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Joint Optimization of Task Offloading and Resource Allocation for Multi-Layer USV-MEC System with Renewable Energy Supply

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Abstract: Mobile edge computing (MEC) plays a vital role in supporting communication, computation, and resource management within the maritime industry. It has become an essential element in the advancement of maritime technology. This study adopts a space-air-sea integrated MEC network, in which high-altitude platforms (HAPs) and low-earth orbit (LEO) satellites powered by renewable energy assist unmanned surface vehicles (USVs) in task offloading. The goal of this study is to minimize the total energy consumption of the system subject to a controllable task backlog queue. The Lyapunov optimization method is adopted to transform the original stochastic optimization problem into a deterministic optimization problem, thereby ensuring the stability of the system. Furthermore, an algorithm based on convex optimization is proposed, which is specifically designed to optimize transmission power allocation and channel allocation. The simulation results verify that the proposed scheme can significantly reduce the total energy consumption of the system compared with other benchmark schemes.

Keywords: Lyapunov optimization; unmanned surface vehicle; convex optimization; mobile edge computing
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0 Introduction

In today's increasingly digitized and automated society, unmanned surface vehicle (USV) systems, as an innovative technology in the field of marine technology, are increasingly demonstrating their unique value in performing remote operations and automation tasks[1]. These systems exhibit extensive potential for application across diverse domains, including marine resource exploration, environmental surveillance, national defense and security measures, as well as scientific research endeavors. Especially in ocean areas that are difficult for humans to directly access, USV systems can perform complex exploration and data collection tasks, greatly improving operational efficiency and safety. However, due to limited resources, USVs are facing significant technical challenges in processing or analyzing data collected locally.

Using mobile edge computing (MEC) technology to provide computing and communication services for USV through low-earth orbit (LEO) satellites or high-altitude platforms (HAPs) has attracted extensive attention in academia in recent years. The cooperative unmanned aerial vehicle (UAV) and USV-assisted MEC platforms were considered[2-5], in which aerial vehicles were deployed to provide communication and computation backhaul for vessels. The current research mainly focuses on short-term operational optimization, such as dynamic task scheduling and instantaneous energy consumption control, while there is relatively less energy consumption optimization work for long-term stable system operation. Long-term energy management requires consideration of complex marine environmental impacts, system reliability, and energy efficiency to maintain continuous operation, which is often not fully taken into account in existing research. Therefore, developing an energy optimization strategy that can effectively support long-term tasks is of great significance.

In multiple research fields, Lyapunov functions have been used to maintain the stability of task queues, while classical drift and penalty techniques have been employed to optimize system performance. Such techniques finely balance system utility and queue backlog, ensuring that task queues are maintained within a reasonable range, thereby effectively improving task processing efficiency[6-8]. Compared with Markov decision processes (MDPs), Lyapunov optimization is more suitable for addressing long-term stability issues primarily because it does not require precise system state transition probabilities and can achieve online optimization using

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only current time-slot information. This significantly reduces computational complexity and avoids the dimensionality curse inherent in MDPs. Furthermore, Lyapunov optimization rigorously guarantees long-term performance convergence through the drift-plus-penalty framework, making it applicable to dynamic stochastic environments (such as time-varying channels or stochastic energy harvesting). In contrast, MDP/reinforcement learning is constrained in real-time applicability due to its dependence on precise modeling and training processes. Consequently, in scenarios requiring low latency and high adaptability, such as edge computing, Lyapunov optimization demonstrates superior advantages in computational efficiency, convergence speed, and engineering feasibility. On this basis, some researchers have designed a series of efficient resource allocation algorithms for the MEC system based on the Lyapunov method. These algorithms not only maintain the continuous stability of the system but also optimize the quality of service[9-12]. This series of studies demonstrates the potential and practical effects of the Lyapunov method in the design of complex systems.

In view of this, this study focuses on the task offloading and energy management issues in space-air-sea integrated MEC, assisted by HAPs and LEO satellites. We apply the Lyapunov optimization method to minimize the total energy consumption of the system while maintaining the stability of the task queue. The main contributions of this study are as follows.

1) The concept of a USV-MEC network assisted by HAPs and LEO satellites was explored. In our system, the HAP, equipped with an MEC server and powered by renewable energy, provides computational capabilities to the USVs.

2) The Lyapunov optimization method was used to transform stochastic optimization problems into deterministic optimization problems to ensure the stability of the system under different operating conditions.

3) A new convex optimization algorithm was developed to solve the optimization problems of computing resources, transmission power, and channel allocation, and reduce the total energy consumption of the system.

4) Simulation results show that the proposed algorithm outperforms other benchmark algorithms in terms of system task queue backlog and energy consumption.

1 System Model

The space-air-sea integrated network is shown in Fig. 1. This system consists of one LEO satellite, one HAP, and M USVs. Define the set of USVs as $\mathcal{M}=\{1, 2, \cdots, m, \cdots, M\}$, which can offload their tasks to the HAP. Furthermore, the HAP can also transfer the tasks to the LEO satellite for processing. Moreover, the total service time is divided into N time slots of length τ, which can be represented as $\mathcal{N}=\{1, 2, \cdots, n, \cdots, N\}$. Similar to most literature (e.g., Refs. [9] and [11]), the download process is ignored. In this paper, the task can be finely divided and processed across time slots.

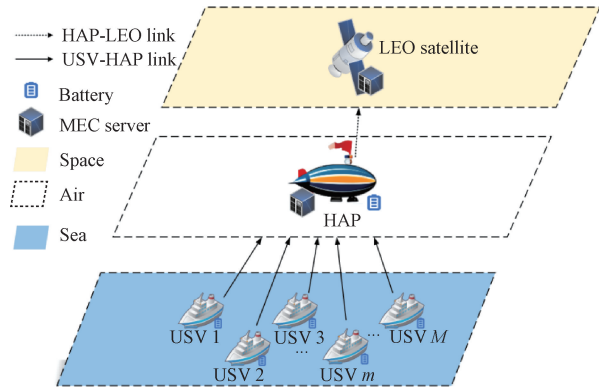


Fig. 1 Space-air-sea integrated network

1.1 Communication model

In this system, the HAP covers a specific area and can provide computational services to a limited number of USVs within its coverage range. The communication between USVs and the HAP uses the orthogonal frequency division multiple access (OFDMA) scheme, which means each USV can offload its tasks without interference. Moreover, considering that there are generally no obstructions on the sea surface, their channels can be modeled as a free-space path loss model[13].

$$h_m = 32.4 + 20\log_{10} d_m, \tag{1}$$

where h_m is the free-space path loss in decibels (dB); d_m represents the distance between USV m ($m = 1, 2, \cdots, M$) and the HAP.

To improve resource utilization efficiency, the channel bandwidth $\beta_m(n)$ used by each USV can be adjusted. Therefore, the transmission rate between the USV m and the HAP, denoted as $R_m(n)$, is expressed as

$$R_m(n) = \beta_m(n) W \log_2\left(1 + \frac{P_m(n) h_m}{\beta_m(n) W N_0}\right), \tag{2}$$

where W is the total bandwidth; $P_m(n)$ is the transmission power of USV m; N_0 is the white noise power spectral density. Similarly, the transmission rate between the HAP and LEO satellite, denoted as $R_{\mathrm{H}}(n)$, is expressed as

$$R_{\mathrm{H}}(n) = B\log_2\left(1 + \frac{P_{\mathrm{H}}(n) h_{\mathrm{H}}}{B N_0}\right), \tag{3}$$

where B is the exclusive bandwidth for the air-space link; h_{H} is their channel gain; $P_{\mathrm{H}}(n)$ is the power of HAP.

1.2 Tasks queues model

Each USV generates a task of size $A_m(n)$ (in bits) in each slot, and the computational density of the task is ρ. Moreover, each USV and HAP is equipped with a task queue, which follows the first-in-first-out principle. The

calculated task in the local, local computation workload, denoted as $D_m(n)$, is defined as

$$D_m(n) = f_m(n) \cdot \tau/\rho, \tag{4}$$

where $f_m(n)$ is the central processing unit (CPU) frequency of USV m in slot n.

The number of tasks offloaded by USV m to HAP is

$$D_{m,\mathrm{H}}(n) = \tau \cdot R_m(n). \tag{5}$$

Therefore, the updated status of the local task backlog queue $Q_m(n+1)$ for USV m can be formulated as

$$Q_m(n+1) = [Q_m(n) - D_m(n) - D_{m,\mathrm{H}}(n)]^+ + A_m(n), \tag{6}$$

where $[x]^+ = \max\{x, 0\}$. Similarly, the CPU frequency of the HAP in slot n is defined as $f_{\mathrm{H}}(n)$, then the workload for calculating time slot n is

$$D_{\mathrm{H}}(n) = f_{\mathrm{H}}(n) \cdot \tau/\rho. \tag{7}$$

The number of tasks offloaded by the HAP to the LEO satellite is

$$D_{\mathrm{H,L}}(n) = \tau \cdot R_{\mathrm{H}}(n). \tag{8}$$

Therefore, the updated status of the tasks backlog queue $L(n+1)$ for the HAP can be formulated as

$$L(n+1) = [L(n) - D_{\mathrm{H}}(n) - D_{\mathrm{H,L}}(n)]^+ + \sum_{m\in\mathcal{M}} D_{m,\mathrm{H}}(n). \tag{9}$$

Considering that the LEO satellite has abundant resources, it is assumed that tasks offloaded to the LEO satellite are processed quickly.

1.3 Energy consumption model

According to Refs. [9] and [12], if κ is defined as the computational architecture coefficient of the CPU, the computational energy consumption of USV m and that of the HAP can be respectively expressed as

$$E_m(n) = \kappa \cdot f_m^3(n) \cdot \tau, \tag{10}$$

$$E_{\mathrm{H}}(n) = \kappa \cdot f_{\mathrm{H}}^3(n) \cdot \tau. \tag{11}$$

The transmission energy consumptions of USV m and that of the HAP are denoted as $E_{m,\mathrm{H}}(n)$ and $E_{\mathrm{H,L}}(n)$, respectively. They are expressed as

$$E_{m,\mathrm{H}}(n) = P_m(n) \cdot \tau, \tag{12}$$

$$E_{\mathrm{H,L}}(n) = P_{\mathrm{H}}(n) \cdot \tau. \tag{13}$$

Moreover, the computational energy consumption of the LEO satellite is overlooked.

1.4 Energy harvesting model

Green energy harvesting devices are typically deployed on USVs and the HAP to capture renewable energy sources such as solar and wind power[14], to meet their communication and computing needs. However, the acquisition of this energy is random, so we construct battery queues to cope with this fluctuation. Specifically, we respectively define the green energy collected by USV m and the HAP in time slot n as $e_m(n)$ and $e(n)$, which are random variables[15]. Therefore, the available energy in the battery of USV m and the HAP can be respectively expressed as

$$G_m(n+1) = [G_m(n) - E_m(n) - E_{m,\mathrm{H}}(n)]^+ + e_m(n), \tag{14}$$

$$H(n+1) = [H(n) - E_{\mathrm{H}}(n) - E_{\mathrm{H,L}}(n)]^+ + e(n). \tag{15}$$

1.5 Problem formulation

The purpose of this paper is to minimize the total energy consumption of the system. However, blindly reducing energy consumption will lead to a large backlog of queues. Therefore, we formulate a problem of minimizing energy consumption under the condition of queue stability by jointly optimizing computing frequency, transmission power, and bandwidth ratio. Then, we model it as a stochastic optimization problem given by

$$\mathrm{P1}: \min_{\Psi(n)} \frac{1}{N} \sum_{n\in\mathcal{N}} \{E_{\mathrm{H}}(n) + E_{\mathrm{H,L}}(n) + \sum_{m\in\mathcal{M}} \{E_m(n) + E_{m,\mathrm{H}}(n)\}\} \tag{16}$$

s. t.

$$\frac{1}{N} \sum_{n\in\mathcal{N}} E\{Q_m(n)\} < \infty, \tag{17}$$

$$\frac{1}{N} \sum_{n\in\mathcal{N}} E\{L(n)\} < \infty, \tag{18}$$

$$0 \leqslant \beta_m(n), \tag{19}$$

$$\sum_{m\in\mathcal{M}} \beta_m(n) \leqslant 1, \tag{20}$$

$$0 \leqslant f_m(n) \leqslant f_{\max}, \tag{21}$$

$$0 \leqslant f_{\mathrm{H}}(n) \leqslant f_{\mathrm{H,max}}, \tag{22}$$

$$0 \leqslant P_m(n) \leqslant P_{\max}, \tag{23}$$

$$0 \leqslant P_{\mathrm{H}}(n) \leqslant P_{\mathrm{H,max}}, \tag{24}$$

$$0 \leqslant E_m(n) + E_{m,\mathrm{H}}(n) \leqslant G_m(n), \tag{25}$$

$$0 \leqslant E_{\mathrm{H}}(n) + E_{\mathrm{H,L}}(n) \leqslant H(n), \tag{26}$$

where $\Psi(n) = \{\beta(n), f(n), f_H(n), P(n), P_H(n)\}$ is the set of the optimization variables; $f(n) = \{f_1(n), f_2(n), \cdots, f_M(n)\}$ is the set of USV computing frequencies; $P(n) = \{P_1(n), P_2(n), \cdots, P_M(n)\}$ is the set of USV transmission powers. Equations (17) and (18) ensure the stability of the system; Eqs. (19) and (20) guarantee that the total bandwidth will not be exceeded; Eqs. (21) and (22) are the maximum computing frequency constraints of the USV and HAP; Eqs. (23) and (24) are the maximum transmission power constraints; Eqs. (25) and (26) represent the energy constraints of USV m and the HAP. The above problem is a long-term stochastic optimization problem, which is usually non-deterministic polynomial-hard (NP-hard).

2 Problem Transformation

Similar to the studies in Refs. [9] and [11], we design a flexible and effective controllable algorithm

based on the Lyapunov theory, and the detailed scheme is presented as follows. Firstly, we define the quadratic Lyapunov function $U(n)$ as

$$U(n) = \sum_{m \in \mathcal{M}} Q_m^2(n)/2 + L^2(n)/2. \quad (27)$$

Then, the conditional Lyapunov drift function between two consecutive slots is

$$\Delta U(n) = E\{U(n+1) - U(n) \mid \boldsymbol{\Theta}(n)\}, \quad (28)$$

where $\Delta U(n) = \{Q_1(n), Q_2(n), \cdots, Q_M(n), L(n)\}$ is the set of the system queues; $\boldsymbol{\Theta}(n)$ is the system state at the beginning of slot n. Based on the above definition, we can obtain the Lyapunov drift penalty function as

$$\Delta U_V(n) = \Delta U(n) + V \cdot E\{E_{\mathrm{H}}(n) + E_{\mathrm{H,L}}(n) + \sum_{m \in} E_{m,\mathrm{H}}(n) \mid \boldsymbol{\Theta}(n)\}, \quad (29)$$

where V is the Lyapunov control parameter. We scale the drift-plus-penalty function and minimize its upper bound[16]. Based on $\{[X-Y]^+ + Z\}^2 - X^2 \leqslant Y^2 + Z^2 + 2X(Z-Y)$, we can get

$$Q_m^2(n+1) - Q_m^2(n) = \{[Q_m(n) - D_m(n) - D_{m,\mathrm{H}}(n)]^+ + A_m(n)\}^2 - Q_m^2(n) \leqslant [D_m(n) + D_{m,\mathrm{H}}(n)]^2 + A_m^2(n) + 2Q_m(n)[A_m(n) - D_m(n) - D_{m,\mathrm{H}}(n)] \leqslant 2C_m(n) - 2Q_m(n)[D_m(n) + D_{m,\mathrm{H}}(n)], \quad (30)$$

where $C_m(n) = [Q_m(n) + A_m(n)]^2/2$ is a constant. Similarly, we can obtain

$$L^2(n+1) - L^2(n) = \{[L(n) - D_{\mathrm{H}}(n) - D_{\mathrm{H,L}}(n)]^+ + \sum_{m \in \mathcal{M}} D_{m,\mathrm{H}}(n)\}^2 - L^2(n) \leqslant [D_H(n) + D_{\mathrm{H,L}}(n)]^2 + [\sum_{m \in \mathcal{M}} D_{m,\mathrm{H}}(n)]^2 - 2L(n)\{D_{\mathrm{H}}(n) + D_{\mathrm{H,L}}(n) - \sum_{m \in \mathcal{M}} D_{m,\mathrm{H}}(n)\} \leqslant 2C_{\mathrm{H}}(n) - 2L(n)[D_{\mathrm{H}}(n) + D_{\mathrm{H,L}}(n) - \sum_{m \in \mathcal{M}} D_{m,\mathrm{H}}(n)], \quad (31)$$

where $C_{\mathrm{H}}(n) = L^2(n)/2 + \sum_{m \in \mathcal{M}} Q_m^2(n)/2$ is also a constant.

According to Eq. (28), dividing both sides of each of Eqs. (29) and (30) by 2, and adding them, we have

$$\Delta U_v(n) \leqslant E\{C(n) - L(n)[D_{\mathrm{H}}(n) + D_{\mathrm{H,L}}(n)] + V[E_{\mathrm{H}}(n) + E_{\mathrm{H,L}}(n)] - \sum_{m \in \mathcal{M}} \{[Q_m(n) - L(n)]D_{m,\mathrm{H}}(n) - V[E_m(n) + E_{m,\mathrm{H}}(n)] + Q_m(n)D_m(n)\} \mid \boldsymbol{\Theta}(n)\}, \quad (32)$$

where $C(n) = C_{\mathrm{H}}(n) + \sum_{m \in \mathcal{M}} C_m(n)$.

According to inequality (32), by deleting the items independent of optimization variables, we can obtain optimization problem P2 equivalent to problem P1, listed as

$$\mathrm{P2}: \min_{\Psi(n)} V[E_{\mathrm{H}}(n) + E_{\mathrm{H}}(n)] - L(n)D_{\mathrm{H}}(n) + D_{\mathrm{H,L}}(n)] - \sum_{m \in \mathcal{M}} \{[Q_m(n) - L(n)]D_{m,\mathrm{H}}(n) + Q_m(n)D_m(n) - V[E_m(n) + E_{m,\mathrm{H}}(n)]\}, \quad (33)$$

s. t. Eqs. (19)–(26).

It is worth noting that problem P2 has become a deterministic online optimization problem.

3 Online Algorithm Design

We will split problem P2 into three sub-optimization problems to solve them separately, namely, local computing resource allocation, computing resource allocation of HAP, the transmission power allocation of HAP, and the joint optimization problem of USV transmission power and channel ratio allocation.

3.1 Local computing resource allocation

The sub-optimization problem of this section can be obtained by presenting only the part related to the local processing frequency in P2. Considering that the computing frequencies between each USV are not correlated with each other, the sub-optimization problem can be further decoupled as

$$\mathrm{P2.1}: \min_{f(n)} \sum_{m \in \mathcal{M}} V\kappa f_m(n)^3\tau - Q_m(n)f_m(n)\tau/\rho, \quad (34)$$

s. t. Eq. (21).

The above problem is a very standard convex optimization problem, and the optimal local frequency allocation can be obtained by analyzing the behavior of its derivative. By taking the derivative of the objective function with respect to the local frequency and making it zero, we can obtain

$$f'_m(n) = \sqrt{\frac{Q_m(n)}{3V\kappa\rho}}. \quad (35)$$

Considering the constraints of Eq. (21), the optimal local computation frequency can be obtained:

$$f_m^*(n) = \min\{f'_m(n), f_{\max}\}. \quad (36)$$

3.2 Computing resource allocation of HAP

The sub-optimization problem of this section can be obtained by presenting only the part related to the processing frequency of the HAP in P2

$$\mathrm{P2.2}: \min_{f_{\mathrm{H}}(n)} V\kappa f_{\mathrm{H}}^3(n)\tau - L(n)f_{\mathrm{H}}(n)\tau/\rho, \quad (37)$$

s. t. Eq. (22).

Similar to P2.1, we can obtain

$$f'_{\mathrm{H}}(n) = \sqrt{\frac{L(n)}{3V\kappa\rho}}. \quad (38)$$

Considering the constraints of Eq. (22), the optimal computation frequency can be obtained as

$$f_{\mathrm{H}}^{*}(n)=\min\left\{\sqrt{\frac{L(n)}{3V\kappa\rho}},f_{\mathrm{H,\,max}}\right\}. \tag{39}$$

3.3 Transmission power allocation of HAP

Similar to the above, extracting items from P2 that are only related to the HAP transmission power can yield

$$\mathrm{P2.3}:\min_{P_{\mathrm{H}}(n)}V\tau P_{\mathrm{H}}(n)-L(n)\tau B\log_2\left(1+\frac{P_{\mathrm{H}}(n)h_{\mathrm{H}}}{BN_0}\right), \tag{40}$$

s.t. Eqs. (24) and (26).

When the other derivative is 0, we can obtain

$$P'_{\mathrm{H}}(n)=\frac{L(n)B}{l\ln 2}-\frac{BN_0}{h_{\mathrm{H}}}. \tag{41}$$

From the expression, it can be seen that the partial derivative of the transmission power must be greater than 0. Substitute the optimal computation frequency of HAP obtained from the above into Eq. (26), and the maximum transmission power that can be used at the current battery level can be obtained, denoted as $P_{\mathrm{H,\,max}}^{*}(n)$.

Therefore, the optimal transmission power can be obtained as

$$P_{\mathrm{H}}^{*}(n)=\min\{P'_{\mathrm{H}}(n),P_{\mathrm{H,\,max}},P_{\mathrm{H,\,max}}^{*}(\mathrm{n})\}. \tag{42}$$

3.4 USV transmission power and channel ratio allocation

The joint optimization problem of USV transmission power and channel ratio allocation can be obtained by organizing the remaining items of P2.

$$\mathrm{P2.4}:\min_{\beta(n),P(n)}\sum_{m\in\mathcal{M}}V\tau P_m(n)+[L(n)-Q_m(n)]\tau\beta_m(n)W\log_2\left(1+\frac{P_m(n)h_m}{\beta_m(n)WN_0}\right), \tag{43}$$

s.t. Eqs. (19), (20), (23), and (25).

According to the convexity preservation of perspective functions, we can achieve that P2.4 is a convex optimization problem. First, we substitute the optimal solution obtained from Subsection 3.1 into Eq. (25) to derive the maximum transmittable power for USV m in time slot n. For arbitrary $\beta_m(n)$, by conducting the first partial derivatives to $P_m(n)$ for the objective function and making it 0, we have

$$P'_m(n)=\left\{\frac{[L(n)-Q_m(n)]W}{Vl\ln 2}-\frac{WN_0}{h_m}\right\}\beta_m(n)=C_{m,A}(n)\beta_m(n). \tag{44}$$

Note that $P_m(n)$ is only related to $\beta_m(n)$, the constraint (19) can be transformed into

$$0\leqslant\beta_m(n)\leqslant\frac{P_{\max}}{C_{m,A}(n)}. \tag{45}$$

Then, substituting Eq. (44) into P2.4, P2.4 can be transformed into a convex problem with a single variable.

$$\mathrm{P2.4'}:\min_{\boldsymbol{\beta}(n)}\sum_{m\in\mathcal{M}}V\tau C_{m,A}(n)\beta_m(n)-[L(n)-Q_m(n)]\tau\beta_m(n)W\log_2\left(1+\frac{C_{m,A}(n)h_m}{WN_0}\right), \tag{46}$$

s.t. Eqs. (20) and (45).

Note that P2.4′ is a standard linear programming problem, and we can quickly obtain its optimal solution through a simple allocation algorithm. Firstly, assigning the maximum bandwidth ratio required to the USV with the minimum weighting coefficient can minimize the objective function. Then, check if there is remaining bandwidth. If there is, continue to find the USV with a smaller weighting coefficient to allocate its required bandwidth. If the bandwidth is insufficient, allocate the remaining bandwidth. If not, terminate the program. In addition, if the coefficient is greater than 0, the bandwidth ratio allocated to the USV is 0 to avoid adding increments to the objective function. After obtaining the optimal bandwidth allocation, it can be substituted into Eq. (44) to obtain the optimal transmission power. The detailed algorithm steps can be found in Algorithm 1.

Algorithm 1: Bandwidth allocation algorithm

1: Initialization: $Q_m(n)$, W, τ, $P_{\max}$, and V;
2: Sort all USVs from small to large based on weighting coefficients;
3: $k=1$;
4: **for** $m\in\mathcal{M}$ **do**
5: **if** the weighting coefficient of USV m is less than 0, **then**
6: $\beta_m^{*}(n)=\dfrac{P_{\max}}{C_{m,A}(n)}$;
7: $t=k-\beta_m^{*}(n)$;
8: **if** $t<0$ **then**
9: $\beta_m^{*}(n)=k$;
10: All subsequent USVs will receive a bandwidth ratio of 0;
11: Break;
12: **else**
13: $k=t$;
14: **end if**
15: **else**
16: Break;
17: **end if**
18: **end for**
19: Substitute the optimal channel bandwidth allocation strategy into Eq. (42) to obtain the optimal transmission power;
20: return $\beta^{*}(n)$ and $P^{*}(n)$.

4 Simulation Results

We simulate a scenario involving an LEO satellite, an HAP, and five USVs. They are distributed in a 10 km × 10 km area. The HAP and the LEO satellite are located at altitudes of 20 and 200 km, respectively. Furthermore, we set $N=1\,000$; $\tau=1$ s; $A_m(n)$ is randomly generated in [5.5, 9.5] Mb; $e(n)$ is randomly generated in [0.5, 1] J; $W=0.2$ MHz; $B=0.4$ MHz; $N_0=-160$ dBW/Hz; $P_{\max}=1$ W; $P_{\mathrm{H,\,max}}=$

5 W; ρ = 1 000; κ = 10^{-25}; $f_{\max}$ = 0.1 GHz; $f_{\mathrm{H,\ max}}$ = 0.5 GHz. To assess the efficacy of the proposed algorithm, we conducted comparative analyses against "The random scheme" and "The fixed scheme".

Figure 2 shows the variation of the USV and HAP queues with time under different Lyapunov control parameters. It can be observed that the length of each task queue exhibits a gradual increase followed by a stabilization trend. Moreover, as the Lyapunov control parameters increase, on the one hand, the length of the task queue gradually increases, and on the other hand, the time required for the queue to remain stable also gradually increases.

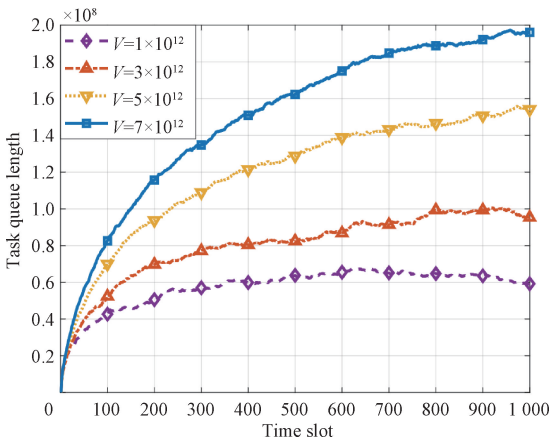


Fig. 2 Task queue length of the system

Figure 3 provides a clearer illustration of the effects of Lyapunov control parameters on task queue length and energy consumption. It can be seen that the task backlog queue is directly proportional to the Lyapunov control parameters, while it is inversely proportional to the energy consumption. This verifies that the proposed algorithm achieves a balance between system stability and energy consumption minimization, achieving long-term optimization of the system.

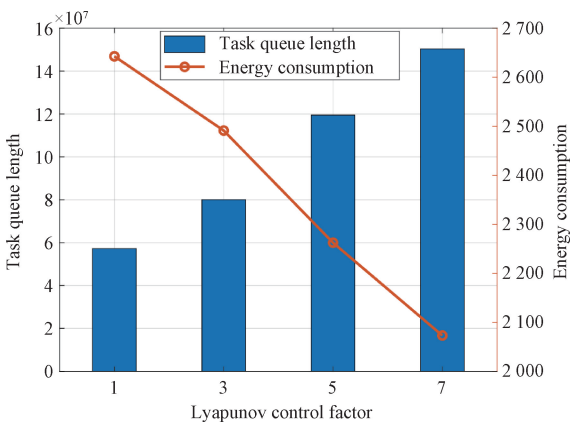


Fig. 3 Task queue length and energy consumption of the system

Figures 4 and 5 show the effects of the number of USVs on the task queue length and average energy consumption under different schemes. As the number of USVs increases, the task queue length and average energy consumption of all schemes show an upward trend. Specifically, as the number of USVs increases, more and more tasks are generated at the edge of the network. In order to handle these tasks, USVs need to offload them to the HAP or LEO satellites for execution, which leads to an increase in the total number of tasks that the HAP and LEO satellites need to handle, thereby increasing the task queue length and energy consumption of the system. However, regardless of how the number of USV changes, the task queue length and the average energy consumption of the proposed algorithm are still lower than those of the other three schemes.

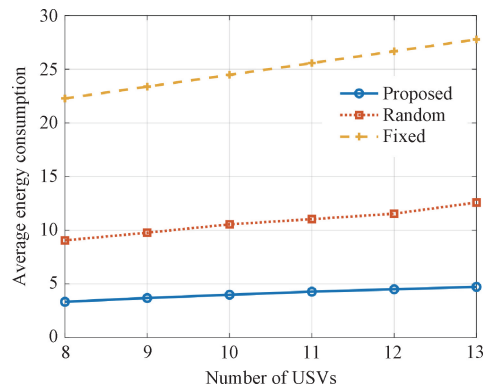


Fig. 4 Average energy consumption of different schemes

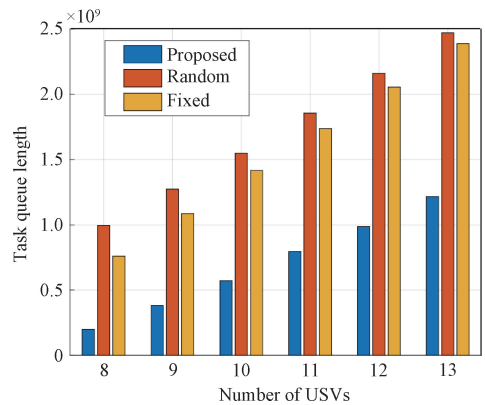


Fig. 5 Task queue length of different schemes

5 Conclusions

In this study, we successfully developed a USV system leveraging the HAP and LEO satellites. Through an innovative Lyapunov optimization method, we transformed the stochastic optimization problem into a deterministic problem, effectively ensuring system stability. We further addressed the non-convex challenges in computing resource allocation, transmission power control, and channel bandwidth allocation through convex optimization methods. Our proposed algorithm achieved improvements in both solution accuracy and algorithmic

efficiency. Simulation results verified the algorithm's convergence and its effectiveness in reducing the total energy consumption of the USV system. These findings contribute to both the theoretical advancement and practical deployment of USV technologies.

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基于可再生能源供应的多层无人水面艇移动边缘计算系统：任务卸载与资源分配优化

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摘　要：移动边缘计算（mobile edge computing，MEC）在支持海事行业的通信、计算和资源管理方面发挥着重要作用，已成为未来海事技术发展的核心要素。本文采用空天海一体化 MEC 网络，使用由可再生能源供能的高空平台和低轨道卫星协助无人水面艇完成任务卸载，在可控任务积压队列约束下，最小化系统的总能耗。采用 Lyapunov 优化方法将原始的随机优化问题转化为确定性优化问题，从而确保系统的稳定性。提出了一种基于凸优化的算法，专门用于优化传输功率分配和信道分配。与其他基准方案相比，仿真结果验证了所提方案可显著降低系统的总能耗。

关键词：Lyapunov 优化；无人水面艇；凸优化；移动边缘计算