Optimal Resource Allocation for Computation Offloading in Maritime Communication Networks: An Energy-Efficient Design via Matching Game

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Abstract. The increasing growth of maritime activities leads to the challenges for processing the maritime data. However, the resources-limited maritime devices cannot meet the requirements of transmission delay and energy consumption. In this paper, we investigate the resource allocation for computation offloading in maritime communication networks via game theory to improve the offloading efficiency and reduce the energy consumption of maritime devices. Specifically, we propose an optimization problem that jointly optimizes the offloading data, the computation resource allocation of unmanned surface vehicle (USV) and the allocation of acoustic channels, with the objective of minimizing the total energy consumption of underwater wireless sensor (UWS). Despite the non-convexity of the joint optimization problem, we propose a layered structure and decompose it into a top-problem for optimizing the data offloading, a middle-problem for optimizing the computation resource allocation of USV, a bottom problem for optimizing the channel allocation. We conduct simulations to validate the effectiveness and efficiency of the proposed algorithms.

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1 Introduction

Maritime communication networks, which are developed to facilitate ocean data gathering, resource exploration, and environment monitoring, have attracted a growing attention in recent years [1–3]. However, the harsh maritime environment and the high cost of underwater equipment pose critical constraints to construct the development of maritime applications. The typical characteristic of maritime communication is the underwater transmission, which is commonly associated with low data rate and high data packet loss due to the complicated maritime environment [4,5]. Therefore, it is important to investigate the underwater channel allocation problem for underwater acoustic communication with the objective of improving the communication efficiency [6,7].

To collect the ocean information, a group of underwater wireless sensors (UWSs) are usually deployed on the seabed to perceive ocean data. However, these UWSs are generally battery-powered [8,9], which are hard to recharge due to the harsh ocean environment. Therefore, the data collected by UWSs needs to be transmitted to the sea surface nodes for further processing. Maritime edge computing is a promising paradigm to improve the computation efficiency and save the energy consumption of UWSs [10–12]. In particular, unmanned surface vehicles (USVs) sailing on the sea surface can provide edge computation and communication capacities to offer services for UWSs. Besides, game theory is widely used for improving the network resource utilization through designing efficient scheme [13], which is a feasible approach in resource-limited maritime networks. However, due to the complicated underwater communications, it is still a critical issue to design an energy-efficient computation offloading scheme in maritime communication networks for reducing the energy consumption of UWSs.

Considering the limited communication resources in maritime networks, the underwater acoustic communication should be well designed to improve the network throughput. In [14], Yang *et al.* proposed a computation task offloading to minimize the energy consumption of vessel terminals and the execution delay of computation task. In [15], Ma *et al.* presented an unmanned aerial vehicle (UAV) aided ocean monitoring network for remote oceanic data collection to maximize the lifetime of UWSs. In [16], Yang *et al.* investigated an offloading optimization problem and proposed a two-stage joint optimal offloading algorithm for optimizing communication resource allocation under limited energy and sensitive latency. Different from the above works, we investigate an optimal resource allocation for computation offloading in maritime communication networks in which a group of UWSs are deployed at the seabed to monitor the ocean environment. A USV sails on the sea to collect data and provide computation offloading service for UWSs. We aim to minimize the energy consumption of UWSs by jointly optimizing the acoustic channel allocation, data offloading, and computation resource allocation of USV. The main contributions of this paper can be summarized as follows:

– Considering the resources-limited maritime devices, we investigate the energy efficient computation offloading scheme for UWS in maritime communication networks to minimize the energy consumption of UWSs.

– We propose a joint optimization problem for optimizing the allocation of underwater acoustic channels, the offloading data, and the computation resource allocation of USV. Despite the non-convexity of the joint optimization problem, we propose a layered structure to decompose it into a top-problem, a middle problem, and a bottom problem to solve it. Simulation results have demonstrated the effectiveness of the proposed algorithms.

The remainder of this paper is organized as follows. Section 2 presents the system model and problem formulation. Section 3 introduces the proposed algorithms. Simulation performance is provided in Sect. 4, and Sect. 5 concludes this work and discusses the future direction.

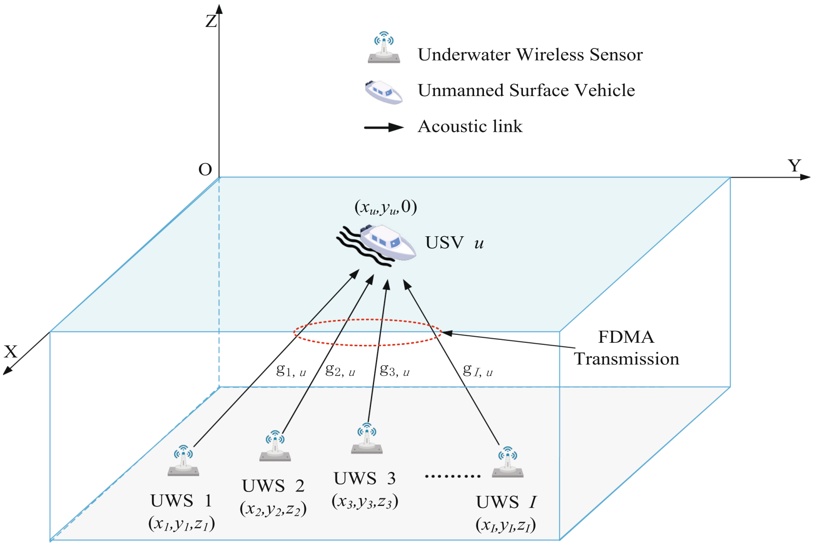

Fig. 1. System model of computation offloading in maritime communication networks.

2 System Model and Problem Formulation

Figure 1 shows the scenario of computation offloading in maritime communication networks. UWSs are deployed at the seabed to monitor the ocean environment, and the set of UWSs is denoted as $\mathcal{I} = \{1, \cdots, i, \cdots, I\}$. The total workloads of UWS i is denoted as S_i^{tot}. One USV u is deployed on the sea to collect and process the data from UWSs. The underwater acoustic channels are expressed as $\mathcal{K} = \{1, \cdots, k, \cdots, K\}$. The data transmission in underwater environment is carried over the acoustic signal with a very fast decaying rate, which thus is different from radio transmission over the air. Based on the Urick's model [17], we can derive the attenuation of underwater acoustic signals, which depends on the transmission distance and the carrier frequency, as follows

$$A(d_{i,u}, k) = (d_{i,u})^{\lambda} \alpha(k)^{\frac{d_{i,u}}{1000}}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \tag{1}$$

where $d_{i,u}$ denotes the distance between USV u and UWS i. In Eq. (1), k is the central frequency of the acoustic signal. λ is constant which is usually set as 1.5. $\alpha(k)$ is the absorption coefficient. For the convenience of expression, we consider a three-dimensional Cartesian coordinate system for the positions of USV and UWSs. The position of UWS i is denoted as (x_i, y_i, z_i). The position of USV is denoted as $(x_u, y_u, 0)$. Therefore, we can express the distance between UWS i and USV u as

$$d_{i,u} = \sqrt{(x_u - x_i)^2 + (y_u - y_i)^2 + {z_i}^2}, \forall i \in \mathcal{I}. \tag{2}$$

The absorption coefficient $\alpha(k)$ can be calculated according to Thorp's empirical formula [17] as

$$10\log_{10}\alpha(k) = \frac{0.11k^2}{1+k^2} + \frac{44k^2}{4000+k^2} + 2.75 \times 10^{-4}k^2 + 0.003, \forall k \in \mathcal{K}. \tag{3}$$

In addition to the path loss, the underwater acoustic signals are also affected by the oceanic noise N_0 and the channel bandwidth W. Therefore, the underwater acoustic channel gain between USV u and UWS i can be expressed as

$$g_i = \frac{1}{A(d_{i,u}, k)N_0W}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}. \tag{4}$$

Let $a_{i,k} \in \{0, 1\}, \forall i \in \mathcal{I}, k \in \mathcal{K}$ denote the association between underwater acoustic channel k and UWS i. $a_{i,k} = 1$ indicates that channel k is allocated to UWS i. Otherwise, $a_{i,k} = 0$. Then, we can express the received signal to interference plus noise ratio (SINR) of UWS i as

$$\phi_i = \frac{a_{i,k}p_ig_i}{N_0W}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \tag{5}$$

where p_i is the transmission power of UWS i. The transmission rate between UWS i and USV u can be calculated by

$$r_i = W\log_2(1+\phi_i), \forall i \in \mathcal{I}, \forall k \in \mathcal{K}. \tag{6}$$

Let s_i denote the offloading data of UWS i, we can obtain

$$\frac{s_i}{t_i} = W\log_2(1+\phi_i), \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \tag{7}$$

where t_i is the transmission time of UWS i. The required transmission power for UWS i can be expressed as [18]

$$p_i = \frac{N_0W}{a_{i,k}g_{i,k}}\left(2^{\frac{s_i}{Wt_i}} - 1\right), \forall i \in \mathcal{I}, \forall k \in \mathcal{K}. \tag{8}$$

The energy consumption of UWS i for offloading data can be expressed by

$$E_i = p_it_i, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}. \tag{9}$$

The local computing time of UWS i can be expressed as

$$t_i^{\text{loc}} = c_i \frac{S_i^{\text{tot}} - s_i}{\mu_i^{\text{loc}}}, \forall i \in \mathcal{I}, \tag{10}$$

where c_i is the number of CPU cycles for processing one bit of data. μ_i^{loc} denotes the processing capability of UWS i which is measured by the CPU cycles per second. Therefore, the energy consumption of local computation is expressed as [19]

$$E_i^{\text{loc}} = \rho_i t_i^{\text{loc}} \left(\mu_i^{\text{loc}}\right)^3 = c_i \left(S_i^{\text{tot}} - s_i\right) \rho_i \left(\mu_i^{\text{loc}}\right)^2, \forall i \in \mathcal{I}, \tag{11}$$

where ρ_i denotes the power coefficient of UWS i.

Let μ_i^{all} denote the allocated processing capability of USV for UWS i in CPU cycles per second. c_u expresses the number of CPU cycles for USV to process one bit of data. The overall delay for UWS i to complete its total computation workload S_i^{tot} can be expressed as

$$t_i^{\text{ove}} = \max\left\{ c_i \frac{S_i^{\text{tot}} - s_i}{\mu_i^{\text{loc}}}, t_i + c_u \frac{s_i}{\mu_i^{\text{all}}} \right\}, \forall i \in \mathcal{I}. \tag{12}$$

The total energy consumption of UWS i can be calculated by

$$\begin{aligned} E_i^{\text{tot}} &= E_i + E_i^{\text{loc}} \\ &= c_i \left(S_i^{\text{tot}} - s_i\right) \rho_i \left(\mu_i^{\text{loc}}\right)^2 + \frac{N_0 W}{a_{i,k} g_{i,k}} \left(2^{\frac{s_i}{W t_i}} - 1\right) t_i, \forall i \in \mathcal{I}. \end{aligned} \tag{13}$$

2.1 Problem Formulation

Based on the above modeling, we formulate the following optimization problem that aims to minimize the total energy consumption (TEC) of UWS, i.e.,

$$\begin{aligned} \text{(TEC)}: \quad & \min \left\{ \max_{i \in \mathcal{I}} \left\{ E_i^{\text{tot}} \right\} \right\} \\ \text{subject to}: \quad & \sum\nolimits_{k=1}^{N} a_{i,k} = 1, \forall i \in \mathcal{I}, && (14) \\ & \sum\nolimits_{i=1}^{I} a_{i,k} \le 1, \forall k \in \mathcal{K}, && (15) \\ & \sum\nolimits_{i=1}^{I} \mu_i^{\text{all}} \le \mu^{\max}, && (16) \\ & \max \left\{ c_i \frac{S_i^{\text{tot}} - s_i}{\mu_i^{\text{loc}}}, t_i + c_u \frac{s_i}{\mu_i^{\text{all}}} \right\} \le T_i^{\max}, \forall i \in \mathcal{I}, && (17) \\ & 0 \le s_i \le S_i^{\text{tot}}, \forall i \in \mathcal{I}, && (18) \\ & 0 \le \frac{N_0 W}{a_{i,k} g_{i,k}} \left(2^{\frac{s_i}{W t_i}} - 1\right) \le P_i^{\max}, \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, && (19) \\ \text{variables}: \quad & \{s_i\}_{i \in \mathcal{I}}, \{a_{i,k}\}_{i \in \mathcal{I}, k \in \mathcal{K}}, \left\{\mu_i^{\text{all}}\right\}_{i \in \mathcal{I}}. \end{aligned}$$

In Problem (TEC), constraints (14) and (15) ensure that each UWS i can only occupy one acoustic channel, and each acoustic channel can only be assigned to one

UWS. Constraint (16) guarantees that the allocated computing-rate of USV cannot exceed the maximum computing-rate $\mu^{\max}$. Constraint (17) ensures that the transmissions delay of each UWS cannot beyond its allowed maximum transmission delay $T_i^{\max}$. Constraint (18) guarantees that the offloading computation workload of each UWS should below its total computation workload. Constraint (19) indicates that the transmission power of UWS cannot exceed the maximum power $P_i^{\max}$.

3 Proposed Algorithm for Solving Problem (TEC)

3.1 Layer Structure of Problem (TEC)

Problem (TEC) is a strictly nonconvex optimization problem. The total energy consumption of UWS i is decreasing with the increase of t_i. Based on constraint (17), we consider that the constraint is strictly binding, and we can obtain $t_i = T_i^{\max} - c_u \frac{s_i}{\mu_i^{\text{all}}}$. The total energy consumption of UWS i can be rewritten as

$$\begin{aligned} E_i^{\text{tot}} &= c_i \left(S_i^{\text{tot}} - s_i\right) \rho_i \left(\mu_i^{\text{loc}}\right)^2 \\ &+ \frac{N_0 W}{a_{i,k} g_{i,k}} \left(2^{\frac{s_i}{W\left(T_i^{\max} - c_u \frac{s_i}{\mu_i^{\text{all}}}\right)}} - 1 \right) \left(T_i^{\max} - c_u \frac{s_i}{\mu_i^{\text{all}}} \right), \forall i \in \mathcal{I}. \end{aligned} \quad (20)$$

Let $\theta = \max_{i \in \mathcal{I}} \{E_i^{\text{tot}}\}$, we obtain $E_i^{\text{tot}} \leq \theta, \forall i \in \mathcal{I}$. Problem (TEC) can be decomposed as the following layer structure

1) Top-problem to find s_i:

$$\begin{aligned} \text{(TEC-Top)}: \ & \min \theta \\ \text{subject to}: \ & E_i^{\text{tot}} \leq \theta, \forall i \in \mathcal{I}, \\ & \text{constraints (17), (18), and (19)}, \\ \text{variables}: \ & \{s_i\}_{i \in \mathcal{I}}. \end{aligned} \quad (21)$$

2) Middle-problem to find μ_i^{all} under given $\{s_i\}_{i \in \mathcal{I}}$:

$$\begin{aligned} \text{(TEC-Mid)}: \ & \min \theta \\ \text{subject to}: \ & \text{constraint (16) and (21)}, \\ \text{variables}: \ & \left\{\mu_i^{\text{all}}\right\}_{i \in \mathcal{I}}. \end{aligned}$$

3) Bottom-problem to find $a_{i,k}$ under given $\{s_i\}_{i \in \mathcal{I}}$ and $\left\{\mu_i^{\text{all}}\right\}_{i \in \mathcal{I}}$:

$$\begin{aligned} \text{(TEC-Bot)}: \ & \min \theta \\ \text{subject to}: \ & \text{constraints (14), (15), and (21)}, \\ \text{variables}: \ & \{a_{i,k}\}_{i \in \mathcal{I}, k \in \mathcal{K}}. \end{aligned}$$

3.2 Matching Game for Solving Channel Allocation in Problem (TEC-Bot)

In Problem (TEC-Bot), we propose the matching game to solve the channel allocation problem. Specifically, in the channel allocation process, UWSs have different preferences (e.g., channel quality) for acoustic channels. The acoustic channels can rank the UWSs based on the energy efficiency of UWS. Therefore, the matching game can be adopted to model the two-side allocation between UWSs and acoustic channels. Each UWS i is matched to at most one acoustics channel, and each acoustic channel k is allocated to at most one UWS.

The matching game between UWSs and acoustics channels can be described as a tuple $\pounds = \{\mathcal{I}, \mathcal{K}, \mathcal{P}\}$, where $\mathcal{I}$ and $\mathcal{K}$ are the set of players (i.e., UWSs and acoustic channels), and $\mathcal{I} \cap \mathcal{K} = \emptyset$. $\mathcal{P}$ indicates the preference lists of UWSs and acoustics channels. Let $\succ$ denote the preference relations of UWSs and acoustic channels. $\mathcal{P}(i)\,|_{\pounds(i)=k} > \mathcal{P}(i)\,|_{\pounds(i)=k'}, k \succ k^{'}$ means that UWS i prefers channel k to channel $k^{'}$. $\mathcal{P}(k)\,|_{\pounds(k)=i} > \mathcal{P}(k)\,|_{\pounds(k)=i'}, i \succ i^{'}$ indicates that channel k prefers UWS i to UWS $i^{'}$.

Definition 1. *Given two disjoint sets of players $\mathcal{I}$ and $\mathcal{K}$, the matching game for channel allocation is defined as $\pounds(i) = \{k \in \mathcal{K} |\, (i, k \in \pounds)\}$ and $\pounds(k) = \{i \in \mathcal{I} |\, (i, k \in \pounds)\}$, such that (i) $\sum_{k=1}^{N} a_{i,k} = 1$ and (ii) $\sum_{i=1}^{I} a_{i,k} \leq 1$.*

Note that Definition 1 guarantees that each player on one side matches to a set of players. Constraints (i) and (ii) make sure that the conditions (14) and (15) in Problem (TEC) are satisfied.

The preference relation is utilized to measure the preference levels of each player. Assume that the current matching result is $\pounds$ and the associated channel allocation vector is represented as $\mathbf{K}^{\pounds}$. The preference relation of UWS i is defined as the achievable rate when matching with a channel, which can be expressed as

$$\mathcal{U}_i(k) = W\log_2\left(1 + \frac{p_i g_{i,k}}{N_0 W}\right), \forall i \in \mathcal{I}, \forall k \in \mathcal{K}. \tag{22}$$

For each acoustic channel, let $E_i^{\max}$ denote the maximum energy of UWS i. The preference relation of channel k is defined as the energy efficiency when matching with a UWS, i.e.,

$$\mathcal{U}_k(i) = \log_2\left(1 + \frac{E_i^{\max}}{E_i^{\mathrm{tot}}}\right), \forall i \in \mathcal{I}. \tag{23}$$

Therefore, for UWS i, the preference relation $\succ_i$ for two channels $k, k^{'} \in \mathcal{K}, k \neq k^{'}$ is defined as $k \succ_i k^{'}$ if and only if $\mathcal{U}_i(k) > \mathcal{U}_i\left(k^{'}\right)$. For channel k, the preference relation $\succ_k$ for two UWSs $i, i^{'} \in \mathcal{I}, i \neq i^{'}$ is defined as $i \succ_k i^{'}$ if and only if $\mathcal{U}_k(i) > \mathcal{U}_k\left(i^{'}\right)$.

Definition 2. *In the matching $\pounds$, UWS i proposes to match its most preferred channel based on the preference list (i.e., $\mathcal{U}_i(k)$). Channel k proposes to match its most preferred channel based on the preference list (i.e., $\mathcal{U}_k(i)$).*

Algorithm 1 presents the proposed channel allocation scheme based on matching game. The key steps are described as follows:

– *Step 4 to Step 9:* UWS $i \in \mathcal{I}$ first searches for the most preferred channel. If a channel k receives more than one proposal from UWSs, denoted by $\mathcal{D}$, it matches with the most preferred UWS $i \in \mathcal{D}$. Otherwise, it matches with the current requested UWS.
– *Step 10 to Step 14:* The current matching players, i.e., i and k, are removed from the sets $\mathcal{I}$ and $\mathcal{K}$. The matching process is conducted until there exist no UWSs blocking the current matching.

Algorithm 1. Channel Allocation Scheme based on Matching Game

1: Input: the set of players $\mathcal{I}$ and $\mathcal{K}$.
2: Initialize: compute the preference relations of UWS i and channel k using Eqs. (22) and (23).
3: **while** there exist UWSs blocking the current matching **do**
4:     **for** any UWS $i \in \mathcal{I}$ **do**
5:         It searches for the most preferred channel k.
6:         **if** channel k receives more than one proposal from UWSs in $\mathcal{D}$ **then**
7:             It matches with the most preferred UWS $i \in \mathcal{D}$.
8:         **else**
9:             It matches with the current requested UWS.
10:         **end if**
11:         Remove the current matching players.
12:     **end for**
13: **end while**
14: Output: the matching result $\pounds\,(i) = \{k \in \mathcal{K} |\, (i, k \in \pounds)\}$.

Proposition 1. *The proposed channel allocation scheme based on matching game is stable. For any UWS $i \in \mathcal{I}$, there exist no UWSs blocking the current matching.*

Proof. The contradiction method is used to prove the stability of the proposed matching algorithm. Specifically, assume that UWS $i \in \mathcal{I}$ and channel $k \in \mathcal{K}$ have no matching after the final matching process. However, both UWS $i \in \mathcal{I}$ and channel $k \in \mathcal{K}$ prefer to match with each other, which means that the matching result $\pounds\,(i) = \{k \in \mathcal{K} |\, (i, k \in \pounds)\}$ is restricted. Considering that both UWS $i \in \mathcal{I}$ and channel $k \in \mathcal{K}$ prefer to match with each other, the UWS i must have proposed to match with channel k in the matching process, and the channel $k \in \mathcal{K}$ has rejected the proposal of UWS i, which contradicts the matching $\pounds\,(k) = \{i \in \mathcal{I} |\, (i, k \in \pounds)\}$. Therefore, the proposed channel allocation scheme based on matching game can achieve a stable matching.

3.3 Analysis of Problem (TEC-Mid) for Solving $\boldsymbol{\mu}_i^{\mathrm{all}}$

Proposition 2. *Given $\{s_i\}_{i \in \mathcal{I}}$ and $\{a_{i,k}\}_{i \in \mathcal{I}, k \in \mathcal{K}}$, Problem (TEC-Mid) is a strictly convex problem.*

Proof. In Problem (TEC-Mid), the first derivative of E_i^{tot} with respect to t_i can be expressed as

$$\frac{\partial E_i^{tot}}{\partial t_i} = \frac{N_0\left(Wt_i\left(-1+2^{\frac{s_i}{Wt_i}}\right) - 2^{\frac{s_i}{Wt_i}} s_i \ln 2\right)}{t_i a_{i,k} g_{i,k}}. \tag{24}$$

The second derivative of E_i^{tot} with respect to t_i can be expressed as

$$\frac{\partial^2 E_i^{tot}}{\partial t_i^2} = \frac{(\ln 2)^2 2^{\frac{s_i}{Wt_i}} N_0 (s_i)^2}{W{t_i}^3 a_{i,k} g_{i,k}} > 0. \tag{25}$$

With (25), we find that E_i^{tot} is strictly convex with respect to t_i, and the first derivative $\frac{\partial E_i^{tot}}{\partial t_i}$ increases with t_i. Due to $\lim_{t_i \to \infty} \frac{\partial E_i^{tot}}{\partial t_i} < 0$, E_i^{tot} is convex and non-increasing with respect to t_i. Furthermore, t_i is strictly concave with respect to μ_i^{all}. Therefore, E_i^{tot} is strictly convex with respect to μ_i^{all}.

Proposition 2 indicates that E_i^{tot} is decreasing with μ_i^{all}. With constraint (21), we can derive $\mu_i^{\text{all}} \geq \ell_i(\theta)$. With constraint (16), we can obtain $\sum_{i=1}^{I} \ell_i(\theta) \leq \mu^{\max}$. Therefore, we can find the optimal value of μ_i^{all} by searching the value of θ. Algorithm 2 presents the iterative searching algorithm for solving Problem (TEC-Mid). The key steps are as follows: we first set the upper bound value as $\theta = \theta^{\max}$. For any UWS $i \in \mathcal{I}$, we need to evaluate the conditions $\mu_i^{\text{all}} \geq \ell_i(\theta)$ and $\sum_{i=1}^{I} \ell_i(\theta) \leq \mu^{\max}$. If it is satisfied, the current θ is feasible, and we update the value of θ with a decreasing way. Otherwise, Problem (TEC-Mid) is infeasible.

Algorithm 2. Iterative Searching Algorithm for Solving Problem (TEC-Mid)

Input: the iterative step size Δ.
Initialize: set the upper bound value as $\theta = \theta^{\max}$.
while $\sum_{i=1}^{I} \ell_i(\theta) \leq \mu^{\max}$ **do**
    for any UWS $i \in \mathcal{I}$ **do**
        if $\mu_i^{\text{all}} \geq \ell_i(\theta)$ **then**
            Current θ is feasible for Problem (TEC-Mid).
            Update $\theta \leftarrow \theta - \Delta$.
        else
            Problem (TEC-Mid) is infeasible.
        end if
    end for
end while
Output: the minimum θ and the corresponding E_i^{tot}.

3.4 Analysis of Problem (TEC-Top) for Solving s_i

Proposition 3. *Given $\{a_{i,k}\}_{i \in \mathcal{I}, k \in \mathcal{K}}$ and $\{\mu_i^{\text{all}}\}_{i \in \mathcal{I}}$, Problem (TEC-Top) is a strictly convex problem.*

Proof. In Problem (TEC-Top), the first derivative of E_i^{tot} with respect to s_i can be expressed as

$$\frac{\partial E_i^{tot}}{\partial s_i} = \frac{N_0 W \left(c_u \left(1 - 2^{\frac{s_i}{W\left(T_i^{\max} - c_u \frac{s_i}{\mu_i^{\text{all}}}\right)}} \right) + \frac{2^{\frac{s_i}{W\left(T_i^{\max} - c_u \frac{s_i}{\mu_i^{\text{all}}}\right)}} T_i^{\max} \ln 2 \left(\mu_i^{\text{all}}\right)^2}{W\left(-c_u s_i + T_i^{\max} c\right)} \right)}{\mu_i^{\text{all}} a_{i,k} g_{i,k}} - c_i \rho_i \left(\mu_i^{\text{loc}}\right)^2. \tag{26}$$

The second derivative of E_i^{tot} with respect to s_i can be expressed as

$$\frac{\partial^2 E_i^{tot}}{\partial s_i^2} = \frac{(\ln 2)^2 2^{\frac{s_i}{W\left(T_i^{\max} - c_u \frac{s_i}{\mu_i^{\text{all}}}\right)}} \left(T_i^{\max}\right)^2 N_0 W \left(\mu_i^{\text{all}}\right)^3}{W\left(-c_u s_i + T_i^{\max} \mu_i^{\text{all}}\right)^3 a_{i,k} g_{i,k}}. \tag{27}$$

With constraint (17), we can obtain $T_i^{max} \mu_i^{all} - c_u s_i > 0$. Therefore, the value of $\frac{\partial^2 E_i^{tot}}{\partial s_i^2}$ is always higher than zero. The objective function of E_i^{tot} is strictly convex with respect to s_i.

The stagnation point can be obtained by $\frac{\partial E_i^{\text{tot}}}{\partial s_i} = 0$, which is denoted by s_i^*. To obtain the minimum value of E_i^{tot}, we need to analyze the feasible region of s_i. Specifically, with (17), we can equivalently obtain $S_i^{\text{tot}} - \frac{\mu_i^{\text{loc}} T_i^{\text{max}}}{c_i} \leq s_i$. The lower bound is $s_i^{\text{low}} = S_i^{\text{tot}} - \frac{\mu_i^{\text{loc}} T_i^{\text{max}}}{c_i}$. With (19), we can obtain the constraint $s_i \leq \frac{r_{i,k}^{\max} \mu_i^{\text{all}} T_i^{\text{max}}}{\mu_i^{\text{all}} + r_{i,k}^{\max}}$. Further combining with (18), we can obtain the upper bound of s_i as $s_i^{\text{upp}} = \min \left\{ S_i^{\text{tot}}, \frac{r_{i,k}^{\max} \mu_i^{\text{all}} T_i^{\text{max}}}{\mu_i^{\text{all}} + r_{i,k}^{\max}} \right\}$. Therefore, the feasible region of s_i is $\left[s_i^{\text{low}}, s_i^{\text{upp}}\right]$. There are three following cases to be discussed:

- *Case 1:* The stagnation point s_i^* satisfies $s_i^{\text{low}} < s_i < s_i^{\text{upp}}$. The optimal value for minimizing E_i^{tot} is obtained at s_i^*.
- *Case 2:* The stagnation point s_i^* satisfies $s_i \leq s_i^{\text{low}}$. The optimal value for minimizing E_i^{tot} is obtained at s_i^{low}.
- *Case 3:* The stagnation point s_i^* satisfies $s_i^{\text{upp}} \leq s_i$. The optimal value for minimizing E_i^{tot} is obtained at s_i^{upp}.

4 Simulation Performance

This section provides the simulation results to validate the effectiveness of the proposed algorithms. We consider a simulation scenario with a size of 1 km $\times$ 1 km $\times$ 0.5 km to model the underwater environment. One USV is deployed on the upper surface and four UWSs are deployed on the seabed to collect ocean data. There are four acoustic channels, and the bandwidth of each underwater acoustic channel is set to 1 MHz. The oceanic noise is set to 10^{-8} W. The maximum transmission power of UWS is set to

1.5 W. The processing capability of UWS is set to 1 Gbps. The maximum processing capability of USV is set to 15 Gbps. The number of CPU cycles for processing one bit of data is set to 1000.

We evaluate the performance of the proposed algorithm with the benchmark algorithms. In random matching algorithm (RMA): the acoustic channels are randomly allocated to UWSs. In random offloading algorithm (ROA): the data is randomly offloaded to USV for processing. In random allocation computation resource algorithm (RACA): the computation resource of USV is randomly allocated to UWSs for processing data.

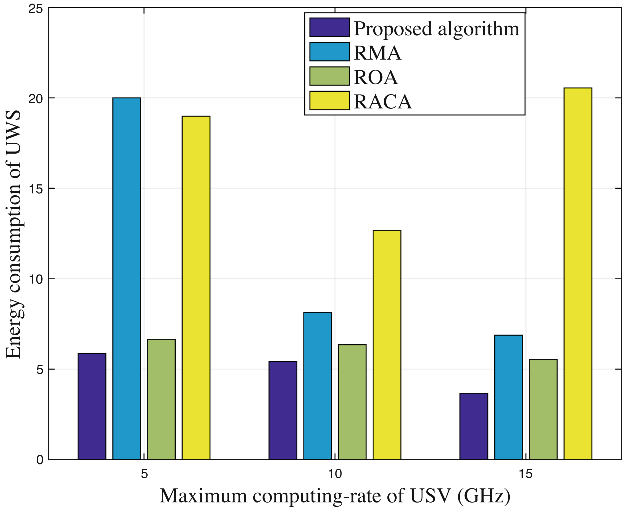

Fig. 2. Energy consumption of UWS with the changes of maximum computing-rate of USV.

Figure 2 shows the energy consumption of UWS with the changes of maximum computing-rate of USV, compared with the benchmark schemes. It can be seen that the proposed algorithm can obtain the low energy consumption for UWS. The reason is that the proposed algorithm jointly considers the acoustic channel allocation, data offloading, and the computation resource allocation of USV to improve the offloading efficiency.

Figure 3 depicts the energy consumption of UWS with the changes of data size. It can be obtained that the energy consumption of each UWS is increasing with the data size. The reason is that the local computation consumption and the offloading consumption will increase when the data size of each UWS is increased, which leads to the increase of energy consumption.

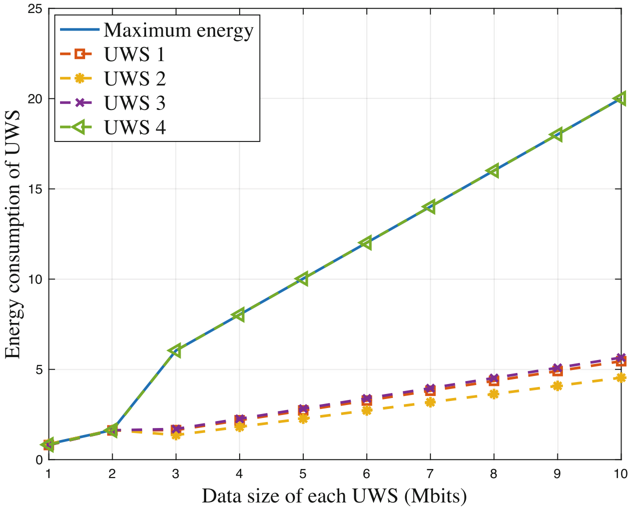

Fig. 3. Energy consumption of UWS with the changes of data size.

5 Conclusion

In this paper, we have investigated an energy efficient computation offloading scheme in maritime communication networks. In particular, we have proposed an optimization problem to minimize the total energy consumption of UWS by jointly optimizing the allocation of underwater acoustic channels, the offloading data, and the computation resource allocation of USV. To address the non-convexity of the joint optimization problem, we have designed a layered structure to derive the optimal solution. Simulation results have demonstrated the effectiveness and efficiency of our proposed algorithms. For the future work, we will plan to investigate the secrecy computation offloading for UWSs in maritime communication networks.

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