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Multi-Round Auction-Based Resource Allocation in Multi-Access Edge Computing Assisted Satellite Networks

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Abstract: In this paper, we study the resource allocation problem of multi-access edge computing (MEC) assisted satellite networks in ocean areas. Considering the demand heterogeneity of users and the limited resources of satellites, we propose an online multi-round auction-based resource allocation (OMARA) approach for resource trading between satellites and users, where satellites are the resource sellers and users are the related resource buyers. The proposed approach can effectively determine the price for the trading of resources and can match the service relationships accordingly between satellites and ground users. Finally, it is shown by the simulation experimental results that the proposed approach outperforms the other existing algorithms in maximizing service satisfaction.

Keywords: computing offloading; satellite; auction mechanism; resource allocation

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1. Introduction

Recently, China, UK, and various countries have carried out studies on environmental monitoring [1], marine investigation [2], security [3], and rescue in territorial seas [4]. In these studies, it was found that ships, IoT devices, and other systems are used to complete some particularly dangerous and boring tasks in the ocean. Meanwhile, as competing demands for ocean resources grow, these systems are facing a series of time-sensitive tasks in different ocean tasks. Only using the limited resources of the current system cannot meet the increasing service demand [5–8]. As the satellite system has become an indispensable part of the mobile communication field by virtue of its unique advantages [9–11], which can be provided any time and any place in the real sense of the mobile communication service, the satellite system has been widely used in maritime communications, weather forecasting, and other fields, and played a vital role in communication and interaction. However, how to allocate the limited resources reasonably and efficiently in the satellite communication system is very important to improve resource utilization and system performance [12–14].

In addition to providing mobile users with global ubiquitous connectivity, the satellite network also needs to provide a variety of computing services support [15–17]. In most cases, mobile users can offload computing tasks to cloud data centers with rich computing resources to make up for limited computing and storage resources on mobile users. However, in order to provide computing services to mobile users in different geographical locations, cloud data centers are often far away from mobile users, resulting in a large delay in the processing of mobile services, which makes it difficult to meet the needs of emerging applications for end-to-end delay as low as milliseconds. In addition, for marine operations and remote mountain users without the support of ground network communications facilities, computing tasks need to be forwarded to cloud data centers through satellite networks as relays. Limited by satellite and other cross-domain platforms, the transmission delay of mobile users in the satellite network also increases correspondingly, and it is difficult to meet the real-time needs of users. Therefore, based on the idea of multi-access edge computing (MEC), MEC technology is introduced into the satellite network. The core idea is to sync the rich computing and caching resources of the cloud data center to the network edge closer to mobile users. This provides users with multi-level and heterogeneous computing resources, enabling users to obtain computing services worldwide, thus improving the quality of the user experience.

However, for the current unmanned ships at sea, it is hard to provide fixed-edge computing servers to provide multi-access edge computing services. With the characteristics of fast deployment and high mobility, satellites can meet the needs of diversified applications and are widely used in traffic monitoring, emergency communications, and so on [18]. In a satellite network, the satellite can be used as a base station to support communication services and IoT applications. Then, the MEC services can be integrated into the satellite network to provide dynamic edge computing services, which have received significant attention [19]. Compared with the traditional networks, the MEC-assisted satellite network can provide better wireless connectivity services and can achieve more flexible network services [20]. It is suitable for all kinds of time-sensitive tasks at sea.

Although the deployment of satellites in wireless networks has offered many advantages, there are still many technical and economic challenges that need to be solved when using them at sea. In a satellite system, the stability of network services is required, and proper service mechanisms are also important for reasonable service cost. The lack of appropriate mechanisms may lead to the pursuit of profit at the expense of internal service standards during the resource allocation of satellite services. This event can cause ocean users to pay more to obtain the same service. In this regard, the economic models and game theory methods are used to solve the resource allocation problems in the satellite networks [21]. As one of the most widely used economic models, the auction method can ensure fair, efficient, and truthful resource allocation, especially if the participants are rational, intelligent, and competing [22–25].

In this paper, we propose an online multi-round auction-based resource allocation method in the MEC-assisted satellite network in ocean areas, which aims to maximize the satisfaction of satellite services for different users. In the proposed auction model, the satellites are considered as the resource sellers, and the users are the buyers. The perspectives of sellers and buyers are both considered, and then a bidding strategy and a matching strategy are introduced to ensure the efficiency of the auction. To ensure the rationality and truthfulness of the auction, we introduce the Vickrey–Clerke–Groves payment mechanism. Finally, the effectiveness of the algorithm is verified by simulation experiments.

The whole paper is organized as follows. In Section 2, we introduce the system model and formulate the resource allocation problem in the proposed system. The auction theory is used in Section 3 to achieve optimal resource allocation and the proposed algorithm is also given. We evaluate the performance of the proposed algorithm and compare it with other algorithms in Section 4. The paper is concluded in Section 5.

2. System Model and Problem Formulation

In this section, we first introduce the system model in Section 2.1. Then, we consider the service satisfaction of satellites and formulate the related resource allocation problem in Section 2.5.

2.1. System Model

With the increasing number of user devices in the sea, business types and business volume surge. These businesses include various domains' ship- and shore-related data in the forms of multiple services supporting marine activities such as safe navigation, security at sea, protection, and management of the marine environment, and others. In terms of quantity and scale, these businesses in the sea generate and transmit data in real time every minute, and the data volume has exploded to exceed the PB level [26]. As users in sea applications are mostly resource-limited nodes with limited computing abilities, it is difficult to meet the increasing demand for data and business services through users' local computing and processing capacity. The traditional center computing method also cannot meet the huge demand of users on the sea. Then, we introduce edge computing techniques to solve the limited resources problems. Many works have been conducted on resource allocation in edge computing networks [27–31]. Generally, in the nearshore sea, multiple coastal base stations integrated with edge computing techniques can cooperate with the user's devices to realize the user's computational unloading. However, in offshore areas, due to the wide range of sea areas, it would introduce large-scale construction costs and other factors when using the multiple coastal base stations integrated with edge computing techniques. In this paper, we consider using the satellite network to provide edge computing services to user devices to ensure the applications' requirements.

As shown in Figure 1, a multi-access edge computing assisted satellite network is given, which is composed of multiple satellites and multiple users. Each satellite is assumed to have an edge computing server. Considering the impact of energy and load, MEC servers on satellites can consider using a lightweight management platform such as Docker. By deploying MEC servers on LEO satellites, satellites are equipped with computing and content distribution capabilities [32], which can not only effectively reduce the frequent satellite-based link transmission and end-to-end service transmission delay between satellites and the ground network but also effectively save the service data transmission bandwidth between the satellite-based links. In this network, there are a set of satellites over the geographic area providing network and computation services, denoted as $N = \{1, \ldots, N\}$. The set of user devices is given by $M = \{1, \ldots, M\}$. The users can connect to the satellites and apply for resources from the edge servers in the satellites to support their computing demands, instead of the traditional cloud computing server. In this paper, a multi-round auction model is proposed to depict the service relationships between the users and the satellites. The satellites with edge computing servers are considered as the sellers, and the users are the buyers.

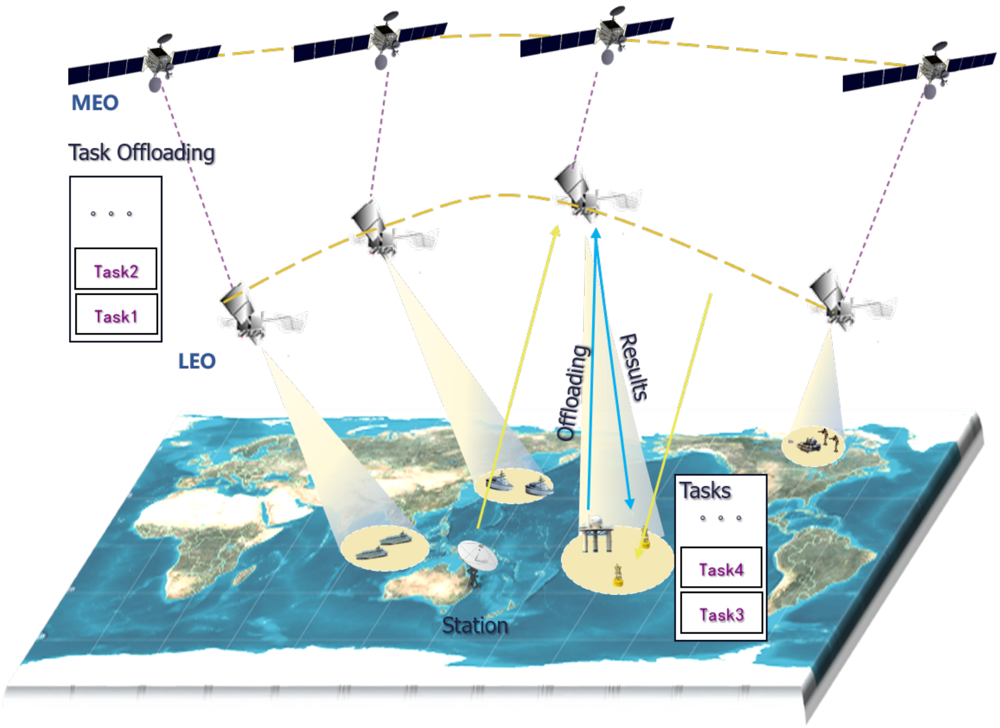

Figure 1. System model.

In offshore applications, each user is assumed to have unique service requirements; thus, the tasks executed by the satellites are different. A tuple $\{D_m, O_m, F_m, V_m, T_m\}$ is used to denote the tasks of user m, where D_m denotes the data size, V_m denotes the number of cycles required to compute 1-bit data of the task, F_m denotes the clock frequency, O_m

denotes the processing results, and T_m denotes the maximum tolerated delay. We use the tuple $\{H_n, L_n, C_n\}$ to denote the resources of satellite n, where H_n denotes the cache size, L_n denotes the maximum number of served users, and C_n denotes the computational capacity.

2.2. Communication Model

The transmission rate of the ground user is related to the channel state and the spectrum state. In this paper, we consider that the user's channel remains unchanged during the task offloading. The achievable rate of uplink transmission is,

$$r^{up} = B\log_2\left(1 + \frac{p_g h}{N_0}\right), \tag{1}$$

where B denotes the bandwidth allocated for the satellite, p_g denotes the transmission power of user, h denotes the channel gain, and N_0 is the channel noise. Then, we can use (1) to denote the transmission rate of the ground user based on the Shannon Theory, where the transmission rate is mainly controlled by the channel bandwidth B allocated for the satellite, and also influenced by the signal-to-noise ratio given by $\frac{p_g h}{N_0}$. Similar to the rate of uplink transmission, the achievable rate of downlink transmission is given by r^{down}, considering the transmission power of the satellite as p_u. Thus, the delay of uplink transmission and downlink transmission can be given by $t^{up} = d/r^{up}$ and $t^{down} = \hat{d}/r^{down}$, respectively, where d is the size of the tasks and $\hat{d}$ is the size of the computation results.

2.3. Computation Model

When a satellite receives a task from a user, it needs to allocate its cache and computational resources appropriately. The energy consumption of caching is mainly dependent on the size of the offloaded tasks, which is denoted as $e_{cah} = \rho d$, where ρ is the energy conversion factor. The satellites are assumed to use the dynamic voltage and frequency scaling (DVFS) technique to adjust their core clock frequency [33], where the DVFS technology can adjust the computation frequency of the CPU according to the different demands of the applications. As a result, the energy consumption generated by the task computation is given by,

$$e_{com} = \kappa a_n C_n^2, \tag{2}$$

where a_n is the number of CPU cycles required by the satellite to complete the tasks, and κ is a coefficient value dependent on the CPU circuit structure [34]. After the computation, the results need to be returned to the users, the energy consumption generated by the return transmission is,

$$e_{tran} = \frac{p_u \hat{d}}{r^{down}}, \tag{3}$$

In this paper, when providing services to the ground users, the satellite is assumed to be in a stable state. It needs to consume additional energy to maintain a stable state. Therefore, additional energy consumption would be brought by the hovering state and is denoted by $e_h ov$. In addition, there exists the circuit energy consumption in each satellite, which is the energy consumed by the on-board circuits, such as the computational chip, rotors, and gyroscopes. There, the circuit energy consumption of the satellite is denoted as e_{cir}.

2.4. Latency Model

The processing delay of tasks includes the uplink transmission delay, the computation delay, and the downlink transmission delay. Therefore, the total processing delay of tasks for user m can be expressed as,

$$T_i = \Sigma_{i \in M}\left(t^{up} + t^{com} + t^{down}\right), \tag{4}$$

where t^{com} is the computation delay. Generally, the latency of tasks would be mainly affected by the task traffic from the user devices. As there are a lot of packets that are sent intermittently in marine communication, task traffic is emergent and autocorrelation. In this paper, we use the "on/off" model to formulate the tasks' traffic. Based on the "on/off" model, the task state of each user device would vary between the on state and the off state. We also have the following assumptions for the tasks of user devices,

$$\lambda = \begin{cases} \lambda_{on} = \frac{1}{\frac{1}{N_{on}} \sum_{i=1}^{N_{on}} t_{on}^{i}}, \\ \lambda_{off} = \frac{1}{\frac{1}{N_{off}} \sum_{i=1}^{N_{off}} t_{off}^{i}}, \end{cases} \tag{5}$$

where λ_{on} and λ_{off} are the exponential distribution parameters, which can affect the channel available time, and then the latency. N_{on} is the number of tasks occurring in the user devices, and the N_{off} is the number of tasks not occurring in the user devices. t_{on} and t_{off} are the state duration.

2.5. Problem Formulation

Consider an MEC-assisted satellite network with multiple satellites and multiple users, where satellites have different resource capacities. Generally, the users prefer satellites with more resources, which ensures that the tasks can be completed within the maximum tolerable delay as much as possible. The ground users should offload the tasks to the satellites to complete the computation, and need to pay the corresponding computation cost to the satellites. Meanwhile, the satellites can obtain revenue by assisting the users with the task computation.

According to [35], we introduce the service satisfaction index $s_{n,m}$ to formulate the relationships between satellites and ground users, which expresses the satisfaction of satellite n with the service benefits of user m. The service satisfaction of the satellite for different users' tasks depends on the service revenue and the computation cost, where the cost is given by the energy consumption associated with the tasks. Then, we can obtain the energy consumption cost as follows,

$$s_{n,m}^{E} = 1 - e^{\theta_e E_n^m}, \tag{6}$$

where θ_e denotes the energy consumption factor and E_n^m denotes the total energy consumption to complete the tasks. Considering the revenue obtained from user m, the revenue of the satellite is given by,

$$s_{n,m}^{R} = 1 + e^{\theta_r R_n^m}, \tag{7}$$

where θ_r denotes the income coefficient and R_n^m denotes the income from completed tasks. Therefore, the overall service satisfaction of satellites can be described as,

$$s_{n,m} = s_{n,m}^{E} + s_{n,m}^{R}, \tag{8}$$

Based on the above equation, the problem of maximizing satisfaction for the satellites can be formulated as follows,

$$
\begin{aligned}
&\max_{x,R}\left(\sum_{i=1}^{M}\sum_{j=1}^{N}s_{i,j}\right)\\
s.t.\ &C1: T_i \le T_m, i \in M,\\
&C2: \sum_{i=1}^{n} F_{ij} \le C_j^{max}, i \in M, j \in N,\\
&C3: \sum_{i=1}^{n} D_{ij} \le H_j^{max}, i \in M, j \in N,\\
&C4: \sum_{i=1}^{n} x_{ij} \le L_j^{max}, i \in M, j \in N,\\
&C5: \sum_{j=1}^{M} x_{ij} \le 1, j \in N,\\
&C6: x_{ij} \in \{0,1\}, i \in M, j \in N.
\end{aligned} \tag{9}
$$

where constraint $C1$ denotes the delay constraint of the tasks, constraint $C2$ denotes the computational resource constraint of the satellites, constraint $C3$ denotes the cache resource constraint of the satellites, constraint $C4$ denotes the communication resource constraint of the satellites, constraint $C5$ denotes that each task is served by at most one satellite, and constraint $C6$ denotes the variable constraint.

3. Online Auction-Based Resource Allocation Method

In this section, we use the auction theory to achieve optimal resource allocation for the researched satellite network. Firstly, a multi-round auction-based method is proposed to accomplish efficient matching between users and satellites in Section 3.1. Then, the optimal solution is obtained according to the payment rule to achieve satisfaction maximization in Section 3.2.

3.1. Auction Mechanism

Generally, there are three important components in an auction model, the buyer, the seller, and the auctioneer. In this paper, the ground users are considered the buyers and the satellites are the sellers. The ground users need to purchase resources from the satellites for the MEC services and the satellites can gain profit by providing MEC services. A satellite with large communication coverage can also be considered as the auctioneer.

The multi-round auction-based satisfaction maximization mechanism is divided into three main phases. Firstly, the ground users provide computation requirements to the auctioneer, and provide bids based on the broadcast information of the auctioneer. Then, the auctioneer performs resource checking, utility calculation, and task assignment based on the bid information. Finally, when the matching between users and satellites is finished, the auctioneer determines the final pricing based on the matching results. In the first phase of the auction, the users provide requirements to the auctioneer. In the second phase of the auction, the auctioneer uses a bidding strategy to measure which satellites better fit the users' criteria, and determines whether the users can be served by the satellites based on a matching strategy. After determining the matching, the final pricing strategy for each user is determined based on the bids.

In this paper, we consider that the bids submitted by the users at different satellites can be different. Since the tasks are also different for each user, the final revenue for the user would be different. In order to allocate the satellites' resources more effectively, the user's initial profit is considered for matching the supply and demand between the satellites and the users. The user's initial cost-benefit represents the difference between the user's bid price and the satellite's declared price, which is given by,

$$\delta_{ij} = bid(i,j) - Ask(j), i \in M, j \in N, \tag{10}$$

where $bid(i, j)$ denotes the bid of user i to satellite j, and $Ask(j)$ denotes the lowest service price of satellite j.

Every user wants to save on cost and obtain the most benefit with the least cost. Therefore, the satellites with a higher initial cost-benefit should have a higher chance of winning the bids. The auctioneer will give priority to the satellites with lower task costs for users. In other words, the auctioneer selects the satellites from the user's perspective and decides which satellite is better for the users. Thus, in order to maximize service satisfaction, we need to design a matching strategy, i.e., to solve the service matching between the satellites and the users.

In this paper, the matching of users can be described as a winner determination problem, i.e., determining whether a satellite is available to serve a user. At the beginning of the auction, all sellers submit their bids to the auctioneer based on the buyers' information. The auctioneer determines the set of user matching candidates, i.e., which buyers and sellers match each other, based on calculating the user's resource requirement bidding ratio. During each round of matching, each satellite is matched with only one buyer. When multiple buyers select the same seller, the seller can make a reverse selection.

To ensure the satisfaction of satellites, service satisfaction is used for seller-to-buyer selection. In other words, in the case of multiple users selecting the same satellite, the satellites pre-calculate the satisfaction brought by each user of the service based on the bid price and select the user with the greatest satisfaction for matching.

As seen from the above equation, the seller prefers to choose the user with a higher overall price–performance ratio for the service. Thus, the seller selects a buyer from the candidate set to match with based on the overall price–performance value. The remaining users in the candidate set are considered failed matches and the next round of the auction is conducted. During the auction process, the auction ends when all buyers are served by the seller. As shown by (7), the satellite's service satisfaction of the user depends on the user's task energy consumption and the bid. The less energy consumed by the user's task during processing, the less cost to the seller. At the same time, a higher bid for the task brings the seller higher revenue. Therefore, the seller selects a buyer from the candidate set to match with based on the service satisfaction.

3.2. Dynamic Pricing and Allocation Algorithm

In the final stage of the auction, the auctioneer needs to determine the final price to be paid by the user. After a bidder has been awarded a bid, they need to pay the pricing according to the relevant payment rules. The determination of the payment rules has a crucial impact on the auction mechanism. At the same time, the payment rules also affect the revenue of satellites. Reasonable payment rules can ensure the incentive compatibility of the auction mechanism and promote the buyer to be able to make reasonable bids. In this paper, the Vickrey auction [36] method is used for the final payment pricing of the buyer, also known as the second-price sealed-bid auction. The highest bidder wins, but only pays the second-highest bidder's price. This auction mechanism can motivate bidders to report their true bids. Therefore, we use the Vickrey auction mechanism by calculating the second-highest bid as the final price.

To maximize the service satisfaction of satellites, we propose an online multi-round auction resource allocation (OMARA) algorithm, as shown in Algorithm 1. In Algorithm 1, the user first bids for the service provider that satisfies the service price and resource requirements. When more than one service provider exists to meet the user's needs, the user selects the service provider with the highest cost-benefit to bid. Secondly, after the user has completed the bidding process, the service provider begins to establish a service relationship with the user. When more than one user selects the same service provider at the same time, the service provider enters a reverse selection, i.e., the right to choose changes. The service provider calculates the service satisfaction level and selects the user with the highest level of satisfaction for the service. In other words, the resource allocation mechanism based on online multi-round auctions selects at most one user per iteration of the process. Finally, when a new service cycle begins, users who have not yet completed their services continue to bid and the service provider selects the most suitable user as the winner. Such an online mechanism guarantees the stability and reliability of the mechanism while safeguarding the interests of the users.

Algorithm 1: Online Multi-round Auction-based Resource Allocation Algorithm

Input: $N, M, Bid, Ask, D_N, O_N, F_N, V_N, T_m^N, H_M, L_M, C_M$
Output: Optimal matching matrix $A^* = \{a_{ij}\}, i \in M, j \in N$; optimal final price $p_{ij}, i \in M, j \in N$;
for $i = 1$ to M
  $s_1 = s_2 = s_3 = s_4 = \varnothing$
  for $t = 1$ to N
    if Bid$(i,j) \geq$ Ask(j) **then**
      if $D_i \leq H_j$ **then** $s_1 \leftarrow j$; **end if**
      if $F_i \leq C_j^{max}$ **then** $s_2 \leftarrow j$; **end if**
      if $L_j > 0$ **then** $s_3 \leftarrow j$; **end if**
      if $T_i \leq T_m^i$ **then** $s_4 \leftarrow j$; **end if**
    end if
    $s_0 = s_1 \cap s_2 \cap s_3 \cap s_4$;
    if $size(s_0) > 1$
      Calculate δ_{ij} by (10);
      the buyer chooses seller m with biggest to server;
      $a(i,m) = 1$;
    elif $size(s_0) == 1$
      $a(i,s_0)$ =1;
    end if
  end for
end for
for $j = 1$ to M
  if $\sum_{i=1}^{M} a_{ij} > 1$ **then**
    calculate s_{ij} by (8);
    The seller chooses the buyer with biggest s_{ij} to server;
  end if
end for

4. Simulation Results

In this section, we evaluate the performance of the proposed OMARA algorithm and compare it with ASCRA [37], PMMRA [38], and Vickrey. We first describe the experimental setup in Section 4.1 and then present the relevant simulation results to demonstrate the advantages of our proposed OMARA algorithm in Section 4.2.

4.1. Simulation Settings

Considering a satellite network with M satellites and N users randomly distributed over a radius of 300 m. The number of satellites varies from 2 to 5 and the number of users varies from 10 to 40. We assume that each user has only one task that needs to be computed, and the user's bid for satellites is set from 8 to 14. The data size of the task is 100 kb to 1024 kb, and the execution result size of the task is 1 kb to 100 kb. Each task has different requirements for latency, so the tolerated latency of the task is from 0.5 s to 1 s. Since different user tasks have different execution characteristics, F_i is set to 200 to 2000 Mega cycles. The ask of satellites is 10 to 12. The computing capacity of the edge server on the satellites is 20 GHz and the maximum number of services is 15. The bandwidth B of satellites is 200 Khz [39].

4.2. Performance Analysis

As can be seen from Figure 2, for all four strategies, the number of tasks served by the seller always increases with the number of user tasks. On the other hand, we can find that the number of successfully completed tasks exceeds the other three strategies under the OMARA method, i.e., more users can be served. Since the OMARA method uses a multi-round auction mechanism, the number of tasks that complete the transaction is greater than that of the Vickrey auction method. Similarly, the PMMPA method and the ASCRA method have a higher number of successfully completed tasks than the Vickrey auction method.

Figure 3 describes the comparison of the total profit of all satellites in the whole system. In general, the total revenue is proportional to the number of user tasks. From Figure 3, it can be seen that under the OMARA mechanism, the overall satellites of the system have higher revenue than other strategies and are able to earn more revenue. In other words, the OMARA mechanism can effectively protect the income of sellers. This is because our mechanism is not only individually rational but also considered from the seller's perspective in the process of user matching to protect the interests of resource providers.

Figure 4 describes the trend of the service satisfaction of the overall satellites of the system for different numbers of tasks. As can be seen from Figure 4, the service satisfaction for all four mechanisms can increase with the number of users. Because the number of users increases, the number of users who successfully complete the transaction also increases, as shown in Figure 2. At the same time, the revenue received by sellers will also increase, thus increasing the service satisfaction of sellers. In addition, it can be seen from Figure 4 that the OMARA method possesses higher service satisfaction. This is because the OMARA method is a bidirectional matching process that considers not only the cost benefits of buyers but also the service benefits of sellers.

Figure 5 describes the overall service satisfaction of satellites in the whole system for different numbers of satellites. We consider the trend of service satisfaction of the overall satellites in the system with the number of users being 40. As can be seen from Figure 5, the overall system satisfaction of the OMARA method, PMMPA method, and ASCRA method gradually increases as the number of satellites increases. This is because the increase in the number of satellites can provide more service choices for users. Whereas, the Vickrey method is unable to complete matching with more users in the matching process due to single-round matching. Meanwhile, the OMARA method is able to obtain higher overall service satisfaction compared to other strategies.

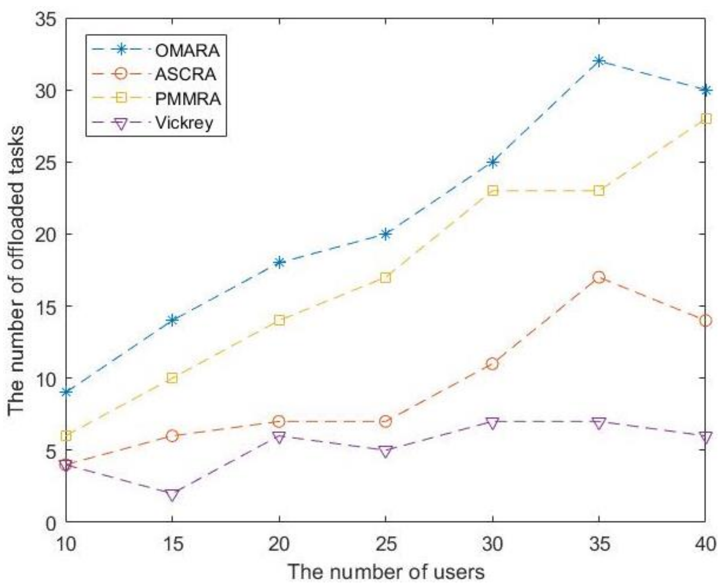

Figure 2. Number of successful trades with different numbers of tasks.

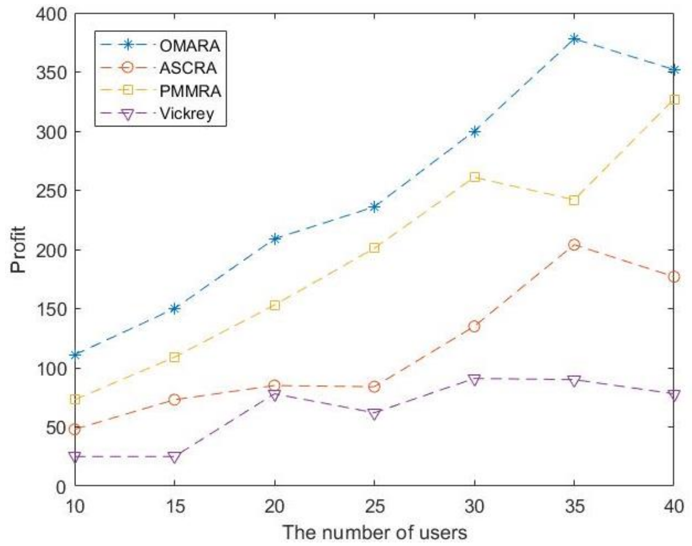

Figure 3. Profit of seller with different numbers of tasks.

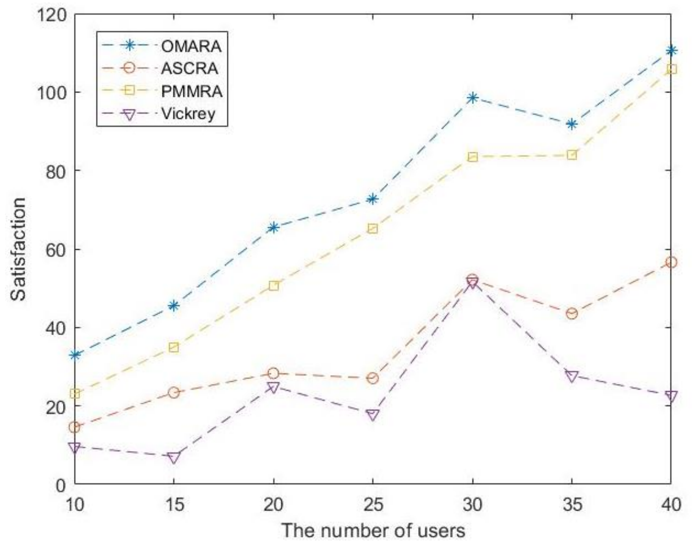

Figure 4. Overall seller satisfaction with different numbers of tasks.

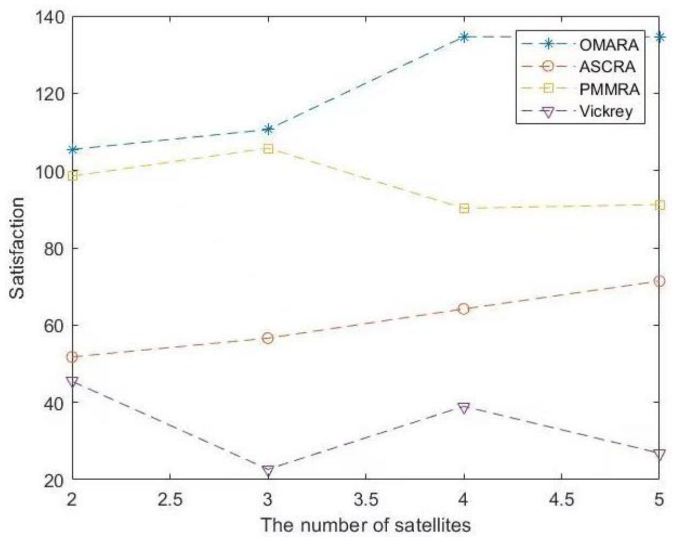

Figure 5. Overall seller satisfaction with different numbers of sellers.

5. Conclusions

In this paper, we study the resource allocation problem in a multi-user and multi-satellite scenario. Using an auction model, we describe the resource supply and demand relationship between users and satellites. In addition, in order to improve the service satisfaction of the overall satellites of the system, an online multi-round auction mechanism for service satisfaction maximization is proposed for the service matching relationship between satellites and users and to determine the final payment price. The OMARA method can ensure the delay tolerance of user tasks and allocate resources more rationally. Through experimental simulations, the results show that the method proposed in this paper can improve the service satisfaction of resource providers (satellites) in the overall system and increase the number of service users as much as possible.

In future work, we should consider the cooperation between the satellites. The satellite should not be limited to providing service to users, they should assist the other satellites after the completion of the current service works from users to improve the overall service satisfaction of the satellite networks. The time sequence relationship between multiple satellites should also be included in the influencing factors of resource allocation problem.

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References

1. Jones, D.; Gates, A.; Huvenne, V.; Phillips, A.; Bett, B. Autonomous marine environmental monitoring: Application in decommissioned oil fields. *Sci. Total Environ.* **2019**, *668*, 835–853. [CrossRef] [PubMed]
2. Liang, Y.; Li, A.; Chen, J.; Tan, Z.; Tong, M.; Liu, Z.; Qiu, J.; Yu, R. Progress on the investigation and monitoring of marine phycotoxins in China. *Harmful Algae* **2022**, *111*, 102152. [CrossRef] [PubMed]
3. Rosenberg, D.; Chung, C. Maritime Security in the South China Sea: Coordinating Coastal and User State Priorities. *Ocean. Dev. Int. Law* **2008**, *39*, 51–68. [CrossRef]
4. Munari, F. Search and Rescue at Sea: Do New Challenges Require New Rules? In *Governance of Arctic Shipping*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 63–81.
5. Pelton, J.N. *Trends and Future of Satellite Communications*; Springer: New York, NY, USA, 2013.
6. Li, W.; Li, Z.; Jiang, W.; Chen, Q.; Zhu, G.; Wang, J. A New Spatial Filtering Algorithm for Noisy and Missing GNSS Position Time Series Using Weighted Expectation Maximization Principal Component Analysis: A Case Study for Regional GNSS Network in Xinjiang Province. *Remote Sens.* **2022**, *14*, 1295. [CrossRef]
7. Mengmeng, C.; Weina, H. A printed quadrifilar-helical antenna for Ku-band mobile satellite communication terminal. In Proceedings of the IEEE 17th International Conference on Communication Technology (ICCT), Chengdu, China, 27–30 October 2017; pp. 755–759.
8. Morana, S. Mobile Satellite Communications. U.S. Patent US8593339B2, 26 November 2013.
9. Hu, Y.; Gong, W. An On-Orbit Task-Offloading Strategy Based on Satellite Edge Computing. *Sensors* **2023**, *23*, 4271. [CrossRef] [PubMed]
10. Wu, J.; Jia, M.; Zhang, L.; Guo, Q. DNNs Based Computation Offloading for LEO Satellite Edge Computing. *Electronics* **2022**, *11*, 4108. [CrossRef]
11. Wang, Q.; Li, W.; Yu, Z.; Abbasi, Q.; Imran, M.; Ansari, S.; Sambo, Y.; Wu, L.; Li, Q.; Zhu, T. An Overview of Emergency Communication Networks. *Remote Sens.* **2023**, *15*, 1595. [CrossRef]
12. De Sanctis, M.; Cianca, E.; Araniti, G.; Bisio, I.; Prasad, R. Satellite Communications Supporting Internet of Remote Things. *IEEE Internet Things J.* **2016**, *3*, 113–123. [CrossRef]
13. He, Y.; Cui, G.; Li, P.; Wang, W. Random access preamble design based on time pre-compensation for LTE-satellite system. *J. China Univ. Posts Telecommun.* **2015**, *22*, 64–73.
14. Jia, M.; Zhang, X.; Gu, X.; Guo, Q.; Li, Y.; Lin, P. Inter-beam Interference Constrained Resource Allocation for Shared Spectrum Multi-beam Satellite Communication Systems. *IEEE Internet Things J.* **2019**, *6*, 6052–6059. [CrossRef]

15. Xu, H.; Han, S.; Li, X.; Han, Z. Anomaly Traffic Detection Based on Communication-Efficient Federated Learning in Space-Air-Ground Integration Network. *IEEE Trans. Wirel. Commun.* 2023, *early access*. [CrossRef]
16. Guo, C.; Gong, C.; Xu, H.; Zhang, L.; Han, Z. A Dynamic Handover Software-Defined Transmission Control Scheme in Space-Air-Ground Integrated Networks. *IEEE Trans. Wirel. Commun.* **2022**, *21*, 6110–6124. [CrossRef]
17. Xu, H.; Huang, W.; Zhou, Y.; Yang, D.; Li, M.; Han, Z. Edge Computing Resource Allocation for Unmanned Aerial Vehicle Assisted Mobile Network with Blockchain Applications. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 3107–3121. [CrossRef]
18. Rakhmanov, A.; Wiseman, Y. Compression of GNSS Data with the Aim of Speeding up Communication to Autonomous Vehicles. *Remote Sens.* **2023**, *15*, 2165. [CrossRef]
19. Sekander, S.; Tabassum, H.; Hossain, E. Multi-Tier Drone Architecture for 5G/B5G Cellular Networks: Challenges, Trends, and Prospects.*IEEE Commun. Mag.* **2018**, *56*, 96–103. [CrossRef]
20. Zhang, J.; Zhou, L.; Tang, Q.; Hu, N.E.C.-H.X.; Zhao, H.; Wei, J. Stochastic Computation Offloading and Trajectory Scheduling for UAV-Assisted Mobile Edge Computing. *IEEE Internet Things J.* **2019**, *6*, 3688–3699. [CrossRef]
21. Luong, N.C.; Wang, P.; Niyato, D.; Liang, Y.-C.; Han, Z.; Hou, F. Applications of Economic and Pricing Models for Resource Management in 5G Wireless Networks: A Survey. *IEEE Commun. Surv. Tutorials* **2019**, *21*, 3298–3339. [CrossRef]
22. Khan, A.S.; Chen, G.; Rahulamathavan, Y.; Zheng, G.; Assadhan, B.; Lambotharan, S. Trusted UAV Network Coverage Using Blockchain, Machine Learning, and Auction Mechanisms. *IEEE Access* **2020**, *8*, 118219–118234. [CrossRef]
23. Zhang, Y.; Lee, C.; Niyato, D.; Wang, P. Auction Approaches for Resource Allocation in Wireless Systems: A Survey. *IEEE Commun. Surv. Tutorials* **2013**, *15*, 1020–1041. [CrossRef]
24. Vinothina, V.; Sridaran, R.; Ganapathi, P. A Survey on Resource Allocation Strategies in Cloud Computing. *Int. J. Adv. Comput. Sci. Appl. (IJACSA)* **2012**, *3*. [CrossRef]
25. Sheikholeslami, F.; Jafari Navimipour, N. Auction-based resource allocation mechanisms in the cloud environments: A review of the literature and reflection on future challenges. *Concurr. Comput. Pract. Exp.* **2018**, *30*, 4456. [CrossRef]
26. Park, D.; Park, S. Multiple-domain marine data utilization structure for e-navigation. *Clust. Comput.* **2016**, *19*, 301–308. [CrossRef]
27. Rajkumar, P.V.; Sandhu, R. Safety Decidability for Pre-Authorization Usage Control with Identifier Attribute Domains. *IEEE Trans. Dependable Secur. Comput.* **2020**, *17*, 465–478. [CrossRef]
28. Rajkumar, P.V.; Sandhu, R. Safety Decidability for Pre-Authorization Usage Control with Finite Attribute Domains. *IEEE Trans. Dependable Secur. Comput.* **2016**, *13*, 582–590. [CrossRef]
29. Rajkumar, P.V.; Sandhu, R. POSTER: Security Enhanced Administrative Role Based Access Control Models. In Proceedings of the 2016 ACM SIGSAC Conference, ACM, Vienna, Austria, 24–28 October 2016.
30. Rajkumar, P.V.; Ghosh, S.K.; Dasgupta, P. Concurrent Usage Control Implementation Verification Using the SPIN Model Checker. In *International Conference on Network Security and Applications*; Springer: Berlin/Heidelberg, Germany, 2020.
31. Ghosh, S.K.; Dasgupta, P. Application Specific Usage Control Implementation Verification. *Int. J. Netw. Secur. Its Appl.* **2009**, *1*, 116–128.
32. Wang, Y.; Zhang, J.; Xing, Z.; Peng, W.; Liu, L. A Computation Offloading Strategy in Satellite Terrestrial Networks with Double Edge Computing. In Proceedings of the 2018 IEEE International Conference on Communication Systems (ICCS), Chengdu, China, 19–21 December 2018.
33. Lin, X.; Wang, Y.; Xie, Q.; Pedram, M. Task Scheduling with Dynamic Voltage and Frequency Scaling for Energy Minimization in the Mobile Cloud Computing Environment. *IEEE Trans. Serv. Comput.* **2015**, *8*, 175–186. [CrossRef]
34. Wu, F.; Zhang, T.; Qiao, C.; Chen, G. A Strategy-Proof Auction Mechanism for Adaptive-Width Channel Allocation in Wireless Networks. *IEEE J. Sel. Areas Commun.* **2016**, *34*, 2678–2689. [CrossRef]
35. Al-Manthari, B.; Hassanein, H.; Ali, N.A.; Nasser, N. Fair Class-Based Downlink Scheduling with Revenue Considerations in Next Generation Broadband Wireless Access Systems. *IEEE Trans. Mob. Comput.* **2009**, *8*, 721–734. [CrossRef]
36. Vickrey, W. Counterspeculation, auctions, and competitive sealed tenders. *J. Financ.* **1961**, *16*, 8–37. [CrossRef]
37. Zhang, R.; Shi, W.; Zhang, J.; Liu, W. An Auction Scheme for Computing Resource Allocation in D2D-Assisted Mobile Edge Computing. In Proceedings of the IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 9–13 December 2019.
38. Wang, Q.; Guo, S.; Liu, J.; Pan, C.; Yang, L. Profit Maximization Incentive Mechanism for Resource Providers in Mobile Edge Computing. *IEEE Trans. Serv. Comput.* **2022**, *15*, 138–149. [CrossRef]
39. Ng, J.S.; Lim, W.Y.B.; Dai, H.-N.; Xiong, Z.; Huang, J.; Niyato, D.; Hua, X.-S.; Leung, C.; Miao, C. Communication-Efficient Federated Learning in UAV-enabled IoV: A Joint Auction-Coalition Approach. In Proceedings of the IEEE Global Communications Conference (GLOBECOM), Taipei, Taiwan, 7–11 December 2020.