UAV-Assisted Multi-Cluster Over-the-Air Computation

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Abstract—In this paper, we study unmanned aerial vehicles (UAVs) assisted wireless data aggregation (WDA) in multi-cluster networks, where multiple UAVs simultaneously perform different WDA tasks via over-the-air computation (AirComp) without terrestrial base stations. This work focuses on maximizing the minimum amount of WDA tasks performed by each cluster by optimizing the UAV trajectory and transceiver design as well as cluster scheduling and association, while considering the WDA accuracy requirement. Such a joint design is critical for interference management in multi-cluster AirComp networks, via enhancing the signal quality between each UAV and its associated cluster for signal alignment while reducing the inter-cluster interference between each UAV and its non-associated clusters. Although it is generally challenging to optimally solve the formulated non-convex mixed-integer nonlinear programming, an efficient iterative algorithm as a compromise approach is developed by exploiting bisection and block coordinate descent methods, yielding an optimal transceiver solution in each iteration. The optimal binary variables and a suboptimal trajectory are obtained by using the dual method and successive convex approximation, respectively. Simulations show the considerable performance gains of the proposed design over benchmarks and the superiority of deploying multiple UAVs in increasing the number of performed tasks while reducing access delays.

Index Terms—Over-the-air computation, UAV communications, wireless data aggregation, multi-cluster cooperation, interference management.

I. INTRODUCTION

MACHINE-TYPE communication (MTC) is one of the disruptive technologies promised by 5G and beyond wireless networks [1]. A fundamental operation is to collect and leverage Big Data effectively for decision-making to automate various intelligent applications. However, collecting data generated by an enormous number of devices is critically challenging in the future Internet of Things (IoT) networks due to the limited spectrum resource [2], [3]. Meanwhile, many emerging IoT applications (e.g., environmental monitoring) only aim to collect a particular function of these massive data rather than to reconstruct individual data, which is referred to as wireless data aggregation (WDA) [4]. To meet these demands, over-the-air computation (AirComp) has recently been considered as an attractive technique to enable fast WDA among massive devices by seamlessly integrating communication and computation processes [5]. The principle of AirComp is to exploit the waveform/signal superposition property of multiple-access channels (MAC) such that an edge server directly receives a function of concurrently transmitted data. This results in low transmission delays regardless of the amount of devices, and makes AirComp particularly appealing to data-intensive and/or latency-critical applications such as consensus control [6], distributed sensing [7], and distributed machine learning [8], [9].

So far, AirComp has been studied from various aspects in single-cell networks, such as single-input-single-output (SISO) AirComp [7], [10], multiple-input-single-output (MISO) AirComp [11], [12], and multiple-input-multiple-output (MIMO) AirComp [13]. In single-cell networks, to achieve accurate computing, AirComp requires the phase and magnitude of all signals to be aligned at the server side. However, channel heterogeneity across devices makes signal alignment challenging. To cope with this issue, different transceiver designs have been proposed to compensate for the non-uniform channel fading and suppress the additive noise. Specifically, for SISO AirComp, the authors in [7] and [10] proposed the optimal transmit power control and receive normalizing factor design. For multi-antenna AirComp systems, beamforming vectors at receivers and/or transmitters were designed to minimize computation error in [11] and [13]. However, the AirComp performance may deteriorate when one or more power-constrained devices are in deep fading. To mitigate the communication bottleneck, the authors in [12] employed a promising reconfigurable intelligent surface (RIS).
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Different from the rate-oriented communications [22], [23]
WDA tasks, which is referred to as multi-cluster AirComp [4].
Hence, researchers recently advocated the study of AirComp
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that only concern about multi-user interference reduction,
the multi-cluster AirComp not only suppresses inter-cluster
interference but also aligns intra-cluster interference for func-
tion computation, thereby reducing the computation error
among multiple clusters. As an initial study, the authors
in [21] proposed a signal-and-interference alignment scheme
to simultaneously eliminate inter-cell interference and align
intra-cell signals in a two-cell MIMO AirComp network.
Subsequently, the authors in [24] studied the weighted sum
mean-square error (MSE) minimization problem in multi-cell
SISO AirComp networks via power control. Results in [24]
showed that the performance of AirComp is limited by the
inter-cell interference when transmit power is relatively large.
The authors in [25] considered a multi-cluster MISO AirComp
network that minimizes the sum MSE of all clusters, where
uniform-forcing precoding was employed at the devices to
align the intra-cluster signals. The authors in [26] studied both
resource allocation and incentive mechanism for multi-cluster
AirComp FL systems. These results are established when the
static terrestrial BS is available. However, in remote and
under-developed areas, the terrestrial BSs are usually sparsely
deployed or not available. In these harsh circumstances, it is
critical to deploy more flexible BSs to unleash the potential
of multi-cluster AirComp.

As a parallel but complementary study, in this paper,
we investigate a novel multi-cluster AirComp framework with
multiple UAVs dispatched as flying BSs to cooperatively
perform diverse AirComp tasks, where no terrestrial BS is
available. Additionally, multiple UAVs have been deployed as
BSs to assist the terrestrial networks for rate-oriented com-
munications [22], [27], [28]. For example, the authors in [22]
studied multi-UAV cooperative communications to achieve a
higher data rate and lower access delay. The authors in [27]
considered a multi-UAV-enabled wireless network for data
collection. In [29], the authors studied a multi-UAV-enabled
FL for AI model training in Internet of Vehicles networks. The
approaches for combining UAV and mobile edge computing
were investigated in [30], where a UAV played the role of an
aerial cloudlet to collect and process the computation tasks
offloaded by ground users. The use of UAV for wireless data
collection was proposed in [31], where a UAV served as
the data collector and energy transmitter for multiple users.
In [32], multiple UAVs were employed as UAV relays between
devices and BS to enhance received signal strength at BS.
This motivates us to study the use of multiple UAVs in multi-cluster
AirComp by taking into account UAV trajectory planning as
well as cluster scheduling and association for interference
management, which has the following advantages. First, multi-
UAV cooperation exploits spectrum sharing to allow multiple
clusters to be simultaneously served, thereby increasing the
amount of performed tasks within the given time duration.
Second, scheduling the clusters that are far from each other
can avoid strong co-channel interference and thus improve
computation accuracy. Furthermore, the joint design not only
shortens the communication distances between the UAV and
its associated cluster to enhance intra-cluster signal alignment
but also enlarges the communication distances between the
UAV and its non-associated clusters to rein in the inter-
cluster interference. This joint design is crucial for interference
management in multi-cluster AirComp networks, but has not
yet been studied in the literature to the best of the author’s
knowledge.

A widely adopted performance metric for quantifying the
AirComp computation error is MSE between the estimated
function value and the ground truth [8], [10], [13]. To pro-
mote fairness among clusters, under the given target MSE
requirements, we aim to maximize the minimum amount of
performed WDA tasks among all clusters by jointly designing
cluster scheduling and association, UAVs’ trajectories, and
transceiver design in given time duration. However, such a
non-convex max-min fairness problem presents unique chal-
enges due to their discontinuous objective functions (as a
result of the binary cluster scheduling and association vari-
bles), non-convex MSE constraints (because of the coupling
between all optimization variables), and non-convex trajectory
design. It is generally challenging to optimally solve such a
mixed-integer non-convex optimization problem.

A. Contributions
The main contributions of this paper are summarized as
follows.
- This paper investigates multi-UAV-enabled multi-cluster
AirComp networks, in which multiple UAVs are deployed to
perform different AirComp tasks. Taking into account
the target accuracy of AirComp and ensuring fairness
among clusters, we aim to maximize the minimum
amount of performed WDA tasks across clusters by
jointly optimizing scheduling and association for clusters,
trajectory, and transceiver design.
- We present the bisection method to reduce the orig-
inal non-convex mixed-integer nonlinear programming
(MINLP) to a sequence of minimum ratio maximization
problems. For the resulting problem, by adopting block
coordinate descent (BCD) [33], we propose the optimal
normalizing factors and power, and also develop a low-
complexity Lagrange duality method to obtain the opti-
mal binary schedule-association variables. In addition,
we propose a suboptimal solution for UAV trajectory based on the successive convex approximation (SCA) method.

- Simulation results are presented to show the effectiveness and superiority of the proposed design and developed algorithm. It is shown that the max-min task amount of the considered UAV network increases with mission duration, revealing a performance-access delay tradeoff in multi-cluster AirComp. Compared to the single-UAV case, the use of multiple UAVs with effective cooperative interference management can considerably increase the amount of tasks performed by each cluster while reducing access delays.

**B. Organization**

The rest of this paper is organized as follows. We present the system model and problem formulation for UAV-assisted multi-cluster AirComp in Section II. We develop an iterative algorithm to solve the formulated problem in Section III. Numerical results are presented in Section IV to evaluate the performance of the proposed design. In Section V, we draw the conclusions. **Notations:** Scalars, column vectors, and matrices are written in italic, boldfaced lower-case, and boldfaced upper-case letters respectively, e.g., $a$, $a$, $A$. $\mathbb{R}^{M \times N}$ denotes the space of a real-valued matrix with $M$ rows and $N$ columns. $\|a\|_2$ denotes the Euclidean norm of vector $a$ and $a^T$ represents its transpose. The main notations used in this paper are listed in Table I.

**II. SYSTEM MODEL AND PROBLEM FORMULATION**

**A. System Model**

As shown in Fig. 1, we consider a multi-cluster wireless network, where each cluster consists of multiple ground devices and multiple UAVs are deployed to support multiple WDA tasks using AirComp. Note that here we consider the scenario that the terrestrial BS is not available, e.g., in wild areas. Under this circumstance, the UAVs are adopted as an alternative to provide wireless services for ground devices [22]. Due to the limited physical size, we assume that UAVs and ground devices are all equipped with one antenna.\(^1\)

Let $\mathcal{M} \triangleq \{1, \ldots, M\}$ and $\mathcal{L} \triangleq \{1, 2, \ldots, L\}$ denote the sets of all UAVs and all clusters, respectively. We denote $\mathcal{K}_l \triangleq \{1, \ldots, K_l\}$ as the set of $K_l$ ground devices in cluster $l$ with $\mathcal{K}_i \cap \mathcal{K}_j = \emptyset, \forall i \neq j, i, j \in \mathcal{L}$, and $\mathcal{C} \triangleq \bigcup_{l \in \mathcal{L}} \mathcal{K}_l$ as the set of all ground devices. Therein, the ground devices in set $\mathcal{K}_i$ need to collaboratively perform the type-$l$ WDA task, i.e., computing a specific nomographic function (e.g., arithmetic mean) with respect to (w.r.t) their measured data, and transmit the aggregated data to one of the UAVs. To avoid excessive communication latency, we adopt the AirComp technique [8] to achieve fast WDA by enabling concurrent transmission among multiple ground devices. Compared to the OMA scheme, the unique feature of AirComp is the utilization of the waveform superposition property of a MAC to harness the intra-cluster interference for function computation. Hereinafter, we refer to this type of WDA task by using the AirComp technique as an AirComp task. We assume that the AirComp tasks in different clusters are distinct.

For UAV deployment, it is not practical to dispatch one or more UAVs for each cluster, especially when the number of clusters served is relatively large. Thus, we assume that

\(^1\)We can extend the considered problem to a general multi-cluster MIMO AirComp network by optimizing transceiver beamforming matrices instead of transmit powers at the devices and normalizing factors at the UAVs. One key challenge of such an extension is to deal with the non-convexity of additional channel equalization constraints that couple all optimization variables at different time slots and devices. Due to the space limitation, such an extension will be left as our future work.
\( M \leq L \) and each UAV can select an appropriate cluster for its association. Different UAVs can simultaneously deal with different AirComp tasks over the same frequency band, thereby reducing the access delay of ground devices in all clusters. As a result, this leads to inter-cluster interference and calls for interference management to balance the computing errors among different clusters.

We aim to optimize the trajectories of UAVs to improve the WDA accuracy of all clusters. This can be achieved by jointly designing the UAVs’ trajectories and UAV-cluster association to shorten the communication distances between the UAV and its associated cluster to enhance intra-cluster signal alignment, and enlarge the communication distances between the UAV and its non-associated clusters to rein in the inter-cluster interference. To facilitate trajectory design, in this paper, time discretization technique is adopted to divide the mission duration \( T \) (s) into \( N \) equal time-slots with time step-size \( \delta = \frac{T}{N} \), as in most of the previous studies on UAV-enabled wireless networks [22], [27], [34]. The set of \( N \) time slots is denoted as \( \mathcal{N} = \{1, \ldots, N\} \). Note that the time interval \( \delta \) needs to be appropriately set, so that in each time slot, each UAV can complete one AirComp task while the changes in the communication distances between the UAVs and ground devices are negligible.

In a three-dimensional (3D) Cartesian coordinate system, we assume that all UAVs have a fixed altitude of \( H \) (m) over the horizontal plane,\(^2\) where \( H \) can be set to the minimum altitude to ensure that the UAVs can avoid obstacles (e.g., buildings or terrain) without the need for frequent ascent and descent. We denote, at time slot \( n \), the horizontal coordinate of UAV \( m \) as \( \bm{a}_m[n] = [x_m[n], y_m[n]]^T \in \mathbb{R}^{2\times 1} \). Moreover, the fixed horizontal coordinate of each ground device \( k \in \mathcal{K} \) is denoted as \( \bm{w}_k = [x_k, y_k]^T \in \mathbb{R}^{2\times 1} \), which is assumed to be known at the UAVs.

1) Channel Model: There are a large body of studies on air-to-ground channel modeling [35], [36]. And recent field experiments by Qualcomm [37] have verified that when UAVs fly above a certain altitude, there is a high probability for the UAV-to-ground channel to be dominated by a line-of-sight (LoS) link. Therefore, the uplink channels from devices to UAVs are assumed to be dominated by LoS links in this paper. The channel between UAV \( m \in \mathcal{M} \) and device \( k \in \mathcal{K} \) at time slot \( n \in \mathcal{N} \) is modeled as

\[
h_{k,m}[n] = \sqrt{\beta_0 d_{k,m}[n]} e^{-j\theta_{k,m}[n]},
\]

where \( \beta_0 \) denotes the channel power gain at the reference distance of \( d_0 = 1 \) m, \( \gamma \geq 2 \) is the path loss exponent, and \( \theta_{k,m}[n] \) is phase shift component. We assume that all devices can perfectly estimate their phase components with their associated UAVs. And \( d_{k,m}[n] \) denotes the distance of UAV \( m \) to ground device \( k \), which is represented as \d_k,m[n] = \sqrt{H^2 + \|\bm{q}_m[n] - \bm{w}_k\|^2} \). Note that the Doppler effect is assumed to be perfectly compensated [38].

2) Multi-Cluster AirComp: We define a set of binary variables \( \{a_{l,m}[n] | l \in \mathcal{L}, m \in \mathcal{M}, n \in \mathcal{N}\} \) to represent UAV-cluster scheduling and association. \( a_{l,m}[n] \) not only indicates the association status between UAV \( m \) and cluster \( l \) at slot \( n \), but also determines the communication scheduling for cluster \( l \) at slot \( n \). Suppose that, in each time slot, the devices in each cluster can communicate with at most one UAV, and each UAV can serve at most one cluster. The binary variables impose the following constraints.

\[
\sum_{m=1}^{M} a_{l,m[n]} \leq 1, \quad \forall l \in \mathcal{L}, n \in \mathcal{N}, \quad (2)
\]

\[
\sum_{l=1}^{L} a_{l,m[n]} \leq 1, \quad \forall m \in \mathcal{M}, n \in \mathcal{N}, \quad (3)
\]

\[
a_{l,m}[n] \in \{0, 1\}, \quad \forall l \in \mathcal{L}, m \in \mathcal{M}, n \in \mathcal{N}. \quad (4)
\]

We consider the case that each cluster aims to compute the average of distributed data measured by the ground devices [8], [10]. In the following, we take cluster \( l \) associated with UAV \( m \) as an example. Let \( z_k[n] \in \mathbb{C} \) denote the measured data from device \( k \in \mathcal{K}_l \) in cluster \( l \) at time slot \( n \). We denote the target function (e.g., arithmetic mean) of \( K \) variables as \( f_l[n] : \mathbb{C}^K \rightarrow \mathbb{C} \). Therefore, the target average function of type-\( l \) data at time slot \( n \) is expressed as \( f_l[n] = \frac{1}{K} \sum_{k \in \mathcal{K}_l} s_k[n] \), where \( s_k[n] = \psi_k(z_k[n]), \forall k \in \mathcal{K}_l \) with \( \psi_k \) denoting the pre-processing function at device \( k \in \mathcal{K}_l \). We assume that \( \{s_k[n]\}_{k \in \mathcal{K}_l} \) are independent and have zero mean and unit variance as in [10] and [7], i.e., \( \mathbb{E}(s_k[n]) = 0, \forall k \neq j \). To focus on interference management in UAV-assisted multi-cluster AirComp systems, we assume that the measured data among devices are uncorrelated, i.e., \( \mathbb{E}(s_i[n]s_j[n]') = 0, \forall i \neq j \), as in most of the existing studies [7], [8], [9], [10], [11], [12], [24]. For the case where sensing observations are correlated among different devices [39], we can use the upper bound (which is a multiple of the MSE derived in the uncorrelated case) as its MSE approximation.

In the sequel, we describe how to estimate the desired function \( f_l[n] \) at UAV \( m \) via AirComp. Let \( \mathcal{J}(n) = \{l \mid \sum_{m \in \mathcal{M}} a_{l,m}[n] = 1, \forall l \in \mathcal{L}\} \) denote the index set of active clusters at time slot \( n \). After all devices in set \( \mathcal{K}_l \) simultaneously send their pre-processed signals \( \{s_k[n]\}_{k \in \mathcal{K}_l} \) to UAV \( m \) over the same radio channel, the received signal at UAV \( m \) is written as

\[
r_m[n] = \sum_{k \in \mathcal{K}_l} b_k[n]h_{k,m}[n]s_k[n] + \sum_{j \in \mathcal{J}(n) \setminus \{l\}} \sum_{i \in \mathcal{K}_j} h_{i,m}[n]b_i[n]s_i[n] + e_m[n],
\]

where \( b_k[n] \in \mathbb{C} \) denotes the transmit precoding coefficient at device \( k \) for channel-fading compensation at time slot \( n \), and \( e_m[n] \) denotes the additive white Gaussian noise at UAV \( m \), i.e., \( e[n] \sim CN(0, \sigma^2) \). The ground devices’ transmissions are assumed to be synchronized [7], [10]. It is worth mentioning that the synchronization techniques reported in the

\(^2\)The 2D trajectory design considered in this paper can be extended to 3D trajectory design by taking into account the minimum and maximum altitudes as well as the maximum vertical speed constraints, and the resulting problem may be solved by applying optimization techniques such as SCA and monotonic optimization, which deserves further investigation in the future.
literature can be applied in our work, such as the AirShare technique [40] and the timing advance mechanism used in the long-term evolution systems [4]. Each device $k$ has a total transmit power budget $P_k$, i.e., $\sum_{n=1}^{N} |b_k[n]|^2 \leq P_k, \forall k$, where the total power constraint at each ground device is considered for adaptive power allocation over different time slots.

Upon receiving signal $r_m[n]$, after post-processing and scaling at UAV, the estimated average function $m$ is given by $\hat{f}_l,m[n] = \eta_{l,m}[n]r_m[n]$, where factor $1/K_l$ is employed for averaging purposes and $\eta_{l,m}[n] \in \mathbb{C}$ is a normalizing factor at UAV $m$ applied to scale received signal $r_m[n]$ for compensating channel fading and suppressing noise, thereby accurately estimating the target function $f_l[n]$. It can be observed from (5) and $\hat{f}_l,m[n]$ that UAV $m$ harnesses the inter-cluster interference for computing the target function but suffers from inter-cluster interference due to the communication resource reuse among UAVs.

B. Performance Metrics

To quantify the performance of AirComp, the computation distortion of the ground true average function $f_l[n]$ is measured by its MSE. Specifically, when $a_{l,m}[n] = 1$, the corresponding instantaneous MSE of type-$l$ AirComp task at UAV $m$ at time slot $n$ is given by

$$
\text{MSE}_{l,m,n} = \mathbb{E}[(\hat{f}_l,m[n] - f_l[n])^2] = \frac{1}{K_l} \mathbb{E}
\left[
\left|
\eta_{l,m}[n]r_m[n] - \sum_{k \in K_l} s_k[n]
\right|^2
\right] = \frac{1}{K_l} \sum_{k \in K_l} \left(\eta_{l,m}[n]|b_k[n]|h_{k,m}[n] - 1\right)^2 + \eta_{l,m}[n]\left(\hat{I}_{l,m}[n] + \sigma^2\right),
$$

where $\hat{I}_{l,m}[n] = \sum_{j \in \mathbb{L}, l} \sum_{i \in K_j} |b_i[n]|^2|h_{i,m}[n]|^2$ represents the inter-cluster interference received at UAV $m$ when it associates with cluster $l$ at time slot $n$. The expectation in (6) is taken over the distributions of signals $\{s_k[n]\}$ and noise $e_m[n]$. The instantaneous MSE of type-$l$ AirComp task at time slot $n$ is represented as

$$
\text{MSE}_{l,n} = \sum_{m=1}^{M} a_{l,m}[n]\text{MSE}_{l,m,n}. \quad (7)
$$

Before formulating the problem, we first simplify the precoding coefficients and binary variables design. The interference term is simplified as $I_{l,m}[n] = \sum_{j \in \mathbb{L}, l} \sum_{i \in K_j} |b_i[n]|^2|h_{i,m}[n]|^2$. This is because if there is no UAV associated with cluster $j$, i.e., $\sum_{m \in \mathcal{M}} a_{j,m}[n] = 0$, then the transmission power of device $i \in K_j$ must be zero (i.e., $b_i[n] = 0$). Furthermore, it can also be observed from (6) that the phases of $b_i[n]$ and $h_{i,m}[n]$ for $\forall j \in \mathbb{L}, l, \forall i \in K_j$ do not affect the inter-cluster interference induced error in $\text{mse}_{l,m,n}$, while the essential condition for $\text{mse}_{l,m,n}$ to reach the minimum value is the terms $\eta_{l,m}[n]|b_k[n]|h_{k,m}[n], \forall k \in K_l$ in (6) must be real and non-negative. Therefore, with (2), when $a_{l,m}[n] = 1$, we have

$$
\text{MSE}_{l,n} \geq \frac{1}{K_l} \left[ \sum_{k \in K_l} \left( \eta_{l,m}[n]\sqrt{p_k[n]}|h_{k,m}[n]| - 1\right)^2 + \eta_{l,m}[n]\left(\hat{I}_{l,m}[n] + \sigma^2\right) \right], \quad (8)
$$

where the equality holds when $\eta_{l,m}[n] \in \mathbb{R}^+$ and $b_k[n] \triangleq \sqrt{p_k[n]}h_k[n]/|p_k[n]|$ with $p_k[n] \in \mathbb{R}^+$ denoting the transmit power of device $k$ at time slot $n$. Please refer to [17] for its proof.

Meanwhile, if $\sum_{m=1}^{M} a_{l,m}[n] = 0$ and $b_k[n] = 0, \forall k \in K_l$. Hence, at time slot $n$, the achievable instantaneous MSE of type-$l$ data can be represented as

$$
\text{MSE}_{l,n} = \sum_{m=1}^{M} a_{l,m}[n] \left[ \sum_{k \in K_l} \left(\eta_{l,m}[n]|h_{k,m}[n]|\sqrt{p_k[n]} - 1\right)^2 + \eta_{l,m}[n]\left(\hat{I}_{l,m}[n] + \sigma^2\right) \right], \quad (9)
$$

which is a linear function of $a_{l,m}[n], \forall m$ but not coupled over different clusters, and is related to real transmit power $p_k[n]$ instead of complex transmit precoding coefficient $b_k[n]$.

Remark 1: One can observe that $\text{MSE}_{l,n}$ is composed of three components, including the signal misalignment error (i.e., $\sum_{m=1}^{M} a_{l,m}[n] \sum_{k \in K_l} \left(\eta_{l,m}[n]|h_{k,m}[n]|\sqrt{p_k[n]} - 1\right)^2$), the inter-cluster interference-induced error (i.e., $\sum_{m=1}^{M} a_{l,m}[n] \sum_{j \in \mathbb{L}, l} \sum_{i \in K_j} p_i[n]|h_{i,m}[n]|^2$), and the noise-induced error (i.e., $\sum_{m=1}^{M} a_{l,m}[n] \eta_{l,m}[n]\sigma^2$). Besides transceiver design for interference management, the trajectory design with cluster scheduling-association can be exploited to balance the trade-off between signal misalignment error reduction and co-channel interference reduction. Specifically, a UAV moves closer to the associated cluster $l$ to construct strong desired links $\{h_{k,m}[n]\}, \forall k \in K_l$ for signal alignment and keeps away from other scheduled clusters to construct weak co-channel interference links $\{h_{i,m}[n]\}^2, i \in K_j, j \neq l$. Different from [18] where inter-cluster interference is absent, this paper not only considers signal alignment reduction and noise suppression for AirComp but also addresses the challenge posed by inter-cluster interference.

C. Problem Formulation

In the sequel, let $\mathbf{A} = \{a_{l,m}[n], \forall l \in \mathbb{L}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}\}$, $\mathbf{P} = \{p_k[n], \forall k \in K_l, \forall n \in \mathcal{N}\}$, $\mathbf{\eta} = \{\eta_{l,m}[n], \forall l \in \mathbb{L}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}\}$, and $\mathbf{Q} = \{q_m[n], \forall m \in \mathcal{M}, \forall n \in \mathcal{N}\}$. Given mission duration $T$ and certain instantaneous MSE requirements for different AirComp tasks, we study the total amount of AirComp tasks maximization problem while ensuring fairness among clusters. Therefore, we maximize the minimum amount of AirComp tasks among all clusters, i.e., $\min_{n=1}^{N} \sum_{m=1}^{M} a_{l,m}[n]$, by jointly optimizing the cluster scheduling and association indicator variables $\mathbf{A}$, transmit power $\mathbf{P}$ at devices, signal normalizing factors $\mathbf{\eta}$ at the UAVs, and UAVs’ trajectories $\mathbf{Q}$. The optimization problem is formulated as

$$
\mathcal{P}: \quad \text{maximize} \; \min_{l} \sum_{l=1}^{L} \sum_{m=1}^{M} a_{l,m}[n]
$$

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subject to $\text{MSE}_{l,n} \leq \varepsilon_l$, $\forall n, \forall l$, \hspace{1cm} (10a)

$0 \leq \sum_{n=1}^{N} p_k[n] \leq P_k$, $\forall k$, \hspace{1cm} (10b)

$q_m[0] = q_m[N]$, $\forall m \in M$, \hspace{1cm} (10c)

$||q_m[n] - q_m[n-1]||_2 \leq V_{\text{max}} \delta$, $\forall n \in N$, $\forall m \in M$, \hspace{1cm} (10d)

$|q_m[n] - q_m[n]| \geq d_{\text{min}}$, $\forall n \neq i, m \in M$, $\forall l, \forall l$, \hspace{1cm} (10e)

$0 \leq \eta_{l,m}[n]$, $\forall m, \forall n$, \hspace{1cm} (10f)

Constraints (10a) describe the minimum instantaneous MSE requirement $\varepsilon_l$ for data aggregation from any cluster $l$ in each time slot. To avoid trivial problems, it is assumed that $\varepsilon_l < 1$, $\forall l$. Otherwise, a trivial solution of problem (10), i.e., $p_k[n] = 0$, $\forall k \in K$, $\forall n \in N$ and $\eta_{l,m}[n] = 0$, $\forall l \in L, \forall m \in M, \forall n \in N$ achieves the certain instantaneous MSE requirements for any given $Q$ and $A$. Constraints (10b) represent the maximum total transmit power constraints of all devices. Constraints (10c) represent that the UAVs’ initial and final locations constraints. Constraints (10d) represent that the UAVs are constrained by the maximum speed $V_{\text{max}}$ in meter/second (m/s).3 Constraints (10e) limit the minimum safe distance between UAVs for collision avoidance with $d_{\text{min}}$, denoting the minimum inter-UAV distance in meters. Constraints (10f) are derived from (8). It can be easily verified that for problem $P$, if the obtained binary variables meet condition $\sum_{m=1}^{M} a_{l,m}[n] = 0$, the power solution for all devices in cluster $l$ must satisfy $p_k[n] = 0, \forall k \in K_l$.

The transformation method adopted in [18] cannot make problem $P$ reduce to a convex subproblem when any three blocks of variables are fixed due to the inter-cluster interference and non-convex trajectory constraints. The main challenges in solving problem (10) arise from the following aspects. First, due to the binary cluster scheduling and association variables $A$, max-min problem (10) involves a discontinuous objective function and integer constraints (10a), (3), and (2). Second, all continuous variables $\{P, \eta, Q\}$ are coupled with binary variables $A$ in constraints (10a), which are non-convex. In addition, collision avoidance constraints (10e) are also non-convex. As such, problem (10) is a nonconvex max-min problem with MINLP, which is generally challenging to be optimally solved. As a compromise approach, in the following subsection, we transform problem (10) into an equivalent MINLP problem to facilitate the development of a low-complexity algorithm.

### D. Problem Reformulation

To address the challenges of the max-min problem with the discontinuous objective function, an auxiliary variable

$$\Gamma = \max_{\{(l,m)\}} \frac{\text{MSE}_{l,m}}{\varepsilon_l}$$

is defined as the maximum achievable Air-Comp MSE ratio among all clusters. Furthermore, we denote the minimum amount of AirComp tasks among all clusters as $D \in \mathbb{Z}$. Given any $D$, we first introduce the following optimization problem:

$$P_1: \begin{array}{l}
\text{minimize} \\
(\mathcal{I}, A, P, Q, \eta) \Gamma(D)
\end{array}$$

subject to $\text{MSE}_{l,n} \leq \Gamma(D)$, $\forall n, \forall l$, \hspace{1cm} (11a)

$\sum_{n=1}^{N} \sum_{m=1}^{M} a_{l,m}[n] \geq D$, $\forall l$, \hspace{1cm} (11b)

Constraints (2) – (4), (10b) – (10f).

Problem $P_1$ aims to minimize the maximum ratio $\Gamma$, which is a function of $D$. By denoting the optimal objective value of $P_1$ as $\Gamma^*(D)$, we have the following proposition.

**Proposition 1:** The optimal objective value $\Gamma^*(D)$ of problem $P_1$ is a non-decreasing of $D$.

**Proof:** For any given task amount, i.e., $D$ and $D'$, such that $D' > D$, we should prove that $\Gamma^*(D') \geq \Gamma^*(D)$. Given $D'$, the optimal solution to $P_1$ is denoted as $\{\bar{A}, \bar{P}, \bar{\eta}, \bar{Q}\}$. As the minimum task amount decreases to $D$, a feasible solution to $P_1$ with the given $D$ denoting as $\{A, \bar{P}, \bar{\eta}, Q\}$ can be constructed by letting $Q = Q', \bar{\eta} = \eta'$, $A = A'$, and $P = P'$. In this case, the objective value $\bar{\Gamma}^*(D') = \bar{\Gamma}(D)$. $\bar{\Gamma}(D)$ is the objective value for a feasible solution $\{A, \bar{P}, \bar{\eta}, Q\}$ to $P_1$, which is obviously no less than the objective function for the optimal solution $\Gamma^*(D)$. Thus, we have $\Gamma^*(D') = \bar{\Gamma}(D) \geq \Gamma^*(D)$, which completes the proof.

For any given $D$, the MSE requirements $\{\varepsilon_l\}$ in each cluster are achievable if and only if $\Gamma^*(D) \leq 1$. Thus, it can be verified that problem $P$ is equivalent to

$$P_2: \begin{array}{l}
\text{maximize} \\
(\mathcal{I}, D) \Gamma^*(D)
\end{array}$$

subject to $\Gamma^*(D) \leq 1$. \hspace{1cm} (12a)

Next, we can concentrate on addressing problem $P_2$ in the remainder of the paper. Fortunately, based on Proposition 1, problem $P_2$ can be efficiently solved by applying the bisection search over the minimum amount of AirComp tasks $D$ until the equality in (12a) holds. Thus, the main difficulty of solving problem $P_2$ lies in finding an efficient algorithm to solve $P_1$ with any given amount $D$. Compared to the original problem $P$, problem $P_1$ eliminates the max-min programming and discontinuous objective function. Although it still involves coupled variables and non-convex constraints, such as (4), (11a), and (10e), problem $P_2$ promotes the development of an efficient suboptimal algorithm, which will be elaborated in section III.

**Remark 2:** All the equations in constraints (11b) hold for the optimal solution of problem $P_1$. If any equality of constraints in (11b) is not met, we can always reduce the value of $\sum_{n=1}^{N} \sum_{m=1}^{M} a_{l,m}[n]$ when other variables are fixed, while all other constraints are still satisfied, and the objective value of $P_1$ remains unchanged.
III. PROPOSED ALGORITHM

In this section, we develop an efficient iterative algorithm to solve problem \( \mathcal{P}_1 \) based on the principle of BCD and SCA techniques. Specifically, we adopt the well-known BCD technique [33] to decouple problem \( \mathcal{P}_3 \) into four subproblems, which optimize cluster association \( A \), transmit power \( P \), normalizing factors \( \eta \), and UAVs’ trajectories \( Q \) in an iterative manner. Besides the convex optimization subproblems related to \( P \) and \( \eta \), we propose a low-complexity dual ascent method to obtain a closed-form binary solution for \( A \) and exploit the SCA to deal with the non-convexity of the optimization subproblem related to \( Q \).

A. Cluster Scheduling and Association Optimization

For given \( \{\eta, Q, P\} \), the optimization subproblem w.r.t \( A \) is reduced to as follows.

\[
\begin{align*}
\text{minimize} & \quad \Gamma \\
\text{subject to} & \quad \sum_{m=1}^{M} a_{l,m}[n] \frac{\text{mse}_{l,m,n}}{\varepsilon_l} \leq \Gamma, \quad \forall l, \forall n, \quad (13a) \\
\text{Constraints} & \quad (2), (3), (4), (11b).
\end{align*}
\]

Problem (13) is a binary linear programming. Although such a problem can be directly solved via CVX and solver (e.g., Mosek), it requires prohibitively high computational complexity due to exhaustive search, which is not practical even for the moderate sizes of \( N \) and \( L \). Alternatively, to gain more design insights and reduce the computational cost, by relaxing the integer constraints (4) with \( a_{l,m}[n] \in [0, 1] \), we exploit the Lagrange duality to solve problem (13) with relaxed constraints. It will show that the obtained closed-form optimal solution ensures not only the dual optimality but also the feasibility of problem (13). Specifically, the partial Lagrangian of problem (13) with relaxed constraints is given by

\[
\mathcal{L}(\eta, A, \lambda, \beta, \nu) = \left(1 - \sum_{l=1}^{L} \sum_{n=1}^{N} \lambda_{l,n} \right) \Gamma \\
+ \sum_{l=1}^{L} \sum_{n=1}^{N} \sum_{m=1}^{M} a_{l,m}[n] \left( \lambda_{l,n} \frac{\text{mse}_{l,m,n}}{\varepsilon_l} + \beta_{l,n} + \nu_{m,n} \right) \\
- \sum_{l=1}^{L} \sum_{n=1}^{N} \beta_{l,n} - \sum_{m=1}^{M} \sum_{n=1}^{N} \nu_{m,n},
\]

where \( \lambda = \{\lambda_{l,n}, \forall l, \forall n\} \), \( \beta = \{\beta_{l,n}, \forall l, \forall n\} \), and \( \nu = \{\nu_{m,n}, \forall m, \forall n\} \) are the Lagrange multipliers associated with constraints (13a), (2), and (3). Accordingly, the Lagrangian dual function of (13) with relaxed constraints is expressed as

\[
g(\lambda, \beta, \nu) = \min_{\Gamma, A} \mathcal{L}(\eta, A, \lambda, \beta, \nu)
\]

To make \( g(\lambda, \beta, \nu) \) bounded, it is easily verified that \( 1 - \sum_{l=1}^{L} \sum_{n=1}^{N} \lambda_{l,n} = 0 \) holds. Accordingly, the dual problem of (13) with relaxed constraints is expressed as

\[
\begin{align*}
\text{maximize} & \quad g(\lambda, \beta, \nu) \\
\text{subject to} & \quad \sum_{l=1}^{L} \sum_{n=1}^{N} \lambda_{l,n} = 1, \quad \beta \geq 0, \quad \nu \geq 0. \quad (16a)
\end{align*}
\]

Next, we apply the Lagrange duality to find the optimal primal solution.

1) Obtaining \( g(\lambda, \beta, \nu) \): First, we obtain the dual function \( g(\lambda, \beta, \nu) \) under given \( \lambda, \beta, \nu \) by solving problem (15). It is observed that we can decompose Problem (15) into \( L + 1 \) subproblems, each of which can be solved in parallel. Particularly, the \( L \) subproblems are for optimizing \( A \), each of which is given by

\[
\begin{align*}
\text{minimize} & \quad \sum_{m=1}^{M} \sum_{n=1}^{N} a_{l,m}[n] \left( \lambda_{l,n} \frac{\text{mse}_{l,m,n}}{\varepsilon_l} + \beta_{l,n} + \nu_{m,n} \right) \\
\text{subject to} & \quad \sum_{m=1}^{M} \sum_{n=1}^{N} a_{l,m}[n] \geq D, \\
& \quad 0 \leq a_{l,m}[n] \leq 1, \quad \forall m, \forall n. \quad (17b)
\end{align*}
\]

To minimize the objective in (17), which is a linear combination of \( a_{l,m}[n] \), we should let the association coefficient corresponding to the UAV with the top \( D \) smallest \( \lambda_{l,n} \frac{\text{mse}_{l,m,n}}{\varepsilon_l} + \beta_{l,n} + \nu_{m,n} \) be 1 for any \( l \). The optimal solution of problem (17) is given by the following theorem.

Theorem 1: For problem (17), by denoting \( x_{l,m}[n] = \lambda_{l,n} \frac{\text{mse}_{l,m,n}}{\varepsilon_l} + \beta_{l,n} + \nu_{m,n} \), the optimal cluster scheduling and association \( A \) is expressed as

\[
a^*_l(\pi_l(i)) = \begin{cases} 1, & i = 1, \ldots, D, \\ 0, & \text{otherwise,} \end{cases}\quad (18)
\]

where vector \( a^*_l(\pi_l(i)) \triangleq [a_{l,1}[1], \ldots, a_{l,1}[N], a_{l,2}[1], \ldots, a_{l,M}[N]]^T \in \mathbb{R}^{MN \times 1} \), vector \( x_l \triangleq [x_{l,1}[1], \ldots, x_{l,1}[N], \ldots, x_{l,M}[N]]^T \in \mathbb{R}^{MN \times 1} \), and permutation \( \pi_l = [\pi_l(1), \ldots, \pi_l(MN)] \) corresponds to the ascendent order such that \( x_{l,\pi_l(1)} \leq \cdots \leq x_{l,\pi_l(MN)} \).

Theorem 1 states that cluster \( l \) should be associated with UAV at time slot \( n \) when coefficient \( x_{l,m}[n] \) is smaller. According to the expression of coefficient \( x_{l,m}[n] \), the term \( \lambda_{l,n} \frac{\text{mse}_{l,m,n}}{\varepsilon_l} \) is the effect of introducing the ratio between the instantaneous MSE \( \text{mse}_{l,m,n} \) that can be achieved for type-\( l \) AirComp task and the target MSE threshold \( \varepsilon_l \) that should be achieved if cluster \( l \) is associated with UAV at time slot \( n \). Furthermore, the remaining term represents other effects due to the problem constraints. When \( x_{l,m}[n] \) is smaller, it brings a smaller achievable ratio if cluster \( l \) is associated with UAV at time slot \( n \).

And one subproblem is for optimizing \( \Gamma \), i.e.,

\[
\begin{align*}
\min_{\Gamma} (1 - \sum_{l=1}^{L} \sum_{n=1}^{N} \lambda_{l,n}) \Gamma 
\end{align*}
\]
Algorithm 1 Dual Method for Problem (13)

1: **Input:** $M$, $N$, $L$, $D$, \{$\text{mse}_{i,m,n}/\varepsilon_l, \forall l, \forall m, \forall n\}$.
2: Initialize dual variables $\{\lambda_{l,n} = 1/(KN)\}$, $\{\beta_{l,n} = 0\}$, and $\{\gamma_{l,m,n} = 0\}$.
3: repeat
4: Update the primal variables $A$ and $\Gamma$ according to (18) and (20).
5: Update the dual variables $\lambda$, $\beta$, and $\nu$ according to (22)-(23).
6: until $\lambda$, $\beta$, and $\nu$ converge within an accuracy.
7: **Output:** $A^*$ and $\Gamma^*$

Since $\sum_{l=1}^{L} \sum_{m=1}^{N} \lambda_{l,m} = 1$, the optimal solution of $\Gamma^*$ of problem (19) can be any arbitrary real number. Without loss of generality, we simply set

$$\Gamma^* = \max\{a_{l,m}\} \frac{\text{mse}_{i,m,n}}{\varepsilon_l}, \forall l, \forall n, \forall m. \quad (20)$$

2) *Updating $\lambda$, $\beta$, $\nu$:*. After obtaining $A^*$ and $\Gamma^*$, the optimal dual variables are obtained by solving problem (16). Since the dual function $g(\lambda, \beta, \nu)$ is concave but non-differentiable, the subgradient projection method is adopted to update dual variables $(\lambda, \beta, \nu)$. Specifically, the $(t+1)$-th iteration, the update of $(\lambda, \beta, \nu)$ is given by

$$\beta_{l,n}^{t+1} = \beta_{l,n}^t + \gamma \sum_{m=1}^{M} a_{l,m}[n] - 1 \right)^+, \quad (21)$$

$$\nu_{l,m,n}^{t+1} = \nu_{l,m,n}^t + \gamma \sum_{l=1}^{L} a_{l,m}[n] - 1 \right)^+, \quad (22)$$

$$\lambda_{l,n}^{t+\frac{1}{2}} = \lambda_{l,n}^t + \gamma \left( \sum_{m=1}^{M} a_{l,m}[n] \left( \frac{\text{mse}_{i,m,n}}{\varepsilon_l} - \Gamma \right) \right)^+, \quad (23)$$

where $\gamma$ is a dynamically chosen step-size sequence and $[a]^+ = \max(a, 0)$.

3) *Constructing the Optimal Solution $\Gamma$:*. With the updated dual variables $\lambda^*$, $\beta^*$, and $\nu^*$, we need to construct the primal solutions $\Gamma^*$ and $A^*$ to problem (13) with relaxed constraints. The key observation is that with given $\lambda^*$, $\beta^*$, and $\nu^*$, the optimal solution $A^*$ can be uniquely obtained from (18). By substituting $A^*$ into the primal problem (13), it is evident that $\Gamma^* = \max\{a_{l,m}\} \frac{\text{mse}_{i,m,n}}{\varepsilon_l}, \forall l, \forall n, \forall m\}$.

Algorithm 1 summarizes how to solve problem (13) via the dual method. The computational complexity of Algorithm 1 for solving problem (13) is $O\left(\sum_{l=1}^{L} \sum_{m=1}^{N} \text{mse}_{i,m,n}/\varepsilon_l, \forall l, \forall n, \forall m\right)$. In contrast, to solve the binary linear programming optimization problem via CVX [41], the computational complexity of the interior-point method is $O\left(\sum_{l=1}^{L} \sum_{m=1}^{N} \text{mse}_{i,m,n}/\varepsilon_l, \forall l, \forall n, \forall m\right)$. Since the dimensions of the variable in problem (13) is $LMN$, which is much higher than the proposed dual algorithm. It is important to note that the obtained solution $a_{l,m}[n]$ is either 1 or 0 according to (18), even though we relax $a_{l,m}[n]$ as (15b). Different from [22], it is evident that the obtained binary cluster scheduling and association variables are also optimal to the original subproblem.

B. Transmit Power Optimization

By substituting $A$ into constraints (11a), we have that \(\text{MSE}_{l,n} = \text{mse}_{i,m,n}(l, m, n) \in A\), otherwise 0, where $A \triangleq \{(l, m, n) | a_{l,m}[n] = 1, \forall l, \forall m, \forall n\}$. Thus, for any given $\{\eta, Q, A\}$, the transmit power optimization problem reduces to the following subproblem:

$$\begin{align*}
\text{minimize}_{\Gamma, P} & \quad \sum_{k \in K_l} \left( \theta_{l,k,m}[n] \sqrt{p_k[n]} - 1 \right)^2 + \phi_{l,m}[n] \\
\text{subject to} & \quad \sum_{j \in K_l} \sum_{k \in K_j} \theta_{l,m}[n] p_j[n] \leq \Gamma \varepsilon_l K_l^2, \\
& \quad \forall (l, m, n) \in A, \quad (24a) \\
& \quad \text{Constraints (10b),}
\end{align*}$$

where $\theta_{l,k,m}[n] \triangleq \eta_{l,m}[n] h_{k,m}[n], \forall l, \forall m, \forall k$ and $\phi_{l,m}[n] \triangleq \eta_{l,m}[n] \sigma^2, \forall l, \forall m, \forall k$. Note that the number of constraints in (11a) is $LN$, whereas the number of constraints in (24a) is $LD$. Problem (24) is a quadratically constrained quadratic programming (QCQP), which can be solved via CVX with interior-point solvers (e.g., Mosek).

Remark 3: From constraints (24a), to minimize $\Gamma$, if there is no UAV associated with cluster $j$, i.e., $\sum_{m \in M} \theta_{l,m}[n] = 0$, then the transmission power of device $i \in K_j$ must be zero (i.e., $p_i[n] = 0$). Otherwise, it will introduce interference for UAVs and thus lead to a larger $\Gamma$.

C. Normalizing Factors Optimization

For given $\{A, Q, P\}$, the normalizing factor optimization subproblem reduces as follows:

$$\begin{align*}
\text{minimize}_{\Gamma, \eta} & \quad \sum_{m=1}^{M} \frac{a_{l,m}[n]}{K_l^2} \eta_{l,m}[n] \varphi_{k,m}[n] - 1 \right)^2 + \eta_{l,m}[n] \left( I_{l,m}[n] + \sigma^2 \right) \leq \Gamma \varepsilon_l K_l^2, \\
& \quad \forall l, \forall n, \forall k, \quad (25a) \\
& \quad \text{Constraints (10f),}
\end{align*}$$

where $\varphi_{k,m}[n] = \left| h_{k,m}[n] \right| \sqrt{p_k[n]}$. Problem (25) is also a convex QCQP. Furthermore, we observe that problem (25) can be decoupled into $LD$ subproblems, each of which optimizes $\eta_{l,m}[n]$ with $a_{l,m}[n] = 1$ to minimize $\text{mse}_{i,m,n}$. For any $(l, m, n)$ with $a_{l,m}[n] = 1$, the subproblem is given by

$$\begin{align*}
\text{minimize}_{\eta_{l,m}[n] \geq 0} & \quad \sum_{k \in K_l} \left( \eta_{l,m}[n] \varphi_{k,m}[n] - 1 \right)^2 + \eta_{l,m}[n] \left( I_{l,m}[n] + \sigma^2 \right). \quad (26)
\end{align*}$$

And the optimal solution of problem (25) is given by the following proposition.

**Proposition 2:** Given by $\{A, Q, P\}$, by setting the first derivative of the objective function to zero, the optimal
solution \( \eta_{l,m}^*[n] \) to problem (26) equals to
\[
\eta_{l,m}^*[n] = \max_{\forall i, m} \left( \sum_{k \in K_i} \frac{p_k[n]}{h_k,n} \right) + \frac{\eta_{l,m}^*[n]}{1 + \sigma^2}.
\]
By substituting the solution \( \eta_{l,m}^*[n] \) into problem (25), the optimal solution \( \Gamma \) is given by
\[
\Gamma^* = \max_{\forall i, m} \sum_{l=1}^{M} a_{l,m}^*[n] \left[ \left( \sum_{k \in K_i} \frac{p_k[n]}{h_k,n} \right) - 1 \right]^2 + \frac{\eta_{l,m}^*[n]}{1 + \sigma^2} \right].
\]
(27)

Remark 4: Note that with \( a_{l,m}[n] = 1 \), the normalizing factor \( \eta_{l,m}^*[n] \) monotonically decreases with respect to the noise power \( \sigma^2 \) and the inter-cluster interference power from other devices associated with other UA Vs, i.e., \( \sum_{j \in L} \sum_{k \in K_j} p_i[n] |h_i,m[n]|^2 \). From (27), we observe that reducing \( \eta_{l,m}^*[n] \) can suppress the noise-induced and inter-cluster interference-induced error components but increase the signal misalignment error.

D. UAV Trajectory Optimization

For given \( A, P, \eta \), UAV trajectory subproblem reduces to the following subproblem:
\[
\begin{align*}
\text{minimize} & \quad \Gamma \\
\text{subject to} & \quad \text{Constraints (10c), (10d), (10e), (11a), (11a).} \quad (28)
\end{align*}
\]

Due to the nonconvexity of constraints (10e) and (11a), problem (28) is non-convex. Generally speaking, there is no efficient method that can be used to attain the optimal solution. To address their non-convexity, we exploit the SCA technique in the sequel. We first transform constraints (11a) into a tractable form, which facilitates the development of the SCA technique. We define
\[
G_{l,m}[n] = \eta_{l,m}^2[n] \sum_{l' \in L} \sum_{k \in K_i} \left( H^2 + \|q_m[n] - w_k\|_2^2 \right)^{\frac{1}{2}},
\]
(29)
\[
F_{l,m}[n] = 2\eta_{l,m}^2[n] \sum_{k \in K_i} \left( H^2 + \|q_m[n] - w_k\|_2^2 \right)^{\frac{1}{2}},
\]
(30)
\[
C_{l,m}[n] = \begin{cases} K + \eta_{l,m}^2[n] \sigma^2, & \text{if } a_{l,m}[n] = 1, \\ 0, & \text{otherwise.} \end{cases}
\]
(31)

Based on the above, by substituting \( A \) into constraints (11a), we have that MSE\(G_{l,m} = G_{l,m}[n] + C_{l,m}[n] - F_{l,m}[n], \forall (l, m, n) \in A \), 0 otherwise. Thus, constraints (11a) are transformed into
\[
G_{l,m}[n] + C_{l,m}[n] - F_{l,m}[n] \leq \Gamma \varepsilon_1 K^2, \quad \forall (l, m, n) \in A. \quad (32)
\]

\(G_{l,m}[n]\) and \(F_{l,m}[n]\) in constraints (32) are convex w.r.t \( \|q_m[n] - w_k\|_2^2 \). Base on the key observation, we first introduce slack variables \( S = \{s_{k,m}[n] \triangleq \|q_m[n] - w_k\|_2^2 | \forall k, \forall m, \forall n\} \) to tackle the non-convexity of \( G_{l,m}[n] \) in constraints (32). The reformulated problem (28) is given by
\[
\text{minimize} \quad \Gamma \\
\text{subject to} \quad \hat{G}_{l,m}[n] + C_{l,m}[n] - F_{l,m}[n] \leq \varepsilon_1 \Gamma, \\
\forall (l, m, n) \in A, \quad (33a)
\]
\[
s_{k,m}[n] \leq \|q_m[n] - w_k\|_2^2, \quad \forall k, \forall m, \forall n, \quad (33b)
\]

Constraints (10c), (10d), (10e),
\[
\hat{G}_{l,m}[n] = \eta_{l,m}^2[n] \sum_{l' \in L} \sum_{k \in K_i} \frac{p_k[n]\beta_0}{(H^2 + s_{k,m}[n])}. \quad \text{Note that for problem (33), it can be easily verified that all constraints in (33b) can be met with equality. Otherwise, when other variables are fixed, we can increase the value of } S \text{ to further decrease the value of } \{G_{l,m}[n]\} \text{ without violating all constraints in problem (33), thereby reducing the objective function. However, problem (33) is still non-convex due to non-convex constraints (33a), (33b), and (10e).}
\]

Fortunately, \( F_{l,m}[n] \) in constraints (33a) is convex w.r.t \( \|q_m[n] - w_k\|_2^2 \). And \( \|q_m[n] - w_k\|_2^2 \) in constraints (33b) and \( \|s_{k,m}[n] - q_m[n]\|_2 \) in constraints (10e) are convex w.r.t \( Q \). It is important to recall that the first-order Taylor expansion of any function at any point serves as a lower bound [42]. Thus, similarly to [22], the SCA technique is adopted to tackle their non-convexity, thus obtaining a suboptimal solution. Specifically, defining \( Q^* \) as the output of the \( r \)-th iteration, we obtain that \( F_{l,m}[n] \) is lower bounded by the following expression, i.e.,
\[
F_{l,m}[n] \geq F_{l,m}[n] + \nabla_{\|q_m[n] - w_k\|_2^2} F_{l,m}[n] (\|q_m[n] - w_k\|_2^2 - \|s_{k,m}[n] - w_k\|_2^2) \triangleq \Phi^{s_{k,m}[n]}_{l,m}[n], \quad (34)
\]
where \( \nabla_{\|q_m[n] - w_k\|_2^2} F_{l,m}[n] (\|q_m[n] - w_k\|_2^2) \triangleq \Phi^{s_{k,m}[n]}_{l,m}[n] \) is concave with regard to \( q_m[n] \).
Algorithm 3 Overall Bisection Algorithm for $\mathcal{P}_2$

1: **Input:** $D_{\min} = 0, D_{\max} = \frac{T_M}{2\lambda L}$.
2: **Initialize:** $P^0, \eta^0$, and $Q^0$, let $t = 1$.
3: **repeat**
4:   **Update** $D = \left[ D_{\min} + D_{\max} \right]$. Initialize $P^0$ and $\eta^0$.
5:   **Obtain** $\Gamma^t, \mathbf{A}^t, P^t, \eta^t$, and $Q^t$ using Algorithm 2.
6:   **if** $\Gamma^t \leq 1$ **then**
7:     **Set** $D_{\min} = D$. And let $D^* = D$, $A^* = A^t$, $P^* = P^t$, $\eta^* = \eta^t$, and $Q^* = Q^t$.
8:   **else**
9:     **Set** $D_{\max} = D$.
10:   **end if**
11: **until** $D_{\max} - D_{\min} \leq 1$.
12: **Output:** $D^*, A^*, P^*, \eta^*$, and $Q^*$.

Hence, $\hat{G}_{l,m}[n] + C_{l,m}[n] - F_{l,m}^{\text{th}}[n]$ is a convex function. Likewise, with the first-order Taylor expansion at point $q_{m}^r[n]$, $\|q_m[n] - w_k\|^2_2$ in constraints (33b) are subject to

$$\|q_m[n] - w_k\|^2_2 \geq \|q_m^{r[n]} - w_k\|^2_2 + 2(q_m^{r[n]} - w_k)^T(q_m[n] - q_m^{r[n]}) \triangleq D_{k,m}^{\text{th}}[n].$$

(35)

The lower bound function $D_{k,m}^{\text{th}}[n]$ is a linear function w.r.t $q_m[n]$. Likewise, $\|q_m[n] - q_l[n]\|^2_2$ in constraint (10e) is lower-bounded by

$$\|q_m[n] - q_l[n]\|^2_2 \geq -\|q_m^{r[n]} - q_l^{r[n]}\|^2_2 + 2(q_m^{r[n]} - q_l^{r[n]})^T(q_m[n] - q_l[n]) \triangleq d_{m,l}[n].$$

(36)

Given point $Q^*$, based on expressions (34), (35), and (36), problem (33) approximates as follows:

$$\begin{align*}
\text{minimize} & \quad \Gamma^{\text{th}}_t Q \\
\text{subject to} & \quad \hat{G}_{l,m}[n] + C_{l,m}[n] - F_{l,m}^{\text{th}}[n] \leq \varepsilon \Gamma^{\text{th}}_t, \\
& \quad \forall (l, m, n) \in \mathcal{A}, \quad (37a) \\
& \quad 0 \leq s_{k,m}[n] \leq D_{k,m}^{\text{th}}[n], \quad \forall k, \forall m, \forall n, \quad (37b) \\
& \quad d_{m,l}[n] \geq d_{\min}, \quad \forall n, \forall m, m \neq i, \quad (37c) \\
& \quad \text{Constraints (10c), (10d).}
\end{align*}$$

Since constraints in (37a), (37b), and (37c) are jointly convex w.r.t $Q$ and $S$ now, problem (37a) is convex, which can be solved via modeling framework CVX and interior-point solvers. Based on the lower bounds in (37a), we can conclude that any feasible solution to problem (37a) is also feasible to (28). Additionally, $-F_{l,m}[n]$ is an upper bound of $-F_{l,m}[n]$. Therefore, the optimal objective value of the approximate problem (37a) is generally an upper bound to (28).

**E. Proposed Overall Algorithm**

The BCD-SCA method for solving $\mathcal{P}_1$ is summarized in Algorithm 2. The computational complexities of solving problems (13) and (24) are $O(LMN)$ and $O(K^3.5L^{1.5}D^{1.5})$, respectively. And the complexities of solving (25) and (28) are $O(KMN)$ and $O(K^{1.5}M^{3.5}N^{3.5})$, respectively. Based on the above, the overall complexity of Algorithm 2 is $O((K^{3.5}L^{1.5}D^{1.5} + K^{1.5}M^{3.5}N^{3.5})\log(1/\epsilon))$. Although we only solve problem (37a) optimally instead of problem (28), the convergence of Algorithm 2 is proved by the following proposition.

**Proposition 3:** The objective value of Problem $\mathcal{P}_1$ decreases as the number of iterations increases until convergence by applying Algorithm 2.

**Proof:** We denote $\Gamma(A, P, \eta, Q)$ as the objective value of $\mathcal{P}_1$ for a feasible solution $(A, P, \eta, Q)$. Define $\Gamma^{\text{th}}(A, P, \eta, Q)$ as the objective value of problem (37a). We denote $(A^*, P^*, \eta^*, Q^*)$ as a feasible solution of $\mathcal{P}_1$ at the $t$-th iteration.

For given $P^r, \eta^r$, and $Q^r$, as shown in step 4 of Algorithm 2, $A^{r+1}$ is the optimal solution to problem (13), and we have

$$\Gamma(A^r, P^r, \eta^r, Q^r) \geq \Gamma(A^{r+1}, P^r, \eta^r, Q^r).$$

(38)

Similarly, as shown in steps 5 and 6 of Algorithm 2, since $P^{r+1}$ and $\eta^{r+1}$ are the optimal solutions to problems (24) and (25), respectively, we have

$$\Gamma(A^{r+1}, P^{r+1}, \eta^{r+1}, Q^r) \geq \Gamma(A^{r+1}, P^{r+1}, \eta^{r+1}, Q^{r+1}).$$

(39)

Furthermore, for given $A^{r+1}$, $P^{r+1}$, $\eta^{r+1}$, $Q^r$ in step 7 of Algorithm 2, it follows that

$$\begin{align*}
\Gamma(A^{r+1}, P^{r+1}, \eta^{r+1}, Q^r) & \overset{(a)}{=} \Gamma^{\text{th}}(A^{r+1}, P^{r+1}, \eta^{r+1}, Q^r) \\
& \overset{(b)}{=} \Gamma^{\text{th}}(A^{r+1}, P^{r+1}, \eta^{r+1}, Q^{r+1}) \\
& \overset{(c)}{=} \Gamma(A^{r+1}, P^{r+1}, \eta^{r+1}, Q^{r+1}),
\end{align*}$$

(40)

where (a) holds since the first-order Taylor expansion in (34), (35), and (36) are tight at the given local points, which means that problem (37a) at $Q^r$ has the same objective value as that of problem (28); (b) holds since problem (37a) is solved optimally with solution $Q^{r+1}$ under given $A^{r+1}, P^{r+1}$, and $\eta^{r+1}$; (c) holds since the objective value of problem (37a) is the upper bound of that of its original problem (28) at $Q^{r+1}$. The inequality in (40) indicates that although only an approximation optimization problem (37a) is solved for obtaining the UAV trajectory, the objective value of problem (28) is still non-increasing after each iteration. Based on (38), (39), and (40), we further obtain

$$\Gamma(A^{r+1}, P^{r+1}, \eta^{r+1}, Q^{r+1}) \leq \Gamma(A^*, P^*, \eta^*, Q^*),$$

(41)

which shows that the objective value of problem $\mathcal{P}_1$ is always non-increasing over iterations. Therefore, the proposed BCD-SCA algorithm converges. This thus completes the proof.
Recall that problem $\mathcal{P}_2$ can be efficiently solved by applying the bisection search over the minimum amount of AirComp tasks, then the overall bisection algorithm for $\mathcal{P}_2$ is summarized in Algorithm 3. Note that the proposed algorithm still works if the probabilistic LoS channel model [43] is considered. Specifically, the only difference between the deterministic LoS and probabilistic LoS channel models is that the latter needs to compute the regularized LoS probability related to UAV trajectory. To address this issue, in the $(r + 1)$-th iteration of the algorithm, we approximate the regularized LoS probability based on the UAV trajectory of the $r$-th iteration (i.e., $q_{m}^{r}[n]$). Then the resulting trajectory subproblem can be solved by employing the SCA technique. Since the procedure of Algorithm 3 is iterative, in the following, we present the initialization. 

1) Transmit power initialization: The transmit powers of the ground devices are initialized by the equal power (i.e., $p_k[n] = P_k/D, \forall k, \forall n$).

2) Trajectory initialization: The trajectory is initialized by a simple circular trajectory scheme, which is detailed in [22].

3) Normalizing factor initialization: Given the initial transmit power and trajectories, the initial normalizing factors are obtained by computing (27).

### IV. Numerical Results

In this section, numerical results are provided to verify the performance gain of the proposed design in terms of the max-min AirComp task amount and the effectiveness of Algorithm 3. We consider $L = 6$ clusters. Therein, each cluster has $|K_l| = 30$, $\forall l$ ground devices, each of which randomly distributes in a circular area with a radius of $r = 50$ meters, where the centers of circles are set to $(x_{C_1}, y_{C_1}, z_{C_1}) = (100, 50, 0)$ meters, $(x_{C_2}, y_{C_2}, z_{C_2}) = (200, 200, 0)$ meters, $(x_{C_3}, y_{C_3}, z_{C_3}) = (-100, 100, 0)$ meters, $(x_{C_4}, y_{C_4}, z_{C_4}) = (-400, 150, 0)$ meters, $(x_{C_5}, y_{C_5}, z_{C_5}) = (-200, -200, 0)$ meters, and $(x_{C_6}, y_{C_6}, z_{C_6}) = (-250, -100, 0)$ meters. All UAVs fly at a fixed altitude $H = 100$ meters to comply with the rule that all commercial UAVs should not fly over 400 feet (122 meters) [44]. In addition, the minimum distance between any two UAVs is set as $d_{\text{min}} = 100$ meters [22]. The maximum speed of all UAVs is assumed to be the same and set as $V_{\text{max}} = 30$ m/s. Time step size $\delta$ is set as 0.5 s, which is small enough to satisfy $\delta V_{\text{max}} \ll H$. The noise power at the receiver and the channel power gain at the reference distance of $d_0 = 1$ m are set as $\sigma^2 = -80$ dBm and $\beta_0 = -50$ dB, respectively. The path-loss exponent is set as $\gamma = 2$. All devices are assumed to have the same power budget, i.e., $P = P_1 = \ldots = P_K = 0.8$ W. The target AirComp MSE threshold for all clusters is set as $\epsilon_l = 2 \times 10^{-3}, \forall l$. Let the threshold $\epsilon$ in Algorithm 2 be $10^{-3}$.

Fig. 2 shows convergence behaviors of Algorithm 2 with different max-min task amounts $D$ and the number of UAVs. We observe that under three settings, the max-min MSE ratio achieved by Algorithm 2 decreases with the number of iterations, and these three curves converge within 35 iterations with the prescribed threshold $\epsilon = 10^{-3}$. In addition, the objective value of problem $\mathcal{P}_1$ with $D = 40$ is smaller than that of $D = 90$. This is in accordance with Proposition 1.

### A. Multi-Cluster AirComp With a Single UAV

In this subsection, to show the superiority of our proposed design and the effectiveness of Algorithm 3, we first consider a special case that there is only one UAV serving ground devices (i.e., $M = 1$), where the system is free of inter-cluster interference.

Fig. 3 illustrates the obtained UAV trajectories optimized by using Algorithm 3 with varying mission duration $T$ when $P = 0.8$ W. Each trajectory is sampled every three seconds marked with “△” by using the same colors. The locations of devices are marked by dark blue “□”. We observe that, when $T = 30$ s, the UAV makes use of its maneuverability and adjusts its trajectory to approach its associated cluster as much as possible. In particular, the UAV hovers over its associated cluster for a certain amount of time, except for the minimum time spent in flight between clusters. Under the given mission duration $T = 150$ s, the UAV can move sufficiently close to each cluster in sequence. To this end, the optimized UAV trajectory contains line segments, which connect the points on the top of all clusters.

Fig. 4 shows the corresponding cluster scheduling along the timeline. The different colored rectangles represent different clusters, and their lengths represent how long these clusters are scheduled. We observe that for both $T = 50$ s and $T = 150$ s, the UAV visits each cluster in turn within an equal time to complete the corresponding AirComp task under the target MSE requirements, which is consistent with the observed results in Fig. 3.

To show the performance gain of the joint design, we consider the following benchmarks. **Static UAV**: This scheme fixes the location of UAV on the geometric point of all devices and only optimizes $A$, $\eta$, and $P$ by using Algorithm 3. **Equal power transmission**: At each scheduled time slot, each device is allocated equal power (i.e., $p_k[n] = P/D$). The remaining
variables are optimized by using Algorithm 3. **Upper bound:** In this scheme, we assume that all devices have sufficient power budgets and the system is interference-free. Therefore, the maximum task amount for each cluster can be achieved, i.e., $P_{\text{ub}} = \frac{MT}{ML}$. Fig. 5 shows the average max-min task amount versus the total power budget when $T = 200$ s. First, with the fixed mission duration, the upper bound of max-min AirComp task amount is fixed. With the increase of power budget $P$, the max-min task amount achieved by all three schemes increases. Because, with a larger $P$, the ground devices can afford more energy to compensate channel fading to reduce the achievable AirComp MSE. However, as long-distance transmission may lead to deep fading, the performance gap between the static UAV scheme and upper bound is large even in the relatively large $P$ (i.e., $P = 0.8$ W). Conversely, by utilizing UAV mobility, the proposed joint design scheme and the equal power transmission scheme significantly outperform the static UAV scheme. This is because the mobile UAV dynamically constructs favorable communication channels to avoid deep attenuation. In addition, the performance of the proposed joint design is the best and reaches the upper bound when $P$ is relatively small (i.e., $P = 0.3$ W). To achieve uniform powers of received signals, higher power is required to compensate for worse channel conditions. Using identical power transmission results in several misaligned signals since all devices’ channel conditions change due to UAV mobility, especially when the power budget is small but ineffectively allocated. Fortunately, the proposed joint design scheme exploits the synergy of trajectory design and power control to improve signal alignment. All the above results illustrate the importance and necessity of the joint design in maximizing the max-min AirComp task amount. This demonstrates the effectiveness of Algorithm 3 for solving problem $P_2$. It shows that in the single-UAV case without inter-cluster interference, the max-min task amount can achieve the upper bound by increasing the transmit power.

Fig. 6 illustrates the average max-min task amount versus the mission duration $T$ when $P = 0.8$ W. In the case of the static UAV, performance is independent of mission duration because of the time-invariant channel conditions between the UAV and devices. Conversely, with the optimized trajectory design, the max-min AirComp task amount achieved by the proposed joint design scheme and the equal power transmission scheme increase with $T$ increasing. There are two main reasons. First, the UAV with the optimized flight trajectory can establish good enough channel conditions with its associated cluster. Second, as $T$ increases, the UAV can spend more time performing tasks from its associated cluster under the established favorable channel conditions. We can further observe that the performance gap between the upper bound and the equal power transmission scheme increases as $T$ increases. However, thanks to effectively allocating power over all time slots, the proposed joint design scheme can reach the upper bound from $T = 160$ s to $T = 360$ s. Nevertheless, we can observe that there is a fundamental tradeoff between performance and delay. In the case of a single UAV, an increased max-min AirComp task amount means an increased access delay since the UAV sequentially visits each cluster.

**B. Multi-Cluster AirComp With Multiple UAVs**

Next, we take double UAVs as a simple example to illustrate its performance gain. Additionally, our proposed algorithm is also valid for more than two UAVs. We consider the following three benchmarks. In the static UAV scheme, the UAVs are located at the geometric points of devices in clusters 1, 2, 6 and 3, 4, 5, respectively. The following transmission scheme is included for comparison. **Orthogonal transmission:** The UAVs provide services to clusters via TDMA without inter-cluster interference. In this scheme, the binary variables are subject to

$$\sum_{l=1}^{L} \sum_{m=1}^{M} a_{l,m}[n] \leq 1, \quad n \in \mathcal{N},$$

$$a_{l,m}[n] \in \{0, 1\}, \quad \forall l \in \mathcal{L}, m \in \mathcal{M}, n \in \mathcal{N}. \quad (43)$$

This is a special instance of problem (10), which can be solved by using a similar Algorithm 3.

Fig. 7 shows the trajectories of double UAVs optimized by the proposed design when $T = 80$ s and $P = 0.8$ W.
To better observe phenomena, we also plot the corresponding cluster scheduling and association schemes along the timeline in Fig. 8. From Fig. 7 and Fig. 8, we observe that each cluster is served by the same UAV and each UAV only needs to be responsible for half of the clusters. From Fig. 8, we can observe that there is at least one UAV to complete one AirComp task at each time slot. Additionally, at some time intervals (e.g., from $t = 0$ s to $t = 3$ s and from $t = 10$ s to $t = 30$ s), there are two scheduled clusters, which means two UAVs actually work simultaneously to deal with different AirComp tasks. Furthermore, observed from Fig. 7 and Fig. 8, with the cluster-UAV scheduling and association design, to avoid strong co-channel interference, in most time slots, UAVs tend to choose to serve two clusters that are geographically far away from each other. As a result, the two UAVs can properly enlarge their trajectories to move closer to their associated cluster for better channel conditions establishment while achieving weak inter-cluster interference. For example, as shown in Fig. 8, from $t = 70$ s to $t = 80$ s (i.e., $t = 0$ s), UAV 2 associates with cluster $C_4$ while UAV 1 associates with cluster $C_1$. During this time interval, from Fig. 7, we can observe that UAV 2 and UAV 1 are respectively closer to cluster $C_4$ and cluster $C_1$. To complete as many tasks as possible for each cluster, two UAVs will at some point have to serve two clusters simultaneously when flying. For example, as shown in Fig. 8, from $t = 35$ s to $t = 40$ s, UAV 2 and UAV 1 associate with cluster $C_3$ and cluster $C_6$, respectively. In these time instants, the optimized trajectories show that UAVs tend to stay away from each other to reduce inter-cluster interference. This is why the UAVs fly along arc paths with opposite opening directions during that time interval.

Fig. 9 shows the max-min task amount versus device power budget when $T = 80$ s. First, due to effective interference management, the proposed joint design scheme outperforms all benchmarks with all regimes considered. Second, in the low power budget regime, the performance gaps between the proposed joint design and other benchmarks are relatively large. This implies the effectiveness of power control optimization in suppressing the noise-induced error that is dominant for the achievable MSE in the low power budget regime. Moreover, the proposed joint design and the equal-power transmission scheme outperform the orthogonal transmission scheme, demonstrating the benefit of cooperative transmission over clusters. And their performance gaps become larger as the power budget increases. In addition, it is observed that all schemes suffering from inter-cluster interference become saturated in the high power budget regime, meaning that the achievable MSE performance is limited by the inter-cell interference and cannot be reduced further by simply increasing the transmit power.

Fig. 10 shows the average max-min task amount versus the mission duration $T$ when $P = 0.8$ W in the case of two UAVs. It can be observed that the performance of static UAVs is the worst due to long-distance transmission. Compared to the curves of the proposed joint design scheme in Fig. 6, it can be observed that with the same given $T$, the deployment of more than one UAV with cooperative interference management achieves a larger max-min task amount, thereby improving the performance-delay tradeoff. For example, when $T = 160$ s, the max-min AirComp task amount achieved by the proposed joint design in the single-UAV system is 53, whereas that in the two-UAV system exceeds 92.

V. CONCLUSION

We studied the minimum task amount maximization problem in a UAV-aided AirComp system with multiple clusters, taking into account cluster scheduling and association, the UAV trajectory design, and AirComp transceiver design.
Such a joint design aimed to align signals within each cluster while mitigating the detrimental inter-cluster interference, thereby improving WDA performance. By applying the Bisection technique, the formulated mixed-integer nonconvex optimization problem was reduced to a sequence of the maximum ratio minimization problems. This resulting problem was further solved by developing an efficient algorithm by applying BCD, Lagrange dual ascent, and SCA techniques. Simulation results demonstrated significant performance gains of our proposed joint design over the benchmark schemes.

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