Integrated Sensing and Multi-Access Computation Offloading in Smart Oceans: A Utility Maximization Design

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***Abstract*—With the increasing exploration of smart oceans, a large number of marine wireless devices have been deployed for different marine applications such as ocean environment monitoring and seabed resource exploitation. Although the paradigm of marine edge computing networks is expected to process a variety of marine tasks with low delay and high data rate, the efficiency of computation offloading is a critical issue due to the complex environment in smart oceans. In this paper, we propose an integrated sensing and multi-access computation offloading scheme in smart oceans, with the objective of maximizing marine wireless devices' utilities. Specifically, underwater wireless sensor (UWS) first perceives ocean information via radar sensing and then uploads its workloads to an unmanned underwater vehicle (UUV) and a sea surface sink node (SN) via non-orthogonal multiple access (NOMA) transmission. To improve the offloading efficiency, we formulate the utility of each party and model the task offloading process among UWS, UUV and SN as a Stackelberg game to optimize the UWS's offloading strategy, UUV's and SN's price strategies. Numerical results demonstrate that the proposed algorithms can obtain the optimal solutions and increase the utilities for marine wireless devices.**

***Index Terms*—Smart oceans, marine edge computing networks, integrated sensing and computing offloading.**

I. Introduction

The rapid development of smart oceans has been envisioned as a promising paradigm for marine industry [1]. Various marine devices (e.g., vessels, buoys, etc.) deployed in the sea can collect oceanic data and then upload data to ocean observation system or cloud platform for diverse applications and services. For instance, a large amount of hydrological data cached in buoys need to be uploaded for analysis. The navigational information is required for vessels navigation, and offshore drilling platform requires reliable communication for safe exploration. Real-time videos are required for marine disaster rescuing, and seafloor oil exploration, etc. These applications yield the demands for high-speed marine communication and powerful computing-rate in smart oceans. Therefore, building an efficient marine communication and computing network is significant for the development of smart oceans, which attracts much attention from academia and industry in recent years [2].

Mobile edge computing is an effective approach to support various marine applications and services in smart oceans by sinking computing capacity to the edge of marine networks [3]. Specifically, marine wireless devices equipped with communication and computing capacities can offload their workloads to nearby marine edge devices for processing. For instance, underwater wireless sensors (UWSs) can monitor ocean environment and then upload their data to sea surface sink nodes (SNs) through acoustic transmission. Unmanned underwater vehicles (UUVs) with high mobility can sail in the ocean to collect data or receive oceanic data from UWSs for local processing. Recently, some research studies have proposed different schemes for marine edge computing to improve the system performance [4], [5]. However, the data collection and offloading efficiency may be low without considering the sensing and transmission modes in underwater communication segment.

Non-orthogonal multiple access (NOMA) technique allows marine wireless devices to reuse the same resource block for data transmission, which can significantly improve transmission efficiency in underwater communication [6], [7]. The transmission mode of multi-access computing offloading enables marine wireless devices to upload their partial workloads to multiple marine edge nodes for processing, thus reducing the computing delay and energy consumption [8]. In addition, game theory-based incentive approach can stimulate marine wireless devices to participate in task computing by providing sufficient incentives [9]. These marine wireless devices (e.g., UWS, SN, UUV, etc.) can be regarded as players in game model. Through designing the utility function of marine wireless devices, the optimal strategy of each participant can be obtained by analyzing their actions. Therefore, a feasible game theory-based scheme should be exploited to improve the participation of marine devices in smart oceans. Motivated by the above considerations, this paper investigates an integrated sensing and multi-access computation offloading scheme in smart oceans.

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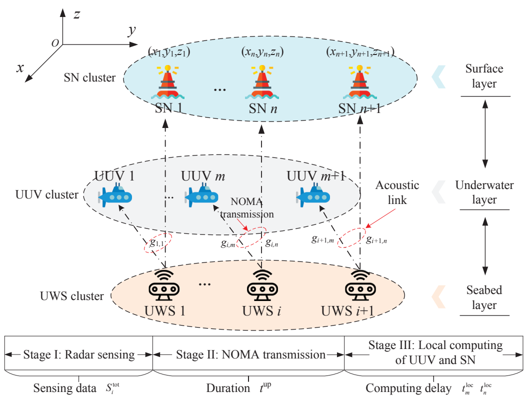


Fig. 1: The scenario of integrated sensing and multi-access computation offloading in smart oceans. In stage I: UWS collects data via radar sensing. In stage II: UWS uploads data to UUV and SN via NOMA. In stage III: UUV and SN process workloads.

The main contributions of this work are as follows.

- *Integrated Sensing and Multi-Access Computation Offloading Framework:* In data sensing phase, we consider that a group of UWSs deployed in the sea to perceive ocean information via radar sensing based on the performance metric of radar information rate. In underwater transmission phase, we propose a multi-access computation offloading scheme, in which UWS uploads its workloads to UUV and SN for task offloading via NOMA transmission to improve channel utilization.
- *Incentive-based Utility Maximization:* We propose an incentive-based scheme to stimulate marine wireless devices to join task computing. We formulate the utility function of each participant (i.e., UWS, UUV and SN) and model the offloading process as a Stackelberg game to optimize UWS's offloading strategy, UUV's and SN's price strategies. The game equilibrium is obtained through analyzing the competition strategies of UWS, UUV and SN.

II. System Model and Problem Formulation

A. System Model

Fig. 1 shows a scenario of integrated sensing and multi-access computation offloading framework in smart oceans. There are a group of UWSs (denoted as $\mathcal{I} = \{1, 2, \ldots, I\}$), which are deployed on the seabed to monitor the ocean environment (e.g., ocean temperature, salinity, etc.). The position of UWS i is denoted as $\mathbf{v}_i = (x_i, y_i, z_i)$. UWSs can perceive oceanic data via ultrasonic radar sensing. We use the radar information rate to evaluate the sensing performance, which can be regarded as the data information rate of marine communication system. Based on [10], the radar information rate of UWS i can be expressed as

$$r_i^{\text{inf}} = \frac{\gamma}{2\Gamma} \log_2 \left(1 + 2\Gamma w_B \text{SNR}\right), \forall i \in \mathcal{I}, \tag{1}$$

where parameter γ is the radar duty factor. Parameter Γ denotes the radar pulse duration. w_B means the bandwidth of acoustic communication. $\text{SNR} = \frac{p_i^{\text{rad}} g^{\text{tar}} \sigma_{\text{pre}}^2 \hat{\chi}^2 w_B^2}{n^2}$ is the signal-to-noise ratio (SNR) for the radar echoes of radar target. p_i^{rad} denotes UWS i's radar sensing power. g^{tar} is the echo signal of radar. σ_{pre}^2 means the variance of the predicted radar return. $\hat{\chi}$ denotes a flat spectral shape. The sensing data within the duration τ can be give by $S_i^{\text{tot}} = r_i^{\text{inf}} \tau$.

A group of UUVs (denoted by $\mathcal{M} = \{1, 2, \ldots, M\}$) equipped with computing capacities can receive data from UWSs for processing. The position of UUV m is denoted by $\mathbf{v}_m = (x_m, y_m, z_m)$. We use $\alpha_{i,m}$ $(0 \le \alpha_{i,m} \le 1)$ to denote the offloading ratio of UWS i to UUV m. UUV m's processing workload can be expressed as $\alpha_{i,m} S_i^{\text{tot}}$. SNs (denoted by $\mathcal{N} = \{1, 2, \ldots, N\}$) are deployed on the sea surface to receive data from UWSs. We use $\mathbf{v}_n = (x_n, y_n, z_n)$ to denote the position of SN n. We consider that each SN equipped with computing capacity can execute task computing. The offloading workload for data processing in SN n is $(1 - \alpha_{i,m}) S_i^{\text{tot}}$.

B. Transmission Model

In underwater acoustic transmission, according to [11], the underwater acoustic communication model between UWS i and UUV m can be expressed as

$$\varphi(d_{i,m}, f) = d_{i,m}^{\pi} \varpi(f)^{\frac{d_{i,m}}{1000}}, \forall i \in \mathcal{I}, \forall m \in \mathcal{M}, \tag{2}$$

where $\varphi(d_{i,m}, f)$ is the attenuation of underwater acoustic signal. $\varpi(f)$ denotes the absorption coefficient. f is the central frequency of the acoustic signal. $d_{i,m}$ denotes the distance between UWS i and UUV m. π means a spreading factor. Based on [12], the absorption coefficient can be expressed as

$$\varpi(f) = 0.11 \frac{f^2}{1+f^2} + 44 \frac{f^2}{4100+f^2} + 2.75 e^{-4} f^2 + 0.003. \tag{3}$$

We can express the distance between UWS i and UUV m as

$$d_{i,m} = \sqrt{(x_i - x_m)^2 + (y_i - y_m)^2 + (z_i - z_m)^2}, \quad \forall i \in \mathcal{I}, \forall m \in \mathcal{M}. \tag{4}$$

The underwater acoustic channel gain between UWS i and UUV m can be denoted as

$$g_{i,m} = \frac{1}{\varphi(d_{i,m}, f) n_B w_B}, \forall i \in \mathcal{I}, \forall m \in \mathcal{M}, \tag{5}$$

where parameter n_B means the ocean noise power. We consider that UWS i adopts NOMA to offload workloads to UUV m and SN n. We use $p_{i,m}$ to denote the transmission power of UWS i to UUV m. The transmission rate from UWS i to UUV m can be denoted as

$$r_{i,m} = w_B \log_2 \left(1 + \frac{p_{i,m} g_{i,m}}{n_B}\right), \forall i \in \mathcal{I}, \forall m \in \mathcal{M}, \tag{6}$$

and the transmission rate from UWS i to SN n can be expressed as

$$r_{i,n} = w_B \log_2 \left(1 + \frac{p_{i,n} g_{i,n}}{p_{i,m} g_{i,m} + n_B}\right), \forall i \in \mathcal{I}, \forall n \in \mathcal{N}. \tag{7}$$

We use t^{up} to denote the NOMA transmission duration, it means that UWS i should complete sending its workloads within duration t^{up}. We have the following conditions

$$r_{i,m}t^{\mathrm{up}} = \alpha_{i,m}S_i^{\mathrm{tot}}, \forall i \in \mathcal{I}, \forall m \in \mathcal{M}, \tag{8}$$

$$r_{i,n}t^{\mathrm{up}} = \left(1-\alpha_{i,m}\right)S_i^{\mathrm{tot}}, \forall i \in \mathcal{I}, \forall n \in \mathcal{N}. \tag{9}$$

Therefore, the required minimum NOMA transmission power of UWS i for transmission can be expressed as

$$p_i = n_B\left(\frac{1}{g_{i,m}} - \frac{1}{g_{i,n}}\right)2^{\frac{\alpha_{i,m}S_i^{\mathrm{tot}}}{t^{\mathrm{up}}w_B}} + \frac{n_B}{g_{i,n}}2^{\frac{S_i^{\mathrm{tot}}}{t^{\mathrm{up}}w_B}} - \frac{n_B}{g_{i,m}}, \quad \forall i \in \mathcal{I}. \tag{10}$$

The energy consumption of offloading workloads to UUV m and SN n can be expressed as

$$E_i^{\mathrm{NOMA}} = p_i t^{\mathrm{up}}, \forall i \in \mathcal{I}. \tag{11}$$

C. Multi-access Computation Offloading Model

The workloads can be offloaded to UUV and SN for processing. The local computing latency by UUV m can be denoted as

$$t_m^{\mathrm{loc}} = c_m\frac{\alpha_{i,m}S_i^{\mathrm{tot}}}{\mu_m}, \forall m \in \mathcal{M}, \tag{12}$$

where parameter c_m denotes the number of CPU cycles for processing one bit of data in UUV m. Parameter μ_m means the processing capability of UUV m in CPU cycles per second. We can express the energy consumption of UUV m for local computing as

$$E_m^{\mathrm{loc}} = \sigma_m\mu_m^3 t_m^{\mathrm{loc}} = \sigma_m\mu_m^2 c_m\alpha_{i,m}S_i^{\mathrm{tot}}, \forall m \in \mathcal{M}, \tag{13}$$

where parameter σ_m denotes the power consumption coefficient of UUV m.

Similarly, the local computing latency by SN n can be expressed as

$$t_n^{\mathrm{loc}} = c_n\frac{\left(1-\alpha_{i,m}\right)S_i^{\mathrm{tot}}}{\mu_n}, \forall n \in \mathcal{N}, \tag{14}$$

where parameter c_n is the number of CPU cycles for processing one bit of data in SN n. Parameter μ_n expresses the processing capability of SN n in CPU cycles per second. The energy consumption of SN n for local computing can be calculated by

$$E_n^{\mathrm{loc}} = \sigma_n\mu_n^3 t_n^{\mathrm{loc}} = \sigma_n\mu_n^2 c_n\left(1-\alpha_{i,m}\right)S_i^{\mathrm{tot}}, \forall n \in \mathcal{N}, \tag{15}$$

where parameter σ_n means the power consumption coefficient of SN n.

D. Utility Model

Based on the above analysis, the overall latency for completing UWS i's workloads can be expressed as

$$t_i^{\mathrm{ove}} = t^{\mathrm{up}} + \max\left\{t_m^{\mathrm{loc}}, t_n^{\mathrm{loc}}\right\}, \forall i \in \mathcal{I}. \tag{16}$$

(i) Utility function of UWS. The utility function of UWS i is defined as the difference between the satisfaction degree for completing its workloads, the cost for offloading the workloads, and the price paid to UUN and SN

$$\mathcal{U}_i\left(\alpha_{i,m}\right) = \underbrace{\lambda_i\log_2\left(t_i^{\mathrm{loc}} - t_i^{\mathrm{ove}}\right)}_{\text{satisfaction degree}} - \underbrace{\chi_i E_i^{\mathrm{NOMA}}}_{\text{cost}} - \underbrace{\varsigma_m^{\mathrm{price}}\alpha_{i,m}S_i^{\mathrm{tot}}}_{\text{price paid to UUV}} - \underbrace{\varsigma_n^{\mathrm{price}}\left(1-\alpha_{i,m}\right)S_i^{\mathrm{tot}}}_{\text{price paid to SN}}, \forall i \in \mathcal{I}. \tag{17}$$

The satisfaction degree means the difference between the local computing delay t_i^{loc} and the overall latency t_i^{ove}. If the time difference (i.e., $t_i^{\mathrm{loc}} - t_i^{\mathrm{ove}}$) is high, UWS i may have high satisfaction degree for offloading processing. Otherwise, the satisfaction degree is low. λ_i indicates the adjustment parameter of satisfaction degree regarding the computing delay. χ_i means the cost parameter of UWS i regarding the energy consumption of NOMA transmission. $\varsigma_m^{\mathrm{price}}$ and $\varsigma_n^{\mathrm{price}}$ denote the unit price for processing workloads by UUV m and SN n, respectively. The local computing delay of UWS i can be expressed as $t_i^{\mathrm{loc}} = c_i\frac{S_i^{\mathrm{tot}}}{\mu_i}$. Here, parameter c_i denotes the number of CPU cycles for processing one bit of data by UWS i. μ_i denotes the processing capability of UWS i in CPU cycles per second.

(ii) Utility function of UUV. UUV is responsible for assisting in computing workloads, and its strategy is to determine the price (i.e., $\varsigma_m^{\mathrm{price}}$) for obtaining rewards. The utility function of UUV m can be defined as the difference between the rewards obtained from UWS and the cost for computing workloads

$$\mathcal{U}_m\left(\varsigma_m^{\mathrm{price}}\right) = \underbrace{\varsigma_m^{\mathrm{price}}\alpha_{i,m}S_i^{\mathrm{tot}}}_{\text{rewards from UWS}} - \underbrace{\chi_m E_m^{\mathrm{loc}}}_{\text{cost}}, \forall m \in \mathcal{M}, \tag{18}$$

where χ_m denotes the cost parameter of UUV m regarding the energy consumption of local computing.

(iii) Utility function of SN. SN can process workload locally, the strategy of SN n is to decide the price of local computing (i.e., $\varsigma_n^{\mathrm{price}}$). The utility function of SN n can be expressed as the difference between the rewards obtained from UWS and the cost for local computing

$$\mathcal{U}_n\left(\varsigma_n^{\mathrm{price}}\right) = \underbrace{\varsigma_n^{\mathrm{price}}\left(1-\alpha_{i,m}\right)S_i^{\mathrm{tot}}}_{\text{rewards from UWS}} - \underbrace{\chi_n E_n^{\mathrm{loc}}}_{\text{cost}}, \forall n \in \mathcal{N}, \tag{19}$$

where χ_n indicates the cost parameter of SN n regarding the energy consumption of local computing.

E. Problem Formulation

Based on the above analysis, we aim to maximize the utility of each participant. For UWS i, the optimization problem can be expressed as ("UM" means "Utility Maximization")

$$\begin{aligned}
\text{(UM-}i\text{)}: \quad & \max \mathcal{U}_i\left(\alpha_{i,m}\right) \\
\text{subject to}: \quad & 0 \le \alpha_{i,m} \le 1, \forall i \in \mathcal{I}, \forall m \in \mathcal{M}, && (20)\\
& 0 \le t^{\mathrm{up}} \le t^{\max}, && (21)\\
& 0 \le p_i \le p^{\max}, \forall i \in \mathcal{I}, && (22)\\
& 0 \le E_i^{\mathrm{NOMA}} \le E_i^{\max}, \forall i \in \mathcal{I}, && (23)\\
& 0 \le \mathcal{U}_i\left(\alpha_{i,m}\right), \forall i \in \mathcal{I}, && (24)\\
\text{variables}: \quad & \alpha_{i,m}, \forall i \in \mathcal{I}, \forall m \in \mathcal{M}.
\end{aligned}$$

In Problem (UM-i), constraint (20) means that the offloading workload cannot exceed the maximum data volume. Constraint (21) guarantees that the NOMA transmission time cannot exceed the maximum $t^{\max}$. Constraint (22) ensures that UWS i's NOMA transmission power cannot exceed the maximum $p^{\max}$. Constraint (23) guarantees that the energy consumption of UWS i cannot exceed the maximum $E_i^{\max}$. Constraint (24) guarantees that the utility of UWS i should be higher than zero.

For UUV m, the optimization problem can be expressed as

$$\begin{aligned} \text{(UM-}m\text{)}: \quad & \max \mathcal{U}_m\left(\varsigma_m^{\text{price}}\right) \\ \text{subject to}: \quad & 0 \leq \varsigma_m^{\text{price}} \leq \varsigma_m^{\max}, \forall m \in \mathcal{M}, && (25) \\ & 0 \leq E_m^{\text{loc}} \leq E_m^{\max}, \forall m \in \mathcal{M}, && (26) \\ & 0 \leq \mathcal{U}_m\left(\varsigma_m^{\text{price}}\right), \forall m \in \mathcal{M}, && (27) \\ \text{variables}: \quad & \varsigma_m^{\text{price}}, \forall m \in \mathcal{M}. \end{aligned}$$

In Problem (UM-m), constraint (25) guarantees that the price determined by UUV m cannot exceed the maximum $\varsigma_m^{\max}$. Constraint (26) ensures that the local computing consumption of UUV m cannot exceed the maximum $E_m^{\max}$. Constraint (27) guarantees that UUV m can obtain a positive reward.

For SN n, the optimization problem can be expressed as

$$\begin{aligned} \text{(UM-}n\text{)}: \quad & \max \mathcal{U}_n\left(\varsigma_n^{\text{price}}\right) \\ \text{subject to}: \quad & 0 \leq \varsigma_n^{\text{price}} \leq \varsigma_n^{\max}, \forall n \in \mathcal{N}, && (28) \\ & 0 \leq E_n^{\text{loc}} \leq E_n^{\max}, \forall n \in \mathcal{N}, && (29) \\ & 0 \leq \mathcal{U}_n\left(\varsigma_n^{\text{price}}\right), \forall n \in \mathcal{N}, && (30) \\ \text{variables}: \quad & \varsigma_n^{\text{price}}, \forall n \in \mathcal{N}. \end{aligned}$$

In Problem (UM-n), constraint (28) means that the price determined by SN n cannot exceed the maximum $\varsigma_n^{\max}$. Constraint (29) guarantee that SN n's local computing consumption cannot exceed the maximum $E_n^{\max}$. Constraint (30) ensures that SN n can obtain a positive profit.

III. Proposed Algorithms to Solve the Formulated Problems

Based on the utility modeling, we model the transaction process among UWSs, UUVs and SNs as the Stackelberg game, in which UUV and SN are the game leaders to determine their prices for processing the workloads. After obtaining the above price strategies, UWS acts as the follower to make decision for offloading ratio, with the objective of maximizing its profits. Moreover, the leaders (i.e., UUV and SN) compete with each other for obtaining more profits from UWS, i.e., the interaction between UUV and SN is non-cooperative.

A. Strategy Analysis for Problem (UM-i)

Given the price strategies of UUV m and SN n (i.e., $\varsigma_m^{\text{price}}, \varsigma_n^{\text{price}}$) in advance, we first analyze the offloading ratio of UWS i (i.e., $\alpha_{i,m}$) to maximize its utility. Base on the objective function of Problem (UM-i), we consider two possible cases.

Case 1: The total latency is comprised of the NOMA transmission duration and the local computing latency of UUV m, i.e., $t_i^{\text{ove}} = t^{\text{up}} + t_m^{\text{loc}}$. The second derivative of $\mathcal{U}_i\left(\alpha_{i,m}\right)$ with respect to $\alpha_{i,m}$ can be expressed as

$$\begin{aligned} \frac{\partial^2 \mathcal{U}_i\left(\alpha_{i,m}\right)}{\partial \alpha_{i,m}^2} = & -\frac{\lambda_i}{\ln 2}\left(\frac{c_m S_i^{\text{tot}}}{\mu_m}\right)^2 \frac{1}{\left(c_m \frac{\alpha_{i,m} S_i^{\text{tot}}}{\mu_m} + t^{\text{up}} - t_i^{\text{loc}}\right)^2} \\ & - \frac{\chi_i n_B}{t^{\text{up}}}\left(\frac{1}{g_{i,m}} - \frac{1}{g_{i,n}}\right) 2^{\frac{\alpha_{i,m} S_i^{\text{tot}}}{t^{\text{up}} w_B}} \left(\frac{S_i^{\text{tot}} \ln 2}{w_B}\right)^2. \end{aligned} \tag{31}$$

It can be identified that $\frac{\partial^2 \mathcal{U}_i(\alpha_{i,m})}{\partial \alpha_{i,m}^2} < 0$, which leads to that $\mathcal{U}_i\left(\alpha_{i,m}\right)$ is strictly concave with respect to $\alpha_{i,m}$, and the first derivative of $\mathcal{U}_i\left(\alpha_{i,m}\right)$ is decreasing with $\alpha_{i,m}$. We calculate the limitation under the lower bound as follows

$$\lim_{\alpha_{i,m} \to 0} \frac{\partial \mathcal{U}_i\left(\alpha_{i,m}\right)}{\partial \alpha_{i,m}} = \left[\left(\varsigma_n^{\text{price}} - \varsigma_m^{\text{price}}\right) - \Delta\right] S_i^{\text{tot}}, \tag{32}$$

where

$$\Delta = \frac{\lambda_i c_m}{\mu_m\left(t_i^{\text{loc}} - t^{\text{up}}\right) \ln 2} + \frac{\chi_i n_B \ln 2}{w_B}\left(\frac{1}{g_{i,m}} - \frac{1}{g_{i,n}}\right). \tag{33}$$

We have the following two conditions:

- If the price difference (i.e., $\varsigma_n^{\text{price}} - \varsigma_m^{\text{price}}$) between SN n and UUV m is lower than Δ, it means that the value of $\mathcal{U}_i(\alpha_{i,m})$ is decreasing with $\alpha_{i,m}$. Therefore, UWS i will not offload its workload to UUV m, i.e., $\alpha_{i,m}^* = 0$.
- If the price difference between SN n and UUV m is higher than Δ, we can obtain $\lim_{\alpha_{i,m} \to 0} \frac{\partial \mathcal{U}_i(\alpha_{i,m})}{\partial \alpha_{i,m}} > 0$ and $\lim_{\alpha_{i,m} \to \infty} \frac{\partial \mathcal{U}_i(\alpha_{i,m})}{\partial \alpha_{i,m}} < 0$. Therefore, there must exit an $\alpha_{i,m}^{\text{exit}}$ that makes $\frac{\partial \mathcal{U}_i(\alpha_{i,m}^{\text{exit}})}{\partial \alpha_{i,m}^{\text{exit}}} = 0$ while maximizing $\mathcal{U}_i(\alpha_{i,m}^{\text{exit}})$. The monotonic feature of the first derivative of $U_i(\alpha_{i,m})$ with respect to $\alpha_{i,m}$ enables us to obtain the value of $\alpha_{i,m}^{\text{exit}}$ via a bisection-search method, which is shown in Algorithm 1.

Based on the above analysis, the optimal offloading strategy for UWS i in Case 1 can be expressed as

$$\alpha_{i,m}^* = \begin{cases} 0, & \varsigma_n^{\text{price}} - \varsigma_m^{\text{price}} < \Delta, \\ \min\left\{1, \alpha_{i,m}^{\text{exit}}\right\}, & \varsigma_n^{\text{price}} - \varsigma_m^{\text{price}} > \Delta. \end{cases} \tag{34}$$

Case 2: The total latency consists of the NOMA transmission duration and the local computing latency of SN n, i.e., $t_i^{\text{ove}} = t^{\text{up}} + t_n^{\text{loc}}$. We can express the second derivative of $\mathcal{U}_i\left(\alpha_{i,m}\right)$ with respect to $\alpha_{i,m}$ as

$$\begin{aligned} \frac{\partial^2 \mathcal{U}_i\left(\alpha_{i,m}\right)}{\partial \alpha_{i,m}^2} = & -\frac{\lambda_i}{\ln 2} \frac{\left(\frac{c_n S_i^{\text{tot}}}{\mu_n}\right)^2}{\left(t_i^{\text{loc}} - t^{\text{up}} - c_n \frac{(1-\alpha_{i,m}) S_i^{\text{tot}}}{\mu_n}\right)^2} \\ & - \frac{\chi_i n_B}{t^{\text{up}}}\left(\frac{1}{g_{i,m}} - \frac{1}{g_{i,n}}\right) 2^{\frac{\alpha_{i,m} S_i^{\text{tot}}}{t^{\text{up}} w_B}} \left(\frac{S_i^{\text{tot}} \ln 2}{w_B}\right)^2. \end{aligned} \tag{35}$$

We can identify that $\frac{\partial^2 \mathcal{U}_i(\alpha_{i,m})}{\partial \alpha_{i,m}^2} < 0$. $\mathcal{U}_i(\alpha_{i,m})$ is strictly concave with respect to $\alpha_{i,m}$, and the first derivative of $\mathcal{U}_i(\alpha_{i,m})$

Algorithm 1: Proposed algorithm to obtain the offloading ratio $\alpha_{i,m}^{\text{exit}}$

Input: Given the computation-error ι.
Initialization: Set the lower bound as $\alpha_{i,m}^{\text{lb}}=0$, set the upper bound as $\alpha_{i,m}^{\text{ub}}=\alpha_{i,m}^{\max}$.
while $\iota<|\alpha_{i,m}^{\text{ub}}-\alpha_{i,m}^{\text{lb}}|$ **do**
    Calculate the current value of $\alpha_{i,m}^{\text{cur}}=\frac{1}{2}(\alpha_{i,m}^{\text{lb}}+\alpha_{i,m}^{\text{ub}})$.
    Calculate the value of $\frac{\partial\mathcal{U}_i(\alpha_{i,m}^{\text{cur}})}{\partial\alpha_{i,m}^{\text{cur}}}$.
    if $\frac{\partial\mathcal{U}_i(\alpha_{i,m}^{\text{cur}})}{\partial\alpha_{i,m}^{\text{cur}}}<0$ **then**
        Set the upper bound as $\alpha_{i,m}^{\text{ub}}=\alpha_{i,m}^{\text{cur}}$.
    else
        Set the lower bound as $\alpha_{i,m}^{\text{lb}}=\alpha_{i,m}^{\text{cur}}$.
    end if
end while
Output: The optimal value $\alpha_{i,m}^{*}=\alpha_{i,m}^{\text{cur}}$ and the corresponding value of $\mathcal{U}_i(\alpha_{i,m}^{*})$.

Algorithm 2: Proposed algorithm to obtain the price strategy $\varsigma_m^{\text{price}}$

Input: Given the price strategy $\varsigma_n^{\text{price}}$, and the step size ℓ.
Initialize: Set the lower bound as $\varsigma_m^{\text{lb}}=0$, set the upper bound as $\varsigma_m^{\text{ub}}=\varsigma_m^{\max}$, set the current best value $\mathcal{U}_m^{\text{CBV}}$ as a very small number, set the current best solution $\varsigma_m^{\text{CBS}}=\emptyset$.
while $\varsigma_m^{\text{lb}}<\varsigma_m^{\max}$ **do**
    Invoke Algorithm 1 to calculate the value $\alpha_{i,m}^{\text{exit}}$ and obtain the solution $\alpha_{i,m}^{*}$.
    if $\mathcal{U}_m^{\text{CBV}}<\mathcal{U}_m(\alpha_{i,m}^{*})$ **then**
        Update the current best value as $\mathcal{U}_m^{\text{CBV}}\leftarrow\mathcal{U}_m(\alpha_{i,m}^{*})$.
        Update the current best solution as $\varsigma_m^{\text{CBS}}\leftarrow\varsigma_m^{\text{lb}}$.
    end if
    Update the step size as $\varsigma_m^{\text{lb}}\leftarrow\varsigma_m^{\text{lb}}+\ell$.
end while
Output: The optimal price strategy $\varsigma_m^{\text{price}*}=\varsigma_m^{\text{CBS}}$ and the corresponding value of $\mathcal{U}_m(\alpha_{i,m}^{*})=\mathcal{U}_m^{\text{CBV}}$.

is decreasing with $\alpha_{i,m}$. We can obtain the limitation under the lower bound as follows

$$\lim_{\alpha_{i,m}\to 0}\frac{\partial\mathcal{U}_i\left(\alpha_{i,m}\right)}{\partial\alpha_{i,m}}=\left[\left(\varsigma_n^{\text{price}}-\varsigma_m^{\text{price}}\right)-\nabla\right]S_i^{\text{tot}},\tag{36}$$

where

$$\nabla=\frac{\chi_i n_B\ln 2}{w_B}\left(\frac{1}{g_{i,m}}-\frac{1}{g_{i,n}}\right)-\frac{c_n\lambda_i}{\mu_n\left(t_i^{\text{loc}}-t^{\text{up}}-c_n\frac{S_i^{\text{tot}}}{\mu_n}\right)\ln 2}.\tag{37}$$

We consider two conditions as follows:

- If the price difference (i.e., $\varsigma_n^{\text{price}}-\varsigma_m^{\text{price}}$) between SN n and UUV m is lower than ∇, it can be identified that the value of $\mathcal{U}_i(\alpha_{i,m})$ is decreasing with $\alpha_{i,m}$. Thus, UWS i will not offload its workload to UUV m, i.e., $\alpha_{i,m}^{*}=0$.
- If the price difference between SN n and UUV m is higher than ∇, we can obtain that $\lim_{\alpha_{i,m}\to 0}\frac{\partial\mathcal{U}_i(\alpha_{i,m})}{\partial\alpha_{i,m}}>0$ and $\lim_{\alpha_{i,m}\to\infty}\frac{\partial\mathcal{U}_i(\alpha_{i,m})}{\partial\alpha_{i,m}}<0$. Thus, there must exist an $\alpha_{i,m}^{\text{exit}}$ that makes $\frac{\partial\mathcal{U}_i(\alpha_{i,m}^{\text{exit}})}{\partial\alpha_{i,m}^{\text{exit}}}=0$ and maximizes $\mathcal{U}_i(\alpha_{i,m}^{\text{exit}})$. $\alpha_{i,m}^{\text{exit}}$ can be derived via a bisection-search method (The detail is similar to Algorithm 1) based on the monotonic feature of the first derivative of $\mathcal{U}_i(\alpha_{i,m})$ with respect to $\alpha_{i,m}$.

According to the above analysis, the optimal offloading strategy for UWS i in Case 2 can be expressed as

$$\alpha_{i,m}^{*}=\begin{cases}0, & \varsigma_n^{\text{price}}-\varsigma_m^{\text{price}}<\nabla,\\ \min\left\{1,\alpha_{i,m}^{\text{exit}}\right\}, & \varsigma_n^{\text{price}}-\varsigma_m^{\text{price}}>\nabla.\end{cases}\tag{38}$$

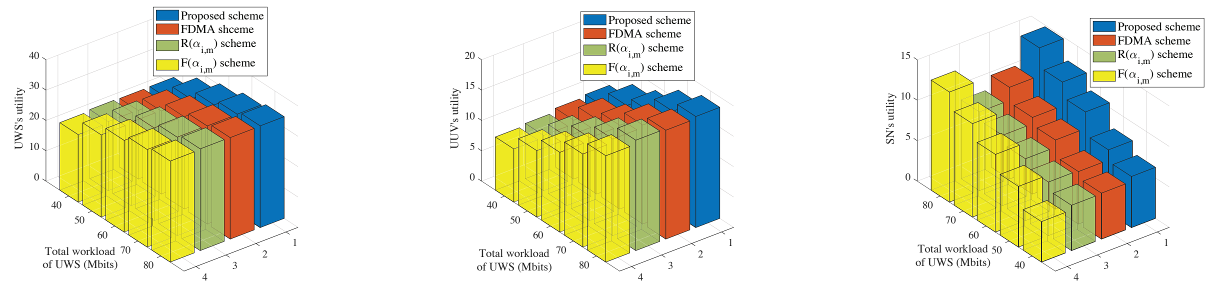
B. Strategy Analysis for Problem (UM-m) and Problem (UM-n)

After obtaining the offloading strategy of UWS i, we then analyze Problem (UM-m) and Problem (UM-n) to derive the price strategies of UUV m and SN n. Since the strategies of UUV and SN are influenced by each other, we adopt a noncooperative strategy to model the competition between UUV and SN, in which the solution is the Stackelberg equilibrium. Due to the fact that the offloading strategy of UWS (i.e., $\alpha_{i,m}^{*}$) is obtained through the bisection-search algorithm, we cannot mathematically express the objective functions of Problem (UM-m) and Problem (UM-n). We first analyze the price strategy of UUV m. An important feature is that the value of $\varsigma_m^{\text{price}}$ falls within the given interval $[0,\varsigma_m^{\max}]$ based on constraint (25). This feature enables us to execute a linear-search with a small step size to numerically obtain the optimal solution of UUV m (i.e., $\varsigma_m^{\text{price}*}$). Specifically, when the price strategy (i.e., $\varsigma_n^{\text{price}}$) of SN n is given, Algorithm 2 shows the linear-search algorithm to obtain the value of $\varsigma_m^{\text{price}}$. Similar to the analysis of Problem (UM-m), we can also adopt Algorithm 1 and Algorithm 2 to solve Problem (UM-n) and obtain the optimal price strategy $\varsigma_n^{\text{price}*}$ of SN n under the given value of $\varsigma_m^{\text{price}}$.

IV. Numerical Results

In the performance evaluation, we simulate the marine environment as a cuboid space with the size of 200m $\times$ 200m$\times$100m. We consider that one UWS collects oceanic data and then uploads its workloads to UUV and SN via NOMA transmission. The positions of UWS, UUV and SN are set as $(100,150,-100)$ m, $(50,-150,-50)$ m and $(10,-100,0)$ m, respectively. The total workload of UWS i is set as $S_i^{\text{tot}}=$ 50Mbits. The number of CPU cycles for processing one bit of data by UWS is set to 1×10^4cycles. The processing capability of UWS in CPU cycles per second is set to 1×10^5 cycles/s. Other parameters used in the simulation are summarized in Table I. We compare the utility performance of the proposed scheme with other benchmark schemes as follows:

- *Frequency division multiple access (FDMA) scheme:* In this scheme, UWS uploads its workloads to UUV and SN via FDMA transmission, and the bandwidth is evenly allocated to UUV and SN.
- *Fixed offloading scheme:* In this scheme, the offloading ratio $\alpha_{i,m}$ is fixed at a determined value when UWS i uploads workloads to UUV m and SN n via NOMA transmission.
- *Random offloading scheme:* In this scheme, the offloading ratio $\alpha_{i,m}$ is randomly determined when UWS i uploads workloads to UUV m and SN n via NOMA transmission.



(a) Utility of UWS

(b) Utility of UUV

(c) Utility of SN

Fig. 2: Performance comparison of our proposed scheme for UWS, UUV and SN by changing the total workloads.

TABLE I: Parameters used in our simulations

Parameters	**Values**
The central frequency of the acoustic signal, f	1kHz
The spreading factor, π	1.5
The channel bandwidth of underwater acoustic transmission, w_B	1kHz
The ocean noise power, n_B	1×10^{-4}dBm
The NOMA transmission duration in underwater, t^{up}	0.5s
The number of CPU cycles for processing one bit of data in UUV m, c_m	1×10^{4}cycles
The processing capability of UUV m in CPU cycles per second, μ_m	1×10^{6}cycles/s
The power consumption coefficient of UUV m, σ_m	1×10^{-20}
The number of CPU cycles for processing one bit of data in SN n, c_n	10^{4}cycles
The processing capability of SN n in CPU cycles per second, μ_n	4×10^{6}cycles/s
The power consumption coefficient of SN n, σ_n	1.25×10^{-22}

Fig. 2 shows the utility comparison of our proposed Stackelberg game for UWS, UUV and SN by changing the total workloads of UWS i. It can be obtained that with the increase of the total workloads of UWS (i.e., S_i^{tot}), the utilities of UWS i, UUV m and SN n are increasing, and the proposed scheme outperforms other benchmark schemes. The reasons are as follows. When increasing UWS i's workload for offloading, the satisfaction degree of UWS i will be high, which brings high utility to UWS i. Moreover, both UUV m and SN n can obtain larger rewards from UWS, which increase the utilities of UUV m and SN n. Moreover, the proposed scheme can achieve the best performance for maximizing UWS i's, UUV m's and SN n's utilities due to the fact that the proposed Stackelberg game takes into consideration of the optimal offloading ratio $\alpha_{i,m}$, and the optimal price strategies of $\varsigma_m^{\text{price}}$ and $\varsigma_n^{\text{price}}$.

V. Conclusion

In this paper, we have proposed an integrated sensing and multi-access computing offloading scheme in smart oceans. In data sensing phase, we exploited the radar information rate to evaluate the sensing performance of UWS. In data offloading phase, we proposed a multi-access computation offloading scheme in underwater transmission, in which the UWS offloads its workloads to UUV and SN via NOMA transmission. We designed the utility function of each party to model the offloading process among UWS, UUV and SN as a Stackelberg game, with the objective of optimizing UWS's offloading strategy, UUV's and SN's price strategies while maximizing their profits. Finally, we provided numerical results to validate the efficiency and effectiveness of the proposed scheme.

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