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Research Article

Fast and Accurate Video PQoS Estimation over Wireless Networks

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This paper proposes a curve fitting technique for fast and accurate estimation of the perceived quality of streaming media contents, delivered within a wireless network. The model accounts for the effects of various network parameters such as congestion, radio link power, and video transmission bit rate. The evaluation of the perceived quality of service (PQoS) is based on the well-known VQM objective metric, a powerful technique which is highly correlated to the more expensive and time consuming subjective metrics. Currently, PQoS is used only for offline analysis after delivery of the entire video content. Thanks to the proposed simple model, we can estimate in real time the video PQoS and we can rapidly adapt the content transmission through scalable video coding and bit rates in order to offer the best perceived quality to the end users. The designed model has been validated through many different measurements in realistic wireless environments using an ad hoc WiFi test bed.

1. INTRODUCTION

It is well known that the goal of any QoS mechanism is to maintain a good level of user-perceived QoS even when the network conditions are changing unpredictably.

Typical QoS provisioning solutions for multimedia video applications have been always based on the idea of trying to reserve or assure certain network guarantees, so that packets coming from delay or bandwidth sensitive applications receive a better treatment in the network. This approach has been demonstrated to work very well in fixed networks. However, in wireless networks it is not always possible to offer any guarantee, due to continuously changing conditions and unpredictable radio link quality.

Increasing bandwidth is a necessary first step for accommodating real-time streaming applications, however it is not sufficient, due to large bandwidth fluctuations experienced in wireless networks. Fluctuations in network resource availability, due to channel fading, variable error rate, mobility, and handoff, make QoS provisioning more complex in wireless networks. Moreover, determining how network congestion manifests itself in degraded stream quality is still an open issue and only some very recent studies are available [1, 2]. Understanding the relationship between stream quality and network congestion is an important step to solving this problem, and can lead to better design of streaming protocols, computer networks, and content delivery systems.

One of the critical issues to keep in mind when dealing with provision of multimedia services is the quality of sound or picture presented to the end user, assuming a high-quality source and an error-free environment. This quality is directly proportional to the bit-rate used in the encoding process, thus more recently, diverse solutions were proposed for scalable multimedia transmissions over wireless networks [3, 4]. Many of these adaptive solutions gradually vary the video streams' characteristics in response to fluctuating network conditions thereby allowing for the perceived quality to be gracefully adapted. Nevertheless, the quality experienced by a user of multimedia service not only depends on network parameters but also on higher layers' characteristics. An alternative way for providing the agreed quality of service is to estimate the *perceived quality of service* (PQoS) index, with the aim of selecting the best scaling for the video content in order to achieve the "golden selection" between quality of service, bandwidth availability, bit rate, and frame transmission rate.

The objective quality perceived by the nonexpert user can be measured with purely subjective criteria, as opposed to the Network QoS, which relies on objective measurable parameters (throughput, BER, etc.). A complicating factor is the individual nature of how users evaluate the quality that they receive. Any two users who may be sharing a common experience (i.e., identical applications) are likely to have significantly different views of the QoS; thus, the important thing is to understand how such individual views are used for estimating the connection between wireless network parameters and user perception of QoS provided over that network.

This linkage will typically take the form of a numerical mapping (mathematical relation) between some measure of the user-perceived quality (e.g., the *mean opinion score* (MOS) [5]) and a particular set of network parameters (e.g., available bandwidth).

Typically, the five-point scale MOS is used to collect feedback from end users on the subjective quality of a media stream. However, assessments of subjective quality are time consuming and expensive; furthermore, they cannot be easily and routinely performed for real time systems. On the other hand, objective metrics would be of great benefit to applications involving scalable video coding and multidimensional bit rate control used in mobile video broadcasting systems. According to these consideration, there is a need for a quality metric estimator, based on the VQM objective metric [6, 7] that accurately matches the subjective quality and can be easily implemented in real-time video systems.

1.1. Paper contributions

This work presents the following key contributions.

(i) We setup an ad hoc test bed for evaluating the perceived video quality of multimedia contents transmitted over a wireless network using the VQM objective metric.

(ii) We examine how network parameters such as congestion, signal power level, and transmission bit rate affect streaming media and video data that are sent on demand over the wireless network from a single server center to one or more users equipped with a handled device.

(iii) We design an accurate analytical model for real-time estimation of the perceived quality according to the network and video parameters. Finally, we verify the quality of the proposed model in several network conditions.

Thanks to this model we can estimate the PQoS of each video and we can rapidly adapt the transmission of the content through scalable video coding and multidimensional bit rate techniques in order to offer the best quality to the end users. Thus, it could be possible to implement and use "*adaptive applications*" as a complement to the traditional network-layer reservations. So, whenever the network resources become scarce and the QoS guarantees are violated, the applications can self-adapt the internal settings (e.g., frame rates, video sizes, etc.) reducing the data rates to those that the network can support in that precise moment and always guaranteeing a good PQoS value.

2. RELATED WORK AND LITERATURE

Most of the proposed solutions [8–10] for QoS guarantee in wireless networks follow a proxy-based approach, and rely on the underlying network to provide services like bandwidth reservation and priority routing and scheduling. Even if the approach is transparent to the applications, lack of support from any intermediate network or node can render the architecture useless. For example, in case priority routing is not supported by a router on the transmission path, the whole scheme will fail. Moreover, proxy-based solutions have scalability problems [11], especially in case of computation intensive proxy functionality like transcoding. With the aim of overcoming the drawbacks of computing the true quality of service perceived by the end users, some quality metric evaluation have been conducted in the last years. Although Feghali et al. [12] proposed a new quality metric for filling the gap between the classical PSNR and the subjective quality metrics, they do not consider other network-level parameters, such as the wireless link power and the effect produced by other data traffic on the same link. In [13] the authors study the user perception of multimedia quality, when impacted by varying network-level parameters such as delay and jitter, however they use subjective quality metrics that are very expensive and time consuming. Paper [14] presents a method for objective evaluation of the perceived quality of MPEG-4 video content, based on a quantification of subjective assessments. Showing that subjectively derived perceived quality of service (PQoS) versus bit rate curves can be successfully approximated by a group of exponential functions, the authors propose a method for exploiting a simple objective metric, which is obtained from the mean frame rate versus bit rate curves of an encoded clip; even in this work no network-level parameters have been considered. Koumaras et al. [1] presented a generic model for mapping QoS-sensitive network parameters to video quality degradation but they considered only the packet loss during the transmission over the wireless link without taking into account the congestion due to the background traffic over the same link and the video resolution in terms of bit rate. Lotfallah et al. [2] identified a parsimonious set of visual content descriptors that can be added to the existing video traces to form advanced video traces, then they developed quality predictors that, based on advanced video traces, predict the quality of the reconstructed video after lossy network transport. Even in this work no considerations are made on video bit rate adaptation according to the background traffic.

In our work, we evaluate the perceived quality value according to the bit rate of the transmitted video, the signal power level, and the data traffic on the wireless link. We design a model that closely approximates VQM objective metric behavior. Thanks to the proposed model; the estimation of the PQoS is extremely easy and fast making the tool suitable for scalable video coding and multidimensional bit rate in mobile wireless video application.

Table 1: Video ITU recommendations.

	Video
Subjective	P.910 video quality assessment
	P.930 reference impairment system
	BT.500-6, BT.601-4, BT.802 TV pictures
	BS.562-3, BS.1116 high quality audio
	G.114 delay
	P.920 interactive test for AV
Objective	P.OAV objective audiovisual quality assessment
	G.191 software tool for evaluation test

3. PERCEIVED QUALITY METER METHODS AND RECOMMENDATIONS

Over the last years, emphasis has been put on developing methods and techniques for evaluating the perceived quality of digital video content. These methods are mainly categorized into two classes: the *subjective* and *objective* ones.

The subjective test methods involve an audience of people, who watch a video sequence and score its quality as perceived by them, under specific and controlled watching conditions.

The following opinion scale used in an absolute category rating (ACR) test is the most frequently used in ITU-T [5]: excellent (5), good (4), fair (3), poor (2), and bad (1). The arithmetic mean of all the opinion scores collected is the MOS. The best known subjective techniques for video are the *single stimulus continue quality evaluation (SSCQE)* and the *double stimulus continue quality evaluation (DSCQE)* [15, 16].

The fact that the preparation and execution of subjective tests is costly and time consuming deprives their use in commercial mobile systems which aim at providing audiovisual services at predefined quality levels.

The objective methods are characterized and categorized into classes, according to the procedure of the quality evaluation.

One of these classes requires the source video sequence as a reference entity in the quality evaluation process, and is based on filtering the encoded and source sequences, using perceptual filters (i.e., Sobel filter). Then, a comparison between these two filtered sequences provides results, which are exploited for the perceived quality evaluation [17, 18].

Another class of objective evaluation methods is based on algorithms, which are capable of evaluating the PQoS level of the encoded test sequences, without requiring any source video clip as reference.

A software implementation, which is representative of this nonreference objective evaluation class, is the *quality meter software (QMS)* [19]. The QMS tool measures objectively the instant PQoS level (in a scale from 1 to 100) of digital video clips. The evaluation algorithm of the QMS is based on vectors, which contain information about the averaged luminance differences of adjacent pixels.

Table 1 summarizes ITU recommendations related to video quality assessment methodologies for video codec.

For all previous reasons, a lot of effort has recently been focused on developing cheaper, faster, and easily applicable objective evaluation methods, which emulate the results that are derived from subjective quality assessments, based on criteria and metrics, which can be measured objectively.

Due to the subjective methods limitations, engineers have turned to simple error measures such as mean-squared error (MSE) or peak signal-to-noise ratio (PSNR), suggesting that they would be equally valid. However, these simple measures operate solely on the basis of pixel-wise differences and neglect the impact of video content and viewing conditions on the actual visibility of videos.

PSNR does not take into account human vision and thus cannot be a reliable predictor of perceived visual quality. Human observers will perceive different kinds of distortions in digital video, for example, *jerkiness* (motion that was originally smooth and continuous is perceived as a series of distinct snapshots), *blockiness* (a form of block distortion where one or more blocks in the image bear no resemblance to the current or previous scene and often contrast greatly with adjacent blocks), *blurriness* (a global distortion over the entire image, characterized by reduced sharpness of edges and spatial detail), and noise. These distortions cannot be measured by PSNR. ANSI T1.801.03-1996 standard [20, 21] defines a number of features and objective parameters related to the above-mentioned video distortions. These include the following.

(i) Spatial information (SI) is computed from the image gradient. It is an indicator of the amount of edges in the image.

(ii) Edge energy is derived from spatial information. The difference in edge energy between reference and processed frames is an indicator of blurring (resulting in a loss of edge energy), blockiness, or noise (resulting in an increase of edge energy).

(iii) The difference in the ratios of horizontal/vertical (HV) edge energy to non-HV edge energy quantifies the amount of horizontal and vertical edges (especially blocks) in the frame.

(iv) Temporal information (TI) is computed from the pixel-wise difference between successive frames. It is an indicator of the amount of motion in the video. Repeated frames become apparent as zero TI, and their percentage can be determined for the sequence.

(v) Motion energy is derived from temporal information.

The difference in motion energy between reference and processed video is an indicator of jerkiness (resulting in a loss of motion energy), blockiness, or noise (resulting in an increase of motion energy).

Motion energy difference, percent repeated frames, and other video parameters can then be combined to a measure of perceived jerkiness.

Starting from all the previous considerations, a considerable amount of recent research has focused on the development of quality metrics that have a strong correlation with subjective data. Three metrics based on models of the

Table 2: Pearson correlation index of the most reliable and famous objective video quality metrics.

peak signal-to-noise ratio (PSNR) [25]	0.793
structural similarity (SSIM) [26, 27]	0.8301
Blurring measure [28]	0.8963
Blocking measure [29]	0.83
motion sum of absolute differences (MSADs) [30]	0.819
video quality metric (VQM) [7]	0.98 (Always over 0.91)

human visual system (HVS) are summarized in [22]: the Sarnoff just noticeable difference (JND) model, the perceptual distortion metric (PDM) model developed by Winkler [23], and Watson's digital video quality (DVQ) metric [24]. Finally, a general purpose video quality model (VQM) was standardized by ANSI in July 2003 (ANSI T1.801.03-2003), and has been included in draft recommendations from ITU-T study group 9 and ITU-R working party 6Q.

The general model was designed to be a general purpose video quality model (VQM) for video systems that span a very wide range of quality and bit rates, thus it should work well for many other types of coding and transmission systems (e.g., bit rates from 10 kbits/s to 45 Mbits/s, MPEG-1/2/4, digital transmission systems with errors). Extensive subjective and objective tests were conducted to verify its performances. The VQM metric computes the magnitude of the visible difference between two video sequences, whereby larger visible degradations result in larger VQM values. The metric is based on the discrete cosine transform, and incorporates aspects of early visual processing, spatial and temporal filtering, contrast masking, and probability summation.

This model has been shown by the video quality experts group (VQEG) [6] in their phase II full reference television (FR-TV) test to produce excellent estimates of video quality for video systems obtaining an average pearson correlation coefficient over tests of 0.91 [7]. To the best of our knowledge, VQM is the only model to break the 0.9 threshold according to previous studies summarized in Table 2; for this reason, we chose to use it in our work as reference model for the PQoS evaluation during the training phase.

4. SYSTEM ARCHITECTURE AND TEST BED DEPLOYMENT

In this section, we describe the network architecture used for evaluating the perceived quality of the transmitted multimedia contents. We recorded several video clips with different bit rates; we used the digital video encoding formats MPEG-4 [31] because it is mostly preferred in the distribution of interactive multimedia services over IP; furthermore, MPEG-4 is also suitable for 3G networks providing better encoding efficiency at low bit rates, compared to the previous formats (MPEG-1, MPEG-2).

The network architecture is shown in Figure 1; it is composed by both wired and wireless segment. The service center belongs to the wired segment and has the task of sending multimedia contents to the wireless clients (e.g., Laptop, PDA, smartphone, see-through glasses for augmented reality, generic head mounted displays HMD, etc.). On the wireless segment the transmission of multimedia contents can take place in both directions, from the clients to the access point (AP) and vice versa. This architecture can be used to provide real-time video with augmented reality: a classical example is offered by a client device equipped with a wireless camera that can be used by a visitor inside a museum; the camera can record and send the video of the ambient in which the visitor is walking to the service center that is in charge of locating the client and send him multimedia contents regarding the paintings or the art work recorded in the video previously sent. A similar service can be offered in an archaeological site to supply augmented reality area wireless network.

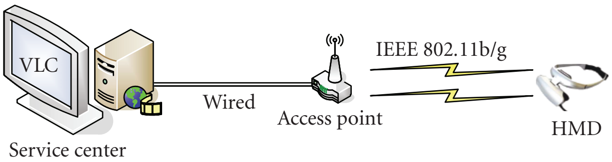

Figure 1: A Simple system architecture.

In order to emulate the previous scenario, we create different multimedia video and we transmit them from the wireless mobile device on the right side of Figure 1, to the service center and vice versa using VLC [32], (*VideoLAN* is a software project, which produces free software for video, released under the GNU general public license. VLC media player is a free cross-platform media player, it supports a large number of multimedia formats, without the need for additional codecs; it can also be used as a streaming server, with extended features (video on demand, on the fly transcoding, etc.).) a powerful software well suited for video streaming transmission.

With the aim of implementing a more realistic scenario, we considered also the data traffic generated from other mobile devices within the AP coverage area; this aggregated data traffic represents a set of different applications such as download of audiovideo contents, text files, or web surfing; it can be considered as "*background traffic*" handled by the access point without stringent delay constraints, nevertheless the amount of this background data traffic has, for sure, a heavy impact on the multimedia video transmission in terms of perceived quality, thus the evaluation of the PQoS metric and the resulting analytical models cannot be designed without considering this kind of traffic.

The background traffic was physically implemented as a download of huge data files, using the classical TCP transport stream. The bursty transmission behavior of TCP [33–35] makes PQoS estimation more challenging due to the variable wireless link occupancy. According to this consideration, the background traffic values used during the simulations have to be considered as mean values computed during the whole test. We did not use any analytical model nor synthetic traffic generator in order to emulate the real world scenario of data traffic coming from other applications.

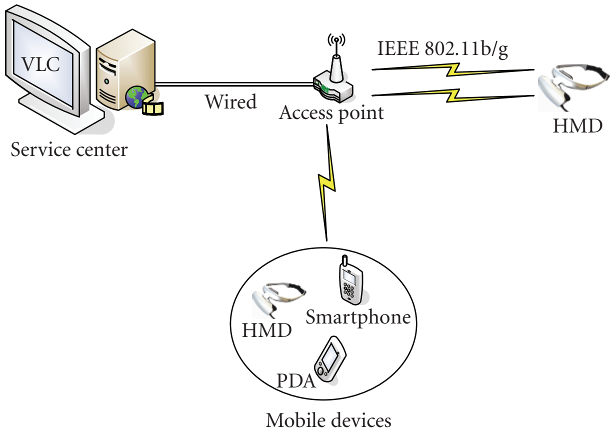

FIGURE 2: The whole test bed system.

The whole system architecture is shown in Figure 2, we used another laptop for generating the aggregated background traffic; moreover, we gradually increased the amount of generated data traffic in order to study the effect on the perceived quality during the transmission on the wireless channel.

Concerning the background traffic values for the whole simulation campaign, the following remark is appropriate. We implemented a wireless IEEE 802.11g [36] network that can support nominal data rate up to 54 Mbps; yet in practice only half of the advertised bit rate can be achieved because wireless networks are particularly error-prone due to radio channel impairments; thus the data signals are subject to attenuation with distance and signal interference.

We observed, through few simple tests, that the perceived video quality is not degraded if the traffic background is smaller than 11 Mbps; this performance is due to the high link capacity supported by the specific AP. (The AP used for the test bed is a USRobotics Wireless MAXg Router 5461A.)

We experimented that 28 Mbps is the maximum background traffic sustainable by our wireless network.

Table 3 summarizes all the system parameters used for the test bed; the transmitted multimedia video contents were extracted from few minutes of an action movie with a high interactivity level in order to evaluate a worse case scenario in terms of variable bit rate; moreover, the contents were chosen in order to cover a wide range of possible applications such as video streaming conference with a variable bit rate satisfying different applications requirements. Each video clip was transcoded to MPEG-4 format, at various variable bit rates (VBR) according to the mean data rates shown in Table 3. Resolution (320×240) and constant frame rate of 25 frames per second (fps) were common parameters for the transcoding process in all test videos. These video parameters are typically supported by hand-held mobile devices.

Finally, we evaluated the system performances varying the wireless link quality in terms of signal power level. Using *network stumbler* [37] we obtained the signal power level values over the wireless link depending on the distance from the access point. For each parameter combination we took several samples repeating the perceived quality measurement 8 times with the aim of considering the natural wireless link and background traffic fluctuations.

In order to measure the video quality over the wireless network we used MSU [38]. This free program has many interesting features to evaluate the video quality according to several metrics (i.e., PSNR, DELTA, MSAD, MSE, SSIM, and VQM). Moreover, the obtained results are collected in a .CVS file, thus they can be easily managed through any spread sheet.

During the transmission over the wireless link, few frames can be lost due to low signal level or to high interference conditions; nevertheless, the software used for the PQoS evaluation needs to compare two videos with exactly the same number of frames, thus we implemented a realignment procedure for replacing the lost frames with the last frame correctly received in order to obtain a consistent analysis.

5. TEST BED RESULTS AND ANALYTICAL MODEL

In this section, we show the results in terms of perceived video quality, obtained from the test bed varying the network parameters and we propose a simple analytical model for estimating the perceived quality.

Our model for PQoS estimation is based on simple parameters that can be easily computed in the first "*training phase*." The implementation of an integrated software for the perceived quality measurement of few video contents and the resulting calibration of the polynomial model coefficients are quite simple. In this way, the analytical model plays a primary role in the PQoS estimation and the consequent real-time video scaling or format adaptation. Finally, the proposed method for PQoS estimation can be integrated in any wireless telecommunication system satisfying the following requirements:

(1) every client has to periodically provide its received power level to the service center through specific backward signalling;

(2) the service center needs to periodically monitor the data traffic, managed by the access point, and measure the background traffic in order to perform PQoS estimation and adapt the video format.

We remark that in our work, we evaluated PQoS in the training phase through the generic VQM objective metric for a specific source and channel coding techniques. In other words, once fixed the source coding, the channel coding, and the streaming protocol used during the training phase, these techniques should not be changed without repeating the training phase. That is a realistic situation since all the multimedia contents are provided by one service center.

5.1. *Fixing the wireless link quality*

First of all we fixed the power level of the wireless signal to the best value (i.e., -15 dBm) in order to study the system performance in a very good condition in which the interference has a negligible effect; in this way the perceived

Table 3: System traffic parameters.

		Video bit rate				
		450 Kbps	810 Kbps	1470 Kbps	1870 Kbps	2350 Kbps
Background traffic	0 Mbps	0.6452	0.5405	0.3552	0.3625	0.3246
	5 Mbps	0.6452	0.5475	0.3552	0.3741	0.3439
	11 Mbps	0.6452	0.5546	0.3552	0.3857	0.3632
	22 Mbps	0.6927	0.5990	0.8080	0.9838	1.2077
	26 Mbps	0.8197	0.6737	1.1294	1.6501	2.4743
	28 Mbps	0.9212	0.7346	1.5547	2.1475	3.2797

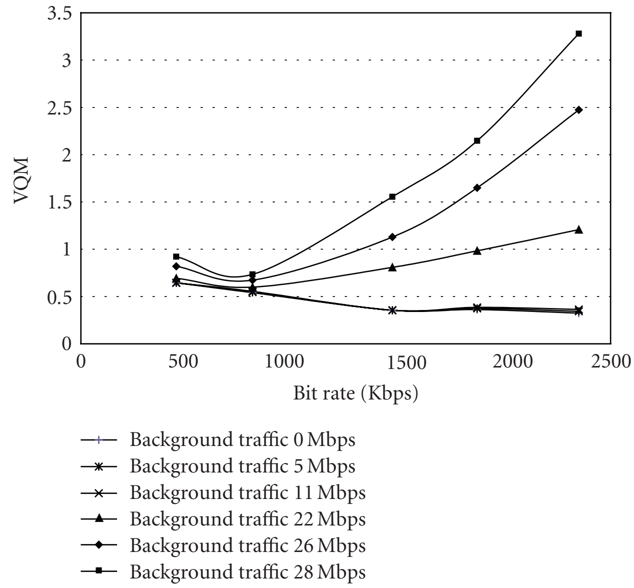

Figure 3: Perceived quality versus background traffic with different video bit rates.

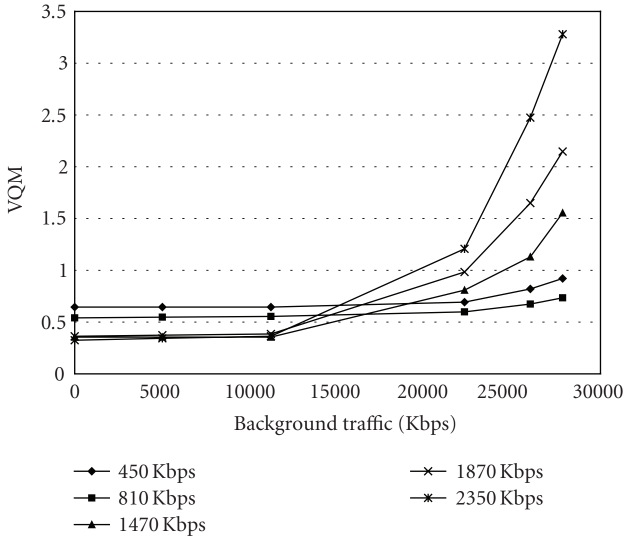

Figure 4: Perceived quality versus video bit rates with different background traffic.

Table 4: Network parameters for the training phase.

Video bit rate	Background traffic	Signal power level
r_1 = 2350 Kbps	b_1 = 0 Mbps	$c_1 = -15$ dBm (excellent)
r_2 = 1870 Kbps	b_2 = 5 Mbps	$c_2 = -40$ dBm (good)
r_3 = 1470 Kbps	b_3 = 11 Mbps	$c_3 = -66$ dBm (fair)
r_4 = 810 Kbps	b_4 = 22 Mbps	$c_4 = -76$ dBm (poor)
r_5 = 450 Kbps	b_5 = 26 Mbps	
	b_6 = 28 Mbps	

video quality is strictly linked only to the background traffic and the bit rates; the following analysis is oriented to discover the relationship between those two system parameters. Figures 3 and 4 show how the perceived quality decreases when both the background traffic and the bit rate of the transmitted video increase. Furthermore, background traffic values smaller than 11 Mbps do not influence the perceived quality index. Choosing an objective VQM value for each video, an accurate scaling can be done according to the trend of those curves. Table 4 summarizes all the measured quality values that will be used for the analytical model fitting.

5.2. Varying the wireless link quality

The link quality is for sure one of the most important parameters in the evaluation of standard QoS index in wireless networks. Its contribution in terms of PQoS is still an open and challenging issue that we consider in this section. Figure 5 shows the perceived quality index with different values of signal strength over the wireless link. This measurement has been carried out by fixing the background traffic value to 11 Mbps in order to study the signal power level effect in a mean working condition in which the background traffic presence cannot drastically affect the contribution of the signal power level. When the measured power level from the receiver is very low (i.e., −76 dBm), the VQM index does not depend on the video bit rate, in fact that curve fluctuates around 1.5 VQM value; thus in this condition, a video with low bit rate has almost the same quality of a video with high bit rate.

In the other two cases (i.e., −66 dBm and −46 dBm) the slight decrease of the VQM value is more evident on videos with higher bit rate.

Following the previous considerations we can argue that the signal power level over the wireless link is weakly related

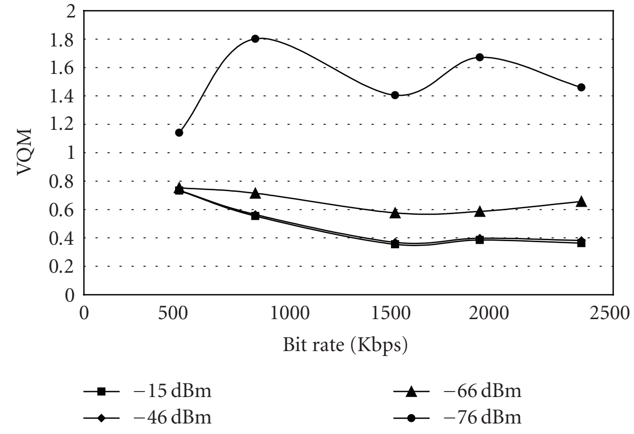

FIGURE 5: PQoS varying the quality link and the bit rate.

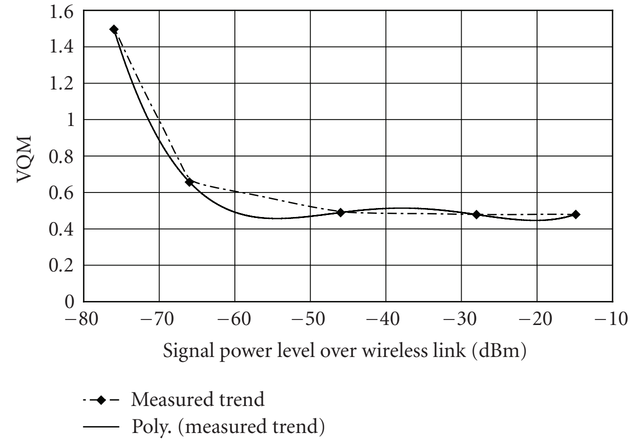

FIGURE 6: PQoS varying the link power level.

to the video bit rate and the background traffic; for this reason we can treat the weight of the power level over the link as an additive value according to the trend in Figure 6. Thanks to the measurements carried out through the test bed we can approximate the trend of the curve with polynomial equation that will be used for designing the analytical model.

5.3. Analytical model for estimating the PQoS value

The main goal of this section is the design of an analytical model in which all the previous PQoS measurements for our wireless network can be used in order to predict the VQM value in a fast, responsive, and reliable way. According to the curves presented in Figures 3 and 4 we pointed out the relations between the video bit rates and the background traffic; now we need to find a mathematical relation that can represent the trend of those curves.

As we already explained, the perceived quality is considered in our work as a function $g(\cdot)$ of three parameters: the video bit rate R, the background traffic B, and signal power level over the wireless link C. Thus the PQoS can be expressed through the following relation:

$$\text{PQoS} = g(R, B, C). \tag{1}$$

For sake of simplicity we used the normalized version of those quantities according to the following formula:

$$x = \frac{X - \mu(X)}{\sigma(X)}, \tag{2}$$

where $\mu(X)$ and $\sigma(X)$ are the mean and the standard deviation of the measured quantities, thus

$$\text{PQoS} = h(r, b, c). \tag{3}$$

As already explained in this section, the signal power over the wireless link is not strictly related with the video bit rate and the background traffic; for this reason, treating the wireless link strength as an additive value, we can rewrite the relation (3) as sum of two different functions

$$h(r, b, c) = f_1(r, b) + f_2(c). \tag{4}$$

Thanks to the measurements carried out through the test bed, we can fit both f_1 and f_2 functions using two polynomials, that is,

$$\begin{aligned} P_1(x, y) &\cong f_1(r, b), \\ P_2(z) &\cong f_2(c), \end{aligned} \tag{5}$$

where

$$\begin{aligned} P_1(x, y) &= \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} a_{ij} x^i y^j \\ &= \sum_{k=0}^{m-1} \alpha_k(x) y^k = \sum_{k=0}^{n-1} \beta_k(y) x^k, \end{aligned} \tag{6}$$

$$P_2(z) = \sum_{k=0}^{v-1} c_k z^k. \tag{7}$$

During the training phase we estimate the a_{ij} and c_k coefficients in (6) and (7).

In our study, we used ($n = 5$) different values for video bit rate and ($m = 6$) different values for background traffic, thus we implemented a linear system of 30 equations in the unknowns a_{ij} for the polynomial P_1 while we used ($v = 4$) values for the power level over the wireless link corresponding to a 4 equations linear system in the unknowns c_k for the polynomial P_2.

Table 4 shows the values $(r_1, r_2 \cdots r_n)$, $(b_1, b_2 \cdots b_m)$, and $(c_1, c_2 \cdots c_v)$ used for the video bit rate, the background traffic, and power link level, respectively.

Equation (8) provides the exact values of a_{ij} and c_k coefficients obtained through the proposed model:

$$\begin{gathered} (a_{ij}) = \begin{pmatrix} 0.5550 & -0.0464 & -0.1227 & -0.0472 & 0.0555 \\ 0.5579 & 0.2703 & -0.9139 & -0.1132 & 0.4152 \\ -0.2049 & 0.4568 & 1.3469 & 0.0296 & -0.4997 \\ -0.6381 & 0.2907 & 2.2181 & 0.1468 & -0.8619 \\ 0.4646 & 0.0246 & -1.0567 & -0.0464 & 0.4932 \\ 0.4925 & -0.0240 & -1.2682 & -0.0771 & 0.5484 \end{pmatrix}, \\ (c_k) = \begin{pmatrix} 0.3541 \\ -0.2235 \\ 0.7584 \\ 0.6865 \end{pmatrix}. \end{gathered} \tag{8}$$

Table 5: Network parameters for model validation.

Video bit rate	Background traffic	Signal power level
630 Kbps	14300 Kbps	−15 dBm
1000 Kbps	18560 Kbps	−32 dBm
1560 Kbps	24160 Kbps	−60 dBm

Table 6: VQM Values measured through MSU software, signal power level −15 dBm.

	Background traffic [Kbps]		
Bit rate [Kbps]	14300	18560	24160
630	0.569878	0.61557	0.653899
1000	0.539471	0.592827	0.694409
1560	0.4555	0.561323	1.031743

Table 7: PQoS Values estimated with the analytical model, signal power level −15 dBm.

	Background traffic [Kbps]		
Bit rate [Kbps]	14300	18560	24160
630	0.609	0.608	0.647
1000	0.497	0.535	0.676
1560	0.415	0.552	1.023

Thanks to the model, we can easily evaluate the performances of different scenarios through a colored scale representing the good mix (green and light green-areas) and the bad mix (red and dark-red) of system parameters in terms of perceived quality values. Many interesting considerations can be made observing Figures 7 and 8 because the relations between all the system parameters involved in the evaluation of the PQoS are mixed together. These figures are two different ways for representing the output of the PQoS estimation model according to the available system parameters; the colored maps can be examined fixing the signal power level (Figure 7) or fixing the video bit rate (Figure 8) and varying the other two parameters; in particular the PQoS index increases at higher video bit rate and background traffic. This causes a degradation in terms of perceived quality (see red and dark-red zone on Figure 7). On the other hand, fixing the video bit rate, the PQoS index increases (i.e., quality degrades) with the background traffic and the signal power level (see red and dark-red zones on Figure 8). Thanks to these maps the reader can appreciate in a visual manner the graceful scaling color of the estimated PQoS.

5.4. *Testing the effectiveness of the analytical model*

In this section we demonstrate the reliability of the proposed model showing the correlation between the measurements executed with the MSU software and the results obtained through the analytical framework.

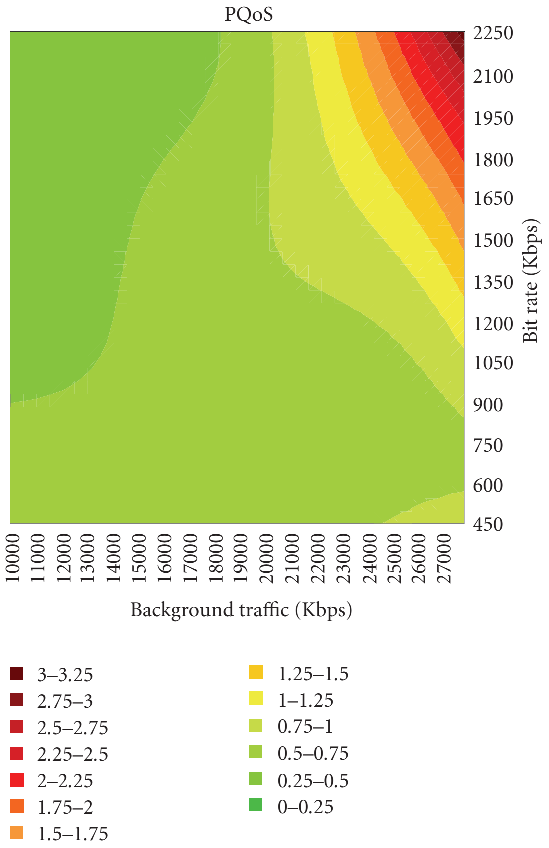

Figure 7: PQoS map obtained from the analytical model, background traffic versus video bit rate.

In support of this analysis we recorded new videos with different parameters according to Table 5. The results summarized in Tables 6 and 7 have been obtained fixing the signal power level at −15 dBm; as we can see, the difference between the two approaches is a negligible quantity. The overall pearson linear correlation coefficient [39] between VQM quality and analytical model for the video sequences is equal to 0.986 making the proposed model very usefull. Finally, the accuracy of the proposed method can be valued looking at Figure 9 where the correlation between the values has been plotted.

In order to discover the possible limitations of our model we repeated the previous analysis taking few measurements with different values for the signal power level (i.e., −32 dBm and −60 dBm).

Figure 10 shows that the model fails only if the effect due to a suboptimal signal power level over the wireless link is coupled with a high background traffic value (i.e., 24160 Kbps). In these conditions the effects of the two phenomena are not predicted by our model (4). In such a case the data traffic over the wireless link is high and makes the network work very close to a congestion zone.

In conclusion, the proposed model is effective and robust up to 18560 Kbps of background data traffic in every tested wireless link conditions; these results make the model very useful and attractive for a wide range of realistic wireless network scenarios and video applications.

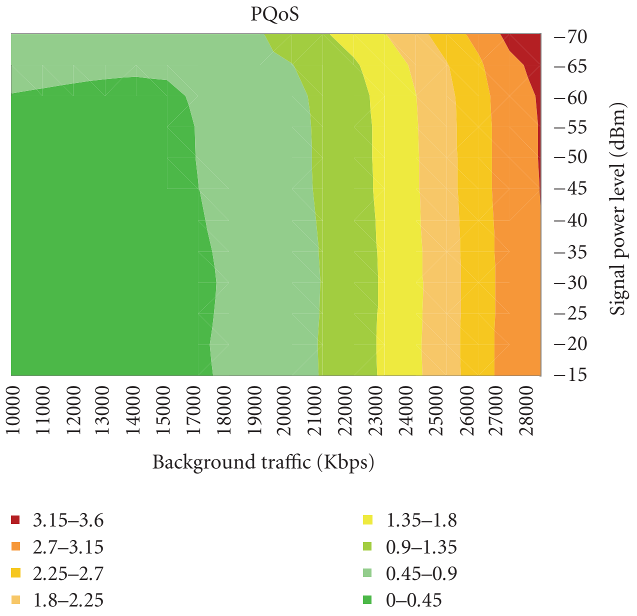

FIGURE 8: PQoS map obtained from the analytical model for a fixed bit rate of 2350 Kbps, background traffic versus signal power level.

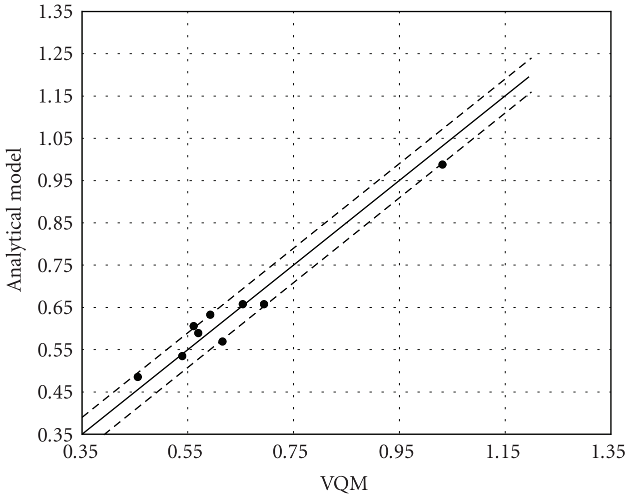

FIGURE 9: VQM quality versus analytical model quality, signal power level −15 dBm.

6. CONCLUSION

In this paper, we have measured the perceived quality of multimedia video contents transmitted over wireless LAN test bed based on the IEEE 802.11g standard. We studied the effects of network parameters on the PQoS index highlighting the connections between them. Finally, we designed an analytical model based on a simple curve fitting technique, well suited for wireless environment, for estimating the PQoS index in a fast and easy way. The proposed analytical model has an average pearson correlation coefficient of 0.986, as proof of its robustness and reliability in many network conditions. Nevertheless, when the background traffic is very high and the signal power level is not excellent, the model does not work well because the combination of those two effects generates an unpredictable behavior in terms of PQoS. This analysis highlights few natural limitations of the proposed technique due to the congestion of the wireless network. Future work includes the testing of additional video sequences with different codec formats and resolutions in a multiuser scenario.

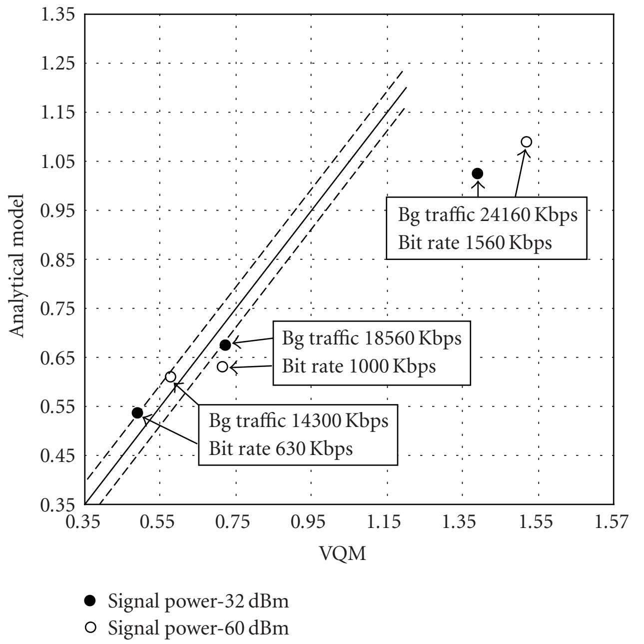

FIGURE 10: VQM quality versus analytical model quality, signal power levels −32 dBm and −60 dBm.

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