Task Offloading Strategy for Ocean Based on MEC

DOI : 10.36909/jer.ICCSCT.19475

Xinxiu jiang[1], Yongtao yu[2], Peng hu[3], Hongwei ding[1*], Zhijun yang[1]

1 School of Information, Yunnan University, Kunming, 650500, China
2 Yunnan Key Laboratory of Smart City and Cyberspace Security, Yuxi , 653100, China
3 Research and Development Department, Youbei Technology Co., LTD, Kunming, 650000, China

* Corresponding Author: dhw1964@163.com

ABSTRACT

With the development of marine business, the diversification of marine business has produced more and more delay-sensitive and computing-intensive tasks, and the demand for marine communication is becoming more and more obvious. Establish a task offloading model between ship users, select offload nodes based on the connectivity probability between ship users, in order to alleviate the problem of data congestion during transmission, use orthogonal frequency division multiple access technology to divide channels, and propose subtasks and Algorithm for subchannel matching. Ship users use solar energy to supply energy, and propose a penalty strategy for insufficient energy collection and a penalty strategy for task delay, so that the system can minimize the actual energy consumption and establish an objective function under the condition of satisfying the delay constraint. The local transmit power is optimized, and the gray wolf optimization algorithm is improved to obtain a better data offloading ratio. The simulation results of EdgeCloudSim show that, compared with other methods, the proposed method can achieve the best performance while guaranteeing the delay.

Keywords: Marine communication; MEC; Compute offload; EdgeCloudSim

INTRODUCTION

With the development of the communication network, the mobile communication network(Zhao et al.,2019), as a key communication carrier, has realized the development from 1G to 6G, which has brought about great changes in people's lives. However, due to the harsh marine environment, the communication network is easily affected by environmental factors, and the deployment of marine infrastructure is dangerous and complicated, the development of marine networks is limited by many factors in the ocean. The ocean is rich in resources and is a huge treasure house of resources, a transport channel for world trade, and a stage for international competition. The ocean has become a system of military, political and economic influences. In order to meet the requirements of increasingly frequent maritime activities, a large number of intelligent devices have been widely used in the fields of marine environment monitoring, marine transportation, marine exploration and marine rescue, resulting in more and more computing-intensive and delay-sensitive tasks, which are urgently needed. A communication and computing architecture provides storage, communication and computing services for user terminals to meet the needs of maritime mission execution. Mobile edge computing emerges in a new way, expanding the computing capabilities of end users to a certain extent. Due to the limited energy of end users, it is difficult to provide services brought by the mobile edge computing (MEC) (Xie et al., 2018 & Mao et al)system for a long time, and in the special environment of the ocean, the transmission of energy is a huge challenge.

1.1 Motivation

Most of the human development of the ocean is concentrated in the near-coastal area, resulting in different requirements for computing nodes in the offshore and far-sea areas. The execution of the task is realized based on the terrestrial communication system. In the distant sea area, the ship is far away from the coastal base station, the signal coverage is limited, it is difficult for ship users to connect to the base station to offload tasks, and the resources are limited, which is prone to problems such as service interruption or task loss. At the same time, the energy resources of ships in the ocean are limited, and the transmission is difficult, therefore, a task offloading model with energy harvesting is established to improve the performance of the system.

1.2 Contribution

The main contributions of this paper are as follows:

- Aiming at the task offloading optimization problem, this paper selects the task offloading node based on the connectivity probability between the ship user to be offloaded and the idle ship user. When the connectivity probability meets the communication threshold, it is used as the candidate node, and the ship user selects the node with the largest connectivity probability among the candidate nodes. as an uninstall node.
- In order to alleviate the problem of data blocking, orthogonal frequency division multiple access technology is used to divide the transmission channel, and a matching algorithm between subtasks and subchannels is proposed to further shorten the time delay of task processing.
- In order to solve the problem of energy supply for ship users, the solar energy collection technology is proposed, and the ship's backup battery is used as energy supplement to ensure the continuity of ship users' task processing.
- Propose a penalty strategy for insufficient energy harvesting and a penalty strategy for too long task delay, so that the ship user's task execution can minimize the actual energy consumption while ensuring the delay.

1.3 Paper Organization

The rest of the work of this paper is arranged as follows. The related work of maritime communication is reviewed in Chapter 2. The model of the system is described in Chapter 3. The problem-solving process is described in Chapter 4, and the experimental results are discussed in Chapter 5. The full text is summarized in Chapter 6.

THERMOPLASTIC COMPOSITE PIPES

As data-driven marine services become more and more important, this puts forward higher requirements for marine communications, including the construction of transmission networks and cloud systems, interface devices and mobile devices, and strategies for task processing. The emergence of MEC provides the possibility to solve problems such as long network delay and lack of terminal computing resources.

In the context of mobile edge computing, (Zeng et al., 2020) considered the fusion of edge computing, network control, and storage into the edge network to achieve efficient resource allocation and reduce redundant data transmission, and optimized tasks using an optimal response offloading algorithm.

In order to be able to process marine data cost-effectively, (Yang et al., 2019) firstly formulated the offloading strategy in the first stage, and decided the processor for the ship user's task processing. In the second stage, the optimization strategy of the combination of edge cloud and central cloud was proposed according to the task attributes.

In the (Yang et al., 2018) cooperative edges were added to the cloud and edge to improve the efficiency of cooperative edge task scheduling, and an improved co-evolutionary algorithm was used to obtain optimal performance.

(Wang et al., 2020) proposed a marine broadband MEC model based on OFDM. The server on the surface provided computing services for UAVs performing monitoring tasks. With the goal of minimizing the energy consumption of UAVs, a task scheduling and offloading strategy was established jointly with transmit power.

Based on the improved Hungarian algorithm, (Yang et al., 2018) taked the ship computing task problem at the terminal as the background, considered the situation of different weights, and builded a mathematical model with the goal of minimizing the energy consumption and delay of ship users.

(Xu et al., 2020) proposed an air-ground-sea collaboration strategy based on edge cloud computing, where satellites and UAVs provided edge computing services and network access in the air, and optimized computing resource allocation and communication problems through deep reinforcement learning to improve the communication and computational efficiency.

In the space-based communication model, (Wang et al., 2018) proposed satellite edge computing, that is, user terminals in areas without MEC coverage can obtain MEC services through satellite links. It designed a dynamic network virtualization technology to integrate network resources, and realized the optimization problem of task scheduling through cooperative computing offloading.

In order to improve user service quality, (Zhang et al., 2019) studied the realization of mobile edge computing technology in satellite and terrestrial networks, designed collaborative computing offload, and optimized the delay and energy consumption of task processing.

In summary, more and more researchers are paying close attention to the application of edge computing in maritime communication networks, and have studied the optimal configuration of computing resources from different perspectives to solve the problems of task processing delay and energy consumption in the network. optimization problem, but there are still some limitations. The maritime mobile edge computing network is in the early stage and still faces many challenges. Therefore, a lot of research is needed to enter a new large-scale application stage in the future.

SYSTEM MODEL

3.1 System Architecture

In far away from the coast scenario, a ship interconnected communication system mode consisting k ship users. Because of its limited resources, the mechanism of offloading node selection based on connectivity probability is proposed, offload the task of the ship user to the idle ship for execution, at the same time, ship users can collect solar energy, and the energy collected in the current time block will be used for task processing in the next time block. Ship communication model is illustrated in Figure 1. The task of each ship user is divided into

N independent sub-tasks, which can be expressed as $\tilde{\tau}_n = (D_{i,n}, a_i)$ $n \in N$, $D_{i,n}$ (bit) is the data size of the sub-task, a_i (cycle/bit) is the average density calculated by the task, Subtasks can be processed locally or offloaded to nearby ships at same times. The transmission channel of task can be divided into $\tilde{N}$ sub-channels by orthogonal frequency division multiple access(OFDMA) technology(Xiong et al., 2012). If a ship user chooses to offload a certain proportion of tasks to other ship users, each subtask is paired with the subchannel one by one to improve the task processing efficiency.

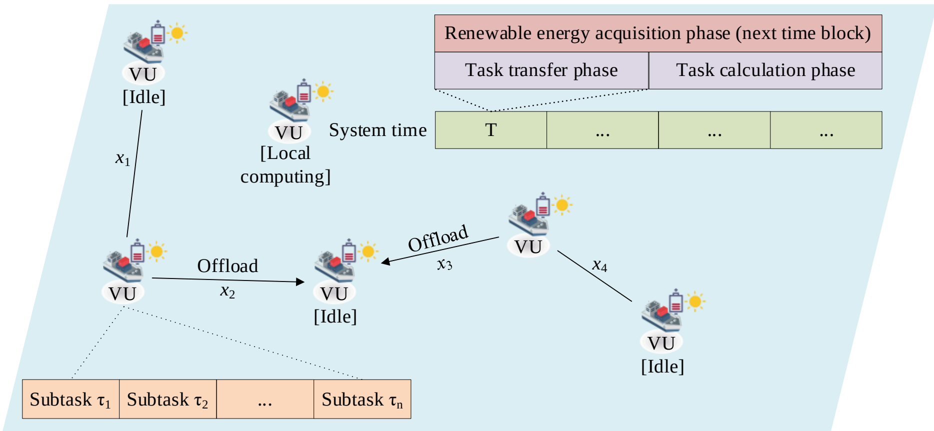

Figure 1. Ship communication model.

3.2 Calculation Model

3.2.1 Node Selection Model

When the ship users are ready to offload the tasks to another ship users for processing, Ship users need to consider the transmission distance between themselves and idle ship users and the remaining computing capacity of idle ship users. Therefore, the connectivity probability between ship users is the key to task transmission. When the connectivity probability is high, the success rate of tasks offloading is high. Assuming that the remaining computing power of idle ships obeys the Poisson distribution, the connectivity probability of ships can be expressed as:

$$P_t' = g_1 \frac{\lambda^{N_m}}{N_m!} e^{-\lambda} + g_2 \frac{x}{r} \tag{1}$$

Where, λ is the average remaining computing power of ship users per unit time, N_m expressed as the number of idle ships, x is the distance between ships, r is the communication coverage radius of the ship itself, $g_1, g_2 \in [0,1], g_1 + g_2 = 1$ is the preference coefficient, when the task is delay-sensitive, the bias is The coefficient selection is biased towards the shorter transmission distance. When the task is computationally intensive, the remaining computing power of the ship to be offloaded is considered to be sufficient. As shown in Figure 2, the ship user object to be offloaded is selected within the coverage of the ship itself.

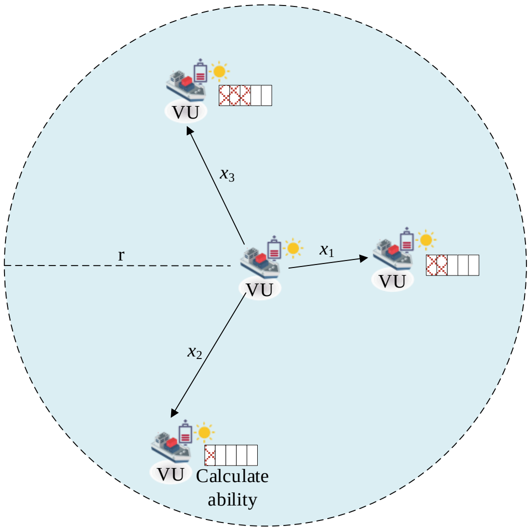

Figure 2. Communication model of adjacent ships.

After the ship user to be offloaded obtains the connection probability with other ship users, it is determined whether the connection probability is greater than the threshold value *P*. If the connection probability is greater than the threshold value, the ship user can be used as an alternative offloading node, and the offloading user selects the candidate offloading node with the highest connection probability. as the best uninstall node for uninstallation.

3.2.2 Local Computing Model

When the task needs to be processed locally, the task is divided into N sub-tasks according to the ship user, each sub-task can be calculated locally according to the task ratio of $\tilde{\mu}_i$, k is the switching coefficient, and the local calculation frequency is set to f_i^l .the working frequency of the CPU is affected by The constraint of the maximum execution frequency $f_i^{\max}$, therefore, the delay and energy consumed by the ship user to process each task are expressed as

$$\tilde{T}_i^l = \sum_{n=1}^{N} \frac{D_{i,n} a_i \tilde{\mu}_i}{f_i^l} \tag{2}$$

$$\tilde{E}_i^l = \sum_{n=1}^{N} k(f_i^l)^2 D_{i,n} a_i \tilde{\mu}_i \tag{3}$$

3.2.3 Channel Model

When the task is offloaded to other ships for processing, due to the instability of the network in the marine scene, the transmission of a large amount of data will be affected by the environment, resulting in the failure of the task transmission. Therefore, the OFDMA technology is used to divide the transmission channel into $\tilde{N}$ sub-channels, so that the sub-task It follows a one-to-one pairing mechanism with sub-channels, and uses variable $H \in (h_{i,n,\tilde{n}}, \forall i, n, \tilde{n})$ for its pairing decision to optimize the delay and energy consumption of the system. The network architecture in the distant sea scene is different from the network architecture on the land in terms of scattering. The sea channel is highly affected by the line-of-sight path and the sea surface reflection path. Therefore, the Rayleigh fading channel model of land communication is difficult to apply to the sea communication scene. This paper adopts the two-path channel model as the transmission model, and the channel gain between the ships can be expressed as:

$$g_{i,\tilde{n}} = (\frac{\lambda}{4\pi x})^2 4\sin^2(\frac{2\pi h_t h_r}{\lambda x}) \tag{4}$$

Where, is the wavelength, x is the communication distance between ships, h_t and h_r are the heights of the transmitting and receiving antennas, respectively. Then the transmission rate of the subtask in subchannel $\tilde{n}$ is:

$$r_{i,n,\tilde{n}} = B\log_2(1+\frac{P_{i,n,\tilde{n}}g_{i,\tilde{n}}}{\sigma_n^2}) \tag{5}$$

Where, B is the system bandwidth, $P_{i,n,\tilde{n}}$ and σ_n^2 are the transmit power of the sub-channel and Gaussian white noise. During time block T, the ship user's subtask is paired with at most one subchannel in the channel, and the condition of this constraint can be described as:

$$\sum_{i=1}^{\tilde{K}}\sum_{\tilde{n}=1}^{\tilde{N}} I(h_{i,n,\tilde{n}},\tilde{n}) \le 1 \quad \forall n \tag{6}$$

A sub-channel receives at most one sub-task's offload selection, and the constraints that must be satisfied are expressed as:

$$\sum_{i=1}^{\tilde{K}}\sum_{n=1}^{N} \mathrm{I}(h_{i,n,\tilde{n}},\tilde{n}) \le 1 \quad \forall \tilde{n} \tag{7}$$

Among them, I represents the exclusive or function, and the specific meaning is that when the values of the variable $h_{i,n,\tilde{n}}$ and the variable $\tilde{n}$ are the same, the value of the function is 1, otherwise it is 0.

3.2.4 Task Offloading Model

When the ship user's connectivity is satisfied, it is ensured that there is no interruption problem during task offloading, when the ship user i offloads its subtask n to the neighboring ship user v in a certain proportion, the task execution in this mode can be divided into three stages, offloading upload, calculation processing, and result return. However, due to the limited computing power of offloading to adjacent ships, the proportion of offloading data is small, so the return result is small, and the model in this paper will ignore the return. Therefore, in the offloading uplink transmission stage, the transmission delay and energy consumption of subtask n offloaded to the neighboring ship user v are expressed as:

$$T_{i,n}^{uv} = \frac{D_{i,n}(1-\tilde{\mu}_i)}{r_{i,n,\tilde{n}}} \tag{8}$$

$$E_{i,n}^{uv} = P_{i,n,\tilde{n}}T_{i,n}^{uv} \tag{9}$$

When the task of ship user *i* is offloaded to ship user *v*, and f_i^v is defined as the calculation frequency of ship user v, the delay and energy consumption required to process the task at ship user v are expressed as:

$$T_{i,n}^{v}=\frac{D_{i,n}a_i(1-\tilde{\mu}_i)}{f_i^v} \tag{10}$$

$$E_{i,n}^{v}=k(f_i^v)^2 D_{i,n}a_i(1-\tilde{\mu}_i) \tag{11}$$

To sum up, it can be concluded that the total delay and total energy consumption required to offload subtask *n* can be expressed as:

$$T_{i,n}^{down}=T_{i,n}^{uv}+T_{i,n}^{v} \tag{12}$$

$$E_{i,n}^{down}=E_{i,n}^{uv}+E_{i,n}^{v} \tag{13}$$

3.2.5 Energy Harvesting Model

Due to the limited energy of ship users, in order to prolong the battery life of ship users, the model in this paper introduces an energy harvesting model to balance the needs of ship users for electrical energy. The photovoltaic modules of solar energy are used to collect renewable energy and store the energy in the battery serves the transmission of data and the processing of tasks in the next time block *T*, and the collected energy is related to the incident power of solar energy, energy collection efficiency and collection time, and the mathematical expression is described as:

$$\tilde{E}_{solar,i}^{s}(t)=P_{solar}^{s}\bar{\eta}_{solar}\tilde{T} \tag{14}$$

Where, P_{solar}^{s} is the incident power of the sun, $\bar{\eta}_{solar}$ is the average collection efficiency of the energy collection node, and $\tilde{T}$ is the time of energy collection. $\tilde{B}_{rem}^{s}(t)$ is used to represent the remaining energy of the previous time block, so at the beginning of the current time block, the energy possessed by the ship user can be expressed as:

$$\tilde{E}_{collect}^{s}(t)=\tilde{E}_{solar,i}^{s}(t-1)+\tilde{B}_{rem}^{s}(t) \tag{15}$$

If at the beginning of the time block $\tilde{T}$, the battery energy level $\tilde{E}_{collect}^{s}(t)$ of the ship user is lower than the battery power threshold E_{th}, that is, the collected energy cannot guarantee the task processing of the ship user *i*, then the backup battery B_t of the ship user is activated to ensure the continuity of the ship task processing. In order to maximize the utilization rate of the collected energy, when the backup power is used, it is denoted χ_i as 1, otherwise it is 0, and a penalty mechanism $G_i=\chi_i\cdot\partial\cdot E_i^{ex}(t)$ is introduced, where ∂ >0 is the penalty coefficient, and $E_i^{ex}(t)$ is the ship user *i* within the specified time block. The energy consumption of the processing task, expressed as $E_i^{ex}(t)=\sum_{n=1}^{N}(E_{i,n}^{uv}(t)+\tilde{E}_i^{l}(t))$, and the battery power of the next time block is updated as:

$$\tilde{B}^{s}_{rem}(t+1) = E^{\tilde{T}}_{have}(t) - E^{ex}_{i}(t) \tag{16}$$

3.2.6 Execution Cost Model

Based on the above discussion, because marine ship users are constrained by the environment, it is necessary to reduce the energy consumption of ship users as much as possible to prolong the battery life and ensure the continuity of task execution during the navigation process of ship users. Therefore, this paper aims to ensure the delay of ship users. In the case of constraints, the objective function is established around the minimization of the energy cost of the ship user. Therefore, the model in this paper sets a penalty mechanism so that the ship user's task execution meets the delay constraint, and defines $\tilde{T}^{delay}_{i}$ as the time required for ship user i to process a set of tasks, then there is $\tilde{T}^{delay}_{i} = \max(T^{uv}_{i,n}) + +\tilde{T}^{l}_{i} + \sum_{n=1}^{N} T^{v}_{i,n}, \forall n$, where the uplink transmission delay of the model is the ship user's time. The maximum transmission delay of subtasks, and the delay constraint penalty mechanism can be expressed as:

$$M_i = \begin{cases} \gamma_i & \tilde{T}^{delay}_{i} \geq \tilde{T} \\ 0 & \tilde{T}^{delay}_{i} < \tilde{T} \end{cases} \tag{17}$$

Among them, γ_i □ 0 is the penalty coefficient, and $\tilde{T}$ is the time block of the ship task execution. Therefore, under the requirement of delay constraint, a fitness function is established by minimizing the energy consumption of ship users, which includes the penalty function of delay constraint, the penalty function of insufficient energy collection and the energy consumption of ship users performing tasks. The mathematical model is described as:

$$\begin{aligned} \text{P}'1: \quad & \min \sum_{i=1}^{\bar{K}} (M_i + G_i + \tilde{E}^{con}_{i}) \\ s.t.\ \ & C_1 : \sum_{n=1}^{N} D_{i,n} = D_i \\ & C_2 : \sum_{i=1}^{\tilde{K}} \sum_{\tilde{n}=1}^{\tilde{N}} I(h_{i,n,\tilde{n}}, \tilde{n}) \leq 1 \ \ \forall n \\ & C_3 : \sum_{i=1}^{\tilde{K}} \sum_{n=1}^{N} I(h_{i,n,\tilde{n}}, \tilde{n}) \leq 1 \ \ \forall \tilde{n} \\ & C_4 : \tilde{E}^{con}_{i} \leq E^{s}_{\max} \\ & C_5 : 0 \leq \tilde{\mu}_i \leq 1 \\ & C_6 : 0 \leq P^{l}_{i} \leq P^{l}_{\max} \\ & C_7 : 0 \leq f^{l}_{i} \leq f^{l}_{\max} \end{aligned} \tag{18}$$

Where, $\tilde{E}^{con}_{i}$ is the energy consumed by ship user i to process a set of tasks, denoted as $\tilde{E}^{con}_{i} = \tilde{E}^{l}_{i} + \sum_{n=1}^{N} E^{off}_{i,n}$, the constraint C_1 means that the data volume of a set of subtasks is equal to the data volume of one task in ship user i, and the constraint C_2 means that a subtask selects at most one subtask Channel, C_3 means that a sub-channel can receive at most one sub-task offloading option, C_4 means that the execution of the task cannot exceed the maximum capacity of the battery $E^s_{\max}$, C_5 is the range of the task offloading ratio, C_6 means the ship user's local transmit power range, C_7 means the ship The value range of the user's local calculation frequency.

PROBLEM SOLVING

4.1 Transmit Power Optimization

In the far-sea scenario, it is of great significance for ship users to effectively reduce energy consumption. When the task is selected to be offloaded to other ships for calculation, optimizing the transmit power can further reduce the energy consumption. Therefore, the derivation of the objective function with respect to the local power of the ship user is expressed as:

$$\frac{\partial P'1}{\partial P_{i,n,\tilde{n}}} = \frac{D_{i,n}(1-\tilde{\mu}_i)}{B\log_2(1+\frac{p_{i,n,\tilde{n}}g_{i,\tilde{n}}}{\sigma_n^2})}(1+\frac{P_{i,n,\tilde{n}}g_{i,\tilde{n}}}{\log_2(1+\frac{p_{i,n,\tilde{n}}g_{i,\tilde{n}}}{\sigma_n^2})\cdot(1+\frac{g_{i,n}}{\sigma_n^2}p_{i,n,\tilde{n}})\ln 2\sigma_n^2}) \tag{19}$$

Since the result of equation (19) is always greater than 0, it can be concluded that the objective function increases monotonically, and increases with the increase of the transmit power. Then, the second derivative is solved as follows:

$$\frac{\partial^2 P'1}{\partial P^2_{i,n,\tilde{n}}} = \frac{A\cdot B(g_{i,\tilde{n}}+1) - P_{i,n,\tilde{n}}\ln 2 g^2{}_{i,\tilde{n}} A\cdot B^2 \frac{\ln 2}{\sigma_n^2}}{(A^2\cdot B)^2} \tag{20}$$

Where, $A = \log_2(1+\frac{P_{i,n,\tilde{n}}g_{i,\tilde{n}}}{\sigma_n^2})$ and $B = \ln 2\cdot\sigma_n^2(1+\frac{g_{i,\tilde{n}}}{\sigma_n^2})$ The numerator of the second derivative can be expressed as $\varphi(p_{i,n,\tilde{n}}) = A\cdot\ln 2[g_{i,\tilde{n}}(1+\frac{g_{i,\tilde{n}}}{\sigma_n^2})\underbrace{(\sigma_n^2 - P_{i,n,\tilde{n}}\ln^2 2\cdot\frac{g_{i,\tilde{n}}}{\sigma_n^2})}_{C}+\sigma_n^2]$, And in this model, C<-1, Then there is formula (20) is negative, it can be concluded that the fitness function is a convex function with respect to the local transmit power, indicating that the extremum exists and is unique, denoted as P_1, There is a delay requirement in the process of ship user processing tasks. Therefore, according to the delay constraint T, we can get:

$$p_{i,n,\tilde{n}} \geq \frac{\sigma_n^2(2^{\frac{DN}{B(\tilde{T}-\tilde{T}_i^l-T_i^{uv})}}-1)}{g_{i,\tilde{n}}} = p_2 \tag{21}$$

Based on the above discussion, under the condition that the local transmit power satisfies the delay constraint, the optimal local transmit power with less energy consumption is expressed as:

$$P^*_{i,n,\tilde{n}} = \begin{cases} P_1 & P_1 \geq P_2 \\ P_2 & P_1 < P_2 \end{cases} \tag{22}$$

4.2 Local Computing Frequency Optimization

The use of dynamic voltage and frequency adjustment technology can make the local computing frequency dynamically adjusted, thereby reducing local energy consumption. According to the constraints on the local computing frequency, first optimize the feasible region of the local computing frequency. From the delay constraint and the constraint C_4, we can get:

$$\frac{a_i D_{i,n} \tilde{\mu}_i N}{\tilde{T}} \le f_i^{\,l} \le \sqrt{\frac{E_{\max}^s}{k a_i D_{i,n} N}} \tag{23}$$

In order to minimize the local delay and energy consumption, so as to further optimize the objective function and improve the energy efficiency of the system, the mathematical expression about the local computing delay and energy consumption can be established:

$$\begin{aligned} F:&\quad \min(\tilde{E}_i^l + \tilde{T}_i^l) \\ s.t.&\quad S_1 : \tilde{T}_i^l < \tilde{T} \\ &\quad S_2 : \tilde{E}_i^l < E_{\max}^s \\ &\quad C_7 \end{aligned} \tag{24}$$

This model rewrites the above problem based on the Lagrangian dual method(Chuong et al., 2018)as:

$$L(f_i^{\,l}, \lambda, \chi, \kappa) = \tilde{T}_i^l + \tilde{E}_i^l + \lambda(\tilde{T} - \tilde{T}_i^l) + \chi(E_{\max}^s - \tilde{E}_i^l) + \kappa(f_{\max}^{\,l} - f_i^{\,l}) \tag{25}$$

Among them, λ , χ and κ are the Lagrangian factor, and the optimal local calculation frequency according to formula (25) and the KKT condition is:

$$f_i^{\,l*} = \left[\sqrt[3]{\frac{1-\lambda}{k(\chi-1)}} \right]^+ \tag{26}$$

According to the above discussion, the Lagrangian factor is updated by the gradient descent method, then in formula (26) there are $\lambda(t+1) = [\lambda(t) - \varphi_1(t)(\tilde{T} - \tilde{T}_i^l)]^+$ and $\chi(t+1) = [\chi(t) - \varphi_2(t)(E_{\max}^s - \tilde{E}_i^l)]^+$. The κ update is expressed as $\kappa(t+1) = [\kappa(t) - \varphi_3(t)(f_{\max}^{\,l} - f_i^{\,l})]^+$, where *t* is the number of iterations and $\varphi_n(t)$ is the update step size.

4.3 Offloading Ratio Solution Based on Improved Grey Wolf Optimization Algorithm

The model in this paper takes into account the different computing capabilities of different ship users, and reduces the energy consumption of the entire system as much as possible by sequentially optimizing the local transmit power and local transmit frequency. Based on the above discussion, substituting $P_{i,n,\tilde{n}}^*$, $f_i^{\,l*}$ into Equation (18) can simplify the problem for:

$$\begin{aligned} \mathrm{P}'2:&\quad \min \sum_{i=1}^{\bar{K}} (M_i + G_i^* + \tilde{E}_i^{con*}) \\ s.t.&\quad C_1 - C_7 \end{aligned} \tag{27}$$

For the optimal offloading strategy problem, the gray wolf optimization algorithm is introduced. The model in this paper analyzes the gray wolf optimization algorithm to solve the constrained problem, and improves it based on the basic gray wolf optimization algorithm to obtain the best offloading strategy. gray wolves hunt according to their hierarchy, the position of each wolf represents an optimal position, and the average of the three wolves with the best iteration results is used as the optimization result, and the model parameters in this paper are mapped to the algorithm, when M wolves are set in the algorithm, each offloading decision represents the position of a wolf. If the ship user is in the time block, a task is divided into N subtasks, and the position vector dimension of each wolf is the same as the number of subtasks. The number N is the same. When there are V offloadable ship users meeting the connectivity threshold, so each sub-task can have (V+1) choices, then the solution space of the algorithm can be expressed as $(V+1)^N$. In the basic Grey Wolf Optimization Algorithm (GWO) (Mirjalili et al., 2011. & Long et al.), in the late stage of iteration, each individual gray wolf iterates toward the position of the head wolf. If the three head wolves fall into a local optimum, the iteration range of the entire algorithm is reduced, and the population evolution mechanism is lacking. Since the model in this paper is limited by delay constraints, the offloading decision of subtasks has high requirements. In order to solve the optimal solution of the offloading decision algorithm, this paper is inspired by tumbling foraging, and the probability of tumbling foraging increases in the later stage of the iteration. It can enable the iterative individuals to update adaptively and avoid premature maturity of the iterative algorithm. The mathematical expression of tumbling foraging is described as:

$$x_{\tilde{k}}^d(t+1) = x_{\tilde{k}}^d(t) + q(r_1 \cdot x_{best}^d - r_2 \cdot x_{\tilde{k}}^d(t)) \tag{28}$$

Among them, $x_{\tilde{k}}^d(t)$ represents the position of the $\tilde{k}$-th individual in the M-dimensional space at time t, r_1 and r_2 are random numbers [0,1], and q is the learning coefficient. In order to better judge whether the iterative algorithm has entered the local optimum prematurely, the local optimum discriminant parameter is introduced, and the Euclidean distance between the M-th dimensional gray wolf individuals at time t is used. When the distance is short, the iterative algorithm is described. May be stuck in a local optimum, define the Euclidean distance:

$$\theta(x_{\tilde{k}}, x_m) = \sqrt{(x_{\tilde{k}}^1 - x_m^1)^2 + (x_{\tilde{k}}^2 - x_m^2)^2 \cdots + (x_{\tilde{k}}^d - x_m^d)^2} = \sqrt{\sum_{d=1}^{D} (x_{\tilde{k}}^d - x_m^d)^2} \tag{29}$$

Among them, $x_{\tilde{k}}^d$ and x_m^d respectively represent the position of the $\tilde{k}$-th gray wolf individual and the m-th gray wolf individual in the M-th dimension, and the discriminant parameter can be defined as:

$$\phi(t) = \frac{1}{\tilde{K}M} \sum_{\tilde{k}=1}^{\tilde{K}} \sum_{m=1}^{M} \theta(x_{\tilde{k}}, x_m) \tag{30}$$

Set the threshold ζ. If the discriminant parameter is less than the threshold ζ, it means that the iterative similarity of the gray wolf individuals in the population is very high, and there is a high probability of falling into the local optimum. If the discriminant parameter is greater than the threshold ζ, it means that the iterative algorithm can avoid getting stuck in a local optimum. Thus, a learning factor ε is introduced:

$$\varepsilon = \begin{cases} 0 & \phi(t) \geq \zeta \\ \phi^2(t) & \phi(t) < \zeta \end{cases} \tag{31}$$

A learning factor is introduced to regulate the position update of the individual gray wolf, so as to avoid the premature maturity of the algorithm and fall into the local optimum. The improved formula is updated as follows:

$$x_i(t) = \frac{x_\alpha + x_\beta + x_\chi}{3} + \varepsilon \cdot r_3 (x_{rand}(t) - x_i(t)) \tag{32}$$

Among them, $x_{rand}(t)$ represents the position of any individual gray wolf, and r_3 r_3 is a random number [0,1].

SIMULATION RESULTS AND DISCUSSIONS

5.1 Simulation experiment environment

This paper conducts experimental simulation based on the EdgeCloudSim simulation platform(Sonmez et al., 2018 & Jammal et al., 2018) simulating a 2000m × 2000m ocean scene within 20 minutes. For the parameter setting of the simulation scenario, refer to (Jaddoa et al., 2020), the processing speed of each ship user is set to 50MIPS, and each ship user in this area is randomly distributed and has similar computing power. The idle ships are used as the data center for task offloading. The task data volume of ship users is created in the form of Poisson distribution in the size of 500-1000KB. In addition, this paper defines different parameters of the simulation platform according to (Su et al., 2020), (Su et al., 2021),such as shown in Table 1.

Table 1. System parameter values.

System parameters	Illustrate	Numerical value
	Number of ship users	5-10
	Subchannel maximum transmit power	250mW
	Ship communication radius	500m
$E^{s}_{\max}$	VU_i	100J
B	$P^{l}_{\max}$	2MHz
P_{solar}	R	100w
a	Solar size	1m^2
N	Number of subtasks	10
$\tilde{N}$	Number of sub-channels	50-100

5.2 Analysis of Simulation Results

This paper simulates the ship user offloading strategy in the far sea scenario, mainly analyzes the energy consumption optimization performance under the delay constraint, and takes the total execution cost as the evaluation index. First, the feasibility of the task segmentation and channel segmentation proposed in this paper is verified. And the influence of the improved algorithm to solve the task offloading ratio on this model, then this paper uses ablation experiments to test the necessity of each module proposed in this paper to improve the overall optimization performance of the model. Finally, in order to verify the superiority of this model strategy, this paper and literature The far-sea scenarios proposed in (Su et al., 2020) and (Su et al., 2021) are compared in terms of energy saving rate and mission failure rate.

5.2.1 Split Strategy Verification

In order to verify the effect of the tasks of this paper and the channel division method on the performance of the model, the relationship between the number of sub-channels and the total execution cost is simulated when the transmit power of the sub-channels is different. The experimental results are shown in Figure 3.

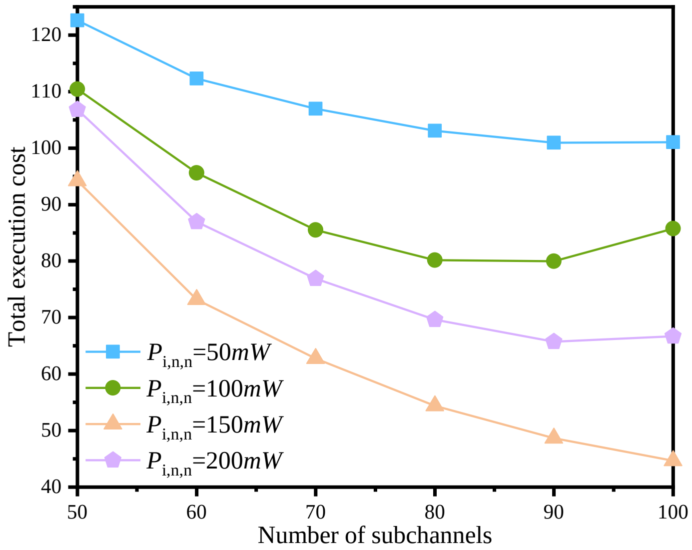

Figure 3. Total cost of execution for different numbers of subchannels.

With the increase of the number of sub-channels, the total execution cost shows a downward trend and the greater the transmit power of the sub-channel, the smaller the total execution cost, but when the sub-channel power exceeds a certain range, the execution total cost increases instead. This is because when the sub-channel increases the transmit power within a certain range and the local task is offloaded to other ships for calculation, the task transmission speed is fast, and the number of tasks transmitted in the same time is large, which reduces the transmission delay and speeds up the task at the same time. The processing time makes the energy consumption relatively small, and it can also save the energy and time consumed by the local task queuing. When the transmission power exceeds a certain range, the sub-channel transmission process consumes more energy, and the ship's task processing capability Similarly, to a certain extent, resources are wasted during transmission, resulting in excessive energy consumption for execution. It shows that within a certain range, the segmentation strategy has a certain role in improving the performance of the model.

5.2.2 Comparison of Improved Algorithms

In order to solve the optimal data offloading ratio, the bionic intelligent algorithm is used in the model of this paper for optimization, as shown in Figure 4. The changes of the total execution cost under different algorithms are evaluated. Among the basic gray wolf optimization algorithm and the basic whale optimization algorithm, the basic gray wolf optimization algorithm has a lower total execution cost than the basic whale optimization algorithm in the iterative process, but the basic gray wolf optimization algorithm The algorithm starts to converge when the number of iterations is close to 90, and its convergence speed is slow. Therefore, this paper improves the basic gray wolf optimization algorithm. It can be seen from Figure 4 that the improved gray wolf optimization algorithm iterates to around 45 times. Convergence begins. While the convergence speed is improved, the total cost of task execution is reduced by nearly 23.6% compared with the basic gray wolf optimization algorithm, and the effect is well improved, indicating that the improved gray wolf optimization algorithm optimizes the proportion of data offloading. The effectiveness of the performance improvement of the model in this paper.

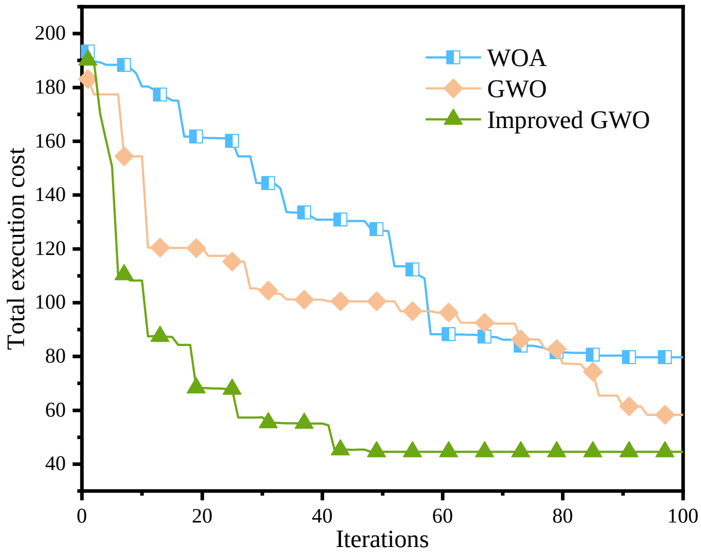

Figure 4. The total execution cost of different algorithms.

5.2.3 Ablation Experiment

Ablation research is very important to the verification of the model. In order to verify the influence of each part of the model in this paper on the model, an ablation experiment is carried out on the model in this paper under the condition that the parameters remain unchanged. Experiment 1 builds the framework of the ocean model, and the calculation method of the task adopts all Local computing, while Experiment 2 increases the probability of ship connectivity, offloads the tasks to be processed to ships that satisfy the connectivity probability in a binary offload manner, and optimizes the local computing power and the local sub-channel transmit power in turn, the total execution cost is obtained as 76.469, which is 33.13% less than the total execution cost of experiment 1. Experiment 3 introduces the method of energy harvesting, which reduces energy consumption by obtaining renewable energy, so that the total execution cost can be effectively reduced by 13.9%. Based on the previous experimental framework, experiment 4 proposes a gray wolf optimization algorithm to optimize the task data offloading ratio, and the total execution cost is 58.325. In experiment 5, the gray wolf optimization algorithm is improved to obtain a more optimized task offloading ratio. Compared with the basic gray wolf optimization algorithm, the total task execution cost is reduced by 23.6%. The results of the ablation experiments are compared in Table 2.

Table 2. Comparison of the results of ablation experiments.

Experiment	Basic model	probability of connectivity	Energy harvesting method	Basic GWOA	Improved GWOA	Execution cost
1	√					114.356
2	√	√				76.469
3	√	√	√			65.764
4	√	√	√	√		58.325
5	√	√	√		√	44.543

5.2.4 Comparative Experiments of Different Methods

After verifying the effectiveness of the various parts mentioned in this paper to improve the performance of the model in this paper, in order to verify the superiority of the strategy of this model, the strategy proposed in this paper is compared with the multi-user single-hop unicast strategy proposed in the (Su et al., 2020). The scheme is compared with the fault-tolerant scheme proposed by the (Su et al., 2021). Since the objective function of the model in this paper needs to minimize the energy consumption of task processing under the condition of delay constraints, under the condition of certain parameters, the definition of (Su et al., 2020), The ratio of the difference between the solution proposed in the (Su et al., 2021) and the results in Experiment 1 and the results of Experiment 1 is the energy saving rate. It can be seen from Figure 5 that when the number of ship tasks is increased, the energy saving rate is all show an increasing trend, because when all tasks are processed locally, the load of local processing is increased, and the local energy consumption is relatively large, and the three strategies can reduce the energy consumption to a certain extent when the number of tasks increases. Effectiveness of task offloading methods for energy reduction. When the algorithm proposed in this paper is compared with other methods, the energy saving rate of the proposed scheme is higher than that of the methods in (Su et al., 2020) and (Su et al., 2021), which shows that the model in this paper has good performance in energy consumption in energy collection and policy optimization. better performance.

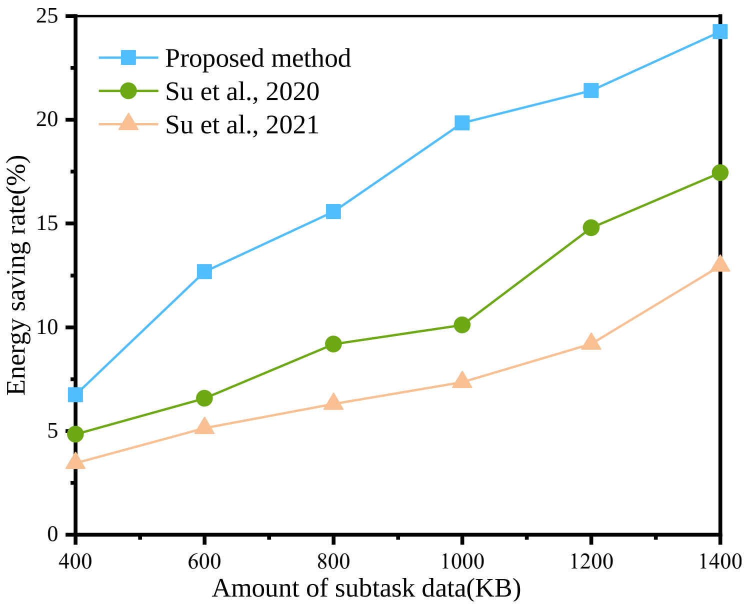

Figure 5. Energy saving rate of different methods.

Due to the complex environment of the distant sea scene, it is easy to cause packet loss in the process of task transmission. The task failure rate can be used as an evaluation index to measure the superiority of the strategy. This paper defines the ratio of successfully processed tasks to the total tasks as the task failure rate. As shown in Figure 6, with the increase in the number of ship users, the method proposed in this paper increases the task failure rate relatively slowly when the number of ships is small. Resource reduction leads to a faster growth rate of mission failure rate. The rate of mission failure rate growth of other methods is significantly faster than that of the method proposed in this paper. (Su et al., 2020) offloads small base stations (large ships, floating objects) to the sea, when the user When the number increases, the base station fails to calculate the task due to its own limitation. (Su et al., 2021) proposes a fault-tolerant retransmission mechanism to reduce the failure of task transmission to a certain extent. However, when the number of tasks increases, the computing resources of the remote base station itself are insufficient or the task is lost due to the long distance in the process of multi-hop transmission.

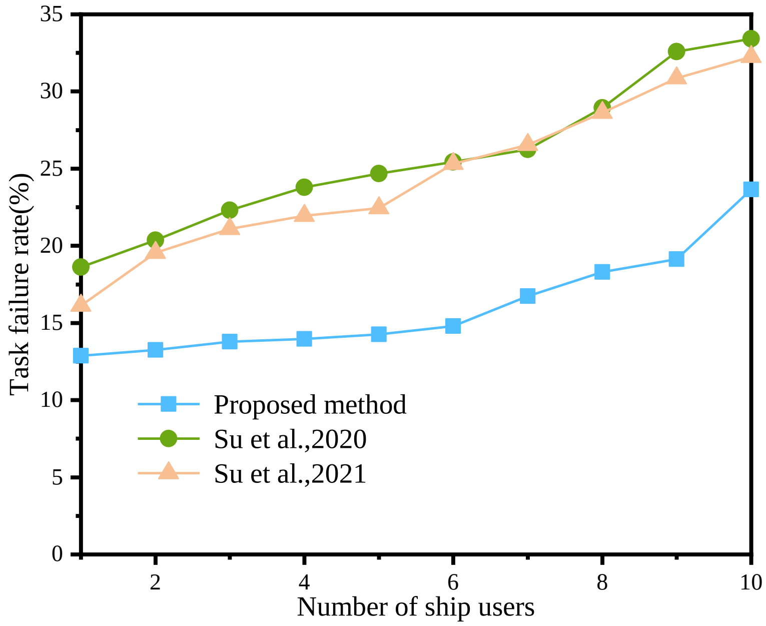

Figure 6. Task failure rates for different methods.

CONCLUSION

Nowadays, the marine industry has attracted much attention, and various new technology projects are carried out at sea. However, the traditional maritime communication network cannot meet the increasingly frequent maritime activities due to inflexible configuration and uneven node coverage. Sensitive maritime tasks have become a bottleneck in the development of maritime communication networks, and the urgent maritime communication problems that need to be solved are becoming more and more acute. Mobile edge computing makes it possible to realize low-latency, high-reliability marine communication networks. Therefore, aiming at the problem of uneven distribution of marine nodes, this paper establishes a task offloading model in the distant sea based on mobile edge computing, and combines the energy harvesting technology to establish a fitness function aiming at the energy consumption-delay trade-off to optimize the strategy of task offloading in the distant sea.

Aiming at the characteristics of unstable communication network in the distant sea area, this paper established an offloading model between ship users in the distant sea based on OFDMA technology, and selected the offloading node of ship users by judging the connection probability between ships. The local computing frequency and transmit power were optimally controlled, and a task delay penalty mechanism was established with the goal of minimizing energy consumption under delay constraints. After simulation analysis, the strategy proposed in this paper can achieve lower energy consumption while ensuring the delay constraint.

ACKNOWLEDGEMENTS

This work was supported by the Opening Foundation of Yunnan Key Laboratory of Smart City in Cyberspace Security (No.202105AG070010); National Natural Science Foundation of China, Research on Theory and Control Protocol of Converged Multiple Access Communication Network (No.: 61461053).

REFERENCES

Zhao, Y., Yu, G. & Xu, H. 2019. 6G mobile communication network: vision, challenges and key technologies. Science in China: Information Science.49(08) 963-987.

Xie, R.C., Lian, X. H. & Jia, Q.M. 2018. Overview of mobile edge computing offload technology. Journal of communications.39(11) 138-155.

Mao, Y., You, C., Zhang, J., Huan, k. & Letaief, K.B. 2017. A survey on mobile edge computing: The communication perspective. IEEE communications surveys & tutorials. 19(4) 2322-2358.

Zeng, J., Sun, J., Wu, B. & Su, X. 2020. Mobile edge communications, computing, and caching (MEC3) technology in the maritime communication network. China Communications. 17(5) 223-234.

Yang, T., Feng, H., Gao, S., Jiang, Z. Qin, M., Chen, N. & Bai, L. 2019. Two-stage offloading optimization for energy–latency tradeoff with mobile edge computing in maritime Internet of Things. IEEE Internet of Things Journal. 7(7) 5954-5963.

Yang, T., Zhang, Y. & Dong, J. 2018. Collaborative optimization scheduling of maritime communication for mobile edge architecture.2018 IEEE International Conference on RFID Technology & Application (RFID-TA).1-5

Wang, H., Wang, Y., Ma, Y. & Lin, B. 2020. Resource allocation for OFDM-based maritime edge computing networks. 2020 13th International Congress on Image and Signal Processing, Medical Engineering and Informatics (CISP-BMEI). IEEE, 983-988.

Yang, T., Feng, H., Yang, C., Wang, Y., Dong, J. & Xia, M. 2018. Multivessel computation offloading in maritime mobile edge computing network. IEEE Internet of Things Journal, 6(3) 4063-4073.

Xu, F., Yang, F., Zhao, C. & Wu, S. 2020. Deep reinforcement learning based joint edge resource management in maritime network. China Communications.17(5) 211-222.

Wang, Y., Zhang, J., Zhang, X, Wang, P. & Liu, L. 2018. A computation offloading strategy in satellite terrestrial networks with double edge computing. 2018 IEEE international conference on communication systems (ICCS). IEEE, 450-455.

Zhang, Z., Zhang, W. & Tseng, F. H. 2019. Satellite mobile edge computing: Improving QoS of high-speed satellite-terrestrial networks using edge computing techniques. IEEE network, 33(1) 70-76.

Xiong, C., Li, G Y., Zhang, S., Chen, Y. & Xu, S. 2012. Energy-Efficient Resource Allocation in OFDMA Network. IEEE Transactions on Communications .60(12) 3767-3778.

Chuong, T. D. & Jeyakumar, V. 2018. Generalized Lagrangian duality for nonconvex polynomial programs with polynomial multipliers. Journal of Global Optimization, 72(4) 655-678.

Mirjalili, S., Mirjalili, S.M. & Lewis, A. 2015. Grey wolf optimizer. Advances in engineering software. 69 46-61.

Long, W., Cai, S., Jiao, J. & Tang, M. 2020. An efficient and robust grey wolf optimizer algorithm for large-scale numerical optimization. Soft Computing, 24(2) 997-1026.

Sonmez, C., Ozgovde, A. & Ersoy, C. 2018. Edgecloudsim: An environment for performance evaluation of edge computing systems. Transactions on Emerging Telecommunications Technologies, 29(11) e3493.

Jammal, M., Hawilo, H., Kanso, A. & Shami, A. 2018. ACE: Availability-aware CloudSim extension. IEEE Transactions on Network and Service Management, 15(4) 1586-1599.

Jaddoa, A., Sakellari, G., Panaousis, E., George Loukas, G. & Sarigiannidis, P.G. 2020. Dynamic decision support for resource offloading in heterogeneous Internet of Things environments. Simulation Modelling Practice and Theory.101 102019.

Su, X., Wang, Z.Y., Wang, Y. & Zhou, S. 2020. Multi access edge computing unloading method for ocean observation monitoring sensor network. Journal of Internet of things 5(01) 36-52

Su, X., Xue, J.Y., Zhou, Y. Q. & Zhu, J.X. 2021. Research on computational unloading method for ocean observation and monitoring sensor network. Journal of communications 42(05) 149-163.