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Distributed Wireless Video Scheduling with Delayed Control Information

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***Abstract*— Traditional distributed wireless video scheduling is based on perfect control channels where instantaneous control information from the neighbors is available. However, it is difficult, sometimes even impossible, to obtain this information in practice especially for dynamic wireless networks. Thus, neither the distortion-minimum scheduling approaches aiming to meet the long term video quality demands nor the solutions that focus on minimum delay can be applied directly. This motivates us to investigate the distributed wireless video scheduling with delayed control information (DCI). First, to exploit in a tractable framework, we translate this scheduling problem into a stochastic optimization rather than a convex optimization problem. Next, we consider two classes of DCI distributions: i) the class with finite mean and variance, and ii) a general class that does not employ any parametric representation. In each case, we study the relationship between the DCI and scheduling performance, and provide a general performance property bound for any distributed scheduling. Subsequently, a class of distributed scheduling scheme is proposed to achieve the performance bound by making use of the correlation among the time-scale control information. Finally, we provide simulation results to demonstrate the correctness of the theoretical analysis and the efficiency of the proposed scheme.**

***Index Terms*— Video communications, wireless networks, distributed scheduling, delayed control information.**

I. Introduction

A. Motivation and Objective

WITH the proliferation of wireless networks, we have witnessed increasing demand of various wireless video applications over the recent years. To provide a satisfactory Quality-of-Service (QoS), various video scheduling schemes have been developed in the past decade [1]–[8]. Most existing works assume that perfect control channels are available, *i.e.*, each network node can obtain instantaneous control information from its neighbors. However, it is well known that obtaining instantaneous control information not only incurs significant communication overhead, but also is extremely difficult in dynamic wireless networks [2].

To address this problem, we propose a novel wireless video scheduling scheme based on delayed control information (DCI). In particular, we try to further understand how the DCI effects the performance of wireless video transmission. We aim to provide a unified theoretical analysis of the performance properties, *i.e.*, performance loss and asymptotic convergence rate in the context of DCI, and to design a distributed video scheduling scheme to realize the theoretical analysis. In addition, the scheduling scheme should be simple enough for online operation. Specifically, we investigate i) how video streams can be scheduled efficiently in the context of DCI? ii) Under what conditions it is possible to reduce the performance loss and enhance the convergence rate as much as possible regardless of the DCI? iii) Also, can we design a distributed scheduling scheme to alleviate the negative impact of DCI? These questions will be explicitly addressed in this work.

B. Related Work

To the best of our knowledge, distributed video scheduling with DCI has not been studied in the multimedia communications literature. The most related work, the general problem with partial or delayed information, has been studied in area of information theory. Notably, the seminal work in [9] considered delayed queue information and its impact on the stability of a back-pressure algorithm. Subsequently, the distributed uplink scheduling algorithms were developed in [10], [11] based on the local network state information of each node, and [12], [13] extended them to the downlink scheduling where the base station can only access the part of users' network state information. Interestingly, it was shown by [14] that partial channel state information (CSI) maybe helpful to improve the achievable rate of wireless networks with multiple flows allowing for the time correlation of the CSI. Similarly, an analytical framework was developed in [15] to study the impacts of network dynamics on the perceived video quality. Moreover, Stanczak *et al.* [16], [17] took into account of the cost of network state test. Simply speaking, one first spends appropriate resource on testing the network state, then optimizes QoS accordingly. Essentially, these works belong to a class of literature that studies the scaling law of the delay in wireless networks ([18], [19] and references therein). Specifically, in [20], Kar *et al.* considered a base-station with a collection of users, and discussed the scheduling problem when the channel states are known periodically. [21] focused on decentralized scheduling scheme with homogenous network information, and showed that the throughput region shrinks with the increase of delay. Furthermore, in [22], constrained control channels were considered in the framework of distributed video scheduling, nevertheless, DCI was not involved.

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Due to the existing of DCI, each node may have different perspectives of network state. As a result, video scheduling can not be formulated as a convex optimization problem. Instead, we translate it into a stochastic optimization problem that opens up a new degree of performance to exploit. Importantly, we extend existing video scheduling scheme in two critical aspects. Firstly, we formulate the distributed wireless video scheduling problem based on real observed DCI. In particular, we study the case of a general network with heterogeneous DCI. Secondly, we design a weight-based distributed video scheduling scheme by taking advantage of the correlation of DCI. Specifically, we analyze the tradeoff between the DCI accuracy and communication overhead in a precisely mathematical manner, and provide the tight performance bounds for the proposed scheduling.

C. Main Contributions

Theoretical part. To establish the scheduling performance in terms of DCI, we present an appropriate Lyapunov function based on observed DCI. This, along with an appropriate scheduling rule, leads to the positive Harris recurrence property of the network Markov process. This is the most challenging part of this work since it needs to prove an effective *time scale separation* between the network state dynamics and scheduling decision dynamics. To make this possible, we design an increase function of queue-size to capture the correlation of the DCI.

Technical part. We propose a distributed video scheduling scheme in terms of DCI. Specifically, it only utilizes local, queue-length information to make scheduling decisions, and it only requires each node to perform a few logical operations at each scheduling decision. Basically, the proposed scheduling design is motivated by a certain product-form distribution that can be characterized as the stationary distribution of a simple and distributed Markovian dynamics over the scheduling space.

The structure of this paper is as follows. Section II describes the system model considered in this work. In Section III, we summarize our main results on the performance loss due to the DCI and achievable asymptotical convergence rate. Rigorous proofs are presented in Sections IV. Subsequently, Section V conducts simulations to validate the theoretical analysis. Section VI concludes the paper with a summary.

II. System Model

In this work, we consider a generic wireless network $\mathcal{G} = \{\mathcal{N}, \mathcal{E}, \mathcal{A}\}$, where $\mathcal{N} = \{1, \cdots, N\}$ denotes network nodes, $(i,j) \in \mathcal{E}$ ($\mathcal{E}$ is the link set) represents a link from node j to node i ($i,j \in \mathcal{N}$), and $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N\times N}$ is a weighted adjacency matrix of $\mathcal{G}$. Network connection Υ is formally defined as the Laplacian matrix of $\mathcal{G}$, that is $\Upsilon = \|\mathcal{D} - \mathcal{A}\|_2$, where $\mathcal{D} = diag(deg_1, \cdots, deg_N)$ and $deg_i = \sum_{j=1}^{N} a_{ij}$.

Moreover, $\mathcal{S} = \{1, \cdots, S\}$ and $\mathcal{Z} = \{1, \cdots, Z\}$ denote the sources and video flows, respectively. Similar to [3], [8], video flows are classified into K classes (*i.e.*, $C_1, \cdots, C_K$), and each class C_k ($k \in [1,K]$) is denoted by (τ_k, R_k, λ_k). Specifically, τ_k represents the transmission deadline of C_k; R_k shows the average source rate of each flow in C_k; λ_k denotes the quality impact factor of C_k. Let N_{sk} denote the number of flows in class C_k streaming from s ($s \in \mathcal{S}$), $T_{(i,j),k}$ be the maximum transmission rate supported by the modulation and coding scheme. Hence, the effective transmission rate for a flow z over a link (i,j) is given by $T_{(i,j),k}t_{(i,j),z}$, where $t_{(i,j),z}$ represents the time sharing fraction for z to transmit over link (i,j).

The packet number of video class C_k in the node i's queue at time t is denoted by $x_{i,k}(t)$, in this case, the *weighted queue length* of node i at time t, $X_i(t)$, can be expressed by[1]

$$X_i(t) = \sum_{k=1}^{K} \frac{\lambda_k R_k}{\tau_k} x_{i,k}(t). \tag{1}$$

In general, $X_i(t)$ is a random variable which can be described as a finite-state Markov chain [1], [23], that is,

$$\mathbb{P}\left(X_i\left(t\right)|X_i\left(t-1\right), ..., X_i\left(0\right)\right) = \mathbb{P}\left(X_i\left(t\right)|X_i\left(t-1\right)\right). \tag{2}$$

In addition, define $\mathcal{X} = [X_1, \cdots, X_N]$ as the scheduling set. Thus, the end-to-end delay for transmitting flow $z \in \mathcal{Z}$ based on $\mathcal{X}$, called $E_z(\mathcal{X})$, can be calculated by

$$E_z(\mathcal{X}) = \sum_{(i,j), t_{(i,j),z}>0} \frac{l_k}{t_{(i,j),z} T_{(i,j),k}}, \text{ for } z \in C_k, \tag{3}$$

where l_k is the average packet length of C_k. Therefore, the received video quality Q_s from $s \in \mathcal{S}$ is given by

$$Q_s(\mathcal{X}) = \sum_{C_k} \sum_{z=1}^{N_{sk}} \lambda_k R_k I\Big\{E_z(\mathcal{X}) \le \tau_k\Big\}, \tag{4}$$

where $I(\cdot)$ is the indicator function [4]. Therefore, a general wireless video scheduling can be formulated as

$$\begin{aligned} &\arg\max_{\mathcal{X}} \left\{ Q(\mathcal{X}) = \sum_{s=1}^{S} Q_s(\mathcal{X}) \right\}, \\ &\textit{s.t.} \quad \sum_{z=1}^{Z} t_{(i,j),z} \le 1, \ \forall (i,j), \\ &E_z(\mathcal{X}) \le \tau_k, \ \forall \ z \in C_k, z = 1, \cdots, Z. \end{aligned} \tag{5}$$

To solve (5) in a distributed fashion, each node should make the scheduling decision based on its neighbors' information of weighted queue length which is obtained via the control channels.

In this work, we consider a practical scenario where each node can only obtain DCI. The main challenge is to design an implementable and robust scheduling strategy based on the inconsistent, sometimes even conflicting, control information. Obviously, it is a notably difficult scheduling problem since the traditional convex optimization can not be applied directly. To reduce the impact of DCI over a period of time scale, we translate the problem into a stochastic optimization by opening up a new degree of performance to exploit. Specifically, we introduce the *loss function* $L(D)$, to measure the video quality

[1] Note that (1) does not preclude any other definition if only it has a rational physical meaning which is usually related to the system function.

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deterioration due to the DCI D. Formally,

$$L(D)=\mathbb{E}\left[\frac{Q(\mathcal{X}_p)-Q(\mathcal{X}_d)}{Q(\mathcal{X}_p)}\right], \tag{6}$$

where $\mathcal{X}_p$ and $\mathcal{X}_d$ denote the scheduling with instantaneous control information and DCI, respectively. In what follows, we mainly concentrate on designing an efficient scheduling scheme to minimize $L(D)$ over a period of time scale.

III. Main Results

In this work, we consider a general wireless network with unknown D ($D \geq 0$). The main results are formally stated in this section, and the rigorous proofs are provided in Section IV.

A. Performance Properties

At first, we restrict ourselves to the performance properties of a class of D with finite mean and variance. The results are summarized in the following theorems.

Theorem 1 *For a general wireless network with N nodes and Υ network connection, assume a class of unknown D with finite mean μ ($\mu \geq 0$) and variance σ^2 ($\sigma^2 \geq 0$). For any distributed video scheduling without knowing D, the loss function $L(D)$ satisfies*

$$L(D)\geq 1-\Theta\left(N^{\frac{-\mu}{2N\cdot(\sigma^2+1)\cdot\Upsilon}}\right). \tag{7}$$

Theorem 1 indicates that, for any end-to-end transmission delay, the performance loss is related to information correlation (*i.e.*, μ and σ^2). Importantly, this theorem establishes a fundamental performance bound for any distributed video scheduling scheme. From the system's perspective, this theorem exhibits the benefits of the large-scale wireless network since large N yields low performance loss. Moreover, this theorem implies that, given μ and σ^2, the network connection is advantageous to the performance loss. As will be apparent in Section IV, the negative impact of the DCI can be alleviated via the information exchange from more neighbors.

Additionally, since the video transmission is usually delay-sensitive, the convergence rate is also a primary metric for the distributed scheduling scheme. In this work, we employ the concept of the *asymptotical convergence rate* (ACR) γ as [22, Definition 2],

$$\gamma=\sup_{\mathcal{X}(0)\neq J_N\mathcal{X}(0)}\lim_{t\to\infty}\left(\frac{\|\mathcal{X}(t)-J_N\mathcal{X}(0)\|_2}{\|\mathcal{X}(0)-J_N\mathcal{X}(0)\|_2}\right)^{1/t},$$

where $J_N=\mathbf{1}\mathbf{1}^*/N$ (star $*$ represents transposition).

Theorem 2 *Under the same conditions of Theorem 1, the asymptotical convergence rate γ for any distributed video scheduling satisfies*

$$\gamma\leq O\left(\exp\left(-\frac{\sqrt{N}t}{\Upsilon}\right)\right). \tag{8}$$

In particular, the upper bound can be achieved by a class of D whose cumulative distribution function (CDF) $Z(\cdot)$ satisfies

$$Z(x)\sim\left(\frac{x-\mu}{\sigma\sqrt{N-1}}\frac{\sqrt{N}-1}{\sqrt{N}}+\frac{1}{\sqrt{N}}\right)^{1/\sqrt{N}-1}, \tag{9}$$

where $\mu-\frac{\sqrt{N-1}}{\sqrt{N}-1}\sigma\leq x\leq\mu+\frac{\sqrt{N-1}}{\sqrt{N}-1}\sigma$.

Theorem 2 establishes a fundamental ACR bound for various distributed scheduling schemes without knowing D. Interestingly, the upper bound of ACR is the same with that of the distortion-minimum distributed scheduling (DMDS) introduced in [8], in the sense that (8) does not depend on μ and σ^2 either. Theorem 2 also implies its significance: i) the attainable upper bound (8) identifies that the DCI does not always affect the convergence rate, and ii) the upper bound of ACR heavily depends on the network connection. Together with Theorem 1, we observe that network connection is indeed an important design element.

Next, we relax the restriction of D, which does not adopt any parametric representation.

Theorem 3 *For a general wireless network with N nodes and Υ network connection, let the average value of D, μ, satisfy $u\leq\mu\leq U$ ($0\leq u\leq U\leq\sqrt{N}$). Then, the loss function $L(D)$ satisfies*

$$L(D)\geq 1-\Theta\left(N^{\frac{-(U-u)}{(2N-U-u)\cdot\Upsilon}}\right), \tag{10}$$

and the corresponding ACR also satisfies (8). In particular, this optimal bound can be achieved by a class of D whose probability distribution function (PDF) $z(\cdot)$ satisfies

$$z(x)\sim\frac{\Gamma\left(\frac{\beta+1}{2}\right)}{\sqrt{\beta\pi}\Gamma\left(\frac{\beta}{2}\right)}\left(1+\frac{x^2}{\beta}\right)^{-\frac{\beta+1}{2}}, \tag{11}$$

where $\beta\in(0,1)$ and $\Gamma(\cdot)$ is the gamma function.

As an illustration of Theorem-3's application, we can show that [1] can be included in this framework, and consequently the performance of [1] follows in a straightforward fashion from this theorem. It is worth pointing out that the CDF provided in (9) and PDF presented in (11) just provide examples of achieving the optimal bounds of ACR; however, they do not exclude other CDFs and PDFs attaining the same bounds.

B. Distributed Video Scheduling Scheme

Subsequently, we design a class of the distributed video scheduling scheme reaching the performance bound given in the above theorems. As stated previously, traditional DMDS is not applicable for DCI. However, it has a desirable property by exploiting the correlation among the heterogeneous video flows. A natural question arises: can we also take advantage of the correlation between the observed control information to alleviate the negative impact of DCI? In this part, we provide a positive answer.

For ease of illustration, we first consider a simple wireless video transmission network shown in Fig. 1(a). Specifically,

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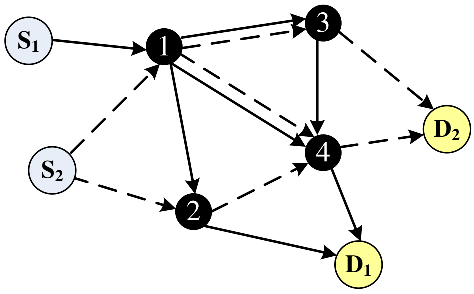
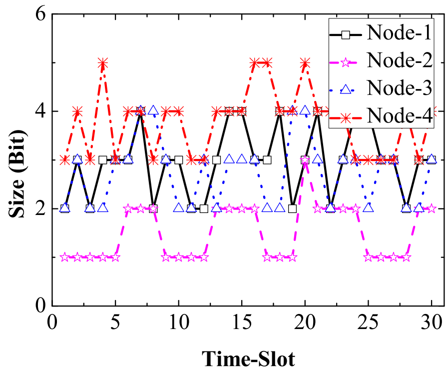


(a) Network topology



(b) Size of the Control Information

Fig. 1. An example of control information exchange. Source S_1 transmits *City* to destination D_1, and source S_2 streams *Mother* to destination D_2.

$$X_i\left(t+1\right)=\begin{cases}\frac{\left|X_i(t)-X_i(t-1)\right|N_i(t)}{\sum_{j=1}^{N_i(t)}\left|X_j(t)-X_j(t-1)\right|}X_i\left(t\right), \; with\ probablity \; \frac{\exp(W_i(t))}{1+\exp(W_i(t))}\\ \frac{\sum_{j=1}^{N_i(t)}\left|X_j(t)-X_j(t-1)\right|}{\left|X_i(t)-X_i(t-1)\right|N_i(t)}X_i\left(t\right), \; with\ probablity \; \frac{1}{1+\exp(W_i(t))}\end{cases} \tag{12}$$

TABLE I

DIFFERENT FUNCTION EXPRESSIONS WITH RESPECT TO DIFFERENT DCI.

Function	$D \sim N\left(\mu,\sigma^2\right)$	$D \in [u,U]$
$W_i\left(t\right)$	$\min\left\{f\left(\sum_{j,k}\frac{T_{(i,j),k}X_i(t)}{KX_j(t)}\right), \sqrt{f\left(\frac{\max_{j,k}T_{(i,j),k}X_i(t)}{X_j(t)}\right)}\right\}$	$\max\left\{f\left(\sum_{j,k}\frac{T_{(i,j),k}X_i(t)}{KX_j(t)}\right), \sqrt{f\left(\frac{\max_{j,k}T_{(i,j),k}X_i(t)}{X_j(t)}\right)}\right\}$
$f\left(x\right)$	$f\left(0\right)=0,\ \lim_{x\to\infty}f\left(x\right)\to\infty,$ $\lim_{x\to\infty}\exp\left(f\left(x\right)\right)f'\left(f^{-1}\left(f\left(x\right)\right)\right)\to 0$	$f\left(0\right)>0,\ \lim_{x\to\infty}f\left(x\right)\to 0,$ $\lim_{x\to\infty}\exp\left(f\left(x\right)\right)f'\left(f^{-1}\left(f\left(x\right)\right)\right)\to\infty$

the network and video parameters are the same as the [22, Fig. 3(a)]. Fig. 1(b) plots the received control information of each node[2]. From the given results, we observe that the average correlation degree of each node is nontrivial. Hence, we can expect that there exists control information correlation, and in this case we do not always need the instant control information. This motivates us, at least in theory, to extend DMDS to the case of DCI. To this end, video scheduling and control information estimation should be *jointly implemented* in this work, while ensuring that the end-to-end transmission delay constraint is satisfied. Due to the correlation among the DCI, the real control information can be predicted over an appropriate time-scale period, which is called *delay-weight* (DW) in this work like the maximum-weight scheduling scheme in [24]. Obviously, how to design DW is the key point of this work.

The sketch of the proposed distributed video scheduling is listed in Table II. In particular, $W_i\left(t\right)$ in (12) denotes the node i's DW at time slot t. Essentially, the above operation translates the distributed video scheduling into a Markov-based stochastic optimization problem (recall that $X_i(t)$ is described as a finite-state Markov chain in (2)), and its underlying logic is that the DCI can be utilized, due to its correlation, to realize the distributed video scheduling. Consequently, the core point is to properly set DW $W_i\left(t\right)$ to improve the estimation accuracy of the control information as much as possible. Intuitively, $W_i\left(t\right)$ depends on not only the received control information from the neighbors, but also the effective transmission rate for a flow over a specific link.

From the perspective of the DW's function, there is an inherent tension between the DCI estimation and communication overhead for determining $W_i\left(t\right)$. Specifically, the longer one spends DCI estimation, the more communication overhead yielding additional end-to-end delay. On the other hand, less time spent on DCI estimation decreases the estimation accuracy that is not conductive to the scheduling. By applying stochastic optimization method to analyze the impact of DCI on video quality, for different scenarios we explicitly derive the expressions of $W_i\left(t\right)$, which are listed in Table I. Using these results, the distributed video scheduling scheme requires each node to perform only a few logical operations at each time step, irrespective of the value of DCI.

[2]Note that the quantitative value is calculated by the standard correlation function [27], and DMDS is employed assuming that the control information is instantaneously available.

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IV. Performance Analysis

In this section, we investigate the theoretical analysis for the performance property in terms of DCI.

A. Performance Loss

The proof is structured as follows. We first focus on establishing a positive Harris recurrence of $\mathcal{X}(t)$ in which all the distributions of $X_i(t)$ are heterogeneous [21]. Specifically, the worst case distribution corresponds to the least correlation of DCI, that is, we can utilize the Lyapunov drift criteria, which can be viewed as the time scale separation, to establish the positive recurrence property of an appropriate scheduling set. Then, we use a split operation to reduce any given instance of our problem to a nice instance such that the positive recurrence property can precisely approximate the correlation between DCI. This will show that distributed Markovian dynamics is useful to estimate the bounds of performance properties with unknown DCI, thus concluding the proof of the theorems.

In terms of unknown DCI, the Glauber dynamics on DW $\mathcal{W}(t) = [W_1, ..., W_N]$, denoted by $\psi(\mathcal{W}(t))$, is a Markov chain on the space of independent scheduling sets [27], [28]. Let $\pi(t)$ be the stationary distribution of the Markov chain $\psi(\mathcal{W}(t))$; $\rho(t)$ be the distribution of the schedule, $\mathcal{X}(t)$, under our scheme at time t. The following Lemma states that $\pi(0)$ is as good as that of the maximum weight scheduling with respect to the weight $f(\mathcal{X}(0))$ where the expressions of the function $f(\cdot)$ are listed at the third line of Table I.

Lemma 1 *Let $W_{avg}(0)$ be the average distribution for $\mathcal{W}(0)$ given $\pi(0)$ and $\mathcal{X}(0)$. Then,*

$$\mathbb{E}\left[f(\mathcal{X}(0)) \cdot W_{avg}(0)\right] \geq \frac{W_{avg}(0)}{\pi(0)} \max_i f(X_i(0) \cdot W_i(0)). \tag{13}$$

Proof: The proof is based on the definition of $\psi(\mathcal{W}(t))$.

TABLE II
DISTRIBUTED VIDEO SCHEDULING

01: **Input:**
02: At time slot t, node i has $N_i(t)$ neighbors;
03: Node j is a neighbor of node i;
04: $X_i(t)$, $X_j(t)$, $X_i(t-1)$, $X_j(t-1)$;
05: **Output:**
06: $X_i(t+1)$;
07: **Procedure Scheduling**
08: **if** $\left(\frac{\sum_{j=1}^{N_i(t)} |X_j(t)-X_j(t-1)|}{N_i(t)} \leq |X_i(t) - X_i(t-1)|\right)$
09: $X_i(t+1) = X_i(t)$;
10: **else**
11: Set $X_i(t+1)$ as (12);
12: **endif**

First, we study the format of the stationary distribution $\pi(t)$

$$\begin{aligned}\pi(t) &\propto \prod_i \frac{\exp(W_i(t) X_i(t))}{\log(W_i(t) X_i(t))} \\ &\propto \exp\left(\sum_i \log(W_i(t) X_i(t))\right).\end{aligned}$$

To simplify the right hand side of the above equation, we set

$$F(\mathcal{X}) = \sum_i F_i(\mathcal{X}) = \sum_i \log(W_i(t) X_i(t)). \tag{14}$$

Moreover, since $W_i(t) X_i(t)$ can not randomly take the values all i, we can get the following inequality:

$$0 \leq \sum_i \log(W_i(t) X_i(t)) \leq O\left(\frac{W_{avg}(0)}{\pi(0)}\right).$$

As a result, we can provide the upper bound of $F(\mathcal{X})$

$$\exp(F(\mathcal{X})) \leq F(\mathcal{X}) + O\left(\frac{W_{avg}(0)}{\pi(0)}\right).$$

Set $\overline{X} = \arg\max_{\mathcal{X}} \sum_i \log(W_i(t) X_i(t))$, we have

$$\begin{aligned}\mathbb{E}\left[\sum_i W_i(t) X_i(t)\right] &\geq \max_{\mathcal{X}} F(\mathcal{X}) - \sum_i \log(W_i(t) X_i(t)) \\ &\geq F(\overline{X}) - \sum_i \log(W_i(t) X_i(t)) \\ &\geq \frac{W_{avg}(0)}{\pi(0)} \sum_i \log(W_i(t) X_i(t)).\end{aligned}$$

We use $\delta = \max_i \frac{\log X_i}{\|X_i\|}$ to act as the *adjust factor*. To obtain an appropriate value of $\mathbb{E}[f(\mathcal{X}(0)) \cdot W_{avg}(0)]$, we consider $\max_i(W_i(t) X_i(t))$ such that it is large enough for all t satisfying

$$\delta f\left(\max_i(W_i(t) X_i(t))\right) \geq \sqrt{f\left(\max_i(W_i(t) X_i(t))\right)}.$$

When $\max_i(W_i(t) X_i(t))$ is small, it is not necessary to argue since in that case (13) is straightforward. Therefore, in the remainder we assume that $\max_i(W_i(t) X_i(t))$ is large enough. In this case, it follows that for all i,

$$\begin{aligned}W_i - f(X_i) &\leq \sqrt{f\left(\max_i(W_i(t) X_i(t))\right)} \\ &\leq \delta f\left(\max_i(W_i(t) X_i(t))\right).\end{aligned} \tag{15}$$

As a result, for any i, it follows that

$$\begin{aligned}\delta f(W_i(t) X_i(t)) &\leq \|X_i\|_1 \|W_i - f(X_i)\|_\infty \\ &\overset{(a)}{\leq} \|X_i\|_1 \delta f\left(\max_i(W_i(t) X_i(t))\right) \\ &\overset{(b)}{\leq} \max_i(f(W_i(t) X_i(t)) \cdot X_i).\end{aligned} \tag{16}$$

In above, (a) follows from the definition of δ, and for (b), we use the fact that a valid scheduling is stable [26]. And, for $i = \arg\max_i X_i$, it has weight $f(\max_i X_i)$. Therefore, the weight of the maximum weighted scheduling among all

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possible schedules is at least $f(\max_i X_i)$. Finally, using (15) and (16), we can complete the proof of Lemma 1. ■

Remark 1 *The above result demonstrates an outcome of the symmetry of the marginal of $\mathcal{W}(0)$ and the uniform bound holds irrespective of the value of $f(X_i(0) \cdot W_i(0))$. Of course, one may expect that, if $\mathcal{X}(0)$ is small, a tighter bound is available. In fact, [27, Theorem 3.1] shows that the bound we derive is also a tight constraint for Markov-based optimization problem. In addition, Lemma 1 also implies that the time scale separation between the network state dynamic and scheduling decision dynamic can be described by $\mathbb{E}[f(\mathcal{X}(0)) \cdot W_{avg}(0)]$, which also acts as the bridge between $\mathcal{W}$ and $\mathcal{X}$.*

Let $\rho(t)$ be the distribution of scheduling $\mathcal{X}(t)$ at time t. We wish to show that for any initial condition $\mathcal{X}(0)$, when t satisfies some condition, $\pi(0)$ can be used to approximate $\rho(t)$. In such case, the characteristics of optimal distributed scheduling can be clearly described.

Lemma 2 *When time t satisfies*

$$t \geq min\left(f_1\left(\max_i X_i(0)\right), f_2\left(\max_i X_i(0)\right)\right),$$

where f_1, f_2 are functions such that

$$f_1 \cdot f_2 \rightarrow \Theta\left(\max_i X_i(0) W_i(0)\right),$$

and

$$f_2/f_1 \rightarrow \Theta\left(\sqrt{\max_i X_i(0) W_{avg}(0)}\right).$$

If an optimal distributed scheduling, which can precisely estimate the DCI, is employed, it should satisfy

$$\|\rho(t) - \pi(0)\|_\infty \rightarrow 0.$$

Proof: See Appendix. ■

Remark 2 *It is interesting to note how the distribution of scheduling $\mathcal{X}(t)$ departs from general wireless network models: Firstly, the arrival rate of video streaming is stochastic, and the distributed scheduling given this rate is not a random parameter due to the delay constraints of the video streams. Secondly, we maximize video quality associated with delay constraints instead of maximizing the network throughput associated with backlog. Therefore, the results of Lemma 2 can be applied to a general wireless video system.*

With the results of the above lemmas, the next step is to establish a Lyapunov function to capture the dynamics of the $X_i(t)$ for any i and t, that is

$$L(\mathcal{X}(t)) = \sum\nolimits_i \int_0^{X_i(t)} f(y)\, dy. \qquad (17)$$

As a result, to connect the relationship between $\pi(0)$ and $f(\mathcal{X}(0))$, we should prove the positive Harris recurrence property of $\mathcal{X}(t)$ with respect to the proposed scheduling scheme. To this end, we need to provide the upper bound of $L(\mathcal{X}(t+1)) - L(\mathcal{X}(t))$ for any t, that is

$$\begin{aligned} &L(\mathcal{X}(\tau+1)) - L(\mathcal{X}(\tau)) \\ &\overset{(a)}{\leq} f(\mathcal{X}(t+1)) \cdot \|\mathcal{X}(t+1) - \mathcal{X}(t)\|_\infty \\ &\overset{(b)}{\leq} f(\mathcal{X}(t)) \cdot \|\mathcal{X}(t+1) - \mathcal{X}(t)\|_\infty + O\left(\tfrac{\mathcal{X}(t+1)}{\mathcal{X}(t)}\right), \end{aligned} \qquad (18)$$

where (a) is from the convexity of f and (b) follows from the fact that f is 1-Lipschitz[3]. We are now ready to get the optimal bound of $L(D)$. For the scenario of the D with finite mean μ ($\mu \geq 0$) and variance σ^2, $W_{avg}(0)$ in this case can be expressed as

$$W_{avg}(0) \propto \Theta\left(N^{\frac{-\mu+1}{2N(\sigma^2+1)\Upsilon}}\right).$$

Combing with Lemma 1, we have

$$\begin{aligned} \mathbb{E}[f(\mathcal{X}(0)) \cdot W_{avg}(0)] &\leq N^{\frac{-\mu+1}{2N(\sigma^2+1)\Upsilon}} \cdot N^{\frac{-1}{2N\Upsilon}} \\ &\leq N^{\frac{-\mu+1}{2N(\sigma^2+1)\Upsilon}} \cdot N^{\frac{-1}{2N(\sigma^2+1)\Upsilon}} = N^{\frac{-\mu}{2N(\sigma^2+1)\Upsilon}}, \end{aligned} \qquad (19)$$

which also asserts that the negative impact of DCI can be alleviated via improving the network connection. Moreover, based on Lemma 2, we can design the function $f(x)$ in Table I to satisfy

$$L(D) \geq 1 - \mathbb{E}[f(\mathcal{X}(0)) \cdot W_{avg}(0)].$$

In particular, $W_i(t)$ can also be set as

$$\min\left\{ f\left(\sum_{j,k} \frac{T_{(i,j),k} X_i(t)}{K X_j(t)}\right), \sqrt{f\left(\frac{\max_{j,k} T_{(i,j),k} X_i(t)}{X_j(t)}\right)} \right\}$$

to enable (19) get the equality operation. That is, in this case, we can achieve the optimal performance loss bound

$$L(D) \geq 1 - N^{\frac{-\mu}{2N(\sigma^2+1)\Upsilon}},$$

which completes the proof Theorem 1. Similarly, we can get the optimal bound of $L(D)$ and how to achieve the bound in terms of the D with mean μ ($u \leq \mu \leq U$). Due to the limited space, we skip the detailed proof here.

B. Asymptotical Convergence Rate

To prove the upper bound of ACR, we give a new characterization for $\{W_i(t)\}$, and then study the bound of $\{W_i(t)\}$ to characterize the bound of ACR. In terms of $\{W_i(t)\}$, we have the following result:

Lemma 3 *For each node i, the convergence of the delay weight $\{W_i(t)\}$ satisfies*

$$\mathbb{P}\left(\lim_{t\rightarrow\infty} W_i(t) \propto \frac{W_{avg}(0)}{\pi(0)} f(X_i(0))\right) = 1, \qquad (20)$$

where $f(x)$ is listed in Table I.

To prove Lemma 3, we first check the relationship between $W_i(t)$ and $W_{avg}(t)$, then we investigate the format of $W_i(t)$

[3]A function $f : \mathbb{R} \rightarrow \mathbb{R}$ is 1-Lipschitz if $f(t_1) - f(t_2) \leq |t_1 - t_2|$ for all $t_1, t_2 \in \mathbb{R}$.

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as $t \to \infty$. In particular, we have the following two propositions.

Proposition 1 *For each node i, we have*

$$\lim_{t\to\infty} \left\| W_i(t) - W_{avg}(t) \right\|_\infty \to \frac{W_{avg}(0)}{\pi(0)}. \tag{21}$$

Proof: Clearly, the connection between $W_i(t)$ and $W_{avg}(t)$ is the difference remains constant at the steady state, in which both of them do not change as the time t. As a result, at the first step we should investigate $X_i(t)$ when $t \to \infty$. Specifically, it is not difficult to check that $X_i(t) \to \max_{j,k} t_{(i,j),z}$ when $t \to \infty$. In this case, we can deliberately choose a finite random variable V_1 such that

$$\sup_{t\geq 0} \left\| \overline{X_j}(t) - \max_{j,k} t_{(i,j),z} \right\|_\infty \leq V_1 \cdot \sup_{t\geq 0} X_i(t), \tag{22}$$

where $\overline{X_j}(t) = \frac{\sum_{j=1}^{N_i(t)} X_j(t)}{N_i(t)}$. With (22), we can further use V_1 to characterize the relationship between $W_i(t)$ and $W_i(0)$. In particular, let $\underline{W_i(t)} = V_1 (W_i(t) - W_i(0))$ denote the deviation of $W_i(t)$ for any t. Also, let $\underline{W_i}$ and A_i respectively denote the matrices $[W_1(t), ..., W_N(t)]$ and $[A_1(t), ..., A_N(t)]$, where

$$A_i(t) = \left(X_i(t) + \overline{X_j(t)} \sum_{k,j} T_{(i,j),k}/K \right)^{-1}.$$

By using the Laplacian property, we get

$$\begin{aligned}\underline{W_i(t+1)} = &\left(\overline{X_j(t)} - \frac{1}{K} \sum_{k,j} T_{(i,j),k} \otimes X_i(t) \right) \underline{W_i(t)} \\ &+ (A_i - A_{avg}(t)),\end{aligned} \tag{23}$$

where $A_{avg}(t) = \frac{1}{N}\sum_{i=1}^{N} A_i(t)$. Note that the function $\{F_i(t)\}$ defined in (14) can be bounded by (22) and (23). For $m \in \{1, ..., M\}$ (M represents the number of the $\underline{W}$ column), let $\underline{W_{m,i}}$ denote the m-th column of $\underline{W_i}$. Hence, the process $\left\{ \underline{W_{m,i}} \right\}$ can be approximated by $\{F_i(t)\}$. Then, by [22, Proposition 1], there exists a sequence $\left\{ \underline{\underline{W_{m,i}}} \right\}$ to describe $\overline{X_j}(t)$, that is

$$\left\| \overline{X_j(t)} - \frac{1}{K} \sum_{k,j} T_{(i,j),k} \otimes X_i(t) \right\|_\infty \leq \left(1 - \underline{\underline{W_{m,i}}}\right) \left\| \underline{W_{m,i}} \right\|_\infty. \tag{24}$$

Taking into account the characteristics of $\underline{W_{m,i}}$ and $\underline{\underline{W_{m,i}}}$, we further have

$$\begin{aligned}&\left\| \overline{X_j(t)} - \frac{1}{K} \sum_{k,j} T_{(i,j),k} \otimes X_i(t) \right\|_\infty^2 \leq \\ &\sum_{m=1}^{M} \left(1 - \underline{\underline{W_{m,i}}}\right)^2 \left\| \underline{W_{m,i}} \right\|_\infty^2 \leq \left(1 - \underline{\underline{W_i}}\right)^2 \left\| \underline{W_i} \right\|_\infty^2,\end{aligned} \tag{25}$$

where $\left\{ \underline{\underline{W_i}} \right\}$ is an adapted process which is given by

$$\underline{\underline{W_i}} = \underline{\underline{W_{1,i}}} \wedge \underline{\underline{W_{2,i}}} \wedge ... \wedge \underline{\underline{W_{M,i}}}.$$

By (25) and since $\underline{\underline{W_i(t)}}$ gets bounded as $t \to \infty$, we can use Lemma 1 to conclude that $\left\| \underline{W_i} \right\|_F \to 0$ as $t \to \infty$. Therefore, the result of Proposition 1 follows immediately. ■

Based on Proposition 1, to study the convergence of $\mathcal{X}(t)$, it suffices to show the convergence of $\{W_{avg}(t)\}$ is $\frac{1}{NK}\sum_{i=1}^{N}\sum_{k,j} T_{(i,j),k} \otimes X_i(t)$. The following proposition states this result.

Proposition 2 *For each node i, we have*

$$\lim_{t\to\infty} W_{avg}(t) \to \frac{1}{NK} \sum_{i=1}^{N} \sum_{k,j} T_{(i,j),k} \otimes X_i(0). \tag{26}$$

Proof: Similar to the analysis in Lemma 1, for any t, $\{W_{avg}(t)\}$ satisfies the following update function:

$$W_{avg}(t+1) = W_{avg}(t) + \frac{A_{avg}(t)}{\max_i A_i(t)} (W_{avg}(t) - W_{avg}(t-1)).$$

Moreover, we define

$$\overline{W_{avg}(t)} = W_{avg}(t) - \frac{1}{NK} \sum_{i=1}^{N} \sum_{k,j} T_{(i,j),k} \otimes X_i(t).$$

As a result, $\left\{ \overline{W_{avg}(t+1)} \right\}$ satisfies:

$$\begin{aligned}\overline{W_{avg}(t+1)} = &\left(1 - \frac{A_{avg}(t)}{\max_i A_i(t)}\right) \overline{W_{avg}(t)} + \\ &\left(1 - \frac{1}{NK} \sum_{i=1}^{N} \sum_{k,j} T_{(i,j),k} \otimes X_i(t)\right) \frac{A_{avg}(t)}{\max_i A_i(t)}.\end{aligned} \tag{27}$$

Also, by the definition of $\underline{\underline{W_i(t)}}$, we can further get that

$$W_{avg}(t) \to \frac{1}{NK} \sum_{i=1}^{N} \sum_{k,j} T_{(i,j),k} \otimes \underline{\underline{W_i(t)}} \tag{28}$$

as $t \to \infty$. Hence, we may choose $t_{thr} > 0$ such that

$$\left\| W_{avg}(t) - \frac{1}{NK} \sum_{i=1}^{N} \sum_{k,j} T_{(i,j),k} \otimes \underline{\underline{W_i(t)}} \right\|_\infty < t_{thr}.$$

From (27), we then have for $t \geq t_{thr}$

$$\begin{aligned}\left\| \underline{\underline{W_i(t)}} \right\|_\infty &\propto \left| \prod_{k=t_{thr}}^{t-1} \left(1 - \frac{A_{avg}(k)}{\max_i A_i(k)}\right) \right| \left\| \underline{\underline{W_i(t_{thr})}} \right\|_\infty \\ &+ \sum_{k=t_{thr}}^{t-1} \prod_{l=k+1}^{t-1} \left(1 - \frac{A_{avg}(l)}{\max_i A_i(l)}\right) \\ &\propto \left| \prod_{k=0}^{t} \left(1 - \frac{A_{avg}(k)}{\max_i A_i(k)}\right) \right| X_i(0).\end{aligned}$$

When $t \to \infty$, we have

$$\lim_{t\to\infty} \underline{\underline{W_i(t)}} \to X_i(0). \tag{29}$$

Combing (29) with (28), the desired assertion follows immediately. ■

We now can complete the proof of Lemma 3.

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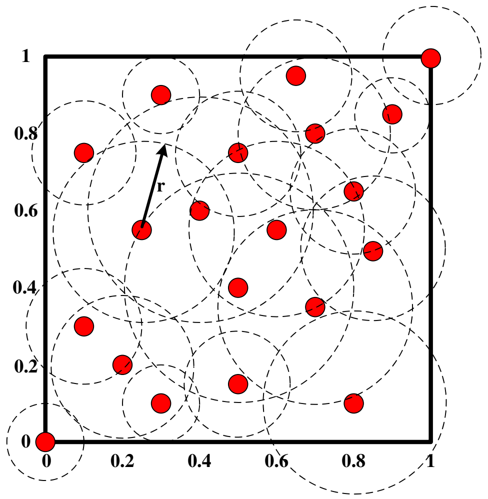

Fig. 2. A wireless network with 20 nodes.

Proof of Lemma 3: It follows from Proposition 1 and Proposition 2 that

$$\mathbb{P}\left(\lim_{t\to\infty} W_i\left(t\right) = \frac{1}{NK}\sum_{i=1}^{N}\sum_{k,j} T_{(\mathrm{i,j}),k}\otimes X_i\left(t\right)\right) = 1, \quad (30)$$

for all $i \in [1, N]$. The assertion in Lemma 3 is immediate from (30) and the observation that $X_i\left(t\right) \to \max_{j,k} T_{(i,j),k}$ as $t \to \infty$. ■

Combing Lemma 1 with Lemma 3, it is straightforward to get the optimal bounds of ACR for Scenario-1 and Scenario-2. More precisely, it can be easily verified that (9) for Scenario-1 and (11) for Scenario-2 both satisfy the Lemma 3. That is, the optimal ACR is attainable given these conditions. Of course, there maybe exist others distributions to achieve the optimal bound iff they satisfy Lemma 3.

V. Numerical Results

In this section, we conduct extensive simulations to test our theoretical analysis and proposed scheduling scheme. Two HD (High-Definition) sequences (*City* and *Mother*) with the spatial resolution of 1280×720 pixels are used, and the frame rate is 60 frames per second. Moreover, the video sequences are encoded using a fast implementation of the H.264/AVC at various quantization step sizes, with a GOP (Group Of Pictures) length of 25 and its "IBBP..." structure similar to that often used in MPEG-2 bitstreams [22]. Each scalable video flow is classified into four classes, and their parameter values are listed in Table III.

First, we still consider a simple network topology shown in Fig. 1(a). Without loss of generality, we randomly set that $T_{(i,j),k} = 1$ Mb/s, $L_k = 1000$ bytes, and

$$\mathcal{A} = \begin{bmatrix} 1 & 0.5 & 0.3 & 0.2 \\ 0.5 & 1 & 0 & 0.5 \\ 0.3 & 0 & 1 & 0.7 \\ 0.2 & 0.5 & 0.7 & 1 \end{bmatrix},$$

thus $\mathcal{D} = diag\left(2, 2, 2, 2.4\right)$, $\Upsilon = 4.4$. With respect to D, we consider two scenarios: 1) Case-1: mean $\mu = 2$ and variance $\sigma^2 = 1$; 2) Case-2: $\mu \in [1, 3]$. We check the working mechanism of the proposed algorithm. Table IV shows the values of $X_i(t)$ and $W_i(t)$ at each time-slot given $f\left(x\right) = \sqrt{\log\left(x+1\right)}$ for Case-1 and $f\left(x\right) = 1/\sqrt{\log\left(x+1\right)}$ for Case-2. From Table IV, the values of X_i and W_i converge to steady states as time goes on. Interestingly, we clearly observe that the value of $W_i(t)$ determines the update of the $X_i(t)$, and the value of the $X_i(t)$ heavily impacts the update of $W_i(t)$ as well. Moreover, we can also find that the average error between the simulation results and the theoretical analysis falls into $[0\%, 2.7\%]$. In other words, our theoretical analysis is consistent with the simulation results.

Next, we apply the proposed scheduling scheme to a more general network in which 20 nodes are arbitrarily placed in a unit area shown in Fig. 2. For each pair (i, j), when their distance falls into the transmission area of node i, we say that node i is able to communicate with node j. In this case, we set $a_{ij} = 1$. Otherwise, let $a_{ij} = 0$. Specifically, the transmission area of each node is characterized by the transmission radium r. In order to imitate a dynamic network, the value of r varies from r_{min} to r_{max} for each node. Table V presents the location and the transmission radium of each node. In Fig. 3, we compare the proposed scheduling scheme with DMDS in terms of the average PSNR at each time slot. For illustration purpose, DMDS is operated at two cases: i) *DMDS*: there is no DCI, in this case, all the control information can be received immediately. Obviously, this case corresponds to the optimal condition. ii) *DMDS-DCI*: There exists DCI, but DMDS still treats the received control information as an instant value. Regarding to our proposed scheduling, we also consider two cases: i) *Proposed-Random*: the distribution of the DCI is random, and ii) *Proposed-Specified*: the CDF of the DCI satisfies with (9) for Scenario-1 and the PDF of the DCI satisfies with (11) for Scenario-2. From Fig. 3, we can observe that the proposed scheduling schemes, including *Proposed-Random* and *Proposed-Specified*, perform well in both scenarios 1 and 2. In particular, the proposed schemes both significantly outperform *DMDS-DCI*. For example, for Scenario-2, the average PSNR value of *DMDS-DCI* is 27.7dB, while the values of *Proposed-Random* and *Proposed-Specified* are 32.4dB and 32.9dB, respectively. Moreover, we find that the ACR of the *Proposed-Specified* is faster than that of *Proposed-Random*, which also conforms to our theoretical analysis. To examine how the number of the nodes impact the performance loss, Fig. 4 plots the value of $L(D)$ as the number of node varies from 2 to 30 using the proposed scheduling, in which Υ keeps 2 all the time. From the given results, we observe that Theorem 1 and Theorem 3 provide tight bounds of performance loss, and our proposed scheme performs well in both Scenario-1 and Scenario-2. Therefore, the above simulations can be viewed as the picture proofs of Theorems 1-3.

Subsequently, we examine the robustness of the proposed scheduling scheme in a dynamic wireless networks in which the distribution of DCI is completely unknown. Specifically, each node can move randomly along four directions, Up, Down, Right, Left, with average velocity 0.25. For comparison purpose, we still use DMDS as the benchmark, and the settings

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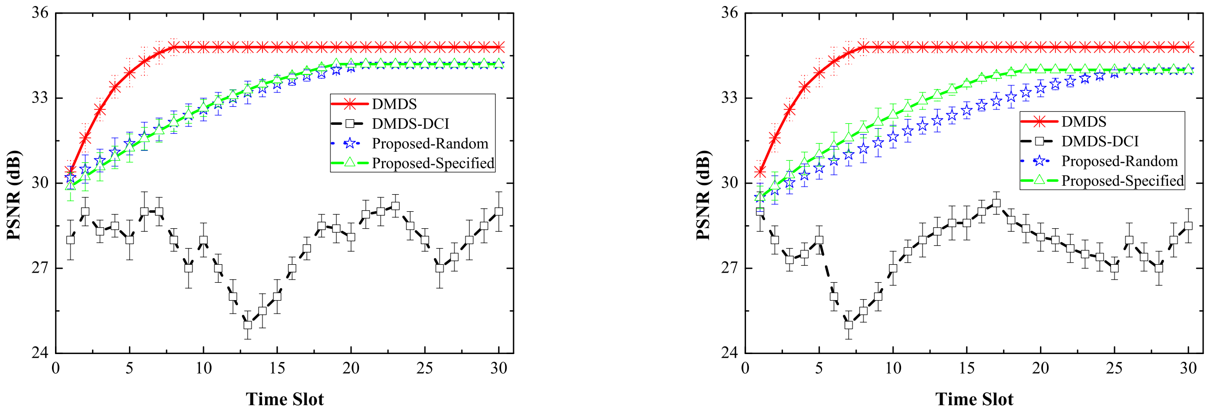
TABLE III
VIDEO SEQUENCE'S PARAMETERS.

Video Classes	Video Sequence *City*				Video Sequence *Mother*			
C_k	C_1	C_3	C_6	C_8	C_2	C_4	C_5	C_7
$\lambda_k(dB/Kbps)$	0.0170	0.0064	0.0042	0.0031	0.0105	0.0060	0.0048	0.0042
$R_k(Kbps)$	550	400	350	400	500	400	450	350
$D_k(ms)$	350	400	500	530	370	420	480	550

TABLE IV
PERFORMANCE COMPARISON FOR DIFFERENT SCHEMES IN DIFFERENT SCENARIOS.

Scheduling	Time-Slot	Scenario-1								Scenario-2							
		Node-1		Node-2		Node-3		Node-4		Node-1		Node-2		Node-3		Node-4	
		X_1	W_1	X_2	W_2	X_3	W_3	X_4	W_4	X_1	W_1	X_2	W_2	X_3	W_3	X_4	W_4
Analytical Result	1	8	1.3	10	1.8	13	2.0	16	2.2	10	1.9	12	2.3	14	2.8	18	1.9
	2	9	1.8	12	2.1	11	1.7	15	2.1	13	2.1	14	2.2	13	2.2	16	1.8
	3	10	1.7	13	1.9	10	1.6	14	2.0	15	2.2	15	2.3	12	2.4	15	1.7
	4	11	2.1	14	2.2	9	1.5	13	2.0	16	2.3	16	2.4	11	2.2	14	1.6
	5	11	2.1	14	2.2	9	1.5	13	2.0	16	2.3	16	2.4	11	2.2	14	1.6
Simulation Result	1	8	1.3	10	1.8	13	2.0	16	2.2	10	1.9	12	2.3	14	2.8	18	1.9
	2	10	1.8	12	2.1	10	1.6	14	2.0	13	2.1	14	2.2	13	2.2	16	1.8
	3	10	1.7	13	1.9	10	1.6	13	2.0	16	2.3	15	2.3	13	2.2	15	1.7
	4	11	2.0	14	2.2	9	1.5	13	2.0	16	2.3	15	2.3	12	2.2	15	1.7
	5	11	2.0	14	2.2	9	1.5	13	2.0	16	2.3	15	2.3	11	2.2	14	1.6
Average Error (%)		**2.1**	**2.2**	**0**	**0**	**1.9**	**1.2**	**2.8**	**1.0**	**1.4**	**0.9**	**2.7**	**1.7**	**3.3**	**1.7**	**1.3**	**1.2**



(a) Scenario-1 ($\mu = 2$ and $\sigma^2 = 1$)

(b) Scenario-2 ($1 \leq \mu \leq 3$)

Fig. 3. Performance comparison in terms of average PSNR value.

of the Scenario-1 and Scenario-2 are identical to those of the Fig. 3. Fig. 5 shows the video quality with various mobility direction probabilities. An important observation drawn from Fig. 5, other than both of the algorithms for Scenario-1 and Scenario-2 outperform DMDS, is that the algorithm for Scenario-2 exhibits a better robustness with respect to PSNR. For example, in Fig. 5(a), the average PSNR value of scenario-1 is 32.7dB, while it is 33.3dB for Scenario-2. Hence, the algorithm of Scenario-2 has the 0.6dB advantage compared to that of Scenario-1. That is because the condition of Scenario-2 is much looser than that of Scenario-1, and thus Scenario-2 is more adaptive to the practical condition. Therefore, this work recommends that one should choose the scheduling algorithm for Scenario-2 when the distribution of the DCI is unknown.

VI. CONCLUSIONS

This paper was devoted to quantifying the impact of delayed control channels on distributed wireless video scheduling. Complementary to the previous works, we advocated the method of distributed video scheduling to shed new light

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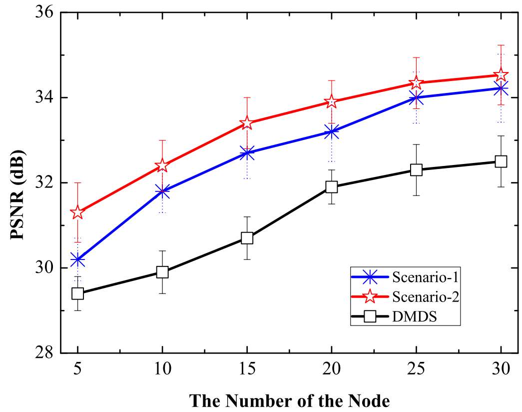
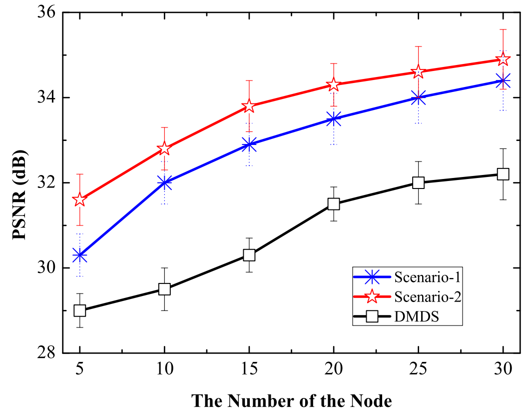
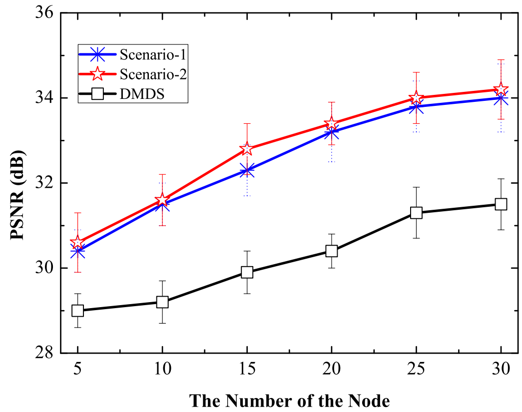


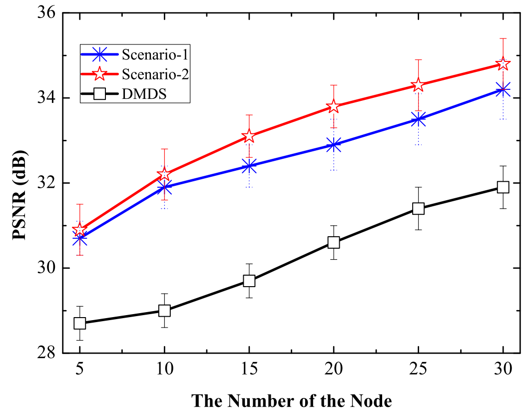
(a) (25%, 25%, 25%, 25%)



(b) (20%, 30%, 30%, 20%)



(c) (10%, 40%, 10%, 40%)



(d) (40%, 10%, 40%, 10%)

Fig. 5. The value of the video quality in the context of a dynamic wireless networks. Note that each node moves along four possible directions (Up, Down, Right, Left), and (a)-(d) denote various possibilities of the mobility direction.

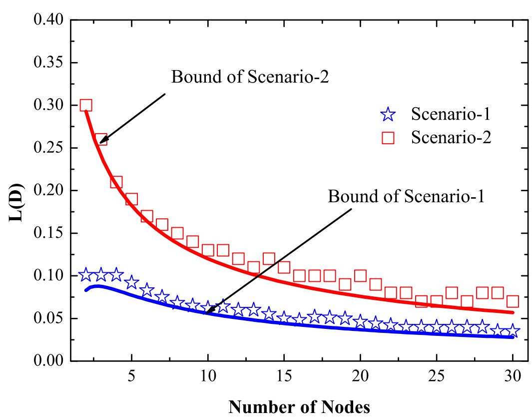


Fig. 4. The value of $L(D)$ as the number of node varies from 2 to 30.

on traditionally challenging issues on DCI. Specifically, we considered two scenarios of DCI: One is a class with finite mean and variance, and the other is a general class that does not have a parametric representation. In each scenario, we investigated the relationship between the DCI and scheduling performance based on observed control information. In particular, we provided a general performance property bound for any distributed scheduling. Importantly, we designed a class of distributed online scheduling scheme to achieve the optimal performance bound by making use of the correlation among the time-scale control information.

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TABLE V
THE INFORMATION OF THE LOCATION AND TRANSMISSION RADIUM OF EACH NODE.

(x_i, y_i)	r_{max}	r_{min}	(x_i, y_i)	r_{max}	r_{min}
(0.00, 0.00)	0.50	0.30	(0.10, 0.30)	0.20	0.10
(0.10, 0.75)	0.40	0.15	(0.20, 0.20)	0.50	0.20
(0.25, 0.55)	0.35	0.20	(0.30, 0.10)	0.30	0.20
(0.30, 0.90)	0.50	0.40	(0.40, 0.60)	0.20	0.10
(0.50, 0.15)	0.30	0.20	(0.50, 0.40)	0.25	0.15
(0.50, 0.75)	0.55	0.25	(0.60, 0.55)	0.30	0.15
(0.65, 0.95)	0.25	0.10	(0.70, 0.35)	0.25	0.10
(0.70, 0.80)	0.30	0.20	(0.80, 0.10)	0.35	0.30
(0.80, 0.65)	0.25	0.10	(0.85, 0.50)	0.45	0.30
(0.90, 0.85)	0.30	0.20	(1.00, 1.00)	0.30	0.10

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APPENDIX: PROOF OF LEMMA 2

We first consider an extreme case $0 \ll t < \infty$, in this case

$$\rho(t+1) = \rho(t) + \sum_{s=0}^{t} e(t-s)\rho(s),$$

where $e(t) = \mathbb{E}[\rho(t) \cdot (\mathcal{X}(t) - \mathcal{X}(0))]$. Hence, we can use the term $\rho(t+1) - \rho(t)$ to describe the time t. To do that, we can design functions f_1 and f_2 with respect to $\max_i X_i(0) W_i(0)$ by using [27, Theorem 2.4], that is

$$f_1 \sim f_2 \rightarrow \Theta\left(\max_i \sqrt{X_i(0) W_i(0)}\right).$$

Actually, f_1 and f_2 can be set at random orders. As a result, we can obtain that

$$\left\| \sum_{s=0}^{t} e(t-s) \cdot \rho(s) \right\|_{\infty} \leq F(\mathcal{X}). \tag{A1}$$

According to f_1, f_2, and (A1), we get $\|e(t) \cdot \rho(t)\|_{\infty}$ as shown in (A2). In (A2), (a) follows from $\|\rho(0)\|_{\infty} \rightarrow \Theta\left(\sqrt{W_{avg}(0)}\right)$, (b) comes from Lemma 1, and (c) derives from the definition of transmission matrix $\psi\left(\sqrt{W_{avg}(0)}\right)$.

Next, we examine the relationship between $W_i(t)$ and $W_i(0)$ when t is large enough. By definition, we have

$$\psi\left(\max_i |W_i(t) - W_i(0)|\right) \rightarrow O\left(\frac{1}{\psi\left(\max_i X_i(0)\right)}\right).$$

Combing with (A1), we can get

$$\left\| \sum_{s=0}^{t} e(t-s) \cdot \rho(s) \right\|_{\infty} \leq O\left(\frac{1}{\psi\left(\sqrt{W_{avg}(0)}\right)}\right).$$

Now, the core problem is to understand the correlation between the functions of f_1 and f_2. Based on the above discussion, we should consider the following two cases:

1) $f_1\left(\max_i \sqrt{X_i(0) W_i(0)}\right) \geq f_2\left(\max_i \sqrt{X_i(0)}\right)$, and
2) $f_1\left(\max_i \sqrt{X_i(0) W_i(0)}\right) < f_2\left(\max_i \sqrt{X_i(0)}\right)$.

Since proof process of case 2) is similar to that of case 1), we mainly focus on case 1) here. Specifically, when the condition of case 1) holds, then we have (A3). In particular, the first term in (A3) can be bounded as (A4), where (a) follows from (15), (b) comes from the standard Cauchy-Schwarz inequality, (c) and (d) follows from the results of Lemma 1.

In terms of the second term in (A3), similarly we have (A5). Specifically, (a) is the same as the condition of (A4), and (b) follows from 1-Lipschitz property of $\sqrt{\cdot}$ function. Therefore, the proof is complete. ■

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$$\begin{aligned} \|e(t)\cdot\rho(t)\|_\infty &\overset{(a)}{\leq} O\left(\|f_1(\psi(W(t))) - f_2(\psi(W(0)))\|_\infty\right) \\ &\overset{(b)}{\leq} O\left(\mathbb{E}\left[\max_i\left\|\frac{1}{1+f_1(W_i(t))} - \frac{1}{1+f_2(W_i(0))}\right\|_\infty\right]\right) \\ &\overset{(c)}{\leq} O\left(f_1\left(\psi\left(\sqrt{W_{avg}(0)}\right)\right) - f_2\left(\psi\left(\sqrt{W_{avg}(0)}\right)\right)\right). \end{aligned} \tag{A2}$$

$$\begin{aligned} &\mathbb{E}\left[f_1\left(\psi\left(\sqrt{W_{avg}(0)}\right)\right) - f_2\left(\psi\left(\sqrt{W_{avg}(0)}\right)\right)\right] \propto \mathbb{E}\left[\left|f_1(W_i(t)) - f_2(W_i(0))\right|\right] \\ &= \mathbb{E}\left[\left|f_1(W_i(t)) - f_2(W_i(0))\right|\cdot\mathbf{1}_{\left\{f_1\left(\max\limits_i\sqrt{X_i(t)W_i(t)}\right)\geq f_2\left(\max\limits_i\sqrt{X_i(0)}\right)\right\}}\right] \\ &+\mathbb{E}\left[\left|f_1(W_i(t)) - f_2(W_i(0))\right|\cdot\mathbf{1}_{\left\{f_1\left(\max\limits_i\sqrt{X_i(t)W_i(t)}\right)< f_2\left(\max\limits_i\sqrt{X_i(0)}\right)\right\}}\right] \end{aligned} \tag{A3}$$

$$\begin{aligned} &\mathbb{E}\left[\left|f_1(W_i(t)) - f_2(W_i(0))\right|\cdot\mathbf{1}_{\left\{f_1\left(\max\limits_i\sqrt{X_i(t)W_i(t)}\right)\geq f_2\left(\max\limits_i\sqrt{X_i(0)}\right)\right\}}\right] \\ &\overset{(a)}{\leq} \mathbb{E}\left[\min\left(f_1(X_i(t)W_i(t)), f_2(X_i(0)W_i(0))\right)\left|f_1\left(\psi\left(\sqrt{W_{avg}(0)}\right)\right) - f_2\left(\psi\left(\sqrt{W_{avg}(0)}\right)\right)\right|\right] \\ &\overset{(b)}{\leq} \sqrt{\mathbb{E}\left[f_1\left(\min\left\{X_i(t)W_i(t), X_i(0)W_i(0)\right\}\right)^2\right]}\cdot\sqrt{\mathbb{E}\left[\left(X_i(t)W_i(t) - X_i(0)W_i(0)\right)^2\right]} \\ &\overset{(c)}{\leq} \sqrt{\left(f_1^{-1}\left(\sqrt{f_1(X_i(0)W_i(0))}\right)\right)^2 + \Theta\left(\frac{1}{f_2^{-1}\sqrt{f_2(X_i(0)W_i(0))}}\right)}\cdot\Theta\left(\max_i X_i(0)W_i(0)\right) \\ &\overset{(d)}{=} \Theta\left(\frac{1}{\psi(\max_i X_i(0)W_i(0))}\right). \end{aligned} \tag{A4}$$

$$\begin{aligned} &\mathbb{E}\left[\left|f_1(W_i(t)) - f_2(W_i(0))\right|\cdot\mathbf{1}_{\left\{f_1\left(\max\limits_i\sqrt{X_i(t)W_i(t)}\right)< f_2\left(\max\limits_i\sqrt{X_i(0)}\right)\right\}}\right] \\ &\propto \mathbb{E}\left[\left(\sqrt{f_1(\max_i X_i(0)W_i(0))} - f_2(\max_i X_i(0)W_i(0))\right)\cdot\mathbf{1}_{\left\{\sqrt{f_1(\max_i X_i(t))}\geq f_2(\max_i X_i(0))\right\}}\right] + \\ &\qquad \mathbb{E}\left[\left(f_1(\max_i X_i(0)W_i(0)) - f_2\sqrt{(\max_i X_i(0)W_i(0))}\right)\cdot\mathbf{1}_{\left\{\sqrt{f_1(\max_i X_i(t))}< f_2(\max_i X_i(0))\right\}}\right] \\ &\overset{(a)}{\leq} \mathbb{E}\left[\left(\sqrt{f_1(\max_i X_i(t)W_{avg}(0))} - f_2(\max_i X_i(0))\right)\cdot\mathbf{1}_{\left\{\sqrt{f_1(\max_i X_i(t))}\geq f_2(\max_i X_i(0))\right\}}\right] + \\ &\qquad \mathbb{E}\left[\left(f_1(\max_i X_i(t)W_{avg}(0)) - f_2\left(\sqrt{\max_i X_i(0)}\right)\right)\cdot\mathbf{1}_{\left\{\sqrt{f_1(\max_i X_i(t))}< f_2(\max_i X_i(0))\right\}}\right] \\ &\overset{(b)}{\leq} \mathbb{E}\left[\left|\sqrt{f_1(\max_i X_i(0)W_i(0))} - \sqrt{f_2(\max_i X_i(0)W_i(0))}\right|\right] = \Theta\left(\frac{1}{\psi(\max_i X_i(0)W_i(0))}\right). \end{aligned} \tag{A5}$$

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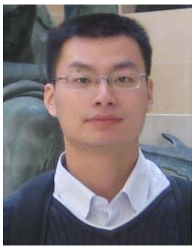

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