Fairness Strategies for Wireless Resource Allocation Among Autonomous Multimedia Users

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***Abstract*—Recent research in wireless multimedia streaming has focused on optimizing the multimedia quality in isolation, at each station. However, the cross-layer transmission strategy deployed at one station impacts and is impacted by the other stations, as the wireless network resource is shared among all competing users. Hence, efficient and fair resource management for autonomous wireless multimedia users becomes very important. We consider quality-based fairness schemes based on axiomatic bargaining theory, which can ensure that the autonomous multimedia stations incur the same drop in multimedia quality as compared to a maximum achievable quality for each wireless station. Implementing this quality-based fairness solution in the time-varying channel condition requires high-computational complexity and communication overheads. Hence, we develop solutions that significantly reduce the computational complexity and communication overheads. Our simulations show that the proposed game-theoretic resource management can indeed guarantee desired utility-fair allocations when wireless stations deploy different cross-layer strategies.**

***Index Terms*—Axiomatic bargaining solution, cross-layer optimization, game-theoretic multimedia resource management, multiuser wireless resource management.**

I. Introduction

A PLETHORA of real-time multimedia streaming applications are starting to be deployed over emerging wireless local area networks (WLANs) infrastructures [1], [2]. However, the time-varying and bandwidth-constrained wireless networks do not provide the quality of service (QoS) required by the delay-sensitive and bandwidth-intensive multimedia applications. To ensure the necessary QoS, recent research has focused on innovative error resilient and bandwidth-adaptive video compression, and cross-layer optimized transmission strategies [3], [4]. However, these adaptation techniques have been performed in isolation, at each multimedia transmitter, and suffer from the important limitation of not considering the interaction (in terms of resource utilization) among wireless stations (WSTAs) sharing a common WLAN infrastructure. Emerging polling-based WLAN standards (e.g., IEEE 802.11e [5]) try to provide QoS to multimedia applications by enabling each WSTA to reserve time slots, i.e., transmission opportunities (TXOPs), where contention-free access to the medium is provided. However, this scheme manages resources in a static, worst-case fashion, since it does not consider the time-varying channel conditions or video content characteristics as well as the resulting utility impact for the various users [6]. To overcome this limitation, a *dynamic* resource management scheme that explicitly considers the time-varying video characteristics and adaptive cross-layer strategies deployed by the stations as well as the resulting multimedia utilities is necessary.

Consequently, the resource manager (e.g., the access point) needs to ensure an efficient and fair resource allocation among autonomous multimedia users trying to maximize their own utilities. Fair resource allocation strategies among multiple competing users have been actively researched. One of the simplest fairness policies is to *equally* allocate resources (e.g., TXOPs in our case) among WSTAs. Alternatively, in a recently proposed air-fairness scheme [4] for IEEE 802.11e networks, the resources can be allocated depending on the experienced channel conditions and the required video rate requirements. An important disadvantage of these fairness is that they do not consider the WSTAs' utility impact, as utility functions are usually nonlinearly increasing with the allocated resources. To alleviate this problem, utility-based allocation has been proposed to explicitly consider the derived utility. Proportional fairness was introduced in [7] to allocate resources while considering the resulting utility. Maximizing the total system utility [8] or maximizing the sum of logarithmic utilities [9], [10] have been proposed as the optimal allocations for wireless transmission. However, this resource allocation becomes unfair in noncollaborative applications, where self-interested and autonomous WSTAs compete for resources. Hence, existing utility-based fairness policies can severely penalize certain WSTAs at the expense of other WSTAs, which is not a desirable feature for self-interested WSTAs.

To address the above limitations, we propose to solve the fair resource allocation directly in the multimedia utility domain. We model WSTAs as autonomous and rational users competing for available resources by proactively adapting their cross-layer transmission strategies in order to maximize their utilities. Then, the resource manager should have the ability to decide how the utilities of the autonomous users are impacted relative to each other based on a predetermined (agreed upon)

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utility-fair criterion. For instance, each user can be penalized an equal amount in terms of multimedia quality (i.e., incur the same drop in multimedia quality as compared to its maximum achievable quality) by participating in the resource allocation. To ensure such a relationship among the utilities of the multimedia users, we rely on a well-known game-theoretic concept—axiomatic bargaining solutions [11], [12].

In this paper, bargaining problems are investigated based on axiomatic approaches, where a solution that satisfies several desirable properties (axioms) is selected from a feasible utility set. The axiomatic bargaining solutions were previously proposed to resolve resource allocation issues for various network applications [13]–[15]. Note that the axiomatic bargaining solutions do not require an iterative bargaining process among users, but rather they select a solution from the Pareto optimal surface that satisfies several predetermined (agreed upon) rationality and fairness criteria [12]. Hence, it is assumed that users can negotiate *before* the game is played, and these negotiations can be settled by a binding agreement represented by a set of fairness axioms [12], which represents a bargaining solution. This is very important for multimedia applications, which are delay-sensitive and thus cannot afford to incur the delay associated with an iterative resource negotiating procedure. Several axiomatic bargaining solutions such as the Nash bargaining solution (NBS) [11] and the Kalai–Smorodinsky bargaining solution (KSBS) [16] are differentiated by their unique fairness criteria. The resource management for networked multimedia applications based on them is theoretically studied in our prior work [17]. Moreover, these approaches have been also deployed in conjunction with various multimedia applications, such as video compression, resource management schemes for multimedia systems, video streaming, and image processing [18]–[20].

Our main contributions are summarized as follows. To efficiently solve the problem of fair allocation of resources among multiple wireless multimedia users, we first review several existing fairness policies and determine their performance in terms of multimedia quality. Next, we propose a new approach, based on axiomatic bargaining solutions, which enables us to define fair-allocation rules in the utility domain. Specifically, we use the KSBS because its axioms can distribute the resources optimally (in a Pareto optimal sense) and fairly among autonomous WSTAs, by ensuring an equal quality penalty from each WSTA's maximum achievable quality given its current channel conditions, content characteristics, and cross-layer strategies. Therefore, the KSBS can be successfully used for autonomous WSTAs. In order to quantify the fairness achieved by several resource allocation schemes, we introduce a new metric, referred to as *fairness comparison metric* (FCM). Moreover, we develop algorithms for practical KSBS implementation, which can significantly reduce the required computational complexity and information exchange. We define a utility function, such that heterogeneous multimedia contents (e.g., audio, video, etc.) can be simultaneously considered in the proposed resource management framework.

This paper is organized as follows. In Section II, we define the utility functions and briefly explain the cross-layer strategies that can be deployed by WSTAs. In Section III, we propose a dynamic resource management and its deployment in the system. In Section IV, we describe and compare different fairness policies for resource allocation. In Section V, we formulate the resource allocation problem based on the KSBS and propose algorithms that can significantly reduce the implementation complexity. Simulation results are provided in Section VI. The conclusions are drawn in Section VII. Several proofs in the paper are presented in Appendixes A–C.

II. Conventional Cross-Layer Strategy Optimization

We consider M competing WSTAs that are streaming video content in real-time over the shared wireless network. The role of the central resource moderator referred to as *resource manager* (e.g., QoS-enabled access point) in this paper is to divide and allocate the available TXOPs to each WSTA based on its declared traffic specification (TSPEC). Based on the negotiated TSPEC, the medium access control (MAC) is polling the various WSTAs for a specific fraction of time in every service interval (SI). In this section, we define the utility function and discuss the conventional cross-layer optimization strategies.

A. Multimedia Utility Function

Multimedia users' satisfaction can be improved as the distortion of multimedia decreases. Hence, the utility function for the video coders given allocated video rate R_i to user i can be expressed as

$$U_i(R_i) \triangleq \begin{cases} 255^2/D_i(R_i), & \text{if } R_i \geq R_{i,min} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $R_{i,min}$ is the minimum required video rate for user i and $D_i(R_i)$ is the incurred distortion given allocated rate R_i, measured as the mean square error (MSE). Note that the discussion below and the proposed solution are unaffected if the video coders [or distortion-rate (DR) model] are changed. The peak signal to noise ratio (PSNR), which is a measure of video quality, can be expressed using the utility function, i.e., PSNR = $10 \log_{10} U(R)$. Note that for all video sequences, depending on the used video coder, a minimum PSNR needs to be achieved corresponding to the minimum acceptable quality by the user [e.g., the base-layer quality in fine granular scalability (FGS)]. This will play an important role in designing the proposed resource allocation discussed in Section V.

B. Cross-Layer Strategy Optimization at Each WSTA

In this section, we formulate the optimal cross-layer strategy that maximizes each WSTA's utility. We assume that each WSTA is autonomous, and thus, each WSTA selects its own cross-layer strategy that maximizes the utility given the content characteristics, allocated time, and the experienced channel condition [i.e., the signal to noise ratio (SNR)]. We limit the cross-layer strategies to only include the application (APP)-layer prioritization and scheduling strategies, MAC-layer retransmission, physical (PHY)-layer modulation, and coding schemes. However, other strategies could also be incorporated in this formulation.

Let $\mathbf{s}_i = [\mathbf{phy}_i^n, \mathbf{mac}_i^m, \mathbf{app}_i^l] \in \mathcal{S}_i$ be a cross-layer strategy vector in the feasible set of cross-layer strategies for WSTA i, where $\mathcal{S}_i = \mathcal{S}_i^{PHY} \times \mathcal{S}_i^{MAC} \times \mathcal{S}_i^{APP}$ and $\mathcal{S}_i^{PHY} = \{\mathbf{phy}_i^1, \ldots, \mathbf{phy}_i^{N_i^{PHY}}\}$, $\mathcal{S}_i^{MAC} = \{\mathbf{mac}_i^1, \ldots, \mathbf{mac}_i^{N_i^{MAC}}\}$, and $\mathcal{S}_i^{APP} = \{\mathbf{app}_i^1, \ldots, \mathbf{app}_i^{N_i^{APP}}\}$ denote the strategy space of PHY, MAC, and APP, respectively.

For a static resource allocation [i.e., the time resource is fixed as $(t_1, \ldots, t_M)$], the optimal cross-layer strategy is to maximize its utility given a TXOP allocation t_i and the channel condition (i.e., the experienced SNR) denoted by SNR_i for WSTA i. Thus

$$\mathbf{s}_i^* = \arg\max_{\mathbf{s}_i \in \mathcal{S}_i} U_i(R_i(t_i, \mathbf{s}_i)) = \arg\max_{\mathbf{s}_i \in \mathcal{S}_i} R_i(t_i, \mathbf{s}_i)$$

i.e., WSTA i selects the cross-layer strategy that maximizes $R_i(t_i, \mathbf{s}_i)$ since the TXOP allocation t_i is given. Subsequently, we outline the steps involved in the passive cross-layer optimization proposed in [21].

The strategy $\mathbf{phy}_i^n$, $n \in \{1, \ldots, N_i^{PHY}\}$ represents the nth modulation and channel coding mode existing for a WLAN standard for WSTA i (e.g., PHY modes for the IEEE 802.11a standard [22]). Given the channel condition SNR_i, the bit error rate (BER) when the PHY-layer strategy $\mathbf{phy}_i^n$ of $\mathbf{s}_i$ is deployed becomes $p_e(SNR_i, \mathbf{phy}_i^n)$. Assuming independent bit error probabilities, the packet loss probability p_l for WSTA i is given by

$$p_l(L_i, \mathbf{phy}_i^n) = 1 - (1 - p_e(SNR_i, \mathbf{phy}_i^n))^{L_i} \tag{2}$$

where L_i denotes the average packet size of WSTA i in bits. For a given PHY-layer strategy $\mathbf{phy}_i^n$, the PHY goodput is given by

$$R_i^{phy}(SNR_i, \mathbf{phy}_i^n) = \frac{N_i^{pkt} \cdot L_i \cdot \left(1 - p_l(L_i, \mathbf{phy}_i^n)\right)}{\left(\frac{L_i}{R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n)} + T_{ack} + T_{OH}\right) N_i^{pkt} + \alpha T_{OH}^{ext}} \tag{3}$$

where $R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n)$ is the maximum achievable data rate for the PHY-layer strategy $\mathbf{phy}_i^n$ and T_{ack} denotes the time for acknowledgment. T_{OH} includes the short interframe space time (T_{SIFS}) and the time for the PHY-layer overheads ($T_{PHY_{OH}}$), i.e., $T_{OH} = 2(T_{SIFS} + T_{PHY_{OH}})$. Additional overhead T_{OH}^{ext} is introduced to consider the required overhead for the external information exchanges for the proposed resource management. Since the external information can be exchanged over each SI or a group SIs, T_{OH}^{ext} is considered only when the external information is exchanged, which is represented by the indicator function $\alpha \in \{0, 1\}$. Hence, the denominator in (3) shows the total required time for transmitting N_i^{pkt}, which represents the number of packets that can be transmitted in t_i, computed by $N_i^{pkt} = \left\lfloor \frac{t_i}{L_i / R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n)} \right\rfloor$. The PHY goodput in (3) can be rewritten as

$$R_i^{phy}(SNR_i, \mathbf{phy}_i^n) = \frac{R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n)(1 - p_l(L_i, \mathbf{phy}_i^n))}{\beta_{i,OH}}$$

where

$$\beta_{i,OH} = \left(1 + \frac{R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n)(T_{ack} + T_{OH})}{L_i}\right) + \alpha \frac{R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n) \cdot T_{OH}^{ext}}{L_i N_i^{pkt}}. \tag{4}$$

The following steps involved in the cross-layer optimization are derived based on [6].

The MAC-layer strategy is able to adapt the retransmission per packet. In [6], it was shown that given the packet distortion impact, the optimal packet scheduling strategy for a scalable video coder is to transmit the highest priority packet with the maximum number of retransmissions given its delay deadline. Thus, given the PHY-layer strategy, the maximum number of retransmission of packet v of WSTA i in a SI can be computed as

$$N_i^{MAX_{RT}}(L_i, v) = \left\lfloor \frac{R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n) \cdot \min(t_i^{DT}(v), t_i)}{L_i} \right\rfloor - 1$$

where $t_i^{DT} \triangleq t_i^{\text{delay}}(v) - t_i^{\text{trans}}(v)$ for the delay deadline $t_i^{\text{delay}}(v)$ of the packet v and the expected time instance $t_i^{\text{trans}}(v)$ that WSTA i starts to transmit the packet v for the first time.

The strategy $\mathbf{app}_i^l$, $l \in \{1, \ldots, N_i^{APP}\}$ may correspond to the adaptation of video compression parameters, packetization, traffic prioritization, and scheduling for WSTA i. The packet prioritization and transmission timing of the packets (scheduling strategy) are determined at the APP-layer. The first packet is transmitted at t_i^{trans}. The subsequent packets, however, need to consider the expected transmission time of the previous packets. Until the packet v is successfully transmitted or the retransmission limit is reached, the average number of transmissions can be computed as

$$\overline{N}_i^{tx}(\mathbf{s}_i, N_i^{MAX_{RT}}(L_i, v)) = \frac{1 - p_l(L_i, \mathbf{phy}_i^n)^{N_i^{MAX_{RT}}(L_i, v)+1}}{1 - p_l(L_i, \mathbf{phy}_i^n)}. \tag{5}$$

Hence, the average number of packets that can be correctly transmitted during the time t_i for WSTA i can be computed as

$$\overline{N}_i^{pkt}(t_i, \mathbf{s}_i) = \max\left\{ q \;\middle|\; t_i \geq \frac{L_i \sum_{k=1}^{q} \overline{N}_i^{tx}(\mathbf{s}_i, N_i^{MAX_{RT}}(L_i, v_i^k))}{R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^n)/\beta_{i,OH}} \right\} \tag{6}$$

where v_i^k denotes the kth packet of WSTA i. Therefore, the average bit rate at the APP-layer for WSTA i in transmitting duration t_i can be computed as

$$R_i(t_i, \mathbf{s}_i) = \frac{\overline{N}_i^{pkt}(t_i, \mathbf{s}_i) \cdot L_i}{t_{SI}}. \tag{7}$$

Given the PHY-layer strategy appropriately selected based on a WSTA's channel condition, the BER (or packet error rate) is very small. Hence, we can approximate the average number of packet transmissions (including retransmissions) given in (5) as follows:

$$\overline{N}_i^{tx}(\mathbf{s}_i^*, N_i^{MAX_{RT}^*}(L_i, v)) \approx \frac{1}{1 - p_l(L_i, \mathbf{phy}_i^*)} \quad (8)$$

where $\mathbf{s}_i^*$ is the optimal cross-layer strategy, $\mathbf{phy}_i^*$ and $N_i^{MAX_{RT}^*}$ denotes the corresponding PHY-layer and MAC-layer strategies for WSTA i. Thus, the average number of packets that can be correctly transmitted during the TXOP allocation t_i can be approximated as

$$\overline{N}_i^{pkt}(t_i, \mathbf{s}_i^*) \approx \frac{R_{MAX}^{phy}(SNR_i, \mathbf{phy}_i^*)}{L_i \beta_{i,OH}^*} \cdot (1 - p_l(L_i, \mathbf{phy}_i^*) t_i$$

where $\beta_{i,OH}^*$ represents $\beta_{i,OH}$ in (4) with the selected PHY-layer strategy $\mathbf{phy}_i^*$. Therefore, the approximate average video bit rate (i.e., bit rate at the APP-layer) can be expressed as

$$R_i(t_i, \mathbf{s}_i^*) = \frac{\overline{N}_i^{pkt}(t_i, \mathbf{s}_i^*) L_i}{t_{SI}} = R_i^{phy}(SNR_i, \mathbf{phy}_i^*)\frac{t_i}{t_{SI}}. \quad (9)$$

III. Dynamic Resource Management and Cross-Layer Optimization

The conventional resource management strategy discussed in the previous section is inefficient because it does not consider the time-varying source and channel characteristics, and the cross-layer strategies adapted by WSTAs are passively optimized. To address this limitation, we propose a dynamic resource management framework which explicitly considers that the WSTAs adapt their cross-layer transmission strategies in real-time. The proposed system is able to determine fair wireless resource allocation strategies across autonomous WSTAs, despite the informationally distributed nature of the problem. This is achieved by allowing WSTAs to dynamically exchange information about their utilities and resource requirements depending on their instantaneous channel and source characteristics.

The dynamic resource allocation means that the TXOP allocation is repeatedly divided every SI or group of SIs depending on the channel condition, cross-layer strategy, and used fairness policy. The result of the resource allocation is represented by the TXOP allocation $\mathbf{t} = (t_1, \ldots, t_M)$, where $t_i\,(0 \le t_i \le t_{SI})$ denotes the allocated TXOP to WSTA i and $\sum_{i=1}^{M} t_i \le t_{SI}$. We model this TXOP allocation problem as a game played by WSTAs through adapting their cross-layer strategies and thus, operating at different quality levels. To enable the proposed dynamic resource management, each WSTA will need to determine its *external information* and transmit it to the resource manager. Note that this external information is the strategy with which a WSTA plays the resource management game, and it will be discussed in Section IV.

Self-interested and autonomous WSTA i tries to obtain as much TXOP allocation t_i as possible, while simultaneously selecting the optimal cross-layer strategy to maximize its utility. In the proposed dynamic resource management approach, the allocated TXOP t_i is a function of the cross-layer strategies of

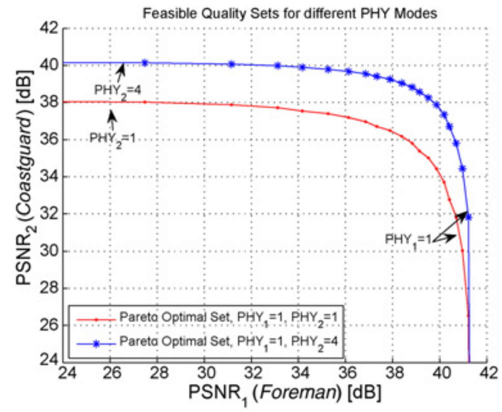

Fig. 1. Achievable feasible quality sets for two WSTAs. WSTAs 1 and 2 transmit *Foreman* and *Coastguard* sequences [common intermediate format (CIF)] under the channel SNRs of 18 dB and 23 dB, respectively. PHY$_i$ denotes the PHY mode choice of WSTA i. The duration of SI is 100 ms (i.e., $t_{SI} = 100$ ms) in this example.

other WSTAs since all WSTAs are sharing the limited resource (i.e., t_{SI}). The corresponding joint TXOP allocation and cross-layer strategy optimization problem is expressed as

$$\begin{aligned}[\mathbf{s}_i^*, t_i^*] &= \underset{\mathbf{s}_i \in \mathcal{S}_i,\, 0 \le t_i(\mathcal{S}_{-i}, \mathbf{s}_i) \le t_{SI}}{\arg\max} U_i(R_i(t_i(\mathcal{S}_{-i}, \mathbf{s}_i), \mathbf{s}_i)) \\ &= \underset{\mathbf{s}_i \in \mathcal{S}_i,\, 0 \le t_i(\mathcal{S}_{-i}, \mathbf{s}_i) \le t_{SI}}{\arg\max} R_i(t_i(\mathcal{S}_{-i}, \mathbf{s}_i), \mathbf{s}_i)\end{aligned}$$

where $\mathcal{S}_{-i} = \bigcup_{k=1, k \ne i}^{M} \mathcal{S}_k$.

We illustrate how the utility set is affected by this resource allocation and cross-layer strategy. Fig. 1 shows the achieved quality sets for the simple case of two WSTAs. In Fig. 1, we observe that the quality derived by one WSTA impacts the quality that can be derived by the other WSTA due to the time resource sharing. Moreover, we observe that different cross-layer strategies induces different feasible utility (or quality) sets, where WSTA 1 has a fixed PHY mode, but WSTA 2 is able to deploy two different PHY modes. As a result, different feasible quality sets are formed depending on the cross-layer strategies deployed by WSTA 2, thereby showing that if one WSTA adopts a better cross-layer strategy, an improved utility set can be formed (i.e., a superset of the original set). Hence, for example, if a WSTA having a limited computational power cannot optimize its cross-layer strategy, the WSTA can be penalized based on the proposed resource management strategy. This will be analytically investigated in Section V.

Based on these examples, we can conclude that an efficient algorithm is required to allocate the time resources fairly and optimally given the competitive multiuser network, and at the WSTA side, the cross-layer strategies need to be optimized as this significantly impacts the video performance. To address this requirement, we propose to implement the following dynamic resource allocation framework at the resource manager side.

1) Session Initialization: Prior to the actual video transmission, the resource manager announces the deployed fairness policy $\mathcal{F}$ and collects basic information about every WSTA,

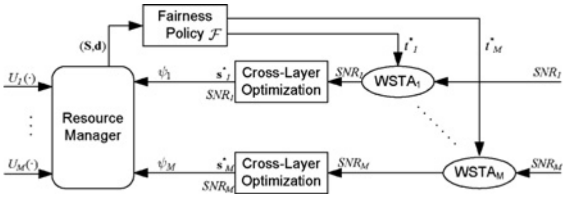

Fig. 2. Overall system for the proposed dynamic resource management framework.

e.g., types of multimedia applications, encoder types, types of transmitted multimedia streams, minimum quality and tolerable delays, used packet lengths, etc. This information can be used to identify the corresponding utility functions. Subsequently, for each SI or group of SIs, the resource manager performs the following steps.

2) Polling and Collecting Information: The resource manager polls WSTAs and collects from them the external information $(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)$, which depends on the deployed resource allocation scheme and is exemplified in detail in Section IV for the various fairness policies. We denote $\boldsymbol{\Psi}$ as the set of possible external information. Note that various algorithms lead to different $\boldsymbol{\Psi}$ and thus to various transmission overheads. In this paper, we assume that the overhead is negligible.

3) Allocating Time Resources: The resource manager decides the nonnegative time resource allocation $(t_1(\mathcal{S}_{-1}, \mathbf{s}_1), \ldots, t_M(\mathcal{S}_{-M}, \mathbf{s}_M))$ based on the collected external information and the deployed fairness policy $\mathcal{F} : \boldsymbol{\Psi} \to \mathbb{R}_+^M$ defined as

$$\mathcal{F}(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M) = (t_1(\mathcal{S}_{-1}, \mathbf{s}_1), \ldots, t_M(\mathcal{S}_{-M}, \mathbf{s}_M)).$$

4) Polling WSTAs: Based on the determined time resource allocation $(t_1(\mathcal{S}_{-1}, \mathbf{s}_1), \ldots, t_M(\mathcal{S}_{-M}, \mathbf{s}_M))$, the WSTAs are polled.

Importantly, in the above resource allocation, we assume that the WSTAs truthfully declare their external information.[1] The wireless system framework is shown in Fig. 2. Note that utilization of some blocks and parameters depends on deployed fairness policy, which will be discussed in Sections IV and V.

The following steps summarize how the WSTAs interact with the resource manager.

1) Session Initialization: Every WSTA sends the basic information to the resource manager and listens to the announced fairness policy. Subsequently, for each SI or group of SIs, WSTAs perform the following steps.

2) Deploying Cross-Layer Strategies: Based on the channel condition, every WSTA deploys the optimal cross-layer strategy that maximizes its own utility.

3) Determining and Announcing External Information: Every WSTA decides which external information $(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)$ should be transmitted based on the fairness policy of the resource manager. More details on the external information are discussed in Section IV. This information is announced to the resource manager when it is polled.

4) Transmitting Data: Every WSTA starts to transmit when it is polled by the resource manager. Various algorithms can be adopted for video streaming [3].

In summary, every WSTA decides and declares the external information based on the fairness policy deployed in the resource manager. Based on the declared external information, the resource manager determine a resource allocation.

[1]This is an implicit assumption used in all MAC wireless resource management implemented today. This assumption might not always be true, and incentives or penalties might be then needed for the WSTA to declare their external information correctly. In this case, mechanism design techniques could be used [23] to provide incentives to WSTAs.

IV. Existing Fairness Policies and Limitations

In this section, we review existing fairness policies for resource management and highlight how these policies can be deployed in the discussed dynamic resource management and what are their limitations for multimedia transmission.

A. Maximum Total System Quality (MTSQ)

If there are no fairness constraints, maximizing the total system quality represents a suitable resource allocation solution [23]. The TXOP allocation $\mathbf{t}^* = (t_1^*, \ldots, t_M^*)$ in MTSQ systems is expressed as

$$\mathbf{t}^* = \underset{\sum_{i=1}^{M} t_i \le t_{SI}}{\arg\max} \sum_{i=1}^{M} 10\log_{10} U_i(R_i(t_i, \mathbf{s}_i^*))$$

where $10\log_{10} U_i(R_i(t_i, \mathbf{s}_i^*))$ is PSNR of WSTA i. This optimization problem can be solved by standard convex optimization methods since each PSNR is either a linear (e.g., the FGS video coder) or concave (e.g., H. 264 video coder) function with respect to the video rate. The TXOP allocation $\mathbf{t}^* = (t_1^*, \ldots, t_M^*)$ in one SI by this strategy is denoted by $\mathcal{F}_{MTSQ}(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)$, where the external information is $\boldsymbol{\psi}_i = (SNR_i, \mathbf{s}_i^*)$ for all i. The limitation of this strategy for competitive networks is that the individual WSTAs' qualities are not explicitly considered.

B. Equal Time Allocation (ETA)

The ETA strategy is the simplest resource allocation scheme. The available time on a channel is equally divided and allocated to WSTAs. Hence, the corresponding TXOP allocation in one SI is expressed as

$$\mathbf{t}^* = \mathcal{F}_{ETA}(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M) = (t_{SI}/M, \ldots, t_{SI}/M)$$

where $\boldsymbol{\psi}_i = \mathbf{0}$ (i.e., no external information is required) for all i. While this allocation seems to be fair, it can be very inefficient in terms of the achieved quality, since it allocates the resources without considering the video quality, which depends on video characteristics, channel conditions, and deployed cross-layer strategies.

C. Air Time Allocation (ATA)

For the ATA strategy [4], the available time on a channel is proportionally divided to the required time for achieving each WSTA's instantaneous rate requirement. This resource allocation can be expressed as

$$\frac{t_1}{t_{1,MAX}} = \cdots = \frac{t_M}{t_{M,MAX}}$$

where $t_{i,MAX}$ denotes the required time to achieve the instantaneous rate requirement of WSTA i. Note that both $t_{i,MAX}$ and t_i are a function of the instantaneous rate requirement and the deployed cross-layer strategy. This policy is equivalent to allocating rate to WSTAs proportionally, according to each WSTA's instantaneous rate requirements denoted by $R_{i,MAX}$ for WSTA i, i.e.,

$$\frac{R_1(t_1, \mathbf{s}_1^*)}{R_{1,MAX}} = \cdots = \frac{R_M(t_M, \mathbf{s}_M^*)}{R_{M,MAX}} \tag{10}$$

where R_i denotes the achievable rate given the TXOP allocation of the resource manager. Using (9), this can be equivalently expressed as a function of the TXOP allocation

$$\frac{R_1^{phy}(SNR_1, \mathbf{phy}_1^*)}{R_{1,MAX}} \frac{t_1}{t_{SI}} = \cdots = \frac{R_M^{phy}(SNR_M, \mathbf{phy}_M^*)}{R_{M,MAX}} \frac{t_M}{t_{SI}} \tag{11}$$

Note that $R_{i,MAX}$ is only a function of the desired quality level and video characteristics and not of the deployed cross-layer strategy. Since the resource manager has already received the basic information during the initializing session, each WSTA needs to only send the channel condition and the optimal cross-layer strategy as its external information. The TXOP allocation $\mathbf{t}^*$ by the ATA policy is denoted by $\mathcal{F}_{ATA}(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)$, where $\boldsymbol{\psi}_i = (SNR_i, \mathbf{s}_i^*)$ for all i. The TXOP allocation $\mathbf{t}^*$ must satisfy (11) and $\sum_{i=1}^{M} t_i^* = t_{SI}$.

D. Generalized Processor Sharing (GPS)

The GPS strategy is introduced in [24] and used as a fair scheduling solution in several applications [4], [25]. For the GPS strategy, the time resources can be allocated proportionally to each WSTA's instantaneous rate requirement. This resource allocation can be expressed as

$$\frac{t_1}{R_{1,MAX}} = \cdots = \frac{t_M}{R_{M,MAX}}. \tag{12}$$

Since the time resources are allocated only proportionally to the instantaneous rate requirements, the resource allocation is independent of the external information. The TXOP allocation $\mathbf{t}^*$ by the GPS policy is denoted by $\mathcal{F}_{GPS}(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)$, where $\boldsymbol{\psi}_i = \mathbf{0}$ for all i. The TXOP allocation $\mathbf{t}^*$ must satisfy (12) and $\sum_{i=1}^{M} t_i^* = t_{SI}$.

Note that the ATA and GPS can have limitations on resource allocations in utility domain for multimedia applications due to the nonlinearity of utility functions even though they can be fair (proportional) solutions in resource domain.

E. Nash Bargaining Solution

The NBS, which was originally introduced by Nash [11], can be deployed to divide resources optimally (in the Pareto optimal sense) to WSTAs based on its fairness axioms. For the NBS, the time allocation vector can be determined such that the resulting utilities are maximizing the *Nash product*, which is the product of utilities. Hence, the TXOP allocation by the NBS policy can be expressed as

$$\mathbf{t}^* = \mathcal{F}_{NBS}(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)$$

where the TXOP allocation $\mathbf{t}^*$ maximizes the Nash product defined as $\prod_{i=1}^{n}(U_i(R_i(t_i^*, \mathbf{s}_i^*)) - d_i)$, or equivalently $\sum_{i=1}^{n} \log(U_i(R_i(t_i^*, \mathbf{s}_i^*)) - d_i)$, while satisfying the resource constraint $\sum_{i=1}^{M} t_i^* = t_{SI}$. The disagreement point $\mathbf{d} = (d_1, \ldots, d_M)$ will be discussed in the next section. Hence, the NBS can be interpreted as the maximizer of the sum of the logarithmic utility functions, and thus, it can be used for *collaborative* WSTAs to achieve the maximum system performance (e.g., for collection of collaborative users such as cameras in a surveillance applications). Therefore, the NBS does not provide a fair resource allocation for self-interested and autonomous WSTAs.

F. Proportional Fairness (PF)

The notion of PF was first introduced in [7], and it proposes a fair solution in utility domain. This fairness notion is used to allocate resources in several applications (e.g., [9] and [10]). In [7], it has been shown that if each user's utility function is logarithmic, then the solution for maximizing the sum of utility functions leads to a proportional fair allocation. By considering the utility functions to be a logarithm of the video rates, the solution that maximizes the sum of the utility functions is the proportional fair allocation of video rates. Thus, the TXOP allocation is a proportional fair solution if

$$\mathbf{t}^* = \underset{\sum_{i=1}^{M} t_i \le t_{SI}}{\arg\max} \sum_{i=1}^{M} \log R_i(t_i, \mathbf{s}_i^*). \tag{13}$$

An interesting property of the PF can be obtained when the utility is set to be the video rate requirement. In this specific case, the solution of (13) is exactly the same as the ETA, i.e., $\mathbf{t}^* = (t_{SI}/M, \ldots, t_{SI}/M)$ (see Appendix A), and thus $\mathcal{F}_{PF} = \mathcal{F}_{ETA}$ with $\boldsymbol{\psi}_i = \mathbf{0}$ for all i.

Alternatively, the utility functions in the PF can be considered as a logarithm of the video utility functions [e.g., the utility functions defined in (1)]. In this case, the solution can be expressed as

$$\begin{aligned}\mathbf{t}^* &= \underset{\sum_{i=1}^{M} t_i \le t_{SI}}{\arg\max} \sum_{i=1}^{M} \log U_i(R_i(t_i, \mathbf{s}_i^*)) \\ &= \underset{\sum_{i=1}^{M} t_i \le t_{SI}}{\arg\max} \sum_{i=1}^{M} PSNR_i. \end{aligned} \tag{14}$$

Thus, in this case, the PF solution becomes exactly the same as the MTSQ, i.e., $\mathcal{F}_{PF} = \mathcal{F}_{MTSQ}$ with $\boldsymbol{\psi}_i = (SNR_i, \mathbf{s}_i^*)$ for all i.

As we discussed in ETA and MTSQ, these fairness policies can result in inefficient resource allocations for autonomous multimedia users. Moreover, it should be noted that the PF is a special case of the NBS when the disagreement point is the origin as we discussed in Section IV-E, i.e., $\mathcal{F}_{PF} = \mathcal{F}_{NBS}$ if $\mathbf{d} = \mathbf{0}$ for the NBS. Hence, the PF also does not provide a fair resource allocation for autonomous WSTAs as the NBS can only be used for maximizing the system performance for collaborative WSTAs.

V. Proposed Utility-Fairness based on KSBS

As mentioned in the introduction, for a fair allocation of resources among autonomous WSTAs, it is essential that we consider the relative impact between the resulting qualities of multimedia users. We argue that the resource management has the following properties.

1) It should be Pareto optimal.
2) It should reward the users' effort to increase their utilities given a certain resource allocation by efficiently adapting their cross-layer strategies.
3) It should not be biased toward any particular user.
4) It should lead to the same resource allocation independently of the utility calibration.

Specifically, the resource management should set the quality drop to be the same among users. Alternatively, bias can be induced by weighing the quality drop according to the importance of users [17]. These utility-based fairness properties can be achieved by the fairness axioms of the well-known KSBS [16].

A. Required Components of Multimedia WSTAs for the KSBS

In this section, we identify the required elements for the KSBS. The notation X_i represents the achievable utility for WSTA i (i.e., $X_i = U_i(\cdot)$) and the vector inequality $\mathbf{x} \leq \mathbf{y}$ represents component-wise inequality (i.e., $x_i \leq y_i$ for all i) throughout this paper.

An *axiomatic bargaining solution* for a *bargaining problem* $(\mathbf{S}, \mathbf{d})$ where a feasible utility set $\mathbf{S}$ and the disagreement point $\mathbf{d}$, is a function $F : (\mathbf{S}, \mathbf{d}) \rightarrow \mathbb{R}^M$ such that $F(\mathbf{S}, \mathbf{d}) \in \mathbf{S}$. Hence, it is necessary to identify the feasible utility set $\mathbf{S}$ and the disagreement point $\mathbf{d}$ for multimedia WSTAs in order to deploy the KSBS.

1) *Feasible Utility Set:* A feasible utility set $\mathbf{S}$ is the set of all utility pairs that every WSTA can jointly form given all possible TXOP allocations. Thus, the feasible utility set can be expressed as

$$\mathbf{S} = \left\{ (U_1(R_1(t_1, \mathbf{s}_1)), \ldots, U_M(R_M(t_M, \mathbf{s}_M))) \;\middle|\; \sum_{i=1}^{M} t_i \leq t_{SI}, \mathbf{s}_i \in \mathcal{S}_i \text{ for all } i \right\}. \quad (15)$$

The feasible utility set needs to be at least comprehensive for the KSBS [26].

Definition 1 ($\mathbf{d}$-Comprehensive Set): Given a point $\mathbf{d} \in \mathbb{R}^M$ and a set $\mathbf{S} \subset \mathbb{R}^M$, the set $\mathbf{S}$ is $\mathbf{d}$-comprehensive if $\mathbf{d} \leq \mathbf{x} \leq \mathbf{y}$ and $\mathbf{y} \in \mathbf{S}$ implies $\mathbf{x} \in \mathbf{S}$.

Proposition 1: The feasible utility set $\mathbf{S}$ is $\mathbf{d}$-comprehensive.

Proof: See Appendix B. ■

2) *Disagreement Point:* A set of minimum achievable utilities for all WSTAs is referred to as the *disagreement point* ($\mathbf{d}$). The disagreement point can be achieved when WSTAs do not reach an agreement in a negotiation process, obtaining their minimum utilities from a game. Hence, if rational WSTAs join the resource management game, they expect to achieve higher utilities than the disagreement point. Thus, the disagreement point can be expressed as

$$\mathbf{d} = \left(X_{min}^1, \ldots, X_{min}^M\right) = \left(\min_{\mathbf{X} \in \mathbf{S}} X_1, \ldots, \min_{\mathbf{X} \in \mathbf{S}} X_M \right) \in \mathbf{S}.$$

This disagreement point plays a very important role in rate allocation for video WSTAs. As we discussed in Section II-A, based on different video characteristics and/or semantic importance, that may be varying over time, the minimum utility (quality) requirements of various WSTAs can be different (i.e., the minimum acceptable PSNR for various video sequences is different). Hence, the resource manager guarantees the minimum utility requirement for each WSTA, by correspondingly adjusting the disagreement point. For instance, the disagreement point can be determined based on the base-layer quality (i.e., minimum acceptable quality) for the MPEG-4 FGS video coder or H. 264, which needs to be satisfied when transmitting video sequences. This feature can be supported by the proposed KSBS, which is essential for multimedia applications streamed over time-varying channels. The decision of the disagreement point can be determined and communicated during the session initialization. For the simplicity of the notation, we assume in the remainder of the paper that the disagreement point coincides with the origin (i.e., $\mathbf{d} = 0$) of the utility domain, as the feasible utility set can be correspondingly translated based on the minimum utility requirement as proven in [26].

3) *Fairness Properties of KSBS:* The KSBS gives a unique Pareto optimal solution that fulfills the fairness axioms proposed in [16]. A general interpretation of these axioms for multimedia application is also provided in [17]. For multimedia WSTAs, the fairness axioms of *individual monotonicity* states that increasing the maximum achievable utility in a direction favorable to WSTA i always benefits WSTA i. Formally, given another feasible utility set $\mathbf{S}'$, if $\mathbf{S}' \supset \mathbf{S}$, $\mathbf{d} = \mathbf{d}'$, and $\max_{\mathbf{X} \in \mathbf{S}, \mathbf{X} \geq \mathbf{d}} X_k = \max_{\mathbf{X}' \in \mathbf{S}', \mathbf{X}' \geq \mathbf{d}'} X'_k$ for all $k \in \{1, \ldots, M\} \backslash \{i\}$, then $[F(\mathbf{S}', \mathbf{d}')]_i \geq [F(\mathbf{S}, \mathbf{d})]_i$. For example, let $(\mathbf{S}, \mathbf{d})$ and $(\mathbf{S}', \mathbf{d})$ be two bargaining problems, where $\mathbf{S} \subset \mathbf{S}'$ and the maximum achievable utilities of all WSTAs are the same except WSTA i. Individual monotonicity states that the WSTA i gains more utility in $(\mathbf{S}', \mathbf{d})$ than in $(\mathbf{S}, \mathbf{d})$ by the KSBS. Based on the effect of different cross-layer strategies on each WSTA, this property provides a strong motivation to deploy the optimal cross-layer strategy for autonomous multimedia WSTAs since the individual monotonicity guarantees to improve one WSTA's utility if it adopts a better cross-layer strategy. This property is shown in Proposition 2.

Proposition 2: When resources are allocated based on the KSBS, if one WSTA deploys a better cross-layer strategy given a channel condition, this always benefits this WSTA.

Proof: See Appendix C. ■

B. The KSBS for Multimedia WSTAs

For the bargaining problem $(\mathbf{S}, \mathbf{d})$ identified in Section V-A, the KSBS $\mathbf{X}^* = F(\mathbf{S}, \mathbf{d}) = (X_1^*, \ldots, X_M^*)$ for M WSTAs satisfies [16]

$$\mathbf{X}^* = F(\mathbf{S}, \mathbf{d}) = \mathbf{d} + \lambda_{MAX}(\mathbf{X}_{MAX} - \mathbf{d}) \quad (16)$$

where $\mathbf{X}_{MAX} = (X_{MAX}^1, \ldots, X_{MAX}^M)$ for $X_{MAX}^l = \max_{\mathbf{X} \in \mathbf{S}, \mathbf{X} \geq \mathbf{d}} X_l$, $l = 1, \ldots, M$, is the *ideal point* and $\lambda_{MAX} = \max_\lambda \{\lambda \mid \mathbf{d} + \lambda(\mathbf{X}_{MAX} - \mathbf{d}) \in \mathbf{S}\}$. The KSBS for multimedia WSTAs can be interpreted as [17]

Algorithm 1 KSBS Implementation

Require: WSTA characteristics information, external information $\psi_i = (\mathbf{s}_i^*, SNR_i)$ for all i.
1: Identify the feasible utility set $\mathbf{S}$ and the disagreement point $\mathbf{d}$ given the external information
2: Compute the KSBS for $(\mathbf{S}, \mathbf{d})$; $(X_1^*, \ldots, X_M^*) = F(\mathbf{S}, \mathbf{d})$
3: Compute the TXOPs; $t_i^* = R_i^{-1}(U_i^{-1}(X_i^*))$ for all i
4: Poll WSTAs based on the allocated TXOPs

$$\triangle PSNR_1 + 10\log_{10}\alpha_1 = \cdots = \triangle PSNR_M + 10\log_{10}\alpha_M \quad (17)$$

where $\triangle PSNR_i \triangleq (PSNR_{MAX}^i - PSNR_i^*)$ denotes the quality decrease (or drop) from WSTA i's maximum achievable quality and α_i is the bargaining power assigned to WSTA i. Hence, the resource allocation based on the fairness provided by the KSBS is suitable for autonomous multimedia WSTAs since the quality drops from their maximum achievable qualities for all WSTAs are the same (if all bargaining powers are the same). Note that different bargaining powers can be assigned to the different users based on their multimedia characteristics (e.g., higher motion, etc.), and it leads to the adjusted quality drop. The bargaining powers can be determined based on several rules for multimedia [17]. The TXOP allocation process in one SI based on the KSBS can be expressed as

$$\begin{aligned}\mathbf{t}^* &= \mathcal{F}_{KSBS}(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)\\ &= (\mathbf{R}^{-1} \circ \mathbf{U}^{-1} \circ F \circ \mathbf{U} \circ \mathbf{R})(\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_M)\end{aligned} \quad (18)$$

where a composite function of f and g is denoted by $f \circ g(x) = f(g(x))$ and F is the KSBS. $\mathbf{U}$ and $\mathbf{R}$ denote a set of utility functions and a set of rate function, i.e., $\mathbf{U} = (U_1(\cdot), \ldots, U_M(\cdot))$ and $\mathbf{R} = (R_1(\cdot), \ldots, R_M(\cdot))$. The external information is $\boldsymbol{\psi}_i = (SNR_i, \mathbf{s}_i^*)$ for all i. The involved steps are shown in Algorithm 1.

C. *Fairness Comparison in Terms of Multimedia Quality*

In this section, we compare the fairness achieved by different resource management strategies discussed in this paper. To quantify how fairly the resources are allocated by the resource manager, we introduce a new FCM. We define the FCM such that it can compare the performances achieved by different resource management strategies. By defining the social utility function for a resource management strategy $\mathcal{F}$ and the corresponding resource allocation $\mathbf{t}_{\mathcal{F}}$ as

$$\begin{aligned}U_{sys}(\mathbf{t}_{\mathcal{F}}) &= \max_{1\le i\le M}\left\{PSNR_{MAX}^i - PSNR_i^*(t_i)\right\}\\ &= \max_{1\le i\le M}\left\{\Delta PSNR_i(t_i)\right\}\end{aligned} \quad (19)$$

the fairness of different resource management strategies can be compared in terms of maximum quality drop. $U_{sys}(\mathbf{t}_{\mathcal{F}})$ defined in (19) represents the largest quality drop among WSTAs in the network. Thus, the social optimal strategy $\mathcal{F}^*$ can be determined such that it minimizes the maximum quality drop, i.e.,

$$\mathcal{F}^* = \arg\min_{\mathcal{F}\in\boldsymbol{\mathcal{F}}} U_{sys}(\mathbf{t}_{\mathcal{F}}) \quad (20)$$

where $\boldsymbol{\mathcal{F}}$ denotes a set of available resource management strategies.

In the considered resource management strategies, $\mathcal{F}^* = \mathcal{F}_{KSBS}$ because the KSBS results in the same quality drop among WSTAs. Note that the definition of function $U_{sys}(\mathbf{t}_{\mathcal{F}})$ in (19) is motivated by an *egalitarian social welfare function* discussed in [27]. For the social utility function in (19), the ratio between $U_{sys}(\mathbf{t}_{\mathcal{F}})$ for $\mathcal{F} \in \boldsymbol{\mathcal{F}}$ and $U_{sys}(\mathbf{t}_{\mathcal{F}_{KSBS}})$ can be used as a similar metric to the price of anarchy [28], which measures the fairness achieved by different resource management strategies, because $\mathcal{F}_{KSBS}$ is the socially optimal strategy. Specifically, the ratio, denoted by $FCM_{\mathcal{F}}$, is defined as

$$FCM_{\mathcal{F}} = \frac{U_{sys}(\mathbf{t}_{\mathcal{F}})}{U_{sys}(\mathbf{t}_{\mathcal{F}_{KSBS}})}. \quad (21)$$

Note that $FCM_{\mathcal{F}}$ becomes larger if strategy $\mathcal{F}$ results in a resource allocation that leads to a larger quality drop among WSTAs. This metric can be further extended by considering other social utility functions (e.g., total aggregated utility, etc.), which can emphasize other aspects of optimality as well as fairness. Alternatively, the reference social utility function $U_{sys}(\mathbf{t}_{\mathcal{F}_{KSBS}})$ determined based on the KSBS can also be generalized by introducing bargaining powers. The FCM for various resource management strategies are quantified in Section VI-A.

D. *Low-Complexity Implementations for the KSBS*

In the preceding sections, we formulate the bargaining problem and provide the interpretation of the KSBS given a fixed channel condition. However, the channel condition is time-varying even in the case when the WSTAs are not mobile. To successfully consider the time-varying channel condition, the complexity required for deploying the KSBS needs to be considered.[2] In this section, we design algorithms for the KSBS in order to reduce the required computational complexity.

1) *External Information Exchanges in Every SI:* If channel condition is time-varying, the optimal strategy is to deploy the KSBS to every SI, i.e., repeatedly apply Algorithm 1 in every SI. However, as discussed, it requires high-computational complexity to obtain the KSBS (including the formation of the feasible utility set) in every SI. More specifically, if the resource manager considers quantized service intervals with step size $\Delta t_{SI}(\le t_{SI})$, then $(\lfloor t_{SI}/\Delta t_{SI}\rfloor)^M$ utility points in the feasible utility set need to be identified. Thus, the computational complexity $C(M)$ required for the KSBS can be expressed as $C(M) = P \cdot (\lfloor t_{SI}/\Delta t_{SI}\rfloor)^M$, where P is a positive constant. This implies that the time required for resource allocation based on the KSBS increases exponentially with respect to the number of users in the network. Hence, the required complexity in total during the transmission time T can be expressed as

$$C_1(M) = \left\lfloor \frac{T}{t_{SI}} \right\rfloor \cdot C(M) = P \cdot \left\lfloor \frac{T}{t_{SI}} \right\rfloor \cdot \left(\left\lfloor \frac{t_{SI}}{\Delta t_{SI}} \right\rfloor\right)^M.$$

[2]We assume that the required overheads for exchanging the external information are negligible, as they can be expressed with a few bytes and can be augmented in TSPEC.

Algorithm 2 Channel condition or video characteristics driven external information exchanges for WSTA

Require: Channel condition variation threshold δ_c, video characteristics variation threshold δ_q, previous and current channel condition: SNR_i^- and SNR_i, previous and current video characteristics: V_i^- and V_i, previous TXOP allocation t_i^-.

loop
  if $|SNR_i - SNR_i^-| \geq \delta_c$ **then**
    Find the best cross-layer strategy given SNR_i; $\mathbf{s}_i^*$
    Request new TXOP allocation: send $\psi_i = (SNR_i, \mathbf{s}_i^*)$ to resource manager
    New TXOP based on the KSBS (Algorithm 1) by the resource manager; t_i^*
  else if $|V_i - V_i^-| \geq \delta_q$ **then**
    Request new TXOP allocation: send multimedia characteristics information to resource manager
    New TXOP allocation based on the KSBS (Algorithm 1) by the resource manager; t_i^*
  else
    Update TXOP allocation; $t_i := t_i^-$
  end if
end loop

Algorithm 3 Iterative method for the KSBS with no external information exchange

Require: TXOP adjustment step Δt.

loop
  Received quality drop for previous allocated TXOP allocation $(t_1^-, \ldots, t_M^-)$; $\Delta\mathbf{PSNR}^- = (\Delta PSNR_1^-, \ldots, PSNR_M^-)$.
  Compute quality drop change; $\Delta\mathbf{P} = (\Delta\mathbf{PSNR}^- - \overline{\Delta\mathbf{PSNR}^-})$
  Adjust TXOP allocation based on $\Delta\mathbf{P}$; $t_i = t_i^- + [\Delta\mathbf{P}]_i \cdot \Delta t$ for all i.
end loop

2) *Channel Condition or Video Characteristics Driven External Information Exchanges:* Small variation of the channel condition or the video characteristics for WSTAs does not induce significant changes in their selected cross-layer strategies or achievable qualities. Hence, there will be small changes in the feasible utility set as well as the resulting KSBS. Hence, the computational complexity for the TXOP allocation can be significantly reduced only by exchanging the external information and computing the KSBS when channel condition or video characteristics changes significantly. WSTAs keep estimating the channel condition and the video characteristics. When the channel condition variation is larger than the predetermined threshold δ_c, or the video characteristics variation is larger than the threshold δ_q, they are allowed to request a new TXOP allocation. Note that threshold δ_c and δ_q can be adaptively adjusted by the resource manager by considering the visual impact of WSTAs on the achieved quality. The required steps for WSTAs are presented in Algorithm 2. Note that this algorithm needs to be implemented by the WSTAs.

As shown in Algorithm 2, the required computational complexity in the resource manager can be estimated as

$$C_2(M) = m \cdot C(M) = P \cdot m \cdot \left(\left\lfloor \frac{t_{SI}}{\Delta t_{SI}} \right\rfloor \right)^M$$

where $m\,(\leq \lfloor T/t_{SI} \rfloor)$ represents the number of SIs where WSTAs request new TXOP allocations during transmission. Therefore, the complexity reduction by deploying Algorithm 2 as compared to the approach in Section V-D1 is given by

$$\frac{C_2(M)}{C_1(M)} = \frac{P \cdot m \cdot (\lfloor t_{SI}/\Delta t_{SI} \rfloor)^M}{P \cdot \lfloor T/t_{SI} \rfloor \cdot (\lfloor t_{SI}/\Delta t_{SI} \rfloor)^M} = \frac{m}{\lfloor T/t_{SI} \rfloor} \leq 1.$$

Thus, the complexity reduction achieved based on Algorithm 2 becomes significant if the channel conditions or the video characteristics of the WSTAs do not considerably change, i.e., smaller value of m.

3) *Quality Drop as External Information:* The required computational complexity can be further reduced by exchanging the information about the quality drop, instead of exchanging the external information or the video characteristics information for the KSBS. Since the external information or the video characteristics information is not exchanged, the resource manager cannot compute the KSBS. However, the resource manager can use the quality drop information for each WSTA to obtain a solution to the KSBS. This algorithm is developed based on the interpretation of the KSBS for the multimedia shown in (17).

In every SI, each WSTA computes its own quality drop for the given TXOP allocation and send this information to the resource manager. Then, the resource manager can adjust its TXOP allocation, such that WSTAs can achieve the same quality drop (or adjusted quality drop based on the bargaining powers). This solution significantly reduces the computational complexity, as the resource manager does not need to compute the KSBS directly. This TXOP allocation algorithm is presented in Algorithm 3. Note that Δt in Algorithm 3 can be adaptively predetermined based on applications. This algorithm requires only a constant computational complexity. Hence

$$C_3(M) = P' \cdot M$$

where P' is a positive constant. Thus, the complexity reduction based on Algorithm 3 as compared to the approach in Section V-D1 is given by

$$\frac{C_3(M)}{C_1(M)} = \frac{P' \cdot M}{P \cdot \lfloor T/t_{SI} \rfloor \cdot (\lfloor t_{SI}/\Delta t_{SI} \rfloor)^M} \ll 1 \qquad (22)$$

for $M \geq 2$. Therefore, the complexity reduction can be significantly improved as the number of WSTAs in a network increases.

VI. Simulation Results

In this section, we first show simulation results comparing the KSBS with the other solutions described in Section IV. Then, we show the effect of bargaining powers in the KSBS. For a simulation setup, each WSTA is assumed to have the ability to choose the optimal cross-layer strategy given the channel SNR. Based on this information, the resource manager allocates the available time resources to the WSTAs during each SI. The parameter values for the DR models of the different coders are determined based on the H.264 video coder and the FGS video coder.

TABLE I
RESOURCE ALLOCATION BASED ON FAIRNESS POLICIES

Scenario	SNR [dB]	Strategy	Time Allocation [ms]	PSNR [dB]	$\triangle PSNR_i$ [dB]	$FCM_{\mathcal{F}}$
1	[28, 23]	MTSQ	[38.0, 62.0]	[38.1039, 30.3372]	[4.1927, 3.8262]	1.0045
		ETA	[50.0, 50.0]	[39.2957, 28.9654]	[3.0008, 5.1979]	1.2453
		ATA	[15.3, 84.7]	[34.1583, 32.9298]	[8.1383, 1.2335]	1.9498
		GPS	[15.9, 84.1]	[34.3283, 32.8599]	[7.9682, 1.3034]	1.9090
		KSBS (0.5, 0.5)	[38.2, 61.8]	[38.1225, 29.9893]	[4.1740, 4.1740]	1.00
		KSBS (0.2, 0.8)	[16.5, 83.5]	[34.4741, 32.3615]	[7.8224, 1.8018]	–
		KSBS (0.6, 0.4)	[46.6, 53.4]	[38.9765, 29.0823]	[3.3201, 5.0810]	–
2	[28, 13]	MTSQ	[98.2, 1.8]	[42.2272, 23.3025]	[0.0694, 2.7845]	1.5035
		ETA	[50.0, 50.0]	[39.2957, 24.7081]	[3.0008, 1.3789]	1.6203
		ATA	[4.4, 95.6]	[28.7519, 26.0376]	[13.5447, 0.0494]	7.3136
		GPS	[15.9, 84.1]	[34.3283, 25.7016]	[7.9682, 0.3853]	4.3025
		KSBS (0.5, 0.5)	[65.3, 34.7]	[40.4445, 24.2349]	[1.8520, 1.8520]	1.00
		KSBS (0.2, 0.8)	[21.7, 78.3]	[35.6604, 25.4714]	[6.6361, 0.6155]	–
		KSBS (0.6, 0.4)	[85.7, 14.3]	[41.6263, 23.6558]	[0.6703, 2.4312]	–

TABLE II
CONSECUTIVE BARGAINING OVER TIME-VARYING CHANNEL

Scenario	Strategy	SNR [dB]	$PSNR_i^*$ [dB]	PSNR Improvement [%]	$\triangle PSNR_i$
1	$[s_1\ s_2\ s_3\ s_4\ s_5]$	[10 18 21 25 28]	[28.14 29.97 30.70 18.85 18.85]	–	7.51 dB
2	$[s_1\ s_2\ s_3\ s_4^*\ s_5^*]$	[10 18 21 25 28]	[29.27 31.10 31.83 29.27 29.37]	[4.0 3.8 3.7 55.3 55.8]	6.38 dB
3	$[s_1\ s_2\ s_3\ s_4\ s_5]$	[23 20 21 25 28]	[29.33 31.16 31.83 29.27 29.37]	[0.2 0.2 0.0 0.0 0.0]	6.38 dB
4	$[s_1^*\ s_2^*\ s_3\ s_4\ s_5]$	[23 20 21 25 28]	[38.01 31.84 31.89 29.33 29.43]	[29.6 2.2 0.2 0.2 0.2]	6.32 dB

A. Comparison with Existing Fairness Policies

In this section, we compare the resource allocations discussed in Section IV. We assume that there are two WSTAs in the system. For the ATA policy, we used the 35 dB quality level, which is considered as a desired video quality level for most videos, and thus, the $R_{1,MAX}$ and $R_{2,MAX}$ in (10) are determined to satisfy this quality level. For the KSBS, we use several bargaining powers. We assume that t_{SI} is 100 ms and the channel SNR is fixed in this duration. The packet length has a maximum length of 500 B.

The simulation results are shown in Table I for two channel condition scenarios. The channel SNRs for WSTAs 1 and 2 are 28 dB and 23 dB in scenario 1, and 28 dB and 13 dB in scenario 2. From the simulation results for the two scenarios, we found that the various fairness criteria of the resource manager derive distinct resource allocations, resulting in different achieved video qualities. In both scenarios, though the MTSQ policy leads to the maximum sum of the PSNRs, the quality difference between WSTAs is significantly large. This is unfair for noncollaborative multiuser transmission. This unfairness is increased when the channel condition is further degraded (see scenario 2 in Table I). The ETA policy achieves a fair allocation in terms of the time resources, but it is inefficient in the utility domain. This policy achieves neither the highest sum of PSNR nor a similar video quality level for WSTAs. The GPS policy leads to proportional allocation in the time resources. Though this policy adapts based on the video sequences characteristics to some extent, it is independent of the channel conditions and it does not consider the utility explicitly. The ATA policy enables the WSTAs to achieve a similar quality level. However, it should be noted that this policy is unfair as it severely penalizes the WSTA experiencing a better channel condition. This unfairness becomes worse when the WSTA channel condition further degrades (see the quality drop). Hence, this policy is unfair and undesirable for multimedia applications. However, the KSBS allocates the resources such that WSTAs achieve the same quality penalty (see the quality drop). The fairness achieved by different resource allocation schemes are quantified based on the FCM defined in (21). As discussed in Section V-C, the value of FCM increases for a resource management strategy $\mathcal{F}$ as it results in larger quality drops among WSTAs. This can be verified from the results in Table I.

Note that even if in some cases the fairness policies provide a similar resource allocation, *only* the KSBS can enable the implementation of different fairness criteria based on the video quality experienced by the WSTAs by introducing bargaining powers. For example, if the goal of the resource management is to achieve a similar quality level for the WSTAs, bargaining powers around (0.2, 0.8) can be used. Alternatively, if the goal of the resource management is to maximize the total sum of PSNR values, bargaining powers around (0.6, 0.4) can be used.

B. Interaction Among WSTAs

In this section, we show simulation results to quantify the impact of one WSTA's cross-layer strategy on the other WSTAs' utilities. For the simulation, we assume that there are five WSTAs transmitting different CIF video sequences at 30 Hz, i.e., *Foreman* (WSTA 1), *Coastguard* (WSTAs 2 and 3), and *Mobile* (WSTAs 4 and 5) encoded by the wavelet video coder. The resource manager deploys the KSBS for the resource allocation. The simulation results for four scenarios are presented in Table II.

In scenarios 1–3, we can observe the impact of the deployed cross-layer strategies given a channel conditions. In scenario 2, WSTAs 4 and 5 deploy better cross-layer strategies

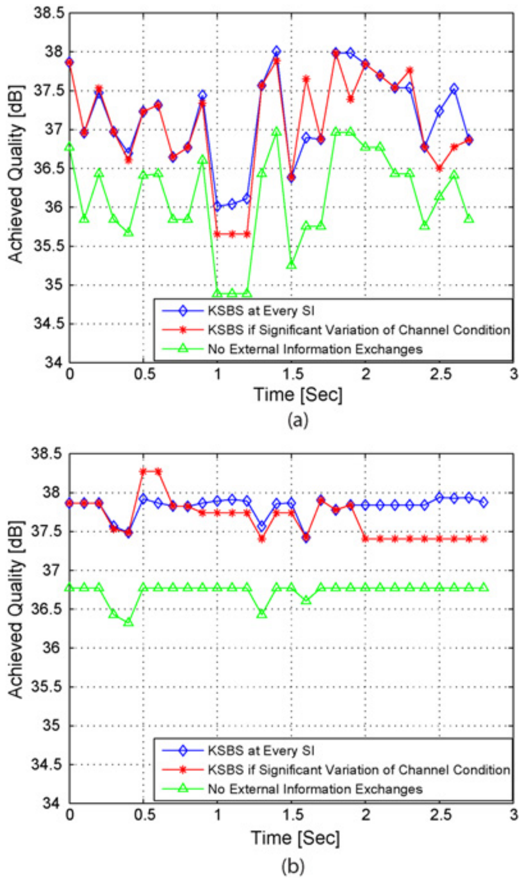

Fig. 3. Achieved quality based on Algorithm 2. (a) Large variation of channel condition. (b) Small variation of channel condition.

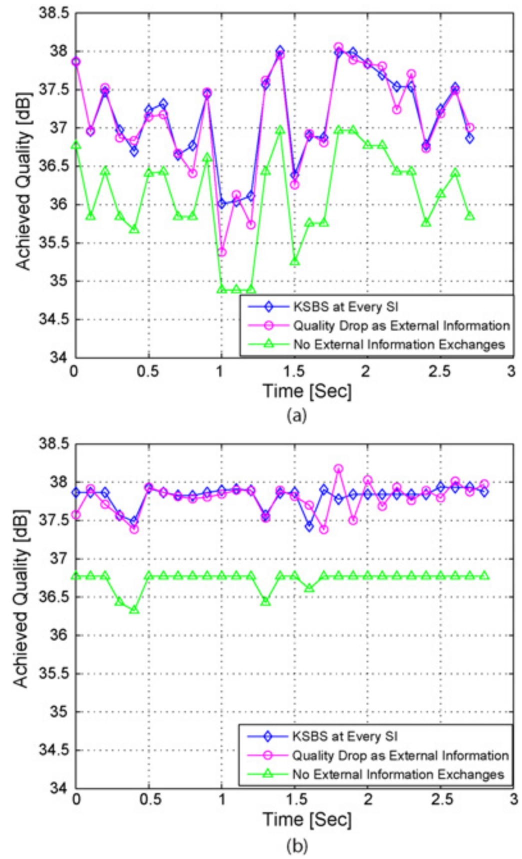

Fig. 4. Achieved quality based on Algorithm 3. (a) Large variation of channel condition. (b) Small variation of channel condition.

than those in scenario 1 given the same channel condition, leading to better quality improvement for them due to the individual monotonicity of the KSBS. In scenarios 2 and 3, all WSTAs maintain their cross-layer strategies (i.e., they do not optimize their cross-layer strategies for the change of channel conditions) even though the channel conditions are improved. In this case, we observe that there is almost no utility improvement for all of them. In scenario 4, WSTAs 1 and 2 deploy optimized cross-layer strategies than those in the scenario 3 given the channel condition, which results in an improved quality for them as well.

From these simulation results, we can conclude that the cross-layer transmission strategies with which WSTAs play the resource management game are very important and have an essential impact on both the individual quality of the WSTAs as well as their impact on the utility of the competing WSTAs.

C. Comparison of Proposed Algorithms

In Section V-D, several algorithms for the efficient KSBS implementations are developed. We quantify the performance of the algorithms focusing on the achieved quality and the required complexity. In the simulations, we assume that the $t_{SI} = 100\,\text{ms}$ and channel condition varies over time for WSTAs [6].

Fig. 3 highlights the achieved quality and the channel adaptation of a WSTA based on the proposed Algorithm 2. When the channel condition changes significantly [Fig. 3(a)], i.e., more than the threshold δ_c, the WSTAs request new TXOP allocations to the resource manager more often, hence the quality achieved by Algorithm 2 coincides at times with those obtained by the KSBS. Thus, Algorithm 2 does not provide considerable gain in terms of the computational complexity when channel condition changes significantly. However, if the channel condition varies slowly [Fig. 3(b)], the WSTAs based on Algorithm 2 do not frequently request new TXOP allocations, which can reduce the computational complexity associated with the resource allocation implementation. Hence, we can observe that there is a small quality gap (at most 0.5 dB PSNR) between the qualities achieved by the KSBS at every SI and Algorithm 2. We assume that if no external information is exchanged, the TXOP allocation is fixed from the beginning of the transmission.

Similarly, Fig. 4 highlights the achieved quality and the channel adaptation of a WSTA based on the proposed Algorithm 3. Note that this algorithm does not require the direct computation of the KSBS, which can significantly reduce the computational complexity. We can observe that this algorithm can provide a quite similar performance in terms of the achieved quality to the KSBS at every SI. Therefore, we conclude that the proposed algorithms can provide practical solutions for implementing the KSBS with significantly less computational complexity and information exchanges.

VII. Conclusion

In this paper, we have aimed at addressing the problem of fair allocation of resources among multiple wireless multimedia users. We review several existing fairness policies, analyze their performance in terms of the resulting multimedia quality, and discuss their limitations. We also propose an utility-based fairness solution (KSBS) that enables every WSTA to experience the same quality drop from its maximum achievable quality. In the simulation results, we show that the KSBS provides a fair resource allocation for multimedia applications. Moreover, we quantify the impact of one WSTA's cross-layer strategies on other WSTAs' achievable quality. Finally, we show that the practical solutions, which significantly reduce the computational complexity, can provide a similar performance to the KSBS when channel condition or video characteristics are changing.

Appendix A

We show that the PF is the ETA if the utility functions are set to be a logarithm of the video rates. The optimization problem in (13) is

$$\mathbf{t}^* = \arg\max_{\sum_{i=1}^{M} t_i \le t_{SI}} \sum_{i=1}^{M} \log R_i(t_i, \mathbf{s}_i^*)$$

$$= \arg\max_{\sum_{i=1}^{M} t_i \le t_{SI}} \sum_{i=1}^{M} \log \left[R_i^{phy}(SNR_i, \mathbf{phy}_i^*) \cdot \frac{t_i}{t_{SI}} \right].$$

To simplify the notation, we substitute a_i for the term $R_i^{phy}(SNR_i, \mathbf{phy}_i^*)$. Then, the objective function is expressed as $\sum_{i=1}^{M} \log a_i \frac{t_i}{t_{SI}} = \log \prod_{i=1}^{M} a_i \frac{t_i}{t_{SI}}$. Since the logarithmic is a nondecreasing function, this optimization problem is equivalent to

$$(t_1^*, \ldots, t_M^*) = \arg\max_{(t_1,\ldots,t_M)} \prod_{i=1}^{M} a_i \cdot \prod_{i=1}^{M} \frac{t_i}{t_{SI}} \tag{23}$$

where $\sum_{i=1}^{M} t_i \le t_{SI}$ and $t_i \ge 0$. Using the well-known relationship between arithmetic and geometric mean and the fact that $\sum_{i=1}^{M} t_i = t_{SI}$, we have

$$\sum_{i=1}^{M} \frac{t_i}{t_{SI}} \ge M \left(\prod_{i=1}^{M} \frac{t_i}{t_{SI}} \right)^{\frac{1}{M}}. \tag{24}$$

The equality holds when $t_1/t_{SI} = \cdots = t_M/t_{SI}$. Since a_i is constant for all i if the cross-layer strategy and the channel condition are given, the solution of the optimization problem (i.e., the TXOP allocation by the proportional fairness) is $(t_1^*, \ldots, t_M^*) = (t_{SI}/M, \ldots, t_{SI}/M)$, which is the ETA. Thus, the achieved rate of WSTA i by the proportional fairness is $a_i \frac{t_i}{t_{SI}} = a_i/M = R_i^{phy}(SNR_i, \mathbf{phy}_i^*)/M$. Note that similar proof was derived from [29].

Inversely, we can show that the ETA satisfies the proportional fairness criteria [7]. A vector of rate $(a_1/M, \ldots, a_M/M)$ is proportionally fair if it is feasible and if for any other feasible vector of rate $x = (a_1 \frac{t_1}{t_{SI}}, \ldots, a_M \frac{t_M}{t_{SI}})$ satisfies

$$\sum_{i=1}^{M} \frac{x_i - a_i/M}{a_i/M} \le 0. \tag{25}$$

For any other feasible vector of rate, this is true because

$$\sum_{i=1}^{M} \frac{x_i - a_i/M}{a_i/M} = \sum_{i=1}^{M} \frac{a_i \frac{t_i}{t_{SI}} - a_i/M}{a_i/M}$$
$$= M \cdot \sum_{i=1}^{M} \frac{t_i}{t_{SI}} - M \le M - M = 0. \tag{26}$$

Appendix B
Proof of Proposition 1

Let $\mathbf{S}$ be the feasible utility set for a certain cross-layer strategy and there is a given point $\mathbf{d} \in \mathbb{R}^M$. Suppose that $\mathbf{d} \le \mathbf{x} \le \mathbf{y}$ and $\mathbf{y} \in \mathbf{S}$. Using the definition of utility functions, we can express $\mathbf{x}$ and $\mathbf{y}$ with respect to feasible TXOP allocations $(t_1, \ldots, t_M)$ and $(t_1', \ldots, t_M')$, where $\sum_{i=1}^{M} t_i \le t_{SI}$ and $\sum_{i=1}^{M} t_i' \le t_{SI}$, as follows:

$$\begin{aligned} \mathbf{x} &= [U_1(R_1(t_1)), \cdots, U_M(R_M(t_M))]^T, \\ \mathbf{y} &= [U_1(R_1(t_1')), \cdots, U_M(R_M(t_M'))]^T. \end{aligned} \tag{27}$$

Note that the rate in (27) is only a function of time not a cross-layer strategy because the feasible utility set $\mathbf{S}$ is already formed by a set of cross-layer strategies. Since the utility function $U_i(R_i(t_i))$ is a nondecreasing for a rate $R_i(t_i)$, the following inequalities are equivalent:

$$\begin{aligned} \mathbf{x}^T \le \mathbf{y}^T &\Longleftrightarrow [U_1(R_1(t_1)), \ldots, U_M(R_M(t_M))] \\ &\qquad \le [U_1(R_1(t_1')), \ldots, U_M(R_M(t_M'))] \\ &\Longleftrightarrow [R_1(t_1), \ldots, R_M(t_M)]^T \le [R_1(t_1'), \ldots, R_M(t_M')]. \end{aligned}$$

From the rate $R_i(t_i)$ in (7), we have the following equivalent inequalities:

$$R_i(t_i) \le R_i(t_i') \Longrightarrow \overline{N}_i^{pkt}(t_i) \le \overline{N}_i^{pkt}(t_i') \Longrightarrow t_i \le t_i'.$$

Hence, $\mathbf{x} \le \mathbf{y} \Longleftrightarrow [t_1, \ldots, t_M]^T \le [t_1', \ldots, t_M']^T$, and therefore, $\mathbf{x} \in \mathbf{S}$, since $\mathbf{y} \in \mathbf{S}$. ■

Appendix C
Proof of Proposition 2

Let $\mathbf{S}$ be the feasible utility set formed by the WSTAs' cross-layer strategies $\{\mathbf{s}_1, \ldots, \mathbf{s}_M\}$, where $\mathbf{s}_i = [\mathbf{phy}_i^{n_i}, \mathbf{mac}_i^{m_i}, \mathbf{app}_i^{l_i}]$. Then, the set $\mathbf{S}$ is expressed as

$$\mathbf{S} = \left\{ (U_1(R_1(t_1, \mathbf{s}_1))), \ldots, (U_M(R_M(t_M, \mathbf{s}_M))) \middle| \sum_{i=1}^{M} t_i \le t_{SI} \right\}$$

where $U_i(\cdot)$ and $R_i(\cdot)$ are the utility function and the average video bit rate function defined in (7), respectively. Let $\mathbf{s}_j' = [\mathbf{phy}_j^{n_j'}, \mathbf{mac}_j^{m_j'}, \mathbf{app}_j^{l_j'}]$ be another cross-layer strategy, which is available to WSTA j and enables it to achieve a higher utility. Hence, the resulting feasible utility set $\mathbf{S}'$ is expressed as

$$\begin{aligned} \mathbf{S}' = \{&(U_1(R_1(t_1, \mathbf{s}_1))), \ldots, (U_j(R_j(t_j, \mathbf{s}_j'))), \ldots, \\ &(U_M(R_M(t_M, \mathbf{s}_M)))| \sum_{i=1}^{M} t_i \le t_{SI}\}. \end{aligned} \tag{28}$$

Based on the cross-layer strategies $\{\mathbf{s}_1, \ldots, \mathbf{s}_j', \ldots, \mathbf{s}_M\}$, a larger feasible utility set can be formed, $\mathbf{S}' \supset \mathbf{S}$. By the axiom of individual monotonicity of the KSBS, the achieved utility for WSTA j is always improved. ■

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