A Probabilistic Scheduling Policy for Energy Efficient UAV Communications with Delay Constraints

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***Abstract*—A typical application of unmanned aerial vehicles (UAVs) is surveillance of distant targets, where data collected by its sensors need to be transmitted back to a ground terminal (GT) for further processing in a timely manner. Due to the limited battery capability of the UAV, the sensed data could be preprocessed in a UAV to reduce the amount of data transmitted, which could potentially reduce the average power consumption at the UAV, especially when the transmission link quality is poor. In this paper, a probabilistic approach is adopted to schedule the transmission and computing of the data tasks based on the UAV and GT's buffer states. The joint transmission and computing problem can be modeled as a four-dimensional Markov chain, based on which the average delay of each task and the average power consumption at the UAV can be obtained. Our design goal is to minimize the average power consumption under the delay constraints. To do that, a delay-constrained power minimization problem is solved by an proposed method to obtain the power-optimal joint transmission and computation scheduling (JTCS) policy efficiently. Finally, the optimization results are validated with extensive simulations.**

I. Introduction

Typical applications of unmmaned aerial vehicles (UAVs), e.g., search and rescue operations, make it necessary for surveillance of distant targets [1][2]. In these scenarios, the data collected by a UAV need to be transmitted back to the ground terminal (GT) quickly with delay requirements, e.g., some mission-critical tasks like counter-terrorism. However, the battery life and computation capability of the UAV is still limited [3]. Therefore, the UAV needs to shift the complex computation tasks to the GT with more powerful computation resources and battery capabilities, e.g., a computer server with adequate supply of electricity, to reduce the computation load. Due to the uncertainty of the wireless channel fading and high mobility of the UAV, transmission power consumption of the tasks will be high and even unacceptable when the channel condition is poor, e.g., a blocking building between the UAV and a GT as shown in Fig. 1. Thus, if we can minimize the

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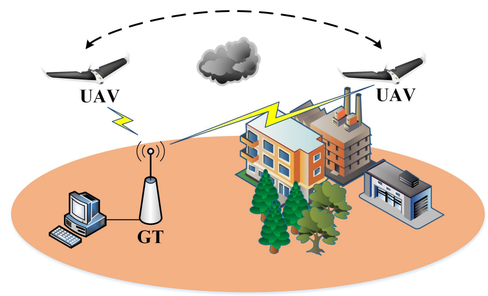

Fig. 1. A scenario of a UAV communication system

data size by preprocessing operation of the UAV itself, it will reduce transmission power, which is widely used in wireless sensor networks [4].

Since both the delay of tasks and power consumption at the UAV are due to transmission and computing, the traditional packet-switched transmission and computing may not provide the best-effort service. In contrast, the joint transmission and computing scheduling policy holds the promise of meeting the above performance requirements based on the state information of both transmission and computing, which has been studied widely. In [5], a method is proposed to jointly optimize the transmit power and the CPU cycles assigned to each application in one mobile cloud computing system and full exploitation of the computing capabilities is achieved when allocation of transmission and computational capabilities is performed jointly. In [6], an online joint radio and computational resource management algorithm for multi-user mobile-edge computing (MEC) systems is developed to minimize the average weighted sum power consumption of mobile devices. In [7], the offloading selection, radio resource allocation, and computational resource allocation are jointly optimized to minimize the energy consumption at mobile devices in the multi-user MEC system.

Furthermore, the probabilistic scheduling approach, which is one of the major methods of achieving the optimal performance in terms of delay or power consumption, has the potential to improve the system performance. To our best knowledge, Collins and Cruz were among the first to study the optimal scheduling policy by jointly using the channel state and the queue state information [8], where a framework of the cross-layer scheduling is proposed. In [9], we investigated the situation with a Bernoulli arrival and a fixed modulation over a block fading channel, and a probabilistic policy based on one queue state is proposed. Based on this policy, we generalized our model in the packet arrival and the transmission rate in [10][11], as well as to adopt the system with two queues in serial connection [12] and parallel connection [13]. In [14], a probabilistic scheduling is studied in a two-user multiple access system with a discrete rate set, where the asymmetric scenario is also included.

In this paper, we generalize this method to a UAV communication system, which is composed of one UAV and one GT. Two kinds of tasks, i.e., original task and compressed task, could be stored in their finite-buffers. The power consumption at the UAV is the sum of transmission power consumption for transmitting data to the GT and computing power consumption for local preprocessing. The considered system can be modeled as two queues in serial connection with two kind of stored packets. The state of this queueing system could be formulated as a four-dimensional Markov chain whose state transition probability is determined by the JTCS policy. Our objective is to find the optimal JTCS policy to minimize the average power consumption at the UAV under the constraints on average delay in order to prolong the UAV's service duration with guaranteed tolerant delay. This optimization problem can be converted into a linear programming problem which can be solved efficiently. Then, a power-optimal JTCS policy could be used to jointly determine the probabilities of the transmission and computing rate at the UAV based on the queue states.

II. System Model

We consider a UAV communication system where the UAV is set to transmit the data collected by its sensors to a GT. Assume that further processing is necessary for the collected data, e.g., image recognition and surveillance monitoring [1], requires a large amount of computing resources, which need to be transported to the GT with more powerful computation resources and battery capabilities.

The UAV is assumed with the computation ability to preprocess the data, e.g., data compression [4], by local processing units in order to reduce data size and save energy consumption. The data preprocessing step at the UAV, however, will also consume power, i.e., the computing power consumption. In this case, from the UAV side, it gives us two design options, namely, to transmit with preprocessing or to direct transmit without preprocessing.

Thus, the data tasks stored in the UAV can be classified into original tasks and compressed tasks, whose parameters are summarized in Table I. Data size of an original task can be reduced from B bits to βB bits with λL CPU cycles,

TABLE I
Parameters of original and compressed tasks

	Data Size	CPU-cycle(UAV)	CPU-cycles(GT)
Original task	B	0	L
Compressed task	βB	λL	γL

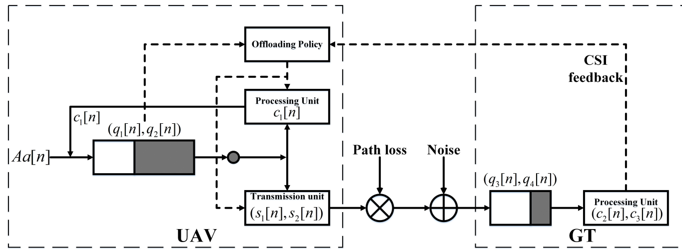

Fig. 2. Queue model.

where $\beta (\beta < 1)$ is the data compression ratio. The further process of each original task and compressed task requires L and γL CPU cycles, respectively, where γ depends on the data preprocessing step. If the data preprocessing is data compression [4], we have $\gamma > 1$ owing to the computation consumption of decompression in the GT. Besides, we also have $0 < \gamma \leq 1$ in some scenarios, e.g., data preprocessing is down-sampling or feature extraction. Thus, the power consumption at the UAV can be divided into two parts: transmission power consumption and computing power consumption.

To simplify the analysis, we assume that the time is divided into time-slots, whose length is T_{s}. Assume that at the beginning of each time-slot, the volume of data collected by the UAV is a random variable following the Bernoulli Process with an arrival rate α, i.e.,

$$\begin{cases} \Pr\{a[n] = 1\} = \alpha, \\ \Pr\{a[n] = 0\} = 1 - \alpha. \end{cases} \tag{1}$$

We assume that each packet arrival contains $N (N \geq 1)$ original tasks, which can be converted into compressed tasks by data preprocessing step at the UAV.

A. Queue Model

Both original and compressed tasks can be stored in the finite-buffers of the UAV and GT, whose buffer sizes are $Q_1 B$ and $Q_2 B$ bits, which are equal to Q_1 and Q_2 original tasks, respectively. The considered system can be modeled by two queues in serial connection, which denote the buffer states of the UAV and the GT, as shown in the Fig. 2.

For the UAV, the number of original tasks and compressed tasks transmitted in the n-th time-slot are denoted by $s_1[n]$ and $s_2[n]$, respectively. Moreover, the number of original packets that is preprocessed in the UAV is denoted by $c_1[n]$. Denote $\mathbf{q}_{\mathrm{uav}}[n] = (q_1[n], q_2[n])$ as the buffer state of the UAV at the end of the n-th time-slot, where $q_1[n]$ and $q_2[n]$ denote the numbers of original and compressed tasks stored in the UAV's buffer.

For the GT, the number of original tasks and compressed tasks processed in the n-th time-slot are denoted by $c_2[n]$ and $c_3[n]$, respectively. Denote $\mathbf{q}_{\text{gt}}[n] = (q_3[n], q_4[n])$ as the buffer state of the GT at the end of the n-th time-slot, where $q_3[n]$ and $q_4[n]$ denote the number of original and compressed packets stored in the GT's buffer. Consider the typical UAV and GT equipments, it is reasonable to assume that the buffer size of the UAV and GT should be larger than the data size of one data packet arrival, i.e., Q_1 and $Q_2 > N$.

In each time-slot, the decision is made by the UAV, which can be characterized by a triplet $\boldsymbol{\tau}[n] = (s_1[n], s_2[n], c_1[n])$. Then, the dynamic of the task buffer $\mathbf{q}_{\text{uav}}[n] = (q_1[n], q_2[n])$ and $\mathbf{q}_{\text{gt}}[n] = (q_3[n], q_4[n])$ can be expressed as

$$\begin{cases} q_1[n+1] = \max\{q_1[n] - s_1[n] - c_1[n], 0\} + Na[n], \\ q_2[n+1] = \max\{q_2[n] - s_2[n], 0\} + c_1[n], \\ q_3[n+1] = \max\{q_3[n] - c_2[n], 0\} + s_1[n], \\ q_4[n+1] = \max\{q_4[n] - c_3[n], 0\} + s_2[n]. \end{cases} \tag{2}$$

Due to the limitation of the buffer size, the buffer state in each time-slot should satisfy

$$\begin{cases} q_1[n] + \beta q_2[n] \leq Q_1, \\ q_3[n] + \beta q_4[n] \leq Q_2; \end{cases} \tag{3}$$

otherwise, it will result in packet dropping owing to the buffer overflow.

B. Power Model

The power consumption due to transmission and computing at the UAV in the n-th time-slot are denoted by $P^{\text{t}}_{\text{uav}}[n]$ and $P^{\text{c}}_{\text{uav}}[n]$, respectively. Assume the length of time-slot T_{s} is long enough, the ergodic channel is considered. Consider that the information-theoretically optimal transmission rate is $R = \log(1 + \frac{h^{\text{t}}_{\text{uav}} P^{\text{t}}_{\text{uav}}}{N_o})$, where $P^{\text{t}}_{\text{uav}}[n]$ is the transmission power consumption, N_o is the background noise power, and $h^{\text{t}}_{\text{uav}}$ is the channel power gain. Then, $P^{\text{t}}_{\text{uav}}[n]$ can be rewritten as

$$P^{\text{t}}_{\text{uav}}[n] = g^{\text{t}}_{\text{uav}}(s_1[n], s_2[n]) = k^{\text{t}}_{\text{uav}}(2^{\frac{B}{T_{\text{s}}}(s_1[n] + \beta s_2[n])} - 1), \tag{4}$$

where $k^{\text{t}}_{\text{uav}} = \frac{N_o}{h^{\text{t}}_{\text{uav}}}$ is the transmission power gain.

Moreover, according to [15], the power consumption per CPU cycle can be expressed as

$$P^{\text{c}}_{\text{uav}}(f^{\text{c}}_{\text{uav}}) = \kappa^{\text{c}}_{\text{uav}} {f^{\text{c}}_{\text{uav}}}^2, \tag{5}$$

where $f^{\text{c}}_{\text{uav}}$ is the clock frequency and $\kappa^{\text{c}}_{\text{uav}}$ is the effective switched capacitance depending on the chip architecture used in the UAV. The total CPU cycles required by the UAV in the n-th time-slot should satisfy

$$f^{\text{c}}_{\text{uav}}[n] T^{\text{c}}_{\text{uav}} = L\lambda c_1[n]. \tag{6}$$

Then $P^{\text{c}}_{\text{uav}}[n]$ can be rewritten as

$$P^{\text{c}}_{\text{uav}}[n] = g^{\text{c}}_{\text{uav}}(c_1[n]) = k^{\text{c}}_{\text{uav}}(c_1[n])^3, \tag{7}$$

where $k^{\text{c}}_{\text{uav}} = \frac{\kappa^{\text{c}}_{\text{uav}} \lambda^3 L^3}{{T_{\text{s}}}^2}$. Likewise, the computing power consumption at the GT in the n-th time-slot is given by

$$P_{\text{gt}}[n] = g^{\text{c}}_{\text{gt}}(c_2[n], c_3[n]) = k^{\text{c}}_{\text{gt}} \left(c_2[n] + \gamma c_3[n]\right)^3, \tag{8}$$

where $k^{\text{c}}_{\text{gt}} = \frac{\kappa^{\text{c}}_{\text{gt}} L^3}{{T_{\text{s}}}^2}$ and $\kappa^{\text{c}}_{\text{gt}}$ is the effective switched capacitance of the GT.

Then, the total power consumption of the UAV in the n-th time-slot is given by

$$P_{\text{UAV}}[n] = P^{\text{t}}_{\text{UAV}}[n] + P^{\text{c}}_{\text{UAV}}[n]. \tag{9}$$

Based on the above analysis, it is able to capture the mathematical relationship between $P_{\text{UAV}}[n]$ and $(s_1[n], s_2[n], c_1[n])$. In addition, to achieve lower delay, the UAV will conduct transmission and computing at higher rate, which may cause more power consumption. Hence there is a fundamental tradeoff between the average delay and average power consumption. Moreover, due to the constraints of the UAV's hardware capabilities, in order to prolong the service lifetime of the UAV, we assume that the maximum available power consumption at the UAV is given by $P^{\max}_{\text{uav}}$, i.e.,

$$P_{\text{UAV}}[n] = P^{\text{t}}_{\text{UAV}}[n] + P^{\text{c}}_{\text{UAV}}[n] \leq P^{\max}_{\text{uav}}. \tag{10}$$

The maximum available power consumption at the GT is given by $P^{\max}_{\text{gt}}$.

The scheduling of the UAV works in the following procedures. The data packet arrival information $Na[n]$ can be obtained at the beginning of each time-slot. Hence, it can be taken into consideration along with the sates of two buffers, i.e., $\mathbf{q}_{\text{uav}}[n]$ and $\mathbf{q}_{\text{gt}}[n]$ by the UAV to make a probabilistic decision $\boldsymbol{\tau}[n]$ for the current time-slot.

III. Delay and Power Analysis based on JTCS

In this section, the JTCS policy of the UAV is introduced in a rigorous way. The considered system with two buffers can be formulated as a four-dimensional Markov chain. Then, by the analysis of the steady-state probabilistic distribution of this Markov chain, the average delay and power consumption of the UAV can be obtained. In the following analysis, we will introduce the probabilistic scheduling policy, and analyze the average delay of each task and the average power consumption of the UAV using Markov chain theory.

A. Joint Transmission and Computing Scheduling Policy

In each time-slot, the scheduling is made by the UAV upon a new data arrival, by which $(q_1[n-1] + Na[n])$ original tasks are left in the buffer. In the sense of the average delay, the scheduling policy is only aware of how many tasks waiting for transmission, irrespective of when the task arrives at the queue. Hence, we rewrite the queue state of the UAV by $\mathbf{q}_{\text{uav}}[n] = (\zeta[n], q_2[n])$, where

$$\zeta[n] = q_1[n-1] + Na[n] \in [0, Q+N]. \tag{11}$$

From Eq. (2), we have

$$\zeta[n+1] = \max\{\zeta[n] - s_1[n] - c_1[n], 0\} + Na[n+1]. \tag{12}$$

The queue state of the system is denoted by $\boldsymbol{q}[n] = (\zeta[n], q_2[n], q_3[n], q_4[n])$.

The current decision of the GT $(c_2[n], c_3[n])$ is made by the GT independent of decisions taken by the UAV. Since the GT has an adequate supply of electricity, the average power consumption of the GT cannot be the bottleneck. Thus, we will not take the energy efficiency into consideration, but only focus on the average delay of the tasks queued in its buffer. Thus, the optimal decision can be determined by Algorithm 1, which aims to minimize the average delay of the task by processing the compressed tasks with higher priority.

Algorithm 1 Computing Scheduling Algorithm in GT

1: Input $q_3[n]$ and $q_4[n]$.
2: Calculate the largest number of the compressed tasks that can be processed by the GT within one time-slot according to Eq. (8), i.e., $C_{\max} = \max\{C|g_{\text{gt}}^{\text{c}}(0, C) \le P_{\text{gt}}^{\max}\}$.
3: Assign $c_3[n] = \min\{q_4[n], C_{\max}\}$.
4: Calculate $C'_{\max} = \max\{C'|g_{\text{gt}}^{\text{c}}(C', c_3[n]) \le P_{\text{gt}}^{\max}\}$.
5: Assign $c_2[n] = \min\{q_3[n], C'_{\max}\}$.
6: Output $(c_2[n], c_3[n])$, then stop.

The probabilistic scheduling policy of the UAV can be formulated by the probability $f_{k_1,k_2,k_3,k_4}^{s_1,s_2,c_1}$, where

$$f_{k_1,k_2,k_3,k_4}^{s_1,s_2,c_1} = \Pr\{\boldsymbol{\tau}[n] = (s_1, s_2, c_1)|\boldsymbol{q}[n] = (k_1, k_2, k_3, k_4)\}. \tag{13}$$

According to Eq. (2) and (3), the current decision $\boldsymbol{\tau}$[n] should satisfy

$$q_1[n] - s_1[n] - c_1[n] \ge 0, \tag{14.a}$$
$$q_2[n] - s_2[n] \ge 0, \tag{14.b}$$
$$q_1[n+1] + \beta q_2[n+1] \le Q_1, \tag{14.c}$$
$$q_3[n+1] + \beta q_4[n+1] \le Q_2; \tag{14.d}$$

Otherwise we set $f_{k_1,k_2,k_3,k_4}^{s_1,s_2,c_1} = 0$ to avoid overflow or underflow. Eq. (14.a) and (14.b) mean that the transmission and computing rates cannot exceed the corresponding numbers of tasks stored in the buffer. Moreover, inequality constraints in Eq. (14.c) and (14.d) are proposed to avoid packet dropping.

B. Delay and Power Analysis

The scheduling problem can be characterized by a four-dimensional Markov chain with $\boldsymbol{q}[n] = (\zeta[n], q_2[n], q_3[n], q_4[n])$ as its states. The state space of this Markov chain is given by

$$\mathbf{M} = \{(\zeta, q_2, q_3, q_4)|\zeta + \beta q_2 \le Q_1, q_3 + \beta q_4 \le Q_1\}, \tag{15}$$

where ζ, q_2, q_3 and q_4 are non-negative integers.

Let $\boldsymbol{\Gamma}(\boldsymbol{q})$ denote the set of all feasible decisions which can guarantee no overflow or underflow in Eq. (14), where $\boldsymbol{q}$ is the state of the Markov chain. Recalling Eq. (10), the feasible domain of $\boldsymbol{\tau}[n]$ is given by $\boldsymbol{\Omega}(\boldsymbol{q}) = \boldsymbol{\Gamma}(\boldsymbol{q}) \cap (s_1[n], s_2[n], c_1[n])|P_{\text{UAV}}[n] \le P_{\text{uav}}^{\max})$ and the normalization condition of the probabilistic scheduling policy holds for any feasible queue state $\boldsymbol{q}$.

$$\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})} f_{\boldsymbol{q}}^{\boldsymbol{\tau}} = 1. \tag{16}$$

Denote $\lambda\boldsymbol{q},\boldsymbol{q}'$ as the one-step state transition probability from state $\boldsymbol{q}$=(k_1, k_2, k_3, k_4) to state $\boldsymbol{q}'$=(n_1, n_2, n_3, n_4) in the four-dimensional Markov chain, which is summarized in the following theorem.

Theorem 1 *The transition probability $\lambda\boldsymbol{q},\boldsymbol{q}'$ satisfies*

$$\lambda\boldsymbol{q},\boldsymbol{q}' = \alpha \sum_{\boldsymbol{\tau}\in\mathcal{X}\boldsymbol{q},\boldsymbol{q}'} f_{\boldsymbol{q}}^{\boldsymbol{\tau}} + (1-\alpha) \sum_{\boldsymbol{\tau}\in\mathcal{N}\boldsymbol{q},\boldsymbol{q}'} f_{\boldsymbol{q}}^{\boldsymbol{\tau}}, \tag{17}$$

where $\mathcal{X}\boldsymbol{q},\boldsymbol{q}'$ is the set of $\boldsymbol{\tau}$= $(s_1, s_2, c_1) \in \boldsymbol{\Omega}(\boldsymbol{q})$ satisfying

$$\begin{cases} n_1 = q_1 - s_1 - c_1 + N, \\ n_2 = q_2 - s_2 + c_1, \\ n_3 = q_3 + s_1 - c_2, \\ n_4 = q_4 + s_2 - c_3, \end{cases} \tag{18}$$

and $\mathcal{N}\boldsymbol{q},\boldsymbol{q}'$ is the set of $\boldsymbol{\tau}$= $(s_1, s_2, c_1) \in \boldsymbol{\Omega}(\boldsymbol{q})$ satisfying

$$\begin{cases} n_1 = q_1 - s_1 - c_1, \\ n_2 = q_2 - s_2 + c_1, \\ n_3 = q_3 + s_1 - c_2, \\ n_4 = q_4 + s_2 - c_3. \end{cases} \tag{19}$$

The (c_2, c_3) in Eq. (18) and (19) can be obtained according to Algorithm 1 based on $(q_3[n], q_4[n]) = (q_3, q_4)$).

When the conditions (14) and (16) are satisfied, one can find a single close positive recurrent aperiodic class in this Markov chain [9]. Moreover, the steady-state probabilistic distribution $\{\pi\boldsymbol{q}\}$ can be obtained by solving the following linear equation set.

$$\begin{cases} \sum_{\boldsymbol{q}\in\mathcal{S}} \lambda_{\boldsymbol{q}',\boldsymbol{q}} \pi_{\boldsymbol{q}'} = \pi_{\boldsymbol{q}}, \forall \boldsymbol{q} \in \mathcal{S} \\ \sum_{\boldsymbol{q}\in\mathcal{S}} \pi_{\boldsymbol{q}} = 1. \end{cases} \tag{20}$$

According to Little's law [16], the average length L is equal to the arrival rate αN multiplied by the average waiting time T that a task spends in the queue. This average waiting time does not include the service time of the task, which is time required for the processing unit at the GT to execute the task. Thus, the total delay is the sum of average waiting time in the queue T and service time in the server of the GT, i.e., one time-slot, which is given by

$$\begin{aligned} D^{\text{ava}} &= T + 1 \\ &= \frac{1}{\alpha N} \lim_{n\to\infty} \mathrm{E}\left\{\sum_{i=1}^{4} q_i[n]\right\} + 1 \\ &= \frac{1}{\alpha N} \lim_{n\to\infty} \mathrm{E}\left\{(\zeta[n] - Na[n]) + \sum_{i=2}^{4} q_i[n]\right\} + 1 \\ &= \frac{1}{\alpha N} \lim_{n\to\infty} \mathrm{E}\left\{\zeta[n] + \sum_{i=2}^{4} q_i[n]\right\} \\ &= \frac{1}{\alpha N} \sum_{\boldsymbol{q}\in\mathcal{S}} (k_1 + k_2 + k_3 + k_4)\pi_{\boldsymbol{q}}, \end{aligned} \tag{21}$$

where $\boldsymbol{q}=(k_1,k_2,k_3,k_4)$.

According to Eqs. (4) and (7), for any buffer state $\boldsymbol{q}$, the power consumption for transmitting and computing at the UAV are given by $g_{\rm uav}^{\rm t}(s_1,s_2)$ and $g_{\rm uav}^{\rm c}(c_1)$ with probability $f_{\boldsymbol{q}}^{\boldsymbol{\tau}=(s_1,s_2,c_1)}$ in each time-slot. Then, the average power consumption is given by

$$P_{\rm uav}^{\rm ava}=\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}\pi_{\boldsymbol{q}}f_{\boldsymbol{q}}^{\boldsymbol{\tau}}g_{\rm uav}(\boldsymbol{\tau}), \tag{22}$$

where $g_{\rm uav}(\boldsymbol{\tau})=g_{\rm uav}^{\rm t}(s_1,s_2)+g_{\rm uav}^{\rm c}(c_1)$.

Based on the above analysis of the average delay and power consumption, a power-optimal JTSC strategy can be obtained in the next section.

IV. Optimal Power-Delay Tradeoff

In the UAV communication system, the task has the tolerant delay $D^{\rm th}$ before the process of the task should be completed, which is a constant design value. We need to guarantee that the average delay does not exceed the tolerant delay $D^{\rm th}$. Moreover, as the battery life of the UAV is limited, it is necessary to reduce the power consumption at the UAV $P_{\rm uav}^{\rm ava}$ as much as possible.

Therefore, we aim to minimize the average power consumption of the UAV under the constraints on average tolerant delay $D^{\rm ava}$ in Eq. (21). Then, we have the following optimization problem:

$$\mathcal{P}_1:\min_{\pi_{\boldsymbol{q}},f_{\boldsymbol{q}}^{\boldsymbol{\tau}}}\quad P_{\rm uav}^{\rm ava}=\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}\pi_{\boldsymbol{q}}f_{\boldsymbol{q}}^{\boldsymbol{\tau}}g_{\rm uav}(\boldsymbol{\tau}) \tag{23.a}$$

$$\text{s.t}\quad \frac{1}{\alpha N}\sum_{\boldsymbol{q}\in\mathcal{S}}(k_1+k_2+k_3+k_4)\pi_{\boldsymbol{q}}\le D^{\rm th} \tag{23.b}$$

$$\sum_{\boldsymbol{q}\in\mathcal{S}}\lambda_{\boldsymbol{q}',\boldsymbol{q}}\pi_{\boldsymbol{q}'}=\pi_{\boldsymbol{q}},\forall\boldsymbol{q}\in\mathcal{S} \tag{23.c}$$

$$\sum_{\boldsymbol{q}\in\mathcal{S}}\pi_{\boldsymbol{q}}=1 \tag{23.d}$$

$$\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}f_{\boldsymbol{q}}^{\boldsymbol{\tau}}=1,\forall\boldsymbol{q}\in\mathcal{S} \tag{23.e}$$

$$f_{\boldsymbol{q}}^{\boldsymbol{\tau}}\ge 0,\forall\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q}),\forall\boldsymbol{q}\in\mathcal{S}, \tag{23.f}$$

where (23.b) is the average delay constraint, (23.c) and (23.d) denote the balance equation set. Clearly, the objective function and constraints in optimization (23) are linear combinations of $\pi_{\boldsymbol{q}}f_{\boldsymbol{q}}^{\boldsymbol{\tau}}$ and $\pi_{\boldsymbol{q}}$. By recalling the normalization condition of $f_{\boldsymbol{q}}^{\boldsymbol{\tau}}$ in Eq. (23.e), $\pi_{\boldsymbol{q}}$ can also be expressed as

$$\pi_{\boldsymbol{q}}=\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}\pi_{\boldsymbol{q}}f_{\boldsymbol{q}}^{\boldsymbol{\tau}}=\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}y_{\boldsymbol{q}}^{\boldsymbol{\tau}}. \tag{24}$$

By substituting Eq. (24) into Eq. (23), the optimization (23) is converted into a linear programming which is summarized in the following theorem.

Theorem 2 The optimization problem $\mathcal{P}_1$ is equivalent to the following linear programming problem $\mathcal{P}_2$

$$\mathcal{P}_2:\min_{y_{\boldsymbol{q}}^{\boldsymbol{\tau}}}\quad P_{\rm uav}^{\rm ava}=\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}y_{\boldsymbol{q}}^{\boldsymbol{\tau}}g_{\rm uav}(\boldsymbol{\tau}) \tag{25.a}$$

$$\text{s.t}\quad \frac{1}{\alpha N}\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}(k_1+k_2+k_3+k_4)y_{\boldsymbol{q}}^{\boldsymbol{\tau}}\le D^{\rm th} \tag{25.b}$$

$$\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}\lambda_{\boldsymbol{q}',\boldsymbol{q}}y_{\boldsymbol{q}'}^{\boldsymbol{\tau}}=\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}y_{\boldsymbol{q}}^{\boldsymbol{\tau}},\forall\boldsymbol{q}\in\mathcal{S} \tag{25.c}$$

$$\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}y_{\boldsymbol{q}}^{\boldsymbol{\tau}}=1 \tag{25.d}$$

$$y_{\boldsymbol{q}}^{\boldsymbol{\tau}}\ge 0,\forall\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q}),\forall\boldsymbol{q}\in\mathcal{S}. \tag{25.e}$$

After the optimal solution $y_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}$ of the linear programming (24) is obtained, the corresponding steady-state distribution can be represented as

$$\pi_{\boldsymbol{q}}^*=\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}y_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}. \tag{26}$$

To obtain the power-optimal strategy, we can derive $f_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}$ from $y_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}$ to satisfy the constraint in Eq. (23.e) as follows:

Case 1 When $\pi_{\boldsymbol{q}}^*\neq 0$, the optimal strategy is given by

$$f_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}=\frac{y_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}}{\pi_{\boldsymbol{q}}^*}. \tag{27}$$

Case 2 When $\pi_{\boldsymbol{q}}^*=0$, which means that the state $\boldsymbol{q}$ is a transient state. A simple strategy can be used, i.e.,

$$f_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}=\frac{1}{|\boldsymbol{\Omega}(\boldsymbol{q})|},\forall\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q}). \tag{28}$$

Theorem 3 *Given $y_{\boldsymbol{q}}^{\boldsymbol{\tau}^*}$, the proportion of the tasks that are preprocessed at the UAV in the long run can be calculated by*

$$\eta=\frac{\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}\pi_{\boldsymbol{q}}f_{\boldsymbol{q}}^{\boldsymbol{\tau}}s_2}{\sum_{\boldsymbol{q}\in\mathcal{S}}\sum_{\boldsymbol{\tau}\in\boldsymbol{\Omega}(\boldsymbol{q})}\pi_{\boldsymbol{q}}f_{\boldsymbol{q}}^{\boldsymbol{\tau}}(s_1+s_2)}, \tag{29}$$

where $\boldsymbol{q}=(k_1,k_2,k_3,k_4)$ and $\boldsymbol{\tau}=(s_1,s_2,c_1)$.

Generally speaking, η will increase to reduce the power consumption with the increase of transmission power gain $k_{\rm uav}^{\rm t}$ and the decrease of the data compression ratio β.

V. Numerical Results

In this section, we evaluate the performance of the power-optimal JTCS policy by simulations. Throughout this section, we set $N=2$, $Q_1=Q_2=4$, $\beta=0.3$, $\gamma=1.3$, $P_{\rm uav}^{\rm max}=50$, $P_{\rm gt}^{\rm max}=100$ and $k_{\rm uav}^{\rm c}=k_{\rm uav}^{\rm c}=5$. For the sake of simplicity, $\frac{B}{T_{\rm s}}$ is set to 1. Based on the optimization problem $\mathcal{P}_2$ described in Eq. (25), the power-optimal JTCS policy can be obtained.

We introduce four baseline scheduling policies, including **probabilistic scheduling with** $\eta=100\%$, in which each task is preprocessed to reduce data size in the UAV; **probabilistic scheduling with** $\eta=0\%$, in which each task is transmitted to

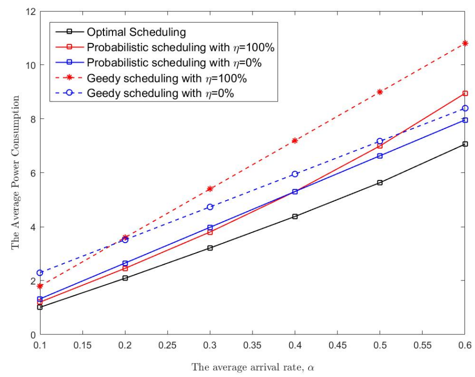

Fig. 3. The average power consumption vs. the average arrival rate α.

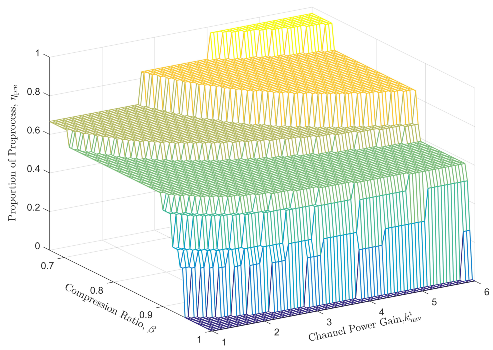

Fig. 4. The proportion of tasks that are preprocessed η vs. the compression ratio and the transmission power gain.

the GT directly and probabilistic scheduling is implemented; **greedy scheduling with** $\eta = 100\%$, in which each task is transmitted in its arrival time-slot and probabilistic scheduling is implemented; **greedy scheduling with** $\eta = 0\%$, in which each task is preprocessed in its arrival time-slot and then be transmitted in the next time-slot.

The average power consumption achieved by our proposed JTCS policy and above four policies are given in Fig. 3. We set compression ratio $\beta = 0.8$, transmission power gain $k^{\mathrm{t}}_{\mathrm{uav}} = 6$ and tolerant delay $D^{\mathrm{th}} = 3$. It can be observed from this figure that the power consumption achieved by each policy increases with the arrival rate α, which is in accordance with our intuition. Moreover, our proposed JTCS policy with an optimal dynamic preprocess has a better performance compared to the policies with a fixed preprocess policy, i.e., $\eta = 0$ or 100%.

The proportion of tasks locally preprocessed η achieved by the JTCS policy with different compression ratio β and transmission power gain $k^{\mathrm{t}}_{\mathrm{uav}}$ is given in Fig. 4. We set arrival rate $\alpha = 0.5$ and tolerant delay $D^{\mathrm{th}} = 3$. As expected, with the decrease of β and increase of $k^{\mathrm{t}}_{\mathrm{uav}}$, more power consumption of a task can be saved by preprocessing this task to reduce its data size, which results in higher η and is matched with the results in Fig. 4.

VI. Conclusion and Future Work

In this paper, we have investigated a power-optimal joint transmission and computing scheduling (JTCS) policy for a UAV communication system. When the transmission environment is poor, the data collected by the UAV could be preprocessed locally to reduce the amount of data transmitted, and thus the transmission power consumption at the UAV can be reduced. The system is modeled as a four-dimensional Markov chain and a probabilistic scheduling method is adopted. By jointly scheduling the rate of transmission and computing for preprocessing based on the buffer states, the energy efficiency of the UAV will be improved significantly. Based on the analysis of average power consumption at the UAV and the average delay of the tasks, the optimization problem could be formulated and solved efficiently. In this way, the power-optimal JTCS policy is obtained, which can achieve the minimum average power consumption at the UAV with the average delay constraints compared to four baseline policies. For the further investigation, we will extend this work to more generalized systems, e.g., adaptive channel fading.

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