A Joint Communication and Computation Framework for Digital Twin over Wireless Networks

Zhaohui Yang*, Mingzhe Chen†, Yuchen Liu‡, Zhaoyang Zhang*
*College of Information Science and Electronic Engineering, Zhejiang University, Hangzhou, China
Zhejiang Provincial Key Laboratory of Info. Proc., Commun. & Netw. (IPCAN), Hangzhou, China
†Department of Electrical and Computer Engineer and Institute of Data Science and Computing,
University of Miami, Coral Gables, FL, 33146, USA
‡Department of Computer Science, North Carolina State University, Raleigh, NC, 27606, USA
E-mails: {yang_zhaohui, ning_ming}@zju.edu.cn, mingzhe.chen@miami.edu, yuchen.liu@ncsu.edu

Abstract—In this paper, the problem of low-latency communication and computation resource allocation for digital twin (DT) over wireless networks is investigated. In the considered model, multiple physical devices in the physical network (PN) needs to frequently offload the computation task related data to the digital network twin (DNT), which is generated and controlled by the central server. Due to limited energy budget of the physical devices, both computation accuracy and wireless transmission power must be considered during the DT procedure. This joint communication and computation problem is formulated as an optimization problem whose goal is to minimize the overall transmission delay of the system under total PN energy and DNT model accuracy constraints. To solve this problem, an alternating algorithm with iteratively solving device scheduling, power control, and data offloading subproblems. Numerical results verify that the proposed algorithm can reduce the transmission delay of the system by up to 51.2% compared to the conventional schemes.

Index Terms—Digital twin (DT), delay minimization, joint communication and computation design.

I. Introduction

Recently, digital twin (DT) technology is envisioned to act as an important role for the modern communication society [1]–[4], in particular for the future Metaverse. DT is the process of using information technology to digitally define and model physical entities. The core concept is to realize feedback optimization of physical entities through the simulation, control and prediction of DTs. Due to the combination of digital and physical worlds, DT technology has many advantages. DT technology requires the construction of digital representations of physical objects in digital space. Physical objects in the real world and twins in digital space can achieve bidirectional mapping, data connection and state interaction. Moreover, based on the acquisition of multiple data such as real-time sensing, the twin body can comprehensively, accurately and dynamically reflect the state changes of physical objects, including appearance, performance, location, anomaly, etc. Besides, in an ideal state, the mapping and synchronization state achieved by the DT should cover the entire life cycle of the twin object from design, production, operation to retirement, and the twin body should continue to evolve and update with the life cycle process of the twin object. The ultimate goal of establishing a twin is to describe the internal mechanism of the physical entity, analyze laws, gain insight into trends, and form optimization instructions or strategies for the physical world based on analysis and simulation, so as to achieve a closed-loop decision-making optimization function for physical entities.

Due to the above distinctive advantages, DT has many emerging applications [2]. Virtual "clones" of these physical operations can help organizations monitor operations, perform predictive maintenance and provide insight for capital purchase decisions. They can also help organizations simulate scenarios that are too time-consuming or expensive to test with physical assets, create long-term business plans, identify new findings and improve processes. DTs can help companies virtually test and validate products before they come out. Engineers can use them to identify process faults. Organizations can use DTs to proactively monitor equipment and systems to schedule maintenance before they fail, increasing productivity. Users can monitor and control systems remotely. Process automation and 24x7 access to system information allow technicians to have more time to focus on collaboration. By integrating financial data, organizations can use DTs to make better, faster-adjusted decisions.

Since the physical world and the digital world needs to communicate, DT over wireless networks has attracted a lot of attentions [5]. The survey of using the future sixth generation (6G) communication techniques for DT was presented in [6]. A blockchain empowered federated learning framework for DT was considered in [7], [8] to solve the edge association problem through optimizing the DT association, training data batch size, and bandwidth allocation. The interplay between Terahertz and DT was considered in [9], where DT can be utilized to predict and simulate the unique propagation properties of Terahertz signals. Furthermore, a DT assisted mobile edge computing network was considered in [10] for Internet of vehicles. In [11], the combination of Bayesian learning of DT was studied, where the DT trained a Bayesian model to predict the epistemic uncertainty of the wireless communication system. In [12], a DT system over wireless communication network was proposed to investigate the tradeoff between the accuracy and delay of the DT system. An weighted sum accuracy and system delay optimization problem was formulated in [12], which was solved by using the edge continual learning. However, the above works [6]–[12] all ignored the joint communication and computation resource allocation with considering energy budget of wireless devices and model accuracy of the DT, even though the wireless devices are usually energy constrained.

In this paper, we consider the delay-efficient communication and computation resource allocation for a DT network with considering energy budget of wireless devices and DT model accuracy constraints. Our contributions are listed as follows.

- We investigate the performance of DT over wireless networks, where multiple physical devices in the physical network (PN) transmit data to the digital network twin (DNT) over multiple time slots. Due to limited energy budget of the physical devices, both computation accuracy and wireless transmission power are considered during the DT procedure.
- This joint communication and computation problem is formulated as an optimization problem whose goal is to minimize the overall transmission delay of the system under total PN energy and DNT model accuracy constraints. To solve this problem, an alternating algorithm with iteratively solving device scheduling, power control, and task offloading subproblems.
- Numerical results show the superiority of the proposed algorithm compared to the conventional schemes in terms of transmission delay.

The rest of this paper is organized as below. Section II presents the system model and problem formulation. The algorithm design is presented in Section III, while simulation results are given in Section IV. Section V concludes this paper.

II. System Model and Problem Formulation

A. System Model

Consider the DNTs that consist of a PN and its mapping DNT generated and controlled by a central server, as shown in Fig. 1. The total number of physical devices in the PN is denoted by K. The physical devices such as base stations and sensors need to transmit status data to the central server, which utilizes the obtained data to generate DNT. We consider a long time period T and the time can be divided into N time slots. The duration of each time can be calculated as $T_0 = \frac{T}{N}$.

The channel gain between physical device k and the server at time slot n is denoted by h_{nk}. At time slot n, the physical device k in PN will generate data D_{nk}. To guarantee synchronization between the PN and the DNT, the physical device k can choose to transmit data d_{nk}

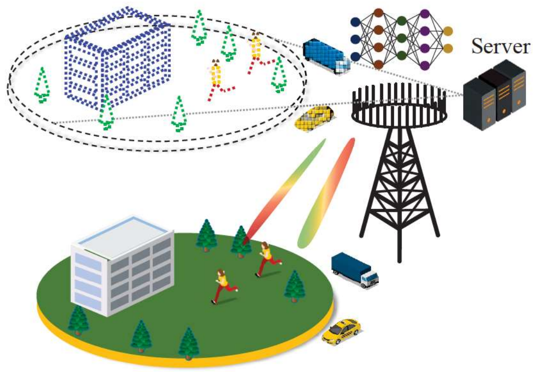

Fig. 1. The considered system model of DNTs.

to the server. The transmission rate between the physical device k and the server is given by

$$r_{nk} = B \log_2 \left(1 + \frac{p_{nk} h_{nk}}{\sigma^2}\right), \tag{1}$$

where B is the bandwidth of the system, p_{nk} is the transmit power of the physical device k at time slot n, and σ^2 is the noise power. Considering the randomness of the wireless channel, the received data at the server can contain error. The error rate of the transmission at time slot n can be given by [13]

$$e_{nk}(p_{nk}) = 1 - e^{-\frac{m\sigma^2}{p_{nk} h_{nk}}}, \tag{2}$$

with m being a waterfall threshold.

Since the transmitted data cannot be large than that of the remaining data, we have

$$\sum_{i=1}^{n} d_{ik} c_{ik}(p_{ik}) \leq \sum_{i=1}^{n} D_{ik}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{3}$$

where

$$c_{ik}(p_{ik}) = \begin{cases} 1 & \text{with probability } e^{-\frac{m\sigma^2}{p_{ik} h_{ik}}} \\ 0 & \text{with probability } 1 - e^{-\frac{m\sigma^2}{p_{ik} h_{ik}}} \end{cases}, \tag{4}$$

$\mathcal{N} = \{1, \cdots, N\}$, and $\mathcal{K} = \{1, \cdots, K\}$.

In each time slot, let $x_{nk} \in \{0, 1\}$ denote whether physical device k in the PN transmits data to the server. The notation $x_{nk} = 1$ implies that physical device k transmits data to the BS; otherwise we have $x_{nk} = 0$. In this paper, frequency division multiple access (FDMA) is considered for the uplink transmission. Due to limited resource blocks of the communication system, the maximum number of associated users at each time slot is limited, i.e.,

$$\sum_{k=1}^{K} x_{nk} \leq K_0, \quad \forall n \in \mathcal{N}, \tag{5}$$

where K_0 is the maximum number of available resource blocks for the communication system.

At each time slot n, the wireless transmission delay and energy can be derived as

$$t_{nk} = \frac{d_{nk}}{r_{nk}}. \tag{6}$$

Since multiple users can simultaneously communicate with the server, the transmission delay of the PN at time slot n can be given by

$$t_n = \max_{k \in \mathcal{K}} x_{nk} t_{nk}. \tag{7}$$

Moreover, at each time slot n, the wireless transmission energy can be given by

$$e_{nk} = t_{nk} p_{nk}. \tag{8}$$

The accuracy of the DNT requires more data from the PN, while large data can lead to high transmission delay and energy. Thus, it is of importance to investigate the tradeoff between the accuracy and the wireless cost of the PN including delay and energy. The accuracy of each time slot n can be modeled as

$$a_n = f\left(\sum_{i=1}^{n}\sum_{k=1}^{K} d_{ik} c_{ik}(p_{ik}), \sum_{i=1}^{n}\sum_{k=1}^{K} D_{nk}\right), \tag{9}$$

where function $f(x, y) \in [0, 1]$ and $f(x, y)$ increases with x while decreases with y. The function of $f(x, y)$ can be obtained through simulations such as [12]. For example, we can set $f(x, y) = \left(\frac{x}{y}\right)^{\alpha}$, where $\alpha > 0$.

B. Problem Formulation

With the considered system model, our aim is minimize the transmission delay of the system with both accuracy and energy constraints. Mathematically, the optimization problem can be formulated as:

$$\begin{aligned}
\min_{\boldsymbol{x},\boldsymbol{d},\boldsymbol{p}} \quad & \sum_{n=1}^{N} \max_{k \in \mathcal{K}} x_{nk} t_{nk} && (10)\\
\text{s.t.} \quad & a_n \ge A_n, \quad \forall n \in \mathcal{N}, && (10a)\\
& \sum_{n=1}^{N} t_{nk} p_{nk} \le Q_k, \quad \forall k \in \mathcal{K}, && (10b)\\
& \sum_{i=1}^{n} d_{ik} c_{ik}(p_{ik}) \le \sum_{i=1}^{n} D_{ik}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, && (10c)\\
& \sum_{i=n}^{n+\tau} x_{ik} \ge \beta_k \tau, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, && (10d)\\
& \sum_{k=1}^{K} x_{nk} \le K_0, \quad \forall n \in \mathcal{N}, && (10e)\\
& d_{nk} \ge 0, x_{nk} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, && (10f)\\
& 0 \le p_{nk} \le P_k, 0 \le t_{nk} \le T_0, \quad \forall n \in \mathcal{N}, && (10g)
\end{aligned}$$

where$\boldsymbol{x} = [x_{11}, \cdots, x_{1K}, \cdots, x_{NK}]^T$, $\boldsymbol{d} = [d_{11}, \cdots, d_{1K}, \cdots, d_{NK}]^T$, $\boldsymbol{p} = [p_{11}, \cdots, p_{1K}, \cdots, p_{NK}]^T$, Q_k is the maximum energy of physical device k, $\beta_k \in (0, 1]$ is a parameter to ensure that the physical device k and the server should have regular communication, τ is a constant parameter to ensure that the each physical device and the server must have at least one communication in τ time slots, and P_k is the maximum transmit power of physical device k.

Problem (10) is mixed integer optimization problem, which is generally hard to solve due to the following three difficulties. The first difficulty is the complicated accuracy function (9), of which the explicit expression is hard to obtain. The second difficulty lies in the nonconvex objective function (10) and constraints (10a)-(10c). The third difficulty lies in the integer scheduling variable x_{nk}. To solve problem (10), we propose an iterative algorithm in the following section.

III. Algorithm Design

In this section, we present the iterative algorithm to solve problem (10), which alternative solves three subproblems at each iteration., i.e., device scheduling subproblem, power control subproblem, and data offloading subproblem.

A. Device Scheduling Subproblem

With given transmission power and data offloading variables in problem (10), the device scheduling subproblem can be given by

$$\begin{aligned}
\min_{\boldsymbol{x}} \quad & \sum_{n=1}^{N} \max_{k \in \mathcal{K}} x_{nk} t_{nk} && (11)\\
\text{s.t.} \quad & \sum_{i=n}^{n+\tau} x_{ik} \ge \beta_k \tau, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, && (11a)\\
& \sum_{k=1}^{K} x_{nk} \le K_0, \quad \forall n \in \mathcal{N}, && (11b)\\
& x_{nk} \in \{0, 1\}, \quad \forall n \in \mathcal{N}. && (11c)
\end{aligned}$$

Problem (11) is a linear integer optimization problem. Relaxing the integer constraints and introducing slack variables y, Problem (11) becomes,

$$\begin{aligned}
\min_{\boldsymbol{x},\boldsymbol{y}} \quad & \sum_{n=1}^{N} y_n && (12)\\
\text{s.t.} \quad & \sum_{i=n}^{n+\tau} x_{ik} \ge \beta_k \tau, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, && (12a)\\
& \sum_{k=1}^{K} x_{nk} \le K_0, \quad \forall n \in \mathcal{N}, && (12b)\\
& y_n \ge x_{nk} t_{nk}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, && (12c)\\
& x_{nk} \in \{0, 1\} \quad \forall n \in \mathcal{N}, && (12d)
\end{aligned}$$

where $\boldsymbol{y} = [y_1, \cdots, y_N]^T$. Problem (12) is a linear optimization problem, which can be effective solved via the simplex method. Having obtain the continuous value of x_{nk}, we use the rounding method to obtain the integer value of x_{nk}.

B. Power Control Subproblem

With given device scheduling and data offloading variables in problem (10), the power control subproblem can be formulated as

$$\min_{\boldsymbol{p}} \quad \sum_{n=1}^{N} \max_{k\in\mathcal{K}} x_{nk}t_{nk} \tag{13}$$

$$\text{s.t.} \quad a_n \geq A_n, \quad \forall n \in \mathcal{N}, \tag{13a}$$

$$\sum_{n=1}^{N} t_{nk}p_{nk} \leq Q_k, \quad \forall k \in \mathcal{K}, \tag{13b}$$

$$\sum_{i=1}^{n} d_{ik}c_{ik}(p_{ik}) \leq \sum_{i=1}^{n} D_{ik}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{13c}$$

$$0 \leq p_{nk} \leq P_k, 0 \leq t_{nk} \leq T_0, \quad \forall n \in \mathcal{N}. \tag{13d}$$

In order to handle problem (13), we use the expect value of $c_{ik}(p_{ik})$ to represent the value of $c_{ik}(p_{ik})$, i.e., we have

$$c_{ik}(p_{ik}) = e^{-\frac{m\sigma^2}{p_{ik}h_{ik}}}. \tag{14}$$

Without loss of generality, we consider the expression of accuracy function $f(x, y) = \left(\frac{x}{y}\right)^{\alpha}$ with α being the constant to be determined in the simulations in the following analysis. Further substituting the expressions of $t_{nk} = \frac{d_{nk}}{r_{nk}}$ and $r_{nk} = B\log_2\left(1 + \frac{p_{nk}h_{nk}}{\sigma^2}\right)$ as well as introducing slack variables t_{nk} and z_n, problem (13) can be equivalent to

$$\min_{\boldsymbol{p},\boldsymbol{t},\boldsymbol{z}} \quad \sum_{n=1}^{N} z_n \tag{15}$$

$$\text{s.t.} \quad z_n \geq x_{nk}t_{nk}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{15a}$$

$$t_{nk} \geq \frac{d_{nk}}{B\log_2\left(1 + \frac{p_{nk}h_{nk}}{\sigma^2}\right)}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{15b}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{K} d_{ik}e^{-\frac{m\sigma^2}{p_{ik}h_{ik}}} \geq A_n^{1/\alpha}\sum_{i=1}^{n}\sum_{k=1}^{K} D_{nk}, \quad \forall n \in \mathcal{N}, \tag{15c}$$

$$\sum_{n=1}^{N} t_{nk}p_{nk} \leq Q_k, \quad \forall k \in \mathcal{K}, \tag{15d}$$

$$\sum_{i=1}^{n} d_{ik}e^{-\frac{m\sigma^2}{p_{ik}h_{ik}}} \leq \sum_{i=1}^{n} D_{ik}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{15e}$$

$$0 \leq p_{nk} \leq P_k, 0 \leq t_{nk} \leq T_0, \quad \forall n \in \mathcal{N}, \tag{15f}$$

where $\boldsymbol{z} = [z_1, \cdots, z_N]^T$. Problem (15) is nonconvex due to constraints (15b)-(15e). To handle the nonconvexity of (15b) and (15d), we use variable substitution. Introducing a new variable $q_{nk} = t_{nk}p_{nk}$ and replacing p_{nk} with q_{nk}, problem (15) becomes

$$\min_{\boldsymbol{q},\boldsymbol{t},\boldsymbol{z}} \quad \sum_{n=1}^{N} z_n \tag{16}$$

$$\text{s.t.} \quad z_n \geq x_{nk}t_{nk}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{16a}$$

$$t_{nk}B\log_2\left(1 + \frac{q_{nk}h_{nk}}{\sigma^2 t_{nk}}\right) \geq d_{nk}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{16b}$$

$$\sum_{i=1}^{n}\sum_{k=1}^{K} d_{ik}e^{-\frac{m\sigma^2 t_{ik}}{q_{ik}h_{ik}}} \geq A_n^{1/\alpha}\sum_{i=1}^{n}\sum_{k=1}^{K} D_{nk}, \quad \forall n \in \mathcal{N}, \tag{16c}$$

$$\sum_{n=1}^{N} q_{nk} \leq Q_k, \quad \forall k \in \mathcal{K}, \tag{16d}$$

$$\sum_{i=1}^{n} d_{ik}e^{-\frac{m\sigma^2 t_{ik}}{q_{ik}h_{ik}}} \leq \sum_{i=1}^{n} D_{ik}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{16e}$$

$$0 \leq p_{nk} \leq P_k, 0 \leq t_{nk} \leq T_0, \quad \forall n \in \mathcal{N}, \tag{16f}$$

where both constraints (16b) and (16d) are convex now. In order to handle the nonveonvexity of constraints (16c) and (16e), we use the first-order Taylor series to approxiamte $e^{-\frac{m\sigma^2 t_{ik}}{q_{ik}h_{ik}}}$, which can be given by

$$\sum_{i=1}^{n}\sum_{k=1}^{K} d_{ik}e^{-\frac{m\sigma^2 t_{ik}^{(m)}}{q_{ik}^{(m)}h_{ik}}}\Bigg(1 - \frac{m\sigma^2}{q_{ik}^{(m)}h_{ik}}(t_{ik} - t_{ik}^{(m)}) + \frac{m\sigma^2 t_{ik}^{(m)}}{(q_{ik}^{(m)})^2 h_{ik}}(q_{ik} - q_{ik}^{(m)})\Bigg) \geq A_n^{1/\alpha}\sum_{i=1}^{n}\sum_{k=1}^{K} D_{nk} \tag{17}$$

and

$$\sum_{i=1}^{n} d_{ik}e^{-\frac{m\sigma^2 t_{ik}^{(m)}}{q_{ik}^{(m)}h_{ik}}}\Bigg(1 - \frac{m\sigma^2}{q_{ik}^{(m)}h_{ik}}(t_{ik} - t_{ik}^{(m)}) + \frac{m\sigma^2 t_{ik}^{(m)}}{(q_{ik}^{(m)})^2 h_{ik}}(q_{ik} - q_{ik}^{(m)})\Bigg) \leq \sum_{i=1}^{n} D_{ik}, \tag{18}$$

where $q_{ik}^{(m)}$ and $t_{ik}^{(m)}$ are respectively the values of q_{ik} and t_{ik} in the m-th iteration. Through replacing constraints (16c) and (16e) with (17) and (18) respectively, problem (16) becomes a convex problem, which can be solved via the existing toolbox, such as CVX.

C. Data Offloading Subproblem

With given device scheduling and power control variables in problem (10), the data offloading subproblem can

Algorithm 1 : Alternating Algorithm

Initialize a feasible solution $(\boldsymbol{x}^{(0)}, \boldsymbol{d}^{(0)}, \boldsymbol{p}^{(0)}$ of problem (10) and set $l = 0$.
repeat
  With given $(\boldsymbol{d}^{(l)}, \boldsymbol{p}^{(l)})$, obtain the solution $\boldsymbol{x}^{(l+1)}$ of problem (11).
  With given $(\boldsymbol{x}^{(l+1)}, \boldsymbol{d}^{(l)})$, obtain the solution $\boldsymbol{p}^{(l+1)}$ of problem (13).
  With given $(\boldsymbol{x}^{(l+1)}, \boldsymbol{p}^{(l+1)})$, obtain the solution $\boldsymbol{d}^{(l+1)}$ of problem (19).
  Set $l = l + 1$.
until objective value (10) converges

be rewritten as

$$\min_{\boldsymbol{d}} \quad \sum_{n=1}^{N} \max_{k\in\mathcal{K}} x_{nk} t_{nk} \tag{19}$$

$$\text{s.t.} \quad a_n \geq A_n, \quad \forall n \in \mathcal{N}, \tag{19a}$$

$$\sum_{n=1}^{N} t_{nk} p_{nk} \leq Q_k, \quad \forall k \in \mathcal{K}, \tag{19b}$$

$$\sum_{i=1}^{n} d_{ik} c_{ik}(p_{ik}) \leq \sum_{i=1}^{n} D_{ik}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{19c}$$

$$d_{nk} \geq 0, \quad \forall n \in \mathcal{N}, \tag{19d}$$

$$0 \leq t_{nk} \leq T_0, n \in \mathcal{N}. \tag{19e}$$

Substituting (6) and (9) into problem (19) yields

$$\min_{\boldsymbol{d}} \quad \sum_{n=1}^{N} \max_{k\in\mathcal{K}} \frac{x_{nk} d_{nk}}{r_n k} \tag{20}$$

$$\text{s.t.} \quad \sum_{i=1}^{n}\sum_{k=1}^{K} d_{ik} e^{-\frac{m\sigma^2}{p_{ik} h_{ik}}} \geq A_n^{1/\alpha} \sum_{i=1}^{n}\sum_{k=1}^{K} D_{nk}, \quad \forall n \in \mathcal{N}, \tag{20a}$$

$$\sum_{n=1}^{N} \frac{p_{nk} d_{nk}}{r_n k} \leq Q_k, \quad \forall k \in \mathcal{K}, \tag{20b}$$

$$\sum_{i=1}^{n} d_{ik} c_{ik}(p_{ik}) \leq \sum_{i=1}^{n} D_{ik}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \tag{20c}$$

$$d_{nk} \geq 0, \quad \forall n \in \mathcal{N}, \tag{20d}$$

$$0 \leq t_{nk} \leq T_0, \quad n \in \mathcal{N}, \tag{20e}$$

which is a linear programming problem and can be effectively solved by using the simplex method.

D. Algorithm Analysis

Through alternatively solving subproblem (11), (13), and (19), the overall procedure to obtain a solution of problem (10) can be shown in Algorithm 1. Since the objective value (10) is nonincreasing and the objective value (10) has a limited lower bound (i.e., zero), Algorithm 1 always converges.

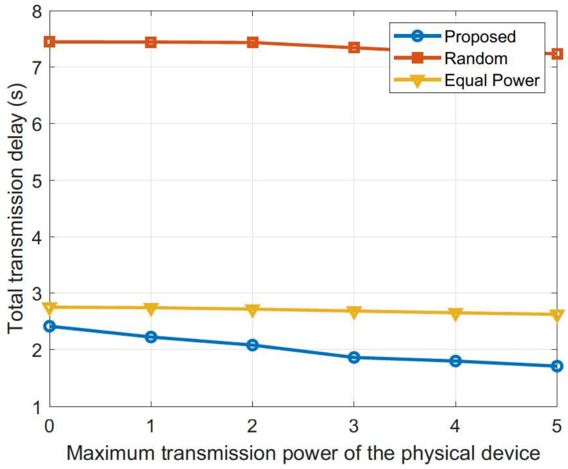

Fig. 2. The transmission delay versus the maximum transmit power of each physical device.

IV. Simulation Results

In this section, we provide the simulation results of the proposed algorithm. We consider a PN with K physical devices uniformly distributed in a square area with size 200m × 200m. The path loss model is $128.1 + 37.6 \log_{10} d$ (d is in km) and the standard deviation of shadow fading is 8 dB [14]. The bandwidth is $B = 1MHz$ and the noise power spectral density is $N_0 = -174$ dBm/Hz. Unless otherwise specified, we set the number of physical devices $K = 10$, the total number of time slots $N = 10$, equal accuracy requirement $A_1 = \cdots = A_n = 0.6$, equal arriving data $D_{11} = \cdots = D_{NK} = 300$ kbits, parameter $\tau = 3$, $K_0 = 5$, equal constant $\beta_1 = \cdots = \beta_K = 1/3$, and equal maximum transmit power $P_1 = \cdots = P_K = 1$dBm.

To show the effectiveness of the proposed algorithm, we consider the following two baselines: the random device selection algorithm (labeled as 'Random'), where the power control and data offloading are optimized by using the proposed algorithm, and the equal power allocation algorithm (labeled as 'Equal Power'), where the device selection and data offloading are solved by using the proposed algorithm.

Fig. 2 shows the transmission delay versus the maximum transmit power of each physical device. According to this figure, it is observed that the proposed algorithm always achieve the best performance among all algorithms. Compare to random device scheduling algorithm, the other two algorithms can great reduce the transmission delay, which indicates the superiority of device scheduling optimization. Compared to equal power allocation algorithm, the proposed algorithm can decrease the transmission delay by up to 51.2% especially when the maximum transmission power is high. The reason is that the proposed algorithm can dynamically allocate different power for each user based on the wireless channel gains to increase the overall transmission rate, thus leading to low transmission delay.

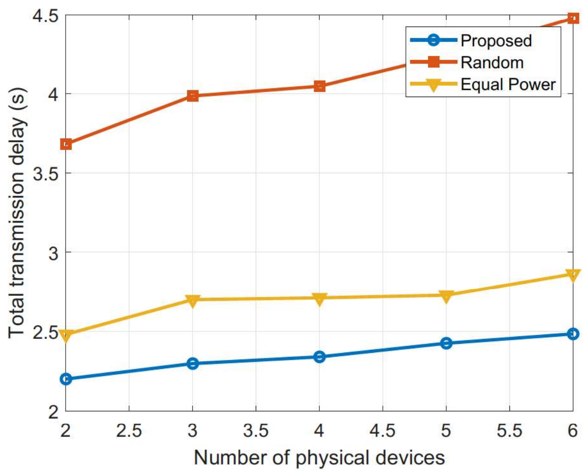

Fig. 3. The transmission delay versus the number of physical devices.

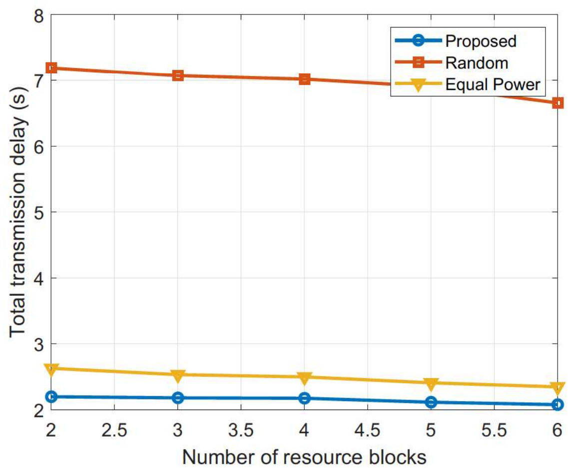

Fig. 4. The transmission delay versus the number of resource blocks.

The trend of transmission delay verses the number of physical devices is presented in Fig. 3. It is found that all algorithm increases with the number of physical devices. This is because more physical devices means more data to offload, which can cause high transmission delay. In this figure, we also can observe that both the proposed algorithm and equal power allocation algorithm can greatly reduce the transmission delay compared the random device scheduling algorithm.

Fig. 4 illustrates the delay performance changes as the number of resource blocks. From this figure, the transmission delay of all algorithms decreases with the number of resource blocks. This is because more resource blocks ensure more devices to upload the data at each time slot, which can decrease the overall transmission time slots and result in low transmission delay. It is shown in Fig. 4 that the proposed algorithm is superior over the equal power allocation algorithm especially for small number of resource blocks.

V. Conclusions

In this paper, we have investigated the delay performance of DT over wireless networks. We have formualted a joint communication and computation problem so as to minimize the total transmission delay of the network with considering both transmission energy and computation accuracy constraints. To solve this problem, we have proposed an alternating algorithm with solving three subproblems iteratively. Numerical results have illustrated that the superiority of the proposed algorithm compared to the conventional schemes in terms of transmission delay, especially for large maximum transmit power and small resource blocks.

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