Wireless Pers Commun manuscript No.
(will be inserted by the editor)

End-to-End Multimedia Quality Estimation with Robust Optimization in Real-World Mobile Computing Networks

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Received: / Accepted: date

Abstract Quality of Experience (QoE) parameters describe the end-to-end (E2E) quality as experienced by the mobile users. These are difficult to measure and quantify. On the one hand, System Quality of Service (SQoS) parameters are metrics that are close related to the network status, and defined from the viewpoint of the service provider rather than the service user. On the other hand, E2E Service Quality of Service (ESQoS) parameters describe the QoS of the services and they are obtained directly from the QoE parameters by mapping them into parameters more relevant to network operators, service providers and mobile users. A useful technique for mobile network planning and optimization is to build quality estimation models for mobile voice and video telephony service. Our research is focused on developing statistical estimation models extracted by measurements acquired via a drive-test measurement campaign of a commercial UMTS multimedia network. Regression estimates, computed with a robust optimization strategy, suggest a weaker dependence between the SQoS and ESQoS parameters and connect the strength of the dependence with the accuracy of the measurements used to compute the estimates.

Keywords Quality of Experience · Quality of Service · Measurement Campaign · Quality Prediction · Non-Linear Regression · Robust Optimization · Mobile Networks

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1 Introduction

Mobile user experience (mUX) is a holistic perspective to how a mobile user feels about using services providing by wireless networks. This term is subjectively described by factors influenced by user's state and previous knowledge, network properties and usage context [1]. Therefore, mUX is a field where studies are rapidly executed and lean prototypes are quickly built and explored with users to evaluate the potential for new services. Whilst, mUX highlights subjectively the experiential user to mobile network/service interaction, various performance evaluation algorithms have been developed for objective E2E quality characterization. Network-based SQoS and service-based ESQoS are defined in ETSI TR 126 944 [2] and they are important factors when providing multimedia services to mobile customers [3]. Both network monitoring systems as well as on-the-field or emulation measurement campaigns [4] are useful in radio network planning and optimization. Indeed, measurements can be utilized in content delivery systems [5], energy saving in smart devices [6], cell selection [7] and human movement estimation [8]. Since network planning today is based on coverage prediction from planning soft-tools, taking into account factors like base station antenna heights, tilts and directivity, cell interference and topography of the terrain, the predicted coverage area is always based on a certain value of SQoS parameters. Consequently, ESQoS prediction is one of the most significant research areas in mobile computing technologies [9,10,11]. Advanced statistical analysis, such as linear and non-linear regression modeling, has been used in order to build prediction models [12] for the simulation a VoIP mobile network. Moreover, regression and logarithmic models are proposed in [13,14] for QoE prediction. Beyond the statistical approach, adaptive neuro-fuzzy inference [15,16] and modern data mining algorithms [17,18] have been employed.

Robust optimization [19,20] has been increasingly used in mathematical optimization as an effective way to immunize solutions against data uncertainty. If the true value of a problem's data is not equal to its nominal value, the optimal solution computed using the nominal value might not be optimal or even feasible for the true value. Robust optimization considers uncertainty sets for the data of a problem and defines solutions that are immune to such uncertainty. In linear optimization problems, box-type uncertainty sets [21], and ellipsoidal uncertainty sets have been considered. In linear, as well as mixed integer optimization problems, robust counterparts with budgeted uncertainty sets that connect the uncertainties developed by the coefficients of the constraints have been efficiently solved [22]. The robust optimization paradigm has been successfully applied to regression and classification problems to deal with uncertainty in the statistical data and has been connected with regularized regression models [23]. Moreover, a robust risk measure with reference to a family of nominal risk measures as well as a robust version of the Conditional Value-at-Risk (CVaR) and of entropy-based risk measures are defined in [24,25].

Extending our first approach on the problem [26], we propose a robust optimization framework for multimedia QoS estimation which is based on a drive-test E2E measurement campaign of live UMTS/3G network with *SwissQual Diversity Benchmarker* [27] as it is depicted in Fig. 1.

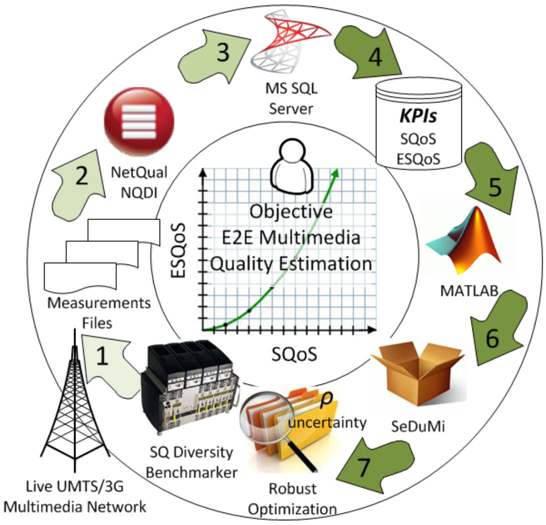


Fig. 1 Multimedia QoS prediction strategy based on drive-test measurement campaign of a live UMTS/3G multimedia network with robust optimization.

Moreover, specifications on quality of mobile phone services are in details defined in ETSI TS 102 250, parts 1–7 [28]. Test video calls are established between the probing system and the fixed/server-side and test voice/video samples are exchanged; while full logging and all layers decoding (RF, L2/L3, TCP/IP) are executed on real time. Afterwards, measurement files both from test-handset and multimedia server sides are merged and processed with *NetQual NQDI*, a compatible post-processing software for in depth analysis of mobile video telephony service, protocol analysis and quality assessment. *Microsoft SQL Server* is used for querying data of ESQoS and SQoS key parameters from the created geospatial-temporal measurements database. Using MATLAB [29] for statistical analysis and SeDuMi [30] for optimization problems solution, QoS non-linear prediction models are proposed.

The rest content of this paper is organized in five sections. Section 2 reviews radio-SQoS key performance indicators (KPIs) of commercial mobile networks as well as modern ESQoS aspects regarding voice and video telephony services. Followingly, Section 3 focuses on the concept of regression analysis and the significant contribution of robust optimization for multimedia quality estimation. Furthermore, Section 4 quotes a useful method of evaluating the robust optimization based models. Finally, the conclusions Section 5 discusses the major endowment of our research work on statistical prediction of objective ESQoS.

2 Quality in Mobile Multimedia Networks

2.1 SQoS in mobile networks

GSM is a cellular mobile communication network operating in 800 MHz (known as GSM900) and 1800 MHz (known as DCS1800). The communication system supports adaptive multi rate (AMR) speech codecs. So, EFR (Enhanced Full Rate), AMR FR (Full Rate) and AMR HR (Half Rate) codecs are used in speech telephony service. The main radio parameters of a GSM EDGE Radio Access Network (GERAN) according to ECC Report 118 [31] are:

- *RxLev* is the received (R_x) signal strength level on serving cell measured, in *dBm*.
- *RxQual* is the received (R_x) signal quality on serving cell. It is a value between 0 (excellent) and 7 (bad) and corresponds to the estimated *BER*.

A UMTS network is based on WCDMA (Wideband Code Division Multiple Access) radio access technology and consists of a radio access network (RAN) and a core network (CN) [32]. RAN basically consists of RNCs (Radio Network Controllers) and NodeBs (base stations) that are connected with UEs (User Equipments). The CN can be interconnected to various backbone networks like IP-networks (Internet) public fixed telephone networks (ISDN/PSTN). The ECC Report 103 [33] presents details for a UMTS coverage measurements methodology in order to characterize the quality of radio network coverage, specifically:

- *RSCP* (Received Signal Code Power) is the received power on one code measured, in *dBm*, on the pilot bits of the P-CPICH (Primary Common Pilot Channel).
- $E_c/(I_0+N_0)$ is the ratio, in *dB*, of the received energy per chip, E_c, to the total received energy or the total interference, I_0, plus noise, N_0. In case no true interference is present, the interference level is equal to the noise level. The *signal-to-interference* ratio E_c/I_0 is actually used instead of the $E_c/(I_0+N_0)$. Due to the fact that the interference level can be higher than the wanted signal level, especially at the coverage border, the value of E_c/I_0 is usually negative.
- *RSSI* (Received Signal Strength Indicator) is a value that takes into account both *RSCP* and E_c/I_0. It is usually measured in *dBm* and can be calculated as:

$$RSSI[dBm] = RSCP[dBm] - E_c/I_0[dB] \tag{1}$$

We note that E_c/I_0 is the most crucial radio quality parameter and we consider in the rest paper that it is identical to the SQoS.

Fourth generation (4G) or LTE (long term evolution) radio access networks (e-UTRAN) provide broadband services beyond telephony. The basic radio KPIs are described in [34]:

- *RSRP* (Reference Signal Received Power) is the linear average, in *dBm*, over the power contributions of the resource elements that carry cell-specific reference signals within the considered measurement frequency bandwidth.

– E-UTRAN Carrier *RSSI* is the linear average, in *dBm*, of the total received power observed only in OFDM symbols containing reference symbols over N number of resource blocks (RBs) by the UE from all sources.
– *RSRQ* (Reference Signal Received Quality) is the ratio, in *dB*, $(N \times RSRP/RSSI)$.

Nowadays, mobile operators operate GSM networks coupled with UTRAN, as well as coupled with e-UTRAN. Beyond 4G communications, like LTE-Advanced or 5G, will deliver mobile services to QoE demanding users.

2.2 ESQoS of Mobile Multimedia Services

Mobile telephony is a multimedia service provided by UMTS networks where a 64 *kbps* (12.2 *kbps* and 50 *kbps* for voice and video coding respectively) transport channel is dedicated for video communication. *SQuad* and *VQuad* algorithms, launched commercially by *SwissQual*, can be used for full reference perceptual voice and video quality assessment in MOS (Mean Opinion Score) scale; or $ESQoS_{voice}$ and $ESQoS_{video}$. More specifically, guidelines for the use of video quality algorithms for mobile applications are presented in ETSI TR 102 493 [35]. For the scope of our research, we use the most popular indices *PESQ* (Perceptual Evaluation of Speech Quality) [36] and *PSNR* (Peak Signal-to-Noise Ratio) [37,38] as objective methods for E2E voice and video quality measurement between the original voice or video sample sent and the signal received. If p is the dynamic range of allowable bits per pixel, for two $X \times Y$ monochrome images s_k and $\tilde{s}_k$ (which are noisy or distorted of s_k) and K frames in the sequence, *PSNR* is computed as

$$PSNR = 10 \cdot log_{10}\left(\frac{(2^p-1)^2}{MSE}\right) \tag{2}$$

where

$$MSE = \frac{\sum_{x=1}^{X}\sum_{y=1}^{Y}\sum_{k=1}^{K}\left[s_k(x,y)-\tilde{s}_k(x,y)\right]^2}{X \cdot Y \cdot K} \tag{3}$$

Also, video quality, $ESQoS_{video}$, is computed with simple linear regression of *PSNR*, or

$$ESQoS_{video} = a \cdot PSNR + b, \tag{4}$$

In Table 1, we computed $\mathrm{SQoS}_{\mathrm{video}}$ (given objective *MOS*) versus *PSNR* values (given in *dB*). So linear, polynomial, exponential, power and logarithmic regression models are presented in Fig. 2.

An other image quality indicator is structural similarity (SSIM) [39] which is computed in fixed windows of one picture. SSIM measurement, $SSIM(x,y)$, between two windows x and y of the same size $N \times N$ is:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{5}$$

where, μ_x and μ_y are the mean values of x and y respectively, σ_x^2 and σ_y^2 is the standard deviation of x and y respectively, σ_{xy} is the correlation of x and y, $c_1 = (k_1 L)^2$ and

Table 1 Regressions on $\mathrm{ESQoS_{video}}$ (given objective MOS) vs. PSNR values(given in dB).

Type	Regression
Linear	$\psi = 0.168x - 2.759$
Polynomial	$\psi = -5 \cdot 10^{-4}x^2 + 0.198x - 3.183$
Exponential	$\psi = 0.138\exp^{0.009x}$
Power	$\psi = 4 \cdot 10^{-4}x^{2.566}$
Logarithmic	$\psi = 4.659\ln x - 13.577$

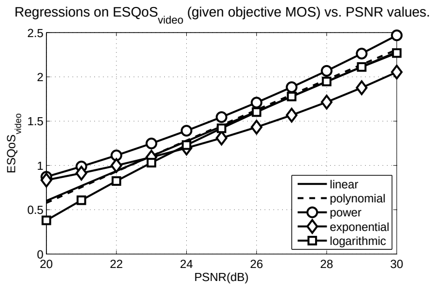


Fig. 2 Regressions on $\mathrm{ESQoS_{video}}$ (given objective MOS) vs. PSNR values(given in dB).

$c_2 = (k_2L)^2$ are two variables that stabilize the division with small devider, $L = 2^B - 1$, where is the number of *bits* per *pixel*, $k_1 = 0.01$ and $k_2 = 0.03$.

Multimedia quality [40], $ESQoS_{mm}$, is suggested in ITU-P.911 [41] to be computed ignoring the *lip-sync* effect or audiovisual synchronization. So, $ESQoS_{mm}$ can be estimated from voice and video quality, as

$$ESQoS_{mm} = c_1 + c_2 \cdot ESQoS_{voice} \cdot ESQoS_{video} \tag{6}$$

$$ESQoS_{mm} = c_1 + c_2 \cdot ESQoS_{voice} \cdot (a \cdot PSNR + b) \tag{7}$$

where $\{c_1, c_2\} = \{0.1925, 0.7650\}$.

The assessment of a ESQoS indicator is made by comparing the original voice/video samples transmitted by the calling party $\{S_i\}_{i=1}^n$, with the corresponding degraded received samples, $\{\tilde{S}_i\}_{i=1}^n$, at the called party by applying the objective assessment algorithm, *PESQ* and *PSNR* for voice and video quality respectively. The ESQoS indicator is computed by an evaluation function f_{MOS};

$$ESQoS_i = f_{MOS}(S_i, \tilde{S}_i). \tag{8}$$

The structure of a typical ESQoS measurement campaign is presented in Fig. 3, where both test voice and video samples are exchanged between the drive-test measurement equipment and the mobile network (or multimedia server side). To sum up, ESQoS is computed by applying full reference objective evaluation algorithms; *PESQ* and *PSNR* for voice and video quality respectively.

A set of graphs in Fig. 4 shows regressions on $ESQoS_{voice}$ (given objective MOS) versus $SQoS_{GSM}$ values (*RxLev* given in *dBm*) for various values of *RxQual* in case

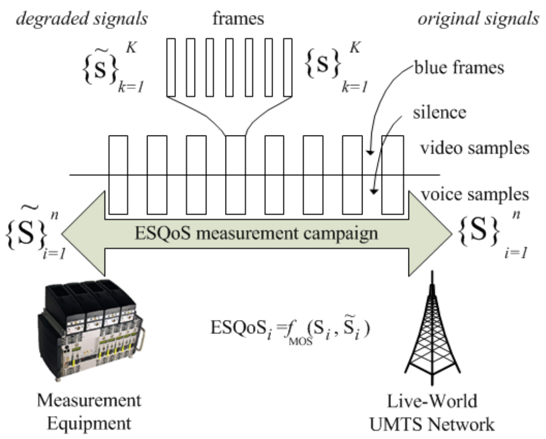


Fig. 3 Structure of a ESQoS measurement campaign. Test voice and video samples are exchanged between the drive-test measurement equipment and the mobile network (or server side). ESQoS is computed by applying full reference objective evaluation algorithms.

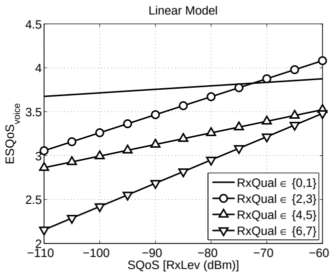
of GSM(900 MHz)/DCS(1800 MHz) telephony. Besides, the graphs in Fig. 5 depict regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{GSM}$ values ($RxLev$ given in dBm) in case of speech codecs (EFR, AMR FR, and AMR HR) for GSM/DCS telephony.

In depth analysis, regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{GSM}$ values ($RxLev$ given in dBm) in case of speech codecs (EFR, AMR FR and HR) for GSM and DCS telephony for downlink (DL) and uplink (UL) are shown in Figs. 6 and 7.

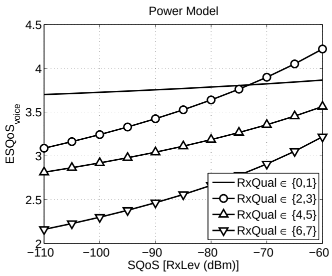
Table 2 Regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{UMTS}$ values (E_c/I_0 given in dB) in case of UMTS telephony.

Type	Regression
Linear	DL: $\psi = 0.033x + 4.030$
	UL: $\psi = 0.035x + 4.059$
Polynomial	DL: $\psi = -5.7 \cdot 10^{-3}x^2 - 0.045x + 3.786$
	UL: $\psi = -2.1 \cdot 10^{-3}x^2 + 0.008x + 3.976$
Power	DL: $\psi = 4.172\lvert x\rvert^{-0.05}$
	UL: $\psi = 4.364\lvert x\rvert^{-0.077}$
Exponential	DL: $\psi = 4.046\exp^{0.01x}$
	UL: $\psi = 4.137\exp^{0.014x}$
Logarithmic	DL: $\psi = -0.173\ln\lvert x\rvert + 4.138$
	UL: $\psi = -0,202\ln\lvert x\rvert + 4.201$

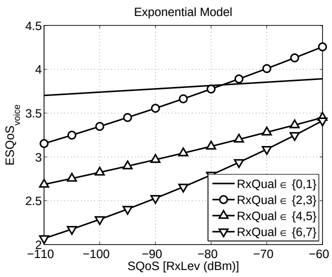
A holistic approach of E2E quality performance in voice and video telephony of UMTS operating networks is depicted in the set of the following graphs. Fig. 8 presents regressions on $ESQoS_{voice}$ versus $SQoS_{UMTS}$ values (E_c/I_0 given in dB) for classic AMR coded telephony. The model equations are presented in Table 2. Subsequently, the regressions on $ESQoS_{voice}$, $ESQoS_{video}$, and $ESQoS_{mm}$ (given objective



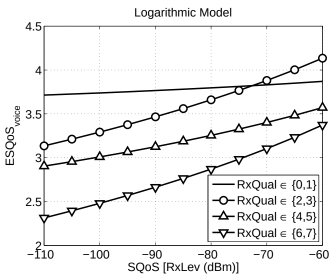
(a) Linear model



(b) Power model

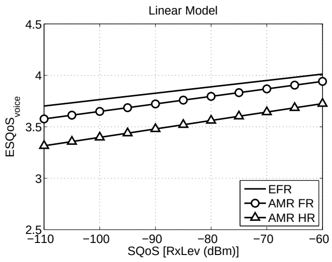


(c) Exponential model

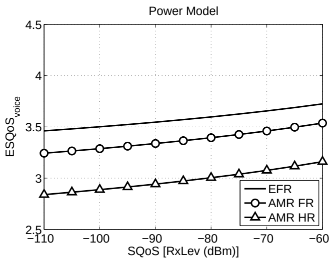


(d) Logarithmic model

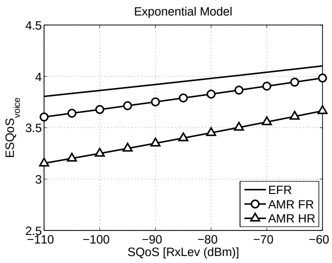
Fig. 4 Regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{GSM}$ values (*RxLev*) and in case of *RxQual* levels for GSM telephony.



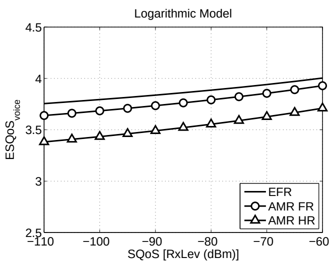
(a) Linear model



(b) Power model

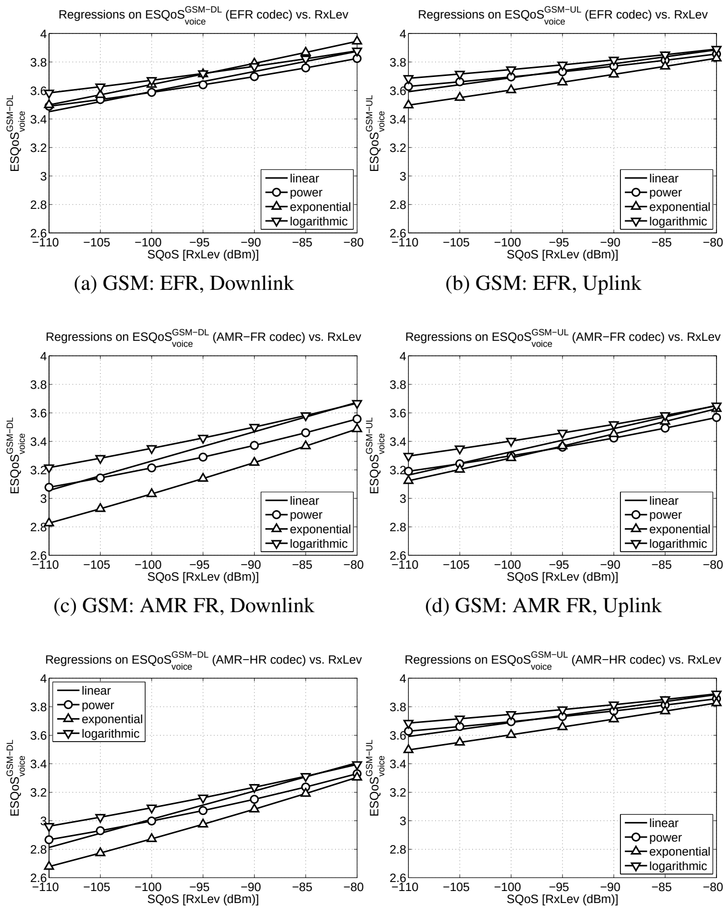


(c) Exponential model



(d) Logarithmic model

Fig. 5 Regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{GSM}$ values (*RxLev* given in *dBm*) in case of speech codecs for GSM telephony.



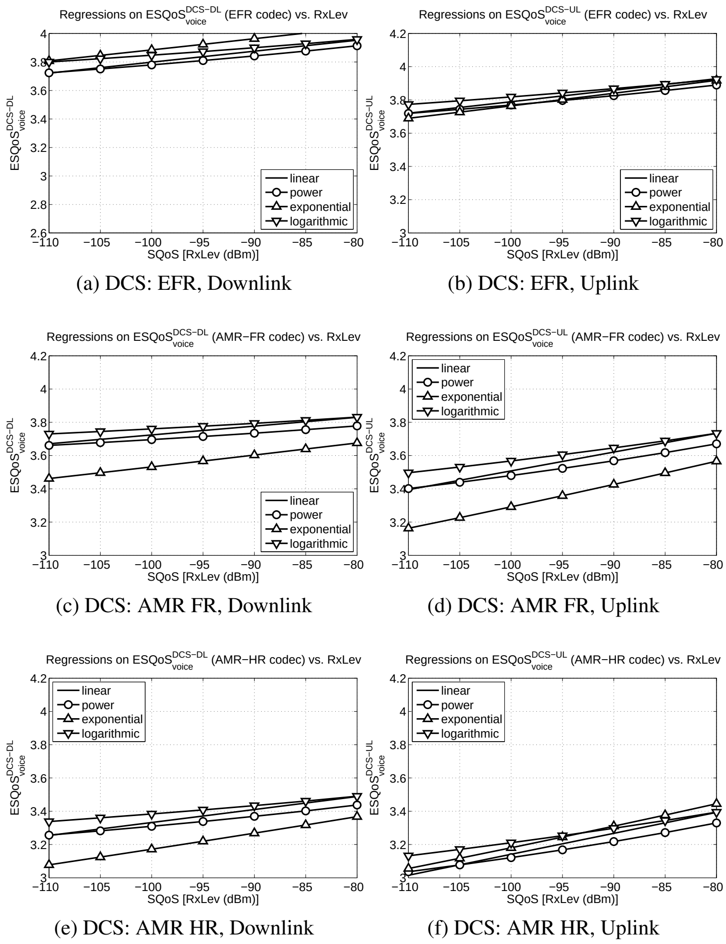
(a) GSM: EFR, Downlink (b) GSM: EFR, Uplink

(c) GSM: AMR FR, Downlink (d) GSM: AMR FR, Uplink

(e) GSM: AMR HR, Downlink (f) GSM: AMR HR, Uplink

Fig. 6 Regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{GSM}$ values ($RxLev$ given in dBm) in case of speech codecs for GSM (900 MHz) telephony.

MOS) versus $SQoS_{UMTS}$ values (E_c/I_0 given in dB) in case of speech codecs for UMTS video-telephony are shown in Fig. 9. Specifically, the model equations are presented in Table 3 for speech, video and multimedia prediction models. It is noted that AMR and MPEG4 codecs is used for speech and video coding respectively, while multimedia quality has been computed according to the Eq. (7).



(a) DCS: EFR, Downlink (b) DCS: EFR, Uplink

(c) DCS: AMR FR, Downlink (d) DCS: AMR FR, Uplink

(e) DCS: AMR HR, Downlink (f) DCS: AMR HR, Uplink

Fig. 7 Regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{DCS}$ values ($RxLev$ given in dBm) in case of speech codecs for DCS (1800 MHz) telephony.

3 ESQoS Estimation with Robust Optimization

For statistical estimation of $ESQoS$ from $SQoS$, equivalently $ESQoS(SQoS)$, regression models that have been presented in the previous section can be expressed under the generic form

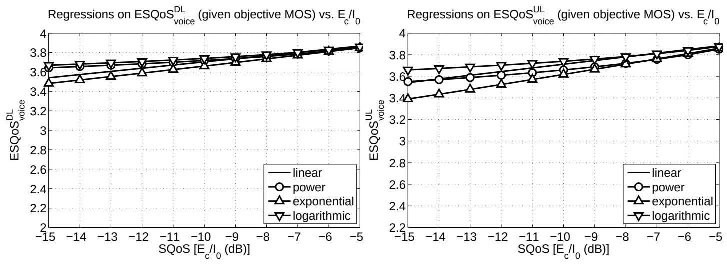
$$f(ESQoS) = \beta g(SQoS) + \varepsilon \tag{9}$$

for some f, g: $(0,+\infty) \mapsto \mathbb{R}$ that are strictly increasing. By specifying f and g, we derive the four regression types described in Table 4. In particular, we get

- linear model for
  $f(ESQoS) = ESQoS$, and
  $g(SQoS) = SQoS$.

Table 3 Regressions on $ESQoS$ (given objective MOS) vs. E_c/I_0(given in dB) for UMTS video-telephony.

		$\mathrm{ESQoS_{voice}}$		$\mathrm{ESQoS_{video}}$		$\mathrm{ESQoS_{mm}}$	
Model / Equation	Dir.	α_1	α_2	α_1	α_2	α_1	α_2
Linear	DL	0,1403	4,5505	0,0020	2,1370	0,0551	2,6206
$ESQoS = \alpha_1 \cdot SQoS + \alpha_2$	UL	0,1526	4,5191	0,0159	2,2332	0,0703	2,6802
Exponential	DL	4,7898	0,0440	1,9680	0,0039	2,5920	0,0250
$ESQoS = \alpha_1 \cdot \exp(\alpha_2 \cdot SQoS)$	UL	5,0536	0,0600	2,1618	0,0080	2,7653	0,0380
Logarithmic	DL	0,8680	5,2464	0,0070	2,1371	0,3370	2,8878
$ESQoS = \alpha_1 \cdot \ln(\alpha_2 \cdot \lvert SQoS \rvert)$	UL	0,8610	5,1330	0,0820	2,2836	0,3800	2,9340
Power	DL	5,9462	0,2720	1,9261	0,0255	2,9261	0,1530
$ESQoS = \alpha_1 \cdot \lvert SQoS \rvert^{\alpha_2}$	UL	6,4116	0,3360	2,2225	0,0430	3,1947	0,2100



(a) AMR, DL (b) AMR, UL

Fig. 8 Regressions on $ESQoS_{voice}$ vs. $SQoS_{UMTS}$ values (E_c/I_0 given in dB) in case of UMTS telephony.

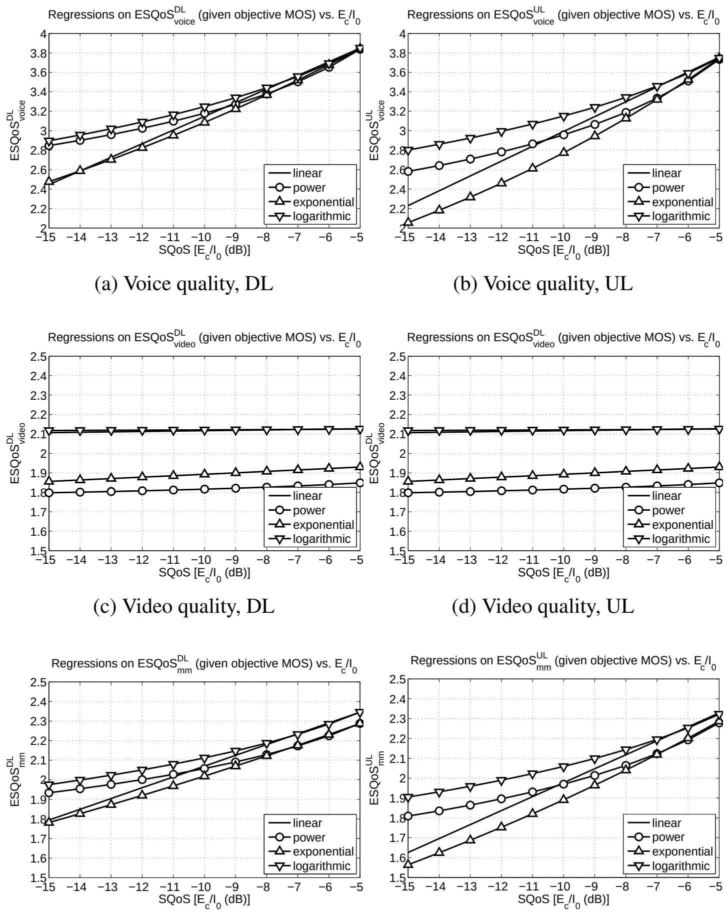
- the logarithmic model for
  $f(ESQoS) = ESQoS$, and
  $g(SQoS) = \ln(SQoS)$.
- the exponential model for
  $f(ESQoS) = \ln(ESQoS)$, and
  $g(SQoS) = SQoS$.
- the power model, for
  $f(ESQos) = \ln(ESQoS)$, and
  $g(SQoS) = \ln(SQoS)$.

The estimates for β and ε can be computed through non-linear regression or linear regression giving almost identical results.
Note that the exponential regression method can be derived by

$$\begin{aligned} ESQoS &= \exp\left(\beta \cdot SQoS + \varepsilon\right) \\ \Rightarrow ln(ESQoS) &= \beta \cdot SQoS + \varepsilon. \end{aligned} \tag{10}$$

Eq. (11) computes the rate of change of $ESQoS$ to $SQoS$ depicts the dependence between service/mUX and network/system KPIs.

$$\begin{aligned} \frac{\partial ESQoS}{\partial SQoS} &= \beta \cdot \exp\left(\beta \cdot SQoS + \varepsilon\right) \\ \Rightarrow \frac{\partial ESQoS}{\partial SQoS} &= \beta \cdot ESQoS. \end{aligned} \tag{11}$$



(a) Voice quality, DL (b) Voice quality, UL

(c) Video quality, DL (d) Video quality, UL

(e) Multimedia quality, DL (f) Multimedia quality, UL

Fig. 9 Regressions on $ESQoS_{voice}$, $ESQoS_{video}$, and $ESQoS_{mm}$ (given objective MOS) vs. $SQoS_{UMTS}$ values (E_c/I_0 given in dB) in case of speech codecs for UMTS video-telephony.

Given a measurements set $\{ESQoS_i, SQoS_i\}_{i=1}^{n}$ the estimates are the optimal solution of the minimization problem below

$$\min_{\beta,\varepsilon} \sum_{i=1}^{n} [f(ESQoS_i) - (\beta \cdot g(SQoS_i) + \varepsilon)]^2. \tag{12}$$

Due to the fact, that the experimental data that are used have usually limited accuracy, we propose to employ the robust optimization approach. We assume that that data $SQoS_i$ incorporate errors and that their true value resides in a ρ-sized interval centered at $SQoS_i$, $\rho \geq 0$. The robust estimates are the optimal solution to the min max

Table 4 ESQoS-SQoS relationships for investigation.

Model Type	ESQoS-SQoS relationship	Functions	Partial differential equation
Linear	$ESQoS \propto SQoS$	$f(ESQoS) = ESQoS$ $g(SQoS) = SQoS$	$\partial ESQoS \propto \partial SQoS$
Power	$\ln(ESQoS) \propto \ln(SQoS)$	$f(ESQoS) = \ln(ESQoS)$ $g(SQoS) = \ln(SQoS)$	$\frac{\partial ESQoS}{ESQoS} \propto \frac{\partial SQoS}{SQoS}$
Exponential	$\ln(ESQoS) \propto SQoS$	$f(ESQoS) = \ln(ESQoS)$ $g(SQoS) = SQoS$	$\frac{\partial ESQoS}{ESQoS} \propto \partial SQoS$
Logarithmic	$ESQoS \propto \log(SQoS)$	$f(ESQoS) = ESQoS$ $g(SQoS) = \log(SQoS)$	$\partial ESQoS \propto \frac{\partial SQoS}{SQoS}$

problem of Eq. (13).

$$\min_{\beta,\varepsilon} \max_{\forall i:\ |x_i - SQoS_i| \leq \rho} \sum_{i=1}^{n} [f(ESQoS_i) - (\beta \cdot g(x_i) + \varepsilon)]^2.$$

Given that g is strictly increasing, the constraint

$$\begin{aligned} &\forall i : |x_i - SQoS_i| \leq \rho \\ \Leftrightarrow\ &SQoS_i - \rho \leq x_i \leq SQoS_i + \rho \end{aligned} \tag{13}$$

is equivalent to

$$\forall i : g(SQoS_i - \rho) \leq g(x_i) \leq g(SQoS_i + \rho) \tag{14}$$

We define

$$\tilde{\rho} := \max_i \max(g(SQoS_i + \rho) - g(SQoS_i), g(SQoS_i) - g(SQoS_i - \rho)) \tag{15}$$

and we consider the more conservative constraint:

$$\forall i :\ g(SQoS_i) - \tilde{\rho}\ \leq\ g(x_i)\ \leq\ g(SQoS_i) + \tilde{\rho} \tag{16}$$

$$\Leftrightarrow \forall i : |g(x_i) - g(SQoS_i)|\ \leq\ \tilde{\rho}. \tag{17}$$

We approximate Problem (13) using this more conservative constraint, i.e. we solve

$$\min_{\beta,\varepsilon} \max_{i} \sum_{i=1}^{n} [f(ESQoS_i) - (\beta \cdot g(x_i) + \varepsilon)]^2 \tag{18}$$

The inner maximization problem constraints can be expressed as $\|\mathbf{z} - \mathbf{z_0}\|_\infty \leq \rho$, where $\|\cdot\|_\infty$ is the infinity norm and $\mathbf{z}$, $\mathbf{z_0}$ are the vectors which contain the $g(x_i)$, $g(SQoS_i)$, respectively. The resulting problem

$$\min_{\beta,\varepsilon} \max_{\forall i:\ \|\mathbf{z}-\mathbf{z_0}\|_\infty \leq \tilde{\rho}} \sum_{i=1}^{n} [f(ESQoS_i) - (\beta \cdot z_i + \varepsilon)]^2 \tag{19}$$

is equivalent [42] to

$$\min_{\beta,\varepsilon} \sum_{i=1}^{n} [f(ESQoS_i) - (\beta \cdot g(SQoS_i) + \varepsilon)]^2 + \rho|\beta| \tag{20}$$

which is the Least Absolute Shrinkage and Selection Operator (Lasso). Using SeDuMi, we computed the robust estimates for β and ε for various values of the size ρ of the uncertainty set. SeDuMi, developed by Sturm [43], implements the self-dual embedding technique for optimization over self-dual homogeneous cones and solve optimization problems with linear, quadratic and semidefiniteness constraints. A recent presentation of SeDuMi package can be found in [44].

Figs. 10 and 11 present voice and multimedia ESQoS estimation models where robust optimization is applied in non-linear regression for various values of parameter $\rho \geq 0$. In case of $\rho = 0$, there is a linear regression. It is depicted that as the size of uncertainty ρ increases, β drops, namely the robust estimates suggests a weaker dependence between *ESQoS* and *SQoS*. This weaker dependence is compensated by the fixed term ε. Thus, in the presence of errors, one should be more conservative in the prediction of *ESQoS* for a given *SQoS*. The rate of change for *ESQoS* with respect to SQoS estimated by linear or non-linear regression is too optimistic in the presence of errors. The regularized estimator of Eq. (20) takes this phenomenon into consideration by adding the trade-off term $\rho\ |\beta|$. That is, the intensity of the dependence is connected to the expected size of the errors in the measurements. Larger errors require a larger increase in the SQoS parameters to achieve a certain level of *ESQoS*.

The robust estimator assumes that the data which are used in training contain errors. Thus, it tries to fit not only the actual data points, but the whole region surrounding them as well. The objective function of the estimation optimization problem, which is the mean squared error in our case, is minimized for all these regions. This is done in order to ensure a low value for the mean squared error not only for the data points, but for all these regions, which contains the possible values for the real data points in the presence of errors. Of course, this is done by increasing the mean squared error value for the actual data points, since the objective function is replaced by its worst-case counterpart. Given that our data sets are highly likely to contain errors, the robust estimators lead to safer and more conservative estimations.

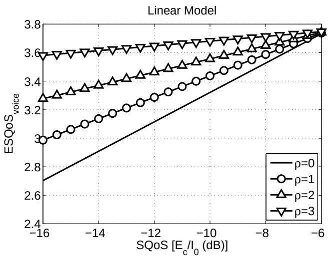
4 Evaluation Method

We present the evaluation method to test our robust-optimization-based estimators for the prediction of *ESQoS* via *SQoS*. Define:

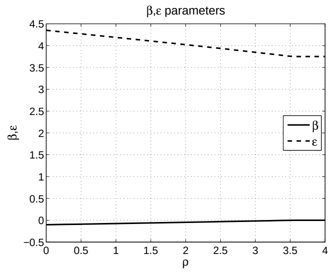
$$y_i = f(ESQoS_i) \tag{21}$$
$$x_i = g(SQoS_i) \tag{22}$$

to be the values which are going to be linearly regressed, where $i = 1, \ldots, n$.
Divide the samples in k clusters $S_1, \ldots, S_k$ using k-means clustering.
Then, repeat the following procedure m times (the iteration runs on j):

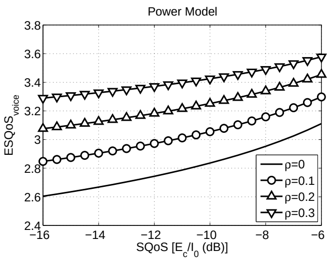
- For each i, randomly assign half of the samples in S_i to the training set R_j and half of them to the testing set T_j, $i = 1, \ldots, k$.
- Compute the (nominal) linear regression estimate $(\hat{\beta}, \hat{\varepsilon})$ on the training set R_j.



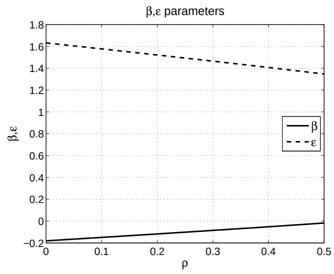
(a) Linear model



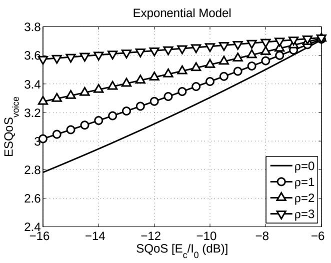
(b) Linear model



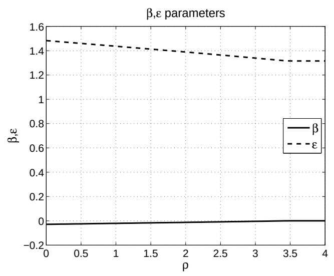
(c) Power model



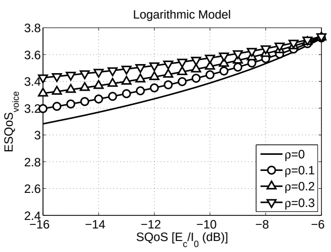
(d) Power model



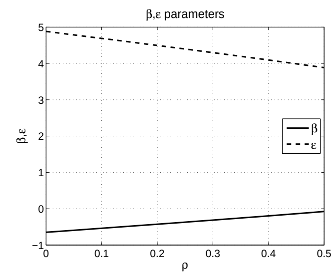
(e) Exponential model



(f) Exponential model

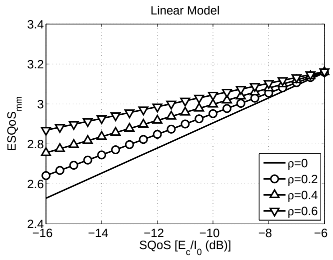


(g) Logarithmic model

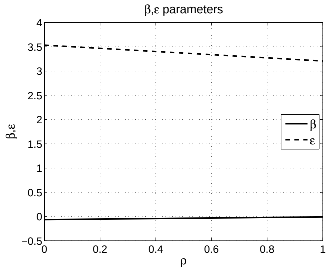


(h) Logarithmic model

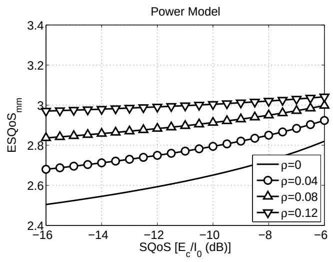
Fig. 10 Regressions on $ESQoS_{voice}$ (given objective MOS) vs. $SQoS_{UMTS}$ values (E_c/I_0 given in dB) in case of UMTS video-telephony, Direction: Downlink.



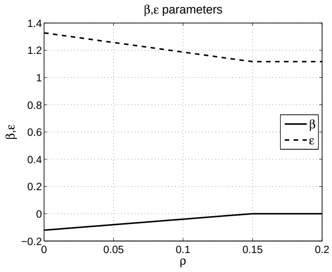
(a) Linear model



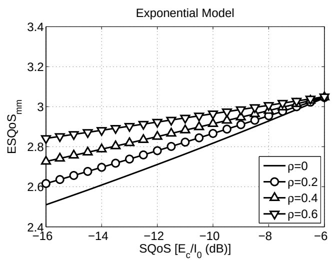
(b) Linear model



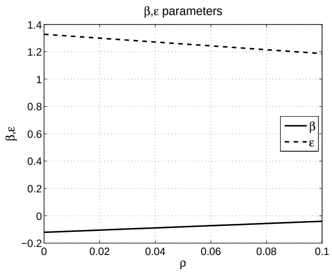
(c) Power model



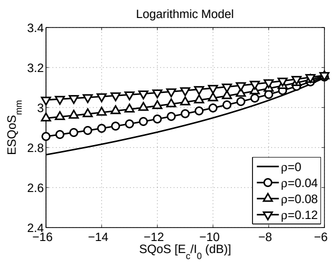
(d) Power model



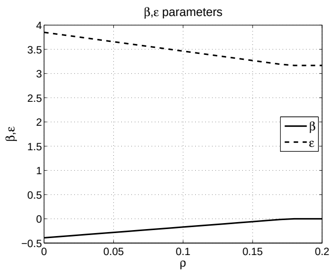
(e) Exponential model



(f) Exponential model



(g) Logarithmic model



(h) Logarithmic model

Fig. 11 Regressions on $ESQoS_{mm}$ (given objective MOS) vs. $SQoS_{UMTS}$ values (E_c/I_0 given in dB) in case of UMTS video-telephony, Direction: Downlink.

- Compute the robust linear regression estimate $(\hat{\beta}_\rho, \hat{\varepsilon}_\rho)$ on the training set R_j for various values of $\rho > 0$.
- Compute the performance of the nominal estimate on the testing set T_j:

$$W_j = \sum_{i \in T_j} (y_i - \hat{\beta} x_i - \hat{\varepsilon})^2 \tag{23}$$

- Compute the performance of the robust estimate on the testing set T_j:

$$W_j^\rho = \sum_{i \in T_j} (y_i - \hat{\beta}_\rho x_i - \hat{\varepsilon}_\rho)^2 \tag{24}$$

Then, compare the statistical properties of the samples W_j, W_j^ρ, $j = 1, \ldots, m$, e.g. sample mean, variance, worst-case (conditioned on some quantile level) sample mean. The evaluation method is depicted in Fig. 12.

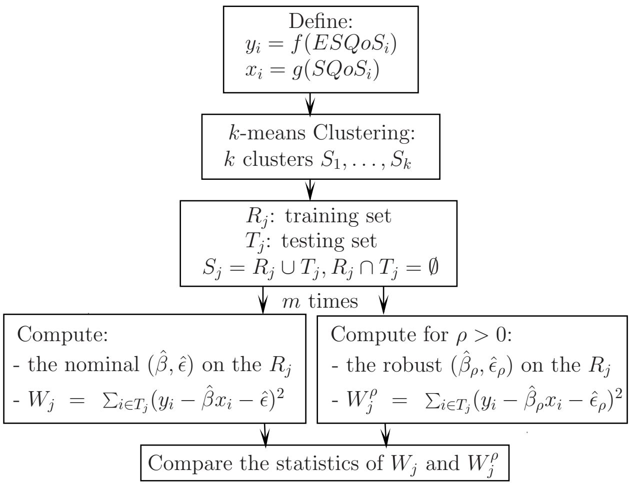


Fig. 12 Evaluation method of robust optimization based models.

5 Conclusions

Objective voice, video and multimedia E2E quality prediction with regression methodology enhanced with robust optimization framework was addressed in our paper. ESQoS empirical models for mobile video telephony have been extracted from live 3G multimedia network measurements. Our method can be applied in mUX-centric network planning and optimization processes to tackle the effect of errors in a measurement campaign. We proposed an enhanced method of ESQoS prediction based on measurement campaign measurements that can cooperate with network planning tools. ESQoS budget can be a modern approach in mobile multimedia networks planning and optimization. The connection of the predicted ESQoS with the expected size of the measurement errors enables a more flexible network planning tool, that manages the trade-off between measurements' precision quality, and targeted values for SQoS parameters. Finally, robust optimization framework models may be recommended in quality estimation of beyond 3G networks, like 4G/5G consumer mobile communications and wireless computer networks.

Acknowledgment

Experimental equipment was acquired by Mobile Radiocommunications Laboratory, NTUA, during *AKMΩN* project funded by the General Secretariat of Research and Technology, Ministry of Development, Greece. We would like to thank Mr. A. Tollenaar from SwissQual AG for making available the data of video telephony.

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