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Application of EEUC-based inter aircraft ultraviolet communication network algorithm in energy consumption optimization of drone swarm

Kun Yue[1*]

*Correspondence:
tjxdwrj@126.com

[1] School of Intelligent Engineering, Tianjin Modern Vocational Technology College, Tianjin 300350, China

Abstract

With the widespread application of drone technology, energy management of drone swarms has become a key challenge in ensuring sustained and efficient operations. To optimize the energy consumption of drone swarms, researchers have proposed the energy balance plane routing algorithm. This algorithm uses ultraviolet light for low visibility communication and has shown promising results in managing the energy of drone swarms. To address the issues of uneven cluster head distribution and reduced energy consumption in other algorithms, an improved non-uniform clustering energy balancing routing algorithm is proposed. Compared to existing algorithms, the improved non-uniform clustering energy balancing routing algorithm achieved the lowest average communication consumption among 5 nodes and prolonged node failure time. The performance of the research method has been verified through simulation experiments, which is of great significance in maintaining energy consumption balance and can improve the energy efficiency and sustainability of the network. This study can provide more effective solutions for the development and application of drone technology, promoting its widespread application and promotion in various fields.

Keywords: Ultraviolet light, Communication network, Drone swarm, Energy consumption optimization, EBRA, EEUC, UCEBRA

Introduction

With the rapid development of drone technology, the drone community, as an emerging technology, has been widely applied in various fields. However, with the complexity of tasks and the expansion of execution scope, higher requirements have been put forward for the reliability, efficiency, and energy consumption of Unmanned Aerial Vehicle (UAV) communication networks (Zhong et al. 2023). Traditional wireless communication has limitations, so finding new communication methods has become the focus of current research (Kuyakhi and Tahmasebi-Boldaji 2021). Ultraviolet communication is considered a promising solution, but its application in the drone community still faces challenges, especially in optimizing energy consumption (Ozdemir 2021). The study proposes an algorithm for an inter-aircraft ultraviolet communication network based on Energy Efficient Unequal Clustering (EEUC) to optimize the energy consumption of drones. The aim is to provide more comprehensive and practical energy efficiency optimization solutions by improving the EEUC algorithm. The study is divided into four main parts. The first part is a literature review, summarizing the research results on energy consumption and other aspects of Drone Swarms (DS). The second part is the research methodology, including Energy Consumption Optimization (ECO) of UAV swarms based on inter machine ultraviolet communication network algorithms and improvement of EEUC. The third part involves analyzing the results, primarily through simulation analysis of the research methods. The fourth part is the conclusion, summarizing the research results and shortcomings.

ECO is crucial in reducing energy consumption and environmental impact in the industrial and transportation sectors. To solve the problem of inaccurate prediction of energy management strategies for fuel cell electric cars under changing driving conditions, scholars such as Lin have designed an online correction prediction energy management strategy. Compared to the benchmark strategy, this strategy had significant advantages in improving economy and effectiveness, especially in real-time adjustment of hydrogen consumption (Lin et al. 2021). Liu et al. proposed an optimized layout method for virtual/synthetic inertial control energy storage systems based on swarm algorithms to solve the low inertia problem in renewable energy power systems. This method was superior to random arrangement in frequency response and was suitable for various unexpected events in different locations (Liu et al. 2021). Chen et al. proposed an improved competitive group optimization algorithm for multi regional economic scheduling problems in power systems. This algorithm improved the efficiency and accuracy of solving complex constraints like valve point effects, multiple fuels, and transmission losses by introducing sorting pairing learning strategies and differential evolution strategies (Chen and Tang 2022). Xiong and other researchers proposed an improved multi-objective PSO algorithm for the economic emission scheduling problem of co-generation. This method performed better in reducing power generation costs and pollution emissions, achieving higher quality scheduling solutions (Xiong et al. 2022). Guo et al. constructed a wind solar storage hybrid power generation system based on charged heaters to address the issues of improving transmission channel utilization, reliability, and economy of power generation systems. This system significantly improved the utilization of transmission channels and demonstrated better reliability and economy (Guo et al. 2020).

The development of UAVs technology has increased the demand for efficient and persistent operations, making the ECO of UAVs a key research area for improving their operational efficiency and endurance time. Piciarelli et al. designed a deep reinforcement learning-based algorithm to solve the visual coverage optimization problem of multiple UAVs in monitoring, environmental monitoring and other applications. This method outperformed standard patrol algorithms in terms of performance (Piciarelli and Foresti 2020). Dbouk et al. developed a high-resolution computational method to predict the aviation acoustic footprint of multi helicopter UAVs in response to the noise problem caused by DS. The V-shaped flight formation had lower noise emission than the

U-shaped or rectangular formation, and could reduce drag and save energy (Dbouk and Drikakis 2021). Miya et al. designed an autonomous gateway mobility control algorithm to address stable and low latency communication issues in heterogeneous DS. This algorithm could improve connection stability and effectively reduce communication delay under different mobile models, approaching the theoretical upper limit of performance (Miya et al. 2022).

Zhang and other scholars have designed a joint optimization method for task time, drone trajectory, and communication base station correlation to solve the problems of energy-saving operation and reliable communication of cellular connected drones. This method minimized the energy consumption of drones and ensured satisfactory communication connection with ground cellular networks. Then, the path discretization techniques were utilized and the convex optimization techniques and deep reinforcement learning algorithms were applied for simulation. The results showed that the design was significantly superior to the baseline scheme, revealing new insights into energy-efficient drone flight with connection requirements, as well as information on the trade-off between drone energy consumption and segment duration (Zhan and Zeng 2022). Researchers such as Ji designed a mathematical model to address the significant impact of changes in fuel cell area on aircraft endurance when using fuel cells as power sources for long-range UAVs. They validated the effect of fuel cell size on engine performance through experimental data. The experimental results indicated that an increase in the number of fuel cell stacks and equivalence ratio would increase the aircraft endurance increment ratio, with a maximum value of 0.152. Compared to turbojet engines, hybrid engines increases thrust by approximately 46%. The rated specific fuel consumption rate was 27.9 (g/s)/kN (Ji et al. 2021). The widespread application of 5G NR in recent times has promoted the development of drone system cluster networks and improved the efficiency of collaboration between drone clusters. Wang J et al. proposed an optimized cell wall paradigm method to increase the throughput of heterogeneous DS networks. Through weight adjustment and algorithm optimization, a fair scheduling improvement of over 40% maximum minimum throughput has been achieved. This method was expected to improve the air maneuverability of UAV network, reduce multi beam events in communication, and provide important ideas for future development (Wang et al. 2022).

The above research indicates that energy efficiency and sustainability are crucial for the progress of modern society. According to the above research results, the ECO of DS operation is important in the rapid growth of UAVs technology. In exploring the intersection of drone technology and energy optimization, different scholars have adopted diverse methods to improve the efficiency and endurance of drone systems. These studies demonstrate the progress of drone technology in energy efficiency and sustainability. They also highlight the importance of interdisciplinary research in addressing the challenges of modern society. By critically analyzing the strengths and limitations of previous research, the current research direction has been further clarified. By improving communication network algorithms and energy management strategies, the energy utilization of the drone population during task execution can be optimized, thereby enhancing the overall performance and efficiency of the system. In this context, this study proposes an Inter-machine Ultraviolet Light Communication (IM-UVLC) algorithm based on EEUC for the ECO of DS. This algorithm aims to optimize the energy efficiency of DS during task execution, and lift the energy consumption performance and operational efficiency of the entire UAVs system by improving communication protocols and algorithms.

ECO design scheme for drone swarm

The paper focuses on optimizing the energy consumption of DS by utilizing the EEUC-based inter-aircraft ultraviolet communication network algorithm. This algorithm achieves ultraviolet communication between drones through the EEUC method, thereby reducing the total energy consumption of the system. The reason for choosing this method in this study is that it effectively reduces the Communication Energy Consumption (CEC) of drones and improves system energy efficiency. However, it is important to note that this algorithm may be influenced by environmental conditions, communication distance, and fluctuations in communication quality. Additionally, it is sensitive to parameter changes and requires further field validation and parameter adjustment.

ECO of drone swarm based on IM-UVLC algorithm

The ultraviolet communication network algorithm has the characteristics of high bandwidth and security, which can effectively improve communication efficiency and ensure communication security. It can reduce energy consumption, improve energy efficiency, and optimize the success rate of task execution in UAV group operations. Therefore, it has become a promising solution for optimizing energy consumption in UAV groups. Due to the involvement of multiple flight units in DS operations, energy management has become particularly complex and has a direct impact on the endurance and mission efficiency of UAVs. Reducing energy consumption and improving energy efficiency are closely related to the successful execution of tasks when performing long-term tasks or avoiding frequent charging. DS energy consumption refers to the total amount of energy consumed by UAVs during flight and mission execution (Shu and Cao 2022; Charin et al. 2021). Figure 1 shows the energy consumption model of UAVs bee colony communication.

The model in Fig. 1 is a mathematical model used to calculate and optimize the energy consumption of DS in the communication process. In reconnaissance missions, UAVs encode and adjust the signal strength of the collected information

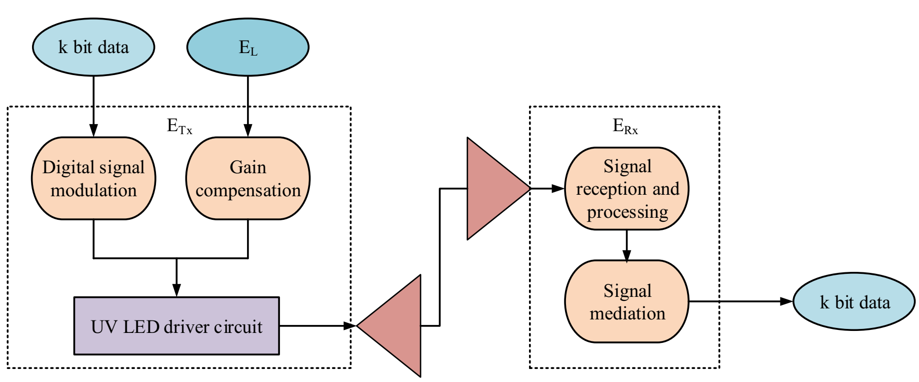

Fig. 1 Energy consumption model for DS communication

through specific signal processing processes, and then use a light-emitting diode array to send ultraviolet light signals that have been compensated for atmospheric attenuation (Li et al. 2021). In the formation of UAVs using UVLC, CEC mainly includes the energy consumption of data transmission and reception. Considering the path loss under non-line of sight transmission conditions, energy consumption can be calculated according to Eq. (1).

$$E_L = E_T\left(1 - \frac{1}{L}\right) \tag{1}$$

In Eq. (1), E_T represents the energy required to send one unit of data. When the distance between two communication nodes is r, the required transmission E_{Tx} and reception energy E_{Rx} for transmitting k bits are estimated according to Eq. (2).

$$\begin{cases} E_{Tx}(k) = k(E_T + E_L) \\ E_{Rx}(k) = kE_R \end{cases} \tag{2}$$

In Eq. (2), E_{Rx} represents the energy consumption parameter that includes receiving a single bit of data. In practical operational scenarios, DS needs to automatically gather and maintain a predetermined flight formation to enter specific fields. During this process, UAVs arrays not only need to overcome environmental limitations, but also ensure the efficiency and reliability of information transmission between machines. Therefore, this study develops a low visibility communication algorithm based on ultraviolet light, called Energy Balanced Routing Algorithm (EBRA), specifically designed to maintain the formation of DS and balance its CEC (Acosta et al. 2021).

During flight missions, a group of N UAVs utilizes distributed control methods to maintain the shape of their formation and ensure safe separation between them. The dynamic network formed by this group during flight can be represented by Figure $G = (V, E, W, Q)$, where V represents the set of UAV nodes. E represents the communication connection between nodes. W is the connection weight. Q is used to describe the spatial location of each UAV i. During the aggregation process, each UAV will periodically send signals at maximum power $P_{\max}$ through its equipped UV emitter to collect information on surrounding UAV nodes. For the network layout during the formation process of UAVs mentioned above, a specific dynamic equation can be used to describe the motion characteristics of each UAV i, as shown in Eq. (3).

$$\begin{cases} \dot{q}_i = p_i \\ \dot{p}_i = u_i \end{cases} \tag{3}$$

In Eq. (3), the position vector $\dot{q}_i$ points towards UAV_i, the velocity vector p_i depicts the motion trend of UAV_i, and the control input u_i affects the heading of UAV_i. $\dot{p}_i$ represents the updated velocity vector. The cluster control strategy is adopted by applying appropriate control inputs u_i. The UAV formation follows the three basic behavioral guidelines proposed by Reynolds, namely avoiding collisions, maintaining consistent speeds, and gathering groups to ensure the stability of the formation structure. The proposed EBRA mechanism involves three key steps, namely power optimization, link weight setting, and routing path selection. Figure 2 shows the specific process.

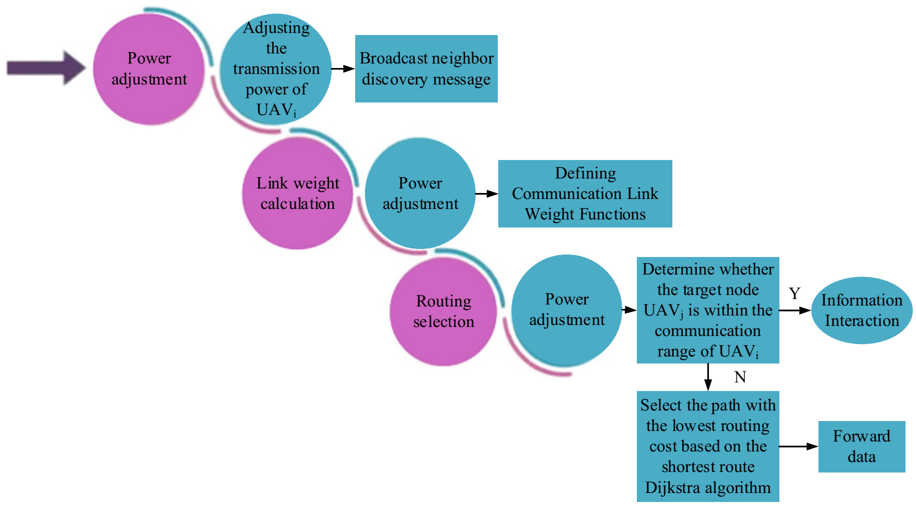

Fig. 2 Implementation of EBRA algorithm

In Fig. 2, to reduce the CEC and communication interference of data transmission between UAVs, UAVs adjust their transmission power to send neighbor detection information within the coverage range of their own network nodes. These pieces of information typically include the node's ID, location q_i, velocity p_i, remaining energy E_{rest}, and link weights w_{ij} calculated based on specific formulas (Mokayed et al. 2023). If node i sends data to node j, to evaluate this situation using Eq. (4).

$$w_{ij} = w_1 \frac{P_{loss}}{\overline{L}} + w_2 \frac{\overline{E}}{E_{rest(j)}} \tag{4}$$

In Eq. (4), w_1 and w_2 are coefficients that affect the link weight, and $w_1 + w_2 = 1$. The path loss value P_{loss} determines the energy consumption during the communication process, and the smaller the value, the lower the energy consumption. $\overline{L}$ is the average value of link loss in the network. $\overline{E}$ and $E_{rest(j)}$ are the mean remaining energy of the network and the remaining energy of node j. This function indicates that if P_{loss} is larger and $E_{rest(j)}$ is smaller, the link weight w_{ij} is higher. This means that the likelihood of node j being the next hop node is reduced. Each node selects the data transmission route based on the calculated link weights. The weight function in Eq. (4) calculates the link weight based on path loss and node residual energy, which affects the decision of the drone when selecting the next hop node. The smaller the path loss, the greater the remaining energy of the node, and the higher the link weight, indicating that the node is more likely to become the next hop node. Therefore, the weight function prioritizes selecting nodes with low path loss and sufficient energy as data transmission routes to optimize energy and maintain communication quality.

In the DS network, assuming that source node UAV_i is responsible for initializing data transmission, this node will check whether the target node is within its communication range, as shown in Fig. 3.

In Fig. 3, if the target node is within the communication range, such as source node UAV_i and another UAV, they can directly exchange information. On the contrary, if the target node is not within the direct communication range, such as source node UAV_i and

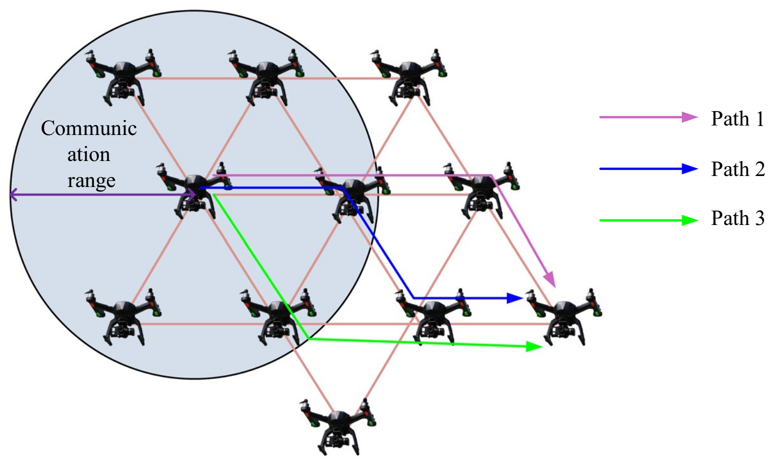

Fig. 3 Routing selection process of DS communication network

further UAVs. The network will use a specific link weight algorithm combined with Dijkstra's shortest path algorithm to determine the most effective data transmission route to achieve the optimal data transmission path from the source to the target nodes.

Drone swarm ECO based on improved EEUC

The IM-UVLC algorithm should focus on optimizing communication networks and controlling energy consumption. To further optimize the energy efficiency of DS and improve the performance of DS system, other algorithms will be introduced to comprehensively optimize the energy control strategy of DS and improve the efficiency of the system. The EEUC algorithm is an energy efficiency clustering algorithm in Wireless Sensor Networks (WSN), used to extend the lifespan of the network. The key implementation idea of the EEUC is to partition the UAVs network by creating circular clusters of different sizes. This algorithm effectively reduces energy consumption through inter cluster multi hop routing technology. Cluster heads are nodes responsible for data aggregation, coordination, and forwarding tasks in sensor networks. In a DS, cluster heads are usually responsible for coordinating and managing their respective clusters, collecting and summarizing data, and communicating with other cluster heads or base stations. A Candidate Cluster Heads (CCHs) refers to a node that, under certain conditions, has the qualifications and potential to become a cluster head. Under certain mechanisms, nodes may voluntarily or be designated as CCHs, competing to become cluster heads under certain conditions. This improves the flexibility and efficiency of the network. A normal node refers to a node other than the cluster head and CCHs, responsible for data collection and transmission, relying on cluster heads for communication, and lacking the management and coordination functions of cluster heads. Each cluster head candidate broadcasts their ID, energy information, and specific non-uniform competition radius through the maximum competition radius R_0. This allows other CCHs to establish a set of adjacent cluster heads based on this. At the same time, other CCHs within this competitive radius will automatically withdraw from this round of competition and be set as ordinary nodes (Shu et al. 2022), as shown in Eq. (5).

$$R_{comp}=\left(1-c\frac{d_{\max}-d(s_i,s_{leader})}{d_{\max}-d_{\min}}\right)R_0 \tag{5}$$

In Eq. (5), $d_{\min}$ and $d_{\max}$ are the closest and farthest distances between UAVs nodes and long-distance machines in the network, respectively. $d(s_i,s_{leader})$ means the distance from node i to the long machine. c is a parameter that controls the value of radius. The size of the radius R_{comp} is dynamically adjusted built on the distance from UAVs to the host. The closer the node is to the host, the smaller its competition radius, resulting in smaller clusters. This way, the cluster head can save more energy for effective data forwarding (Eltamaly et al. 2020).

The EEUC algorithm optimizes the communication process through data transmission mechanisms of single hop within clusters and multi hop between clusters. Compared to other similar algorithms, the EEUC exhibits better energy balance and network lifecycle management capabilities. However, the EEUC also has some limitations, such as not treating the initial energy state of nodes differently, and all nodes are equally likely to be selected as cluster head candidates. This could result in an increase in the number of CCHs, leading to higher energy consumption for controlling information transmission. Additionally, nodes with lower energy may quickly deplete their energy after serving as cluster heads multiple times, which could negatively impact network performance (Fan et al. 2022).

In the formation control system of UAVs formation, a special "Long-Wingman" mode is adopted to maintain the stability of the formation. In this mode, all UAVs nodes remain consistent in state and the network structure remains unchanged. This formation consists of three parts: a leader, a cluster leader, and a regular member. Each UAV owns a specific ID and the original energy is the same, as displayed in Fig. 4.

In this system, the long aircraft first broadcasts signals to the entire network through onboard ultraviolet devices. After receiving this signal, the wingman determines the distance from the long aircraft based on the signal strength, and calculates its non-uniform competition radius R_{comp} based on this. Using this radius, DS is segmented into circular areas of different sizes. The cluster size far from the long machine is larger, while the cluster near the long machine contains fewer member drones. For reducing energy consumption, the cluster head selects the best relay cluster head node and forwards information to the long machine through multi hop mode. Thus, an improved Unequal Clustering Energy-Balanced Routing Algorithm (UCEBRA) can be obtained. The implementation of UCEBRA consists of two parts: the establishment of protocol clusters and data transmission. The DS completes cluster head election during the establishment phase of the protocol cluster and implements node entry into the cluster according to certain rules. During the data transmission phase, the path weight function is used to select the optimal cluster head node to forward the remaining cluster head data to the long machine.

UCEBRA is an algorithm applied in fields such as WSN and UAVs networks, aiming to optimize the energy utilization of nodes and improve the overall efficiency. The implementation of UCEBRA is divided into 2 stages: cluster establishment and data transmission. In the first stage, DS completes the election of cluster heads and divides nodes into clusters according to rules. In the second stage, the optimal cluster head

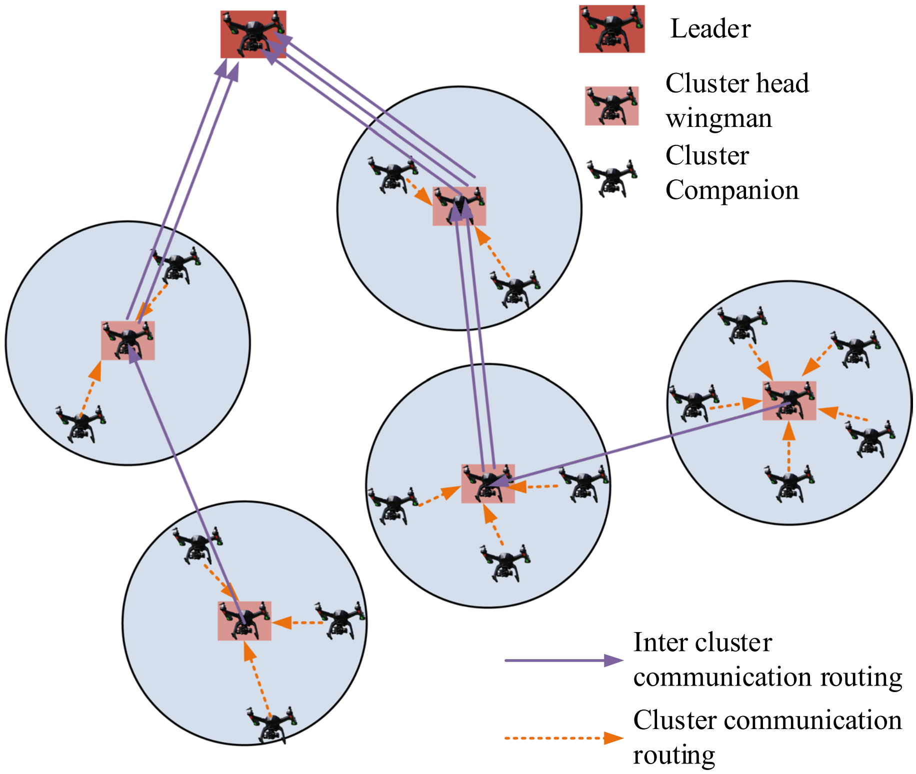

Fig. 4 Non-uniform clustering model for drones

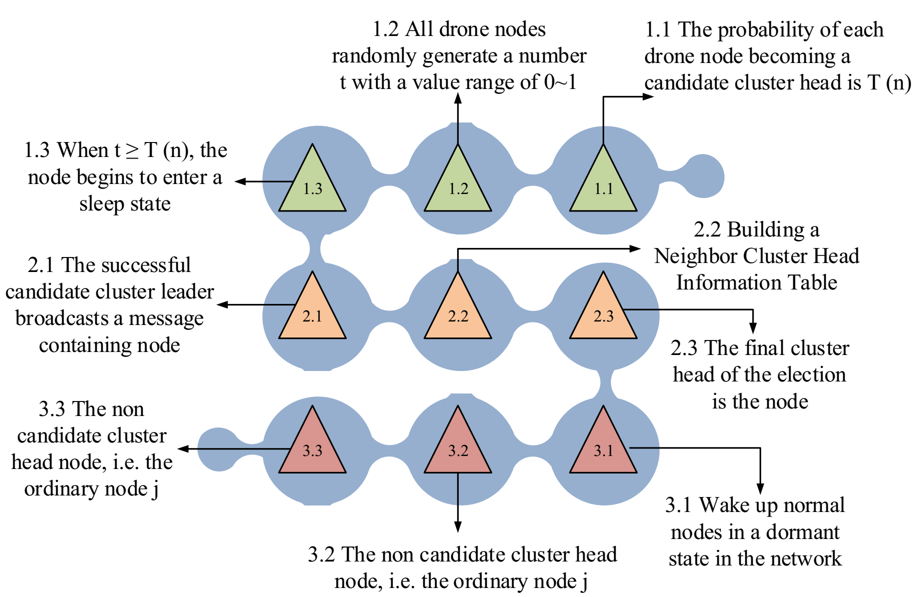

Fig. 5 Steps for establishing protocol clusters in the UCEBRA algorithm

node is selected through a set path and weight function, and the data from others is efficiently forwarded to the host. Figure 5 shows the protocol cluster establishment process of the UCEBRA algorithm.

In Fig. 5, the UCEBRA algorithm first assumes that in the UAVs network, during the cluster establishment stage, each UAV node becomes a CCH with a certain probability $T(n)$. All nodes randomly generate a number t between 0 and 1. If $t <$ probability $T(n)$, the node becomes a CCH. Otherwise, the node enters a sleep state. The EEUC protocol stipulates that the probability of all nodes becoming cluster head candidates is fixed. This may cause some problems, such as nodes with lower energy becoming cluster heads, accelerating their energy depletion and causing fluctuations in the number of cluster heads. To deal with these, this study proposes a priority function C_i based on the current state of the node, taking into account the remaining energy $E_{rest(r)}$ of the node and its distance $d(s_i, s_{leader})$ from the host, thereby defining an improved probability threshold, as shown in Eq. (6).

$$T(n) = \begin{cases} \frac{pC_i}{1-p\left(r \bmod \frac{1}{p}\right)}, & n \in G \\ 0, & othersize \end{cases} \tag{6}$$

In Eq. (6), p means the ratio of the expected quantity of CCHs to the total amounts of UAVs. r is the current round. G means the set of UAVs that did not become cluster heads in the first $\frac{1}{p}$ rounds. The distance $d(s_i, s_{leader})$ between the node and the host is also taken into account. Thus, the enhanced algorithm increases the likelihood of nodes with higher remaining energy and closer proximity to the host becoming CCHs. This is achieved by adjusting the election threshold, which effectively controls the number of cluster heads, reduces the energy consumption of control information, and prevents premature depletion of low-energy nodes. Equation (6) presents the probability threshold function that adjusts the election threshold based on factors such as the ratio of the number of CCHs to the total number of drones, the number of rounds, and the distance between the node and the host. This adjustment increases the probability of a node with high remaining energy and proximity to the host becoming the CCH. This can effectively control the number of cluster heads, reduce energy consumption, extend network lifespan, and improve network performance.

Next is the second step, where the successful candidate cluster leader s_i will broadcast a message containing the node ID and related information. The final cluster head is the node with the highest energy among the neighboring cluster heads, and the CCHs within the competition radius of the cluster head no longer participate in this round of elections and become ordinary nodes. The third step is to wake up the dormant nodes in the network after the successful cluster head election. The cluster head broadcast contains messages containing the remaining energy Es_i of s_i, and non CCH nodes, namely ordinary node s_i, are added to the cluster with the smallest weight using an improved inbound weight $V(i,j)$ based on this information. The expression is Eq. (7).

$$V(i,j) = \frac{d^2(s_i, s_j)}{Es_i \cdot Es_j} \tag{7}$$

In Eq. (7), when s_i chooses to join a specific cluster, UAVs nodes tend to join cluster heads that have higher residual energy and are closer to themselves. This can reduce energy consumption during the communication process and achieve balanced energy consumption between cluster heads. $d^2(s_i, s_j)$ represents the distance from node j

to cluster head i, and $V(i,j)$ represents the weight of ordinary node j joining cluster head i. Es_j and Es_i represent the remaining energy of ordinary node B and cluster head C, respectively. Figure 6 is a specific diagram of the establishment of the UCEBRA protocol cluster.

In the initial execution stage of UCEBRA, a total of $N \times T$ nodes compete to become CCHs through broadcasting $N \times T$ messages. Each CCH further broadcasts winning or losing messages. The number of successfully elected cluster heads in the network is set to k, which broadcasts k competitive winning information, and the remaining $N - k$ ordinary nodes publish cluster entry requests. The total message volume of the network can be calculated according to Eq. (8).

$$N \times T + N \times T + k + N - k = (2T + 1)N \tag{8}$$

This indicates that during the cluster establishment phase, the message interaction complexity of UCEBRA is $O(N)$, reflecting the linear growth characteristic of the algorithm in communication overhead. The energy required to fuse k-bit data is related to the number of UAVs within the cluster, and is calculated in units of bit fusion energy, as expressed in Eq. (9).

$$E_c(M, K) = (M + 1)kE_{DA} \tag{9}$$

In Eq. (9), E_{DA} represents the energy used to fuse unit bit data, and M is the drone numbers in the cluster. When selecting the next hop node, factors such as inter node distance and remaining energy are considered, and the optimal relay cluster head is determined through the path weight function. UCEBRA focuses on efficiency and energy balance during data transmission, ensuring optimal energy allocation during information transmission through intelligent algorithms, and achieving energy balance between cluster heads in UAVs networks.

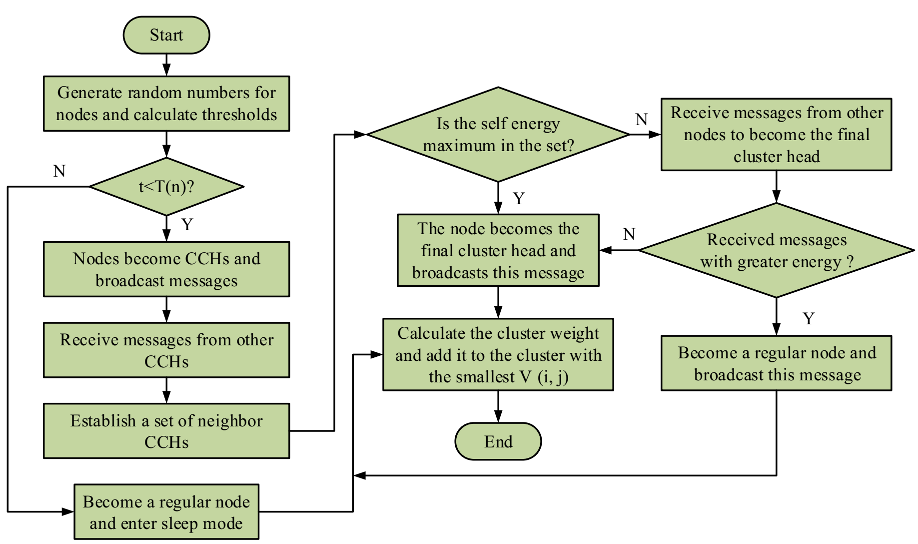

Fig. 6 The specific establishment process of the UCEBRA algorithm protocol cluster

Application analysis of IM-UVLC algorithm based on EEUC in done swarm ECO

To analyze and compare the application effects of EEUC algorithm in DS ECO, this study explores the performance of three different algorithms, EBRA, EEUC, and UCEBRA, in DS ECO through simulation experiments. As a research focus, UCEBRA has demonstrated significant advantages in improving energy efficiency and balancing energy consumption. Subsequent researchers can evaluate the performance of UVLC, visible light communication, and radio frequency communication in different environments through experiments and simulations. They can also propose a scheme for integrating multiple communication technologies to expand their applicability and robustness. By combining research on UVLC communication algorithms, incorporating energy harvesting technology, and implementing intelligent charging strategies, researchers can design a more comprehensive UAV cluster energy management system. This will improve service life and optimize operational energy management strategies.

Comparative analysis of algorithms

The study is based on the EEUC algorithm and conducts simulation comparative analysis in ECO of DSs, covering three algorithms: EBRA, EEUC, and UCEBRA. A simulation experiment scenario is designed to simulate different communication distances, communication quality, and energy consumption to simulate a real DS environment. The selection of parameters considers the stability and reliability of communication, and evaluation indicators include energy efficiency and energy balance. Through such scenario design and parameter selection, it is ensured that the performance of different algorithms is comprehensively evaluated in practical DS applications.

The collected and generated flight data of DS includes flight trajectory, energy consumption, communication data, etc. To build a dataset and ensure that it covers different types of flight environments and conditions. 80% of the dataset is taken as the training set, and 20% is the testing set. The training set is utilized to train EBRA, EEUC, and UCEBRA algorithms, adjusting model parameters to achieve optimal performance. The performance of three algorithms under the same conditions is compared, and their respective advantages and limitations are identified. Five important nodes are selected to compare the average CEC of UAVs under three algorithms, as shown in Fig. 7.

Among the EBRA, EEUC, and UCEBRA algorithms in Fig. 7, UCEBRA has the lowest average communication consumption among the 5 nodes. Compared to EBRA and

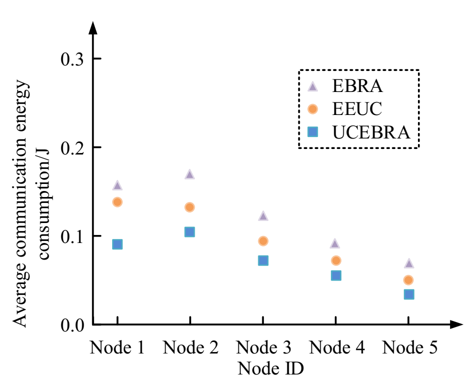

Fig. 7 The average CEC of drones under three algorithms

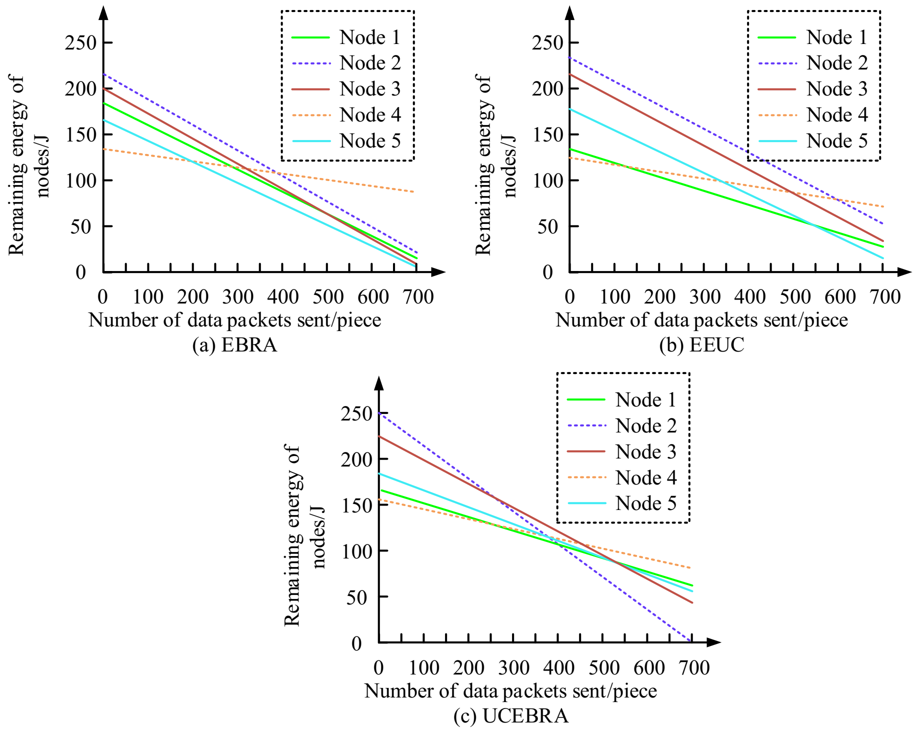

Fig. 8 Remaining energy of nodes under three algorithms

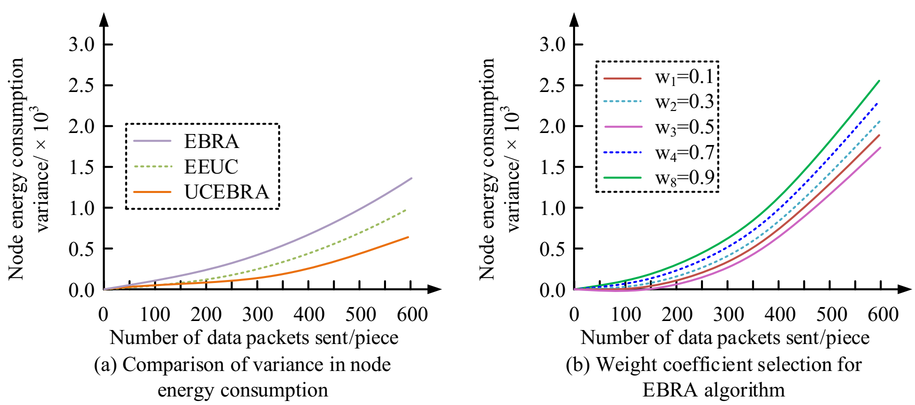

Fig. 9 Variance curves of energy consumption of drone network nodes at different times

EEUC, UCEBRA exhibits a more balanced CEC. The next step is to analyze the remaining energy of nodes under three algorithms, as shown in Fig. 8.

Figure 8a–c respectively represent the remaining energy of nodes under the action of three different routing algorithms: EBRA, EEUC, and UCEBRA. Compared to EBRA and EEUC algorithms, UCEBRA extends the time to failure of the first node by 15.4% and 7.1%, respectively, in both cases. The result of comparing the variance curves of energy consumption of UAV network nodes at different times is Fig. 9.

Figure 9a and b represent the variance of node energy consumption for the three algorithms and the selection of weight coefficients for the UCEBRA algorithm. When both w_1 and w_2 are set to 0.5, the impact of path loss and node residual energy on the weight is balanced, and the Energy Consumption Variance (ECV) of the UAVs network reaches its minimum. As the number of transmitted data packets T increases, the energy consumption of relay nodes accelerates, and the energy consumption gap with other nodes increases. The ECV curves of the three algorithms show an upward trend, but the curve under UCEBRA is always lower than that of EBRA and EEUC, indicating that UCEBRA performs greater than others in terms of balancing node energy consumption. Next, the trend of changes in the number of UAV nodes, packets sent by the UAV network when the first node fails, and the Average Remaining Energy (ARE) of nodes under three routing algorithms are analyzed, as shown in Fig. 10.

Figures 10a and b respectively represent the number of data packets sent and the ARE of UAVs nodes under various nodes. As the nodes increase, the distance required for UAVs to move to the formation position decreases, resulting in a decrease in initial energy consumption, making more energy available for subsequent IMCs. Therefore, among all three algorithms, the packets sent is on the rise. Under the UCEBRA algorithm, the number of packets sent when the first node fails is greater than that of EBRA and EEUC, indicating that UCEBRA effectively prolongs the network's survival time. However, in UCEBRA, due to the algorithm's goal of balancing the load on each node to extend the survival time of the entire network, the ARE is lower than that of EBRA and EEUC when the network life ends. This reflects the advantage of the UCEBRA algorithm in maintaining energy consumption balance.

Simulation analysis of UCEBRA algorithm in drone group ECO

The study uses MATLAB for simulation and assumes that the communication between drones in the system has a certain degree of stability and reliability. The simulation model has been specifically set based on communication distance, communication quality, and energy consumption data in actual scenarios to ensure that the results can reflect the situation in the real world. In a network consisting of 100 UAVs, each UAV maintains a consistent flight direction and speed, and their operational objectives are synchronized, keeping the network structure unchanged. Figure 11 shows the simulation analysis of the UAVs network performance of the UCEBRA algorithm at different node densities.

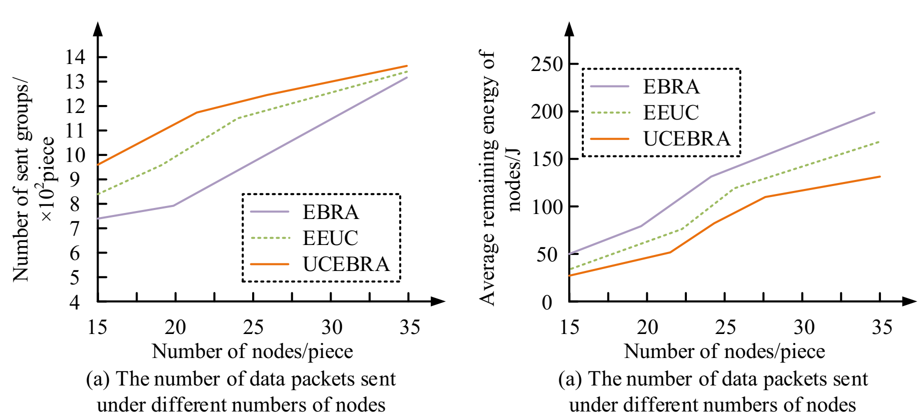

Fig. 10 The trend of changes in the number of packets and the ARE of nodes

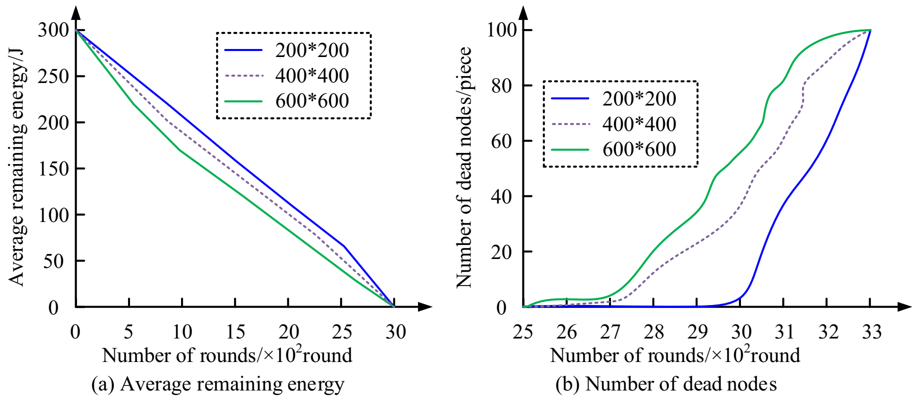

Fig. 11 Performance comparison of UAV networks under different node densities

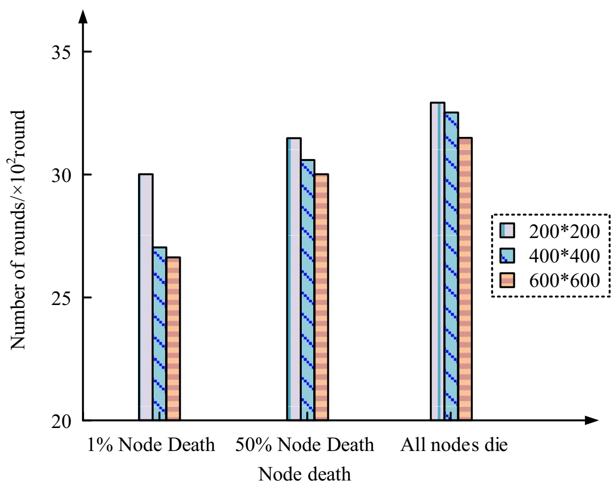

Fig. 12 Performance results of UAV networks under different node densities

Figures 11a and b show the ARE and number of dead nodes at different node densities, respectively. The simulated area sizes are 200×200 m^2, 400×400 m^2, and 600×600 m^2, respectively. Figure 11 shows that as the density of UAVs nodes grows, the ARE of each node increases, and the lifespan of nodes is correspondingly extended. The network lifetime under different node densities is Fig. 12.

In Fig. 12, compared to the regions of 400×400 m^2 and 600×600 m^2, the time required for 1%, 50%, and all node failures in 200×200 m^2 is extended by 11%, 2.6%, 1.4%, and 12.2%, 4.5%, and 4.8%, respectively. The reason is that within a fixed area, as the density of UAV nodes decreases, the IMC distance increases. The energy loss of using UVLC increases with distance, leading to an accelerated energy consumption rate of the entire network.

To further confirm the practicality of the research method, its performance and practical applications in dynamic environments of DS scenes are compared with other advanced methods in the field. The comparison methods are Collaborative Communication Optimization Algorithm based on Multi hop Networks (CCOA) and Adaptive Scheduling Algorithm (ASA). CCOA is an advanced method for optimizing energy consumption in UAV swarms. In the communication between UAV swarms, multi hop network technology is used to optimize energy consumption through collaborative communication. This method can reduce CEC, improve communication coverage and reliability, and optimize the energy consumption of the entire drone fleet by relay and collaborative forwarding data between drones. ASA dynamically adjusts task allocation and communication routing by monitoring the workload and environmental conditions of DSs in real-time. This ensures the reliability and efficiency of communication networks while minimizing energy consumption. These advanced methods have unique advantages in ECO, energy management, and communication efficiency, providing important support for the performance improvement and sustainable operation of UAVs. Therefore, comparing the research method with CCOA and ASA can better demonstrate its practical applicability in optimizing the energy consumption of DSs.

The drone device model used is DJI Phantom 4 Pro, with a built-in dual band communication module that supports the 2.4 GHz and 5.8 GHz frequency bands. It has a GPS, an Inertial Measurement Unit (IMU), and visual sensors. The receiver of the ground control center is the Skydroid T10, with an Intel Core i7 processor and a 15 inch high-definition display screen. The communication between the drone and the ground control center adopts WiFi wireless communication technology based on the 802.11 protocol. Using TCP/IP protocol for data transmission, the drone is connected to the ground control center through a standard USB interface for data transmission and control command sending. A DS consisting of 10 drones needs to perform collaborative search and surveillance tasks in a large open area. To set a virtual task area, including different types of terrain and possible obstacles to simulate a real task scene. Data transmission and collaborative search tasks of drones are simulated within the mission area in the experiment. Each drone needs to regularly transmit the collected data to the ground control center and collaborate with other drones to search for targets. The energy consumption and other data for each drone, including CEC and flight energy consumption, are monitored and recorded in real-time. The data is then uploaded to the data center for analysis. The actual applicability comparison results of the three methods in DSs are shown in Fig. 13.

Figures 13a–c represent the throughput, fault recovery ability, reliable communication maintenance, and energy efficiency of the three algorithms in the dynamic environment of DSs. From Fig. 13, as the experiment progresses, the throughput and fault recovery ability of the UCEBRA, CCOA, and ASA all increase. Compared to CCOA and ASA, the research method has higher throughput and higher ability to recover from faults and reliable communication maintenance and energy efficiency. In practical applications and dynamic scenarios, UAV communication networks can transmit data quickly and reliably, recover communication connections efficiently when encountering faults, and utilize energy efficiently due to the high throughput and superior fault recovery capability of research methods. Next, the performance of the three methods in dynamic environments are analyzed, as shown in Fig. 14.

Figures 14a and b respectively represent the time complexity and spatial complexity of the three algorithms in dynamic environments. From Fig. 14, the computational complexity of the three methods is relatively close, and the overall complexity is less than 40%, proving the superiority of the three methods in dynamic

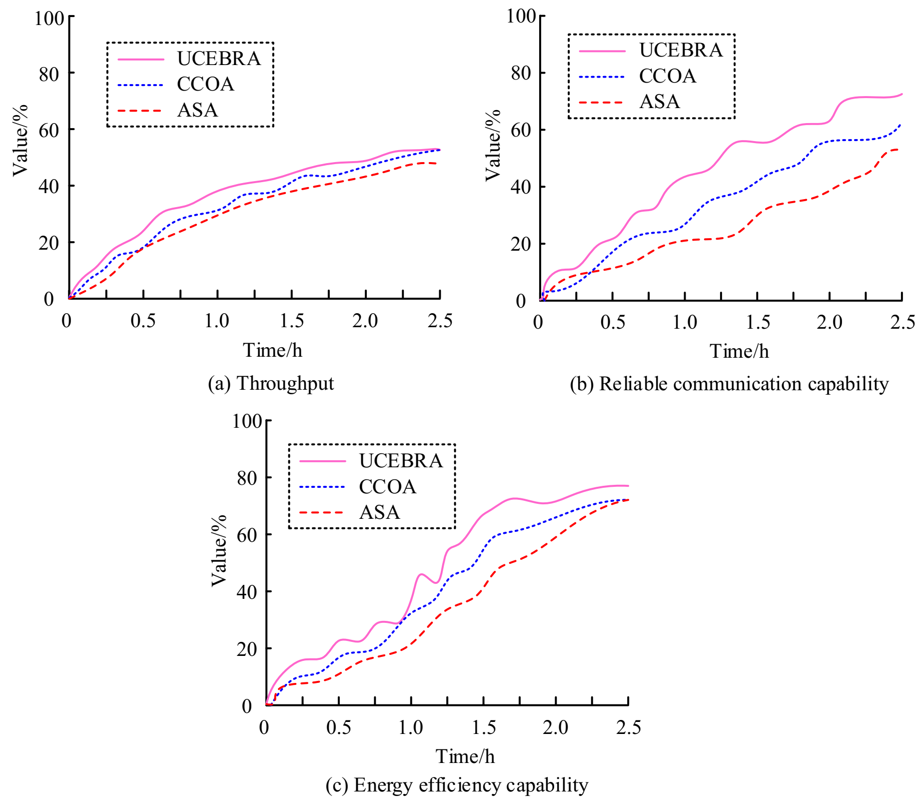

Fig. 13 Comparison of practical applicability of three methods in DSs

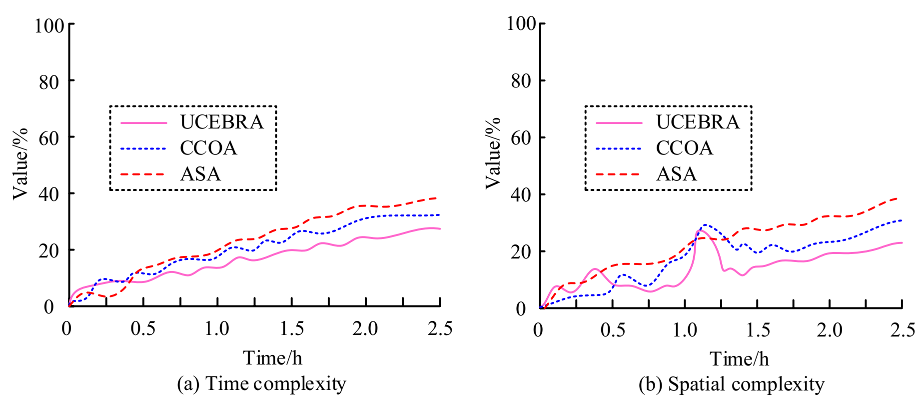

Fig. 14 The computational complexity of three methods in dynamic environments

environments. However, upon careful analysis, the time and spatial complexity of the research method are significantly lower than those of CCOA and ASA. In dynamic scenes, research methods with low time and spatial complexity allow for faster adaptation to changes, higher flexibility, real-time performance, and superior stability for collaborative tasks of DSs in complex environments.

Discussion

The study examined the contributions of other scholars in optimizing energy use for drone technology and related fields. It was found that the drones communicate through ultraviolet communication networks, which improves communication efficiency and system security. Studying and reviewing the contributions of other scholars highlights the significance of energy informatics in addressing the challenges of energy efficiency and sustainability faced by modern society. Whether in drone technology, electric vehicles, renewable energy systems, or other fields, interdisciplinary research and technological innovation can effectively optimize energy use, reduce environmental impact, and promote society towards more efficient and sustainable development. This study explores this direction and provides a practical case of improving energy efficiency by optimizing the communication network of UAVs, further demonstrating the potential and important value of energy informatics in addressing contemporary challenges.

Conclusion

In modern UAV applications, ensuring the reliability and efficiency of communication networks is crucial, especially when performing complex tasks or operating in extreme environments. Traditional wireless communication methods face spectrum congestion and security issues, while ultraviolet communication has become a promising alternative due to its high bandwidth and security characteristics. However, ECO of ultraviolet communication in UAV applications remains an important and challenging issue. The EEUC-based inter machine ultraviolet communication network provides a possible solution. To further reduce energy consumption, the cluster head selected the optimal relay cluster head node and forwarded information to the long machine through multi hop mode, thereby improving the UCEBRA algorithm. The research results indicated that the improved EEUC-based inter machine ultraviolet communication network algorithm was an effective energy optimization solution for UAV swarms, which could significantly reduce energy consumption and extend the lifespan of nodes. This had important practical significance for improving the energy efficiency and communication performance of drone networks. As the density of drone nodes increased, the ARE of each node in the network increased, and the lifespan of nodes was correspondingly extended. In the simulation area of $200 \times 200\ \mathrm{m}^2$, the time required for 1% node failure, 50% node failure, and all node failures was extended by 11%, 2.6%, 1.4%, and 12.2%, 4.5%, and 4.8%, respectively, compared to the areas of $400 \times 400\ \mathrm{m}^2$ and $600 \times 600\ \mathrm{m}^2$. In summary, this study provided powerful practical cases and potential research directions for promoting the development of drone technology, improving its performance, and providing research in the field of energy informatics. However, this study only considered the impact of CEC on network performance. Future research directions can include combining the dynamic behavior characteristics of drones to further explore and optimize the energy balance routing algorithm of wireless ultraviolet communication technology in collaborative DSs.

Author contributions

K. Y. conducted all related works.

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Availability of data and materials
All data and materials are within this article.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
There is no competing interests in this research.

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