Energy harvesting assisted UAV sensing integrated system resource allocation

Guangjun Liang[1*], Hailiang Xu[2], Xilong Liu[2] and Chuang Chen[3]

[1] Department of Computer Information and Cyber Security, Jiangsu Police Institute, Nanjing 210031, China
[2] Pukou Branch of Nanjing Public Security Bureau, Nanjing 211800, China
[3] School of Communication Engineering, Nanjing University of Posts and Telecommunications, Nanjing 210023, China
* Correspondence: lianggjun@126.com (Liang G)

Abstract

In the context of the deep integration of wireless communication and perception technology, this paper examines the resource allocation problem of an energy harvesting-assisted unmanned aerial vehicle (UAV) communication and perception integrated systems. Firstly, an energy harvesting-assisted UAV sensing integrated system was constructed, which consists of a sensing integrated base station, sensing terminals, and ground sensing energy stations. Then, based on the separate study of energy consumption models, communication models, and perception models, an integrated energy harvesting-assisted UAV sensing system model was established. Considering the optimization objectives of communication and perception, communication metrics were transformed into constraints and the research focussed on studying the perception performance of the system. A series of convex optimization methods were used to solve the conversion optimization problem, and the optimal energy harvesting time slot allocation was solved using the binary method. The established optimization model takes into account the deep coupling between the drone beamforming vector and the position decision variable. Finally, the optimal solution was obtained through alternating iterations using semi-definite programming (SDP), the Dinkelbach method, and the successful convex approximation (SCA) method. The simulation experiment fully verifies the effectiveness of the proposed algorithm.

Introduction

With the rapid advancement of unmanned aerial vehicle (UAV) technology and continuous innovation in wireless communication networks, unmanned aerial vehicles (UAVs) have emerged as a pioneering force in promoting the deep integration of communication and perception technologies[1–4]. As a cutting-edge trend in network evolution, communication-perception integration (CPI) corely relies on physical infrastructure and resource sharing to significantly enhance system-wide efficiency and adaptability[5–7]. UAVs, with their unique aerial perspective, excellent maneuverability, and rapid response capabilities, enable wide coverage of communication networks and precise acquisition of perception data, thereby opening new avenues for CPI implementation. In this context, analyzing the core role and precise positioning of UAVs in CPI systems becomes particularly urgent. Designing efficient resource allocation and scheduling strategies based on such analysis not only maximizes UAV-specific advantages but also directly influences the intelligent and flexible development of future network systems. This endeavor is crucial for harnessing the full potential of UAVs in next-generation integrated networks.

The UAV resource allocation problem mainly focuses on trajectory optimization, channel allocation, and power control[8–12]. The trajectory optimization problem of multiple three-dimensional UAVs as aerial base stations (BS) was studied[8]. Wireless coverage for Internet of Things (IoT) devices is considered by optimizing the trajectory and power of drones to minimize communication time for all IoT devices. Furthermore, a solution based on Hierarchical Reinforcement Learning (HRL) has been proposed. In reliability-oriented downlink wireless network assisted by drones, a deep embedding deterministic policy gradient (DDPG) algorithm was proposed, and the trajectory and transmission power allocation of unmanned aerial vehicles were jointly determined through alternately optimizing iterative schemes[9].

The application of unmanned aerial vehicles in auxiliary hybrid non-orthogonal multiple access (NOMA) systems was studied[10]. To improve UAV spectrum efficiency and communication connectivity, a joint optimization model for UAV positioning and user grouping that maximizes system speed was established. Finally, the paper swarm optimization algorithm and neural network method were used to iteratively solve the problem. Channel allocation and power control for uplink NOMA-assisted multi-UAV networks were researched[11]. A mixed integer nonlinear programming model was established, and a feasible algorithm proposed to obtain the power and channel allocation scheme for the drone. A drone relay network based on NOMA was studied[12]. A joint optimization model for NOMA user grouping, drone location, and drone transmission power were established. Similarly, an iterative algorithm was used to obtain an approximate optimal solution.

The resource allocation problem of sensory integrated systems was studied[13–15]. In the scenario of unmanned aerial vehicle multi-cell collaborative integrated sensing and communication (ISAC), a collaborative control strategy for base station power and unmanned aerial vehicles was designed, considering the maximization of QoS (Quality of Service), and communication efficiency[13]. To ensure the safety of ISAC-UAV systems, a joint optimization algorithm for UAV trajectory and launch power was proposed[14], maximizing the secure communication rate under the constraints of UAV maneuverability, power, and perception. In multi UAV assisted dual function base station (BS) scenarios, a Stackelberg game model was proposed to consider the physical layer security of ISAC signals[15].

In recent years, the energy consumption issue of UAVs has attracted increasing attention[16–25]. The application of energy harvesting (EH) technology in unmanned aerial vehicle communication scenarios was studied[16]. A rate-limited solution for UAV networks was proposed through UAV-assisted communication and EH channel modeling. An EH scheme based on the UAV-RIS system was proposed, enabling simultaneous signal transmission, and energy harvesting on the RIS metasurface[17]. A robust near-end policy optimization algorithm has been developed with QoS as a constraint in dynamic wireless environments. A graph theory-based UAV energy harvesting assisted communication resource allocation algorithm was proposed[18]. A EH optimization model based on imperfect channel state information (CSI) was established and solved to maximize network throughput.

An EH scenario based on meta reinforcement learning (RL) was studied[19]. A joint optimization scheme for UAV trajectory and EH strategy was designed, taking QoS as the constraint condition, considering unmanned aerial vehicles with both energy collection and data transmission capabilities. An unmanned aerial vehicle RIS assisted maritime communication system in the presence of malicious interference was designed[20]. A problem of maximizing energy efficiency (EE) in an adaptive energy harvesting system was proposed by adjusting the position and surface elements of the RIS. The UAV selection algorithm for UAV-assisted relay networks was studied[21]. A two-stage drone selection strategy was developed. The closed-form expressions for the total interruption probability, average throughput, and average symbol error probability were derived.

A joint optimization scheme for UAV flight trajectory, user assignment, and power control was designed, with the objective of maximizing the minimum user rate[22]. The reliability and security of unmanned aerial vehicle communication systems were studied[23]. Taking into account the energy consumption issue of UAV ground networks, an approximate closed-form expression for the system interruption probability (OP) was provided. A drone-assisted MEC network for EH was considered[24]. A joint optimization algorithm for user assignment, power allocation, computation offloading, and drone location was proposed with the optimization objective of improving the computational efficiency of the network. A new UAV model was constructed, which improves UAV energy efficiency via the proposed Lyapunov chain offloading algorithm[25].

This paper proposes a joint optimization algorithm for UAV transmission beamforming and UAV position, based on optimal communication and perception performance, for the scenario of energy harvesting-assisted UAV communication-perception integration. Through a series of convex optimization processes and optimization problem transformations, the minimum perceptual performance was maximized while ensuring the communication performance of communication users. The main contributions of this paper are as follows:

(1) This study considers the energy harvesting time slots of the energy harvesting-ISAC-UAV system and solves the optimal energy harvesting time slot allocation via a binary search method.

(2) For the beamforming vector optimization of the energy harvesting-assisted ISAC-UAV system, a convex semidefinite programming approach is adopted to solve the beamforming vectors under a given UAV position.

(3) For UAV position optimization for the energy harvesting-assisted ISAC-UAV system, a continuous convex approximation method was used to solve the UAV position under the condition of beamforming vectors.

System and problem modeling

Scene description

This section studies the EH-assisted UAV communication perception integrated system model (EAU-ISAC). As shown in Fig. 1, the system consists of an ISAC BS, cellular terminals (CTs), and ground perception energy stations (PET).

The ISAC base station adopts UAVs that can be quickly and flexibly used. Multi-antenna UAVs are equipped with both communication and perception transceiver modules. Among them, the UAV is equipped with M linear uniform antenna arrays, denoted as B_{UAV}. To receive wireless energy transmission from ground energy stations, UAVs are equipped with corresponding RF energy coupling modules. The N single antenna communication modules on the ground are denoted as C_n, $n = 1, 2, ..., N$. The ground energy station is mainly used for wireless charging of UAVs, denoted as B_{EH}. As an important part of the system, the ground energy station is also equipped with a sensing function module, which is used to sense the position, speed, and other information of the drone, so as to better complete the wireless transmission of energy and other functions.

In the energy harvesting-assisted UAV sensor integration system shown in Fig. 2, a sensor integration transmission protocol based on EH technology is proposed. A system transmission cycle T is divided into three time slots, represented by $\tau_1 T$, $\tau_2 T$, and $\tau_3 T$ respectively.

$$\tau_1 T + \tau_2 T + \tau_3 T = T \tag{1}$$

We assume that $\tau = \{\tau_1, \tau_2, \tau_3\}$, one of the most important factors in this transmission protocol, is to allocate the length τ of the three time slots reasonably, to achieve the best resource allocation efficiency. In the first time slot $\tau_1 T$, where $0 < \tau_1 < 1$, the ground perception energy station B_{EH} wirelessly charges UAV B_{UAV}. In the second time slot $\tau_2 T$, where $0 < \tau_2 < 1$, UAV UAV B_{UAV} sends communication signals x_c to N single antenna ground terminals. In the third time slot $\tau_3 T$, where $0 < \tau_3 < 1$, the UAV UAV B_{UAV} sends a sensing signal x_s to the ground sensing energy station UAV B_{EH}.

Energy harvesting model

The total energy E_{UAV} collected by the UAV in the first time slot is represented as:

$$E_{UAV} = \eta \tau_1 T P_E \sum_{i=1}^{M} h_{i,1}^{EU} \tag{2}$$

where, η is the energy harvesting efficiency, $0 < \eta < 1$. P_E represents the transmission power of the ground energy station B_{EH}. To ensure that the UAV collects sufficient energy for normal operation, P_E needs to be large enough so that the energy harvested from noise can be ignored. $h_{i,1}^{EU}$ represents the wireless channel gain from B_{EH} to B_{UAV} on antenna i,
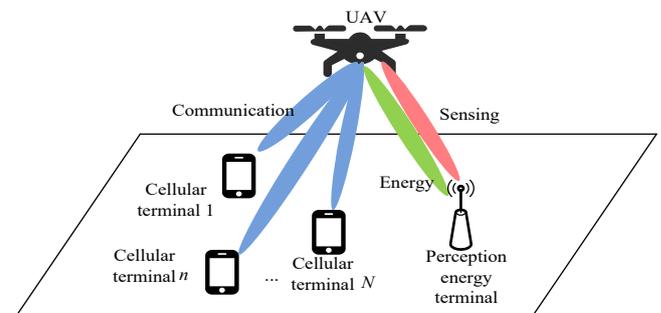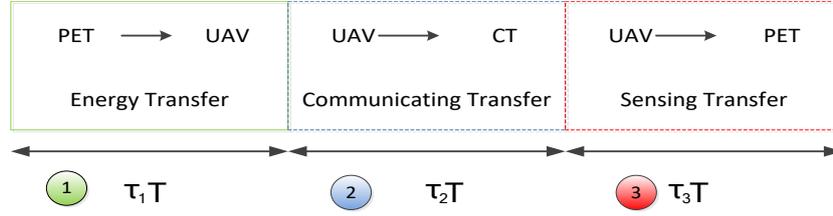

Fig. 1 EAU-ISAC scenario.

Fig. 2 EAU-ISAC protocol.

which follows a complex Gaussian distribution and is defined as $h_{i,1}^{EU} \sim CN(0, \sigma_{EU(i,1)}^2)$, where $\sigma_{EU(i,1)}^2$ represents the Gaussian white noise at the receiving end.

In the first time slot, the UAV harvests enough energy E_{UAV} to support the transmission of communication signals and perception signals in the following two time slots. Dividing the energy consumption of the system into three parts: UAV total energy consumption P^U, cellular terminal total energy consumption P^C, and perception terminal total energy consumption P^S. The total energy consumption of the system can be expressed as:

$$P^{total} = P^U + P^C + P^S \qquad (3)$$

Among them, the total energy consumption P^U of UAV is divided into three parts: communication module power consumption P_{com}^u, perception module power consumption P_{sen}^u, and UAV inherent power consumption P_{inh}^u. Thus, the total energy consumption P^U of UAV can be expressed as:

$$P^U = P_{com}^u + P_{sen}^u + P_{inh}^u \qquad (4)$$

Among them, the power consumption P_{com}^u of the communication module and the power consumption P_{sen}^u of the perception module can be expressed as:

$$P_{com}^u = \sum_{n=1}^N \left\| \boldsymbol{\omega}_n^c \right\|^2 \qquad (5)$$

$$P_{sen}^u = \sum_{n'=1}^N \left\| \boldsymbol{\omega}_{n'}^s \right\|^2 \qquad (6)$$

The inherent power consumption P_{inh}^u of UAV can be expressed as:

$$P_{inh}^u = P_{mov}^u + P_{ho}^u \qquad (7)$$

where, P_{mov}^u and P_{ho}^u respectively represent the energy consumption during UAV flight and hovering.

Communication model

In the second time slot, the UAV BS sends communication signals to the ground sensing integrated terminal.

s_n^c represents the expected communication signal sent by the drone to the nth ground sensing integrated terminal. $\boldsymbol{\omega}_n^c \in \mathbb{C}^{N \times 1}$ represents the corresponding communication beamforming vector. Thus, the transmission signal of UAV can be represented as:

$$\boldsymbol{x}_c = \sum_{n=1}^N \boldsymbol{\omega}_n^c s_n^c \qquad (8)$$

Assuming s_n^c is an independent and identically distributed standard conjugate complex Gaussian signal[18], satisfying $s_n^c \sim CN(0,1)$. The average transmission power P_{tran}^{u2} of the UAV at the second time slot can be expressed as:

$$P_{tran}^{u2} = \mathbb{E}\left(\|\boldsymbol{x}_c\|^2 \right) = \sum_{n=1}^N \left\| \boldsymbol{\omega}_n^c \right\|^2 \qquad (9)$$

As shown in the Cartesian coordinate system in Fig. 1, assuming the flight altitude of the drone is h^0, the coordinates of the drone are denoted as (x, y, h^0), where $\mathbf{u} = (x,y)$ represents its horizontal coordinates.

The integrated ground sensing terminals are all located on a horizontal plane. The coordinates of $n \in N$ integrated ground sensing terminals are represented as $(x_n, y_n, 0)$. $c_n = (x_n, y_n)$ represents their horizontal coordinates.

Considering that UAVs serve as aerial base stations and their altitude generally does not change, this paper does not study the optimization of UAV altitude, but only the optimization of its horizontal position. UAV base stations usually hover in open positions, so we establish a Line of Sight (LOS) channel. The channel gain $h_n(u, c_n) \in \mathbb{C}^{N \times 1}$ of the nth communication terminal is represented as:

$$\boldsymbol{h}_n(\boldsymbol{u}, \boldsymbol{c}_n) = \sqrt{\alpha d^{-2}(\boldsymbol{u}, \boldsymbol{c}_n)}\boldsymbol{b}(\boldsymbol{u}, \boldsymbol{c}_n) = \sqrt{\frac{\alpha}{H^2 + \|\boldsymbol{u} - \boldsymbol{c}_n\|^2}}\boldsymbol{b}(\boldsymbol{u}, \boldsymbol{c}_n) \qquad (10)$$

Among them, α, $d(u, c_n)$, and $\boldsymbol{b}(u, c_n) \in \mathbb{C}^{N \times 1}$ respectively represent the reference signal attenuation gain, the distance between UAV and the n-th communication terminal, and the beamforming guidance vector.

The signal received by the n-th communication terminal can be represented as:

$$y_n = \boldsymbol{h}_n^H(\boldsymbol{u}, \boldsymbol{c}_n)\boldsymbol{x} + N_n^0 = \boldsymbol{h}_n^H(\boldsymbol{u}, \boldsymbol{c}_n)\boldsymbol{\omega}_n^c s_n^c + \sum_{i=1, i \neq n}^N \boldsymbol{h}_n^H(\boldsymbol{u}, \boldsymbol{c}_n)\boldsymbol{\omega}_i^c s_i^c + N_n^0 \qquad (11)$$

Among them, $N_n^0 \sim CN(0, \sigma_n^2)$ represents the AWGN of the n-th communication terminal.

After decomposing the received signal using Eq. (4), the SINR of the n-th communication terminal is expressed as:

$$\text{SINR}_n = \frac{\left| \boldsymbol{h}_n^H(\boldsymbol{u}, \boldsymbol{c}_n)\boldsymbol{\omega}_n^c \right|^2}{\left| \sum_{i=1, i \neq n}^N \boldsymbol{h}_n^H(\boldsymbol{u}, \boldsymbol{c}_n)\boldsymbol{\omega}_i^c \right|^2 + \sigma_n^2} \qquad (12)$$

Furthermore, we can provide the total achievable rate of UAV downlink communication as:

$$R_{total}(\boldsymbol{u}, \omega_n^c) = \frac{1}{2} \sum_{n=1}^N \log_2 \left(1 + \frac{\left| \boldsymbol{h}_n^H(\boldsymbol{u}, \boldsymbol{c}_n)\boldsymbol{\omega}_n^c \right|^2}{\left| \sum_{i=1, i \neq n}^N \boldsymbol{h}_n^H(\boldsymbol{u}, \boldsymbol{c}_n)\boldsymbol{\omega}_i^c \right|^2 + \sigma_n^2} \right) \qquad (13)$$

Perception model

In the third time slot, the UAV aerial base station sends a sensing signal to the ground sensing energy station B_{EH}.

s^s represents the expected perception signal sent by the drone to the ground sensing integrated terminal. $\omega_m^s \in \mathbb{C}^{M \times 1}$ represents the corresponding perceptual beamforming vector. Thus, the perception signal sent by UAV can be represented as:

$$\boldsymbol{x}_s = \sum_{m=1}^{M} \omega_m^s s_m^s \tag{14}$$

Assuming s_m^s is an independent and identically distributed standard conjugate complex Gaussian signal[18], satisfying $s_m^s \sim \mathcal{CN}(0,1)$. The average perceived transmission power P_{tran}^{u3} of UAV can be expressed as:

$$P_{tran}^{u3} = \mathbb{E}\left(\|\boldsymbol{x}_s\|^2\right) = \sum_{m=1}^{M} \|\omega_m^s\|^2 \tag{15}$$

The ground perception energy station B_{EH} is located in the horizontal plane and its coordinates are represented as $(x_s, y_s, 0)$, where s = (x_s, y_s) represents its horizontal coordinates.

Similar to the signals received by communication terminals, the signals received by ground perception energy station B_{EH} for perception and monitoring can be represented as:

$$y_s = \sum_{m=1}^{M} \boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_m^s s_m^s + N_s^0 = \boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_n^c s_i^c + \sum_{m=1}^{M} \boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_m^s s_m^s + N_s^0 \tag{16}$$

Similarly, the perceived channel gain can be expressed as:

$$\boldsymbol{g}(\boldsymbol{u},\boldsymbol{s}) = \sqrt{\alpha_s d_s^{-2}(\boldsymbol{u},\boldsymbol{s})} \boldsymbol{b}_s(\boldsymbol{u},\boldsymbol{s}) \in \mathbb{C}^{N \times 1} \tag{17}$$

Among them, α_s, $d_s(\boldsymbol{u}, \boldsymbol{s})$, and $\boldsymbol{b}_s(\boldsymbol{u}, \boldsymbol{s}) \in \mathbb{C}^{N \times 1}$ respectively represent the reference signal attenuation gain, the distance between the UAV and the Z-th sensing terminal, and the beamforming guidance vector. $N_s^0 \sim \mathcal{CN}(0,\sigma_n^2)$ represents the AWGN of the sensing terminal.

Therefore, the monitoring signal-to-noise ratio of ground perception energy station B_{EH} can be written as:

$$\mathrm{SINR}_n^s = \frac{\left|\boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_n^c\right|^2}{\left|\sum_{m=1}^{M} \boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_m^s\right|^2 + \sigma_s^2} \tag{18}$$

Problem modeling

This model mainly studies the integrated resource allocation of sensing, considering energy harvesting factors. Therefore, decision variables include time allocation (energy harvesting time $\tau_1 T$, communication signal transmission time $\tau_2 T$, perception signal transmission time $\tau_3 T$), power allocation (communication beamforming vector $\omega_n^c \in \mathbb{C}^{N \times 1}$ and perception beamforming vector $\omega_m^s \in \mathbb{C}^{M \times 1}$), and UAV position (UAV horizontal coordinate $\boldsymbol{u} = (x, y)$). We define the time allocation factor and power allocation factor as $\tau = \{\tau_1, \tau_2, \tau_3\}$ and $\omega = \{\omega_n^c, \omega_m^s\}$, respectively.

This model considers two objectives: communication and perception, and should be a multi-objective optimization model. Regarding communication indicators, we hope to maximize the total achievable rate $R_{total}(u, \omega_n^c)$ of UAV downlink communication. Meanwhile, regarding the perception indicators, we hope that the perceived signal is as good as possible, and here we choose to maximize and minimize the perceived signal-to-noise ratio SINR_n^s.

Next, we will analyze the constraints and consider the energy consumption optimization problem of UAVs. Although the inherent power consumption P_{inh}^u of UAVs can also be optimized, we will study the energy consumption optimization problem of UAVs from the perspective of communication, mainly focusing on the power consumption P_{com}^u of communication modules and perception modules P_{sen}^u.

We assume that the maximum transmission power of the UAV is P_{max}, and we can obtain the UAV communication and perception power and limitations as follows:

$$\sum_{n=1}^{N} \|\omega_n^c\|^2 + \sum_{n'=1}^{N} \|\omega_{n'}^s\|^2 \le P_{max} \tag{19}$$

$$P_{max}(\tau_2 + \tau_3) = E_{UAV} + E_{UAV}^0 \tag{20}$$

Among them, E_{UAV}^0 represents the remaining energy before UAV energy harvesting.

In summary, the resource allocation problem of the EH assisted unmanned aerial vehicle communication perception integrated system is expressed as follows:

$$P1: \max_{\tau,u,\omega} R_{total}(\boldsymbol{u},\omega_n^c) = \frac{1}{2} \sum_{n=1}^{N} \log_2 \left(1 + \frac{\left|\boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n) \omega_n^c\right|^2}{\left|\sum_{i=1,i\neq n}^{N} \boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n) \omega_i^c\right|^2 + \sigma_n^2}\right)$$

$$\max_{\tau,u,\omega} \min \mathrm{SINR}_n^s = \frac{\left|\boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_n^c\right|^2}{\left|\sum_{m=1}^{M} \boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_m^s\right|^2 + \sigma_s^2} \tag{21}$$

$$s.t. \quad C1: \sum_{n=1}^{N} \|\omega_n^c\|^2 + \sum_{n'=1}^{N} \|\omega_{n'}^s\|^2 \leqslant P_{max}$$

$$C2: \tau_1 + \tau_2 + \tau_3 = 1$$

$$C3: P_{max}(\tau_2 + \tau_3) = E_{UAV} + E_{UAV}^0$$

where, C1 represents the energy consumption constraint condition of the UAV system. C2 is the time constraint condition for UAV systems.

Problem solving

Convex optimization processing and time slot allocation

Optimization problem P1 is a multi-objective optimization problem, and in the actual solving process, one optimization objective can be transformed into a constraint condition, with a focus on the optimization problem of the other optimization objective. This model transforms communication metrics into constraints and instead studies the perception performance of the system.

Here we make a reasonable approximation to transform the maximum achievable rate $R_{total}(\boldsymbol{u},\omega_n^c)$ of UAV downlink communication into any rate $R_n(\boldsymbol{u},\omega_n^c)$ greater than a certain threshold R_{min}, expressed as:

$$R_n(\boldsymbol{u},\omega_n^c) = \frac{1}{2} \log_2 \left(1 + \frac{\left|\boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n) \omega_n^c\right|^2}{\left|\sum_{i=1,i\neq n}^{N} \boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n) \omega_i^c\right|^2 + \sigma_n^2}\right) \geqslant R_{min} \tag{22}$$

Thus, the new optimization problem P2 can be expressed as:

$$P2: \max_{\tau,u,\omega} \min \mathrm{SINR}_n^s = \frac{\left|\boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_n^c\right|^2}{\left|\sum_{m=1}^{M} \boldsymbol{g}^H(\boldsymbol{u},\boldsymbol{s}) \omega_m^s\right|^2 + \sigma_s^2}$$

$$s.t. \quad C1: \sum_{n=1}^{N} \|\omega_n^c\|^2 + \sum_{n'=1}^{N} \|\omega_{n'}^s\|^2 \le P_{max}$$

$$C2: \tau_1 + \tau_2 + \tau_3 = 1 \tag{23}$$

$$C3: P_{max}(\tau_2 + \tau_3) = E_{UAV} + E_{UAV}^0$$

$$C4: R_n(\boldsymbol{u},\omega_n^c) = \frac{1}{2} \log_2 \left(1 + \frac{\left|\boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n) \omega_n^c\right|^2}{\left|\sum_{i=1,i\neq n}^{N} \boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n) \omega_i^c\right|^2 + \sigma_n^2}\right) \geq R_{min}$$

Continuing to analyze optimization problem P2, according to its objective function, P2 is an MM problem. By introducing auxiliary variable A and adding a constraint condition C5, the MM problem can be transformed into a minimax problem, which can be rephrased as:

$$P3: \max_{\tau,u,\omega} A$$

$$s.t. \; C1: \sum_{n=1}^{N} \left\| \omega_n^c \right\|^2 + \sum_{n'=1}^{N} \left\| \omega_{n'}^s \right\|^2 \leq P_{\max}$$

$$C2: \tau_1 + \tau_2 + \tau_3 = 1$$

$$C3: P_{\max}(\tau_2 + \tau_3) = E_{UAV} + E_{UAV}^0$$

$$C4: R_n(\boldsymbol{u},\omega_n^c) = \frac{1}{2}\log_2\left(1 + \frac{\left| \boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n)\omega_n^c \right|^2}{\left| \sum\limits_{i=1,i\neq n}^{N} \boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n)\omega_i^c \right|^2 + \sigma_n^2}\right) \geq R_{\min} \quad (24)$$

$$C5: \text{SINR}_n^s = \frac{\left| \boldsymbol{g}^H(\boldsymbol{u},s)\omega_n^c \right|^2}{\left| \sum\limits_{m=1}^{M} \boldsymbol{g}^H(\boldsymbol{u},s)\omega_m^s \right|^2 + \sigma_s^2} \geq A, n \in N$$

The new optimization problem P3 contains three decision variables. To simplify the expression, we assume $\tau_1 = \tau$ and $\tau_2 = \tau_3$, and the length of the second and third time slots is $(1-\tau)T/2$. Upon careful observation of problem P3, the simplified time decision variable τ has no coupling relationship with the power allocation factor $\omega = \{\omega_n^c, \omega_m^s\}$ and UAV horizontal coordinates $\boldsymbol{u} = (x, y)$. Therefore, we can use the binary method to first obtain τ^*, and then continue to solve ω and $\boldsymbol{u}$. Further transforming the new optimization problem P4 gives:

$$P4: \max_{u,\omega} A$$

$$s.t. \; C1: \sum_{n=1}^{N} \left\| \omega_n^c \right\|^2 + \sum_{m=1}^{M} \left\| \omega_m^s \right\|^2 \leq P_{\max}$$

$$C4: R_n(u,\omega_n^c) = \frac{1}{2}\log_2\left(1 + \frac{\left| h_n^H(u,c_n)\omega_n^c \right|^2}{\left| \sum\limits_{i=1,i\neq n}^{N} h_n^H(u,c_n)\omega_i^c \right|^2 + \sigma_n^2}\right) \geq R_{\min} \quad (25)$$

$$C5: \text{SINR}_n^s = \frac{\left| g^H(u,s)\omega_n^c \right|^2}{\left| \sum\limits_{m=1}^{M} g^H(u,s)\omega_m^s \right|^2 + \sigma_s^2} \geq A, n \in N$$

$$C6: P_{\max}(1 - \tau^*) = E_{UAV} + E_{UAV}^0$$

Optimization of the algorithm for the beamforming vector under a fixed UAV position

Given the position u of the drone, the optimization subproblem of the beamforming vector set $\omega = \{\omega_n^c, \omega_m^s\}_{n=1,2,\dots,N}^{m=1,2,\dots,M}$ can be expressed as:

$$P5: \max_{\omega} A$$
$$s.t. \; C1,C4,C5,C6 \quad (26)$$

Analyzing the constraints of optimization problem P5, it can be found that constraint C1, C4–C5 contains quadratic variables $\{\omega_n^c\}_{n=1}^{N}$ and $\{\omega_m^s\}_{m=1}^{M}$. Due to the dimensionality issue of the two vectors, P5 is difficult to solve. Here, we attempt to use the convex semi definite programming (SDP) relaxation method. Defining

$W_n^c \triangleq \omega_n^c[\omega_n^c]^H$, $n \in N$, $W_m^s \triangleq \omega_m^s[\omega_m^s]^H$, $m \in M$, where the matrix rank one constraint is represented as:

$$\text{Rank}(W_n^c) = 1, \; n \in N \quad (27)$$

$$\text{Rank}(W_m^s) = 1, \; m \in M \quad (28)$$

Thus, problem P5 can be transformed into:

$$P6: \max_{W_n^c, W_m^s} A$$

$$s.t. \; C6: P_{\max}(1 - \tau^*) = E_{UAV} + E_{UAV}^0$$

$$C7: \sum_{n=1}^{N} \text{tr}(W_n^c) + \sum_{m=1}^{M} \text{tr}(W_m^s) \leq P_{\max}$$

$$C8: R_n(\boldsymbol{u},W_n^c) = \frac{1}{2}\log_2(1 + \frac{\text{tr}\left(\boldsymbol{h}_n(\boldsymbol{u},\boldsymbol{c}_n)\boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n)W_n^c\right)}{\sum\limits_{i=1,i\neq n}^{N} \text{tr}\left(\boldsymbol{h}_n(\boldsymbol{u},\boldsymbol{c}_n)\boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n)W_i^c\right) + \sigma_n^2}) \geq R_{\min}$$

$$C9: \text{SINR}_n^s = \frac{\text{tr}\left(\boldsymbol{g}_n(\boldsymbol{u},\boldsymbol{c}_n)\boldsymbol{g}_n^H(\boldsymbol{u},\boldsymbol{c}_n)W_n^c\right)}{\text{tr}(\boldsymbol{g}_n(\boldsymbol{u},\boldsymbol{c}_n)\boldsymbol{g}_n^H(\boldsymbol{u},\boldsymbol{c}_n)W_m^s) + \sigma_s^2} \geq A, n \in N$$

$$C10: \text{rank}(W_n^c) \leq 1, n \in N$$

$$C11: \text{rank}(W_m^s) \leq 1, m \in M \quad (29)$$

After a series of convex optimization processes in this section, if we ignore the rank one constraint of the optimization problem P6, we can use common convex optimization methods, such as the CVX toolbox, or use intelligent optimization algorithms or machine learning methods for optimization. It should be noted that after using Eigen Value Decomposition (EVD), it is necessary to verify the rank one problem, that is, the feasibility of the solution.

In summary, the beamforming vector optimization algorithm under a fixed UAV position is shown in Algorithm 1 below.

Position optimization algorithm under a fixed UAV beamforming vector

After the beamforming vector $\{\omega_n^c, \forall n, \omega_m^s, \forall m\}$ is determined, the optimization subproblem of drone position u can be expressed as:

$$P7: \max_{u} A$$
$$s.t. \; C4,C5 \quad (30)$$

Adopting a trust region based continuous convex approximation optimization algorithm, the constraints C4 and C5 are first processed.

By transforming C4, we can obtain:

$$\left(2^{2R_{\min}} - 1\right)\left(\left| \sum_{i=1,i\neq n}^{N} \boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n)\omega_i^c \right|^2 + \sigma_n^2\right) \geq \left| \boldsymbol{h}_n^H(\boldsymbol{u},\boldsymbol{c}_n)\omega_n^c \right|^2 \quad (31)$$

Algorithm 1. The optimization algorithm for the beamforming vector under a fixed UAV position.

---

1. Initialization: Set the iteration termination number N_P^{max}, iteration termination accuracy ε_P, and iteration initial values $W_n^c, \forall n$ and $\omega_m^s, \forall m$.

2. Loop body:

3. Update iteration index $i = i + 1$;

4. Solve the optimization problem $F(q_i) = \max\limits_{W_n^c, W_m^s} A$ and obtain $\{W_n^{c*}, W_m^{s*}\}$;

5. Perform EVD decomposition on W_n^{c*} and W_m^{s*}, and calculate $w_n^c, \forall n$ and $w_m^s, \forall m$ under the current iteration index;

6. End condition: $|F(q_i) - F(q_{i-1})| < \varepsilon_P$ or $i > N_P^{max}$.

7. Output the optimal solution $\{q^*, W_n^{c*}, W_m^{s*}\}$.

Define $W_i^c = \omega_n^c[\omega_n^c]^H$, $W_j^s = \omega_m^s[\omega_m^s]^H$. After removing the denominator, C4 can be rephrased as:

$$\left(2^{2R_{\min}} - 1\right)\left(\sum_{i=1,i\neq n}^{N} (W_i^c, d(\boldsymbol{u}, \boldsymbol{c}_n)) + \sigma_n^2\right) \geq (W_n^c, d(\boldsymbol{u}, \boldsymbol{c}_n)) \quad (32)$$

Using the same method, C5 removes the denominator and obtains:

$$\left|\boldsymbol{g}^H(\boldsymbol{u}, \boldsymbol{s})\omega_n^c\right|^2 \geq A\left(\left|\sum_{m=1}^{M}\boldsymbol{g}^H(\boldsymbol{u}, \boldsymbol{s})\omega_m^s\right|^2 + \sigma_s^2\right), \; n \in N \quad (33)$$

Further transformation of C5 yields:

$$(W_n^c, d(\boldsymbol{u}, \boldsymbol{c}_n)) \geq A\left(\sum_{m=1}^{M}(W_m^s, d(\boldsymbol{u}, \boldsymbol{c}_n)) + \sigma_s^2\right), \; n \in N \quad (34)$$

Based on the above processing, problem P7 can be transformed into an approximately convex problem P8:

$$\text{P8}: \max_{u} A$$

$$s.t. \; C12: \left(2^{2R_{\min}} - 1\right)\left(\sum_{i=1,i\neq n}^{N}(W_i^c, d(\boldsymbol{u}, \boldsymbol{c}_n)) + \sigma_n^2\right) \geq (W_n^c, d(\boldsymbol{u}, \boldsymbol{c}_n)) \quad (35)$$

$$C13: (W_n^c, d(\boldsymbol{u}, \boldsymbol{c}_n)) \geq A\left(\sum_{m=1}^{M}(W_m^s, d(\boldsymbol{u}, \boldsymbol{c}_n)) + \sigma_s^2\right), \; n \in N$$

Considering the accuracy and efficiency of UAV position optimization, we set the iteration accuracy. As long as the iteration accuracy is set small enough, the convergence of the optimization algorithm can always be ensured. The specific optimization algorithm is shown in Algorithm 2, which gives the optimal UAV position under a fixed beamforming vector.

Joint optimization algorithm for beamforming and position based on UAV energy harvesting

In the earlier sections, Algorithm 1 solved the optimal beamforming vector $\{W_n^{c*}, W_m^{s*}\}$ under a fixed UAV position, while Algorithm 2 solved the optimal UAV position u^* under a fixed UAV beamforming vector. Below is a joint resource allocation algorithm for an energy harvesting-assisted UAV sensing integrated system based on iterative thinking, as shown in Algorithm 3. First, the initial value and loop termination conditions are set. Then, the energy efficiency problem is solved based on the Dinkelbach method. Finally, the SDP method is used to obtain the optimal UAV ISAC resource allocation solution.

Simulation and verification

This study employs MATLAB for Monte Carlo simulations. The simulation encompasses an area of 1 km × 1 km, equipped with

---

Algorithm 2. UAV position optimization algorithm under a fixed beamforming vector.

---

1. Initialization: Set the iteration termination number N_u^{max}, iteration termination accuracy ε_u, and iteration initial values u.

2. Loop body:

3. Update iteration index $i = i + 1$;

4. Solve the optimization problem $F(q_i) = \max_{u} A$ and obtain u^*;

5. Analyze the position information of u^* and calculate the UAV position (x, y, h^0) under the current iteration index;

6. End condition: $|F(q_i) - F(q_i-1)| < \varepsilon_u$ or i > N_u^{max}.

7. Output the optimal solution $\{q^*, u^*\}$.

Algorithm 3. UAV position optimization algorithm under a fixed beamforming vector.

---

1. Initialization: Set the termination times N_{outer}^{max} and N_{inner}^{max} for the outer loop and inner loop, as well as the termination precision ε_{outer} and ε_{inner}

2. External circulation body :

3. Set the initial values $q_0 = 0$ and $n = 0$ for the outer loop;

4. Using binary method to solve the optimal energy harvesting time slot allocation factor τ;

5. Internal circulation body 1:

6. Set the iteration termination number N_P^{max}, iteration termination accuracy ε_P, and iteration initial values $W_n^c, \forall n$ and $\omega_m^s, \forall m$;

7. Run Algorithm 1 to solve the optimization problem and run $F(q_i) = \max_{W_n^c, W_m^s} A$.

8. Output the optimal solution $\{q^*, W_n^{c*}, W_m^{s*}\}$;

9. End condition of inner loop 1: $|F(q_i - F(q_{i-1})| < \varepsilon_P$ or i > N_P^{max}

10. Internal circulation body 2:

11. Set the iteration termination number N_u^{max}, iteration termination accuracy ε_u, and iteration initial value $\boldsymbol{u}$;

12. Run Algorithm 2 to solve the optimization problem $F(q_i) = \max_{u} A$;

13. Output the optimal solution $\{q^*, \boldsymbol{u}^*\}$;

14. End condition for inner loop 2: $|F(q_i) - F(q_{i-1})| < \varepsilon_u$ or i > N_u^{max}.

15. Calculate $F(q) = \max_{\tau, u, \omega} A$ and update q;

16. End condition of outer loop: $|q_n - q_{n-1}| < \varepsilon_{outer}$ or n > N_{outer}^{max}.

17. Output the optimal solution $\{q^*, \tau^*, \boldsymbol{u}^*, \omega^*\}$ and obtain the joint resource allocation scheme for the energy harvesting assisted UAV sensing integration system.

$N = 4$ communication terminals and one ground sensing terminal. Four communication terminals are situated at (250, 250, 0), (250, 750, 0), (750, 250, 0), and (750, 750, 0). The ground sensing terminal is located at (500, 500, 0). The UAV flight altitude $H = 100$ m with the number of antennas $M = 4$. UAV maximum transmission power $p_{\max} = 0.3$ W. There is also a threshold for the sensing terminal $SINR_{\min}^3 = 3$ dB. Additionally, the received noise power for each communication and sensing terminal is $\sigma_n^2 = \sigma_s^2 = -110$ dbm. $\alpha = -60$ dB is the channel power gain at the reference distance $d_0 = 1$ m.

As shown in Fig. 3, with the increase of transmission power P_A, both the algorithm proposed in this paper and the algorithms in previous research studies[9–11] can significantly improve the perceptual spectrum performance. The difference is that the joint optimization algorithm proposed in this paper for EH time slots, UAV
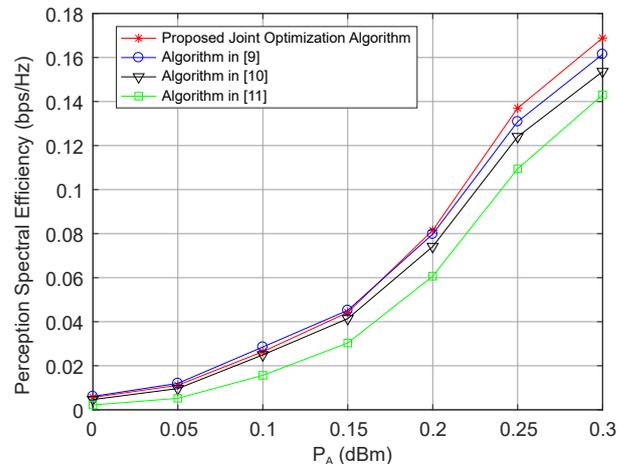

Fig. 3 Perceived spectral efficiency with $N = 4$ and $M = 4$.

positions, and beamforming vectors performs the best. Although Yang & Gursoy[9] did not consider EH time slot allocation, they jointly optimized UAV positioning and beamforming, achieving the second-best performance. Sun et al.[10] focused on UAV positioning with equal power allocation, while Wen et al.[11] optimized only power allocation without considering UAV positioning, resulting in the worst performance among the three. The position optimization of UAVs is more cost-effective than power allocation.

As shown in Fig. 4, the overall performance curve is consistent with that in Fig. 3. We are considering a larger number of array antennas, M = 16. The use of large-scale antennas can improve the system's perceptual spectrum performance. However, as the transmission power P_A increases, this improvement in performance gain gradually decreases.

As shown in Fig. 5, we focus on the relationship between the number of array antennas and the perceived spectral efficiency of the system from another perspective. It is not difficult to find that the larger the number of antennas, the better the perceived spectrum performance. However, as the number of antennas increases from 4 to 8, there is a significant improvement in system performance. However, as the number of antennas further increases, the gain in perceived spectrum performance gradually decreases. This indicates that blindly increasing the number of large-scale antennas is not ideal.
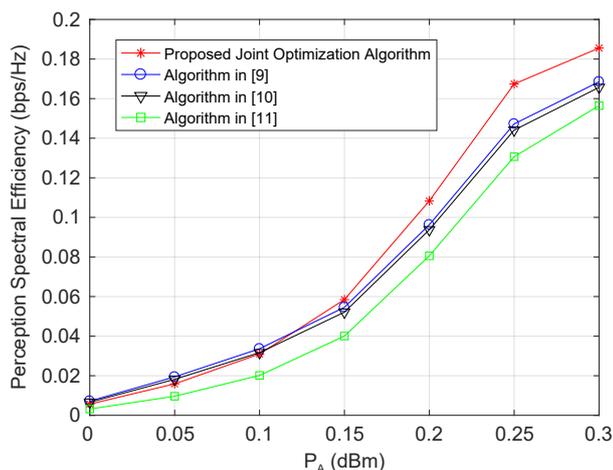

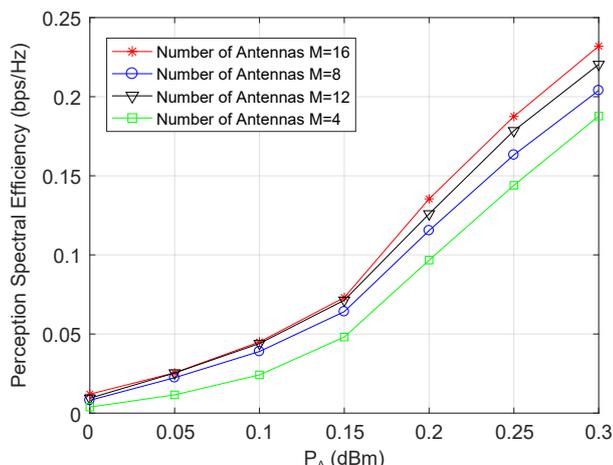**Fig. 4** Perceived spectral efficiency with $N = 4$ and $M = 12$.

Fig. 5 Relationship between perceived spectrum efficiency and number of antenna.

Conclusions

This paper focuses on the integration of UAV communication and perception with energy harvesting assistance, and proposes an innovative joint optimization algorithm aimed at maximizing the minimum perception performance while ensuring communication user performance standards by optimizing the UAV's launch beamforming and flight position. Given the crucial role of energy harvesting in maintaining unmanned aerial vehicles for prolonged mission execution, this paper first considers the optimization problem of energy harvesting time slots. By introducing the binary search method, it effectively solves the problem of how to allocate time reasonably for energy harvesting within limited flight time, to ensure that drones have sufficient energy support when performing communication and perception tasks. Given the position of the drone, further exploration was conducted on how to improve system performance by optimizing the transmission beamforming vector. The SDP technology has successfully transformed the complex beamforming optimization problem into a solvable convex optimization problem, thereby optimizing perception performance while ensuring communication quality. Given the optimal beamforming vector, the original non-convex position optimization problem is transformed into a series of easily solvable convex optimization subproblems using SCA technology. By iteratively solving these sub problems, this paper gradually approaches the global optimal solution and achieves precise optimization of the drone's position. This step not only improves the perception performance of the system but also enhances the flexibility and adaptability of the drone when performing complex tasks. In the future, ISAC-UAV research will be more in-depth, and the direction of energy optimization and time efficiency optimization may be very valuable.

Author contributions

The authors confirm their contributions to the paper as follows: conceptualization, validation: Liang G, Xu H; methodology, software, formal analysis, data curation, writing, visualization: Liang G; investigation: Liu X; resources: Xu H; supervision, project administration, funding acquisition: Chen C. All authors have read and agreed to thepublished version of the manuscript.

Data availability

All data analysed or used in this study are are contained within the published paper.

Acknowledgments

Conflict of interest

The authors declare that they have no conflict of interest.

Dates

References

[1] Gupta L, Jain R, Vaszkun G. 2015. Survey of important issues in UAV communication networks. *IEEE Communications Surveys & Tutorials* 18:1123−1152

[2] Yu LS, Li B, Yao YZ, Wen JJ, Li ZP, et al. 2024. Performance optimization of blockchain-assisted unmanned aerial vehicle mobile edge computing system. *Netinfo Security* 24(9):1432−1443

[3] Khuwaja AA, Chen Y, Zhao N, Alouini MS, Dobbins P. 2018. A survey of channel modeling for UAV communications. *IEEE Communications Surveys & Tutorials* 20:2804−2821

[4] Fotouhi A, Qiang H, Ding M, Hassan M, Giordano LG, et al. 2019. Survey on UAV cellular communications: Practical aspects, standardization advancements, regulation, and security challenges. *IEEE Communications Surveys & Tutorials* 21(4):3417−3442

[5] Xiao Z, Zhu L, Liu Y, Yi P, Zhang R, et al. 2022. A Survey on Millimeter-Wave Beamforming Enabled UAV Communications and Networking. *IEEE Communications Surveys & Tutorials* 24:557−610

[6] Liu A, Huang Z, Li M, Wan Y, Li W, et al. 2022. A survey on fundamental limits of integrated sensing and communication. *IEEE Communications Surveys & Tutorials* 24(2):994−1034

[7] Wei Z, Qu H, Wang Y, Yuan X, Wu H, et al. 2023. Integrated sensing and communication signals toward 5G-A and 6G: a survey. *IEEE Internet of Things Journal* 10(13):11068−11092

[8] He C, Xu J, Li X, Li Z. 2024. Three-dimensional deep reinforcement learning for trajectory and resource optimization in UAV communication systems. *Physical Communication* 63:102306

[9] Yang Y, Gursoy MC. 2024. Joint trajectory design and resource optimization in UAV-assisted caching-enabled networks with finite blocklength transmissions. *Drones* 8:12

[10] Sun Y, Dong Z, Yang L, Cai D, Zhou W, et al. 2024. Joint optimization of UAV position and user grouping for UAV-assisted hybrid NOMA systems. *Computational Intelligence* 40:e12625

[11] Wen S, Deng L, Liu Z. 2021. Joint Channel Allocation and Power Control for Uplink NOMA-Assisted Multi-UAV Networks. *Wireless Communications and Mobile Computing* 3:8337419

[12] Li B, Zhang R, Yang L. 2021. Joint user grouping and power allocation for NOMA-based UAV relaying networks. *2021 IEEE International Conference on Communications Workshops (ICC Workshops), Montreal, QC, Canada, 2021.* USA: IEEE. pp. 1−5 doi: 10.1109/ICCWorkshops50388.2021.9473849

[13] Li P, Lv Z, Fang Y, Xu J. 2022. Resource allocation for multi-cell cooperative integrated sensing and communication with UAVs. *Journal of Signal Processing* 38:1592−1600

[14] Tong X, Li X, Wang W, Dong F. 2022. Secrecy rate optimization for ISAC-UAV system via joint trajectory and power control. *IEICE Communications Express* 11:417−422

[15] Li B, Liao J, Gong X, Xiang H, Yang Z, et al. 2024. UAV-assisted ISAC network physical layer security based on Stackelberg game. *Ad Hoc Networks* 152:103304

[16] Pandey GK, Gurjar DS, Yadav S, Jiang Y, Yuen C. 2024. UAV-assisted communications with RF energy harvesting: a comprehensive survey. *IEEE Communications Surveys & Tutorials* 1:782−838

[17] Xiao K, Yu Z, Wang J, Gao F. 2024. Proximal policy optimization algorithm for enhancing energy harvesting in UAV-assisted communications with RIS. *IEEE Wireless Communications and Networking Conference (WCNC), Dubai, United Arab Emirates, 2024.* USA: IEEE. pp. 1−6 doi: 10.1109/WCNC57260.2024.10570743

[18] Huang J, Yu T, Chakraborty C, Yang F, Lai X, et al. 2024. An energy harvesting algorithm for UAV-assisted TinyML consumer electronic in low-power IoT networks. *IEEE Transtions on Consumer Electronics* 7:7346−7356

[19] Dhuheir M, Erbad A, Al-Fuqaha A and Seid AM. 2024. Meta reinforcement learning for UAV-assisted energy harvesting IoT devices in disaster-affected areas. *IEEE Open Journal of the Communications Society* 5:2145−2163

[20] Yang H, Lin K, Xiao L, Zhao Y, Xiong Z, et al. 2024. Energy Harvesting UAV-RIS-Assisted Maritime Communications Based on Deep Reinforcement Learning Against Jamming. *IEEE Transactions on Wireless Communications* 23:9854−9868

[21] Aboulhassan MA, El-Malek AHA, Zummo SSA, Salhab AM, Zummo SA. 2024. Performance analysis and path-planning for self-energized UAV-assisted relay networks. *IEEE Transactions on Aerospace and Electronic Systems* 60:907−917

[22] Fu CW, Ku ML, Chen YJ, Quek TQS. 2024. UAV trajectory, user association, and power control for multi-uav-enabled energy-harvesting communications: offline design and online reinforcement learning. *IEEE Internet of Things Journal* 11:9781−9800

[23] Nguyen TN, Tu LT, Fazio P, Van Chien T, V Le C, et al. 2024. On the Dilemma of Reliability or Security in Unmanned Aerial Vehicle Communications Assisted by Energy Harvesting Relaying. *IEEE Journal on Selected Areas in Communications* 42:52−67

[24] Khalid R, Shah Z, Naeem M, Ali A, Al-Fuqaha A, et al. 2024. Computational Efficiency Maximization for UAV-Assisted MEC Networks With Energy Harvesting in Disaster Scenarios. *IEEE Internet of Things Journal* 11:9004−9018

[25] Zeng K, Li X, Shen T. 2024. Energy-Stabilized Computing Offloading Algorithm for UAVs With Energy Harvesting. *IEEE Internet of Things Journal* 11:6020−6031