

# On the Aggregated Resource Management for Satellite Edge Computing

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**Abstract**—Geosynchronous Earth Orbit (GEO) satellites, which can relay image data for Low Earth Orbit (LEO) satellites, play an important role in remote sensing. With the development of satellite technologies, the significantly improved computation capabilities of GEO satellites have enabled space service computing, through which GEO satellites can provide data processing services before forwarding to reduce the quantity of transmitted data. In the presence of multiple LEO satellites, how to make effective use of limited communication and computation resources in GEO satellites has become crucial. At present, the research on satellite resource management typically focuses on either communication or computation resources. Existing resource management algorithms are usually of slow convergence speed, which limits their applicability in real-time remote sensing scenarios. Therefore, we propose an aggregated resource management method for remote sensing applications. We first propose models for transmission tasks and processing tasks of remote sensing images. Then we formulate the aggregated resource management for satellite edge computing as a hybrid Stackelberg game and simplify the problem to speed up its convergence speed. Then we propose a distributed resource management algorithm to determine the optimal strategies. Simulation results show that the proposed method can quickly obtain the optimal resource allocation strategy and outperforms typical dynamic iterative algorithms in terms of service quantity and throughput.

**Index Terms**—Remote sensing, mobile edge computing, resource management, Stackelberg game

## I. INTRODUCTION

With the rapid development of satellite launching technology, satellite applications have received great attention. Remote sensing data being relayed by GEO satellites have become a major way of data transmission for LEO satellites [1]. The numbers of GEO satellites provide relay services is very limited by the orbiting space and costs. How to effectively

use limited communication resources of GEO satellites has become crucial. With the development of electronic component manufacturing technology, computing hardware in satellites has been enhanced [2]. GEO satellites are with the capability of space service computing, which can provide process services and reduce the quantity of transmitted data effectively. In order to make better use of satellite communication and computation resources, resource management of satellite edge computing has attracted broad interests from academia and industry.

Current research usually focuses on communication resource management or computing resource management. Hu *et al.* proposed a competitive market setting model for resource management to achieve a balance between quality of service (QoS) and energy consumption [3]. Kawamoto *et al.* proposed a flexible frequency resource allocation method to deal with inter-beam interference [4]. Jia *et al.* proposed an intelligent resource management scheme composed of spectrum sensing, prediction and allocation to improve spectrum efficiency with different user densities [5]. Jiao *et al.* investigated a joint network stability and resource allocation optimization problem to maximize the long-term network utility [6]. Liao *et al.* proposed a cooperative multi-agent deep reinforcement learning framework for radio resource management [7]. Chen *et al.* proposed a layered architecture and multiple M/M/1 queuing models, then designed a resource cube algorithm to reduce the total system delay [8]. He *et al.* proposed a stochastic optimization framework to maximize the time average number of hybrid tasks by jointly optimizing scheduling periods and antenna time block allocation [9]. Li *et al.* proposed a dynamically optimal cooperation scheme between terrestrial agents and satellite systems based on a stochastic process and optimal contract principle to improve spectrum efficiency [10]. Li *et al.* propose a computation offloading mechanism based on a two-stage Stackelberg game

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to analyze the interaction between multiple edge clouds and multiple IIoT devices [11].

On the basis of the aforementioned existing solutions, we propose to further consider aggregated management for communication and computation resources based on a hybrid Stackelberg game. We enhance the convergence speed of the algorithm as well, so that it can be better applied to real-time application scenarios. The main contributions of this paper are as follows:

- We model the transmission and computation of remote sensing images, and the process of integrated resource management as a hybrid Stackelberg game.
- We simplify the Stackelberg game model based on requirements of the application scenario, so that the Nash equilibrium point of the model can be quickly calculated.
- We propose an efficient method of resource allocation in remote sensing image application, which can quickly achieve optimal resource allocation strategy of LEO satellites.

The rest of the paper is organized as follows. In section II, the remote sensing image service is modeled as a hybrid Stackelberg game model. Section III simplifies the model based on the requirements of the application scenario and proposes a fast convergent resource allocation algorithm. Section IV shows the experimental results. Section V concludes the paper.

## II. HYBRID STACKELBERG GAME MODEL

### A. Application Scene Modeling of Remote Sensing Image

In remote sensing applications, GEO satellites can divide remote sensing data of each LEO satellite into two parts, one of which is forwarded directly to the ground, and the other is forwarded to the ground after processing. The process is shown in Fig. 1.

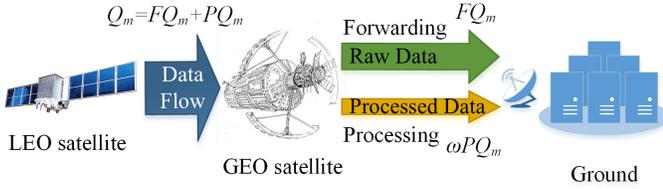


Fig. 1. Schematic diagram of remote sensing image application

Suppose that there are  $M$  LEO satellites, denoted as:  $LEO = \{1, 2, \dots, M\}$ . And  $N$  GEO satellites, denoted as:  $GEO = \{1, 2, \dots, N\}$ . For the  $m^{th}$  LEO satellite, the total amount of data uploaded is  $Q_m = (FQ_m, PQ_m)$ , where  $FQ_m > 0$  represents the amount of data forwarded directly, and  $PQ_m > 0$  represents the amount of data processed. The quantity of processed data is  $\omega PQ_m$ , where the compression ratio of data processing is recorded as  $\omega, 0 < \omega < 1$ .

In the process of remote image sensing, LEO satellites only need to send all the raw data to GEO satellites, so the cost mainly comes from the energy consumed by transmission. We model the energy consumption as follows: the total amount

of data sent by LEO satellite  $m$  is  $FQ_m + PQ_m$ . The transmission time  $T_{mn}^t$  from LEO satellite  $m$  to GEO satellite  $n$  is  $T_{mn}^t = \frac{FQ_m + PQ_m}{r_{mn}}$ , where  $r_{mn}$  denotes the transmission rate from satellite  $m$  to satellite  $n$ . The energy consumption of transmission from satellite  $m$  to satellite  $n$  is  $E_{mn}^t = \rho_{mn} T_{mn}^t$ , where  $\rho_{mn}$  denotes the transmission power from satellite  $m$  to satellite  $n$ .

The costs of GEO satellites consist of calculation costs and transmission costs. For the task of satellite  $m$ , the processing time in satellite  $n$  is  $T_{mn}^c = \frac{PQ_m}{c_n}$ , where  $c_n$  denotes the calculation ability of satellite  $n$ . The energy consumption of processing is  $E_{mn}^c = \eta_n T_{mn}^c$ , where  $\eta_n$  represents the energy consumption coefficient per CPU cycle of satellite  $n$ .

The total amount of data to be transmitted by satellite  $n$  is  $GQ_{mn} = FQ_m + \omega PQ_m$ , then the time for transmitting data from satellite  $n$  to the ground station is expressed as  $GT_{mn}^t = \frac{GQ_{mn}}{r_n}$ , where  $r_n$  denotes the rate of data transmission from satellite  $n$  to the ground station. And then the transmission energy consumption is  $GE_{mn}^t = \rho_n GT_{mn}^t$ , where  $\rho_n$  represents the data transmission power of satellite  $n$  to the ground station.

### B. Hybrid Stackelberg Game Model

The management of transmission and computation resources can be modeled as a hybrid Stackelberg game model. GEO satellites, as service providers and leaders in the game, will first give pricing strategies of communication and computation resources. LEO satellites are not only consumers of the service, but also followers of the game, so they will determine the data processing and transmission schemes according to pricing strategies. We denote the set of remote sensing image transmission requirements of LEO satellites as  $\mathcal{Q} = \{Q_1, Q_2, \dots, Q_M\}$ , and the computation resource pricing set of GEO satellites as  $\mathcal{P} = \{P_1, P_2, \dots, P_N\}$ , where  $P_i = (CP_i, TP_i)$ ,  $CP_i > 0, TP_i > 0$ . The utility functions of service providers and consumers are as follows:

For the LEO satellite  $m$ , the utility function  $F_m(TP_n, CP_n, FQ_m, PQ_m)$  is expressed as:

$$F_m(TP_n, CP_n, FQ_m, PQ_m) = U_m - D_m - \gamma E_{mn}^t. \quad (1)$$

Where  $U_m$  denotes the satisfaction of satellite  $m$ ,  $U_m = a \ln(1 + FQ_m) + b \ln(1 + PQ_m)$ .  $a, b$  denotes the coefficients of satisfactions with communication and computation.  $D_m$  denotes pay for expenses of satellite  $m$ ,  $D_m = TP_n \times FQ_m + CP_n \times PQ_m$ .  $E_{mn}^t$  denotes the transmission energy consumption of satellite  $m$ , and  $\gamma$  denotes the coefficient factor of energy consumption. Then  $F_m$  is calculated as below.

$$\begin{aligned} F_m(TP_n, CP_n, FQ_m, PQ_m) &= a \ln(1 + FQ_m) + b \ln(1 + PQ_m) - TP_n \times FQ_m \\ &\quad - CP_n \times PQ_m - \frac{\gamma \rho_{mn} (FQ_m + PQ_m)}{r_{mn}}. \end{aligned} \quad (2)$$

For the GEO satellite  $n$ , its utility function is shown in equation (3). □

$$G_n(TP_n, CP_n, FQ_m, PQ_m) = \sum_{S_{mn}=1} (D_m - \delta E_{mn}^c - \delta GE_{mn}^t). \quad (3)$$

Where  $\delta$  is the coefficient factor of energy consumption.  $S_{mn} = 1$  means that satellite  $m$  choose the services in satellite  $n$  to forward and process the image data. Then  $G_n$  is obtained as below.

$$G_n(TP_n, CP_n, FQ_m, PQ_m) = \sum_{S_{mn}=1} (TP_n \times FQ_m + CP_n \times PQ_m - \frac{\delta \eta_n PQ_m}{c_n} - \frac{\delta \rho_n (FQ_m + \omega PQ_m)}{r_n}). \quad (4)$$

### C. Nash Equilibrium Analysis

This section proves that there is a Nash equilibrium point in the hybrid Stackelberg game model proposed in this paper.

**Theorem 1.** *Considering dynamic transmission requirements with a fixed number of LEO satellites, for a certain LEO satellite whose utility function satisfies equation (2), there exists a unique Nash equilibrium point.*

*Proof.* The first-order partial derivative of the utility function of the  $m^{\text{th}}$  satellite (eqn.(2)) are calculated as follow.

$$\frac{\partial (F_m(TP_n, CP_n, FQ_m, PQ_m))}{\partial FQ_m} = \frac{a}{1 + FQ_m} - TP_n - \frac{\gamma \rho_{mn}}{r_{mn}}, \quad (5)$$

and

$$\frac{\partial (F_m(TP_n, CP_n, FQ_m, PQ_m))}{\partial PQ_m} = \frac{b}{1 + PQ_m} - CP_n - \frac{\gamma \rho_{mn}}{r_{mn}}. \quad (6)$$

Then the second-order partial derivative of equation (2) are calculated as follows.

$$A = \frac{\partial (F_m^2(TP_n, CP_n, FQ_m, PQ_m))}{\partial FQ_m^2} = -\frac{a}{(1 + FQ_m)^2}, \quad (7)$$

$$B = \frac{\partial (F_m^2(TP_n, CP_n, FQ_m, PQ_m))}{\partial FQ_m \partial PQ_m} = 0, \quad (8)$$

and

$$C = \frac{\partial (F_m^2(TP_n, CP_n, FQ_m, PQ_m))}{\partial PQ_m^2} = -\frac{b}{(1 + PQ_m)^2}. \quad (9)$$

Since  $AC - B^2 > 0$  and  $A < 0$ , the maximum value of utility function and the Nash equilibrium both exist.

When the utility function takes its maximum, the values of equations (5) and (6) are equal to zero, and the optimal data quantities for transmission and computation can be obtained as:

$$FQ_m^* = \frac{ar_{mn}}{r_{mn}TP_n + \gamma \rho_{mn}} - 1, \quad (10)$$

and

$$PQ_m^* = \frac{br_{mn}}{r_{mn}CP_n + \gamma \rho_{mn}} - 1. \quad (11)$$

**Theorem 2.** *We consider a fixed number of GEO satellites with dynamic prices of resources. For each GEO satellite whose utility function satisfies equation (4), there is a unique Nash equilibrium point for the utility function.*

*Proof.* The utility function of the GEO satellite  $n$  is constructed in equation (4). The first-order partial derivative of  $TP_n$  and  $CP_n$  are calculated as follows.

$$\frac{\partial (G_n(TP_n, CP_n, FQ_m^*, PQ_m^*))}{\partial TP_n} = \sum_{S_{mn}=1} \left( \frac{ar_{mn}(\gamma r_n \rho_{mn} + \delta \rho_n r_{mn})}{r_n(r_{mn}TP_n + \gamma \rho_{mn})^2} - 1 \right), \quad (12)$$

and

$$\frac{\partial (G_n(TP_n, CP_n, FQ_m^*, PQ_m^*))}{\partial CP_n} = \sum_{S_{mn}=1} \left( \frac{br_{mn}(\gamma c_n r_n \rho_{mn} + \delta \eta_n r_n r_{mn} + \delta \omega \rho_n c_n r_{mn})}{c_n r_n (r_{mn}CP_n + \gamma \rho_{mn})^2} - 1 \right). \quad (13)$$

The second-order partial derivative of equation (4) are calculated as follows.

$$A = \sum_{S_{mn}=1} \frac{\partial (G_m^2(TP_n, CP_n, FQ_m^*, PQ_m^*))}{\partial TP_n^2} = \sum_{S_{mn}=1} -\frac{2ar_{mn}^2(\gamma r_n \rho_{mn} + \delta \rho_n r_{mn})}{r_n(r_{mn}TP_n + \gamma \rho_{mn})^3}, \quad (14)$$

$$B = \sum_{S_{mn}=1} \frac{\partial (G_m^2(TP_n, CP_n, FQ_m^*, PQ_m^*))}{\partial TP_n \partial CP_n} = 0, \quad (15)$$

and

$$C = \sum_{S_{mn}=1} \frac{\partial (G_m^2(TP_n, CP_n, FQ_m^*, PQ_m^*))}{\partial CP_n^2} = \sum_{S_{mn}=1} -\frac{2br_{mn}^2(\gamma c_n r_n \rho_{mn} + \delta \eta_n r_n r_{mn} + \delta \omega \rho_n c_n r_{mn})}{c_n r_n (r_{mn}CP_n + \gamma \rho_{mn})^3}. \quad (16)$$

Since  $AC - B^2 > 0$  and  $A < 0$ , the maximum value of utility function and the Nash equilibrium both exist. □

## III. AGGREGATED RESOURCE MANAGEMENT METHOD BASED ON HYBRID STACKELBERG GAME

### A. Model Simplification

In equations (12) and (13),  $r_{mn}$  and  $\rho_{mn}$  change with  $m$ . However, in practical network applications, network infrastructure often provides the same transmission rate for terminal devices, and similar terminals often have the same standardized transmission power. Assuming that in the future 6G scenario, GEO satellites, as space-based 6G base stations, provide general network access services to LEO satellites. LEO satellites send data to GEO satellites at the same rate (denoted as  $r_{mn}$ ) with the same transmission power (denoted as  $\rho_{mn}$ ), i.e.,  $r_{mn} = r$ ,  $\rho_{mn} = \rho$ , where  $r$  and  $\rho$  are both

constant. Equation (12) and equation (13) are then rewritten as follows:

$$\begin{aligned} & \frac{\partial (G_n(TP_n, CP_n, FQ_m^*, PQ_m^*))}{\partial TP_n} \\ &= m \left( \frac{\ar(\gamma r_n \rho + \delta \rho_n r)}{r_n (r TP_n + \gamma \rho)^2} - 1 \right), \end{aligned} \quad (17)$$

and

$$\begin{aligned} & \frac{\partial (G_n(TP_n, CP_n, FQ_m^*, PQ_m^*))}{\partial CP_n} \\ &= m \left( \frac{br(\gamma c_n r_n \rho + \delta \eta_n r_n r + \delta \omega \rho_n c_n r)}{c_n r_n (r CP_n + \gamma \rho)^2} - 1 \right). \end{aligned} \quad (18)$$

The zeros of equations (12) and (13) are solved as follows.

$$TP_n^* = \sqrt{\frac{a(\gamma r_n \rho + \delta \rho_n r)}{r r_n} - \frac{\gamma \rho}{r}}, \quad (19)$$

and

$$CP_n^* = \sqrt{\frac{b(\gamma c_n r_n \rho + \delta \eta_n r_n r + \delta \omega \rho_n c_n r)}{r c_n r_n} - \frac{\gamma \rho}{r}}. \quad (20)$$

### B. Distributed Resource Management Algorithm

Based on the analysis of Nash equilibrium in the hybrid Stackelberg game, we proposed a distributed resource management algorithm.

GEO satellites first provides their initial pricing strategies and broadcasts them to LEO satellites. The resource requirements of LEO satellites is initialize to be 0, i.e.,  $FQ_m^* = PQ_m^* = 0$ . Then,  $TP_n = a - \frac{\gamma \rho}{r}$ ,  $CP_n = b - \frac{\gamma \rho}{r}$ . After receiving the pricing strategy, LEO satellites choose suitable GEO satellites and send their optimal resource requirements to selected GEO satellites. GEO satellites calculate the optimal pricing strategies according to the requirements of LEO satellites, this process is repeated until the algorithm converges. This process is described in details in Algorithm 1.

Through algorithm 1, both GEO satellites and LEO satellites can quickly calculate the optimal prices and resource requirements. In the worst case, the amount of computation on a certain GEO satellite is the same with the number of messages from LEO satellites, and the computational complexity of each round is  $O(M)$ . Similarly, the calculation complexity of each round of each LEO satellite is  $O(N)$  in the worst case. In real applications, due to the limited number of satellites, this algorithm usually converges as a much faster speed.

## IV. NUMERICAL RESULTS

In order to verify the performances of the resource management method proposed in this paper, a typical remote sensing satellite application scenario is designed and simulated based on MATLAB 2019b.

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### Algorithm 1 Distributed Resource Management Algorithm

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#### GEO satellites:

**Input:** Threshold of task quantity  $QT$ .

**Output:** Optimal pricing  $TP_n^*, CP_n^*$ .

- 1: Generate initial prices:  $TP_n = a - \frac{\gamma \rho}{r}$ ,  $CP_n = b - \frac{\gamma \rho}{r}$ .
- Initialization:**
- 2: **for** any  $m$ ,  $FQ_m = PQ_m = 0$ .
- 3: Broadcast  $TP_n, CP_n$  to LEO satellites.
- 4: Receive task requirements  $FQ_m^*, PQ_m^*$ .
- 5: **while** new  $FQ_m^*, PQ_m^*$  received
- 6:   **if**  $|FQ_m^* - FQ_m| > QT$  OR  $|PQ_m^* - PQ_m| > QT$
- 7:    Computing  $TP_n^*$  and  $CP_n^*$  according to equation (19) and (20).
- 8:    Broadcasting  $TP_n^*$  and  $CP_n^*$  to all LEO satellites.
- 9:     $FQ_m = FQ_m^*$ ;  $PQ_m = PQ_m^*$ .
- 10:   **end if**
- 11: **end while**

#### LEO satellites:

**Input:** Threshold of price  $PT$ .

**Output:** Optimal task quantity  $FQ_m^*, PQ_m^*$ .

- Initialization:**
  - 1:  $FQ_m = PQ_m = 0$ .
  - 2: **for** any  $n$ ,  $TP_n = a - \frac{\gamma \rho}{r}$ ,  $CP_n = b - \frac{\gamma \rho}{r}$ .
  - 3: **while** new  $TP_n^*, CP_n^*$  received
  - 4:   **if**  $|TP_n^* - TP_n| > PT$  OR  $|CP_n^* - CP_n| > PT$
  - 5:    Computing  $FQ_m^*$  and  $PQ_m^*$  according to equation (10) and (11).
  - 6:    Broadcasting  $FQ_m^*$  and  $PQ_m^*$  to all GEO satellites.
  - 7:    **end if**
  - 8: **end while**
- 

### A. Parameters Setup

The typical experimental scenarios designed in this paper consist of 18 LEO satellites for remote sensing images and 3 GEO satellites for data forwarding and processing. Each GEO satellite provides relay service for 6 LEO satellites. Although data processing can reduce the data quantity of transmissions, some original information can get lost, so we set the satisfaction coefficient of transmission  $a$  higher than the satisfaction coefficient of computation  $b$  ( $a = 10$ ,  $b = 6$ ). For GEO and LEO satellites, each side formulates its own strategy, which is called one-round game. The time duration of 1 round is denoted as  $T$ . Parameter settings of the simulation are listed in Table I.

### B. Analysis of The Result of Resource Allocation

In this subsection, we investigate the utilities of players, as shown in Fig. 2, the total utilities and average utilities of LEO satellites and GEO satellites reach their optimal values in the second round. This verifies the fast convergence speed of the proposed algorithm.

The fast convergence speed is a result of the simplification of hybrid Stackelberg game model, which makes the optimal prices of GEO satellites computable. Most existing approaches

TABLE I  
PARAMETER SETTINGS

Notation	Description	Value
$a$	Satisfaction coefficient of transmission	10
$b$	Satisfaction coefficient of computation	6
$\gamma$	Energy consumption coefficient of LEO satellites	0.1
$\delta$	Energy consumption coefficient of GEO satellites	0.1
$r$	Transmission rate of LEO satellites	10 MBps
$r_n$	Transmission rate of GEO satellite $n$	100 MBps
$\rho$	Transmission power of LEO satellites	10 W
$\rho_n$	Transmission power of GEO satellite $n$	100 W
$C_n$	Computing capability of GEO satellite $n$	5 GB/s
$\eta_n$	Computation power GEO satellite $n$	50 W
$\omega$	Compression ratio of processing	0.01
$T$	Time duration of 1 round	10 s
$QT$	Threshold of task quantity	0.01
$PT$	Threshold of price	0.01

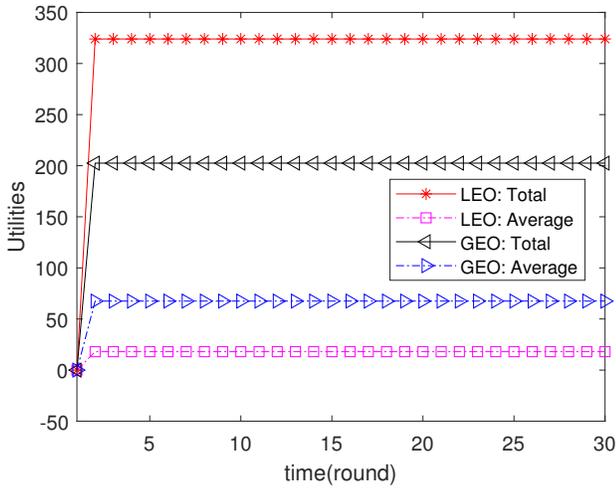


Fig. 2. Utilities of players

use dynamic iterative algorithms (DIAs) to find optimal prices [11]. To evaluate the proposed approach comprehensively, we compare the proposed approach with a typical DIA-based approach [11]. In DIA, step sizes are set to be 0.1, 0.08, 0.06, respectively. Other parameters are set to be the same with the proposed algorithm. We define social welfare as the sum of utilities of all players. The comparison on social welfare is shown in Fig. 3.

As shown in Fig. 3, the convergence speed of DIA is determined by the step size. Larger step size leads to shorter convergence time. Through DIA, the social welfare reaches its maximum value in the 20<sup>th</sup> round when its step size is set to be 0.1. Nonetheless, the convergence time is still much longer than the proposed approach. In practical scenarios, fast convergence speed leads to performance improvement, which is discussed in the next subsection.

### C. Performance Discussions and Comparisons

To investigate the performance of the proposed approach, we evaluate the performance of the proposed approach in terms

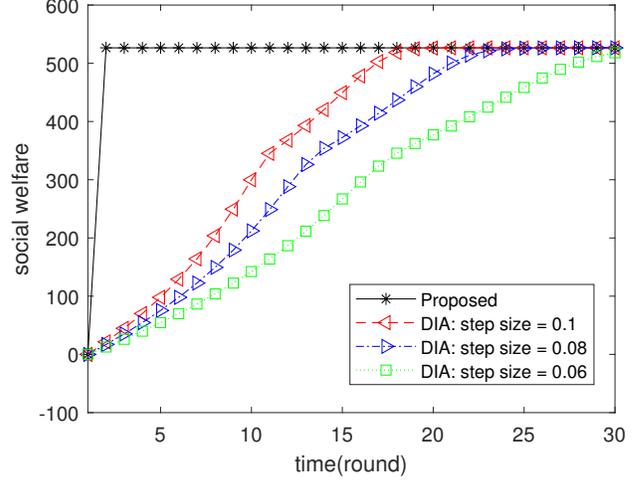


Fig. 3. Comparison on social welfare

of quantity of service and throughput, respectively.

The quantity of service includes quantity of transmission and computation, which are denoted as  $TFQ$  and  $TPQ$ , respectively.  $TFQ$  and  $TPQ$  can be calculated in eqns (21) and (22), respectively.

$$TFQ = \sum FQ_m, \quad (21)$$

and

$$TPQ = \sum PQ_m. \quad (22)$$

We investigate the quantity of remote sensing data transmitted to the ground per time slot (refer to as throughput), and the total quantity of remote sensing data transmitted to the ground in time  $t$  (refer to as average throughput). The throughput (denoted as  $TPS$ ) and average throughput (denoted as  $ATPS$ ) can be computed as shown in eqns.(23) and (24).

$$TPS = \frac{\sum(FQ_m + PQ_m)}{T}, \quad (23)$$

and

$$ATPS = \frac{\sum_{t_0}^t \sum(FQ_m + PQ_m)}{t - t_0}. \quad (24)$$

where  $t_0$  denotes the beginning time of application,  $t$  denotes the time.

In these simulations, the step size of DIA is set to be 0.1. Simulation results on quantity of service and throughput are shown in Fig. 4 and Fig. 5, respectively. As shown in Fig. 4,  $TFQ$  and  $TPQ$  of the proposed approach reach their maximum in the second round. However, through DIA,  $TFQ$  and  $TPQ$  reach their maximum at the 11th and the 20th round, respectively. Before DIA reach its optimal solution, the proposed approach forward and process more data to the ground, which increases the quantity of space-based service.

As shown in Fig. 5, the throughput and average throughput of the proposed approach are always larger than that of DIA. The throughput of DIA reaches its maximum at the 20th round, which is the same as the result in Fig. 4. Over time, the

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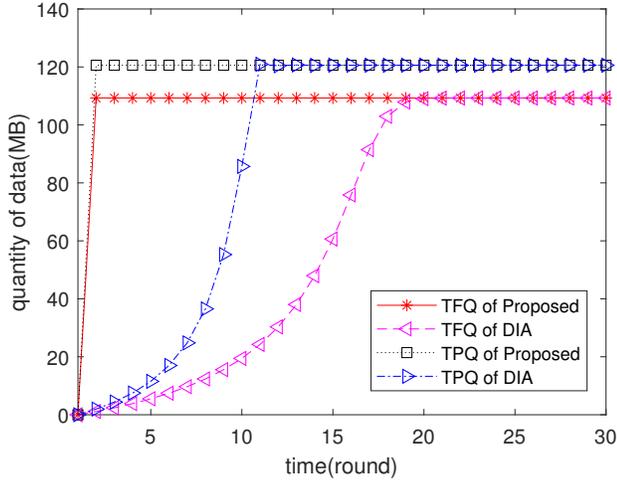


Fig. 4. Comparison on service quantity

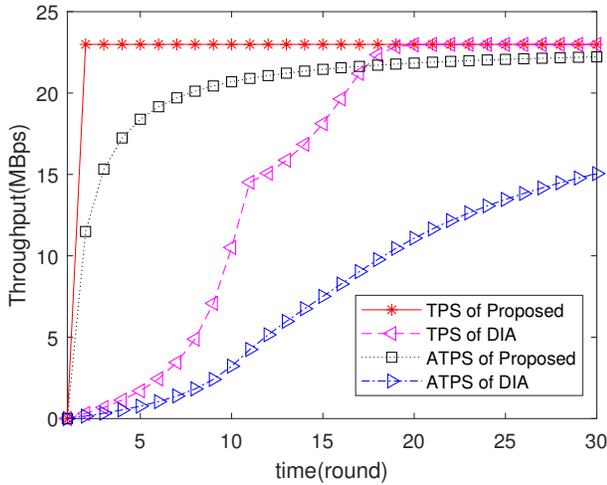


Fig. 5. Comparison on throughput

average throughput of DIA increases much slower than the average throughput of the proposed approach. This is because that the fast convergence speed improves the throughput of the application.

These simulations show that the proposed approach has a higher convergence speed compared with existing dynamic iterative algorithms. Higher convergence speed leads to higher performances in terms of quantity of service and throughput.

## V. CONCLUSION

In this paper, a hybrid Stackelberg game is modeled based on the remote sensing image transmission scenario. With the simplification of the hybrid Stackelberg game model, we proposed a novel approach with high convergence speed. The performance of the proposed approach is verified by simulations and shows higher forwarded and processed quantity of service and throughput.