Quality Optimal Policy for H.264 Scalable Video Scheduling in Broadband Multimedia Wireless Networks

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***Abstract*—In this paper we consider the problem of optimal H.264 scalable video scheduling, with an objective of maximizing the end user video quality while ensuring fairness in 3G/4G broadband wireless networks. We propose a novel framework to characterize the video quality based utility of the H.264 temporal and quality scalable video layers. Subsequently we formulate the scalable video scheduling framework as a Markov decision process (MDP) for long term average video utility maximization and derive an optimal index based scalable video scheduling policy (ISVP) towards video quality maximization. This framework employs a reward structure which incorporates video quality and user starvation, thus leading to video quality maximization, while not compromising fairness. Simulation results demonstrate that the proposed ISVP outperforms the Proportional Fairness (PF) and Linear Index Policy (LIP) schedulers in terms of end user video quality.**

I. Introduction

Video content, which is the key to popular 3G/4G services, is expected to progressively comprise a dominating fraction of the wireless traffic in next generation wireless networks based on LTE, WiMAX. However, the erratic wireless environment coupled with the tremendous heterogeneity in the display and decoding capabilities of wireless devices such as smart phones, tablets, notebooks etc. renders conventional fixed profile video transmission unsuitable in such scenarios. H.264 based scalable video coding (SVC) has gained significant popularity in the context of video transmission as it avoids the problem of simulcasting fixed profile video streams at different spatial and temporal profiles by embedding a base layer low resolution stream in a hierarchical stream consisting of several differential enhancement layers. Another significant advantage of SVC over conventional video coding is graceful degradation of video quality in the event of packet drops due to network congestion. Efficient video scheduling algorithms are critical towards QoS enforcement and end-user video quality maximization in broadband 4G networks. However, existing schemes such as [1] and [2] are generic data scheduling schemes and video agnostic. They do not utilize the unique structure of coded digital video and thus result in suboptimal schemes for video quality maximization.

In this paper we consider the problem of optimal scheduler design for scalable video data transmission in downlink 3G/4G wireless networks. In this context, we present a novel framework to characterize the utility of the different scalable video layers in an H.264 SVC video stream. Further, it is essential to derive optimal scheduling algorithms towards net video quality maximization also ensuring fairness based QoS. Recently, in [3], a novel index based scheduling policy has been derived for fairness aware throughput maximization in wireless networks based on a Markov decision process (MDP) formulation. Based on the scheme proposed therein, we set up the video scheduling problem as an MDP and derive a novel video utility index based scalable video scheduling policy (ISVP) for scheduling of scalable video data. Simulation results demonstrate that this scheme outperforms the proportional fair resource allocation and linear index policy (LIP) based schedulers in terms of net video quality.

The rest of the paper is organized as follows. In section II we present the wireless video system model and develop a novel framework to characterize the utility of the H.264 scalable coded video frames. In section III we formulate the optimal SVC scheduling problem as a MDP and demonstrate an optimal index based video scheduling policy. We present simulation results in section IV to illustrate the performance of the proposed scheme and conclude with section V.

II. Wireless Scalable Video Framework

In this section we describe the wireless network system model for scalable video streaming and present a novel framework to compute the transmitted video utility towards characterizing the end user video experience. We consider a cell supporting a total of U broadband wireless users, with u, $1 \leq u \leq U$ denoting the user index. We consider infinite queue lengths and slotted time for packet transmission. H.264 supports three modes of video scalability - temporal, quality and spatial. In our work we consider video scheduling for temporal and quality scalable H.264 video and the extension to spatially scalable video sequences is relatively straight forward. Coded digital video streams such as H.264 employ a *group of pictures* (GOP) structure for differential pulse-code modulation (DPCM) based video coding. In a scalable

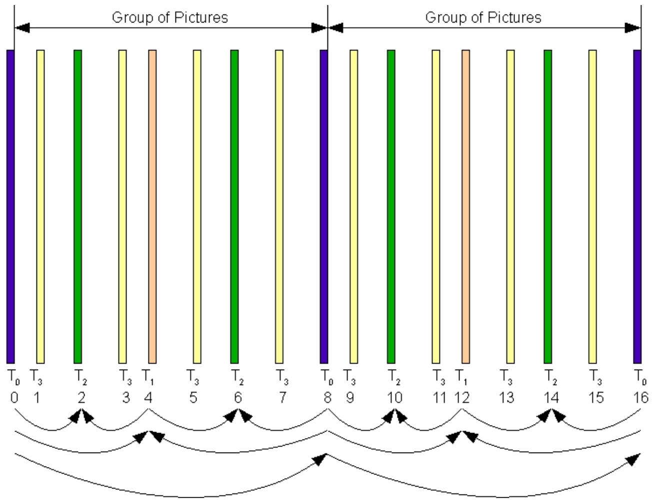

Fig. 1. Group of Pictures - Temporal Scalability

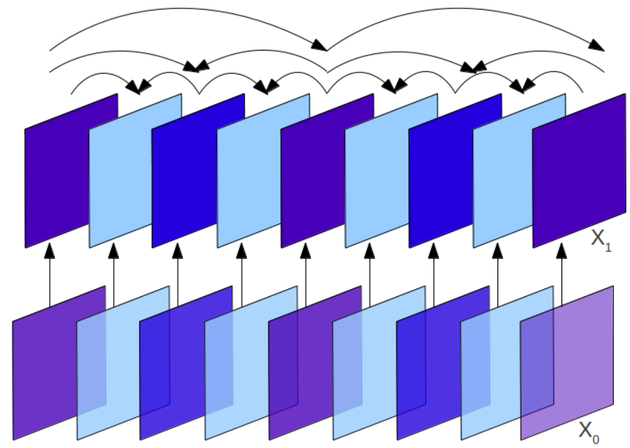

Fig. 2. Temporal and Quantization Scalability

video sequence, temporal scalability is achieved through dynamic GOP size scaling by insertion or deletion of additional temporal layers. An example of the temporally scalable GOP structure with dyadic temporal enhancement video layers is shown in the Fig.1. The T_0 frames are the base layer *intra-coded* video frames while T_1 frames are *inter-coded* and those of subsequent layers such as T_2 are *bi-directional predictively* coded from frames in lower layers. Quality scalability is achieved by using different quantization parameters for the quality video layers. The base quality layer X_0 as shown in Fig.2 is coded with a coarse quantization parameter q_0. The subsequent higher layer X_1 is differentially coded with a lower quantization parameter q_1 and so on for each higher layer. The highest quality corresponds to the lowest quantization parameter $q_{\min}$. Thus, the net video rate can be scaled dynamically by appropriately choosing the temporal and quality video layers.

A. *Video Utility Framework*

It can be readily seen from the above GOP description that different component frames of the H.264 salable video GOP have differing impacts on the net video quality and hence have different utilities. For example considering temporal scalability, it can be observed that the base layer T_0 has a significant impact on video quality compared to the enhancement layers T_1, T_2, since frames in T_0 can be decoded independently as they are intra-coded. However, failing reception of T_0 frames, one cannot decode the enhancement layer frames of T_1, T_2. Hence, a realistic video scheduling framework is needed which ascribes differentiated video utilities accurately characterizing the impact of a particular GOP component on the net video quality. Further, we define the per bit normalized utility $\mathcal{U}_{(i,j)}$ associated with temporal layer i and quality layer j as the ratio of the impact on video quality $\tilde{Q}_{(i,j)}$ to frame size $B_{(i,j)}$ as,

$$\mathcal{U}_{(i,j)} = \frac{\tilde{Q}_{(i,j)}}{B_{(i,j)}}. \tag{1}$$

The above quantity $\mathcal{U}_{(i,j)}$ can be interpreted as the utility of scheduling each bit of the video layer, thus associating a higher utility with video sequences of smaller frame sizes compared to larger ones. Below, we propose a framework to compute the quality and size parameters $\tilde{Q}_{(i,j)}$, $B_{(i,j)}$ in H.264 scalable video scenarios.

1) Video Layer Frame Size Model: The JSVM reference H.264 codec [4] developed jointly by the ITU-T H.264 and the ISO/IEC MPEG-4 AVC groups can be conveniently employed to characterize the frame sizes of the respective scalable video coded streams. Let $\mathcal{V}_{(m,n)}$ denote the scalable video stream comprising of $m+1$, i.e. $0, 1, ..., m$ temporal layers and $n+1$ quality video layers, while $\tilde{\mathcal{V}}_{(m,n)}$ denotes the exclusive m^{th} temporal and n^{th} quality layer. We consider 4 temporal layers at the standard frame rates of 3.75, 7.5, 15, and 30 frames per second and 3 quantization layers in JSVM corresponding to quantization parameters (QP) 40, 36 and 32. The quantization step-size q corresponding to the quantization parameter QP is given as $q = 2^{((\mathrm{QP}-4)/6))}$ [5]. Hence, the quantization step-sizes corresponding to QP = 40, 36, 32 are q = 64, 40.32, 25.40 respectively. We employ the notation $R_{(m,n)}$ to denote the bit-rate of the stream $\mathcal{V}_{(m,n)}$. Table I illustrates the computed layer rates and frame sizes for the standard *Crew* video [6]. For instance, the rate $R_{(0,0)}$ comprising of the spatial and quality base layers exclusively is given as $R_{(0,0)} = 79.2$ Kbps. Hence, the average base layer frame size can be derived by normalizing with respect to the base-layer frame rate of $f_{(0,0)} = 3.75$ frames per second as,

$$B_{(0,0)} = \frac{R_{(0,0)}}{f_{(0,0)}} = 21.12\,\text{Kb}.$$

The JSVM codec yields the cumulative bit-rate corresponding to the combination of base and enhancement layers of the video stream. Hence the rate $R_{(0,1)}$ corresponds to the cumulative bit-rate of the scalable video stream consisting of video layers $\tilde{\mathcal{V}}_{(0,0)}$ and $\tilde{\mathcal{V}}_{(0,1)}$. The differential rate $\tilde{R}_{(0,1)}$ comprising exclusively of the differential video rate arising

Video Stream	Cumulative Rate $R_{(m,n)}$	Cumulative Quality $Q_{(m,n)}$	Differential Relation $Y_{(m,n)} = R_{(m,n)}$ *or* $Q_{(m,n)}$	Differential Rate $\tilde{R}_{(m,n)}$	Differential Quality $\tilde{Q}_{(m,n)}$	N (Kb)	Utility $\mathcal{U}_{(m,n)}$
$\mathcal{V}_{(0,0)}$	79.2	41.301	$Y_{(0,0)}$	79.2000	41.3012	21.120	1.9556
$\mathcal{V}_{(0,1)}$	165.80	48.395	$Y_{(0,1)} - Y_{(0,0)}$	86.6000	7.0943	23.093	0.3072
$\mathcal{V}_{(0,2)}$	315.80	53.477	$Y_{(0,2)} - Y_{(0,1)}$	150.0000	5.0822	40.000	0.1271
$\mathcal{V}_{(1,0)}$	107.40	57.801	$Y_{(1,0)} - Y_{(0,0)}$	28.2000	16.5005	7.520	2.1942
$\mathcal{V}_{(1,1)}$	226.40	67.730	$(Y_{(1,1)} - Y_{(0,1)}) - (Y_{(1,0)} - Y_{(0,0)})$	32.4000	2.8343	8.640	0.3280
$\mathcal{V}_{(1,2)}$	441.60	74.843	$(Y_{(1,2)} - Y_{(0,2)}) - (Y_{(1,1)} - Y_{(0,1)})$	65.2000	2.0304	17.386	0.1168
$\mathcal{V}_{(2,0)}$	137.50	67.027	$(Y_{(2,0)} - Y_{(1,0)})/2$	15.0500	4.6130	4.013	1.1494
$\mathcal{V}_{(2,1)}$	292.80	78.541	$((Y_{(2,1)} - Y_{(1,1)}) - (Y_{(2,0)} - Y_{(1,0)}))/2$	18.1500	0.7924	4.840	0.1637
$\mathcal{V}_{(2,2)}$	575.90	86.788	$((Y_{(2,2)} - Y_{(1,2)}) - (Y_{(2,1)} - Y_{(1,1)}))/2$	33.9500	0.5676	9.053	0.0627
$\mathcal{V}_{(3,0)}$	171.40	68.735	$(Y_{(3,0)} - Y_{(2,0)})/4$	8.4750	0.4269	2.260	0.1889
$\mathcal{V}_{(3,1)}$	369.70	80.542	$((Y_{(3,1)} - Y_{(2,1)}) - (Y_{(3,0)} - Y_{(2,0)}))/4$	10.7500	0.0733	2.866	0.0256
$\mathcal{V}_{(3,2)}$	727.30	89.000	$((Y_{(3,2)} - Y_{(2,2)}) - (Y_{(3,1)} - Y_{(2,1)}))/4$	18.6250	0.0525	4.966	0.0106

TABLE I

CALCULATION OF BIT RATE FOR SVC VIDEO WITH 4 TEMPORAL AND 3 QUANTIZATION LAYERS FOR *Crew* VIDEO

from the quality layer enhancement frames is given as,

$$\tilde{R}_{(0,1)} = R_{(0,1)} - R_{(0,0)}, \\ = 165.80 - 79.2 = 86.6\,\text{Kbps}.$$

Further, employing the dyadic video scalability model, the exclusive rate of the $\tilde{\mathcal{V}}_{(0,1)}$ layer frames is 3.75 fps, as one such differential frame is added for each $\tilde{\mathcal{V}}_{(0,0)}$ base layer frame. Therefore, the size of each frame belonging to layer $\tilde{\mathcal{V}}_{(0,1)}$ is given as $B_{(0,1)} = \frac{86.6}{3.75} = 23.09$ Kb. Similarly one can derive the differential rate and frame sizes associated with the temporal layer $\tilde{\mathcal{V}}_{(1,0)}$. Further, as the cumulative rate $R_{(1,1)}$ incorporates the layers $\tilde{\mathcal{V}}_{(1,1)}$, $\tilde{\mathcal{V}}_{(0,1)}$, $\tilde{\mathcal{V}}_{(1,0)}$, and $\tilde{\mathcal{V}}_{(0,0)}$, the differential rate $\tilde{R}_{(1,1)}$ is given as,

$$\tilde{R}_{(1,1)} = \left(R_{(1,1)} - R_{(0,1)}\right) - \left(R_{(1,0)} - R_{(0,0)}\right) = 32.4\text{Kbps}.$$

The differential bit-rates and frame sizes of the higher enhancement layers can be derived similarly. It can be noted that because of the dyadic nature of the scalability, the differential frame rates progressively double for every higher enhancement layer. Hence, the frame rates associated exclusively with enhancement layers $\tilde{\mathcal{V}}_{(2,0)}$ etc. are 7.5 and so on. Following the described procedure one can successively compute the corresponding bit-rates and associated frame sizes of the differential video layers. The bit-rates of several enhancement layers of the video sequence *Crew* are shown in Table I. It can be seen that the frame sizes progressively decrease with increasing enhancement layer identifier due to the progressively increasing coding gain arising from the DPCM coding.

Video	*Akiyo*	*City*	*Crew*	*Football*
c	0.11	0.13	0.17	0.08
d	8.03	7.35	7.34	5.38

TABLE II

QUALITY PARAMETER VALUES c, d FOR STANDARD VIDEOS.

2) Video Layer Quality Model: We employ the standard video quality model proposed in paper [5], which gives the quality of the scalable video stream coded at frame rate t and quantization step-size q as,

$$Q = Q_{\max}\left(\frac{e^{-c\frac{q}{q_{\min}}}}{e^{-c}}\right)\left(\frac{1-e^{-d\frac{t}{t_{\max}}}}{1-e^{-d}}\right), \tag{2}$$

where $q_{\min} = 25.40$ is the minimum quantization-step size corresponding to QP $= 32$, t is frame rate or temporal resolution, t_{max} is the maximum frame rate, $Q_{\max}$ is the maximum video quality at $t = t_{\max}, q = q_{\min}$, set as $Q_{\max} = 89$ and c, d are the characteristic video quality parameters. The procedure for deriving the parameters c, d specific to a video sequence is given in [5]. These are indicated in Table II for the standard video sequences *Akiyo*, *City*, *Crew* and *Football*. The procedure to compute the differential video layer quality can be described as follows. Consider the standard video sequence *Crew*. Let the cumulative impact of the scalable video stream comprising of m temporal and n quality layers be denoted by $Q_{(m,n)}$. Hence, the quality associated with the video stream $\tilde{\mathcal{V}}_{(0,0)} = \mathcal{V}_{(0,0)}$ consisting of the base temporal and quality layers coded at $t = 3.75$ fps and $q = 64$ corresponding to quantization parameter QP $= 40$ is given as,

$$Q_{(0,0)} = Q_{max}\left(\frac{e^{-0.17\frac{64}{25.398}}}{e^{-0.17}}\right)\left(\frac{1-e^{-7.34\frac{3.75}{30}}}{1-e^{-7.34}}\right) = 41.30.$$

Employing the frame size as computed in the section above, the per-bit normalized video utility can be computed utilizing the relation in (1) as,

$$U_{(0,0)} = \frac{Q_{(0,0)}}{B_{(0,0)}} = \frac{41.30}{21.12} = 1.95.$$

Thus, the above utility can be employed as a convenient handle to characterize the scheduler reward towards scheduling a particular video stream. Further, similar to the rate derivation in the above section, the quantity $Q_{(m,n)}$ denotes the cumulative quality. Hence, the differential quality $\tilde{Q}_{(1,0)}$ associated with layer $\tilde{\mathcal{V}}_{(1,0)}$ for instance is derived as $\tilde{Q}_{(1,0)} =$

$Q_{(1,0)} - Q_{(0,0)} = 16.50$ for *Crew*. The differential per-bit utility associated with layer $\tilde{\mathcal{V}}_{(1,0)}$ can be computed as, $U_{(1,0)} = 2.19$ and so on. The differential layer qualities and per-bit utilities of the scalable GOP frames for the standard video sequence *Crew* are shown in the Table I. The utilities of the four standard video sequences mentioned above are shown in Table III. It can be seen from the table that the utility exhibits a decreasing trend across the enhancement layers, thus clearly demonstrating the different priorities associated with the GOP components. In the next section we derive an optimal policy towards video quality maximization while ensuring fairness in QoS.

Video Layer	*Akiyo*	*City*	*Crew*	*Football*
$\tilde{\mathcal{V}}_{(0,0)}$	12.6906	3.2618	1.9556	1.2266
$\tilde{\mathcal{V}}_{(0,1)}$	1.1172	0.3178	0.3072	0.1185
$\tilde{\mathcal{V}}_{(0,2)}$	0.4269	0.1223	0.1271	0.0466
$\tilde{\mathcal{V}}_{(1,0)}$	24.2893	6.0859	2.1942	1.1310
$\tilde{\mathcal{V}}_{(1,1)}$	2.0239	0.6943	0.3280	0.1049
$\tilde{\mathcal{V}}_{(1,2)}$	0.8982	0.3289	0.1168	0.0389
$\tilde{\mathcal{V}}_{(2,0)}$	9.3842	2.7179	1.1494	0.7410
$\tilde{\mathcal{V}}_{(2,1)}$	0.8447	0.2993	0.1637	0.0639
$\tilde{\mathcal{V}}_{(2,2)}$	0.3737	0.1405	0.0627	0.0223
$\tilde{\mathcal{V}}_{(3,0)}$	1.2832	0.4206	0.1889	0.2299
$\tilde{\mathcal{V}}_{(3,1)}$	0.1351	0.0424	0.0256	0.0170
$\tilde{\mathcal{V}}_{(3,2)}$	0.0638	0.0198	0.0106	0.0063

TABLE III
UTILITY FOR DIFFERENT STANDARD VIDEOS

III. INDEX BASED SCALABLE VIDEO POLICY (ISVP)

Employing the framework illustrated in [3], we model the scalable video scheduling scenario as a Markov Decision Process (MDP). The state of user u at time n is modeled as a combination of the channel state s_u^n and the video state v_u^n of the head of the queue frame of user u. Further, we also incorporate the user starvation age a_u^n in the system state to ensure fairness in video scheduling. We assume that $s_u^n \in \{1, 2, \ldots L+1\}$, where each state represents a maximum bit-rate $\mathcal{R}(s_u^n)$ supported by the fading channel between user user u and base station at time instant n. The vector $\mathbf{s}^n$ at time instant n defined as $\mathbf{s}^n = [s_1^n, s_2^n, \ldots, s_U^n]^T$ characterizes the joint channel state of all users. We assume that $\{\mathbf{s}^n, n \geq 0\}$ is an irreducible discrete time Markov Chain [7] with the $L+1$ dimensional probability transition matrix $\mathbf{P}^u = [p_{i,j}^u]$.

From the GOP structure illustrated previously in the context of scalable video, the video data state for each user $v_u^n \in \{1, 2, \ldots, G\}$, where G is the number of frames in a GOP. Similar to above, the joint video state of the U users can be denoted as $\mathbf{v}^n = [v_1^n, v_2^n, \ldots, v_U^n]^T$. The starvation age a_u^n corresponds to the number of slots for which a particular user has not been served. This quantity is initialized as 0 to begin with and incremented by one for every slot for each user who is not served in that slot. If a particular user is served in the current slot, his starvation age is reset to 0. Let $\omega(n)$ denote the user scheduled at time slot n. The starvation age transition for a particular user is given as,

$$a_u^n = \begin{cases} a_u^n + 1, & \text{if } \omega(n) \neq u \\ 0, & \text{if } \omega(n) = u. \end{cases}$$

The total user starvation age is similarly denoted by vector $\mathbf{a}^n$ obtained by stacking the starvation ages of all the users. Hence, the system state vector $\mathbf{g} = \left[(\mathbf{v}^n)^T, (\mathbf{s}^n)^T, (\mathbf{a}^n)^T\right]^T$ characterizes the complete state of the system. The action $\omega(n)$ at any time instant n corresponds to choosing one of the U users. Employing the video utility framework developed above, the reward corresponding to serving user u in slot n is given as,

$$r_n(u) = \mathcal{U}(v_u^n)\mathcal{R}(s_u^n) - \sum_{l \neq u} K_l a_l^n, \tag{3}$$

where $\mathcal{U}(v_u^n)$ gives the utility of the video packet of user u in state v_u^n and K_l is a constant which can control the trade-off between quality and fairness. The transition probability from state $\mathbf{g} = \left[(\mathbf{v})^T, (\mathbf{s})^T, (\mathbf{a})^T\right]^T$ to $\tilde{\mathbf{g}} = \left[(\tilde{\mathbf{v}})^T, (\tilde{\mathbf{s}})^T, (\tilde{\mathbf{a}})^T\right]^T$ contingent on scheduling user u, is given as,

$$p(\tilde{\mathbf{g}}|\mathbf{g}, u) = p_{s_1,\tilde{s}_1}^1 p_{s_2,\tilde{s}_2}^2 \ldots p_{s_U,\tilde{s}_U}^U,$$

if $\tilde{v}_u = v_u + 1 \mod G$, $\tilde{a}_u = 0$ and $\tilde{a}_z = a_z + 1, \tilde{v}_z = v_z$ for all $z \neq u$. Our objective is to derive the optimal policy which maximizes the long term average reward $\lim_{T\to\infty} \frac{1}{T} E_T(\mathbf{g})$, where $E_T(\mathbf{g})$ denotes the maximum reward over T time periods with initial state $\mathbf{g}$. As this is an infinite horizon problem [8] with a very large state space, conventional schemes for policy derivation are impractical. We therefore employ the novel procedure proposed in [3] to derive the optimal scalable video scheduling policy termed ISVP.

Corollary 1: An index policy $I_u(\mathbf{g})$ close to the optimal policy for long term expected average reward maximization in the context of the video scheduling paradigm defined above is given as,

$$I_u(\mathbf{g}) = \mathcal{U}(v_u)\mathcal{R}(s_u) + K_u a_u(U+1) + K_u U.$$

Proof: As described in (3), the proposed reward structure is $\mathcal{U}(v_u)\mathcal{R}(s_u) - \sum_{z\neq u} K_z a_z$. Replacing the channel state with the joint video and channel state vector $\left[\mathbf{v}^T, \mathbf{s}^T\right]^T$, reward with the proposed reward in (3) and applying Theorem 2 in [3] yields the desired result. ■

The above result guarantees that ISVP, which schedules the video user with the highest index $I_u(\mathbf{g})$, is close to the optimal policy and maximizes the video utility while minimizing the starvation age of all users.

IV. SIMULATION RESULTS

We compare the performance of the proposed optimal video scheduling policy with that of the LIP proposed in [3] and also the standard proportional fair (PF) scheduler. The LIP is an index policy with index $I_u^l(\mathbf{s}^n, \mathbf{a}^n)$ defined exclusively in terms of the channel state vector $\mathbf{s}^n$ and multi-user starvation vector $\mathbf{a}^n$ as $I_u^l(\mathbf{s}^n, \mathbf{a}^n) = \mathcal{R}(s_u^n) + K_u a_u(U+1) + K_u U$.

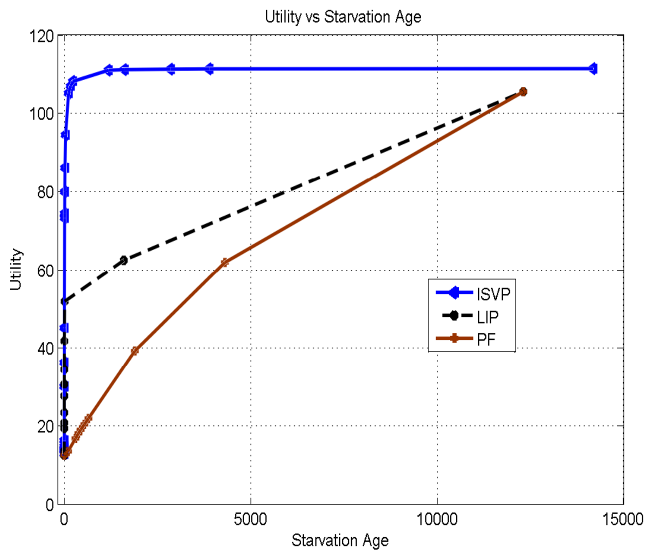

Fig. 3. Utility($\widehat{\Psi}$) vs Starvation Age ($\widehat{\chi}$)

The PF scheduling policy is equivalent to an Index policy $I_u^p(\mathbf{s}^n) = \mathcal{R}(s_u^n)/Q_u(n)$ where $Q_u(n)$ is given as,

$$Q_u(n+1) = \begin{cases} (1-\tau)Q_u(n) + \tau\mathcal{R}(s_u^n), & \text{if } u = \omega(n) \\ (1-\tau)Q_u(n), & \text{if } u \neq \omega(n), \end{cases}$$

where $\omega(n)$ is the scheduled user in slot n and τ is the damping coefficient. We consider the performance measures Ψ, the expected per-slot long term utility, χ, the expected starvation age and ρ_d, the probability that a user is not served for longer than d time slots, for evaluation of the policies. We consider an $L+1 = 5$ channel state model with supported rate states $\mathcal{R}(s_u^n) \in \{38.4, 76.8, 102.6, 153.6, 204.8\}$ Kbps. We considered $U = 4$ users transmitting the standard videos *Akiyo*, *City*, *Crew* and *Football*. We use $T = 10^5$ slots and $P = 100$ sample paths of the Markov chain. The state transition matrix is similar to the one considered in [3], with $\beta = 0.999$. The K_u value is varied for the ISVP and LIP schemes while τ is varied for the PF scheme.

Fig.3 shows a comparison of the video utility of the proposed ISVP policy with that of the LIP and PF policies. The starvation age and utility are calculated for different values of parameter K_u in the range $[0, 500]$. In case of the PF policy, the parameter τ is varied appropriately in the range $[0, 1]$. It can be observed that the proposed ISVP policy yields the maximum video utility amongst the three competing policies. Further, as $K_u \to \infty$ and $\tau \to 1$, the LIP and PF policies effectively converge to the round-robin policy. Hence, the utility and starvation age coincide at this point. Fig.4 shows the plot between utility and the probability ρ_d that a user is starved for more than d slots. This is also plotted by varying the parameters as mentioned above. We observe that the utility is maximum for a particular probability for the proposed ISVP scheme compared to PF and LIP. Thus, the proposed ISVP scheduler maximizes the net video quality while not compromising on fairness.

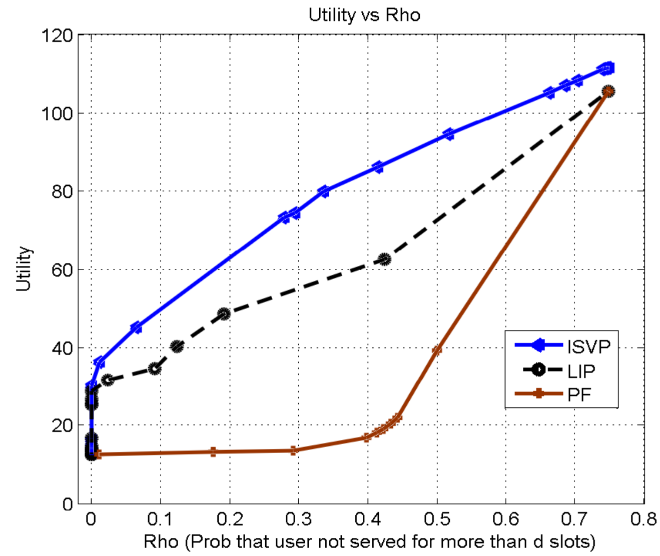

Fig. 4. Utility($\widehat{\Psi}$) vs Rho ($\widehat{\rho_d}$)

V. Conclusions and Future Work

In this paper we developed a novel framework to characterize the differential utility of the H.264 scalable video stream layers. Based on the proposed framework, a utility-starvation based reward paradigm has been proposed to characterize the scheduling decisions. The end-user video quality maximization has been formulated as an appropriate Markov decision process and an optimal index based ISVP has been derived towards scheduling the scalable video frames for net video quality maximization in next generation wireless networks. Simulation results demonstrate that the proposed policy outperforms the PF and LIP policies in terms of video quality.

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