# Evaluation of Quality of Experience for Video Streaming over Dynamic Spectrum Access Systems

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*Abstract*— **In this paper we study the problem of quantifying the value of spectrum opportunities to secondary users in Dynamic Spectrum Access (DSA) systems. We especially focus on estimating the impact of key channel parameters, namely the activity patterns of the primary users on the expected quality of experience for secondary users accessing video streams over a DSA system. In our study we consider three basic types of video representing typical video content categorized according to scene change rate ranging from low-activity newscast to high-activity sports video. Through extensive simulations we show that given some information on the expected level of activity in the video, the duty cycle of the primary user alone can yield good predictors for the expected quality of experience of secondary users. Knowledge of the precise distributions of the primary user ON and OFF periods can be used to further enhance the precision of the prediction, but at least for exponential and log-normal channel access patterns the differences are rather small. Finally, we study the problem of determining the channel statistics that are needed to apply the predictor in an optimization setting. Our simulations show that high accuracy can be achieved in matter of minutes of estimation time, which is more than enough for practical deployments in typical urban environments.**

## I. INTRODUCTION

Dynamic spectrum access (DSA) has become an intensely studied approach for dealing with the perceived shortage of wireless spectrum. In typical DSA systems a secondary user can access a licensed frequency band provided that the license holder, the primary user, is not transmitting on the band. Most of the work towards enabling DSA systems has focused on solving issues related to accurate sensing of the primary user and other enabling technologies, such as support for dynamic updates of transmission policies. Also, numerous measurement campaigns have been carried out around the world in order to assess the amount of spectrum DSA techniques could provide access to. These measurement campaigns have obtained widely varying results on amount of available spectrum, but the common conclusion is that there still are relatively large spectrum opportunities DSA could take advantage of. *Spatial* spectrum opportunities, in which a given frequency band is not used at all over a large region of space are easiest to exploit. But such cases seem to be quite rare in typical urban environments where most of the secondary users would be expected to reside as well. In such environments *temporal* spectrum opportunities appear to be commonplace, induced by bursty nature of the primary user traffic. However, comparatively little work has been done on evaluating quantitatively how valuable such temporal spectrum opportunities would be for secondary users.

In this paper we take first steps towards such an evaluation by combining simple but realistic spectrum availability models with a network emulation environment. Using this environment we evaluate the quality of experience secondary users can achieve under different spectrum utilization scenarios, assuming Wi-Fi like secondary network. As an additional research topic, we look into prediction of Quality of Experience (QoE) for secondary users based on channel parameters and primary user activity levels. We show through examples that this kind of network emulation approach is both feasible and effective, and can be used for other types of content as well. The results also show that for highly occupied frequency bands significant technological advances would be required in order to be able to benefit from unused spectrum opportunities.

The rest of the paper is structured as follows. We first present our system model in Section II, including the assumptions made on the coexistence properties of the primary and secondary system. The approach and methodology for evaluating the utility of the temporal spectrum opportunities is then discussed in Section III. The simulation environment used for emulating the secondary network together with the rest of the toolchain is described in Section IV, in which results obtained are also given and discussed. Finally, in Section V conclusions are drawn and future work is outlined.

## II. SYSTEM MODEL

We assume that the secondary system is deployed in a similar manner to current Wi-Fi hotspots, that is, the access points of the secondary system are stationary. As usual for dynamic spectrum access systems, we assume that the secondary network can transfer data only during times the primary user is not transmitting. We model the detected primary user activity as a Semi-Markov ON/OFF process, in which the primary network is detected to be in either ON or OFF state for a time period given by specific probability distributions. In the literature, lengths of ON and OFF periods are often assumed to be exponentially distributed and independent random variables. Based on extensive spectrum

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measurements [1] we have shown that the independence of successive ON and OFF period distributions is a valid assumption, but that the actual distributions of those periods are not always exponentially distributed. Thus, in addition to the exponential distribution, we apply log-normal distributions in our work.

Note that our system model makes no particular assumptions on the structure of the primary network, or the detection mechanism used by the secondary user. We also do not consider interference arising from misdetections of the primary user state. These assumptions cover many of the typical DSA scenarios in which nodes of the secondary system are nearby each other, but distance to the primary network nodes is large. Impact of any particular detection mechanism can also be incorporated into our framework by first considering a model of "true" primary user behavior, and then fitting a Semi-Markov ON/OFF model on the output of the chosen detector. However, inclusion of such additional details requires further assumptions on the spatial relations of the primary and secondary networks and on the channel conditions between them, thus leading to reduction in generality.

Finally, for concreteness, we assume that the secondary network uses a CSMA/CA Medium access protocol similar to current Wi-Fi networks. This assumption is quite natural, and commonly made in recent literature on DSA systems [2], [3]. We also assume that the secondary network is lightly loaded in order to focus on impact of the primary system to the QoE of the secondary user. The latter assumption can easily be relaxed in our simulation environment, but we shall not do so here due to space reasons.

## III. METHODOLOGY

### A. *Quality of Experience Measurements*

One of the basic success factors for next generation networks is their ability to provide qualitative multimedia services like video streaming such that the customer satisfaction is maximized to ensure customer loyalty and also growth of the customer base. So far most of the mechanisms employed in communication networks for providing multimedia services at certain quality levels, have been based on tuning key QoS performance indicators. Those indicators consist mainly of network performance metrics such as packet delay, delay jitter, bit error rate and throughput. However, employing such a network-oriented approach to characterize and provision for video quality is less than sufficient, since important factors related to how humans actually perceive quality are neglected.

New approaches have been relatively recently introduced, under the term Quality of Experience (QoE), that take into account human perception in measuring the quality of multimedia. QoE approaches actually provide extra information using which a network can be managed to better meet the real user requirements and increase user satisfaction. This means that the QoE monitoring mechanisms allow the network to become aware of extra information of higher granularity and closer to the user sense of quality, compared to having only raw network-plane information. As a result QoE monitoring becomes an essential part of modern network for delivering multimedia services, supplementing the existing QoS provisioning mechanisms but also opening the way for the introduction of new networking paradigms (e.g. QoE-aware routing etc.).

There are two basic categories in which all QoE evaluation methods fall. There are the objective methods and the subjective methods. The basic distinction between those two categories is that with objective methods all metrics can be measured automatically, while in subjective methods human intervention for ranking quality levels is required. Actually, the objective methods try to get enough technical information (key performance indicators) available at various levels ranging from the user level, to application level and down to the link level, to approximate the result of a subjective method in the same context. Typically, in subjective methods humans use the Mean Opinion Score scale proposed by the International Telecommunication Union [4] to rank the quality of a multimedia stream. The Mean Opinion Score scale specifies the following five levels used for evaluating quality: Level 5 corresponds to Excellent Quality (Imperceptible distortions), Level 4 corresponds to Good Quality (Perceptible distortions but not annoying), Level 3 corresponds to Fair Quality (Slightly annoying distortions), Level 2 corresponds to Poor Quality (Annoying distortions) and Level 1 corresponds to Bad Quality (Very annoying distortions). The shortcoming of subjective methods is that they totally rely on human experience and can be easily biased (e.g. two native speakers rank the quality of a VoIP conversation higher than the case when one of them is not a native speaker of the language spoken during the same conversation). On the other hand, in objective methods, generic metrics that measure the distortion are used. Those metrics give more consistent evaluations but can also miss certain -difficult to model and measure- human perception-related factors.

The objective methods can be further categorized according to the required amount of information on the original stream (i.e. the stream before encoding and/or before transmission) that they need in order to assess the quality of the received stream. Full reference methods require access to the whole original stream for deciding on the quality of the received stream, and thus are cumbersome to use in real commercial networks (since they require too much traffic in both directions between sender and receiver). Reduced reference methods normally require partial information on the original stream and thus are more preferable then full reference methods. Finally, no reference methods, which are also the most difficult to develop, do not require any information on the original stream and try to infer the perceived quality of the stream by using general metrics measuring various types of distortions. As it will be seen later in the simulations section we will be using a full reference method, since we are performing the experiments in simulation (lab environment) and we have the ability to easily access the original stream residing in the local file system. Also full reference methods can give the highest accuracy. For a detailed analysis on subjective and objective quality evaluation the reader is referred to [5].

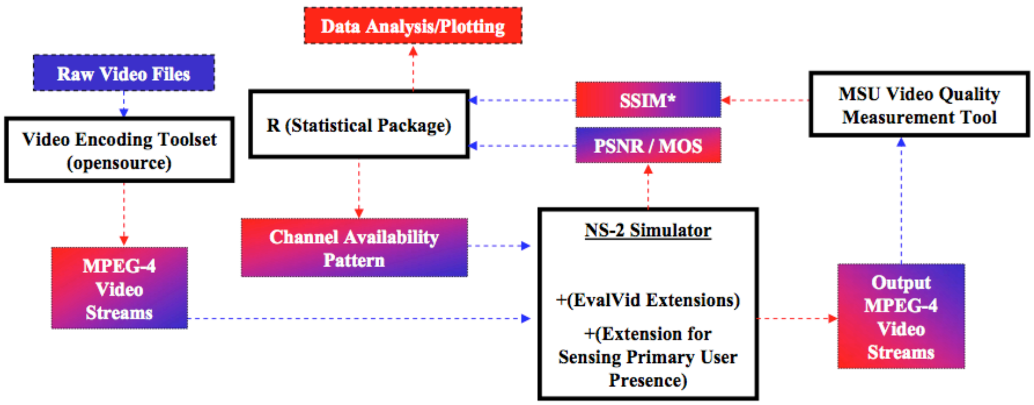


Figure 1. Simulation Testbed.

### B. *Developing QoE Predictors*

For a variety of decision and optimization problems in the secondary network it would be useful to be able to estimate the likely QoE for different channel parameters before actually initiating communications. Predictors based on slowly changing channel properties would be especially useful in this context, since no frequent measurements of channel parameters would be needed. In our spectrum occupancy measurements we observed that the ON/OFF patterns of the primary were a good example of such slowly changing characteristic, and that especially the *duty cycle* of the primary users, that is the proportion of time the primary is detected to be in the ON state, tends to remain constant over long periods of time. Based on this observation, we study how accurately duty cycle or more detailed knowledge of the durations of the ON and OFF periods can be used to predict the resulting QoE for the secondary user. This is precisely what we shall do in the following.

## IV. EXPERIMENTAL EVALUATION

### A. *Simulation Setup*

The testbed we used for our simulations consists of a series of tools as depicted in Figure 1.

We will start by explaining the capabilities and functionalities for each major block (or tool) used in this testbed and also present the flow of processes in a step by step manner. In the provided figure the dark bordered blocks represent software entities, while the two-colored blocks represent input or output or intermediate results. Also, the red arrows coming out of a software block signify the block's output, while the blue arrows entering a software block signify the block's input.

We begin with the selection of the video files used in our simulations. As we have been explaining one of the aims of the simulations was to investigate the performance of video streams with different scene change rates so that we can evaluate the impact of errors in transmission for different types of content. In order to do so we have selected 3 different video traces. Two of them belong to the video trace library of Arizona State University (ASU) [6], which provides the commonly used video test sequences in the uncompressed YUV format for download. The other video came from our personal collection. The first video from the ASU library (called Grandma) presents a person being interviewed. The characteristic of this video is that the main moving parts are the person's lips while talking, and slight movements of the head (newscast style). This matches perfectly to our low scene change rate video needs. The other video from the ASU library (called Highway) presents a camera recording of a low speed trip on the motorway. While most of the scenery in the frame remains fixed (sky, road), there are certain parts changing as the car moves (like lanes, bridges, bypassing of other cars). This video matches our need for Medium scene change rate video. And finally the third video presents a famous formula 1 racefight, where the scenes rapidly change due to fast motion and many camera zoom-ins and zoom-outs as well as view angle changes. This video perfectly fits our needs for a fast scene change rate video. All those videos have been received in YUV format.

The next step was to encode all the video streams. In order to have consistency when comparing the results across the video streams, all streams have been encoded with exactly the same parameters, which are presented in Table I.

TABLE I. VIDEO ENCODING SETTINGS AND VIDEO STREAM CHARACTERISTICS

| **Encoder Settings** | |
|---|---|
| **GOP size** | 9 frames |
| **Frame rate** | 25 frames per second |
| **Target bit rate** | 200kbps |
| **Frame types supported** | I, P, B |
| **Resolution** | QCIF |
| **Video Stream Characteristics** | |
| **Length** | 80 seconds |
| **Frames** | 2000 |

We have used an open source encoder called ffmpeg [7] to encode the aforementioned YUV sequences into mpeg-4 streams. Our choice of using ffmpeg as our media encoder is that 1) it is compatible with the rest of the tools in our testbed, 2) that it is a fast encoder and it also supports all major video format conversions.

The next building block of our testbed is related to the creation of the channel availability pattern. In our earlier research work [8] we have shown that primary user activity patterns can often well be modeled by Semi-Markov ON/OFF processes (also known as alternating renewal processes) illustrated in Figure 2. The model is completely specified by the distributions *f(t)* and *g(t)* of the lengths of ON and OFF periods. In our studies we mainly apply exponential and lognormal distributions, since these were shown to lead into good fits in the article referred to above. Thus key parameters to vary in the channel models are the mean value parameters of the said distributions. We use the R environment for statistical computing [9] for generating realizations of the channel occupancy processes, which are placed in a text file for consumption by the simulator in the next step.

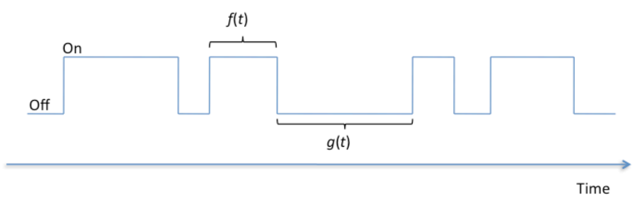


Figure 2. Semi-Markov ON/OFF channel model .

As mentioned in the previous paragraph the channel availability pattern is “fed” into the ns-2 simulator [10] such that the opportunistic access of secondary users can be implemented. The scenario tested in the ns-2 simulator involves one secondary node (the sender) streaming video to another secondary node (the receiver) over an 802.11 WLAN. Since our assumption has been that the secondary nodes are able to perform perfect sensing such that they will never interfere with primary users, primary user presence is implied by the channel availability (as described in the file given as input to ns-2). We have extended the 802.11 MAC protocol of ns-2 (version: ns-2.28) such that each node before transmitting any packet, it checks first the input file having the primary activity pattern, in order to check if the channel is occupied by primary transmissions, or if it is free for use by the secondary. The specific settings for the ns-2 scenario setup are presented in the Table II.

The simulation scenario involved testing over different channel availability patterns leading to different loss patterns of the video stream and hence affecting experienced quality differently. As mentioned in Section II, we assume that the bandwidth that is available to the secondary user when the primaries are inactive is greater than the required video stream bit rate. This is because in this paper our focus is centered on understanding the impact of the primary access pattern alone to the QoE of the secondary. Thus isolating our analysis from effects stemming from insufficient bandwidth is mandatory. For the same reason in all the scenarios we monitor the effect of spectrum availability on the QoE of a single secondary user. However, since our simulation environment is CSMA-CA based, we can easily explore in the future the combined impact of spectrum availability and also of the contention between secondary users for accessing the channel on the QoE of secondary users.

TABLE II. NS-2 SIMULATION SCENARIO SETTINGS

| | |
|---|---|
| **Packet Size** | 1500 bytes |
| **Max fragmentation size** | 1024 bytes |
| **Channel Type** | Wireless Channel |
| **Radio-Propagation Model** | Two Ray Ground |
| **MAC** | 802.11 |
| **PHY** | Wireless Phy |
| **Interface Queue Type** | Queue/DropTail/PriQueue |
| **Antenna model** | Omnidirectional |
| **Max packets in interface queue** | 50 |
| **RTS Threshold** | 3000 bytes |
| **Long Retry Limit** | 7 |
| **Short Retry Limit** | 4 |
| **Data rate** | 0.32Mb |
| **CWmin** | 31 |
| **CWmax** | 1023 |
| **Slot duration** | 20us |
| **SIFS duration** | 10us |

Besides the aforementioned extensions, which we introduced to ns-2, we have also used the EvalVid extensions. EvalVid [11] is a publicly available toolset for performing evaluation of network designs or setups or architectures in terms of user perceived video quality. EvalVid was our choice since in contrast to other evaluation tools it is open source, it does support evaluation on incompletely received video streams and it allows flexibility in the selection of codecs and the underlying transmission system. For the tools of EvalVid the network is seen as a “black box” which generates delay, loss and possibly reorders packets. In that sense, the network part can be a real network or, as it is in our case, a simulated network. The way that EvalVid operates is the following: first the raw video at the sender side is encoded to a format determined by the selected encoder, then the encoded video is “packetized” according to the defined maximum transfer unit that the network can support, each packet is given a unique id and when streaming starts the sender puts a time stamp on every packet for the time of transmission. Upon reception of a packet the receiver puts a time stamp on the packet for the receive time. Then based on the raw and encoded files and the time stamps of the received packets and taking into account possible transmission errors too the EvalVid tools reconstruct the video as it would be seen at the receiver side. Finally, the EvalVid tools perform an evaluation of the quality of the received video file, having as a reference the original video file at the receiver. The video quality evaluation is done using the PSNR (Peak Signal to Noise Ratio) metric, which is shown to have high correlation to the subjective quality perception. PSNR is computed frame by frame between the received video and the original video at the sender, and average and standard deviation are also reported. Moreover, the PSNR values are mapped to the MOS (Mean Opinion Score) scale and calculations of the percentage of frames with MOS worse than that of the original can also by calculated by EvalVid.

Using the toolset of EvalVid we are allowed to perform only PSNR-based video quality measurement (which is then mapped to a MOS score). However, although the PSNR metric is the standard metric to use, it may not capture significant characteristics that the human vision is able to capture, like structural features on an image. This means that PSNR based evaluation can be occasionally misleading. For this reason we have performed additional test runs for video quality measurement using the SSIM (Structural SImilarity Metric [12]) metric, which can capture structural features too and we have validated PSNR's accuracy for our cases. In order to perform the SSIM based test run evaluations we used the publicly available Video Quality Metric (VQM) Software [13]. The SSIM is computed based on raw YUV video sequences. In our case we use the ffmpeg codec to produce the raw YUV sequence out of the received (and possibly distorted) video at the receiver, and then compare this sequence with the original raw YUV sequence of the video at the sender. The results from the SSIM based evaluation are consistent with the ones obtained from the MOS one, and due to the easier interpretability of the latter we shall focus on reporting MOS-related results in the following.

### *B. Key Findings*

Let us remind at this point that since video decoders have the ability to replay the last frame when the new one has not arrived due to problems in the channel, the difference between current and previous frame actually depends on the rate of scene changes of the clip. Intuitively high rate corresponds to high probability of experiencing very bad quality when losses happen but when there is a low scene change rate losses can be "concealed" by replay of previous frames and hence experienced quality may not be affected much. In order to also test (and also validate our hypothesis) how video of different content is affected by the channel availability we used the three different types of video streams described in section IV.a (i.e. one with high scene rate change (formula 1 race), one with Medium scene change rate (motorway drive) and one with low scene rate change (newscaster-style)). We will refer to the first stream as 'High activity video', to the second as 'Medium activity video' and to the third as 'Low activity video'.

Figures 3 to 5 present the obtained MOS scores for all 3 types of video streams transmitted under a channel where the primary is occupying the channel in an ON-OFF fashion, with the duration of ON and OFF periods being *exponentially* distributed and for duty cycles of the primary user ranging from 0.1 to 0.8 (with an interval of 0.1).

For each duty cycle we created 20 different types of the primary activity patterns by changing the mean ON and mean OFF period durations in the used distribution in order to investigate the sensitivity of MOS not only on the duty cycle but also on the duration of primary ON and OFF periods. The chosen mean values ranged from approximately 100ms to 2s for the mean primary ON period, and the corresponding mean OFF period length was computed for each fixed duty cycle. The resulting ON and OFF period lengths covered a wide range, and specifically covered the range of temporal white spaces observed in our earlier measurements. It is worth noting that each pattern instance set consisted of 400 instances created by altering the simulation seed, and each dot in the figures represent the average MOS score obtained over those 400 runs.

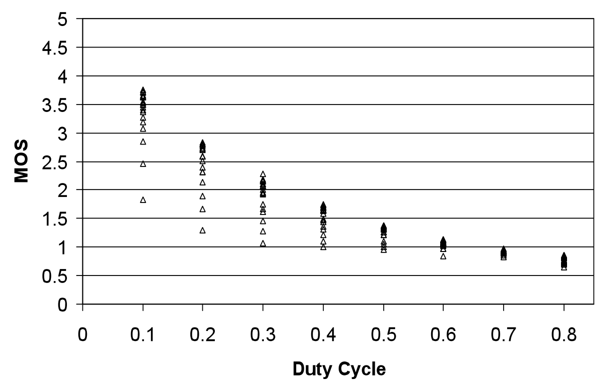


Figure 3. MOS for High activity video (Exponential Case).

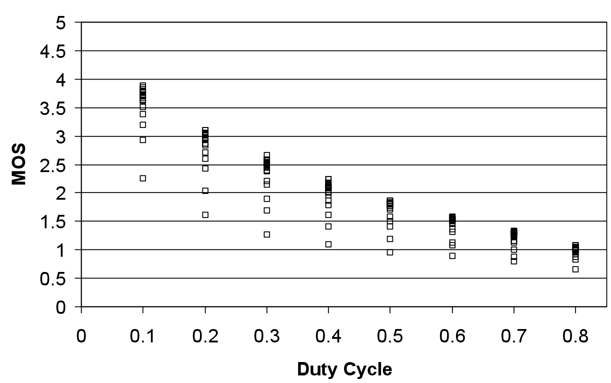


Figure 4. MOS for Medium activity video (Exponential Case).

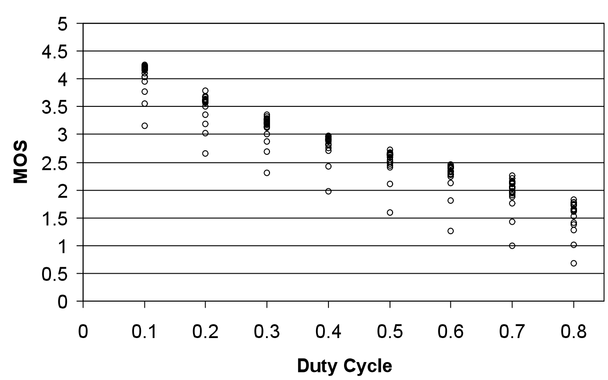


Figure 5. MOS for Low activity video (Exponential Case).

The results show that the Low activity video is the least affected in terms of quality degradation due to losses and/or delays in the delivery of the video stream's packets. The MOS score for the Low activity video is on the average higher (which means better video quality, hence higher user satisfaction) than the Medium and the High activity video. This is due to the fact that when there is not much activity in the video this means that the differences of one frame from the previous frame are small. Hence, even if one whole frame is lost and the video player replaces it with the previous frame that was correctly received, then the errors are actually concealed effectively from the user. So the less the activity the more robust is the video stream to errors and the less the perceived quality is affected.

To make this even clearer in Figure 6 for each video type we plot the average MOS obtained over all different instance sets per duty cycle. It is evident that the quality of the Low activity video is the least affected by the losses caused when the primary occupies the channel and the secondary is deferred from transmission until the channel becomes free again. This directly points to the conclusion that for the same network and channel conditions, the QOE for users depends heavily on the characteristics of the video, hence knowledge on those characteristics by the service provider could make resource allocation or admission control decisions even more efficient.

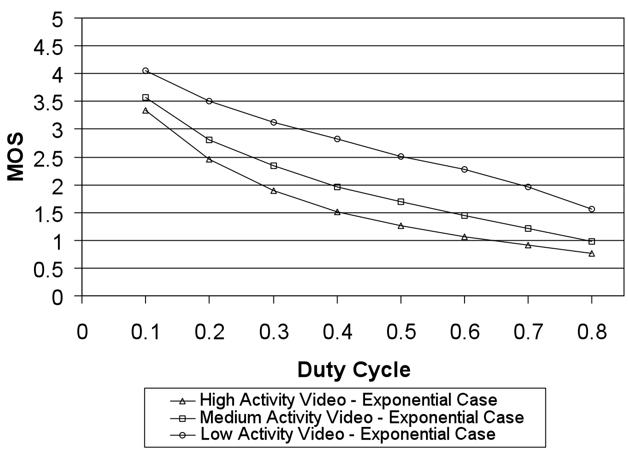


Figure 6. Average MOS over all channel instance sets for all types of video.

Figure 7 depicts the sensitivity of perceived video quality on the duration of primary ON and OFF periods (since those signify the pattern and amount of losses in the video transmitted by the secondaries) for the case that the primary duty cycle is 0.1. It is evident from this figure that as the average duration of primary OFF periods increases, this corresponds to fewer packets lost and hence to better quality. The different video types, however, have different sensitivity to changes of the average OFF period durations (for the same duty cycle). This is related to the fact stated earlier that when the player cannot decode a frame due to too many errors it replaces it with the previously received frame.

In the case of the Low activity video it seems that the sensitivity to the average duration of primary OFF period is lower than the sensitivity of the Medium and High activity video (demonstrated in the figure by the range of MOS values). The change in the duration of the primary OFF period causes a change of quality by 1.0 unit in the MOS scale for the Low activity video, while it changes the quality by 1.5 and 1.8 units for the Medium and High activity videos respectively. This is due to the fact that error concealment by frame replays is more effective for Low activity video for a low primary duty cycle of 0.1 and the specific pattern (defined by the average length of the primary OFF period) is not very important. On the other hand this specific pattern for primary activity seems to be more important for Medium activity videos and even more for High activity videos, since the effectiveness of frame replaying as an error concealment method deteriorates as the scene change rate (activity) increases. For the latter types of video it is important that the primary OFF periods are long enough such that totally non-decodable frames are avoided (and thus frame replays are not required) as much as possible.

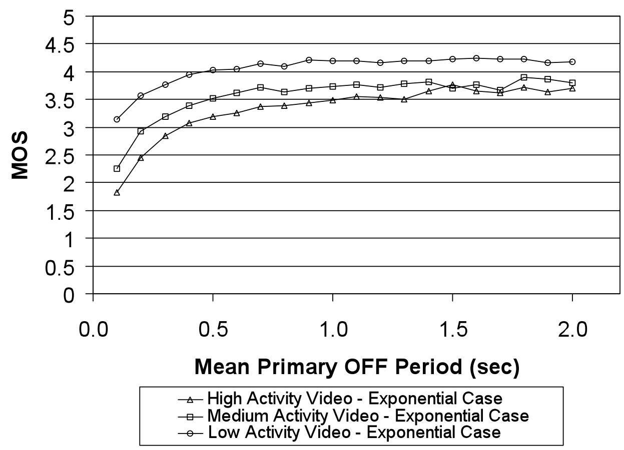


Figure 7. MOS sensitivity of all types of video for different average OFF periods for the primary (Duty Cycle=0.1).

However, if we draw the same plot for a primary with duty cycle of 0.8 (Figure 8), then we see that the High and Medium activity video are almost insensitive to changes of the mean duration of the primary OFF period, in contrast to the Low activity video which preserves its sensitivity (~1.0 unit in MOS scale). This is due to the fact that for such a high duty cycle for the primary it is very rare in general to get a decodable frame, and frame replays are common place irrespectively of the duration of the primary OFF period. This means that the perceived quality is consistently very bad for the High and Medium activity videos and that the effect of actual durations of primary ON and OFF periods deteriorates in importance.

As a second step in this study we assumed *lognormally* distributed ON and OFF periods for our Semi-Markov model. Figure 9 presents obtained MOS scores for all 3 types of video streams transmitted under the logonormal channel pattern for duty cycles of the primary user ranging from 0.1 to 0.8 (with an interval of 0.1) and compares them to the related scores for the exponential channel pattern. The main findings for the exponential case still hold for the lognormal case.

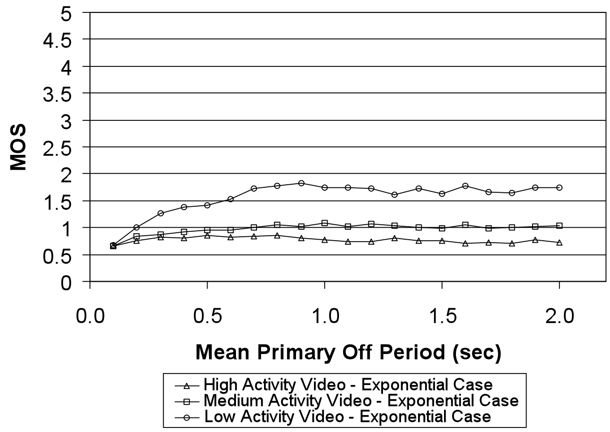


Figure 8. MOS sensitivity of all types of video for different average OFF periods for the primary (Duty Cycle=0.8).

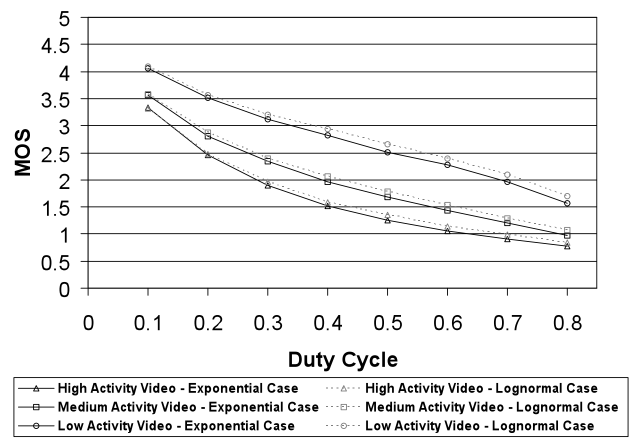


Figure 9. Comparison of average MOS over all instance sets for all types of video and both channel types.

### C. *Developing Predictors for secondary user QoE*

From all the results presented above it is clear that the primary user's duty cycle plays the key role in determining the expected utility (or perceived quality or satisfaction) of the secondary user measured in terms of MOS. The actual average duration of ON and OFF periods seems to have a much smaller impact on the MOS. We have validated this last argument by obtaining the 95% confidence interval for the average MOS score obtained over all the different average ON and OFF combinations for both the lognormal and the exponential model for each duty cycle. As stated earlier, for each duty cycle we test 20 different combinations of mean ON and OFF durations, which have been selected to be in a realistic range based on our findings from real life monitoring of primary user activity in spectrum occupancy measurement campaigns. As it is shown in Table III the maximum change that the mean ON and OFF periods can cause 95% of the time to the average MOS for any type of video for any given duty cycle in the range 0.1 to 0.8 is less than 0.22 MOS scale units. On the average over all video types, distributions and duty cycles and for 95% of the time the change that the ON/OFF period durations can cause to the average MOS associated to a duty cycle is around 0.11 MOS scale units. Taking those indications into account it would be safe to start investigating the duty cycle as one of the most basic foundations for developing a predictor for the expected MOS for secondary users accessing video streaming services.

TABLE III. 95% CONFIDENCE INTERVALS FOR MOS GIVEN THE DUTY CYCLE OVER REALISTIC ON/OFF PERIOD MEAN DURATION COMBINATIONS FOR ALL VIDEO TYPES

**Exponential Case**

| DC | Low Activity Video | Medium Activity Video | High Activity Video |
|---|---|---|---|
| 0.1 | 0.120444 | 0.170106 | 0.209943 |
| 0.2 | 0.116813 | 0.167945 | 0.185447 |
| 0.3 | 0.111344 | 0.153495 | 0.143064 |
| 0.4 | 0.103312 | 0.127824 | 0.095444 |
| 0.5 | 0.111686 | 0.106846 | 0.055961 |
| 0.6 | 0.122232 | 0.084261 | 0.029886 |
| 0.7 | 0.127553 | 0.065941 | 0.014401 |
| 0.8 | 0.127291 | 0.043367 | 0.024539 |

**Lognormal Case**

| DC | Low Activity Video | Medium Activity Video | High Activity Video |
|---|---|---|---|
| 0.1 | 0.131216 | 0.186442 | 0.217034 |
| 0.2 | 0.131567 | 0.184759 | 0.182928 |
| 0.3 | 0.118576 | 0.166279 | 0.147684 |
| 0.4 | 0.125531 | 0.152252 | 0.103019 |
| 0.5 | 0.136903 | 0.134663 | 0.069414 |
| 0.6 | 0.150597 | 0.111264 | 0.0357 |
| 0.7 | 0.161968 | 0.081098 | 0.020808 |
| 0.8 | 0.157371 | 0.063721 | 0.034032 |

We have also studied the problem of determining the primary ON and OFF rates through measurements. More specifically, we simulated a variety of channel access patterns with known statistics, and then fitted by maximum likelihood technique parametric models to the simulated access patterns. This is an approach a fixed secondary network node, such as an access point in Wi-Fi like deployment, could use to obtain duty cycle estimates of the different frequency bands available. Our simulations also show that high accuracy can be achieved in matter of minutes of estimation time, which is more than enough for practical deployments in typical urban environments. This is illustrated in Figure 10, showing the mean relative estimation error for the average ON period duration (for OFF period estimation similar behavior was observed). We see that 90%

accuracy can be achieved in less than three minutes, which in most of the above cases would allow prediction of MOS within an accuracy of 0.2-0.3 MOS scale units. Since according to our measurement duty cycle tends to remain relatively constant over time (after usual diurnal variation between day and night is compensated for), indicating that the duty cycle based prediction of quality of experience eminently feasible.

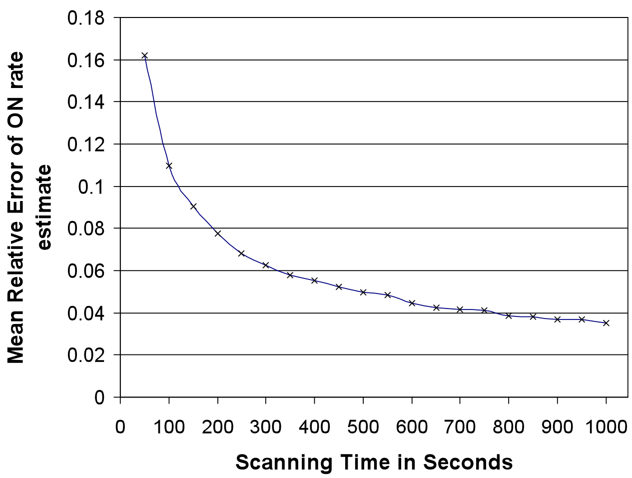


Figure 10. Comparison of average MOS over all instance sets for all types of video and both channel types.

## V. Conclusions

In this paper we have focused on the problem of quantifying the value of spectrum opportunities to secondary users accessing video streaming services over a Dynamic Spectrum Access (DSA) system. We have experimentally investigated the impact of the primary user spectrum usage patterns on the quality of experience of the secondary user streaming a video. Our results show that the primary user's duty cycle is the key factor in determining the expected QoE of video streaming applications that secondary users can achieve. More detailed characteristics of the primary user activity such as distribution of ON and OFF periods do play a role, but their impact on QoE is significantly smaller. The impact of the primary user's duty cycle on the QoE of video streaming applications varies for different types of video, mainly depending on the overall level of activity depicted. Secondary users receiving videos of low activity levels can tolerate much higher primary user activity compared to secondary users receiving high activity videos.

As an application of these results we also studied the problem of predicting the achieved quality of experience based on statistics of the primary user activity patterns. Our results show that rather accurate prediction is possible with duty cycle information only, and that the duty cycle can be measured by the secondary system accurately in time scales short enough for practical deployments. As future work we are currently building a prototype, first for the 2.4 GHz ISM bands, to test these techniques in more realistic conditions compared the emulated wireless connection used here.

## Acknowledgment


We would also like to thank Huawei Technologies CO., LTD for providing partial funding of this work through the HADOR project.


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