Collaborative Computation Offloading and Resource Allocation in Satellite Edge Computing

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***Abstract*—In this paper, we investigate the collaborative computation offloading method in satellite edge computing by allowing computation tasks to be executed by multiple satellites with computing capacity. The main purpose is to optimize the resource allocation to minimize the energy consumption of the network, which is formulated as a non-convex optimization problem. To solve it efficiently, we first provide the optimal task allocation scheme and then divide the original optimization problem into two subproblems based on an alternative optimization method. Although two subproblems are still non-convex, we can apply successive convex approximation method to deal with them and design an iterative algorithm to solve them. Finally, simulation results demonstrate the superiority and effectiveness of our proposed algorithm.**

***Index Terms*—Collaborative computation offloading, resource allocation, edge computing, satellite networks.**

I. Introduction

Satellite networks have attracted much attention due to the advantages of full ground coverage and real-time response [1–3]. In the traditional satellite networks, they are only responsible for data collection and transmission where the satellite transmits the collected data to the ground data center for processing and then the ground station transmits the processed task to the user or relevant satellites. It is not difficult to see that the data transmission and processing are completely separated in this process. Nowadays, with the enhancement of satellite data collection capacity, the bandwidth required for data transmission generated by satellite big data applications such as remote sensing, meteorology and resource observation also increases. This processing mode will result in long delay due to insufficient bandwidth resources in the transmission process, so it is difficult to complete the delay sensitive task.

At present, the main solution is to install the edge computing server on the satellite to form a satellite network, and use the distributed characteristics of edge computing to reduce the dependence on the ground station and improve the flexibility of the system. However, due to the limited resources on board, the hot problem is how to allocate the corresponding resources reasonably. In [4], the authors propose a computation offloading scenario assisted by satellites and high altitude platforms and provide the optimized resource allocation method to minimize the energy consumption. In [5], the authors utilize the deep Q-learning approach to establish a centralized resource allocation framework for satellite-terrestrial networks. The authors in [6] assume that the satellites are equipped with the computing servers to act as edge computing nodes and investigate the energy consumption optimization problem. Similarly, the authors in [7] provide a double auction mechanism to model the resource allocation problem in satellite edge computing from the perspective of economics.

However, the existing research works aim at the situation of satellite edge computing assisted terrestrial network while ignore the collaborative processing among multiple edge satellites. At present, some work has been devoted to the research of collaborative computation offloading schemes to meet the requirements of large-scale computing tasks and improve the resource utilization. For example, the authors in [8] consider a double-layer satellite edge computing architecture where low earth orbit (LEO) satellites and high-orbit satellites serve as edge server and cloud server, respectively. The authors in [9] demonstrate the feasibility of satellite edge computing for future Mega-LEO satellite constellations. Moreover, they have shown that satellite edge computing has great potential and are beneficial to performance improvement. In [10], the authors propose a satellite-terrestrial integrated edge computing network architecture and discuss the role of satellite network in edge computing. In [11], the authors investigate how to deploy virtual network functions in satellite network to meet the requirements of possible computation tasks by

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optimizing the available resources. Motivated by the existing work above, this paper focus on the collaborative computation offloading strategy in satellite edge computing and aim to optimize the multi-dimensional resources to reduce network energy consumption.

II. System Model and Problem Formulation

A. System Model

In this paper, we consider a computation offloading scenario for low earth orbit (LEO) satellite networks which consists of N source satellites and M edge satellites. Suppose that the edge satellites carry the servers with computing capacities, but the LEO satellites do not. In the beginning, the source satellites such as military reconnaissance satellite, military meteorological satellites and so on, generate some computation tasks with specific delay requirements. However, due to the lack of computing capabilities, the source satellites have to offload the task to the edge satellites within its visible range. In the edge computing scenario on the ground, it is usually assumed that the users offload the computation tasks to the nearest edge node. However, due to the time varying network topology, the traditional distance based offloading method may be inefficient. Therefore, this paper proposes a collaborative offloading method to deal with the dynamic changes of the satellite network topology, that is, each source satellite can deliver computation tasks to multiple edge satellites by dividing them into multiple subtasks. Although satellite network topology is time-varying, it can be regarded as static when the time interval is very small. Hence, the duration of the satellite network is usually divided into many time slots for convenience. This paper discusses a simple case that the computation tasks from each source satellite can be successfully offloaded and processed in one time slot.

B. Problem Formulation

It is assumed that the source satellites have generated computation tasks with a given feature $\langle X_n, T_n^{max} \rangle$ in which X_n denotes the amount of data for the task and T_n^{max} denotes the delay requirement that the task can tolerate. In order to reduce the delay and make full use of computing and communication resources, the source satellites can deliver the computation task to multiple edge satellites to execute. Hence, the total computation task can be divided into M subtasks of which the size is $x_{n,m}$. Moreover, the relationship between total computation task and subtasks is expressed as

$$\sum_{m=1}^{M} x_{n,m} = X_n \tag{1}$$

The source satellites can offload the subtasks to the edge satellites through the inter-satellite links. The transmission rate between source satellite n and edge satellite m can be calculated as follows.

$$C_{n,m} = B \log \left(1 + \frac{p_{n,m} L_{n,m} G_n^{TR} G_m^{RE}}{\kappa T B}\right) \tag{2}$$

where B is the available bandwidth, $p_{n,m}$ is the transmission power allocated to transmit subtask $x_{n,m}$, G_n^{TR} and G_m^{RE} are respectively the transmission antenna gain of the source satellite n and the receiving antenna gain of edge computing satellite m, κ is Boltzmann constant, T is the noise temperature. $L_{n,m}$ represents the pathloss of inter-satellite link and is expressed as

$$L_{n,m} = \left(\frac{c}{4\pi d_{n,m} f}\right)^2 \tag{3}$$

where c is the velocity of light, f is the carrier frequency, $d_{n,m}$ is the distance between source satellite n and edge computing satellite m.

Let's denote $T_{n,m}^{TR}$ as the transmission delay for the delivery of computation task $x_{n,m}$. The transmission delay $T_{n,m}^{TR}$ can be provided as follows.

$$T_{n,m}^{TR} = \frac{x_{n,m}}{C_{n,m}} \tag{4}$$

The communication energy consumption is denoted as

$$E_{n,m}^{TR} = \frac{p_{n,m} x_{n,m}}{C_{n,m}} \tag{5}$$

Obviously, the communication delay and energy consumption depend on the power allocation scheme of each inter-satellite link. However, the sum of power allocation cannot exceed the maximum transmission power of the source satellite. That is,

$$\sum_{m=1}^{M} p_{n,m} \leq P_n^{max} \tag{6}$$

After receiving the computing tasks from the source satellite, the edge satellites will further execute them and then return the computation results to the source satellites. Generally speaking, the size of the computation result is much smaller than the size of the original computation task. Therefore, the return process of computation results is not considered in this paper. Since the edge satellite may receive many computing tasks from multiple source satellites, the edge satellite needs to allocate corresponding computing resources for each computing task to execute. Then, let $z_{n,m}$ denote the computing resources allocated to the computation task from source satellite n by the edge satellite m. Moreover, the computing delay and energy consumption can be given respectively.

$$T_{n,m}^{COM} = \frac{x_{n,m}}{z_{n,m}} \tag{7}$$

$$E_{n,m}^{COM} = x_{n,m} \xi \vartheta z_{n,m}^2 \tag{8}$$

where ξ is the number of cycles required per bit, ϑ is the constant coefficient depending on chip architecture.

Although the edge satellite is equipped with servers with computation power, the computation capacity is considered to

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be limited. Therefore, the sum of computation resources allocated to all computation tasks cannot exceed the computation capacity of edge satellites.

$$\sum_{m=1}^{M} z_{n,m} \leq Z_n^{max} \tag{9}$$

Now let's analyze the total delay and energy consumption of each computation task. For the given computation subtask with data size $x_{n,m}$, the total energy consumption consists of two parts, i.e., communication energy consumption and computation energy consumption. That is,

$$E_{n,m} = E_{n,m}^{TR} + E_{n,m}^{COM} \tag{10}$$

Similarly, the delay of dealing with this subtask is given as follows.

$$T_{n,m} = T_{n,m}^{TR} + T_{n,m}^{COM} \tag{11}$$

It is noticed that the total delay of computation task X_n is equivalent to the maximal delays of all subtask $x_{n,m}$. As mentioned earlier, we need to ensure that the delay of computation task X_n meets the delay requirement T_n^{max}, which can be expressed as follows.

$$\max_{m} T_{n,m} \leq T_n^{max} \tag{12}$$

This paper aims to minimize the energy consumption of all computation tasks by optimizing the task allocation $\mathbf{x} = \{x_{n,m}\}$, power allocation $\mathbf{p} = \{p_{n,m}\}$, and computation resource allocation $\mathbf{z} = \{z_{n,m}\}$. The final optimization problem is given as follows.

$$\begin{aligned} \min_{\mathbf{x},\mathbf{p},\mathbf{z}} \quad & \sum_{n=1}^{N}\sum_{m=1}^{M} E_{n,m} \\ s.t. \quad & (1),(6),(9),(12) \\ & x_{n,m} \geq 0, p_{n,m} \geq 0, z_{n,m} \geq 0 \end{aligned} \tag{13}$$

Obviously, the proposed optimization problem is a non-convex optimization problem due to variable coupling, which means direct solution method is very difficult to find optimal solution. Hence, an efficient solution method is necessary to reduce the complexity of solving the problem. In the next section, an effective algorithm is given by decoupling the problem into different subproblems.

III. Suboptimal Resource Allocation Scheme

In this section, we aim to provide a suboptimal but efficient resource allocation algorithm. First, the optimal task allocation can be given through the problem analysis. Then, based on the given task allocation scheme, an alternative optimization method is given to iteratively optimize power allocation scheme and computation resource allocation scheme.

A. Optimal Task Allocation Scheme

It can be seen that energy consumption and delay are two opposite performance indicators. Therefore, in order to minimize the total energy consumption of the network, the delay performance of computing tasks has to be sacrificed. In other words, even if each computing task can be executed successfully, the total delay is just equal to the maximum delay requirement. Moreover, the constraint (12) must be met with equality. In fact, a more general conclusion can be given as follows.

Theorem 1: The constraint (12) can be replaced equivalently by the formula $T_{n,m} = T_n^{max}, \forall m$.

Proof: Suppose that the theorem above doesn't hold, then there must be at least one optimal solution $(x_{n,m}^*, p_{n,m}^*, z_{n,m}^*)$ satisfying $T_{n,m} < T_n^{max}$. Then, according to the formulas (7) and (11), there must be $z_{n,m}^{**} < z_{n,m}^*$ such that the solution $(x_{n,m}^*, p_{n,m}^*, z_{n,m}^{**})$ still satisfies the constraint $T_{n,m} < T_n^{max}$. It can be seen that the constraint (9) is still satisfied due to $z_{n,m}^{**} < z_{n,m}^*$. Hence, $(x_{n,m}^*, p_{n,m}^*, z_{n,m}^{**})$ is also a feasible solution. Moreover, we can know that the total energy consumption must be reduced according the formula (8). However, this contradicts that $(x_{n,m}^*, p_{n,m}^*, z_{n,m}^*)$ is the optimal solution. The proof has been completed. ■

Then, based on the Theorem 1, the constraint (12) can be equivalent to following equality.

$$\frac{x_{n,m}}{C_{n,m}} + \frac{x_{n,m}}{z_{n,m}} = T_n^{max} \tag{14}$$

Moreover, the optimal task allocation scheme can be given as follows.

$$x_{n,m} = \frac{T_n^{max} C_{n,m} z_{n,m}}{C_{n,m} + z_{n,m}} \tag{15}$$

B. Alternative Optimization Based Resource Allocation Scheme

Substituting the optimal task allocation scheme to the optimization problem (13), the optimization problem can be rewritten as

$$\min_{\mathbf{p},\mathbf{z}} \sum_{n=1}^{N}\sum_{m=1}^{M} \frac{T_n^{max} C_{n,m} z_{n,m}}{C_{n,m} + z_{n,m}} \left(\frac{p_{n,m}}{C_{n,m}} + \xi \vartheta z_{n,m}^2 \right) \tag{16}$$

$$s.t. \sum_{m=1}^{M} \frac{T_n^{max} C_{n,m} z_{n,m}}{C_{n,m} + z_{n,m}} = X_n \tag{16a}$$

$$\sum_{m=1}^{M} p_{n,m} \leq P_n^{max} \tag{16b}$$

$$\sum_{n=1}^{N} z_{n,m} \leq Z_n^{max} \tag{16c}$$

$$p_{n,m} \geq 0, z_{n,m} \geq 0 \tag{16d}$$

It is obvious that the transformed problem is still a non-convex problem and difficult to solve directly. In order to improve the solution efficiency, the alternative optimization method is used to solve this problem. First, for given power

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allocation scheme $\mathbf{p}$, the optimization problem (16) is rewritten as

$$\min_{\mathbf{z}} \sum_{n=1}^{N}\sum_{m=1}^{M}\left(\frac{T_n^{max}p_{n,m}z_{n,m}}{C_{n,m}+z_{n,m}}+\frac{\xi\vartheta T_n^{max}C_{n,m}z_{n,m}^3}{C_{n,m}+z_{n,m}}\right) \tag{17}$$

$$s.t. \sum_{m=1}^{M}\frac{T_n^{max}C_{n,m}z_{n,m}}{C_{n,m}+z_{n,m}} \geq X_n \tag{17a}$$

$$\sum_{n=1}^{N} z_{n,m} \leq Z_n^{max} \tag{17b}$$

$$z_{n,m} \geq 0 \tag{17c}$$

It is obvious that optimization problem (16) is not convex because the first item in the objective function $F(\mathbf{z}) = \sum_{n=1}^{N}\sum_{m=1}^{M}\frac{T_n^{max}p_{n,m}z_{n,m}}{C_{n,m}+z_{n,m}}$ is a concave function. To solve this problem efficiently, we use the successive convex approximation method to overcome it, i.e., take the first-order Taylor expansion to replace concave items. The proposed approximation method is given as follows.

$$F(\mathbf{z},\mathbf{z}(k)) = F(\mathbf{z}(k)) + \nabla F(\mathbf{z}(k))(\mathbf{z}-\mathbf{z}(k)) \tag{18}$$

where $\mathbf{z}(k)$ refers to the initial value at k-th iteration.

Then, the optimization problem (16) can be solved by iteratively solving the following subproblems.

$$\min_{\mathbf{z}} F(\mathbf{z},\mathbf{z}(k)) + G(\mathbf{z}) \tag{19}$$

$$s.t. \sum_{m=1}^{M}\frac{T_n^{max}C_{n,m}z_{n,m}}{C_{n,m}+z_{n,m}} \geq X_n \tag{19a}$$

$$\sum_{n=1}^{N} z_{n,m} \leq Z_n^{max} \tag{19b}$$

$$z_{n,m} \geq 0 \tag{19c}$$

where $G(\mathbf{z}) = \sum_{n=1}^{N}\sum_{m=1}^{M}\frac{\xi\vartheta T_n^{max}C_{n,m}z_{n,m}^3}{C_{n,m}+z_{n,m}}$.

To show the convexity of optimization problem (19), we provide the following theorem.

Theorem 2: The optimization problem (19) is a convex optimization problem.

Proof: This is equivalent to proving that the function $G(\mathbf{z})$ is convex with respect to $\mathbf{z}$. Therefore, we take the second-order differential of $G(\mathbf{z})$ as follows.

$$\frac{\partial^2 G}{\partial z_{n,m}^2} = \frac{6C_{n,m}z_{n,m}}{(C_{n,m}+z_{n,m})^2} \geq 0 \tag{20}$$

The function $G(\mathbf{z})$ is convex according to the definition. Therefore, the proof has been completed. ■

Then, for given resource allocation scheme $\mathbf{z}$, we can further optimize the power allocation scheme by rewriting the optimization problem (16) as

$$\min_{\mathbf{p}} \sum_{n=1}^{N}\sum_{m=1}^{M}\left(\frac{T_n^{max}p_{n,m}z_{n,m}}{C_{n,m}+z_{n,m}}+\frac{\xi\vartheta T_n^{max}C_{n,m}z_{n,m}^3}{C_{n,m}+z_{n,m}}\right) \tag{21}$$

$$s.t. \sum_{m=1}^{M}\frac{T_n^{max}C_{n,m}z_{n,m}}{C_{n,m}+z_{n,m}} \geq X_n \tag{21a}$$

$$\sum_{m=1}^{M} p_{n,m} \leq P_n^{max} \tag{21b}$$

$$p_{n,m} \geq 0 \tag{21c}$$

Obviously, the new subproblem is also a non-convex optimization problem. Before solving it, a variable substitution method has been adopted by letting $y_{n,m} = \frac{C_{n,m}+z_{n,m}}{B\log 2(e)}$. Moreover, the origin optimization problem (21) can be equivalently transformed as

$$\min_{\mathbf{y}} \sum_{n=1}^{N}\sum_{m=1}^{M}\left(\frac{a_{n,m}(e^{y_{n,m}}-1)}{y_{n,m}}+\frac{s_{n,m}}{y_{n,m}}\right) \tag{22}$$

$$s.t. \sum_{m=1}^{M} b_{n,m}\left(B\log 2(e) - \frac{z_{n,m}}{y_{n,m}}\right) \geq X_n \tag{22a}$$

$$\sum_{m=1}^{M}\frac{1}{h_{n,m}}\left(e^{y_{n,m}-\frac{z_{n,m}}{B\log 2(e)}}-1\right) \leq P_n^{max} \tag{22b}$$

$$y_{n,m} \geq \frac{z_{n,m}}{B\log 2(e)} \tag{22c}$$

where the relevant parameters are defined as follows.

$$\begin{aligned} a_{n,m} &= \frac{T_n^{max}e^{\frac{z_{n,m}}{B\log 2(e)}}}{h_{n,m}B\log 2(e)} \geq 0 \\ h_{n,m} &= \frac{L_{n,m}G_n^{TR}G_m^{RE}}{\kappa TB} \geq 0 \\ b_{n,m} &= \frac{T_n^{max}z_{n,m}}{B\log 2(e)} \geq 0 \\ s_{n,m} &= 1 - e^{\frac{z_{n,m}}{B\log 2(e)}} - \xi\vartheta b_{n,m}z_{n,m}^3 \leq 0 \end{aligned} \tag{23}$$

Then, it can be seen that the second term of the objective function is concave about $y_{n,m}$ since the constant coefficient $s_{n,n}$ is non-positive, which means that the optimization problem (22) is not convex. Hence, let $\Psi(\mathbf{y}) = \sum_{n=1}^{N}\sum_{m=1}^{M}\frac{s_{n,m}}{y_{n,m}}$ and use the same successive convex approximation method to deal with the non-convex term. That is,

$$\Psi(\mathbf{y},\mathbf{y}(i)) = \Psi(\mathbf{y}(i)) + \nabla\Psi(\mathbf{y}(i))(\mathbf{y}-\mathbf{y}(i)) \tag{24}$$

where $\mathbf{y}(i)$ denotes the initial value at i-th iteration.

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Then, a suboptimal solution can be obtained by iteratively solving the following subproblems.

$$\min_{\mathbf{y}} \ \Phi(\mathbf{y}) + \Psi(\mathbf{y}, \mathbf{y}(i)) \tag{25}$$

$$s.t. \ \sum_{m=1}^{M} b_{n,m} \left(B \log 2(e) - \frac{z_{n,m}}{y_{n,m}} \right) \geq X_n \tag{25a}$$

$$\sum_{m=1}^{M} \frac{1}{h_{n,m}} \left(e^{y_{n,m} - \frac{z_{n,m}}{B \log 2(e)}} - 1 \right) \leq P_n^{max} \tag{25b}$$

$$y_{n,m} \geq \frac{z_{n,m}}{B \log 2(e)} \tag{25c}$$

where $\Phi(\mathbf{y}) = \sum_{n=1}^{N} \sum_{m=1}^{M} \frac{a_{n,m}(e^{y_{n,m}} - 1)}{y_{n,m}}$.

Moreover, we can indicate that the optimization problem (25) is convex by using the following theorem.

Theorem 3: The optimization problem (25) is a convex optimization problem.

Proof: Obviously, the constraints (25a)-(25c) are convex and the proof has been omitted. Then, we just need to prove that the function $\Phi(\mathbf{y})$ is convex. To do it, we take the second-order differential of this function as $\frac{\partial^2 \Phi}{\partial y_{n,m}^2} = \frac{\Omega(y_{n,m})}{y_{n,m}^3}$ where $\Omega(y_{n,m}) = (y_{n,m} - 1)^2 e^{y_{n,m}} + e^{y_{n,m}} - 2$. Then, taking the first-order differential of it, we can obtain $\frac{\partial \Omega}{\partial y_{n,m}} = y_{n,m}^2 e^{y_{n,m}} \geq 0$.

It is obvious that the function $\Omega(y_{n,m})$ is incremental since $\frac{\partial \Omega}{\partial y_{n,m}} \geq 0$. Moreover, we can know $\Omega(y_{n,m}) \geq 0$ due to $\Omega(0) = 0$. Hence, we have completed the proof. ■

Based on the analysis above, the original optimization problem (16) can be solved by solving subproblems (19) and (25) iteratively. For specific details, please refer to the proposed Algorithm 1.

Algorithm 1 Alternative Optimization Based Resource Allocation Algorithm

Initialize the resource allocation results $\mathbf{z}^*(0)$, $\mathbf{p}^*(0)$, and the maximum number of iterations K.
repeat
  repeat
    Solve the optimization problem (19).
    Set the optimal solution as initial value $\mathbf{z}(i+1)$ at the next iteration.
    $i = i + 1$.
  until the iteration process converges.
  Let $\mathbf{z}^*(k) = \mathbf{z}(i)$.
  repeat
    Solve the optimization problem (25).
    Set the optimal solution as initial value $\mathbf{y}(j+1)$ at the next iteration.
    $j = j + 1$.
  until the iteration process converges.
  Let $\mathbf{y}^*(k) = \mathbf{y}(j)$ and reconstruct the power allocation result $\mathbf{p}^*(k)$ according to variable substitution method.
  $k = k + 1$.
until the iteration process converges or $k = K$.
Reconstruct the task allocation results $\mathbf{x}$ according the equation (15).

TABLE I
THE PARAMETERS IN SIMULATION.

Parameters	Value
The orbit altitude	1000 km
The carrier frequency f	20 GHz
The transmission antenna gain G^{TR}	27 dBi
The receiving antenna gain G^{RE}	24 dBi
Noise temperature T	350 K
The bandwidth B	20 MHz
The computational intensity ξ	1000 cycle/bit
The computational coefficient υ	$3 * 10^{-24}$ J/(cycle $\cdot$ bit^2)

IV. Simulation Results and Discussions

In this section we provided the simulation results for evaluating the effectiveness of proposed algorithm. We generate the satellites network based on a walker constellation of type "delta" which includes 5 satellite planes and 6 satellites per plane. Other parameters used in this paper are listed in Table I. In addition, two benchmarks are provided for comparing with the proposed collaborative computation offloading with optimized resource allocation (CCO-ORA). One of them is collaborative computation offloading with equal resource allocation (CCO-ERA) that all the resources are allocated equally to each task. The other is non-collaborative computation offloading with optimized resource allocation (NCCO-ORA) that the source satellite is required to offload computing tasks to only one edge satellite.

In Fig. 1, the relationship between total energy consumption and number of source satellites is revealed. It has shown that the total energy consumption is increasing along with the number of source satellites, which is consistent with our expectation. Moreover, it can be seen that the proposed CCO-ORA is always superior to two benchmarks CCO-ERA and NCCO-ORA. Specially, the advantages of proposed CCO-ORA become more and more obvious with the increase of the number of source satellites. In fact, the total amount of data will increase with the increase of the number of satellites, which leads to the obvious disadvantages of uneven resource allocation under the two benchmarks.

Fig. 2 has shown the relationship between total energy consumption and number of edge satellites. As we would expect, the total energy consumption goes down as the number of edge satellites increase because there are more available resources to deal with the computation tasks. Compared with CCO-ERA, the energy consumption is significantly reduced with the proposed algorithm, which means that it is important to optimize the resource allocation scheme. On other hand, the proposed algorithm is always better than NCCO-ORA. It shows that collaborative computation offloading is beneficial to reduce energy consumption.

In Fig. 3, we have provided the effect of delay requirement on the total energy consumption of satellite networks. It can be seen that the total energy consumption is decreasing when the delay requirement becomes relaxed. This is reasonable be-

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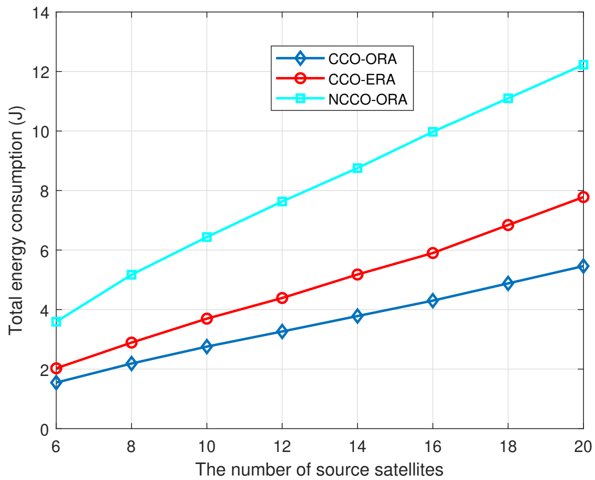

Fig. 1. The total energy consumption versus number of source satellites.

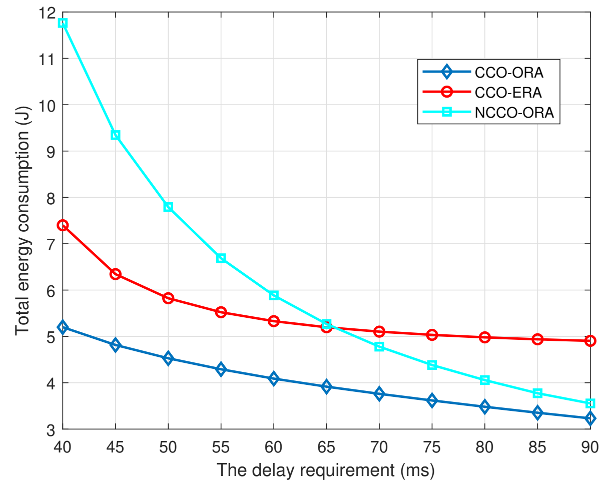

Fig. 3. The total energy consumption versus delay requirement.

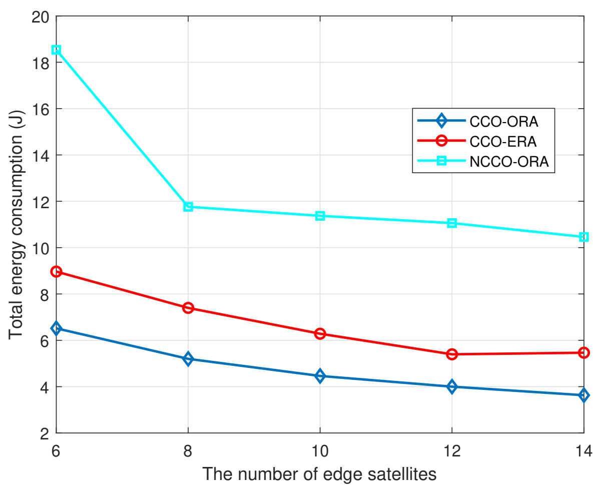

Fig. 2. The total energy consumption versus number of edge satellites.

cause delay and energy consumption are opposite performance indicators. In order to ensure the strict delay requirements, the network has to pay more communication and computing resources, resulting in high energy consumption. For the strict delay requirement, the performance of CCO-ERA is better than NCCO-ORA, which indicates the benefits of collaborative computation offloading are more obvious. Instead, optimized resource allocation is more beneficial for non-strict delay requirement. Meanwhile, the proposed algorithm always maintains optimal performance in any case.

V. Conclusions

In this paper, we investigate the collaborative computation offloading strategy and resource allocation problem in satellite edge computing networks and aim to minimize the total energy consumption with given delay requirement. The proposed problem is modeled as a non-convex optimization problem about task allocation, power allocation and computing resource allocation. Then, we can achieve an optimal task allocation scheme with other given resource allocations. Moreover, the original problem is divided into two non-convex optimization problems which are solved by using successive convex approximation method. Simulation results indicate the energy consumption was obviously reduced by using the proposed method.

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