

# Multi-domain Resource Management for Space-Air-Ground Integrated Sensing, Communication and Computation Networks

Sun Mao, Lei Liu, Xiangwang Hou, Mohammed Atiquzzaman, and Kun Yang

**Abstract**—To support emerging environmentally-aware intelligent applications, a massive amount of data needs to be collected by sensor devices and transmitted to edge/cloud servers for further computation and analysis. However, due to the high deployment and operational cost, only depending on terrestrial infrastructures cannot satisfy the communication and computation requirements of sensor devices in the unexpected and emergency situations. To tackle this issue, this paper presents a digital twin-enabled space-air-ground integrated sensing, communication and computation network framework, where unmanned aerial vehicles (UAVs) serve as aerial edge access point to provide wireless access and edge computing services for ground sensor devices, and satellites provide access to cloud data center. In order to tackle the complex network environments and coupled multi-dimensional resources, the digital twin technique is utilized to realize real-time network monitoring and resource management, and the mapping deviation is also considered. To realize real-time data sensing and analysis, we formulate a maximum execution latency minimization problem while satisfying the energy consumption constraints and network resource restrictions. Based on the block coordinate descent method and successive convex approximation technique, we develop an efficient algorithm to obtain the optimal sensing time, transmit power, bandwidth allocation, UAV deployment position, data assignment strategy, and computation capability allocation scheme. Simulation results demonstrate that the proposed method outperforms several benchmark methods in terms of maximum execution latency among all sensor devices.

**Index Terms**—Space-air-ground integrated network, integrated sensing, communication and computation, resource management, latency.

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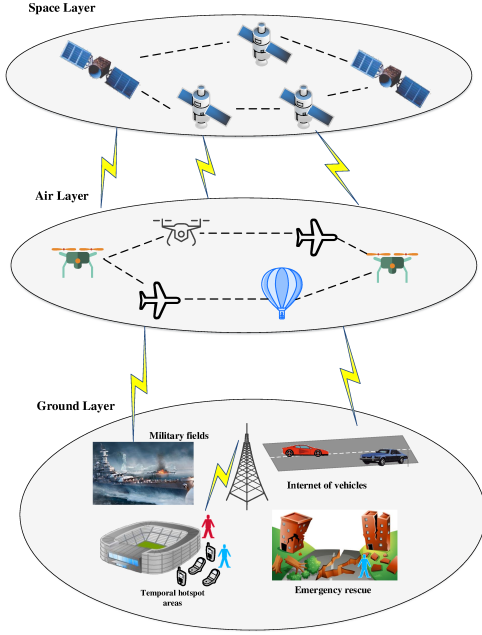
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## I. INTRODUCTION

The rapid development of sixth-generation (6G) promotes the emergence of various intelligent applications, such as emergency rescue, intelligent agriculture, smart cities, etc [1]–[3]. To support such applications, massive environmental data need to be collected by sensor devices and transmitted to the edge/cloud server for further processing and computation. To this end, integrated sensing, communication and computation (ISCC) is proposed as a promising technique in 6G era [4], [5]. However, due to the network resource restrictions (e.g., limited spectral resource, computing capability, etc.), it is essential to design efficient multi-domain resource management strategy to satisfy strict performance requirements of emerging applications [6], [7]. In [8]–[11], the authors focused on integrating ISCC technique into various applications including intelligent machine systems, vehicular networks, and so on. Besides, they aimed at promoting the coordination gains of sensing, communication and computation through joint multi-dimensional resource scheduling.

Furthermore, 6G is expected to achieve ubiquitous and seamless network coverage [12], [13]. Nevertheless, due to the high deployment and operational cost, only depending on terrestrial infrastructures cannot satisfy the service requirements of smart applications in the unexpected and emergency situations, such as earthquake, flood, etc. To tackle this issue, as shown in Fig. 1, existing literature has presented space-air-ground integrated network (SAGIN) framework [14]–[18], which can be divided into space layer, air layer and ground layer. In the ground layer, heterogeneous networks are deployed to serve a variety of wireless terminals in urban areas. The air layer utilizes UAVs as aerial access points to provide wireless access and edge computing services for remote wireless terminals. In the space layer, satellites ensure global network coverage and provide access to cloud data centers. Recently, the integration of space-air-ground coordination framework and ISCC has become a hot research topic. Existing works in [19], [20] utilized UAVs to provide sensing, communication and computation services for remote sensor devices, and they further investigated the joint resource management and mobility optimization strategy. Moreover, the authors in [21] presented the ISCC framework with space-ground cooperation, where ground sensor devices perform target sensing, and the raw data can be processed and analyzed locally, at the edge, or in the cloud data center via satellite communication links. In addition, they further

designed the resource management method to maximize the utility performance of ISCC networks. In [22], Zhang *et al.* developed the architecture of space-air-ground ISCC networks, and presented the handover scheme to satisfy the diverse quality of service requirements for various smart applications.



**Fig. 1:** Space-air-ground ISCC networks.

Despite the benefits brought by space-air-ground ISCC networks, the complex network environments and coupled multi-dimensional resources make the network resource management extremely challenging. Nowadays, digital twin technique is proposed to create a digital space model to evaluate the state information of physical entities in wireless networks, and thus it can be used to achieve real-time network monitoring and resource management [23]–[26]. In [27], Zhou *et al.* presented the digital twin-enabled UAV swarm-based multiple target tracking algorithm, which can realize efficient sensing and communication resource integration to improve the target sensing performance. In [28], [29], the authors investigated digital twin-empowered dynamic resource management strategy for UAV-aided edge computing networks. In [30], Li *et al.* further extended these works to digital twin-empowered UAV-aided ISCC networks, where ground nodes conduct radar sensing and computation offloading simultaneously, and UAV is released to provide edge computing services for ground nodes. Different from above literature focusing on air-ground cooperation, Paul *et al.* in [31] developed novel design framework of digital twin-assisted SAGIN for vehicular edge computing, and they proposed deep reinforcement learning-based computing offloading method to minimize the overall latency of vehicles.

For ease of comparison, we summarize some of most related literature in Table I. As indicated, despite the research

efforts in existing literature, several design challenges for space-air-ground integrated ISCC networks still exist, which are listed as follows.

- Existing literature in [19]–[21] considered the space-ground/air-ground cooperation-enhanced ISCC. As expected, the network resources between the space layer and air layer complement each other. The space layer provides ubiquitous access to remote cloud data center with powerful computation capability but high communication latency, while the air layer offers edge computing service with restricted computing capability but low communication latency. Hence, it is essential to study the cross-layer resource optimization framework of space-air-ground ISCC to meet strict service requirements in future 6G.
- Although digital twin technique can reflect real-time states of physical entities, mapping errors still occur due to the restrictions of data acquisition and digital twin modelling methods. Conventional resource management methods for digital twin-empowered space-air-ground ISCC networks ignored these mapping errors of physical entities [27]–[31], leading to resource mismatch problems and negatively impacting system performance. Hence, it is necessary to investigate the fault-tolerant resource management method for digital twin-empowered space-air-ground ISCC networks.
- While existing literature in [19]–[22] and [27]–[31] generally focuses on optimizing metrics like energy consumption and sensing accuracy, it often underemphasizes the importance of latency, which is crucial in delay-sensitive applications (e.g., emergency rescue, autonomous driving, and so forth.). Nevertheless, in space-air-ground ISCC networks, the complex latency expression and coupled cross-layer network resources of sensing, communication and computation make the latency optimization problem extremely challenging. Therefore, it is meaningful to develop the efficient latency-oriented resource allocation strategy.

Based on the above descriptions, we find that existing literature has overlooked the cross-layer cooperation framework and latency-oriented resource management for digital twin-empowered space-air-ground ISCC networks. This gap restricts the potential of space-air-ground ISCC networks and hinders their promotion and application in delay-sensitive scenarios. This observation motivates our study in this article. In summary, the main contribution of this article is outlined as follows.

- To the best of our knowledge, this article is the first to present the design framework for digital twin-enabled space-air-ground ISCC networks. In this framework, ground sensor devices perform environmental sensing tasks, and the sensed raw data can be offloaded to UAVs and remote data center for processing and analysis. To achieve efficient network monitoring and resource management, the digital twin technique is leveraged to estimate the sensing and computation requirements of sensor devices, as well as the operating states of UAV

**TABLE I:** Synopsis of relevant research works

| Ref.         | Resource management | ISCC                                   | Space-air-ground cooperation | Digital twin |
|--------------|---------------------|----------------------------------------|------------------------------|--------------|
| [8]–[11]     | ✓                   | ✓                                      | ✗                            | ✗            |
| [19], [20]   | ✓                   | ✓                                      | Air-ground cooperation       | ✗            |
| [21]         | ✓                   | ✓                                      | Space-ground cooperation     | ✗            |
| [22]         | ✗                   | ✓                                      | ✓                            | ✗            |
| [27]         | ✓                   | Sensing-communication coordination     | Air-ground cooperation       | ✓            |
| [28], [29]   | ✓                   | Communication-computation coordination | Air-ground cooperation       | ✓            |
| [30]         | ✓                   | ✓                                      | Air-ground cooperation       | ✓            |
| [31]         | ✓                   | Communication-computation coordination | ✓                            | ✓            |
| This article | ✓                   | ✓                                      | ✓                            | ✓            |

servers and cloud servers, where the mapping deviation is also considered.

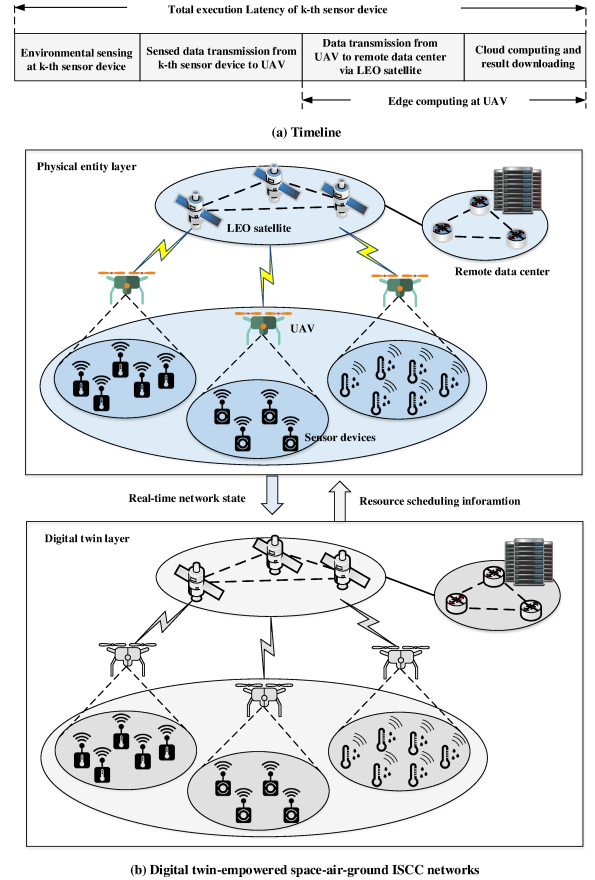
- Unlike existing literature that focuses on optimizing energy consumption or sensing accuracy, we formulate a maximum execution latency minimization problem subject to the sensing requirements and maximum energy consumption constraints, via jointly optimizing UAV deployment position, sensing time, computing capability allocation, data assignment, bandwidth allocation and transmit power control.
- To solve the strictly non-convex problem, we develop an efficient multi-domain resource management algorithm with proved convergence, through utilizing the block coordinate descent method and successive convex approximation technique. In particular, the optimal sensing time, transmit power and bandwidth allocation strategy are derived in closed-form expressions by adopting the Lagrange duality method. Meanwhile, we further extend the proposed method to the weighted total execution latency minimization problem.
- Numerical results reveal the coordination gains of sensing, communication and computation achieved by proposed multi-domain resource management strategy, as compared to several benchmark methods. Besides, we also demonstrate that the optimal deployment of UAV will contribute to reduce the execution latency of sensor devices.

The rest of this paper is summarized as follows. Section II presents the system model of digital twin-enabled space-air-ground ISCC networks. Section III formulates the maximum execution latency minimization problem, and presents multi-domain resource management algorithm. Section IV extends the proposed method to the total latency minimization problem. Section V provides the simulation results to verify the performance of proposed method. Section VI concludes this paper.

## II. SYSTEM MODEL

As shown in Fig. 2, this article considers a digital twin-empowered space-air-ground ISCC network, which can be divided into physical entity layer and digital twin layer. The physical entity layer is composed by low earth orbit (LEO) satellite, UAV,  $K$  ground sensor devices indexed by  $\mathcal{K} = \{1, 2, \dots, K\}$ . The digital twin layer is the virtual mappings of physical entities, and it can be used to realize

the real-time network monitoring and resource management. In the considered system, each sensor device first performs environmental sensing, and then transmits the sensed raw data to the UAV. Next, UAV utilizes its computing capability to analyze partial received raw data, and transmits the rest of data to the remote data center with the aid of LEO satellite<sup>1</sup>. For ease of reference, the major symbols used in this article are summarized in TABLE II.



**Fig. 2:** Digital twin-empowered space-air-ground ISCC networks.

<sup>1</sup>Noted that the considered scenario can be found in practical systems. For instance, the proposed framework can be utilized in smart forestry to avoid forest fire, where ground sensor devices are deployed to execute environmental sensing tasks, and the sensed raw data can be transmitted to UAVs and remote data center for processing and analyzing. According to the computation results, corresponding actions can be taken to avoid forest fire.

## A. Modelling of Digital Twin-Empowered Space-Air-Ground ISCC Networks

This article considers three types of digital twin models: 1) sensor devices' digital twin model, 2) UAV's digital twin model, and 3) assigned cloud servers' digital twin model. Although the digital twin can be utilized to record the real-time states of physical entities, there exist mapping errors due to the limitations of modelling method and data acquisition. For the  $k$ -th sensor device, the virtual twin is created to record its sensing requirement, energy supply, transmit power and location information, which is expressed as  $\text{DT}^{\text{sd}}(L_{k,\min}, t_{k,\max}, E_{k,\max}^I, P_{k,\max}^I, \mathbf{u}_k^I)$ , where  $L_{k,\min}$  denotes its minimum sensing data requirement,  $t_{k,\max}$ ,  $E_{k,\max}^I$  and  $P_{k,\max}^I$  represent its maximum tolerable latency, maximum available energy, and maximum transmit power, respectively,  $\mathbf{u}_k^I$  indicates its horizontal coordinate. UAV serves as an aerial access point to provide wireless access and edge computing services for sensor devices. For the UAV, the virtual twin need to be created to reflect its resource scheduling and position optimization. Thus, the digital twin of UAV is indicated by  $\text{DT}^{\text{U}}(\mathbf{u}^U, f_k^U - \hat{f}_k^U)$ , where  $\mathbf{u}^U$  represents its horizontal coordinate,  $f_k^U$  denotes the estimated computation capability of UAV allocated to  $k$ -th sensor device,  $\hat{f}_k^U$  indicates the corresponding computation resource deviation. Moreover, the digital twin of cloud server located at remote data center allocated to such a particular application is also created as  $\text{DT}^{\text{C}}(f_k^C - \hat{f}_k^C)$ , where  $f_k^C$  is the estimated cloud computation capability assigned to  $k$ -th sensor device, and  $\hat{f}_k^C$  stands for the corresponding deviation. Similar to existing literature [32], this article assumes that the estimated difference  $\hat{f}_k^U$  and  $\hat{f}_k^C$  can be obtained in advance.

## B. Data Sensing Model

Defining  $s_{r,k}$  as the sensing data rate, the size of raw data sensed by  $k$ -th sensor device is expressed as  $d_{s,k} = s_{r,k}t_{s,k}$ , where  $t_{s,k}$  represents the sensing duration. According to the energy consumption model in [33], the sensing energy consumption of  $k$ -th sensor device is given by  $E_{s,k}^I = e_{s,k}d_{s,k}$ , where  $e_{s,k}$  represents the energy consumption for sensing 1-bit data at the  $k$ -th sensor device.

Then, each sensor device transmits its sensed raw data to the UAV for further processing. Similar to existing literature, we adopt a three-dimensional (3D) Euclidean coordinate model [34], [35]. It is assumed that the UAV flies at a fixed altitude  $H$  with horizontal coordinate  $\mathbf{u}^U = (x^U, y^U)$ . The horizontal coordinate of  $k$ -th ground sensor device is indicated by  $\mathbf{u}_k^I = (x_k^I, y_k^I)$ . Therefore, the distance between  $k$ -th sensor device and the UAV is calculated by

$$\begin{aligned} d_k &= \sqrt{H^2 + (x_k^I - x^U)^2 + (y_k^I - y^U)^2} \\ &= \sqrt{H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2}, \forall k. \end{aligned} \quad (1)$$

Hence, the channel coefficient from the  $k$ -th sensor device to the UAV is modelled as

$$h_k = \Delta_k \hat{h}_k, \forall k, \quad (2)$$

TABLE II: Summary of major symbols

| Notation                              | Description                                                                                                |
|---------------------------------------|------------------------------------------------------------------------------------------------------------|
| Superscript $I/U/C$                   | Variable associated with sensor device/UAV/cloud data center                                               |
| Subscript $r/s/t/c$                   | Variable associated with sensing rate/sensing /transmission/computation                                    |
| $k$                                   | Index of sensor devices                                                                                    |
| $K$                                   | Number of sensor devices                                                                                   |
| $s_{r,k}$                             | Sensing rate of $k$ -th sensor device                                                                      |
| $t_{s,k}$                             | Sensing time of $k$ -th sensor device                                                                      |
| $d_{s,k}$                             | Amount of raw data sensed by $k$ -th sensor device                                                         |
| $e_{s,k}$                             | Sensing energy consumption of 1-bit data at $k$ -th sensor device                                          |
| $E_{s,k}^I$                           | Total sensing energy consumption of $k$ -th sensor device                                                  |
| $P_{t,k}^I$                           | Transmit power of $k$ -th sensor device                                                                    |
| $B$                                   | System bandwidth                                                                                           |
| $b_k$                                 | Bandwidth allocation ratio for $k$ -th sensor device                                                       |
| $P_{t,k}^I$                           | Transmission power of $k$ -th sensor device                                                                |
| $P^U$                                 | Transmit power of UAV                                                                                      |
| $N_0$                                 | Noise power spectral density                                                                               |
| $t_{t,k}^I$                           | Transmit time of $k$ -th sensor device                                                                     |
| $E_{t,k}^I$                           | Transmit energy consumption of $k$ -th sensor device                                                       |
| $f_k^U / f_k^C$                       | Estimated edge/cloud computation capability assigned to $k$ -th sensor device                              |
| $\hat{f}_k^U / \hat{f}_k^C$           | Estimated derivation of edge/cloud computation capability assigned to $k$ -th sensor device                |
| $L_k^U / L_k^C$                       | Raw data of $k$ -th sensor device processed at UAV/remote data center                                      |
| $\hat{t}_{c,k}^U / \hat{t}_{c,k}^C$   | Estimated computing latency for processing the raw data of $k$ -th sensor device at UAV/remote data center |
| $\Delta t_{c,k}^U / \Delta t_{c,k}^C$ | Computing latency deviation for processing the raw data of $k$ -th sensor device at UAV/remote data center |
| $t_{c,k}^U / t_{c,k}^C$               | Computing latency for processing the raw data of $k$ -th sensor device at UAV/remote data center           |
| $c_k$                                 | Number of CPU cycles for processing 1-bit raw data of $k$ -th sensor device                                |
| $E_{c,k}^U / E_{t,k}^U$               | Computing/communication energy consumption for processing the raw data of $k$ -th sensor device at UAV     |
| $t_{t,k}^U$                           | Communication latency for transmitting $L_k^C$ from UAV to remote data center                              |
| $t_k^{\text{tot}}$                    | Total execution latency of raw data of $k$ -th sensor device                                               |
| $t_{k,\max}$                          | Maximum tolerable execution latency of $k$ -th sensor device                                               |
| $E_{k,\max}^I$                        | Maximum energy consumption of $k$ -th sensor device                                                        |
| $E_{\max}^U$                          | Maximum energy consumption of UAV                                                                          |
| $f_{\max}^U / f_{\max}^C$             | Maximum CPU-cycle frequency of UAV/remote data center                                                      |
| $P_{k,\max}^I$                        | Maximum transmit power of $k$ -th sensor device                                                            |

where  $\Delta_k$  and  $\hat{h}_k$  stand for the path-loss factor and small-scale fading, respectively. In particular, the path-loss factor can be written as  $\Delta_k = h_0 d_k^{-\alpha}$ , where  $h_0$  denotes the reference channel gain at the distance  $d_0 = 1$ ,  $\alpha$  is the path-loss exponent. It is assumed that  $\alpha = 2$  and the same assumption has been extensively adopted in existing literature [36], [37]. Meanwhile, the small-scale fading follows that

$$\hat{h}_k = \sqrt{\frac{M_r}{M_r + 1}} \bar{h}_k + \sqrt{\frac{1}{M_r + 1}} \tilde{h}_k, \forall k, \quad (3)$$

where  $M_r$  is Rician fading factor,  $\bar{h}_k$  represents the line-of-sight (LoS) component satisfying  $|\bar{h}_k| = 1$ , and  $\tilde{h}_k$  denotes the Non-line-of-sight (NLoS) component that follows  $\tilde{h}_k \sim \mathcal{CN}(0, 1)$ . Let  $P_{t,k}^I$  denotes the transmission power of  $k$ -th sensor device. The transmission rate from  $k$ -th sensor device

to the UAV is expressed as

$$R_k = b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k}{b_k B N_0} \right), \forall k, \quad (4)$$

where  $b_k \in (0, 1]$  denotes the bandwidth allocation ratio,  $B$  represents the total bandwidth, and  $N_0$  is the noise power spectral density. Hence, the transmission time of  $k$ -th sensor device is denoted by  $t_{t,k}^I = \frac{s_{r,k} t_{s,k}}{R_k}$ . According, the transmit energy consumption of  $k$ -th sensor device is given by  $E_{t,k}^I = \frac{s_{r,k} t_{s,k} P_{t,k}^I}{R_k}$ .

### C. Edge Computing Model

After receiving the raw data from sensor devices, UAV divides it into two parts, one part is executed locally and the rest part is transmitted to the remote cloud data center with the aid of LEO satellite. In particular,  $L_k^U$  and  $L_k^C$  denote the raw data of  $k$ -th sensor device processed at the UAV and remote data center, respectively. Therefore, the estimated data analysis latency caused by processing  $L_k^U$  at the UAV is given by

$$\hat{t}_{c,k}^U = \frac{L_k^U c_k}{f_k^U}, \forall k, \quad (5)$$

where  $c_k$  represents the number of CPU cycles required for processing 1-bit raw data of  $k$ -th ground sensor device. Moreover, the computing delay deviation is expressed as

$$\Delta t_{c,k}^U = \frac{L_k^U c_k \hat{f}_k^U}{f_k^U (f_k^U - \hat{f}_k^U)}, \forall k. \quad (6)$$

Therefore, the computing delay for processing the raw data of  $k$ -th ground sensor device at the UAV is calculated as

$$t_{c,k}^U = \hat{t}_{c,k}^U + \Delta t_{c,k}^U, \forall k. \quad (7)$$

Accordingly, the computation energy consumption of the UAV to process the raw data of  $k$ -th sensor device is given by

$$E_{c,k}^U = \kappa (f_k^U - \hat{f}_k^U)^2 c_k L_k^U, \forall k, \quad (8)$$

where  $\kappa$  is a constant depending on the circuit architecture [38], [39].

### D. Cloud Computing Model

With the development of microwave communications and multi-beam antenna technique, direct air-space and space-ground transmissions have been demonstrated in [40], [41]. Let us define  $R_{s,a}$  and  $R_{s,g}$  as the transmission rate between the UAV and LEO satellite, and between the LEO satellite and the remote data center, respectively. Therefore, the communication delay for transmitting  $L_k^C$  to data center is represented as

$$t_{t,k}^U = \frac{L_k^C}{R_{s,a}} + \frac{L_k^C}{R_{s,g}}, \forall k. \quad (9)$$

Let us define  $P^s$  as the transmission power of the UAV for transmitting raw data to the satellite. Hence, the communication energy consumption of the UAV for transmitting data

$L_k^C$  to satellite is given by

$$E_{t,k}^U = \frac{P^U L_k^C}{R_{s,a}}, \forall k. \quad (10)$$

Moreover, the estimated cloud computing latency can be expressed as

$$t_{c,k}^C = \frac{L_k^C c_k}{f_k^C}, \forall k. \quad (11)$$

Meanwhile, the cloud computing latency deviation is calculated as

$$\Delta t_{c,k}^C = \frac{L_k^C c_k \hat{f}_k^C}{f_k^C (f_k^C - \hat{f}_k^C)}, \forall k. \quad (12)$$

Therefore, the actual cloud computing delay for processing  $L_k^C$  is given by

$$t_{c,k}^C = \hat{t}_{c,k}^C + \Delta t_{c,k}^C, \forall k. \quad (13)$$

According to above descriptions, the total execution latency of the raw data of  $k$ -th sensor device includes sensing, communication and computation duration, which is given by

$$t_k^{\text{tot}} = t_{s,k} + t_{t,k}^I + \max \{t_{c,k}^U, t_{t,k}^U + t_{c,k}^C\}, \forall k. \quad (14)$$

Since the computation result is generally smaller than the raw data, this paper neglects the transmissions of computation results, and the same assumption has been extensively adopted in existing literature [42].

## III. MAXIMUM EXECUTION LATENCY MINIMIZATION PROBLEM

In this paper, we aim at minimizing the maximum execution latency of sensor devices, while satisfying the network resource restrictions, individual execution latency and sensing requirement constraints. In such an optimization problem, the sensing time  $\mathbf{t}_s = \{t_{s,k}, \forall k \in \mathcal{K}\}$ , network bandwidth  $\mathbf{b} = \{b_k, \forall k \in \mathcal{K}\}$ , transmit power  $\mathbf{P} = \{P_{t,k}^I, \forall k \in \mathcal{K}\}$ , CPU-cycle frequency  $\mathbf{f} = \{f_k^U, f_k^C, \forall k \in \mathcal{K}\}$ , data assignment  $\mathbf{L} = \{L_k^U, L_k^C, \forall k \in \mathcal{K}\}$ , and UAV deployment position  $\mathbf{u}^U$  are jointly scheduled to minimize the maximum execution latency among all sensor devices. The corresponding optimization problem is expressed as

$$\underset{\{\mathbf{t}_s, \mathbf{b}, \mathbf{P}, \mathbf{f}, \mathbf{L}, \mathbf{u}^U\}}{\text{minimize}} \quad \max_{k \in \mathcal{K}} t_k^{\text{tot}} \quad (15a)$$

$$\text{s.t.} \quad t_k^{\text{tot}} \leq t_{k,\max}, \forall k, \quad (15b)$$

$$E_{s,k}^I + E_{t,k}^I \leq E_{k,\max}^I, \forall k, \quad (15c)$$

$$\sum_{k=1}^K (E_{c,k}^U + E_{t,k}^U) \leq E_{\max}^U, \quad (15d)$$

$$s_{r,k} t_{s,k} \geq L_{k,\min}, \forall k, \quad (15e)$$

$$L_k^U + L_k^C = s_{r,k} t_{s,k}, \forall k, \quad (15f)$$

$$\sum_{k=1}^K b_k = 1, \quad (15g)$$

$$0 \leq P_{t,k}^I \leq P_{k,\max}^I, \forall k, \quad (15h)$$

$$\sum_{k=1}^K f_k^U \leq f_{\max}^U, \quad (15i)$$

$$\sum_{k=1}^K f_k^C \leq f_{\max}^C, \quad (15j)$$

$$b_k \geq 0, \forall k, \quad (15k)$$

$$L_k^U \geq 0, \forall k, \quad (15l)$$

$$L_k^C \geq 0, \forall k, \quad (15m)$$

$$f_k^U \geq 0, \forall k, \quad (15n)$$

$$f_k^C \geq 0, \forall k, \quad (15o)$$

where (15b) restricts the maximum execution latency of sensor devices, (15c) and (15d) denote the maximum available energy consumption constraints of sensor devices and UAV, respectively, (15e) represents the sensing requirement constraints, (15f) indicates that the amount of analyzed raw data is equal to the sensed data, (15g) and (15k) stand for the bandwidth allocation constraints, (15h) are the transmit power constraint of sensor devices, (15i) and (15j) denote the maximum CPU-cycle frequency constraints of UAV and cloud data center, respectively.

*Remark 1:* Unlike the total execution latency minimization problem focusing on reducing the overall latency of all sensor devices, this paper aims at minimizing the maximum execution latency experienced by any individual sensor device. Our proposed method tends to allocate the network resources to ensure that no sensor device experiences excessively high latency, even if it means that the overall latency of all sensor devices might be slightly higher.

*Remark 2:* As observed, the formulated problem (15) is strictly non-convex due to the highly coupled optimization variables and complex execution latency expression. In general, there is no standard method to obtain the optimal solution in polynomial time<sup>2</sup>. Therefore, this article aims at developing low-complexity algorithm to obtain the suboptimal solution of (15).

*Theorem 1:* For the maximum execution latency minimization problem (15), the optimal sensing time should satisfy  $t_{s,k}^* = \frac{L_{k,\min}}{s_{r,k}}, \forall k$ .

*Proof:* With the increase of  $t_{s,k}$ , a larger amount of raw data will be transmitted and analyzed at the UAV and remote data center. Therefore, the execution latency of each sensor device increases with  $t_{s,k}$ . Meanwhile,  $t_{s,k} \geq \frac{L_{k,\min}}{s_{r,k}}$  according to (15e). Hence, the optimal sensing time of each sensor device should be selected to satisfy its minimum sensing requirement, i.e.,  $t_{s,k}^* = \frac{L_{k,\min}}{s_{r,k}}, \forall k$ . ■

Next, introducing  $t = \max_{k \in \mathcal{K}} t_k^{\text{tot}}$  and  $t_{s,k}^* = \frac{L_{k,\min}}{s_{r,k}}$  into Eq. (15), the maximum execution latency minimization problem is rewritten as

$$\underset{\{\mathbf{b}, \mathbf{P}, \mathbf{f}, \mathbf{L}, \mathbf{u}^U, t\}}{\text{minimize}} \quad t \quad (16a)$$

<sup>2</sup>It is worth noting that conventional convex optimization methods cannot be used to solve the formulated non-convex problem. Moreover, heuristic algorithms (such as particle swarm optimization and greedy algorithms) typically exhibit high complexity and provide uncertain convergence rates. Meanwhile, machine learning methods generally lack interpretability, require computationally expensive training processes, and can struggle with the curse of dimensionality.

$$\text{s.t.} \quad \frac{L_{k,\min}}{s_{r,k}} + \frac{L_{k,\min}}{R_k} + \max \{t_{c,k}^U, t_{t,k}^U + t_{c,k}^C\} \leq \min\{t_{k,\max}, t\}, \forall k, \quad (16b)$$

$$e_{s,k} L_{k,\min} + \frac{L_{k,\min} P_{t,k}^I}{R_k} \leq E_{k,\max}^I, \forall k, \quad (16c)$$

(15d), (15f)-(15o). (16d)

It is worth noting that Eq. (16) is still strictly non-convex problem. Based on block coordinate descent method, this paper divides the coupled optimization variables into four blocks, i.e.,  $\{\mathbf{b}, \mathbf{P}\}, \mathbf{u}^U, \mathbf{L}, \mathbf{f}\}$ . Next, the transmit power and bandwidth allocation strategy  $\{\mathbf{b}, \mathbf{P}\}$ , UAV deployment position  $\mathbf{u}^U$ , data assignment  $\mathbf{L}$ , and CPU-cycle frequency  $\mathbf{f}$  are alternately optimized, while keeping the other block-s fixed. Moreover, the detailed procedure for solving the four subproblems is illustrated in following subsections. In summary, we present the flowchart of proposed method for solving formulated maximum execution latency minimization problem in Fig. 3.

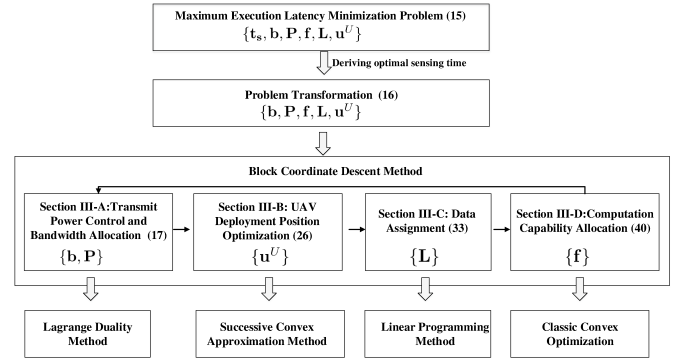


Fig. 3: The flowchart for solving formulated problem (15).

#### A. Transmit Power and Bandwidth Allocation

Given  $\{\mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}\}$  at the  $n$ -th iteration, Eq. (16) is simplified as the following transmit power and bandwidth allocation subproblem

$$\underset{\{\mathbf{b}, \mathbf{P}, t\}}{\text{minimize}} \quad t \quad (17a)$$

$$\text{s.t.} \quad \frac{L_{k,\min}}{s_{r,k}} + \frac{L_{k,\min}}{b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right)} + t_{c,k}^{(n)} \leq \min\{t_{k,\max}, t\}, \forall k, \quad (17b)$$

$$e_{s,k} L_{k,\min} + \frac{L_{k,\min} P_{t,k}^I}{b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right)} \leq E_{k,\max}^I, \forall k, \quad (17c)$$

$$\sum_{k=1}^K b_k = 1, \quad (17d)$$

$$0 \leq P_{t,k}^I \leq P_{k,\max}^I, \forall k, \quad (17e)$$

$$b_k \geq 0, \forall k, \quad (17f)$$

where

$$t_{c,k}^{(n)} = t_{c,k}((L_k^U)^{(n)}, (L_k^C)^{(n)}, (f_k^U)^{(n)}, (f_k^C)^{(n)}) = \max \left\{ \frac{(L_k^U)^{(n)} c_k}{(f_k^U)^{(n)} - \hat{f}_k^U}, \frac{(L_k^C)^{(n)}}{R_{s,a}} + \frac{(L_k^C)^{(n)}}{R_{s,g}} + \frac{(L_k^C)^{(n)} c_k}{(f_k^C)^{(n)} - \hat{f}_k^C} \right\}, \quad (18)$$

and

$$\Delta_k^{(n)} = \frac{h_0}{H^2 + \|\mathbf{u}_k^I - (\mathbf{u}^U)^{(n)}\|^2}, \forall k. \quad (19)$$

After basic inequality transformations, (17b) and (17C) are transformed as

$$b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right) \geq \frac{L_{k,\min}}{\min\{t_{k,\max}, t\} - \frac{L_{k,\min}}{s_{r,k}} - t_{c,k}^{(n)}}, \forall k, \quad (20)$$

and

$$b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right) \geq \frac{L_{k,\min} P_{t,k}^I}{E_{k,\max} - e_{s,k} L_{k,\min}}, \forall k, \quad (21)$$

respectively. Therefore, Eq. (17) is reformulated as

$$\text{minimize } t \quad (22a)$$

$$\text{s.t. } b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right) \geq \frac{L_{k,\min}}{\min\{t_{k,\max}, t\} - \frac{L_{k,\min}}{s_{r,k}} - t_{c,k}^{(n)}}, \forall k, \quad (22b)$$

$$b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right) \geq \frac{L_{k,\min} P_{t,k}^I}{E_{k,\max} - e_{s,k} L_{k,\min}}, \forall k, \quad (22c)$$

$$\sum_{k=1}^K b_k = 1, \quad (22d)$$

$$0 \leq P_{t,k}^I \leq P_{k,\max}^I, \forall k, \quad (22e)$$

$$b_k \geq 0, \forall k, \quad (22f)$$

Based on convex optimization theory,  $B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{B N_0} \right)$  is a typical concave function of  $P_{t,k}^I$ , so its perspective function  $b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right)$  is also concave associated with  $P_{t,k}^I$  and  $b_k \geq 0$ . Moreover,  $\frac{L_{k,\min}}{\min\{t_{k,\max}, t\} - \frac{L_{k,\min}}{s_{r,k}} - t_{c,k}^{(n)}}$  is convex function of  $t$  according to convexity of composite function. Therefore, (22b)-(22c) are convex constraints. Combined with other linear objective function and constraints, Eq. (22) is a convex optimization problem, and existing convex

toolbox can be utilized to obtain the optimal solution of transmit power and bandwidth allocation.

In order to gain more insights, we utilize the Lagrange duality method to derive the optimal transmit power and bandwidth allocation. The partial Lagrange function is expressed as

$$L(\lambda, u_1, \mathbf{b}, \mathbf{P}, t) = t + \sum_{k=1}^K \lambda_{1,k} (-b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right) + \frac{L_{k,\min}}{\min\{t_{k,\max}, t\} - \frac{L_{k,\min}}{s_{r,k}} - t_{c,k}^{(n)}}) + \sum_{k=1}^K \lambda_{2,k} \left( \frac{L_{k,\min} P_{t,k}^I}{E_{k,\max} - e_{s,k} L_{k,\min}} - b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right) \right) + u_1 \left( \sum_{k=1}^K b_k - 1 \right) + \sum_{k=1}^K \lambda_{3,k} (P_{t,k}^I - P_{k,\max}^I), \quad (23)$$

where  $\lambda = (\lambda_{1,k}, \lambda_{2,k}, \lambda_{3,k})$  and  $u_1$  represent the lagrange multipliers.

*Theorem 2:* For the transmit power and bandwidth allocation subproblem (22), the optimal transmit power is expressed as

$$(P_{t,k}^I)^* = \left[ \frac{(\lambda_{1,k} + \lambda_{2,k}) b_k B}{\ln(2) \left( \frac{L_{k,\min} \lambda_{2,k}}{E_{k,\max} - e_{s,k} L_{k,\min}} + \lambda_{3,k} \right)} - \frac{N_0 b_k B}{|\hat{h}_k|^2 \Delta_k^{(n)}} \right]^+ \quad (24)$$

*Proof:* See Appendix A. ■

*Remark 3:* As shown in Eq. (24), we find that the optimal transmit power of each sensor device increases inversely with minimum sensing data requirements  $L_{k,\min}$  and per-bit sensing energy consumption  $e_{s,k}$ . Due to energy restrictions of sensor devices, the available communication energy will be inevitably reduced with the increase of sensing energy consumption. Meanwhile, it is also observed that the transmit power of each sensor device increases with the available transmit bandwidth  $b_k B$  and uplink channel gain  $|\hat{h}_k|^2 \Delta_k^{(n)}$ . It reveals that each sensor device will enlarges its transmit power to upload a lager amount of raw data to UAV for processing and analyzing, when the uplink channel quality is good and the available transmit bandwidth is large.

*Theorem 3:* For the transmit power and bandwidth allocation subproblem (22), the optimal bandwidth allocation strategy is given by

$$b_k^* = - \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{B N_0 (1 + \frac{1}{\mathcal{W}(-\exp(-(\frac{1}{(\lambda_{1,k} + \lambda_{2,k}) B} + 1)))})}, \forall k. \quad (25)$$

*Proof:* See Appendix B. ■

### B. UAV Deployment Position Optimization

Under given  $\{\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}\}$ , Eq. (16) is converted to the following UAV position optimization subproblem

$$\text{minimize } t \quad (26a)$$

$$\begin{aligned} \text{s.t.} \quad & \frac{L_{k,\min}}{s_{r,k}} + \frac{L_{k,\min}}{b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 (H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2)} \right)} \\ & + t_{c,k}^{(n)} \leq \min\{t_{k,\max}, t\}, \forall k, \end{aligned} \quad (26b)$$

$$\begin{aligned} & \frac{L_{k,\min}(P_{t,k}^I)^{(n)}}{b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 (H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2)} \right)} \\ & + e_{s,k} L_{k,\min} \leq E_{k,\max}^I, \forall k, \end{aligned} \quad (26c)$$

Similar to Section III-A, Eq. (26) is transformed as

$$\begin{aligned} \text{minimize} \quad & t \\ \text{s.t.} \quad & \{\mathbf{u}^U, t\} \end{aligned} \quad (27a)$$

$$\begin{aligned} & b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 (H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2)} \right) \\ & \geq \frac{L_{k,\min}}{\min\{t_{k,\max}, t\} - \frac{L_{k,\min}}{s_{r,k}} - t_{c,k}^{(n)}}, \forall k, \end{aligned} \quad (27b)$$

$$\begin{aligned} & b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 (H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2)} \right) \\ & \geq \frac{L_{k,\min}(P_{t,k}^I)^{(n)}}{E_{k,\max} - e_{s,k} L_{k,\min}}, \forall k, \end{aligned} \quad (27c)$$

In order to tackle the non-concave and non-convex transmission rate expression  $R_k$ , we introduce the auxiliary variables  $\{z_k, \forall k\}$ , to reformulate (27b)-(27c) as

$$\begin{aligned} & b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 z_k} \right) \\ & \geq \frac{L_{k,\min}}{\min\{t_{k,\max}, t\} - \frac{L_{k,\min}}{s_{r,k}} - t_{c,k}^{(n)}}, \forall k, \end{aligned} \quad (28)$$

$$\begin{aligned} & b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 z_k} \right) \\ & \geq \frac{L_{k,\min}(P_{t,k}^I)^{(n)}}{E_{k,\max} - e_{s,k} L_{k,\min}}, \forall k, \end{aligned} \quad (29)$$

and

$$H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2 \leq z_k, \forall k. \quad (30)$$

In addition, the left side of Eqs. (28)-(29) can be rewritten as their first-order Taylor expression at the given local optimal

point  $\{z_k^{(j)}\}$ , and we have

$$\begin{aligned} & b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 z_k} \right) = \\ & b_k^{(n)} B \log_2 \left( z_k + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0} \right) - b_k B \log_2(z_k) \geq \\ & b_k^{(n)} B \log_2 \left( z_k + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0} \right) - \\ & \left( b_k B \log_2(z_k^{(j)}) + \frac{b_k^{(n)} B (z_k - z_k^{(j)})}{z_k^{(j)} \ln(2)} \right), \forall k. \end{aligned} \quad (31)$$

By replacing the left hand side of Eqs. (28)-(29) as their lower bound at the given local feasible point, we can obtain the UAV deployment position by iteratively solving the following convex problem

$$\begin{aligned} \text{minimize} \quad & t \\ \text{s.t.} \quad & \{\mathbf{u}^U, z_k, t\} \end{aligned} \quad (32a)$$

$$\begin{aligned} & b_k^{(n)} B \log_2 \left( z_k + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0} \right) - \\ & \left( b_k B \log_2(z_k^{(j)}) + \frac{b_k^{(n)} B (z_k - z_k^{(j)})}{z_k^{(j)} \ln(2)} \right) \end{aligned} \quad (32b)$$

$$\begin{aligned} & \geq \frac{L_{k,\min}}{\min\{t_{k,\max}, t\} - \frac{L_{k,\min}}{s_{r,k}} - t_{c,k}^{(n)}}, \forall k, \\ & b_k^{(n)} B \log_2 \left( z_k + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0} \right) - \\ & \left( b_k B \log_2(z_k^{(j)}) + \frac{b_k^{(n)} B (z_k - z_k^{(j)})}{z_k^{(j)} \ln(2)} \right) \end{aligned} \quad (32c)$$

$$\begin{aligned} & \geq \frac{L_{k,\min}(P_{t,k}^I)^{(n)}}{E_{k,\max} - e_{s,k} L_{k,\min}}, \forall k, \\ & H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2 \leq z_k, \forall k. \end{aligned} \quad (32d)$$

We summarize the detailed procedure for solving the UAV deployment optimization subproblem in Algorithm 1.

---

**Algorithm 1:** Proposed algorithm for solving UAV deployment optimization subproblem (26)

---

- 1 **Initialize:** Setting  $(z_k^{(0)}, (\mathbf{u}^U)^{(0)})$ , and  $j = 1$ .
  - 2 **Repeat:**
  - 3   Solve convex optimization problem (32) by CVX to
  - 4   obtain  $((\mathbf{u}^U)^{(j)}, z_k^{(j)}, t)$ ;
  - 5   Update the iterative number  $j = j + 1$ ;
  - 6   **Until Convergence.**
  - 7 **Return** optimal UAV position  $\{(\mathbf{u}^U)^*\}$ .
- 

### C. Data Assignment

Given  $\{\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{f}^{(n)}, (\mathbf{u}^U)^{(n)}\}$ , Eq. (16) is converted as the data assignment subproblem

$$\begin{aligned} \text{minimize} \quad & t \\ \text{s.t.} \quad & \{\mathbf{L}, t\} \end{aligned} \quad (33a)$$

$$\begin{aligned}
& \frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \\
\text{s.t. } & \max \left\{ \frac{L_k^U c_k}{(f_k^U)^{(n)} - \hat{f}_k^U}, \frac{L_k^C}{R_{s,a}} + \frac{L_k^C}{R_{s,g}} + \frac{L_k^C c_k}{(f_k^C)^{(n)} - \hat{f}_k^C} \right\} \\
& \leq \min\{t_{k,\max}, t\}, \forall k,
\end{aligned} \tag{33b}$$

$$\sum_{k=1}^K (\kappa((f_k^U)^{(n)} - \hat{f}_k^U)^2 c_k L_k^U + \frac{P^U L_k^C}{R_{s,a}}) \leq E_{\max}^U, \tag{33c}$$

$$L_k^U + L_k^C = L_{k,\min}, \forall k, \tag{33d}$$

$$L_k^U \geq 0, \forall k, \tag{33e}$$

$$L_k^C \geq 0, \forall k, \tag{33f}$$

where

$$(t_{t,k}^I)^{(n)} = \frac{L_{k,\min}}{R_k^{(n)}}, \forall k, \tag{34}$$

and

$$\begin{aligned}
R_k^{(n)} &= R_k((P_{t,k}^I)^{(n)}, b_k^{(n)}, (\mathbf{u}^U)^{(n)}) = \\
& b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^I)^{(n)} |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 (H^2 + \|\mathbf{u}_k^I - (\mathbf{u}^U)^{(n)}\|^2)} \right), \forall k.
\end{aligned} \tag{35}$$

It is worth noting that (33b) can be rewritten as

$$\begin{aligned}
& \frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \frac{L_k^U c_k}{(f_k^U)^{(n)} - \hat{f}_k^U} \\
& \leq \min\{t_{k,\max}, t\}, \forall k,
\end{aligned} \tag{36}$$

and

$$\begin{aligned}
& \frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \frac{L_k^C}{R_{s,a}} + \frac{L_k^C}{R_{s,g}} + \frac{L_k^C c_k}{(f_k^C)^{(n)} - \hat{f}_k^C} \\
& \leq \min\{t_{k,\max}, t\}, \forall k.
\end{aligned} \tag{37}$$

Therefore, Eq. (33) is transformed as

$$\begin{aligned}
& \text{minimize } t \\
& \{\mathbf{L}, t\}
\end{aligned} \tag{38a}$$

$$\begin{aligned}
\text{s.t. } & \sum_{k=1}^K (\kappa((f_k^U)^{(n)} - \hat{f}_k^U)^2 c_k L_k^U + \frac{P^U L_k^C}{R_{s,a}}) \leq E_{\max}^U, \\
& L_k^U + L_k^C = L_{k,\min}, \forall k, \\
& L_k^U \geq 0, \forall k, \\
& L_k^C \geq 0, \forall k, \\
& (36)-(37).
\end{aligned} \tag{38b}$$

$$L_k^U + L_k^C = L_{k,\min}, \forall k, \tag{38c}$$

$$L_k^U \geq 0, \forall k, \tag{38d}$$

$$L_k^C \geq 0, \forall k, \tag{38e}$$

$$(36)-(37). \tag{38f}$$

To further reduce the computational complexity, we introduce (38c) into the optimization problem, and transform Eq. (38) as

$$\begin{aligned}
& \text{minimize } t \\
& \{L_k^U, t\}
\end{aligned} \tag{39a}$$

$$\begin{aligned}
\text{s.t. } & \sum_{k=1}^K (\kappa((f_k^U)^{(n)} - \hat{f}_k^U)^2 c_k L_k^U + \frac{P^U (L_{k,\min} - L_k^U)}{R_{s,a}}) \\
& \leq E_{\max}^U,
\end{aligned} \tag{39b}$$

$$\begin{aligned}
& \frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + (L_{k,\min} - L_k^U) \left( \frac{1}{R_{s,a}} + \frac{1}{R_{s,g}} \right) \\
& + \frac{c_k (L_{k,\min} - L_k^U)}{(f_k^C)^{(n)} - \hat{f}_k^C} \leq \min\{t_{k,\max}, t\}, \forall k,
\end{aligned} \tag{39c}$$

$$(36) \text{ and } (38d). \tag{39d}$$

As observed, (39) is a linear programming (LP) problem, and a variety LP algorithms can be utilized to solve it.

#### D. Computation Capability Allocation

Given  $\{\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}\}$ , Eq. (16) is reduced to the computation capability allocation subproblem

$$\begin{aligned}
& \text{minimize } t \\
& \{\mathbf{f}, t\}
\end{aligned} \tag{40a}$$

$$\begin{aligned}
& \frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \\
\text{s.t. } & \max \left\{ \frac{(L_k^U)^{(n)} c_k}{f_k^U - \hat{f}_k^U}, \frac{(L_k^C)^{(n)}}{R_{s,a}} + \frac{(L_k^C)^{(n)}}{R_{s,g}} + \frac{(L_k^C)^{(n)} c_k}{f_k^C - \hat{f}_k^C} \right\} \\
& \leq \min\{t_{k,\max}, t\}, \forall k,
\end{aligned} \tag{40b}$$

$$\begin{aligned}
& \sum_{k=1}^K (\kappa(f_k^U - \hat{f}_k^U)^2 c_k (L_k^U)^{(n)} + \frac{P^U (L_k^C)^{(n)}}{R_{s,a}}) \\
& \leq E_{\max}^U,
\end{aligned} \tag{40c}$$

$$\sum_{k=1}^K f_k^U \leq f_{\max}^U, \forall k, \tag{40d}$$

$$\sum_{k=1}^K f_k^C \leq f_{\max}^C, \tag{40e}$$

$$f_k^U \geq 0, \forall k, \tag{40f}$$

$$f_k^C \geq 0, \forall k. \tag{40g}$$

By rewriting (40b), the computation capability allocation subproblem is converted as

$$\begin{aligned}
& \text{minimize } t \\
& \{\mathbf{f}, t\}
\end{aligned} \tag{41a}$$

$$\begin{aligned}
& \frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \frac{(L_k^U)^{(n)} c_k}{f_k^U - \hat{f}_k^U} \leq \\
& \min\{t_{k,\max}, t\}, \forall k,
\end{aligned} \tag{41b}$$

$$\begin{aligned}
& \frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \frac{(L_k^C)^{(n)}}{R_{s,a}} + \frac{(L_k^C)^{(n)}}{R_{s,g}} + \\
& \frac{(L_k^C)^{(n)} c_k}{f_k^C - \hat{f}_k^C} \leq \min\{t_{k,\max}, t\}, \forall k,
\end{aligned} \tag{41c}$$

$$\begin{aligned}
& \sum_{k=1}^K (\kappa(f_k^U - \hat{f}_k^U)^2 c_k (L_k^U)^{(n)} + \frac{P^U (L_k^C)^{(n)}}{R_{s,a}}) \\
& \leq E_{\max}^U,
\end{aligned} \tag{41d}$$

$$\sum_{k=1}^K f_k^U \leq f_{\max}^U, \tag{41e}$$

$$\sum_{k=1}^K f_k^C \leq f_{\max}^C, \quad (41f)$$

$$f_k^U \geq 0, \forall k, \quad (41g)$$

$$f_k^C \geq 0, \forall k. \quad (41h)$$

According to the definition of convex function,  $\frac{1}{f_k^U - \hat{f}_k^U}$  and  $(f_k^U - \hat{f}_k^U)^2$  are convex function of  $f_k^U$ . In addition,  $\min\{t_{k,\max}, t\}$  is concave function associated with  $t$ . Therefore (41b) and (41d) are typically convex constraints. Meanwhile, (41c) is also convex due to the convexity of  $(f_k^C - \hat{f}_k^C)^2$  and  $-\min\{t_{k,\max}, t\}$ . Integrated with other linear objective function and constraints (41e)-(41h), we can derive that Eq. (41) is a convex optimization problem, and conventional convex optimization algorithms can be utilized to obtain the optimal computation capability allocation strategy.

### E. Algorithm Convergence and Complexity

The proposed alternating optimization method is summarized at Algorithm 2.

---

**Algorithm 2:** Proposed method for solving the maximum execution latency minimization problem (15)

---

- 1 **Initialize:** Setting  $\{\mathbf{b}^{(0)}, \mathbf{P}^{(0)}, \mathbf{f}^{(0)}, \mathbf{L}^{(0)}, (\mathbf{u}^U)^{(0)}\}$ , and  $n = 1$ .
  - 2 Obtaining the optimal sensing time according to *Theorem 1*;
  - 3 **Repeat:**
  - 4   Given  $\{\mathbf{L}^{(n-1)}, \mathbf{f}^{(n-1)}, (\mathbf{u}^U)^{(n-1)}\}$ , calculating the optimal transmit power and bandwidth allocation  $\{\mathbf{b}^{(n)}, \mathbf{P}^{(n)}\}$  by solving (22);
  - 5   Given  $\{\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{L}^{(n-1)}, \mathbf{f}^{(n-1)}\}$ , executing Algorithm 1 to obtain optimal UAV deployment position  $(\mathbf{u}^U)^{(n)}$ ,
  - 6   Given  $\{\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{f}^{(n-1)}, (\mathbf{u}^U)^{(n)}\}$ , acquiring the optimal data assignment strategy  $\{\mathbf{L}^{(n)}\}$  by solving (39);
  - 7   Given  $\{\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}\}$ , acquiring the optimal data assignment strategy  $\{\mathbf{f}^{(n)}\}$  by solving (41);
  - 8   Updating iteration factor  $n = n + 1$ ;
  - 9 **Until** convergence.
  - 10 **Return:** the optimal solution  $\{\mathbf{t}_s^*, \mathbf{b}^*, \mathbf{P}^*, \mathbf{L}^*, \mathbf{f}^*, (\mathbf{u}^U)^*\}$ .
- 

*Theorem 4:* Algorithm 2 can converge to a stationary point after a finite number of iterations.

*Proof:* See Appendix C. ■

Finally, we will analyze the computational complexity of Algorithm 2. Let us define  $J_1$  and  $J_2$  as the iteration number of Algorithm 1 and Algorithm 2, respectively. In each iteration of Algorithm 2, four subproblems are alternately solved, and the corresponding computational complexity will be summarized as follows.

- *Transmit power and bandwidth allocation:* As observed, transmit power and bandwidth allocation subproblem (22) includes  $2K + 1$  optimization variables and  $4K + 1$

constraints, and the computational complexity for solving convex problem (22) is expressed as  $\mathcal{O}(2(3K + 1)(2K + 1)^2 \sqrt{4K + 1} \log(\frac{1}{\epsilon_1}))^3$ .

- *UAV deployment position optimization:* Algorithm 1 is called to acquire the optimal UAV deployment position. In Algorithm 1, problem (32) with  $K + 3$  variables and  $3K$  constraints is solved iteratively, and the pre-iteration complexity is expressed as  $\mathcal{O}((4K + 3)(K + 3)^2 \sqrt{3K} \log(\frac{1}{\epsilon_2}))$ .
- *Data assignment:* This article converts the data assignment subproblem to a LP problem (39), which consists of  $K + 1$  variables and  $3K + 1$  constraints. Therefore, the computational complexity for solving data assignment subproblem (39) is given by  $\mathcal{O}(2(2K + 1)(K + 1)^2 \sqrt{3K + 1} \log(\frac{1}{\epsilon_3}))$ .
- *Computation capability allocation:* The computation capability allocation subproblem (41) includes  $2K + 1$  variables and  $5K + 3$  constraints, and the computational complexity is written as  $\mathcal{O}((7K + 4)(2K + 1)^2 \sqrt{5K + 3} \log(\frac{1}{\epsilon_4}))$ .

According to above descriptions, the total computational complexity of Algorithm 2 will be  $\mathcal{O}(J_2(2(3K + 1)(2K + 1)^2 \sqrt{4K + 1} \log(\frac{1}{\epsilon_1})) + J_1(4K + 3)(K + 3)^2 \sqrt{3K} \log(\frac{1}{\epsilon_2}) + (4K + 3)(K + 3)^2 \sqrt{3K} \log(\frac{1}{\epsilon_2}) + 2(2K + 1)(K + 1)^2 \sqrt{3K + 1} \log(\frac{1}{\epsilon_3}) + (7K + 4)(2K + 1)^2 \sqrt{5K + 3} \log(\frac{1}{\epsilon_4})))$ .

## IV. DISCUSSION OF WEIGHTED TOTAL LATENCY MINIMIZATION PROBLEM

Above section aims at minimizing the execution latency of worst-case sensor devices, which is essential for the application scenarios where anyone high-latency task could cause a system failure, such as emergency rescue. However, the resource allocation strategy discussed in Section III may reduce the overall performance of considered systems. Therefore, this section further investigates the weighted total latency minimization problem to reveal the overall performance limits. The corresponding problem can be formulated as

$$\begin{aligned} & \underset{\{\mathbf{t}_s, \mathbf{b}, \mathbf{P}, \mathbf{f}, \mathbf{L}, \mathbf{u}^U\}}{\text{minimize}} && \sum_{k=1}^K w_k t_k^{\text{tot}} \end{aligned} \quad (42a)$$

$$\text{s.t.} \quad (15b)-(15o). \quad (42b)$$

where  $w_k \geq 0$  denotes the weight factor associated to  $k$ -th sensor device, and it satisfies  $\sum_{k=1}^K w_k = 1$ . As expected, the optimal sensing time can be decided to satisfy  $t_{s,k}^* = \frac{L_{k,\min}}{s_{r,k}}$  for reducing the total execution latency. Next, we introduce a set of auxiliary variables  $t_k \geq t_k^{\text{tot}}$  to transform Eq. (42) as

$$\underset{\{\mathbf{b}, \mathbf{P}, \mathbf{f}, \mathbf{L}, \mathbf{u}^U, t_k\}}{\text{minimize}} \quad \sum_{k=1}^K w_k t_k \quad (43a)$$

<sup>3</sup> $\epsilon_1, \epsilon_2, \epsilon_3$  and  $\epsilon_4$  denote the tolerance factor.

$$\text{s.t.} \quad \frac{L_{k,\min}}{s_{r,k}} + \frac{L_{k,\min}}{R_k} + \max \{t_{c,k}^U, t_{t,k}^U + t_{c,k}^C\} \leq \min\{t_{k,\max}, t_k\}, \forall k, \quad (43b)$$

$$e_{s,k} L_{k,\min} + \frac{L_{k,\min} P_{t,k}^I}{R_k} \leq E_{k,\max}^I, \forall k, \quad (43c)$$

$$(15d), (15f)-(15o). \quad (43d)$$

Then, Eq. (43) can be decoupled into several subproblems including transmit power and bandwidth allocation subproblem, UAV position optimization subproblem, data assignment subproblem, and computing capability allocation subproblem. Compared to the maximum execution latency minimization problem, we only need to make a simple modification for solving the decoupled subproblems in the total latency minimization problem. In particular, the objective function of each subproblem should be modified as the linear function  $\sum_{k=1}^K w_k t_k$ , and execution latency constraints in the transmit power and bandwidth allocation subproblem, UAV position optimization subproblem, data assignment subproblem, and computation capability allocation subproblem can be rewritten as

$$\frac{L_{k,\min}}{s_{r,k}} + \frac{L_{k,\min}}{b_k B \log_2 \left( 1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} \right)} + t_{c,k}^{(n)} \leq \min\{t_{k,\max}, t_k\}, \forall k, \quad (44)$$

$$\frac{L_{k,\min}}{s_{r,k}} + \frac{L_{k,\min}}{b_k^{(n)} B \log_2 \left( 1 + \frac{(P_{t,k}^{(n)}) |\hat{h}_k|^2 h_0}{b_k^{(n)} B N_0 (H^2 + \|\mathbf{u}_k^I - \mathbf{u}^U\|^2)} \right)} + t_{c,k}^{(n)} \leq \min\{t_{k,\max}, t_k\}, \forall k, \quad (45)$$

$$\frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \max \left\{ \frac{L_k^U c_k}{(f_k^U)^{(n)} - \hat{f}_k^U}, \frac{L_k^C}{R_{s,a}} + \frac{L_k^C}{R_{s,g}} + \frac{L_k^C c_k}{(f_k^C)^{(n)} - \hat{f}_k^C} \right\} \leq \min\{t_{k,\max}, t_k\}, \forall k, \quad (46)$$

and

$$\frac{L_{k,\min}}{s_{r,k}} + (t_{t,k}^I)^{(n)} + \max \left\{ \frac{(L_k^U)^{(n)} c_k}{f_k^U - \hat{f}_k^U}, \frac{(L_k^C)^{(n)}}{R_{s,a}} + \frac{(L_k^C)^{(n)}}{R_{s,g}} + \frac{(L_k^C)^{(n)} c_k}{f_k^C - \hat{f}_k^C} \right\} \leq \min\{t_{k,\max}, t_k\}, \forall k. \quad (47)$$

Since Eqs. (44)-(47) are similar to the counterparts of decoupled subproblems in maximum execution latency minimization problem, so we can utilize the same methods to tackle it. In summary, we can extend the proposed resource management algorithm in Section IV to the weighted total latency minimization problem after simple modifications.

## V. NUMERICAL RESULTS

In this section, we provide extensive simulation results to reveal the performance advantages of proposed method. For

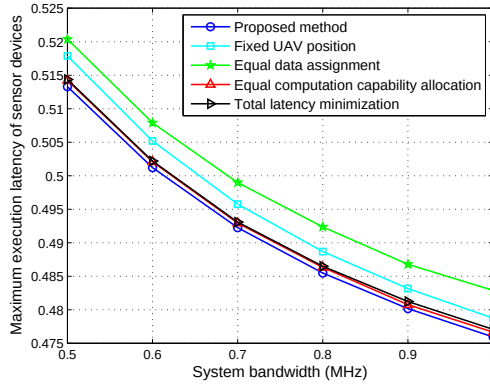
comparison, the following benchmark methods are considered.

- *Fixed UAV position:* In this scheme, the UAV is deployed at  $[0,0,10]$ , and the sensing time, data assignment, computation capability allocation, transmit power and bandwidth allocation are optimally selected according to the proposed method.
- *Equal data assignment:* In this scheme, the raw data of each sensor device is equally assigned to UAV and remote data center. Besides, the optimal sensing time, UAV deployment position, computation capability allocation, transmit power and bandwidth allocation strategy are decided by the proposed method.
- *Equal computation capability allocation:* In this scheme, edge and cloud computation capability are equally assigned to process the raw data of all sensor devices. In addition, the UAV deployment position, sensing and communication resources are selected according the proposed method.
- *Total latency minimization:* In this scheme, the total latency is selected as the objective function with  $w_k = \frac{1}{K}$ , and multi-domain network resources are optimized according the proposed method in Section IV.

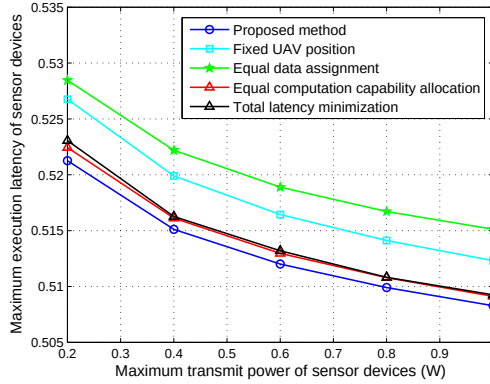
In simulations, we consider a scenario with  $K = 3$  sensor devices located at  $([5,10,0], [-4,8,0], [1,4,0])$ . Moreover, the noise power spectral density is set as  $N_0 = 10^{-15}$  W/Hz, Rician fading factor is  $M_r = 3$ , pathloss factor is  $\alpha = 3$ , the sensing rate is  $s_{r,k} = 1$  Mbits/s, the estimated deviation of edge/cloud computation capability assigned to sensor devices is set as  $\hat{f}_k^U = \hat{f}_k^C = 0.1$  GHz, the maximum execution latency of sensor devices is  $t_{k,\max} = 1$  second, total communication and computation energy consumption of UAV is set as  $E_{\max}^U = 2$  Joule, the transmission power of UAV is set as  $P^U = 2$  W, the maximum energy consumption of sensor devices is  $E_{k,\max}^I = 1$  Joule, the sensing energy consumption is  $e_{s,k} = 10^{-6}$  Joule/bit, the space-ground transmit rate between LEO and remote data center is  $R_{s,g} = 1$  Mbits/s, the flying height of UAV is set as  $H = 10$  m, and  $\kappa = 10^{-27}$  [43]–[45]. According to above parameter settings, our proposed method and benchmark methods are simulated by MATLAB R2012a.

Figs. 4-5 show the relationship between the sensor devices' communication capability (i.e., system bandwidth and maximum transmit power) and the maximum execution latency among all sensor devices, where the minimum sensing rate requirement is  $L_{k,\min} = 0.2$  Mbits, the computational complexity  $c_k = 600$ , the air-space transmission rate is set as  $R_{s,a} = 1$  Mbits/s, the maximum CPU-cycle computation frequency of UAV and remote data center are set as  $f_{\max}^U = 1.5$  GHz and  $f_{\max}^C = 5$  GHz, respectively. As expected, the maximum execution latency of sensor devices decreases with the increase of sensor devices' communication capability, since the transmission latency of the sensed raw data will be decreased as the increase of system bandwidth or maximum transmit power of sensor devices. In addition, the decreasing rate of execution latency decreases with the increase of system bandwidth or maximum transmit power of

sensor devices. It can be explained by the reciprocal/ $\frac{1}{\log_2(\cdot)}$  function relationship between the transmission latency and system bandwidth/maximum transmit power of sensor devices. Meanwhile, we observe from these figures that the maximum execution latency among all sensor devices achieved by the proposed method is significantly lower than considered benchmark methods. The reason is that the joint resource scheduling and UAV deployment optimization has higher degree of freedom to reduce execution latency of sensor devices than the separated UAV deployment optimization strategy or resource scheduling scheme. In addition, as compared to *Equal data assignment* scheme and *Total latency minimization problem*, the latency reduction achieved by our proposed method increases with the system bandwidth.



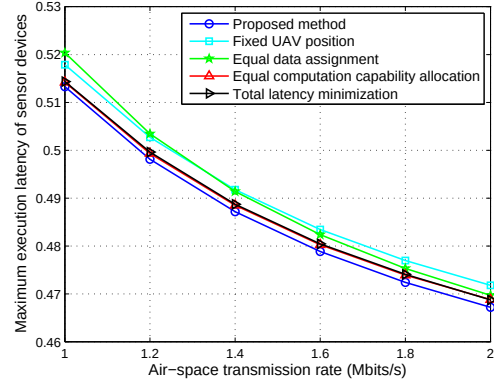
**Fig. 4:** System bandwidth versus maximum execution latency among all sensor devices.



**Fig. 5:** Maximum transmit power of sensor devices versus maximum execution latency among all sensor devices.

Fig. 6 shows the air-space transmission rate versus maximum execution latency among all sensor devices, where the system bandwidth is set as  $B = 0.5$  MHz, the maximum transmit power of sensor devices is  $P_{k,\max}^I = 0.5$  W,  $L_{k,\min} = 0.2$  Mbits,  $c_k = 600$ ,  $f_{\max}^U = 1.5$  GHz, and  $f_{\max}^C = 5$  GHz. We observe that the maximum execution latency achieved by all schemes decreases with the increase of air-space transmission rate. Moreover, the proposed method can realize remarkably lower execution latency than the *Equal*

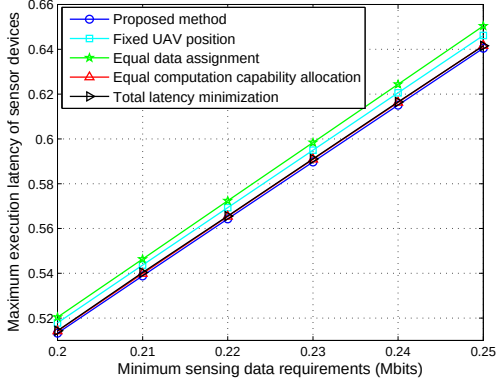
*data assignment* strategy, and the performance gap increases with the decrease of air-space transmission rate. The reason is that the equal data assignment is inefficient when the air-space transmission rate is low, since the cloud computing will lead to unacceptable communication latency. In contrast, the proposed method can allocate the raw data to be processed by the UAV or the remote data center, according to the edge/cloud computation capability and air-ground transmit rate. Therefore, the proposed method tends to allocate a larger amount of raw data to the UAV for reducing the maximum execution latency among all sensor devices. Moreover, it is also observed that our proposed method can achieve significantly lower execution latency than *Fixed UAV position* scheme, *Equal computation capability allocation* scheme, and *Total latency minimization* scheme, especially in the scenario with low air-space transmission rate.



**Fig. 6:** Air-space transmission rate versus maximum execution latency among all sensor devices.

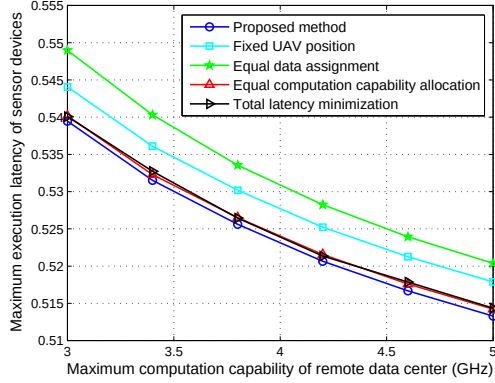
Fig. 7 plots the minimum sensing data requirement versus the maximum execution latency among all sensor devices, where  $B = 0.5$  MHz,  $P_{k,\max}^I = 0.5$  W,  $c_k = 600$ ,  $R_{s,a} = 1$  Mbits/s,  $f_{\max}^U = 1.5$  GHz and  $f_{\max}^C = 5$  GHz. As observed in this figure, the maximum execution latency among all sensor devices increases with the minimum sensing data requirements. Because the sensing, communication and computation duration will be inevitably increased with the minimum sensing data requirements.

Figs. 8-9 reveal the impact of maximum edge/cloud computation capability on the maximum execution latency among all sensor devices, where  $B = 0.5$  MHz,  $P_{k,\max}^I = 0.5$  W,  $L_{k,\min} = 0.2$  Mbits,  $c_k = 600$ , and  $R_{s,a} = 1$  Mbits/s. As observed in these figures, the maximum execution latency among all sensor devices decreases with the increase of maximum CPU-cycle frequency of UAV/remote data center. Moreover, the rate at which the maximum execution latency decreases slows down as the maximum edge/cloud computation capability increases. This is because the data processing latency at the edge/cloud is inversely proportional to the computation capability. Meanwhile, the proposed method exhibits significantly lower latency performance than *Equal data assignment* strategy, especially in the scenario with large  $f_{\max}^U$  or small  $f_{\max}^C$ . It verifies the necessity to optimize the data



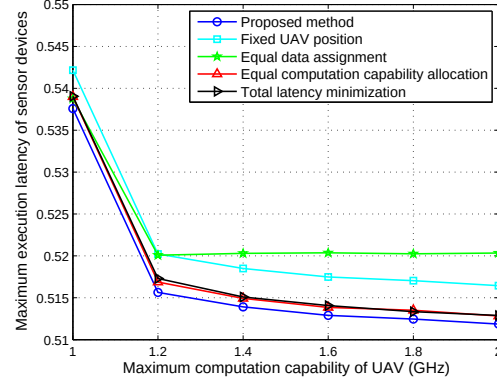
**Fig. 7:** Minimum sensing data requirements versus maximum execution latency among all sensor devices.

assignment to the UAV and remote data center for reducing the data execution latency of sensor devices. Furthermore, it is also observed that the proposed method can realize larger latency reduction than the *Fixed UAV position* scheme when  $f_{\max}^C$  or  $f_{\max}^U$  is large. This observation demonstrates that the optimal UAV position optimization will enhance the additional degree of freedom to reduce the maximum execution latency among all sensor devices.



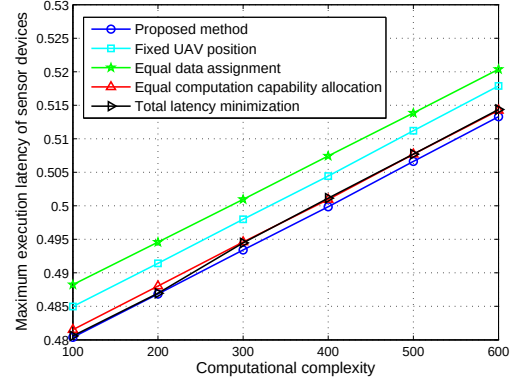
**Fig. 8:** Maximum computation capability of remote data center versus maximum execution latency among all sensor devices.

Fig. 10 plots the computational complexity of raw data versus maximum execution latency among all sensor devices, where  $B = 0.5$  MHz,  $P_{k,\max}^I = 0.5$  W,  $L_{k,\min} = 0.2$  Mbits,  $f_{\max}^U = 1.5$  GHz,  $f_{\max}^C = 5$  GHz, and  $R_{s,a} = 1$  Mbits/s. As expected, the maximum execution latency among all sensor devices increases with the computational complexity of raw data. Because the computation latency of sensor devices increases with computational complexity of raw data. Besides, as observed in Fig. 10, when the computational complexity  $c_k \leq 200$ , the total execution latency minimization-based method achieves almost the same maximum execution latency among all sensor devices compared to the proposed method. Moreover, the proposed method exhibits a significantly lower maximum execution latency compared to the total execution latency-based method when  $c_k \geq 300$ . It reveals that the *total*



**Fig. 9:** Maximum computation capability of UAV versus maximum execution latency among all sensor devices.

*latency minimization* scheme tends to sacrifice the performance of worst-case sensor devices in order to reduce the total execution latency, while the computational complexity  $c_k$  remains high.



**Fig. 10:** Computational complexity versus maximum execution latency among all sensor devices.

## VI. CONCLUSION

This article investigated the resource management strategy for digital twin-enabled space-air-ground ISCC networks. To realize real-time sensing and data analysis, we formulated a maximum execution latency minimization problem with the jointly optimization of sensing time and transmit power of sensor devices, bandwidth allocation, data assignment, UAV deployment position, computation capability scheduling. Moreover, we developed an alternating optimization algorithm by utilizing the block coordinate descent method and successive convex approximation technique. Simulation results demonstrated that the flexible UAV deployment and joint resource scheduling have great potential to reduce the execution latency of sensor devices.

## APPENDIX A: PROOF OF THEOREM 2

The derivation of  $L(\lambda, u_1, \mathbf{b}, \mathbf{P}, t)$  to  $P_{t,k}^I$  is given by

$$\begin{aligned} \frac{\partial L(\lambda, u_1, \mathbf{b}, \mathbf{P}, t)}{\partial P_{t,k}^I} &= -\frac{(\lambda_{1,k} + \lambda_{2,k})b_k B}{\ln(2)} \frac{\frac{|\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}}{1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}} \\ &+ \frac{L_{k,\min} \lambda_{2,k}}{E_{k,\max} - e_{s,k} L_{k,\min}} + \lambda_{3,k}, \forall k. \end{aligned} \quad (48)$$

Letting  $\frac{\partial L(\lambda, u_1, \mathbf{b}, \mathbf{P}, t)}{\partial P_{t,k}^I} = 0$ , we can derive the optimal transmit power as given in Eq. (24).

## APPENDIX B: PROOF OF THEOREM 3

The derivation function of  $L(\lambda, u_1, \mathbf{b}, \mathbf{P}, t)$  to  $b_k$  is expressed as

$$\begin{aligned} \frac{\partial L(\lambda, u_1, \mathbf{b}, \mathbf{P}, t)}{b_k} &= -\frac{(\lambda_{1,k} + \lambda_{2,k})B}{\ln(2)} \left( \ln\left(1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}\right) \right. \\ &\left. - \frac{\frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}}{1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}} \right) + u_1, \forall k. \end{aligned} \quad (49)$$

According to KKT condition, the optimal transmit bandwidth should satisfy  $\frac{\partial L(\lambda, u_1, \mathbf{b}, \mathbf{P}, t)}{b_k} = 0$ . Therefore, we have

$$\ln\left(1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}\right) - \frac{\frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}}{1 + \frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0}} = \frac{u_1 \ln(2)}{(\lambda_{1,k} + \lambda_{2,k})B}. \quad (50)$$

Based on Lemma 2 in [46], we have

$$\frac{P_{t,k}^I |\hat{h}_k|^2 \Delta_k^{(n)}}{b_k B N_0} = -\left(1 + \frac{1}{\mathcal{W}(-\exp(-(\frac{u_1 \ln(2)}{(\lambda_{1,k} + \lambda_{2,k})B} + 1)))}\right), \quad (51)$$

where  $\mathcal{W}$  denotes the Lambert function. After basic equality transformation, we derive the optimal bandwidth allocation strategy as given in Eq. (25).

## APPENDIX C: PROOF OF THEOREM 4

Let us define  $t(\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)})$  as the optimal solution of Eq. (16) at the  $n$ -th iteration. Given  $\{\mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}\}$ , the optimal transmit power and bandwidth allocation strategy is obtained by solving Eq. (22), and we have

$$\begin{aligned} t(\mathbf{b}^{(n)}, \mathbf{P}^{(n)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}) &\geq \\ t(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}). \end{aligned} \quad (52)$$

Next, given  $t(\mathbf{t}_s^{(n)}, \mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)})$ , Algorithm 1 is adopted to monotonically decreases the objective value of Eq. (26), it follows that

$$\begin{aligned} t(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}) &\stackrel{(\alpha_1)}{=} \\ t^{\text{up}}(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n)}) &\stackrel{(\alpha_2)}{\geq} \\ t^{\text{up}}(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n+1)}) &\stackrel{(\alpha_3)}{\geq} \\ t(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n+1)}). \end{aligned} \quad (53)$$

where  $(\alpha_1)$  holds since the first-order Taylor approximation of  $R_k$  is tight at given local optimal solution,  $(\alpha_2)$  holds because the optimal UAV deployment position is acquired at the steps 3-4 of Algorithm 1, and  $(\alpha_3)$  holds since the objective function value of Eq. (32) is the upper bound of original optimization problem. Then, the optimal data assignment and computation resource allocation strategies are obtained by solving Eq. (39) and Eq. (41) alternately, we have

$$\begin{aligned} t(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n)}, (\mathbf{u}^U)^{(n+1)}) &\geq \\ t(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n)}, \mathbf{L}^{(n+1)}, (\mathbf{u}^U)^{(n+1)}) &\geq \\ t(\mathbf{b}^{(n+1)}, \mathbf{P}^{(n+1)}, \mathbf{f}^{(n+1)}, \mathbf{L}^{(n+1)}, (\mathbf{u}^U)^{(n+1)}). \end{aligned} \quad (54)$$

According to above descriptions, we find that the maximum execution latency among sensor devices keeps non-increasing after each iteration. Meanwhile, due to the restrictions of network resources, the execution latency is lower bounded by a finite value. Therefore, Algorithm 2 is able to converge to a stationary point after several iterations.

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