

# Energy Efficient Hybrid Offloading in Space-Air-Ground Integrated Networks

Bingchang Chen<sup>\*†</sup>, Na Li<sup>\*†</sup>, Yan Li<sup>‡</sup>, Xiaofeng Tao<sup>\*</sup>, Guen Sun<sup>\*</sup>

<sup>\*</sup>Beijing University of Posts and Telecommunications, Beijing, 100876, China

<sup>†</sup>Beijing University of Posts and Telecommunications Research Institute, Shenzhen, China

<sup>‡</sup>China Satellite Communications Co., Ltd.

Emails: {cbcbupt, Lina\_Lena, taoxf, sgn}@bupt.edu.cn, liyan2@chinasatcom.com

**Abstract**—Space-air-ground integrated network (SAGIN) is a prominent architecture for the future wireless communication system. Due to the long distance transmission of the satellite communication and the limited battery capacity of aircrafts, the energy cost has become one of the dominant problems of SAGIN. Mobile edge computing (MEC) offers a potential solution by offloading partial tasks to nodes with higher computational capability. In this paper, we study a hybrid offloading problem where both unmanned aerial vehicles (UAVs) and ground users have tasks to be processed, and UAVs and the satellite can provide offloading service. The aim is to minimize the system energy consumption under time delay constraint by choosing the optimal offloading objects and jointly optimizing the offloading proportion and computing resource allocation. The optimization problem is highly nonconvex and difficult to solve optimally. To tackle the problem, we first derive the closed-form solution of computation resources allocation and further propose a low-complex algorithm based on successive convex approximation (SCA). Simulation results show that the proposed hybrid offloading scheme can significantly reduce energy consumption compared to benchmark schemes. Moreover, by increasing the transmission power of users and UAVs in a certain range, total energy consumption can be effectively reduced. And increasing the number of UAVs can improve the energy efficiency.

**Index Terms**—SAGIN, Mobile edge computing (MEC), unmanned aerial vehicles (UAVs).

## I. INTRODUCTION

With the rapid development of the Internet of Things (IoT), the space-air-ground integrated network (SAGIN) architecture is proposed to provide ubiquitous coverage, high quality connection and task processing capability to IoT devices [1]. However, the energy consumption is one of the important and challenging issue in SAGIN which has drawn increasing attention [2]. The long transmission distance from ground devices to the satellite and the large amount of computation-intensive tasks dramatically increase the energy cost during transmission and computation [3], [4]. A prospective solution is to offload the tasks to nodes with rich computation resources [5], such as base stations, unmanned aerial vehicles (UAVs), satellites, etc.

To settle the energy consumption problem, some novel offloading schemes have been developed. The authors in [6] investigated an UAV-enabled offloading system, where the positions of UAVs are optimized to minimize the total time required for computing the users' tasks. In [7], the UAVs process the offloading tasks of ground users or relay the tasks

to the terrestrial edge clouds, and the energy consumption is minimized by jointly optimizing the positions of UAVs, communication and computation resources allocation and splitting decisions of users' tasks. In [8], the tasks of users are offloaded to the near edge servers via UAVs or far cloud servers via satellites, and the time delay and energy cost are minimized by optimizing the computation resources and offloading schedule of users' tasks. The above researches assume that the UAV provides relay communication or computation service for users. In [9], both ground users and UAVs have tasks to be processed, and they offload tasks to satellites to minimize the energy. However, this work ignores the advantage of processing tasks of ground users at UAVs.

In this article, we consider a more practical scenario in SAGIN where the users and UAVs both generate tasks, while UAVs and the satellite can offer offloading service. We propose a hybrid offloading scheme in which the UAV can help process part of the users' tasks in addition to its own tasks. The sum of energy consumption of users, UAVs and the satellite is minimized under the maximum tolerance time constraints and the available computation resources constraints. The optimal solutions of the computation resources allocation are first derived in closed forms, and then the problem is simplified and solved by using the classical successive convex approximation (SCA) methods. Simulation results show that the proposed offloading algorithm can effectively reduce the energy consumption compared with benchmark schemes.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

### A. System Model

As shown in Fig. 1, we consider a SAGIN system consisting of a set of ground users  $\mathcal{K} = \{1, 2, \dots, K\}$ , a set of UAVs  $\mathcal{M} = \{1, 2, \dots, M\}$ , and a satellite. Both users and UAVs have tasks to process. The users can process part of tasks locally and offload the rest part of tasks to UAVs through link  $L^{GU}$  or satellite through link  $L^{GS}$ , and each UAV can handle the tasks of users and UAVs locally or offload them to the satellite through link  $L^{US}$ . The location of user  $k$ , UAV  $m$  and satellite are represented in three-dimensional coordinate system denoted as  $Q_k^{user} = (a_k^{user}, b_k^{user}, 0)$ ,  $Q_m^{uav} = (a_m^{uav}, b_m^{uav}, h_m^{uav})$  and  $Q^{sat} = (a^{sat}, b^{sat}, h^{sat})$ . We assume that in a short time, the positions of all devices are stable and all tasks can be

processed within this time. The time of sending results back to users is ignored since the data size is small.

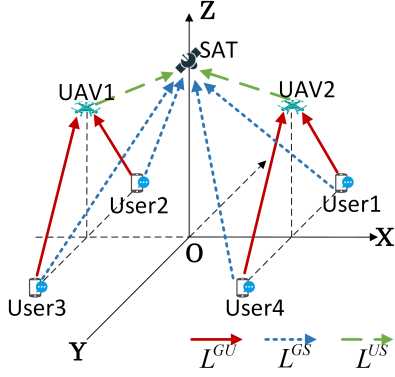


Fig. 1. Illustration of a MEC-enhanced SAGIN system

1) *Communication Model*: The pathloss of the link between UAV  $m$  and the ground user  $k$  can be calculated as [10]

$$L_{k,m}^{GU} = 20 \log_{10} \left( \frac{4\pi f_u d_{k,m}^{GU}}{v_c} \right) + P_{LoS} \eta_L + P_{NLoS} \eta_N, \quad (1)$$

where  $d_{k,m}^{GU}$  denotes the distance between user  $k$  and UAV  $m$ .  $f_u$  denotes the carrier frequency and  $v_c$  represents the speed of light.  $\eta_L$  and  $\eta_N$  are average additional losses for the LoS link and the NLoS link, whose probabilities are defined as

$$P_{LoS} = \frac{1}{1 + a \exp \left( -b \left( \arctan \left( \frac{h_m^{uav}}{r_{k,m}^{GU}} \right) - a \right) \right)}, \quad (2)$$

$$P_{NLoS} = 1 - P_{LoS}, \quad (3)$$

where  $h_m^{uav}$  denotes the flight altitude of UAV  $m$  and  $r_{k,m}^{GU}$  denotes the horizontal distance between user  $k$  and UAV  $m$ .  $a$  and  $b$  are constant values determined by the environment.

As for the satellite links, the free-space pathloss is much more dominant than other channel pathlosses [11], the free pathloss between ground user  $k$  and the satellite  $L_{k,s}^{GS}$  and the pathloss between UAV  $m$  and the satellite  $L_{m,s}^{US}$  are defined as [10]

$$L_{\Psi} = 92.44 + 20 \log_{10} (d_{\Psi}) + 20 \log_{10} (f_s), \quad (4a)$$

$$L_{\Psi} = \{L_{k,s}^{GS}, L_{m,s}^{US}\}, d_{\Psi} = \{d_{k,s}^{GS}, d_{m,s}^{US}\}, \quad (4b)$$

where  $d_{k,s}^{GS}$  and  $d_{m,s}^{US}$  denote the distances to the satellite.  $f_s$  denote the carrier frequency.

The transmission data rate can be calculated as

$$R = W \log_2 \left( 1 + \frac{P \cdot 10^{\frac{-L_p}{10}}}{\sigma^2} \right), \quad (5)$$

where  $L_p = \{L_{k,m}^{GU}, L_{k,s}^{GS}, L_{m,s}^{US}\}$ ,  $W = \{W_B, W_S\}$  and  $P = \{P_k, P_m\}$ .  $P_k$  and  $P_m$  denote the transmission power of user  $k$  and UAV  $m$ .  $W_B$  and  $W_S$  are the bandwidths assigned to the UAV channel and the satellite channel respectively. And  $\sigma^2$  denotes the noise power.

2) *Offloading Decision*: Due to the limited computing power of ground users, their tasks can be offloaded to one of the UAVs or the satellite. Let  $\mathcal{T}_k = \{\tau_{k,m}, \tau_{k,s}, \tau_{k,m,s}\} \in \mathcal{T}$  denotes the binary offloading decision of user  $k$  and  $\mathcal{T}$  denotes the set of the offloading decisions. If  $\tau_{k,m} = 1$ , user  $k$

offloads its tasks to UAV  $m$  and UAV  $m$  processes it locally; if  $\tau_{k,s} = 1$ , user  $k$  offloads its tasks to the satellite; and if  $\tau_{k,m,s} = 1$ , the tasks of user  $k$  are offloaded to the satellite by the relaying of UAV  $m$ . Hence, we have

$$\sum_{m=1}^M \tau_{k,m} + \sum_{m=1}^M \tau_{k,m,s} + \tau_{k,s} = 1, \quad (6a)$$

$$\tau_{k,m}, \tau_{k,s}, \tau_{k,m,s} \in \{0, 1\}, \forall k \in \mathcal{K}, \forall m \in \mathcal{M}. \quad (6b)$$

3) *Time Delay Analysis*: We assume that computation module and transmission module of users and UAVs can work in parallel. The time consumptions of processing the user's tasks and the UAV's tasks are, respectively

$$T_k^{user} = \max(T_{loc}^{user}, T_{edge}^{user}), \forall k \in \mathcal{K}, \quad (7)$$

$$T_m^{uav} = \max(T_{loc}^{uav}, T_{edge}^{uav}), \forall m \in \mathcal{M}, \quad (8)$$

where  $T_{loc}^{\Theta}$  represents the computing time if tasks are processed locally;  $T_{edge}^{\Theta}$  denotes the time of transmitting the tasks and processing it in other devices, where  $\Theta = \{user, uav\}$ .  $T_{loc}^{user}$  and  $T_{edge}^{user}$  are calculated by

$$T_{loc}^{user} = \frac{(1 - x_k) C_k L}{f_k}, \quad (9)$$

$$T_{edge}^{user} = \begin{cases} \frac{x_k C_k}{R_{k,m}^{GU}} + \frac{x_k C_k L}{f_{m,k}} & \tau_{k,m} = 1, \\ \frac{x_k C_k}{R_{k,m}^{GU}} + \frac{x_k C_k L}{R_{m,s}^{US}} + \frac{x_k C_k}{f_{s,m}} & \tau_{k,m,s} = 1, \\ \frac{x_k C_k}{R_{k,s}^{GS}} + \frac{x_k C_k L}{f_{s,k}} & \tau_{k,s} = 1, \end{cases} \quad (10)$$

where  $x_k$  and  $C_k$  denote the offloading proportion and task size of user  $k$ .  $f_k$  represents the computation capacity of user  $k$ .  $f_{m,k}$  and  $f_{s,k}$  denote the computation resources allocated to user  $k$  by UAV  $m$  or the satellite respectively.  $R_{k,m}^{GU}$ ,  $R_{k,s}^{GS}$ ,  $R_{m,s}^{US}$  denote the transmission data rate of links  $L_{k,m}^{GU}$ ,  $L_{k,s}^{GS}$ ,  $L_{m,s}^{US}$  respectively.  $L$  denotes the number of CPU cycles required to process 1-bit of data.

Note when user  $k$  offloads the tasks to UAV  $m$  or the satellite,  $T_{edge}^{user}$  includes the transmission time of offloading the tasks of user  $k$  to UAV  $m$  or the satellite and the computing time. When UAV  $m$  relays user's tasks to satellite, the transmission time consists of two parts: the time delay from user  $k$  to UAV  $m$  and from UAV  $m$  to satellite.

Similarly,  $T_{loc}^{uav}$  and  $T_{edge}^{uav}$  can be respectively calculated as

$$T_{loc}^{uav} = \frac{(1 - y_m) D_m L}{f_{m,0}}, \quad (11)$$

$$T_{edge}^{uav} = \frac{y_m D_m}{R_{m,s}^{US}} + \frac{y_m D_m L}{f_{s,m}}, \quad (12)$$

where  $y_m$  denotes the offloading proportion of UAV  $m$  and  $D_m$  represents the tasks of UAV  $m$ .  $f_{m,0}$  denotes the computation resources used to process UAV's tasks and  $f_{s,m}$  denotes the computation resources allocated to UAV  $m$  by satellite.

4) *Energy Consumption Analysis*: The total system energy consumption is denoted by

$$P = \sum_{k=1}^K P_k^{user} + \sum_{m=1}^M P_m^{uav} + P_{loc}^{sat}, \quad (13)$$

where the user's energy consumption  $P_k^{user}$  consists of the local computing energy  $P_{loc}^{user}$  and the transmission energy for offloading  $P_{tran}^{user}$ , i.e.,

$$P_k^{user} = P_{loc}^{user} + P_{tran}^{user}, \forall k \in \mathcal{K}, \quad (14)$$

$$P_{loc}^{user} = \delta_1 f_k^3 T_{loc}^{user} = \delta_1 f_k^2 (1 - x_k) C_k L, \quad (15)$$

$$P_{tran}^{user} = \begin{cases} \frac{p_k^{uav} x_k C_k}{R_{k,m}^{GU}} & \tau_{k,m} = 1, \\ \frac{p_k^{sat} x_k C_k}{R_{k,s}^{GS}} & \tau_{k,s} = 1. \end{cases} \quad (16)$$

Similarly, the energy consumption of UAV  $m$  is calculated as

$$P_m^{uav} = P_{loc}^{uav} + P_{tran}^{uav}, \forall m \in \mathcal{M}, \quad (17)$$

$$P_{loc}^{uav} = \sum_{k=1}^K \delta_2 f_{m,k}^2 x_k C_k L \tau_{k,m} + \delta_2 f_{m,0}^2 (1 - y_m) D_m L, \quad (18)$$

$$P_{tran}^{uav} = \sum_{k=1}^K \frac{p_m x_k C_k}{R_{m,s}^{US}} \tau_{k,m,s} + \frac{p_m y_m D_m}{R_{m,s}^{US}}. \quad (19)$$

where  $\delta_1$  and  $\delta_2$  denote the energy consumption coefficients of the user and the UAV.

If no user offloads the tasks to the UAV or the UAV forwards the tasks of users to the satellite, the first term of (18) is 0. Besides, if the UAV processes the user's tasks locally or no tasks of users are offloaded to it, then no tasks of users are relayed to the satellite by the UAV, thus the first term of (19) is 0.

The satellite needs to deal with the tasks offloaded by UAVs or directly by users. Its energy consumption is calculated as

$$P_{loc}^{sat} = \sum_{k=1}^K \delta_3 f_{s,k}^2 x_k C_k L (\tau_{k,s} + \tau_{k,m,s}) + \sum_{m=1}^M \delta_3 f_{s,m}^2 y_m D_m L. \quad (20)$$

where  $\delta_3$  represents the energy consumption coefficients the satellite.

### B. Problem Formulation

In this article, we aim at minimizing the system energy consumption under time delay constraints of users and UAVs, by jointly optimizing the user's offloading proportion  $x_k$  and UAV's offloading proportion  $y_m$ , the allocation of computation resources  $\mathcal{F} = \{f_k, f_{m,k}, f_{s,k}, f_{s,m}\}$  and offloading decisions  $\mathcal{T}_k$ . The optimization problem can be formulated as

$$\mathbf{P1}: \min_{\{x_k\}, \{y_m\}, \mathcal{F}, \mathcal{T}_k} P \quad (21a)$$

$$s.t. \quad T_k^{user} \leq T_{max}^{user}, \forall k \in \mathcal{K}, \quad (21b)$$

$$T_m^{uav} \leq T_{max}^{uav}, \forall m \in \mathcal{M}, \quad (21c)$$

$$f_k \leq F_k, \forall k \in \mathcal{K}, \quad (21d)$$

$$\sum_{k=0}^K f_{m,k} \leq F_m, \forall m \in \mathcal{M}, \quad (21e)$$

$$\sum_{k=1}^K f_{s,k} + \sum_{m=1}^M f_{s,m} \leq F_s, \quad (21f)$$

$$(6a), (6b), \quad (21g)$$

$$0 \leq x_k, y_m \leq 1, \forall k \in \mathcal{K}, m \in \mathcal{M}, \quad (21h)$$

$$f_k, f_{m,k}, f_{s,k}, f_{s,m} \geq 0, \forall k \in \mathcal{K}, m \in \mathcal{M}. \quad (21i)$$

where (21b) and (21c) ensure that tasks of users and UAVs can be processed in limited time. (21g) constraints that tasks of users can only be processed in one way.  $F_k$ ,  $F_m$  and  $F_s$  denote the available computation resources of user  $k$ , UAV  $m$  and the satellite respectively.  $T_{max}^{user}$  and  $T_{max}^{uav}$  represent the maximum tolerance time of the user and the UAV, where the

of time constraint is set according to the task quantity and calculation capacity.

### III. PROBLEM SOLUTION METHODOLOGY

Due to the nonconvexity of the objective function (21a) and constraints (21b) and (21c), Problem (P1) is difficult to be solved. In this paper, we first simplify the problem by deriving the closed-form solutions of the computing resource allocation parameters, and then propose a low-complex algorithm using SCA. Since  $\mathcal{T}$  is a finite set, the optimal decision can be found by exhaustive searching. In the following, we clarify the proposed algorithm for given  $\mathcal{T}_k$ .

#### A. Closed-form solutions for computation resources

Using less computation resources can decrease the system energy consumption. Thus when given the offloading proportion  $x_k, y_m$ , according to (21b) the optimal value of  $f_k, f_{m,k}, f_{s,k}$  denoted as  $f_k^*, f_{m,k}^*, f_{s,k}^*$  can be calculated

$$f_k^* = \frac{(1 - x_k) C_k L}{T_{max}^{user}}, \quad (22)$$

$$f_{m,k}^* = \frac{x_k C_k L}{T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}}}, \tau_{k,m} = 1, \quad (23)$$

$$f_{s,k}^* = \begin{cases} \frac{x_k C_k L}{T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}} - \frac{x_k C_k}{R_{m,s}^{US}}} & \tau_{k,m,s} = 1, \\ \frac{x_k C_k L}{T_{max}^{user} - \frac{x_k C_k}{R_{k,s}^{GS}}} & \tau_{k,s} = 1. \end{cases} \quad (24)$$

Then according to constraint (21c),  $f_{m,0}^*$  and  $f_{s,m}^*$  can be computed as

$$f_{m,0}^* = \frac{(1 - y_m) D_m L}{T_{max}^{uav}}, \quad (25)$$

$$f_{s,m}^* = \frac{y_m D_m L}{T_{max}^{uav} - \frac{y_m D_m}{R_{m,s}^{US}}}. \quad (26)$$

Through bringing (22)-(26) into (21d), (21e) and (21f), the constraints (21d), (21e) and (21f) are transformed into

$$x_k \geq 1 - \frac{F_k T_{max}^{user}}{C_k L}, \forall k \quad (27)$$

$$F_m \geq \sum_{k=1}^K \frac{x_k C_k L}{T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}}} + \frac{(1 - y_m) D_m L}{T_{max}^{uav}}, \forall m, \quad (28)$$

$$F_s \geq \sum_{k=1}^K \frac{x_k C_k L}{T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}} - \frac{x_k C_k}{R_{m,s}^{US}}} + \sum_{m=1}^M \frac{y_m D_m L}{T_{max}^{uav} - \frac{y_m D_m}{R_{m,s}^{US}}} + \sum_{k=1}^K \frac{x_k C_k L}{T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}} - \frac{x_k C_k}{R_{m,s}^{US}}}, \quad (29)$$

Similarly, parts of the object function: (15), (18) and (20) are transformed into

$$P_{loc}^{user} = \frac{\delta_1 (1 - x_k)^3 C_k^3 L^3}{(T_{max}^{user})^2}, \quad (30)$$

$$P_{loc}^{uav} = \sum_{k=1}^K \frac{\delta_2 x_k^3 C_k^3 L^3 \tau_{k,m}}{(T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}})^2} + \frac{\delta_2 (1 - y_m)^3 D_m^3 L^3}{(T_{max}^{uav})^2}, \quad (31)$$

$$P_{loc}^{sat} = \sum_{k=1}^K \frac{\delta_3 x_k^3 C_k^3 L^3 \tau_{k,s}}{\left(T_{max}^{user} - \frac{x_k C_k}{R_{k,s}^{GU}}\right)^2} + \sum_{m=1}^M \frac{\delta_3 y_m^3 D_m^3 L^3}{\left(T_{max}^{uav} - \frac{y_m D_m}{R_{m,s}^{US}}\right)^2} + \sum_{k=1}^K \frac{\delta_3 x_k^3 C_k^3 L^3 \tau_{k,m,s}}{\left(T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}} - \frac{x_k C_k}{R_{m,s}^{US}}\right)^2}. \quad (32)$$

Thus Problem (P1) is simplified into

$$\mathbf{P2}: \min_{\{x_k\}, \{y_m\}} P \quad (33a)$$

$$s.t. \quad (27), (28), (29), \quad (33b)$$

$$(21g), (21h), (21i). \quad (33c)$$

### B. Problem Transform

Because (33a) and (33b) are still nonconvex with  $x_k, y_m$  and hard to be solved, we solve this problem by leveraging SCA. We first reformulate the constraints (28) and (29) into tractable expressions by leveraging auxiliary variables  $\alpha_k = T_{max}^{user}/x_k$  and  $\beta_m = T_{max}^{uav}/y_m$ .

$$F_m \geq \sum_{k=1}^K \frac{C_k L}{\alpha_k - \frac{C_k}{R_{k,m}^{GU}}} + \frac{(1-y_m) D_m L}{T_{max}^{uav}}, \forall m, \quad (34)$$

$$F_s \geq \sum_{k=1}^K \frac{C_k L}{\alpha_k - \frac{x_k C_k}{R_{k,s}^{GS}}} + \sum_{m=1}^M \frac{D_m L}{\beta_m - \frac{y_m D_m}{R_{m,s}^{US}}} + \sum_{k=1}^K \frac{C_k L}{\alpha_k - \frac{x_k C_k}{R_{k,m}^{GU}} - \frac{x_k C_k}{R_{m,s}^{US}}}, \quad (35)$$

$$\alpha_k \leq T_{max}^{user}/x_k, \beta_m \leq T_{max}^{uav}/y_m. \quad (36)$$

By Taylor expansion, (36) is transformed into

$$\frac{1}{2}(\alpha_k + x_k)^2 \leq T_{max}^{user} + \frac{1}{2}\alpha_k(t)^2 + \alpha_k(t)(\alpha_k - \alpha_k(t)) + \frac{1}{2}x_k(t)^2 + x_k(t)(x_k - x_k(t)), \quad (37)$$

$$\frac{1}{2}(\beta_m + y_m)^2 \leq T_{max}^{uav} + \frac{1}{2}\beta_m(t)^2 + \beta_m(t)(\beta_m - \beta_m(t)) + \frac{1}{2}y_m(t)^2 + y_m(t)(y_m - y_m(t)). \quad (38)$$

Similarly, we reformulate the nonconvex part in (31) and (32) by leveraging auxiliary variables  $\varphi_{k,m}, \varphi_{k,m,s}, \varphi_{k,s}, \varphi_{m,s}$

$$\varphi_{k,m} \geq \frac{x_k^3}{\left(T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}}\right)^2}, \quad (39a)$$

$$\varphi_{k,m,s} \geq \frac{x_k^3}{\left(T_{max}^{user} - \frac{x_k C_k}{R_{k,m}^{GU}} - \frac{x_k C_k}{R_{m,s}^{US}}\right)^2}, \quad (39b)$$

$$\varphi_{k,s} \geq \frac{x_k^3}{\left(T_{max}^{user} - \frac{x_k C_k}{R_{k,s}^{GS}}\right)^2}, \quad (39c)$$

$$\varphi_{m,s} \geq \frac{y_m^3}{\left(T_{max}^{uav} - \frac{y_m D_m}{R_{m,s}^{US}}\right)^2}. \quad (39d)$$

By Taylor expansion, constraints (39a)-(39d) are transformed into,

$$(T_{max}^{user})^2 \varphi_{k,m} + \frac{C_k^2}{(R_{k,m}^{GU})^2} E1_{k,m} \geq \frac{T_{max}^{user} C_k}{R_{k,m}^{GU}} E2_{k,m} + x_k^3, \quad (40a)$$

$$(T_{max}^{user})^2 \varphi_{k,m,s} + \left(\frac{C_k}{R_{k,m}^{GU}} + \frac{C_k}{R_{m,s}^{US}}\right)^2 E1_{k,m,s} \geq T_{max}^{user} \left(\frac{C_k}{R_{k,m}^{GU}} + \frac{C_k}{R_{m,s}^{US}}\right) E2_{k,m,s} + x_k^3, \quad (40b)$$

$$(T_{max}^{user})^2 \varphi_{k,s} + \frac{C_k^2}{(R_{k,s}^{GS})^2} E1_{k,s} \geq \frac{T_{max}^{user} C_k}{R_{k,s}^{GS}} E2_{k,s} + x_k^3, \quad (40c)$$

$$(T_{max}^{uav})^2 \varphi_{m,s} + \frac{C_k^2}{(R_{m,s}^{US})^2} E3 \geq \frac{T_{max}^{uav} D_m}{R_{m,s}^{US}} E4 + y_m^3. \quad (40d)$$

where  $\omega, E1_\omega, E2_\omega, E3, E4$  are defined as

$$\omega = \{\{k, m\}, \{k, m, s\}, \{k, s\}\}, \quad (41a)$$

$$E1_\omega = x_k(t)^2 \varphi_\omega(t) + x_k(t)^2 (\varphi_\omega - \varphi_\omega(t)) + 2x_k(t) \varphi_\omega(t) (x_k - x_k(t)), \quad (41b)$$

$$E2_\omega = (x_k + \varphi_\omega)^2 - x_k(t)^2 - x_k(t)(x_k - x_k(t)) - \varphi_\omega(t)^2 - \varphi_\omega(t)(\varphi_\omega - \varphi_\omega(t)), \quad (41c)$$

$$E3 = y_m(t)^2 \varphi_{m,s}(t) + y_m(t)^2 (\varphi_{m,s} - \varphi_{m,s}(t)) + 2y_m(t) \varphi_{m,s}(t) (y_m - y_m(t)), \quad (41d)$$

$$E4 = (y_m + \varphi_{m,s})^2 - y_m(t)^2 - y_m(t)(y_m - y_m(t)) - \varphi_{m,s}(t)^2 - \varphi_{m,s}(t)(\varphi_{m,s} - \varphi_{m,s}(t)). \quad (41e)$$

Then  $P_{loc}^{uav}$  and  $P_{loc}^{sat}$  can be replaced by approximation upper bounds

$$\tilde{P}_{loc}^{uav} = \sum_{k=1}^K \delta_2 C_k^3 L^3 \varphi_{m,s} \tau_{k,m} + \frac{\delta_2 (1-y_m)^3 D_m^3 L^3}{(T_{max}^{uav})^2}, \quad (42)$$

$$\tilde{P}_{loc}^{sat} = \sum_{k=1}^K \delta_3 C_k^3 L^3 \varphi_{k,s} \tau_{k,s} + \sum_{m=1}^M \delta_3 D_m^3 L^3 \varphi_{m,s} + \sum_{k=1}^K \delta_3 C_k^3 L^3 \varphi_{k,m,s} \tau_{k,m,s}, \quad (43)$$

then the objective function is transformed into

$$\tilde{P} = P_{loc}^{user} + P_{tran}^{user} + \tilde{P}_{loc}^{uav} + P_{tran}^{uav} + \tilde{P}_{loc}^{sat}. \quad (44)$$

Set  $\Xi = \{\alpha_k, \beta_m, \varphi_{k,m}, \varphi_{k,m,s}, \varphi_{k,s}, \varphi_{m,s}\}$  represents the set of auxiliary variables, then Problem (P2) can be transformed into

$$\mathbf{P3}: \min_{\{x_k\}, \{y_m\}, \Xi} \tilde{P} \quad (45a)$$

$$s.t. \quad (27), (34), (35), (37), (38), (40a) - (40d), \quad (45b)$$

$$(21g), (21h), (21i). \quad (45c)$$

The optimization Problem (P3) above is a convex problem and can be solved by a low-complex algorithm using CVX. The SCA-based algorithm is summarized as Algorithm 1, where  $MAX\_VALUE$  equals to a value much

greater than the total energy consumption. Convergence can be guaranteed, since the objective is lower bounded by a positive value and is non-decreasing after each iteration. It is not difficult to prove the non-decreasing property from Problem (P3) that  $P\{x_k(t-1), y_m(t-1), \Xi(t-1)\} \geq P\{x_k(t), y_m(t), \Xi(t)\}$ , where  $P\{x_k(t), y_m(t), \Xi(t)\}$  represents the value of object function in  $t$ -th iteration. When running Algorithm 1, the value of  $P$  is monotonically decreased at each iteration and finally converges. The complexity of Algorithm 1 is  $O\left((K+M)^{3.5} \log\left(\frac{1}{\epsilon}\right) + (2M+1)^K\right)$  where  $\epsilon$  denotes the accuracy in Algorithm 1.

#### IV. NUMERICAL RESULTS

##### A. Simulation Setup

TABLE I. SIMULATION PARAMETERS [7], [10], [11]

Parameter	Default Values	Parameter	Default Values
$P_k$	[0.1, 2]W	$P_m$	[0.1, 2]W
$L$	500 CPU cycles/bit	$\sigma^2$	-100 dBm
$\theta, \delta, \rho$	$10^{-28}$	$h^{sat}$	1000 km
$C_k$	[2, 5] Mbits	$D_m$	[2, 4] Mbits
$F_k$	[1, 5] GHz	$F_m$	[6, 9] GHz
$F_s$	[6, 9] GHz	$f_u$	1 GHz
$f_s$	2 GHz	$v_c$	$3 \times 10^8$ m/s
$T_{max}^{user}$	[0.3, 0.8] sec	$T_{max}^{uav}$	[0.3, 0.8] sec
$W_S$	50 MHz	$W_B$	10 MHz
$\eta_L$	1	$\eta_N$	20
$a$	9.61	$b$	0.16

In this paper, we consider 4 ground users symmetrical distributed within a two-dimensional area of  $200 \times 200$  m<sup>2</sup> and 2 UAVs hover in (200, 0, 500) and (-200, 0, 500) in meter as illustrated in Fig. 1. The detailed simulation parameter settings are summarized in Table I.

##### B. Simulation Results

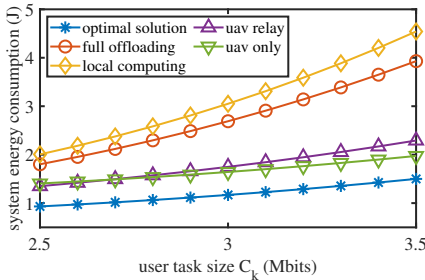


Fig. 2. Comparison of system energy consumption between optimal solution, full offloading, local computing, UAV relay and UAV only versus  $C_k$ .

In Fig. 2, we compare the proposed hybrid offloading algorithm with benchmark schemes. In the full offloading or local computing scheme, the tasks of ground users are either totally offloaded or locally processed. In the UAV-relay scheme, UAV only works as a relay, and both the tasks of users and UAVs are offloaded to the satellite. In the UAV-only scheme, users can only offload tasks to UAVs. It is obvious that our proposed algorithms provides a much lower energy cost solution, because this scheme considers the computing

##### Algorithm 1 Proposed iterative algorithm for solving optimization Problem (P3)

- 1: Initialization:  $P^* = MAX\_VALUE$
- 2: **repeat**
- 3:   Choose an offloading decision  $\mathcal{T}_k \in \mathcal{T}$ .
- 4:   Find a feasible set  $(x_k, y_m, \mathcal{F})$  to (P1).
- 5:   Calculate the object function  $P$ .
- 6:   **if**  $P \leq P^*$  **then**
- 7:      $P^* = P, \mathcal{T}_k^* = \mathcal{T}_k, x_k(0) = x_k, y_m(0) = y_m$ .
- 8:   **end if**
- 9: **until** all  $\mathcal{T}_k \in \mathcal{T}$  has been chosen
- 10: Set  $t = 1$ .
- 11: Calculate auxiliary variables  $\Xi(0)$  based on (36) and (39).
- 12: **repeat**
- 13:   Solve (P3) when given  $(x_k(t-1), y_m(t-1), \Xi(t-1), \mathcal{T}_k^*)$  for  $(x_k(t), y_m(t), \Xi(t))$ .
- 14:   update  $(x_k(t-1), y_m(t-1), \Xi(t-1)) = (x_k(t), y_m(t), \Xi(t))$ .
- 15:    $t = t + 1$ .
- 16: **until** the fractional reduce of the objective value is below a threshold  $\xi > 0$
- 17: Get  $x_k^* = x_k(t), y_m^* = y_m(t)$ , and calculate optimal computation resources allocation  $\mathcal{F}^*$  by closed-form solution.

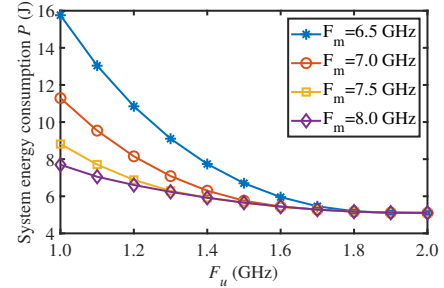
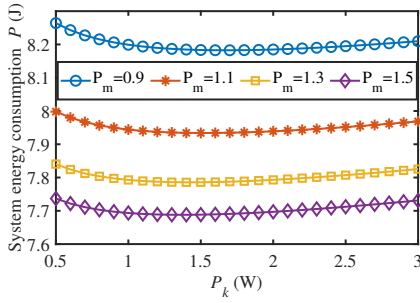
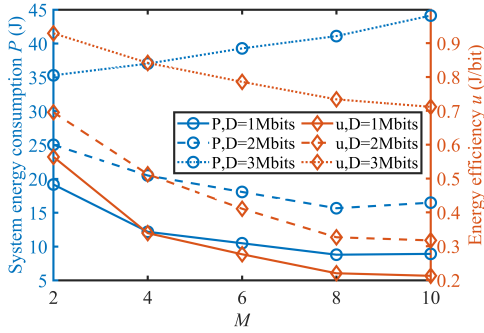


Fig. 3. System energy consumption versus  $F_u$

power of both UAVs and the satellites.

In Fig. 3, we observe that when the available computation resources increase, the system energy consumption decreases. When there are few available computation resources, users offload large amount of tasks to the UAV and the energy cost of processing users' offloading tasks is dominant. When the computation resources of users increase, the user can process more tasks locally so the energy consumption decreases. While the local energy cost of users increases with the proportion of the tasks processing locally, and the total energy consumption increases when the local energy cost becomes the dominant part. As a result, the offloading proportion of users remains unchanged when the available computation resources are large, and the total energy consumption is approximately unchanged.

Fig. 4 illustrates the system energy consumption versus the transmission power of users and UAVs. We observe that the energy consumption first decreases and then increases as the transmit power of ground users. This is reasonable since the computing energy cost is dominant when the transmission power is small, and transmission time of users decreases

Fig. 4. System energy consumption versus  $P_k$ Fig. 5. Energy consumption and energy efficiency versus  $M$ , with  $K = 8$ 

with transmission rate and UAVs only need to allocate less computing resources to process user's tasks thus the computing energy cost decreases. While when transmission power is large, the transmission energy cost takes the lead so the total energy consumption increases with transmission power. Similarly, when transmission power of UAV increases, the system energy consumption also declines.

Fig. 5 demonstrates the system energy consumption and energy efficiency versus the number of UAVs. The energy efficiency  $u$  is defined as the ratio of total energy consumption to total task size, which represents the energy consumption for processing 1 bit of data. When the tasks of each UAV are large, the energy consumption increases with the UAVs' tasks. While when the tasks of each UAV are small, more UAVs with larger amount of computation resources can reduce the system energy consumption. When the number of UAVs exceeds the number of users, the computation resource of some UAVs are only used to process their own tasks and thus not helpful to reduce the total energy consumption. Besides, though more UAVs generate larger amount of task data, the energy efficiency can always be improved.

## V. CONCLUSION

In this article, we investigated a SAGIN consists of ground users, UAVs and a satellite, where both UAVs and users have tasks to be processed. In order to minimize the total system energy consumption, we proposed a hybrid offloading strategy where both UAVs and the satellite provide offloading services to ground users. We formulate a energy minimization problem by choosing the optimal offloading objects and jointly the offloading proportion and computation resources allocation.

To solve this nonconvex problem, we first derived the closed-form solutions of computation resources allocation, and then developed a low-complex algorithm using SCA. Finally, simulation results verified that the proposed scheme outperforms all benchmark schemes. And the increase of the available computation resources and transmission power can reduce the system energy cost. Moreover, increasing the number of UAVs improves the energy efficiency, and when the tasks size of UAVs are small it can also reduce the energy consumption.

## ACKNOWLEDGEMENT

This work is supported by the National Natural Science Foundation of China (No.61941105, 61601051), the Shenzhen science and technology innovation commission free exploring basic research project (No.2021Szzup008, No. JCYJ20170307172830043), and the 111 Project of China (B16006).

## REFERENCES

- [1] J. Ye, S. Dang, B. Shihada, and M.-S. Alouini, "Space-air-ground integrated networks: Outage performance analysis," *IEEE Transactions on Wireless Communications*, vol. 19, no. 12, pp. 7897–7912, Dec 2020.
- [2] J. Liu, Y. Shi, Z. M. Fadlullah, and N. Kato, "Space-air-ground integrated network: A survey," *IEEE Communications Surveys Tutorials*, vol. 20, no. 4, pp. 2714–2741, Fourthquarter 2018.
- [3] M. Zhao, X. Chang, Z. Wang, Q. Sun, G. Lv, and Y. Jin, "A space-air-ground enabled edge computing architecture for the internet of things," in *2021 IEEE 4th International Conference on Electronics Technology (ICET)*, May 2021, pp. 752–757.
- [4] X. Li, W. Feng, Y. Chen, C.-X. Wang, and N. Ge, "Maritime coverage enhancement using uavs coordinated with hybrid satellite-terrestrial networks," *IEEE Transactions on Communications*, vol. 68, no. 4, pp. 2355–2369, April 2020.
- [5] R. Xie, Q. Tang, Q. Wang, X. Liu, F. R. Yu, and T. Huang, "Satellite-terrestrial integrated edge computing networks: Architecture, challenges, and open issues," *IEEE Network*, vol. 34, no. 3, pp. 224–231, May 2020.
- [6] S. Sun, G. Zhang, H. Mei, K. Wang, and K. Yang, "Optimizing multi-uav deployment in 3-d space to minimize task completion time in uav-enabled mobile edge computing systems," *IEEE Communications Letters*, vol. 25, no. 2, pp. 579–583, Feb 2021.
- [7] Z. Yu, Y. Gong, S. Gong, and Y. Guo, "Joint task offloading and resource allocation in uav-enabled mobile edge computing," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 3147–3159, April 2020.
- [8] N. Cheng, F. Lyu, W. Quan, C. Zhou, H. He, W. Shi, and X. Shen, "Space/aerial-assisted computing offloading for iot applications: A learning-based approach," *IEEE Journal on Selected Areas in Communications*, vol. 37, no. 5, pp. 1117–1129, May 2019.
- [9] Z. Zhang, W. Zhang, and F.-H. Tseng, "Satellite mobile edge computing: Improving qos of high-speed satellite-terrestrial networks using edge computing techniques," *IEEE Network*, vol. 33, no. 1, pp. 70–76, January 2019.
- [10] W. Shi, J. Li, W. Xu, H. Zhou, N. Zhang, S. Zhang, and X. Shen, "Multiple drone-cell deployment analyses and optimization in drone assisted radio access networks," *IEEE Access*, vol. 6, pp. 12 518–12 529, 2018.
- [11] S. Fu, J. Gao, and L. Zhao, "Integrated resource management for terrestrial-satellite systems," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3256–3266, March 2020.