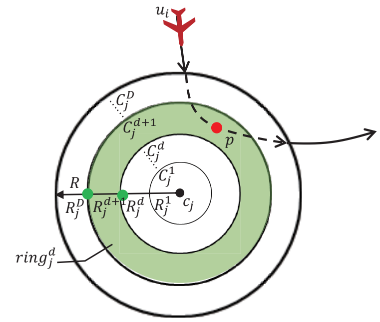


Fig. 3: Flight path discretization

The d-th ring is denoted as $ring_j^d$, whose inner radius and outer radius are R_j^d and R_j^{d+1} respectively. The number of rings D is related to the charging radius R, which can be calculated as:

$$D = \left\lceil \frac{2 \ln\left(1 + \frac{R}{\beta}\right)}{\ln(1+\epsilon)} \right\rceil \tag{6}$$

With (2), the power received from c_j at all points on the circle C_j^d is:

$$Pr(c_j, C_j^d) = \frac{\alpha}{(\beta + R_j^d)^2}$$

We restrict the ratio of power received at points on adjacent circles C_j^d and C_j^{d+1} with the power error threshold $\epsilon (0 < \epsilon < 1)$ [17], which means the division of SES must satisfy the following condition:

$$Pr(c_j, C_j^{d+1}) = \frac{Pr(c_j, C_j^d)}{1+\epsilon} \tag{7}$$

Therefore, the ratio of the power received at any two locations p_1 and p_2 in d-th ring $ring_j^d$ meets the following condition:

$$(1+\epsilon)^{-1} \leq \frac{Pr(c_j, p_1)}{Pr(c_j, p_2)} \leq 1 + \epsilon \tag{8}$$

To deal with the continuous charging power received by UAVs, we approximate the power received at any location in ring $ring_j^d$ as $Pr(c_j, C_j^{d+1})$, so that the received power of UAVs in each ring is a constant. Then the flight path in a ring can be approximated as a discrete location, and the energy received in each ring is approximately the power received at this discrete location times the flight time in the ring. In this way, we can calculate the power received by UAVs in each ring that is bounded by power error ϵ.

As shown in Fig. 3, when UAV u_i flies to the position p in ring $ring_j^d$, whose inner radius and outer radius is R_j^d and R_j^{d+1}, the received power of u_i are approximated as $Pr(c_j, p) \approx Pr(c_j, C_j^{d+1})$. Then the energy received by u_i in $ring_j^d$ is $\Delta E \approx \Delta t \cdot Pr(c_j, p)$, where Δt is the flight time in $ring_j^d$.

C. Transform nCTSP into a linear programming problem

In this section, we transform nCTSP into a LBIP problem to determine whether WSC c_j releases energy in each time period T_m, that is, $x_m^j = 0$ or 1.

After time period segmentation and path dicretization, nCTSP can be reformulated as:

$$\max f(X) = \sum_{j=1}^{J} \sum_{m=1}^{M} R_m^j \tag{9}$$

subject to:

$$\begin{cases} ere_m^i > 0 \\ ere_m^i < E_{\max}^i \end{cases} \tag{10}$$

where:

$$R_m^j = \frac{\sum_{i=1}^{I} \Delta E_i^{m,j}}{P_0 \cdot \Delta T} \tag{11}$$

$$\Delta E_i^{m,j} = x_j^m \cdot \sum_{k=1}^{K_i} \sum_{d=1}^{D_{i,j}^k} (Pr_{i,j}^{k,d} \cdot \Delta t_{i,j}^{k,d}) \tag{12}$$

$$x_j^m \in \{0, 1\} \tag{13}$$

$$Pr_{i,j}^{k,d} = Pr(c_j, C_j^d) \tag{14}$$

$$ere_m^i = sre_m^i + \sum_{j=1}^{J} \Delta E_i^{m,j} - \Delta T \cdot v_c^i \tag{15}$$

$$sre_m^i = \begin{cases} initE_i, m = 1 \\ ere_{m-1}^i, m > 1 \end{cases} \tag{16}$$

As shown in (9), the energy utilization rate R_j of each WSC $c_j (1 \leq j \leq J)$ in (3) is reformulated as the sum of the utilization rate R_j^m of c_j in each time period $T_m (1 \leq m \leq M)$. Besides, to ensure UAVs do not run out energy, the constraint in (4) is denoted as (10). As long as the residual energy ere_m^i of UAV u_i at the end time of each time period $T_m (1 \leq m \leq M)$ is more than 0, u_i will not run out of energy during the flight.

In (11), $\Delta E_i^{m,j}$ is the energy that u_i received from c_j in T_m. After path deiscretizetion in Section V-B, $\Delta E_i^{m,j}$ can be calculated as (12), in which we use $Pr_{i,j}^{k,d}$ to denote the energy that u_i received from c_j in the d-th discretized location in the k-th rechargeable time period of u_i and $\Delta t_{i,j}^{k,d}$ is the time duration when u_i flies in the ring $ring_j^d$.

From (15), the residual energy ere_m^i of u_i at the end time of T_m is equal to the residual energy of u_i at the start time sre_m^i plus the energy that u_i received from all WSCs in T_m minus the energy u_i consumed. If $m = 1$, the residual energy of u_i at the start time sre_m^i is the initial energy $initE_i$ of u_i, otherwise, sre_m^i is equal to the residual energy ere_{m-1}^i at the end time of previous time period T_{m-1}.

In order to calculate the optimal charging time periods WSCs, that is, to determine $x_m^j = 0$ or 1, we deduce (9) and (10), and transform nCTSP into a binary linear programming (LBIP) problem as below.

First, combined (16) and (15), the constraint of u_i in each time periods are transformed into a linear constraint:

$$\begin{aligned} ere_m^i &= sre_m^i + \sum_{j=1}^{J} \Delta E_i^{m,j} - \Delta T \cdot v_c^i \\ &= ere_{m-1}^i + \sum_{j=1}^{J} \Delta E_i^{m,j} - \Delta T \cdot v_c^i \\ &= \cdots \\ &= sre_1^i + \sum_{m'=1}^{m} \sum_{j=1}^{J} \Delta E_i^{m',j} - m \cdot \Delta T \cdot v_c^i \end{aligned} \tag{17}$$

$$E_{max}^i > sre_1^i + \sum_{m'=1}^{m} \sum_{j=1}^{J} \Delta E_i^{m',j} - m \cdot \Delta T \cdot v_c^i > 0 \tag{18}$$

Learned from (12), we use $w_i^{m,j}$ to represent all the energy that u_i can receive in time period T_m when the WSC c_j is releasing energy.

$$w_i^{m,j} = \sum_{k=1}^{K_i} \sum_{d=1}^{D_{i,j}^k} Pr_{i,j}^{k,d} \cdot \Delta t_{i,j}^{k,d} \tag{19}$$

Thus, we have:

$$\Delta E_i^{m,j} = x_m^j \cdot w_i^{m,j} \tag{20}$$

After getting $w_i^{m,j}$, we define the matrix W to represent the energy that each UAV received from each WSC in each time period.

$$W = \begin{bmatrix} W_1 & W_2 & \cdots & W_I \end{bmatrix}^T \tag{21}$$

where:

$$W_i = \begin{bmatrix} W_i^1 & 0 & \cdots & 0 \\ W_i^1 & W_i^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ W_i^1 & W_i^2 & \cdots & W_i^M \end{bmatrix} \tag{22}$$

$$W_i^m = \begin{bmatrix} w_i^{m,1} & w_i^{m,2} & \cdots & w_i^{m,J} \end{bmatrix} \tag{23}$$

From (18), we have:

$$\begin{cases} \sum_{m'=1}^{m} \sum_{j=1}^{J} x_{m'}^j \cdot w_i^{m',j} > m \cdot \Delta T \cdot v_c^i - initE_i \\ \sum_{m'=1}^{m} \sum_{j=1}^{J} x_{m'}^j \cdot w_i^{m',j} < E_{max}^i + m \cdot \Delta T \cdot v_c^i - initE_i \end{cases} \tag{24}$$

We define the matrices U and L to represent the upper and lower bounds of the remaining energy of UAVs, which satisfy the constraint (10).

$$L = \begin{bmatrix} L_1 & L_2 & \cdots & L_I \end{bmatrix}^T \tag{25}$$

$$U = \begin{bmatrix} U_1 & U_2 & \cdots & U_I \end{bmatrix}^T \tag{26}$$

where:

$$L_i = \begin{bmatrix} L_i^1 & L_i^2 & \cdots & L_i^M \end{bmatrix}^T \tag{27}$$

$$L_i^m = v_c^i \cdot m \cdot \Delta T - initE_i \tag{28}$$

$$U_i = \begin{bmatrix} U_i^1 & U_i^2 & \cdots & U_i^M \end{bmatrix}^T \tag{29}$$

$$U_i^m = v_c^i \cdot m \cdot \Delta T - initE_i + E_{\max}^i \tag{30}$$

We define the independent variable matrix X, where X_j represents the status of each WSC c_j in M time periods, that is, $x_m^j = 0$ or 1.

$$X = \begin{bmatrix} X_1 & \cdots & X_M \end{bmatrix}^T \tag{31}$$

$$X_m = \begin{bmatrix} x_m^1 & x_m^2 & \cdots & x_m^J \end{bmatrix}^T \tag{32}$$

So far, the constraints of nCTSP in (10) can be transformed into a set of linear binary constraints:

$$L < W \times X < U \tag{33}$$

Combined (12) and (19), the objective function (9) can be denoted as:

$$f(X) = \sum_{j=1}^{J} \sum_{m=1}^{M} \frac{\sum_{i=1}^{I} \left(x_m^j \cdot w_i^{m,j} \right)}{P_0 \cdot \Delta T} \tag{34}$$

We define a matrix O to denote the energy that each UAV $u_i (1 \leq i \leq I)$ received from each WSC during all time periods.

$$O = \begin{bmatrix} O_1 & O_2 & \cdots & O_M \end{bmatrix} \tag{35}$$

where:

$$O_m = \begin{bmatrix} w_1^{m,1} & w_1^{m,2} & \cdots & w_1^{m,J} \\ w_2^{m,1} & w_2^{m,2} & \cdots & w_2^{m,J} \\ \vdots & \vdots & \ddots & \vdots \\ w_I^{m,1} & w_I^{m,2} & \cdots & w_I^{m,J} \end{bmatrix} \tag{36}$$

Therefore, combined with the auxiliary matrices P and Q, the objective function $f(X)$ is transformed into a $(J \times M) \times 1$ dimension linear objective function:

$$f(X) = P \times O \times Q \times X \tag{37}$$

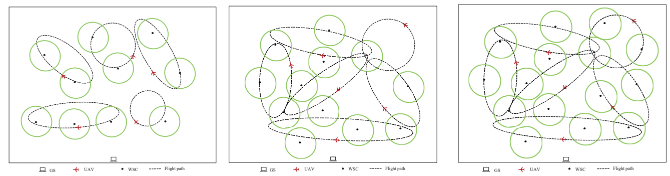
where:

$$P = \begin{bmatrix} 1 & \cdots & 1 \end{bmatrix}_{1 \times I} \tag{38}$$

$$Q = \begin{bmatrix} Q_1 & 0 & \cdots & 0 \\ 0 & Q_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & Q_M \end{bmatrix} \tag{39}$$

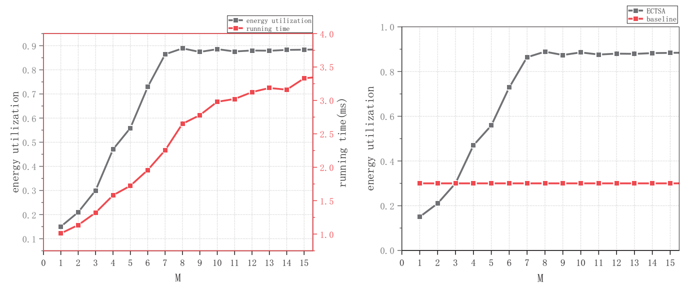
$$Q_m = \frac{1}{P_0 \cdot \Delta T} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}_{J \times J} \tag{40}$$

In this way, nCTSP is transformed into a LBIP problem. Considering the computational complexity, the heuristic algorithm based on Lagrangean relaxation [3] is used to solve this problem.



(a) (b) (c)

Fig. 4: Different WRUNs



(a) The impact of M on ECTSA

(b) The impact of M on ECTSA and baseline algorithm

Fig. 5

VI. Experiment Simulation

In this section, we evaluate ECTSA by analyzing the influence of different parameters on the energy utilization rate of WSCs, including the dispersion factor e, the charging radius R, the number of UAVs I, the number of WSCs J, and the number of time periods M.

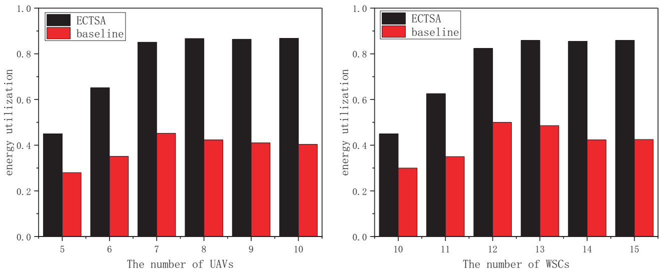
A. Simulation Setup

The algorithms are implemented on MATLAB, and the linear binary integer programming (LBIP) problem is solved by the heuristic algorithm based on Lagrangean relaxation [3]. As shown in Fig. 4(a), we deploy 5 UAVs and 10 WSCs in advance and the parameters in WRUN are set according to [4]. To compare the discrete granularity of different R more intuitively, we define the discrete factor $e = \frac{R}{D}$, which represents the distance between adjacent discrete locations obtained in Section V-B.

B. Experimental results

1) The influence of e: To evaluate the influence of the dispersion factor e on energy utilization, e is set from 0.1 to 10. We take simulation experiments under different WRUNs in Fig.4. The simulation results are shown in Fig. 8 - Fig. 10.

Our simulation results show that ECTSA outperforms the baseline algorithm in terms of energy utilization by up to 125%. As Fig. 8(f) shows, when e increases, the energy utilization rate of the baseline algorithm remains unchanged basically. However, with the increase of e, the energy utilization rate of ECTSA fluctuates more violently but is still larger than the baseline algorithm.



(a) The impact of I (b) The impact of J

Fig. 6

2) The influence of R: To evaluate the influence of the charging radius R on energy utilization rate, R is set to 140, 150, 160, 170, 180, and 190 respectively. The result is shown in Fig. 8.

Our simulation results show that on average, ECTSA outperforms the baseline algorithm in terms of energy utilization by up to 157%. When R keeps increasing, the energy utilization rate keeps the same trend with the change of the dispersion factor e. Only when R is 150 and 160, the energy utilization rate drops rapidly when e is very large. This is mainly because when the value of R is very small and the distance of different discrete locations e is large, there are too few locations that UAVs can be charged within R, so the UAVs cannot receive enough energy and the energy utilization rate decreases.

3) The influence of I: To evaluate the influence of the number of UAVs I on energy utilization, I increases from 5 to 10, and the number of WSCs is 10. We perform multiple experiments and the average energy utilization rate is shown in Fig. 6(a).

Our simulation results show that on average, ECTSA outperforms the baseline algorithm in terms of energy utilization by up to 92.16%. When I increases, the gap between ECTSA and baseline algorithm in energy utilization rate becomes larger, and ECTSA has more obvious advantages in improving energy utilization rate. This is because when I increases, it means that the number of UAVs that can receive energy from a WSC increases. For the baseline algorithm, it is necessary to consider the rechargeable time periods of more UAVs to merge, and the charging time of the WSC will be extended accordingly. But for ECTSA, as long as M remains unchanged, the charging time of the WSC will not be prolonged.

4) The influence of J: To evaluate the influence of the number of WSCs on energy utilization, we increase the number of WSCs from 10 to 20 and the number of UAVs is 6. The average energy utilization rate is shown in Fig. 6(b).

Our simulation results show that on average, ECTSA outperforms the baseline algorithm in terms of energy utilization by up to 90.5%. When J increases, the gap between ECTSA and baseline algorithm in energy utilization rate becomes larger, and ECTSA has more obvious advantages in improving energy utilization rate. This is because the increase of J means that UAVs have more rechargeable time periods. For the baseline algorithm, a UAV will pass more WSCs, and the charging time of a WSC is unchanged, but the energy that all WSCs released is increased. For ECTSA, the objective function takes into account the energy utilization rate of each WSC. When J increases, it means that a UAV can be charged from more WSCs, so the energy that a WSC released decreases, and the energy utilization rate increases.

5) The influence of M: To compare with the baseline algorithm under the different number of time periods M, we set M =2,4,6,7,9. The time periods and charging status of WSCs under different M are shown in Fig. 7. Fig. 7(a)-(e) show the rechargeable time periods in Section IV. st and et are the start and end time when the UAV closes to a WSC, that is, $[st, et]$ is a rechargeable time period. Fig. 7(f)-(j) show the impact of M on the status of each WSC obtained by ECTSA. The red rectangles represent that the WSC is charging and $x_m^j = 1$. As M increases, the number of time periods that the WSC is idle increases, so the energy waste is reduced.

To study the impact of M on computational overhead, M is set from 1 to 15 and the computational overhead of ECTSA is represented by the running time. Fig. 5(a) shows the impact of M on the computational overhead and the energy utilization rate of WSCs in ECTSA. Besides, we compare the impact of M in ECTSA and the baseline algorithm, the results are shown in Fig. 5(b).

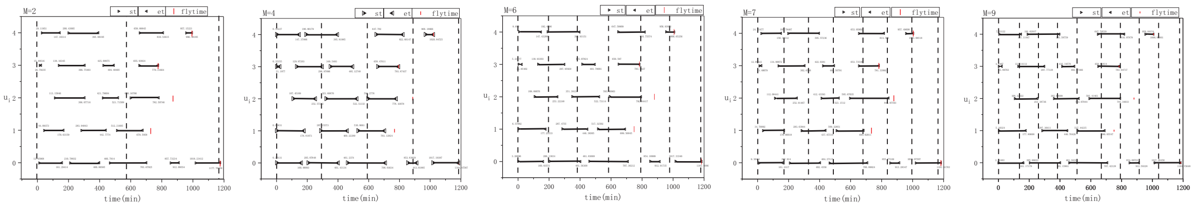
From Fig. 5(a), we can find that the running time of the ECTSA, that is, the computational overhead is constantly increasing with the increase of M. And as shown in Fig. 5(b), no matter what value M takes, ECTSA performs much better than the baseline algorithm in most cases.

VII. Conclusion

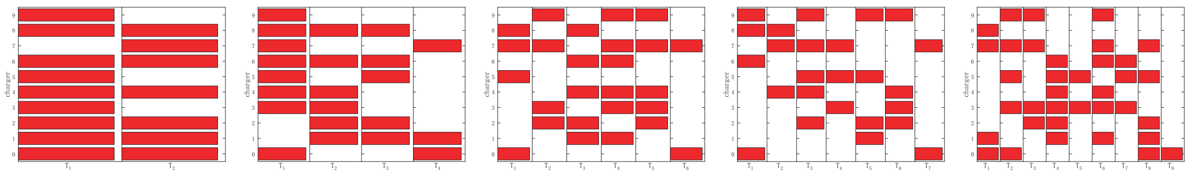
This paper proposes the nondisruptive charging time schedule problem (nCTSP) in WRUN. By scheduling WSCs to turn on or off in appropriate time periods, the energy utilization rate is maximized. First, a baseline algorithm is proposed to solve nCTSP which can ensure UAVs do not run out of energy. To further improve the energy utilization rate of WSCs, ECTSA is proposed, in which we discretized the flight paths and flight time of UAVs and transformed nCTSP into a linear binary integer programming (LBIP) problem to be solved. Finally, the results of simulation experiments show that ECTSA outperforms the baseline algorithm in terms of energy utilization rate by 90.5%-157%.

Acknowledgment

This work is supported by the National Natural Science Foundation of China under Grant No.61402225, the project of Natural Science Research of the Universities of Jiangsu Province (19KJB520012) and the Science and Technology Funds from National State Grid Ltd. (The Research on Key Technologies of Distributed Parallel Database Storage and Processing based on Big Data).

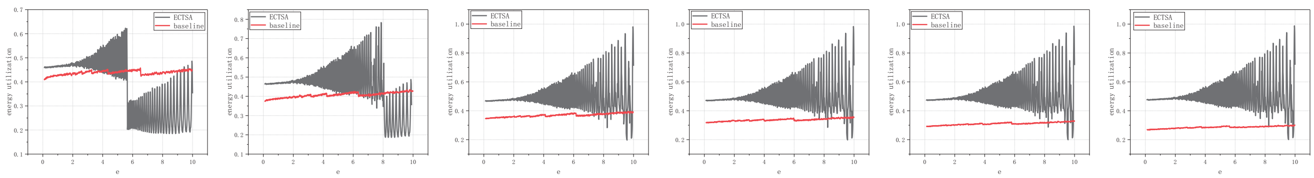


(a) M=2 (b) M=4 (c) M=6 (d) M=7 (e) M=9



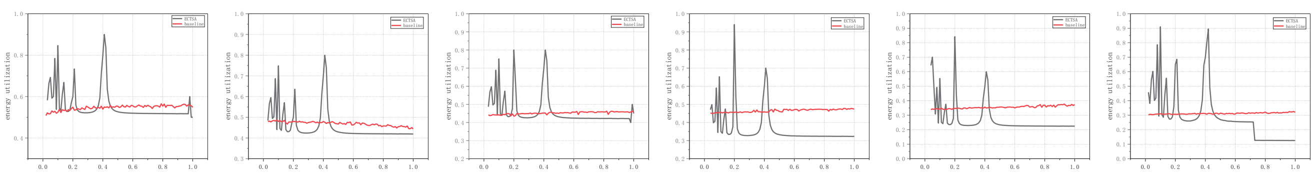
(f) M=2 (g) M=4 (h) M=6 (i) M=7 (j) M=9

Fig. 7: Time periods and the status of each WSC obtained by ECTSA in Fig. 4(a)



(a) R=140 (b) R=150 (c) R=160 (d) R=170 (e) R=180 (f) R=190

Fig. 8: Comparison of baseline algorithm and ECTSA of WRUN in Fig. 4(a)



(a) R=35 (b) R=40 (c) R=45 (d) R=50 (e) R=55 (f) R=60

Fig. 9: Comparison of baseline algorithm and ECTSA of WRUN in Fig. 4(b)

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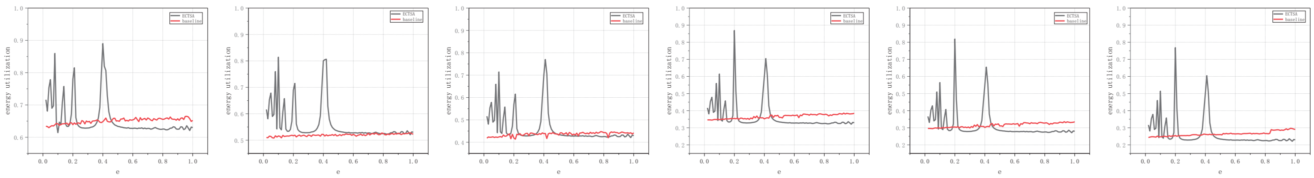

(a) R=35 (b) R=40 (c) R=45 (d) R=50 (e) R=55 (f) R=60

Fig. 10: Comparison of baseline algorithm and ECTSA of WRUN in Fig. 4(c)

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