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ORIGINAL PAPER

Energy-balanced path optimization of UAV-assisted wireless power and information system

Jing Guo[1] · Shuai Yang[1] · Zhile Yang[2] · Lei Lei[3] · Xu Zhang[4]

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Abstract
The unmanned aerial vehicle (UAV)-assisted wireless power and information system is one of the great choices for energy supplement and information collection of the wireless sensor network (WSN). The ground wireless sensors are operating by the harvested radio frequency (RF) energy from UAVs. The lifetime of the wireless sensor network is affected by the minimal, mean and variance of harvested energy. In this paper, an energy-balanced path optimization of a single UAV is proposed. The proposed framework (1) utilizes the Lagrangian method and an energy threshold to obtain a relaxation solution without maximum speed constraint, (2) implements a genetic algorithm and continuous convex optimization algorithm to obtain optimal trajectory and power allocation strategy. Numerical results show that the minimal, average and variance of harvested energy of wireless sensors are improved under the different distributions of sensors. Based on the proposed framework, the minimal operational requirement of the UAV could be used to guide the model selection of the UAV.

Keywords UAV communication · Energy harvesting · Trajectory optimization · Data collection

1 Introduction

The Internet of Things (IoT) is growing rapidly and so more and more wireless sensors are needed to enable IoT-based services [1, 2]. Concurrently, emerging scenarios, such as smart cities and intelligent manufacturing, further drive the growth of wireless sensor network (WSN). Thanks to energy harvesting (EH) advances, wireless sensors are now harnessing the power of renewable energy sources, such as solar, RF and vibration [3]. Simultaneous information and power transfer over the wireless channel utilizing RF-EH technique, and it is a great choice for enabling and deploying WSN [4]. The RF power transfer and wireless information highly rely on distance, and "near-far" fairness issue [5] is challenge with static RF source. The received energy by the sensors varies significantly with their distances to the RF energy source, and the uneven harvested energy leads to poor overall performance.

UAV-assisted wireless power and information systems have attracted attention as the mobility of UAV could relieve the severe impact of the distance [6–11]. The overall metrics could be optimized by careful trajectory design of the UAVs. The throughput is maximized in UAV-assisted mobile relaying systems with trajectory optimization [6, 7]. Besides UAV-assisted wireless information system, UAVs can be deployed to charge ground sensors via wireless power transfer (WPT) and collect information via wireless information transmission (WIT) [8–11]. In [8], the authors minimize the time required by a UAV via jointly optimizing the trajectory of the UAV and

Jing Guo and Shuai Yang have contributed equally to this work.

✉ Xu Zhang
xzhang2433@cityu.edu.hk

Jing Guo
guojing_cc@163.com

1 Department of Automation, Foshan University, Foshan, China

2 Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China

3 Department of Advanced Design and Systems Engineering, City University of Hong Kong, Kowloon Tong, Hong Kong

4 Centre for Smart Energy Conversion and Utilization Research and Department of Electrical Engineering, City University of Hong Kong, Kowloon Tong, Hong Kong

the transmission scheduling for all the ground sensors. In [10], the authors propose a reinforcement learning-based approach to plan the route of UAV to collect sensor data from sensor devices scattered in the physical environment. The authors in [11] jointly optimize the sensors' wake-up schedule and UAV's trajectory to minimize the maximum energy consumption of all sensors, and then prolong the lifetime of WSN. In [12], a two-way relay system with multiple users and a multi-antenna relay employing SWIPT strategy is considered to provide a rate-energy trade-off.

Previous works [13–16] have good performance on the mean of harvested energy, while the harvested energy of individual sensor must be above its operational level [17] in practical scenarios, such like in EH-based WSN. The minimal, mean and variance of harvested energies of all ground sensors should be considered together when optimizing the trajectory of UAV [18, 19]. Energy-balanced path planning is needed to cover above three metrics. In this paper, an alternate optimization framework is proposed as follows: Firstly, without considering the UAV speed constraint, the original non-convex problem is transformed into a convex optimization problem. Then the lagrangian method is used to obtain the optimal solution (relaxation solution) of the convex optimization problem [20–22]. Secondly, the ant colony algorithm [23–25] is used to obtain the optimized flight trajectory of the UAV based on the known relaxation solution. Finally, considering the maximal speed constraint of the UAV, previous UAV flight trajectory is used as the initial value, and the UAV flight trajectory and energy allocation strategy are obtained.

The main contributions of this paper include:

1. Comparing to [5], an energy neutral constraint of ground sensor is introduced. In this paper, the minimal, mean and variance of harvested energies of all ground sensors have been considered for path planning of UAV.
2. The proposed alternate optimization framework obtains UAV flight trajectory and energy allocation strategy to meet the energy-neutral constraint of ground sensor and maximal speed constraint of UAV. The harvested energies of all ground sensors are balanced, and the throughput is maximized. Numerical results show the performance under different sensor distributions, and it demonstrates the effectiveness of the proposed framework.
3. Given an EH-based WSN, the energy-neutral constraint of the ground sensor is determined. The proposed alternate optimization framework could obtain the minimal operational requirement of UAV, which help guide the model selection of UAV. Numerical results show the flight time to meet different settings of energy-neutral constraints.

The rest of this paper is organized as follows: The second section introduces the system model and the optimization problem. The third section introduces the proposed framework. The fourth section gives numerical results to demonstrate the performance. Finally, conclusion is presented.

2 System model

A wireless sensor network based on UAV-assisted wireless power and information system is considered. As shown in Fig. 1, the UAV serves a group of ground sensor equipment, the number is known and it is N, where $N > 1$. The UAV hovered continuously from the initial position to visit M track points, to transfer RF energy to ground sensors and to collect information from the ground sensors within the overall time T. The RF energy transfer and wireless information collection share the same frequency [5, 15]. The parameters of UAV-assisted wireless power and information system are shown in Table 1.

Here, we define $n \in \{1, \cdots, N\}$,$m \in \{1, \cdots, M\}$ and use $\alpha_{n,m}(t)$ to represents the working mode of the UAV, define a binary variable $\alpha_{n,m}(t) \in \{0, 1\}, \forall \mathrm{n, m, t}$, when $\alpha_{n,a}(t) = 1, \alpha_{b,m}(t) = 0, \forall \mathrm{a} \in \{1, \cdots, M\}, \mathrm{b} \in \{1, \cdots, N\}$ represents the downlink wireless energy transmission mode. $\alpha_{n,a}(t) = 0, \alpha_{b,m}(t) = 1, \forall \mathrm{a} \in \{1, \cdots, M\}, \mathrm{b} \in \{1, \cdots, N\}$, which represents the uplink wireless sensor data transmission mode. The coordinates of UAV projected on the horizontal plane are expressed as: $\mathrm{P}_m(\mathrm{t}) = [x_m(\mathrm{t}), \mathrm{y}_m(\mathrm{t})]^T$, $\mathrm{m} \in \{1, \cdots, M\}, 0 \le \mathrm{t} \le \mathrm{T}$, and have $P_m(0) = P_m(T)$. Suppose the UAV is flying on a horizontal plane with a fixed height of H. When $\alpha_{n,a}(t) = 1, \alpha_{b,m}(t) = 0, \forall \mathrm{a} \in \{1, \cdots, M\}, \mathrm{b} \in \{1, \cdots, N\}$, at any given time t, $0 \le \mathrm{t} \le \mathrm{T}$, the distance between the UAV and each user is expressed as follows:

$$d_{n,m}(\mathrm{P(t)}) = \sqrt{\|P_m(t) - g_n\|^2 + H^2} \tag{1}$$

It is assumed that the doppler effect caused by the maneuverability of the UAV is well compensated at the receiving end. The wireless channels between the UAV and ground sensors are dominated by LoS link, the free-space path model is assumed. At any given time t, $0 \le \mathrm{t} \le \mathrm{T}$, the channel power gain between UAV and user n [5, 15] can be expressed as:

$$h_{n,m}(P_m(t)) = \mu_0 d_{n,m}^{-2}(P_m(t)) = \frac{\mu_0}{\|P_m(t) - g_n\|^2 + H^2} \tag{2}$$

The UAV uses constant power PT_m for wireless energy transmission. When

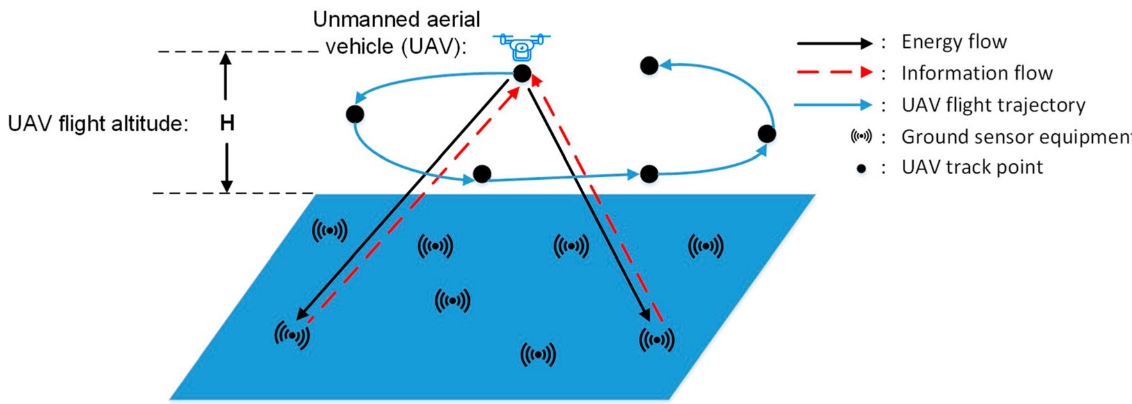

Fig. 1 Wireless sensor network supported by UAV.

Table 1 Abbreviations

Parameter	Meaning
N	Number of ground users
M	Number of UAV track points
T	Total time to traverse M track points
$\alpha_{n,m}(t)$	UAV working mode
$x_m(t)$	The coordinates of the UAV projected on the X axis
$y_m(t)$	The coordinates of the UAV projected on the y axis
$p_m(t)$	UAV track point coordinates
H	UAV flying height
g_n	Ground sensor device coordinates
$d_{n,m}(\mathrm{p(t)})$	The distance between the UAV and the ground sensor
μ_0	Channel power gain per unit distance
$h_{n,m}(P_m(t))$	User n channel power gain
PT_m	Transmission power
η	Transmission efficiency
$E_{n,m}(P_m(t), \alpha_{n,m}(t))$	Radio frequency energy transmitted on the downlink
$C_n(t)$	Energy consumed on the uplink
σ^2	Noise power
$\varepsilon_{n,m}(C_n(t), h_{n,m}(t))$	User n corresponds to the signal-to-noise ratio
$R_{n,m}(\alpha_{n,m}(t), P_m(t), C_n(t))$	User n achievable data transmission rate
P_{th}	Energy threshold

$$0 \leq \mathrm{t} \leq \mathrm{T}, \alpha_{n,a}(t) = 1, \alpha_{b,m}(t) = 0,$$
$$\forall \mathrm{a} \in \{1, \cdots, M\}, \mathrm{b} \in \{1, \cdots, N\},$$

the energy collected by each user from the UAV can be expressed as:

$$E_{n,m}(P_m(t), \alpha_{n,m}(t)) = \eta PT_m \alpha_{n,a}(t) h_{n,m}(P_m(t)) = \frac{\eta PT_m \mu_0 \alpha_{n,a}(t)}{\|P_m(t) - g_n\|^2 + H^2} \tag{3}$$

where $0 < \eta \leqslant 1$ is the conversion efficiency of radio frequency (RF) energy into direct current (DC). Ground sensor equipment uses radio frequency energy to supply energy, collect data and transmit it to the UAV wirelessly. When $\alpha_{n,a}(t) = 0, \alpha_{b,m}(t) = 1, \forall \mathrm{a} \in \{1, \cdots, M\}, \mathrm{b} \in \{1, \cdots, N\}$, the signal-to-noise ratio corresponding to user n can be expressed as:

$$\varepsilon_{n,m}(C_n(t), h_{n,m}(t)) = \frac{C_n(t) h_{n,m}(P_m(t))}{\sigma^2} \tag{4}$$

The achievable data transmission rate (bps/Hz) of each user n is:

$$R_{n,m}\left(\alpha_{n,m}(t), P_m(t), C_n(t)\right) = \alpha_{b,m}(t)\log_2\left(1+\varepsilon_{n,m}\left(C_n(t), h_{n,m}(t)\right)\right) \tag{5}$$

Therefore, the average upload rate of N users can be expressed as:

$$\mathrm{R} = \frac{1}{T}\sum_{t=0}^{T} R_{b,m}\left(\alpha_{n,m}(t), P_m(t), C_n(t)\right)$$

The maximum speed of UAV and energy neutrality of the UAV are expressed as follows:

$$\left\|\dot{\mathrm{P}}_m(\mathrm{t})\right\| \le V_{\max}, \quad 0 \le \mathrm{t} \le \mathrm{T} \tag{6}$$

$$\sum_{t=0}^{T}\alpha_{b,m}(t)C_n(t) \le \sum_{t=0}^{T} E_{n,m}\left(\alpha_{n,a}(t), P_m(t)\right), 0 \le \mathrm{t} \le \mathrm{T} \tag{7}$$

The energy neutral of ground sensor node is the energy collected by each user node must be greater than the set energy threshold P_{th}. The optimization goal is to maximize the system throughput under the condition of meeting energy neutral and UAV's maximum speed constraint. The mathematical expression of the optimization problem is:

$$\max_{\left\{\alpha_{n,m}(t), C_n(t), P_m(t)\right\}} \min_{n\in\{1,\cdots,N\}} R_{n,m}\left(\left\{\alpha_{n,m}(t), P_m(t), C_n(t)\right\}\right)$$

The optimization variables include UAV trajectory $\{P_m(t)\}$, transmission mode $\left\{\alpha_{n,m}(t)\right\}$, and user uplink energy consumption $\{C_n(t)\}$. For the convenience of representation, let $\mathrm{A} = \left\{\alpha_{n,m}(t), \forall \mathrm{t}, \mathrm{n}, \mathrm{m}\right\}$, $\mathrm{Q} = \{P_m(t), \forall \mathrm{t}, \mathrm{m}\}$, $\mathrm{P} = \{C_n(t), \forall \mathrm{t}, \mathrm{m}\}$. Define function:

$$\omega(A, Q, P) = \min_{n\in\{1,\cdots,N\}} R_{n,m}\left(\left\{\alpha_{n,m}(t), P_m(t), C_n(t)\right\}\right)$$

Regarding $\omega(\mathrm{A}, \mathrm{Q}, \mathrm{P})$ as a function of A, Q, P, the optimization problem can be further described as (OP1):

$$\max_{\omega, A, Q, P} \omega \text{s.t: } \frac{1}{T}\sum_{t=0}^{T} R_{n,m}\left(\alpha_{b,m}(t), P_m(t), C_n(t)\right) \ge \omega, \quad \forall n \in \{1,\cdots,N\}, m \in \{1,\cdots,M\} \tag{8}$$

$$P_{th} \le E_{n,m}\left(\alpha_{n,a}(t), P_m(t)\right), \forall n \in \{1,\cdots,M\}, 0 \le \mathrm{t} \le \mathrm{T} \tag{9}$$

$$\sum_{t=0}^{T}\alpha_{b,m}(t)C_n(t) \le \sum_{t=0}^{T} E_{n,m}\left(\alpha_{n,a}(t), P_m(t)\right) \quad \forall n \in \{1,\cdots,N\}, m \in \{1,\cdots,M\} \tag{10}$$

$$\left\|\dot{\mathrm{P}}_m(\mathrm{t})\right\| \le V_{\max}, 0 \le \mathrm{t} \le \mathrm{T}, \forall \mathrm{m} \in \{1,\cdots,M\} \tag{11}$$

$$\sum_{n=1}^{N}\alpha_{n,m}(t) \le 1, 0 \le \mathrm{t} \le \mathrm{T}, \forall \mathrm{m} \in \{1,\cdots,M\} \tag{12}$$

$$\sum_{m=1}^{M}\alpha_{n,m}(t) \le 1, 0 \le \mathrm{t} \le \mathrm{T}, \forall \mathrm{n} \in \{1,\cdots,N\} \tag{13}$$

$$0 \le \mathrm{PT}_m \le PT_{\max}, m \in \{1,\cdots,M\} \tag{14}$$

where (10) denotes energy threshold constraint of the ground sensor node, (11) denotes the energy neutral constraint of the UAV, and (12) is the maximum speed constraint of the UAV. The objective function of the problem is a non-concave function. Constraints (11) and (12) are non-convex, and there are coupled variables A, Q and P, which contain infinite optimization variables in continuous time. It is difficult to obtain the optimal solution for this problem. In order to solve this complicated optimization problem, the specific solution is given in the third section below.

3 Alternate optimization (AO) framework

As the original problem (OP1) is a non-convex optimization problem, an alternate optimization (AO) framework is presented in Fig. 2. Firstly, without considering the maximum speed constraint of the UAV, the non-convex problem (OP1) is transformed into a convex optimization problem (OP2). With the solution of relaxation problem (OP2), the UAV flight trajectory optimization is transformed into a traveling salesman problem. The shortest flight trajectory of the UAV based on the relaxation solution is obtained.

Secondly, (OP1) is discretized into (OP3) where maximum speed constraint of the UAV is considered. Based on (OP3) and relaxation solution of (OP2), A UAV trajectory optimization update method (OP4) is proposed to solve the UAV flight trajectory and energy allocation strategy via the alternative optimization algorithm of genetic algorithm and continuous convex optimization. The UAV's flight trajectory can maximize the throughput of the wireless sensor network under the conditions of satisfying the maximum speed constraint of the UAV, the neutral energy constraint of the ground user, and meeting the energy threshold constraints of all nodes.

The flow of framework is given:

(a) *Initialization* Sensor node location g_n. Node weight W_n.
(b) *Calculation* The relaxation problem solution P_m without the maximum speed constraint.
(c) *Repeat* Judge whether the relaxation solutions $P_m^*, \alpha^*, \beta^*, \gamma^*$ obtained by using the gradient descent method and the Karush-Kuhn-Tucher condition meet the node energy threshold. If not return to step *b*, otherwise proceed to step *d*.

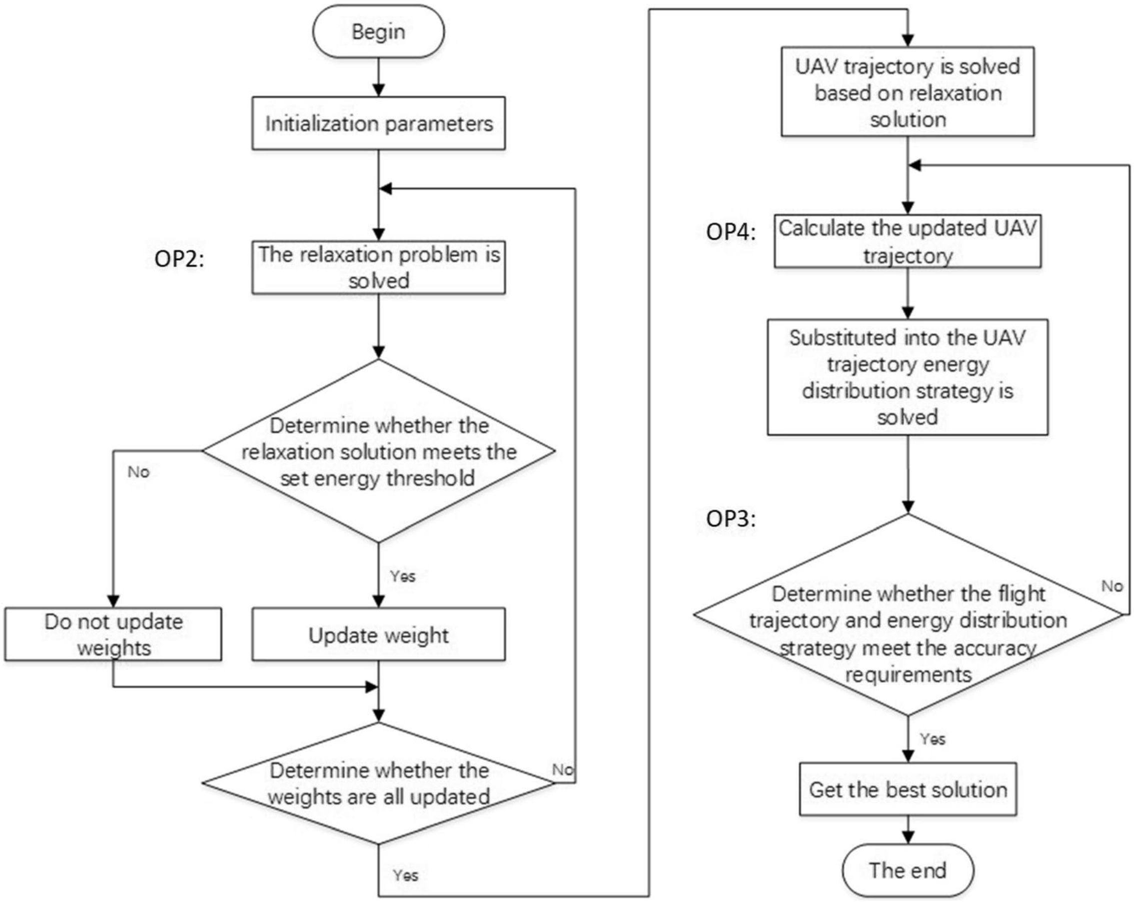

Fig. 2 The flow chart of proposed framework

(d) *Set* Obtain the optimal solution for the relaxation problem, $P_m = P_m^*, \alpha = \alpha^*, \beta = \beta^*, \gamma = \gamma^*$.

(e) *Optimization* The ant colony algorithm is used to optimize the flight trajectory of the UAV based on the known relaxation solution, and the trajectory is used as the initial value to alternately optimize the UAV flight trajectory Q and the energy allocation strategy A, P to get the optimal solution of the general problem:$P_m^*[k], \alpha_{n,m}^*[k], C_n^*[k]$.

(f) *The end:* Obtain the optimal solution to the original problem.

3.1 The optimal solution of the relaxation problem

Firstly, the non-convex optimization problem (OP1) is converted into a convex optimization problem (OP2). By relaxing the binary variables to continuous variables, and without considering the maximum speed constraint of the UAV, the non-convex optimization problem can be rewritten as (OP2):

$$
\begin{aligned}
&(\mathrm{OP2}): \max_{\omega,A,Q,P} \omega \\
&\text{s.t: } \frac{1}{T}\sum_{t=0}^{T} R_{n,m}\left(\alpha_{b,m}(t), P_m(t), C_n(t)\right) \\
&\geq \omega, \forall b \in \{1,\cdots,N\}, \forall m \in \{1,\cdots,M\} \\
&P_{th} \leq E_{n,m}\left(\alpha_{n,a}(t), P_m(t)\right), \forall a \in \{1,\cdots,M\}, 0 \leq \mathrm{t} \leq \mathrm{T} \\
&\sum_{t=0}^{T} \alpha_{b,m}(t) C_n(t) \leq \sum_{t=0}^{T} E_{n,m}\left(\alpha_{n,a}(t), P_m(t)\right) \\
&0 \leq \mathrm{PT}_m \leq PT_{\max}, m \in \{1,\cdots,M\}
\end{aligned}
$$

Construct the lagrangian function according to the relaxation problem, that is, using the existing mathematical model $R_{n,m}$, $E_{n,m}$ can construct a Lagrange function:

$$
\begin{aligned}
&\mathcal{L}_{n,\mathrm{m}}(\{A,Q,\mathrm{P}\},\mathrm{R},\alpha_n,\beta_n,\gamma_n) \\
&\quad = (1-\alpha_n)\omega + \alpha_{b,m}(t)\left(\frac{\alpha_n}{T}\log_2\left(1+\varepsilon_{\mathrm{n,m}}\left(\mathrm{Q_n(t)},\mathrm{h_{n,m}(t)}\right)\right)\right) \\
&- \alpha_{b,m}(t)(\beta_n Q_n(t) + \gamma_n P_{th}) + (\gamma_n + \beta_n)\left(\frac{\eta PT_m \mu_0 \alpha_{n,a}(t)}{\|p_m(t) - g_n\|^2 + H^2}\right)
\end{aligned} \tag{15}
$$

Secondly, consider using the UAV working mode $\alpha_{n,m}(t)$ to decompose the convex optimization problem into several equivalent sub-optimization problems [26, 27]. When the UAV is working in the downlink wireless energy transmission mode, there are $\alpha_{n,a}(t) = 1, \alpha_{b,m}(t) = 0, \forall \mathrm{a} \in \{1, \cdots, M\}, \mathrm{b} \in \{1, \cdots, N\}$. So the convex optimization problem can be transformed into:

$$\mathcal{L}_{n,\mathrm{a}}(\{A, Q, \mathrm{P}\}, \mathrm{R}, \alpha_n, \beta_n, \gamma_n) = (1 - \alpha_n)\omega + (\gamma_n + \beta_n)\left(\frac{\eta PT_m \mu_0 \alpha_{n,a}(t)}{\|P_m(t) - g_n\|^2 + H^2}\right) \tag{16}$$

When the UAV is working in the uplink wireless data transmission mode, there are $\alpha_{n,a}(t) = 0, \alpha_{b,m}(t) = 1, \forall \mathrm{a} \in \{1, \cdots, M\}, \mathrm{b} \in \{1, \cdots, N\}$. The convex optimization problem can be transformed into:

$$\mathcal{L}_{b,\,\mathrm{m}}(\{A, Q, \mathrm{P}\}, \mathrm{R}, \alpha_n, \beta_n, \gamma_n) = (1 - \alpha_n)\omega - \alpha_{b,m}(t)(\beta_n Q_n(t) + \gamma_n P_{th}) + \alpha_{b,m}(t)\left(\frac{\alpha_n}{T}\log_2\left(1 + \varepsilon_{n,m}(Q_n(t), h_{n,m}(t))\right)\right) \tag{17}$$

where

$$C_n \triangleq \max\left(0, -\left(\left[\frac{\alpha_n}{T\beta_n\gamma_n \ln 2}\right] - \left[\frac{\sigma^2 \mathrm{H}^2}{\mu_0}\right]\right)\right), Q_j = 0, \forall \mathrm{j} \in \{1, \cdots, N\}, \mathrm{j} \neq \mathrm{n}.$$

The gradient descent method and Kuhn-Tucker conditions are used to iteratively solve the sub-problems in order to obtain the solution of the convex optimization problem.

Finally, consider the node energy threshold constraint. That is, initialize the weight of each node W_n. Then calculate the energy value collected by each node, and compare the energy value of each node $E_{n,m}(\alpha_{n,a}(t), P_m(t))$ and the set energy threshold P_{th}. If the energy value collected by the node is greater than the set threshold, update the node weight. Otherwise, recalculate the UAV flight path $\mathrm{p}_m(t)$.

3.2 Optimizing UAV trajectory based on relaxation solution

Firstly the UAV flight trajectory optimization problem is converted into a traveling salesman problem. In order to use the standard traveling salesman optimization method to solve the UAV flight trajectory, a virtual hovering position, that is, $M + 1$ hovering positions, is added. The distance between them is $d_{\mathrm{M+1,n}} = d_{n,\mathrm{M+1}} = 0, \forall \mathrm{n} \in \{1, \cdots, \mathrm{M} + 1\}$. This virtual hovering position is a virtual node, which does not physically exist. After the solution is finished, delete the path related to the virtual position.

Then, based on the known flight track points of the UAV, a continuous hovering UAV flight trajectory design scheme is proposed. First, we define a set of binary variables $\{f_{a,b}\}, \forall a, b \in \{1, \cdots, M\}, a \neq b$, here $f_{a,b} = 1$ and $f_{a,b} = 0$ indicate whether the UAV is flying from position a to position b, $d_{a,b} = \|p_a - p_b\|$ represents the distance of the UAV from a to b. Then use the traveling salesman optimization problem to solve the UAV flight trajectory optimization problem, and most of the traveling salesman problem is solved by the ant colony algorithm. Here, the ant colony algorithm is used to solve the shortest UAV flight trajectory under M hovering coordinates. [27, 28]. The flight trajectory related to the virtual node is deleted, and the UAV flight trajectory that meets the energy threshold of all nodes is obtained.

3.3 UAV trajectory and energy allocation strategy for solving non-convex problems

The convex optimization problem is transformed into multiple sub-problems through the UAV working mode. The problem (OP2) could be discretized into (OP3). The period T is divided into K time periods, expressed as: $\mathrm{k} = 1, \cdots, \mathrm{K}$. The length of each time period δ_t can be expressed as: $\delta_t = \frac{T}{K}$. In this way, when each k is divided into M sub-time periods, $\alpha_{n,a}[k], \forall \mathrm{a} \in \{1, \cdots, M\}$ represent the time for the UAV downlink wireless energy transmission. In addition, N sub-times $\alpha_{b,m}[k], \forall \mathrm{b} \in \{1, \cdots, N\}$ represent the time for user uplink wireless data transmission. And the energy consumed by wireless data transmission is $\mathrm{C}_n[k]$. In this way, even at the maximum speed $V_{\max}$, it can be ensured that the position of the UAV can be approximately unchanged in each small period of time, and the accuracy requirements can be met by selecting the size of K.

$$(\mathrm{OP3}): \max_{\{A,P,Q\}} \omega$$

$$\text{s.t:} \frac{1}{T}\sum_{n=1}^{N} R_{n,m}(\alpha_{b,m}[k], P_m[\mathrm{k}], C_n[\mathrm{k}]) \geq \omega, \forall n \in \{1, \cdots, N\}, m \in \{1, \cdots, M\} \tag{18}$$

$$P_{th} \leq E_{n,m}(\alpha_{n,a}[\mathrm{k}], P_m[\mathrm{k}]), \forall k \in \{1, \cdots, K\} \tag{19}$$

$$\sum_{n=1}^{N} \alpha_{b,m}[\mathrm{k}], C_n[\mathrm{k}] \leq \sum_{\mathrm{n}=1}^{N} E_{n,m}(\alpha_{n,a}[k], P_m[\mathrm{k}]), \forall k \in \{1, \cdots, K\} \tag{20}$$

$$\|P_m[k+1] - P_m[k]\|^2 \leq V_{\max}^2, \quad \forall \mathrm{k} \in \{1, \cdots, K - 1\} \tag{21}$$

$$\sum_{a=1}^{M} \alpha_{n,a}[k] + \sum_{b=M+1}^{M+N} \alpha_{b,m}[k] \leq \delta_t, \quad \forall k \in \{1, \cdots, K\} \tag{22}$$

$$0 \leq \mathrm{PT}_m \leq PT_{\max}, \forall m \in \{1, \cdots, M\} \tag{23}$$

In the original problem, where (21) denotes the discretization of node energy threshold constraints. (22) denotes the discretization of energy neutral constraints. (23) is the discretization of UAV maximum speed constraints. A method of continuously approaching UAV flight trajectory is updated. According to the nature of the inequality, continuous approximation obtains the optimal $R_{n,m}(\alpha_{b,m}[k], C_n[k], \mathrm{P}_m[\mathrm{k}])$, and obtains the updated UAV flight trajectory $p_m^{i+1}[k]$. The inequality can be expressed as follows:

$$R_{n,m}(\alpha_{b,m}[k], C_n[k], \mathrm{P}_m[\mathrm{k}]) \geq R^i_{n,m}(\alpha_{b,m}[k], C_n[k], \mathrm{P}_m[\mathrm{k}]) \tag{24}$$

The result after each iteration should satisfy this inequality, otherwise the result of this iteration is discarded, and the next iteration is entered. And the known flight trajectory of the UAV is taken as the initial value, and the equivalent expression of $R^i_{n,m}(\alpha_{b,m}[k], C_n[k], \mathrm{P}_m[\mathrm{k}])$ can be obtained:

$$\begin{aligned} R^i_{n,m}(\alpha_{b,m}[k], C_n[k], \mathrm{P}_m[\mathrm{k}]) &\triangleq \alpha_{b,m}[k]\log_2(1+\varepsilon_{n,m}(C_n[\mathrm{k}], h_{n,m}[k])) \\ &- \frac{\varepsilon_{n,m}(C_n[\mathrm{k}], h_{n,m}[k])\alpha_{b,m}[\mathrm{k}]\log_2(C_k[k]-C^i_k[k])}{C^i_k[k]+H^2+\xi C_n[\mathrm{k}]\alpha_{b,m}[\mathrm{k}]} \end{aligned} \tag{25}$$

Here $C^i_k[k] \triangleq \left\|P^i_m[k]-g_n\right\|^2$, $C_k[k] \triangleq \|P_m{}^i[k]-g_n\|^2$, $\xi = \mu_0/\sigma^2$. Load the above constraint conditions to get a mathematical model for updating the flight trajectory of the UAV (OP4), which can be expressed as:

(OP4):

$$P^{i+1}_m[k] = \max_{P_m[k]} \min_{k\in\{1,\cdots,K\}} \frac{1}{T}\sum_{n=1}^{N} R^i_{n,m}(\alpha_{b,m}[k], P_m[\mathrm{k}], C_n[\mathrm{k}]) \tag{26}$$

$$\begin{aligned} &\text{s.t: } P_{th} \leq E_{n,m}(\alpha_{n,a}[\mathrm{k}], P_m[\mathrm{k}]), \\ &\forall k \in \{1,\cdots,K\}, n \in \{1,\cdots,N\} \\ &\sum_{n=1}^{N} \alpha_{b,m}[\mathrm{k}], C_n[\mathrm{k}] \leq \sum_{\mathrm{n}=1}^{N} E_{n,m}(\alpha_{n,a}[k], P_m[\mathrm{k}]), \\ &\forall m \in \{1,\cdots,M\}, k \in \{1,\cdots,K\} \\ &\|P_m[k+1]-P_m[k]\|^2 \leq V^2_{\max}, \forall k \in \{1,\cdots,K-1\} \\ &\sum_{a=1}^{M} \alpha_{n,a}[k] + \sum_{b=M+1}^{M+N} \alpha_{b,m}[k] \leq \delta_t, \forall k \in \{1,\cdots,K\} \\ &0 \leq \mathrm{PT}_m \leq PT_{\max}, \forall m \in \{1,\cdots,M\} \end{aligned}$$

Given the energy allocation strategy and the known flight trajectory of the UAV as the initial value, the mathematical model is used to iteratively update the UAV trajectory $p^{i+1}_m[k]$.

Finally, the optimal UAV flight trajectory and energy allocation strategy are solved, substitute the updated UAV flight trajectory into the original discretized mathematical model, reconstruct the constraints of the problem and use genetic algorithm to find the optimal energy distribution strategy $\alpha_{b,m}[k], Q_n[k]$. In this way, the UAV trajectory $p_m[\mathrm{k}]$ and the corresponding energy distribution strategy $\alpha_{b,m}[k], Q_n[k]$ are continuously alternately optimized and calculated, until the accuracy requirements are met and the optimal solution of the original problem $p^*_m[k]$ and $\alpha^*_{n,m}[k], Q^*_n[k]$.

4 Experiments

4.1 Experiments design

In this section, numerical simulation results will be given to verify the performance of the proposed UAV flight trajectory and transmission energy distribution strategy in wireless sensor networks. The experimental setting is shown in Table 2.

In the simulation, the UAV flight height H, the number of ground user nodes N, and the UAV received noise power σ^2 parameters are set. And when the reference distance $d_0 = 1$ m, the channel power gain μ_0, energy collection efficiency η, the maximum speed of the UAV $V_{\max}$, the transmission power PT of the UAV. *Var* is used to represent the variance of energy collected by ground sensors, which is used to evaluate the fairness of energy collected by each sensor.

4.2 UAV trajectory simulation with constant threshold

The proposed framework is firstly validated under a constant energy threshold. In this case, N = 9 ground users are randomly distributed in a two-dimensional area of 20 × 20 m^2. Figure 3 shows the flight trajectory of the UAV before and after the energy threshold is set. According to the simulation results in Fig. 3, there are 12 best hovering positions for the UAV, and comparing the flight trajectory after setting the energy threshold, the best hovering position of the UAV is changed and the flight trajectory of the UAV is improved. Figure 4 shows that the continuous

Table 2 Experimental parameter setting table [5, 15]

Parameter	Value	Parameter	Value
H	5 m	N	9
σ^2	−80 dBm	μ_0	−30 dB
η	50%	$V_{\max}$	10 m/s
PT	40 dBm		

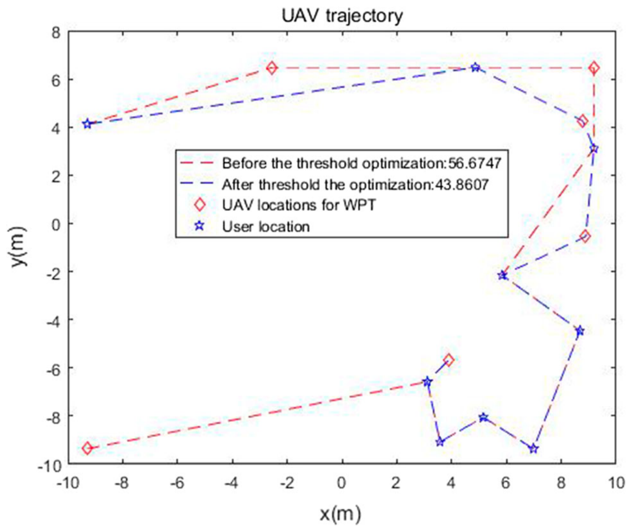

Fig. 3 UAV flight trajectory before and after threshold optimization

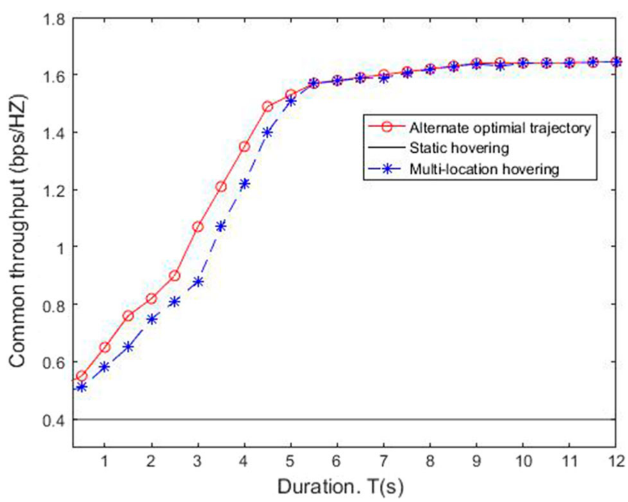

Fig. 4 The relationship between uplink throughput and flight time

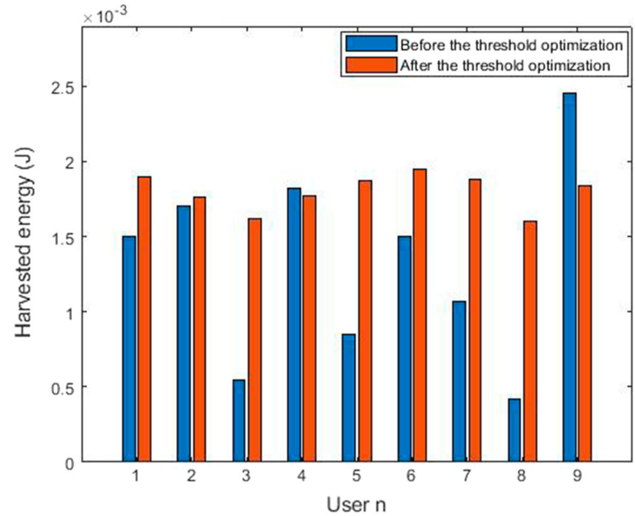

Fig. 5 The energy collected under the random distribution of user nodes

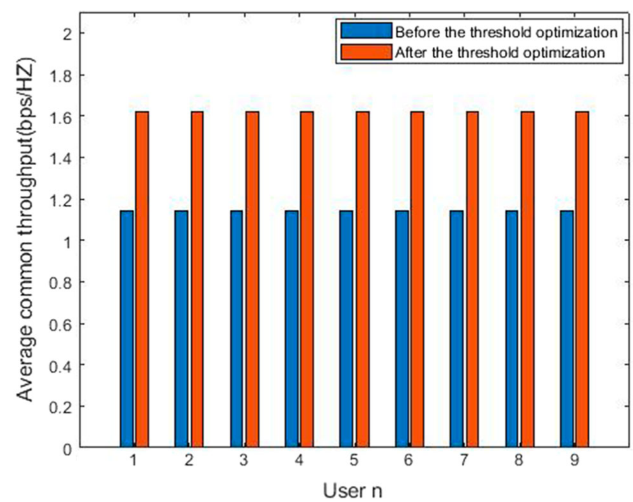

Fig. 6 Average uplink throughput under the random distribution of user nodes

hovering flight trajectory and the alternately optimized flight trajectory obtain higher public throughput than the static hovering, and when the flight time is small, the alternately optimized flight trajectory is better than the continuous hovering flight trajectory. However, if T is large enough, the throughput obtained by the multi-position continuous hovering flight trajectory will gradually approach the throughput obtained by the alternately optimized UAV flight trajectory. This verifies that the relaxation solution is effective as the initial value of the alternate optimization, and the proposed alternate optimization algorithm is feasible to solve the UAV trajectory planning and transmission energy allocation scheme optimization.

Figures 5 and 6 are the simulation results of the average throughput of the uplink sensor data transmission and the energy collected by the user nodes before and after the energy threshold is set. With the threshold optimization, the minimal, average and variance of harvested energy are improved. In Fig. 5, the minimal harvested energy has been guaranteed so that the energy collected by each sensor device is greater than the energy consumed by the sensor data collection. Meantime, it can be seen that the energy collected by the ground user node has been effectively balanced, ensuring the normal operation of the ground sensor node far away from the UAV. Figure 6 shows that after setting the energy threshold, the average throughput of the system has increased significantly, which further verifies that setting the energy threshold can improve the

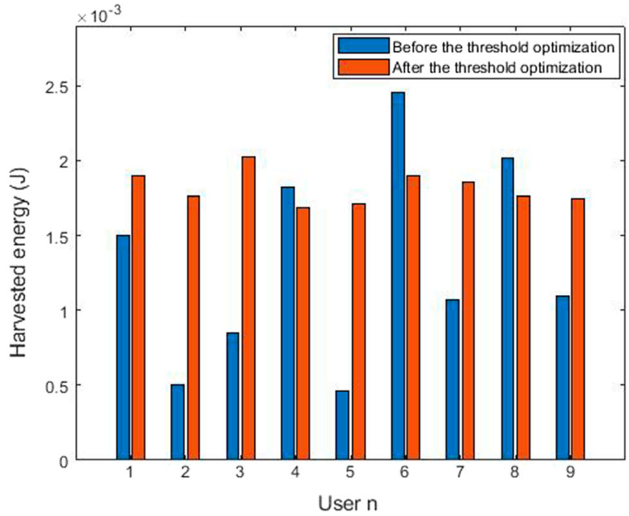

Fig. 7 Energy harvesting under the obey poisson distribution of user nodes

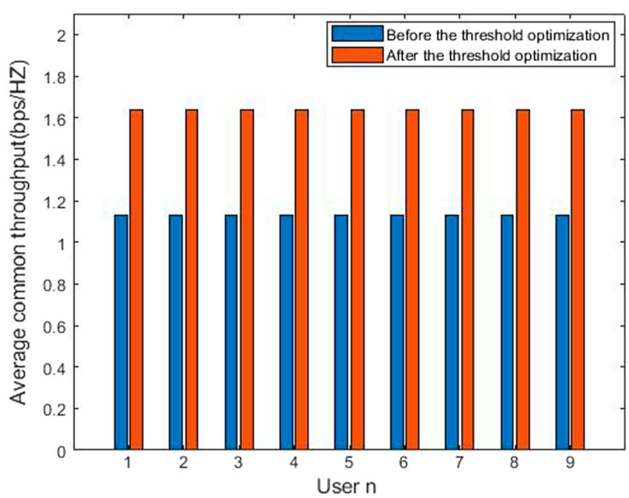

Fig. 8 Average uplink throughput under the obey poisson distribution of user nodes

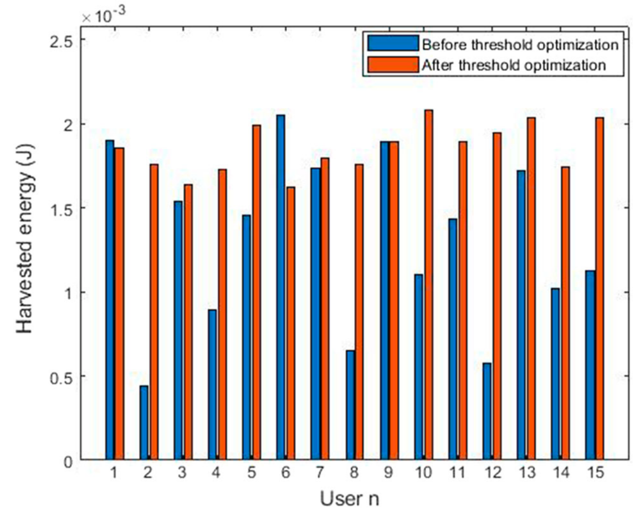

Fig. 9 N = 15, The energy values collected under the random distribution of user nodes

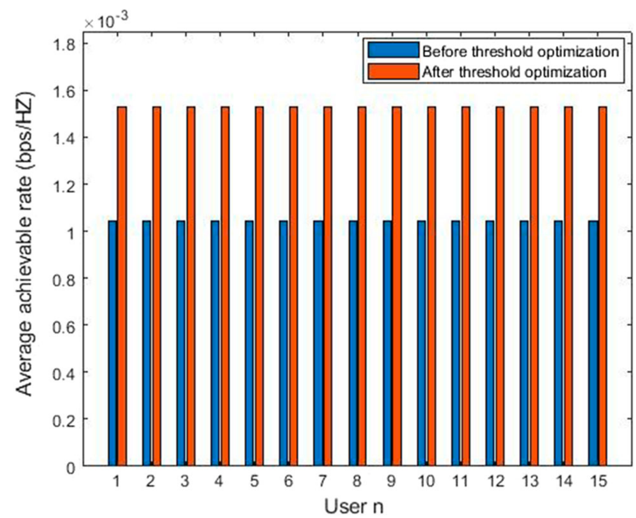

Fig. 10 N = 15, Average uplink throughput under the random distribution of user nodes

performance of the system and ensure the overall lifespan of the sensor network.

Figures 7 and 8 show the result under the Poisson distribution with a Poisson coefficient of 0.06 for the user nodes. The proposed framework has similar performance as under the random distribution. In Figs. 9 and 10, the number of user nodes increases, setting the energy threshold can also effectively balance the energy collected by the user nodes, and the public throughput of the system's uplink sensor data remains relatively stable.

4.3 UAV trajectory simulation with different threshold

The proposed framework is then analyzed under a variable energy threshold. The ground user nodes obey the random distribution, different energy thresholds are set, and the energy collected by the user nodes and the throughput of uplink sensor data transmission are simulated and analyzed. The simulated energy threshold is $P_{\text{th}} = 0.3 \times 10^{-3}$ J, $P_{\text{th}} = 0.6 \times 10^{-3}$ J and $P_{\text{th}} = 0.9 \times 10^{-3}$ J [29, 30], which represents low,middle,high energy requirement, respectively.

As shown in Figs. 11 and 12 the collected energy of each sensor node is effectively balanced, the

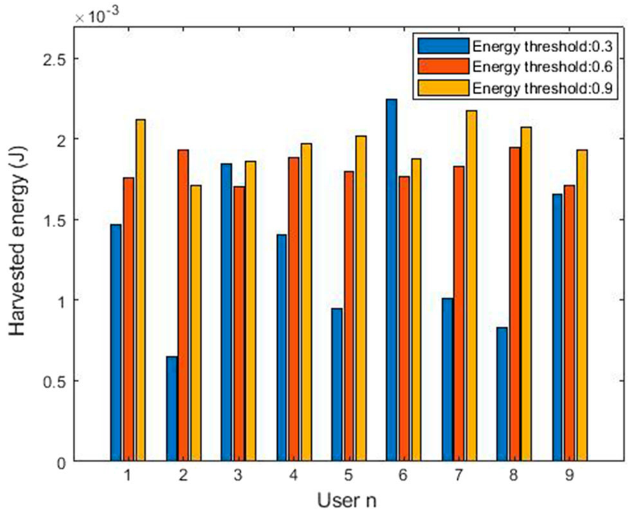

Fig. 11 The energy value collected by the node under different thresholds

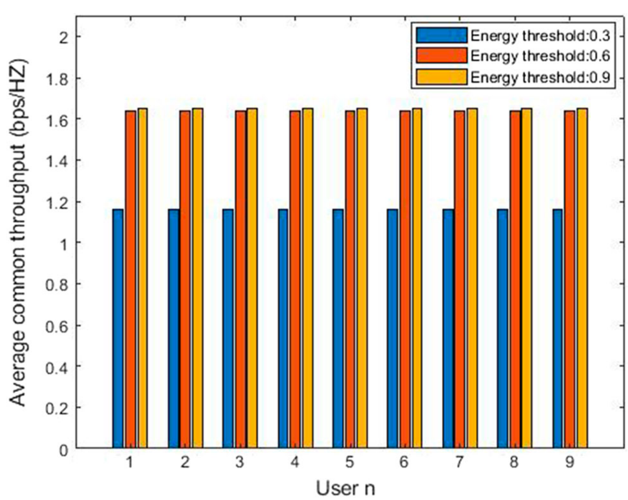

Fig. 12 The average uplink throughput of different thresholds

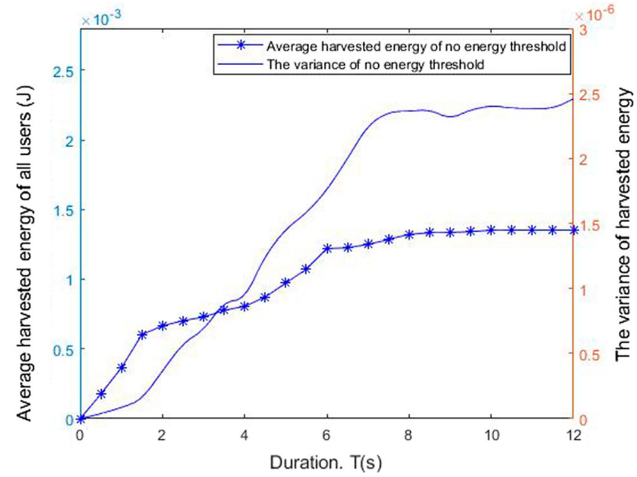

Fig. 13 No energy threshold, average energy and variance of energy over time

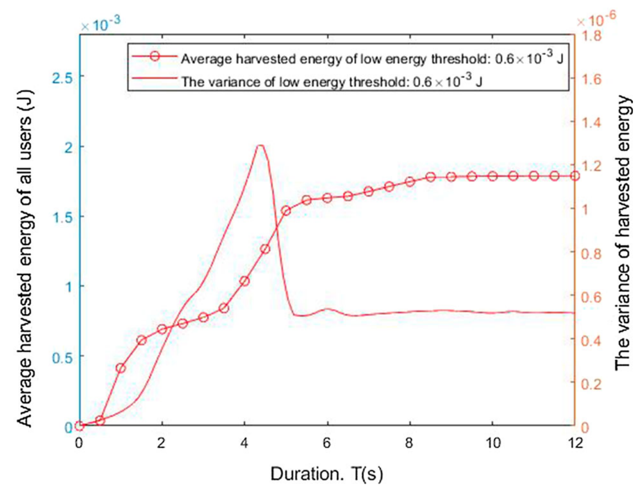

Fig. 14 Low energy threshold, average energy and variance of energy over time

improved average common throughput of sensor node further ensures the overall lifespan of the entire sensor network. When the energy threshold is set to $P_{\mathrm{th}} = 0.3 \times 10^{-3}$ J, compared with Fig. 6, it can be seen that after the energy threshold is set, the energy collected by the ground sensor nodes cannot be effectively balanced. When the energy threshold is set to $P_{\mathrm{th}} = 0.6 \times 10^{-3}$ J, the energy collected by ground sensors can be effectively balanced, and the average throughput of the system's uplink sensor data transmission can be improved. Therefore, in order to maximize the system throughput, ensure that the ground sensor nodes use the collected energy to upload sensor data information to the greatest extent, and ensure the overall life of the sensor network, it is necessary to set an effective energy threshold. According to different energy thresholds, the change of the energy collected by the user node over time is simulated, and the variance of the energy collected by the node is solved. The following gives the node-free energy threshold, low energy threshold, and high energy threshold, the changes in the energy collected by the node over time (Fig. 12).

Figures 13, 14 and 15 show the average energy collected by the ground user node and the variance of the energy collected by the node under no energy threshold, low energy threshold: $P_{\mathrm{th}} = 0.6 \times 10^{-3}$ J, high energy threshold: $P_{\mathrm{th}} = 5 \times 10^{-3}$ J, respectively. By comparing the case of the no energy threshold in Fig. 13 with the lower energy threshold in Fig. 14. When the flight time can meet a cycle of flight, after setting the energy threshold constraint, the variance of the energy collected by the node is significantly reduced, indicating that a lower energy threshold can effectively balance the energy collected by each ground

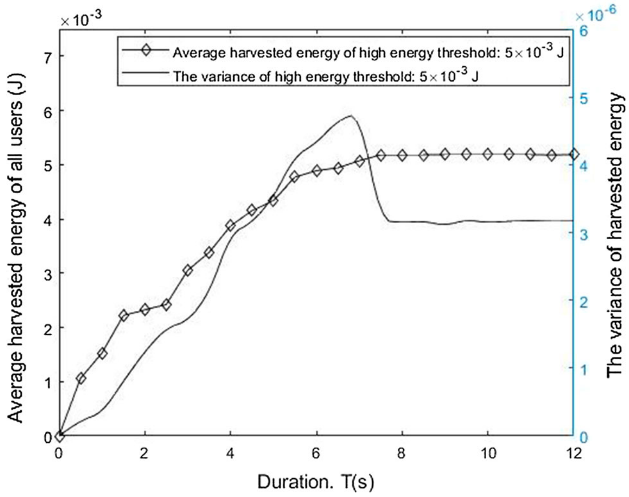

Fig. 15 High energy threshold, average energy and variance of energy over time

node. Figure 15 setting the high energy threshold, without UAV resource restrictions, the ground nodes can collect more energy. However, considering that the high energy threshold requires more flight time to meet its energy threshold constraint, the energy value collected by the user node will never meet the set energy threshold, and the energy threshold constraint will become invalid. In different application scenarios, the energy required by the sensor to work normally varies greatly, this framework is suitable for setting different energy thresholds. In actual deployment, the energy required by the sensor is often determined in advance, and the energy collected by the sensor node can be guaranteed based on the energy threshold. Based on proposed framework, the minimum energy requirement of the UAV can be used to guide the model selection of UAV in practical scenarios.

5 Conclusions

In this paper, by alternately optimizing the UAV flight trajectory and the transmission energy allocation strategy, the flight trajectory of the UAV is optimized to maximize the wireless sensor network throughput when considering the overall life of the wireless sensor network and all constraints. In order to solve this complicated problem, firstly, the maximum speed constraint of the UAV is ignored, and the non-convex optimization problem is transformed into a convex optimization problem. Secondly, the convex optimization problem is solved by judging whether each relaxation solution meets the energy threshold. The energy collected by each ground user node is required to be greater than the energy consumed by the uplink data transmission. Thirdly, on the basis of the known relaxation solution, the UAV flight trajectory optimization is transformed into a travelling salesman problem, and a UAV flight trajectory is optimized using the ant colony algorithm. Finally, considering the non-convex optimization problem with the maximum speed constraint of the UAV, an approximation UAV trajectory update method is designed by using the known UAV trajectory as the initial value, and alternately optimizing the UAV flight trajectory and energy transmission, resource allocation strategy.

A discrete UAV flight trajectory is obtained after performing alternate optimization in this paper. Numerical results show that setting the energy threshold can effectively balance the energy collected by each ground user node. The UAV flight path in the wireless sensor network satisfies the constraints and maximizes the throughput of the wireless sensor network. A continuous and smooth trajectory of UAV has advantages in implementing UAV flight control and decreasing UAV energy consumption. In addition, multiple UAVs cooperatively assisting wireless power and information transfer could be expanded.

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Jing Guo is currently a Lecturer with the Department of Automation, Foshan University, China. She received the Ph.D degree in Control Theory an Control Engineering from Zhejiang University, Hangzhou, China, in 2011. From 2011, she was an Assistant Researcher in Shenzhen, China. From 2012, she joined Foshan University, China. From 2017 to 2018, She was a Guest Researcher with the Engineering and Technology institute of Groningen, University of Groningen. Her research interests include control of multi-agent and network systems, distributed decision-making and coordination, wireless networks and cooperation optimization.

Shuai Yang received a bachelor's degree in automation from the Chongqing College of Mobile Communication in 2015. He is currently pursuing a master's degree in control engineering at Foshan University. His research interest is UAV path planning.

Zhile Yang (S'13, M'17) obtained his BSc in Electrical Engineering and the MSc degree in Control Engineering both from Shanghai University (SHU) in 2010 and 2013 respectively, and he then received Ph.D. degree at the School of Electrical, Electronics and Computer Science, Queenâ€™s University Belfast (QUB), UK. He worked as a research assistant in QUB and is currently an associate professor in Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China. His research interests focus on artificial intelligence methods and their applications on smart grid and advanced manufacturing. He is the founding chair of IEEE QUB student branch and an active member of IEEE PES, CIS and SMC societies. He is the author or co-author of more than 100 articles in peer reviewed international journals and conferences, and an active reviewer for over 40 international journals.

Lei Lei received the B.E. degree in Ship and Ocean Engineering from the Department of Ship Engineering, Harbin Engineering University, Harbin, China in 2016, the M.E. degree in Mechanical Engineering from the Department of Mechanical Science and Engineering, Huazhong University of Science and Engineering, Wuhan, China in 2019. He is currently pursuing the Ph.D. degree in machine learning and intelligent modelling with the Department of Advanced Design and Systems Engineering, City University of Hong Kong, Hong Kong. His research interests include machine learning, computer vision, and application in robotics.

Xu Zhang received his B.E. degree in communication engineering from University of Electronic Science and Technology of China, Chengdu, China in 2006, and M.E. degree in electromagnetic field and microwave technology from Beijing University of Posts and Telecommunications, Beijing, China in 2009. He is currently pursuing the Ph.D degree at Central South University, Changsha, China and City University of Hong Kong, Hong Kong. His current research interests include radio frequency identification, smart sensing and Internet of Things.