On Some Physical Layer Design Aspects for Machine Type Communication

Metin Vural
Fraunhofer Institute for Telecommunications,
Heinrich Hertz Institute, Berlin
metin.vural@hhi-extern.fraunhofer.de

Peter Jung
CommIT - The Communications and Information Theory Group,
Technical University Berlin
peter.jung@tu-berlin.de

Sławomir Stańczak
Fraunhofer Institute for Telecommunications,
Heinrich Hertz Institute, Berlin
slawomir.stanczak@hhi.fraunhofer.de

***Abstract*—With the development of current wireless systems, new type of communication is gaining a massive interest. It enables the communication of machines through a mobile network that is called machine type communication (MTC). Because of wide range of potential applications, MTC is a popular topic in research and industry area. It is important to develop technologies that support current MTC requirements and lead to near future technologies which are compatible with current MTC-like traffic. In this study, some physical layer design approaches for quantize and forward strategies are investigated to improve and support MTC in existing and near future small-cell networks. Results will be considered in terms of the tasks of macro base station and mini base stations. In addition, quantization effects on sum rate, equalization and soft demodulation are pointed out with these approaches.**

I. Introduction

Wireless communication systems became an indispensable part of daily life. Mobile devices and the mobile communication networks that provide a wide range of application and services are rapidly increased with leading to start machine type communication (MTC). Current networks are mostly created for human-to-human and human-to-machine communication [1]. Whereby MTC networks include little or no human interaction. It requires efficient, reliable and secure transmission of relatively short messages and characterized by massive number of devices with frequent transmission [1], [2].

MTC has many application fields like medical services, intelligent transportation systems, public security etc. And global MTC connections are increasing rapidly [3]. Hence MTC can be considered as a potential setting up technology for an emerging scenario of Internet of Things where a huge number of sensors is integrated into physical objects and connected wirelessly to a wired backbone. Other examples of technological trends behind MTC applications are Smart Factoring and Smart Cities [2], [4]. Most of those sensing devices convey information to a centralized service via a network of fixed and inter-connected access points called infrastructure nodes (e.g. base stations or relay stations).

Implementing MTC applications in wireless networks comes with some fundamental challenges. For example, MTC networks have much larger number of devices than human-to-human or human-to-machine networks [5], [6]. That may cause large delays, undesirable power consumption, network congestion and system overload. In order to prevent this kind of shortcomings, optimizations are needed at different layers. There are some other challenges to employ of existing network topology for MTC networks like traffic pattern issues, no human interaction problems, security issues, low cost, reliability etc. To overcome this challenges and meet market demands, different standardization studies of MTC are in progress by 3GPP, IEEE, ETSI and TIA [7]. In order to create a firm, reliable and robust communication network for MTC, standardization plays an essential role. With the standardization, optimizations and improvements are expected at different layers of network protocol. There are many studies that focus on designing network protocol for MTC networks which are mostly ultra dense networks that includes massive number MTC devices [8], [9]. An important issue about ultra dense networks is the communication between mini base stations and the macro base station. There are several relaying protocols like Decode-, Compress-, Amplify-, and Compute-and-Forward (CF). As it proposed in [10], CF is a promising protocol for robust physical layer network coding and it has a relatively lower complexity [11]. However, it is needed a complete redesign of existing infrastructure and communication strategies.

In this study, some physical layer design aspects for quantize and forward strategies are investigated to improve and support MTC in existing and near future small-cell networks. One of the research challenges of future networks (e.g. 5G) is requiring efficient signal quantization and compression techniques [12]. It is analyzed that what possible gains could be achieved with the adaption of conventional methods. Results should be considered for those who focus on the tasks of macro base station and mini base stations. Quantization effect on data rate and equalization for physical layer design is also examined.

II. The System Model

Representation of the considered network architecture consisting of mini base stations, MTC devices and macro base station is shown in Fig. 1. Considering the system architecture is shown in Fig. 1 with L user devices and K mini base stations, the received signal during each symbol time duration, y, which is a $K \times 1$ column vector, can be modeled as

$$y = Hx + n, \tag{1}$$

where H is an $K \times L$ matrix, whose elements represent the channel coefficients h_{kl} between the l^{th} user device $(l = 1, 2, ..., L)$ and the k^{th} mini base station $(k = 1, 2, ..., K)$.

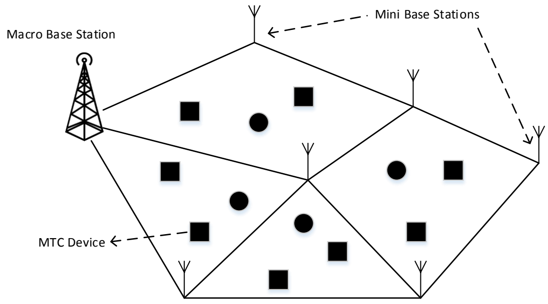


Fig. 1: Considered network architecture.

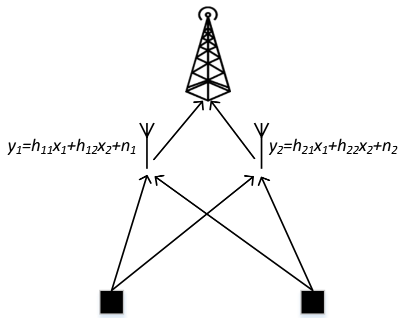


Fig. 2: Standard scenario with $L = 2$ user devices, $K = 2$ mini basestations and a single macro basestation.

x is the $L \times 1$ vector that includes the transmitted signals from user devices and n denotes the $K \times 1$ noise vector whose elements are complex Gaussian random variables with zero mean and σ_n^2 variances.

In the following only a *single* subchannel will be considered to investigate the principal gains whereby for channel estimation issues the physical reasoning for the different subchannels will be relevant.

Two important aspects which should be covered by a future physical layer design:

(A) the mini basestations should operate directly on the channel outputs (user to mini basestations) and map this to a pure bit stream. In a straightforward line this could mean that after some preprocessing of the received complex samples and after a modification of the complex effective channel coefficients both should be quantized and packaged into a digital data frame to be forwarded to macro basestation.

(B) Optimally, the user devices should use a coding (bits to symbol sequences) which exploits the superposition principle due to the wireless channel (from user devices to the mini basestations).

It is clear that step (A) is much more straightforward to achieve whereby (B) requires more significant modifications in the overall communication chain. The different strategies will be investigated mainly using a setup of $L = 2$ user devices, $K = 2$ mini basestations and a single macro basestation (see Fig. 2). The objective is to convey the messages of the users to the macro base station via the mini base stations.

In order to investigate potential gains that could be obtained by step (A) with adaption of conventional methods and ignoring coding issues due to step (B), following situation is considered:

Each of the K user devices (a predefined group) wants to communicate an individual message of N information bits and generates a symbol/sample sequence to be transmitted within a common time slot of given length T. In particular two practical strategies is compared with two approaches Quantize and Forward at mini basestations (QF) and Conventional Processing/Baseline (BS).

A. Quantize and Forward at Mini Basestations (QF)

For approach QF, it is assumed that the devices transmit with power P simultaneously on the same resource (subchannel), i.e., N information bits are transmitted during time T. As long there are sufficient independent observations of different independent mixtures (due to different channel coefficients), it is likely that the macro base station is able to separate the signal contributions from the different user devices as long as the knowledge on the received signals y and the channel coefficients h_{kl} is precise enough. Thus, each mini base station receives its own linear combination, performs a preprocessing of received samples and channel estimates. Both, the receive signal y_k and channel coefficients are quantized at each mini base station k:

$$(y_k^{(Q)}, \{a_{kl}\}_{l=1}^{L}) = Q(y_k, \{h_{kl}\}_{l=1}^{L}) \qquad (2)$$

and then transmitted as a message of $\bar{N} \geq LN$ bits.

The macro base station gets such messages from K mini base stations. The overall system equation is solved then. We have focussed on the case where the channel coefficients are constant over the time instants $t = 0 \ldots T-1$. Define $y^{(Q)} = (y_1^{(Q)}, \ldots, y_K^{(Q)})$ (same for y and n), $x = (x_1, \ldots, x_L)$ and denote with A the $K \times L$ matrix with elements a_{kl} which are quantized channel coefficients. Thus, for each time–instant the linear equation becomes:

$$y^{(Q)} = Ax + \underbrace{\underbrace{(H-A)}_{n_H} x + \underbrace{(y^{(Q)} - y)}_{n_y} + n}_{n^{\text{eff}}}, \qquad (3)$$

where n^{eff} is the effective noise, n_H and n_y are channel quantization error and signal quantization error respectively, caused by the quantizer.

There are many ways to estimate x from the linear system above. Particular methods are to linearly invert the problem by using matrix W which can be the inverse A^{-1} (if exists), the pseudo–inverse $A = (A^*A)^{-1}A^*$ or it can be found via minimum mean square error (MMSE) $(A^*A + \sigma^2)^{-1}A^*$. On the other hand these standard approaches can not account for characteristics of practical quantizers. Here, new approaches are necessary for inversion and even for modeling soft decoding operations. Hence, estimator could also be a regularized form depending on further knowledge of the individual contributions like $(AA^* + \sigma_H^2 + \sigma_n^2 + \sigma_Y^2)^{-1}A^*$, where σ_H^2 and σ_y^2 denotes the variances of quantization errors. Because of the heterogeneous nature of n^{eff}, Gaussian Mixture Model (GMM) based MMSE estimator can also be applied to estimate x. Parameters of mixture distribution can be obtained by Expectation Maximization (EM) algorithm. After obtaining the estimate:

$$\hat{x} = Wy^{(Q)} = WAx + Wn^{\text{eff}}, \tag{4}$$

demodulation and decoding of the information bits is done at the macro base station. Based on quantized information, W is computed also at the macro base station . Regularized MMSE estimation method which includes the effect of quantization error and GMM based MMSE estimator will be explained in Section III.

B. Conventional Processing/Baseline (BS)

Contrary to (QF), we assume here that the user messages are transmitted in orthogonal resources, i.e., for example in a time division multiple access (TDMA) like fashion. This means that each device has exclusive access on the subchannel during a time of T/L units for transmitting its N information bits, i.e., it has to use a weaker code to achieve this. On the other hand, it should be allowed, that each device could use a power LP during this time such that it is comparable to (QF) in terms of total energy. The received signals are here already decoded at the mini base stations and then forwarded as LN information bits. The assignment from devices to mini base stations are fixed for first evaluations. Mini base station assignments are shown in Table I. Gains have to be expected by adaptive assignments.

TABLE I: Mini base station assignments for the approach BS

Fixed	each device exclusively transmits to a fixed mini base station
Best	device transmit exclusively to this mini base station from a pool having the best channel conditions (after that the mini basestation is remove from the pool).
Worst	each device transmits to the mini base station having the worst channel (for comparisons)

Overall comparison of QF and BS is shown in Fig. 3.

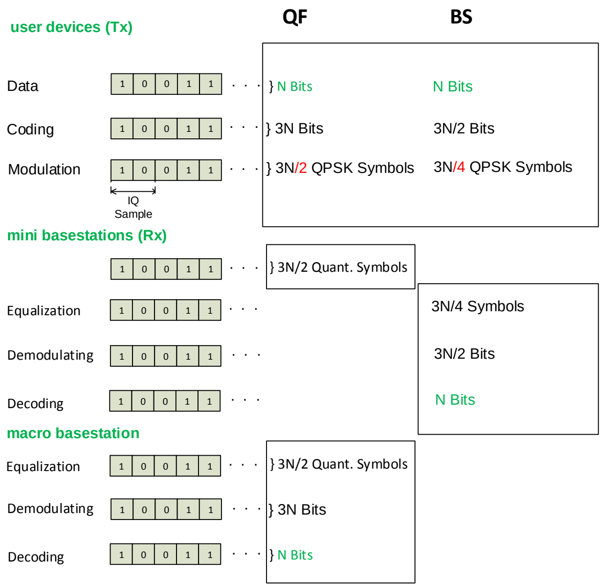


Fig. 3: Scheme of QF and BS with convolutional coding (with 1/3 and 2/3 coding rate respectively) for QPSK modulation.

III. Effects of Quantization on Equalization, Decoding and Data Rate

A. Quantization

In order to transmit the received data and the channel knowledge from the mini base stations to the macro base stations digitally for QF, the signals have to be quantized with a finite number of quantization levels for signal and channel, see (2). Hence, a generic scalar quantizer for real and imaginary parts is used in the simulations. The received signal is first sampled (called above as y) and quantized with sufficiently high resolution to digital frame of complex (quantized) symbols. Then real and imaginary parts are independently scaled to be supported on the interval $[-1, 1]$. Scaled versions of signal and channel are quantized with a given number level $L = 2^b$, where b is the quantization bit number. At this point the signal data corresponds to $y^{(Q)}$ and the quantized channel matrix (A) are quantized with lower resolution. Then A, y_Q and the scaling variables are packaged into a digital data frame to communicate to the macro base station.

B. Regularized MMSE Estimator for QF

As already indicated in Section II-A, in order to estimate the signal which is distorted by channel, it is possible to employ not only well known pseudo-inverse ("zero forcing") and MMSE linear equalizers but also a new regularized MMSE estimator which includes quantization noise. Regularized MMSE estimator utilizes the second order statistics of the channel conditions to minimize the mean squared error by including the quantization effects.

In order to estimate the received signal and the channel with regularized MMSE estimator, it has to be found a matrix W that minimizes $E\{[(Wy - x)(Wy - x)^*]\}$. Solving the equation with under the assumption that all noises, n_H, n_Y and n, are independent and Gaussian, W is found:

$$W = (AA^* + \sigma_H^2 + \sigma_n^2 + \sigma_Y^2)^{-1}A^*, \tag{5}$$

where σ_H^2 and σ_y^2 denotes the variances of quantization errors.

Although there are some other considered distributions for quantization error, Gaussian is the commonly utilized one. However, the key point of regularized-MMSE estimator is to have a zero mean noise regardless of the noise distribution. Since a uniform quantizer is used in this study which means quantization intervals are constant and equal, this condition is satisfied [13].

C. GMM Based MMSE Estimator for QF

As it indicated before, because of heterogeneous nature of n^{eff}, Gaussian Mixture Model (GMM) based MMSE estimator can also be applied to estimate x. In order to apply GMM based MMSE estimator, it is assumed that x and n^{eff} are mutually independent random vectors and the probability density funcion of n^{eff} equals to $n^{\text{eff}} \sim \sum_{m=1}^{M} w_m \mathcal{N}(n^{\text{eff}}; \mu_n^m, C_{nn}^m)$, where $\sum_{m=1}^{M} w_m = 1$, μ_n^m and C_{nn}^m are mean vector and covariance matrix of the mth Gaussian component of GMM. Under the observation model in equation (3), GMM based MMSE estimator can be written as in (6)

$$\hat{x} = \sum_{m=1}^{M} \beta_m(y^{(Q)})[\mu_x + C_x A^T [AC_x.A^T + C_{nn}^m]^{-1} \times (y^{(Q)} - [A\mu_x + \mu_n^m])], \tag{6}$$

where

$$\beta_m(y^{(Q)}) = \frac{w_m \mathcal{N}(y^{(Q)}; (A\mu_x + \mu_n^m), (AC_x A^T + C_{nn}^m))}{\sum_{j=1}^{M} w_j \mathcal{N}(y^{(Q)}; (A\mu_x + \mu_n^j), (AC_x A^T + C_{nn}^j))}, \tag{7}$$

μ_x and C_x are respectively the mean vector and covariance matrix of x. Detailed analysis and derivation of (6) can be found in [14], [15].

D. Quantization Effect on Decoding

In this section, hard decision decoding and soft decision decoding for convolutional coding is compared with including the noises caused by the quantizer. It is a well known fact that soft decision decoding improves the overall error performance [16]. But, it requires certain knowledge on the distribution of the effective noise. The goal of this part is to show the gains of QF over BS persists also this strategy.

Hard decision decoding works like a threshold detector. Received codewords are selected with minimum Hamming distance with possible codewords. However, in soft decision decoding soft bits are needed. Detector decides with the Euclidean distances between received codeword and possible codewords [17] or log-likelihood ratio as formulated in equation (8). Because of additional information like Euclidean distance or log-likelihood ratio, decision calculation is more reliable.

In this study, log-likelihood ratio is calculated instead of Euclidean distance. In that case output of demodulator should also be decided with log-likelihood ratio.

Consider the system model $r = s + n$ where r and s is the transmitted constellation. Under the assumption of all symbols have equal probability, the log-likelihood ratio for an additive white Gaussian noise (AWGN) channel can be formulated as:

$$L(b) = \log \left(\frac{\sum_{s \in S_0} e^{-\frac{1}{\sigma_c^2}\left((r-s)^2\right)}}{\sum_{s \in S_1} e^{-\frac{1}{\sigma_c^2}\left((r-s)^2\right)}} \right), \tag{8}$$

where

symbol	description
r	Coordinates of the received signal,
b	Transmitted bit,
S_0	Ideal constellation points with bit 0, at the received bit position.
S_1	Ideal constellation points with bit 1, at the received bit position.
s	Ideal constellation point.
σ_c^2	Variance of all noisy contributions.

For QF, the log-likelihood decision depends also on the quantization errors. This dependency will be indicated for $W = (H^*H)^{-1}H^*$ for the standard scenario of 2 devices and 2 mini base stations. Recall the equation (4), in order to decode the first device, the variance of the effective (decision) noise of Wn^{eff} for QF can be written as [18]:

$$\sigma_{QF}^2 = \frac{|a_{22}|^2 + |a_{21}|^2}{|a_{11}a_{22} - a_{21}a_{12}|^2} \times \frac{\sigma_{n^{\text{eff}}}^2}{2}. \tag{9}$$

For BS instead, the variance of all noise contributions to decode the first device, can be written:

$$\sigma_{BS}^2 = \frac{|h_{22}|^2}{|h_{11}h_{22}|^2} \times \frac{\sigma_n^2}{2}. \tag{10}$$

E. Data Rate Analysis

In order to see the quantization effect on data rates for QF, sum rate analysis is performed from user device to macro base station in terms of bits per channel use (bpcu). End to end transmission rate (sum rate) can be calculated as:

$$R_{sum} = \min\{R_1, R_2\} \tag{11}$$

where R_1 is the data rate between user device and mini basestation and R_2 denotes the data rate between mini basestation and macrobasestation. For a given received signal power, achievable sum rates for different quantization bits will be shown in Section IV-B.

IV. Simulation Results and Discussion

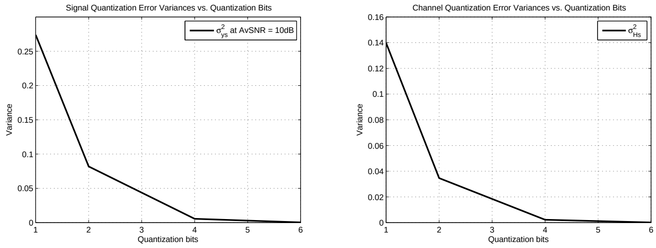
A. Simulation Parameters

Averaged SNR: In this study, the bit error rates (BER) are obtained for several values of the noise power (σ^2) and averaged over the channel statistics, i.e., the *averaged receive signal-to-noise ratio* at the mini base station is defined as:

$$\text{AvSNR} := \frac{\mathbb{E}(\|Hx\|_2^2)}{K\sigma^2}. \tag{12}$$

where K is the mini base station number.

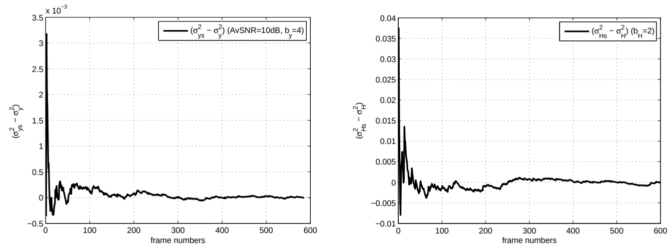
Further System Parameters: For applying the new regularized MMSE estimator and GMM based MMSE estimator to (3), the macro base station has to know σ_y^2 and σ_H^2. Empirically obtained error variance values (for the signal σ_{ys}^2, and the channel σ_{Hs}^2) for the simulations with different quantization bit numbers are presented in Fig. 4. b_y and b_H represent the quantization bit numbers for signal and channel. To obtain σ_{ys}^2 and σ_{Hs}^2, error variances are averaged over time. Assuming a



(a) $\sigma^2_{y_s}$ vs. b_y.

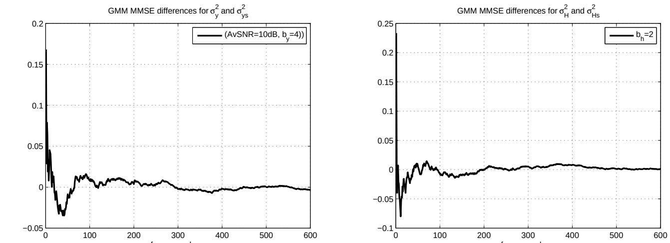
(b) $\sigma^2_{H_s}$ vs. b_H.

Fig. 4: Empirically obtained error variances.



(a) (σ^2_{ys}-σ^2_{y}) (AvSNR=10dB, b_y=4, b_H=0).

(b) ($\sigma^2_{Hs} - \sigma^2_{H}$) ($b_H$=2, b_y=0).



(c) GMM MMSE differences for σ^2_{ys} and σ^2_{y} in every frame (b_y=4, b_H=0, AvSNR=10dB).

(d) GMM MMSE differences for σ^2_{Hs} and σ^2_{H} in every frame (b_H=2, b_y=0).

Fig. 5: Necessary frame numbers to obtain error variances for a training data.

frame consists of N information bits (see Table II), necessary frame numbers to get σ^2_{ys} and σ^2_{Hs} are closer to σ^2_{y} and σ^2_{H} are shown in Fig. 5 for a particular communication channel. Difference between real error variances (σ^2_{y}, σ^2_{H}) and averaged error variances in every frame (σ^2_{ys}, σ^2_{Hs}) are shown in Fig. 5a and 5b. Similarly, the difference between real GMM MMSE results (for σ^2_{y}, σ^2_{H}) and averaged GMM MMSE results in every frame (for σ^2_{ys}, σ^2_{Hs}) are shown in Fig. 5c, 5d.

According to Fig. 5, in order to use training quantization error variances (σ^2_{ys}, σ^2_{Hs}), real time variances should be averaged over ~ 400 frames.

B. Results

In the following simulation results will be shown. Comparison of approach (QF) and conventional approach (BS) will be performed with different parameters that are shown in Table II.

	QF	BS
Modulation	- BPSK - QPSK - 16QAM	- BPSK - QPSK - 16QAM
Coding	- $1/3$ convolutional	- $2/3$ convolutional
Quantization (b_y/b_H bits, per I and Q components)	- No quantization - 2bits for signal, No quantizaiton (2/0) - 2bits for signal, 2bits for channel (2/2) - 4bits for signal, No quantizaiton (4/0) - 4bits for signal, 4bits for channel (4/4)	- No quantization
Info. bits N	- 5000	- 5000

TABLE II: Simulation parameters

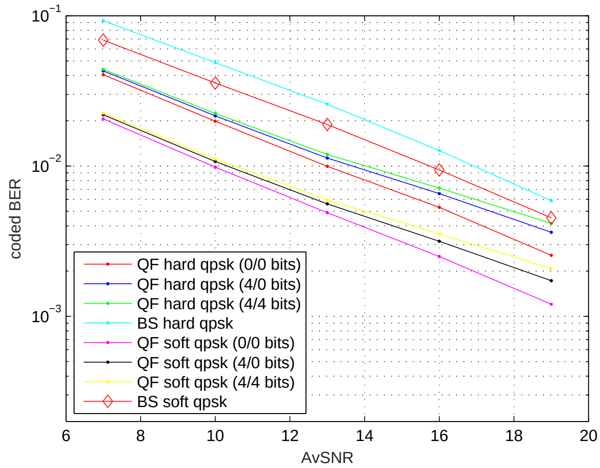


Fig. 6: Hard decision decoding vs soft decision decoding with convolutional codes for QPSK modulation (b_y/b_H).

In Fig. 6, soft decision decoding is compared with hard decision decoding. It can be easily seen that soft decision decoding improves decision making process for QF and BS in terms of bit error rate (BER). The gains are about $\sim$ 3dB for QF.

Fig. 7 shows the results for convolutional encoding with BPSK modulation with different quantization settings. As it can be seen from the Fig. 7, considerable lower bit error rates are obtained for QF and this particular modulation and coding scheme with unquantized data. If only the signal y is quantized with 4bits per I and Q components, bit error rate is slightly increased but still considerable lower than the conventional BS approach. The same remains true of both signal y and channel matrix H is quantized with 4bits per I and Q. The approximate gains (in dB) in BER of QF over BS are summarized in Table III.

	QF(0/0)	QF(4/0)	QF(4/4)
BPSK	5.5dB	5.4dB	5.3dB
QPSK	4dB	3.9dB	3.8dB
16QAM	3.7dB	3.6dB	3.5dB

TABLE III: Approximate gains for QF convolutional encoding compared to BS convolutional encoding

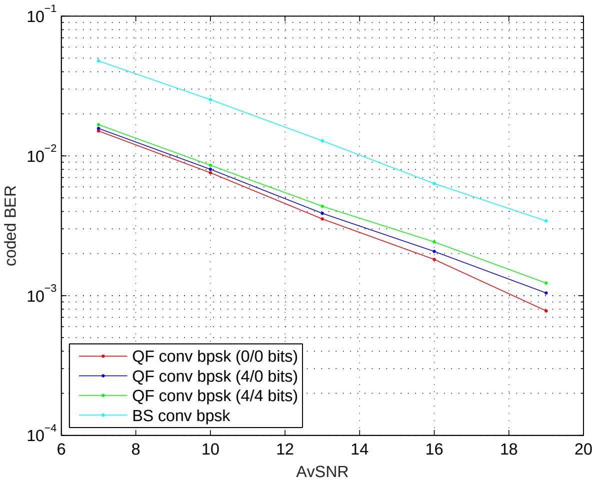


Fig. 7: BER results for BPSK modulation, fixed assignment for BS (b_y/b_H bits).

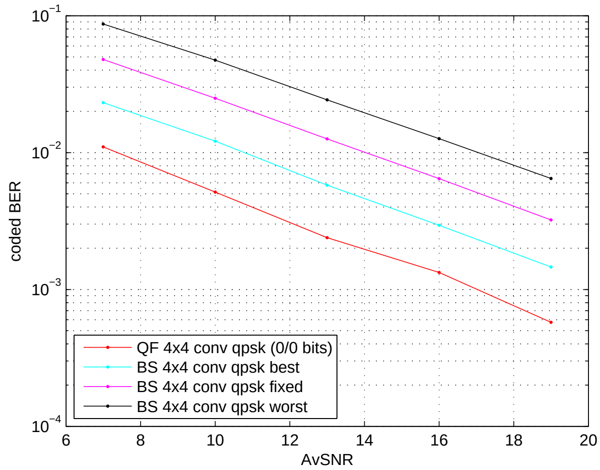


Fig. 9: BER results with 4 transmitter and 4 receiver system (b_y/b_H bits).

The BER-performance of QF for the 2x2 scenario is in the same order as BS with *base station assignments* (here the comparison is done using QPSK with convolutional encoding), see Fig. 8.

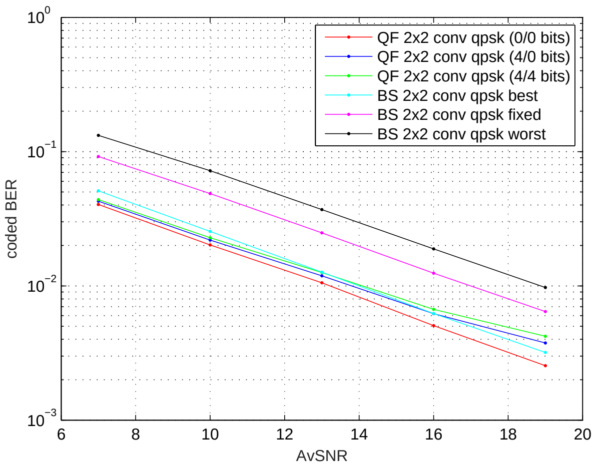


Fig. 8: BER results with 2 devices and 2 mini base stations (b_y/b_H bits).

Although no substantial gain can be achieved for this particular coding scheme in terms of BER of QF over BS (with *best* adaptive mini base station assignments!), it has to be remarked that also *no* mini base station assigment is required for QF. In order to configure the TDMA-like transmission mode for BS without reconfiguring the encoder/decoder, it assumed that for BS the same coding rate is used as in the standard scenario, see Table II. The reason is that at the moment the code configuration only support mother-code rates at $1/3$. This means that in this case BS needs twice the time to support 4 devices as compared to QF but still using power $4P$ (QF uses power P). The corresponding results are depicted in Fig. 9. The *Best* assignment rule of BS is approximately 6dB better than $worst$ channel assignment and 3dB better than $fixed$ channel assignment while QF is approximately 3.2dB better than $worst$ channel assignment of BS for 4x4 scenario.

In order to demonstrate the quantization effect for QF, data rate analysis is also performed. To achieve expected transmission rate from user device to macro base station, how many quantization bits should be spend for signal/channel is an important issue. Since quantization noise will reduce the sum rate (R_{sum}), three thresholds are assigned for the loss rate over sum rate for a given avSNR. To achieve 90% of sum rate, ξ_1 is defined at AvSNR=11dB, similarly ξ_2 and ξ_3 are used to accomplish 85% and 80% of sum rate, respectively.

Sum rates from user devices to macro basestation for different signal/channel quantization bits between mini basestation and macro basestation are shown in Fig. 10 and the numerical values (at AvSNR=11dB) can be found in Table IV. Without quantization ($b_y = 0, b_H = 0$), R_{sum} is equal to 1.122 bpcu at AvSNR=11dB. Acceptable sum rates for ξ_1 is depicted bold. Achievable minimum sum rates for thresholds ξ_1, ξ_2 and ξ_3 are 1.0098, 0.9537 and 0.8976 bpcu respectively. For example, 3bits signal and 2bits channel quantization would be enough to satisfy ξ_3, while ξ_1 and ξ_2 needs more quantization bits.

Considering the quantization errors, the improvement of using GMM MMSE estimator is shown for different signal and channel quantization bit numbers in Fig. 11. Since lower quantization bits cause higher quantization error noises, GMM MMSE estimator is more useful with lower quantization bits. For example, the approximate gains of GMM MMSE estimator compared to MMSE estimator are higher for ($b_y = 2$ / $b_H = 0$) than for ($b_y = 4$ / $b_H = 0$) (almost three times at AvSNR=10dB). Component numbers of GMM model is an important issue. In this paper it is chosen as three. Detailed analysis of convenient mixture numbers and some applications of EM algorithm can be found in [19], [20], [21].

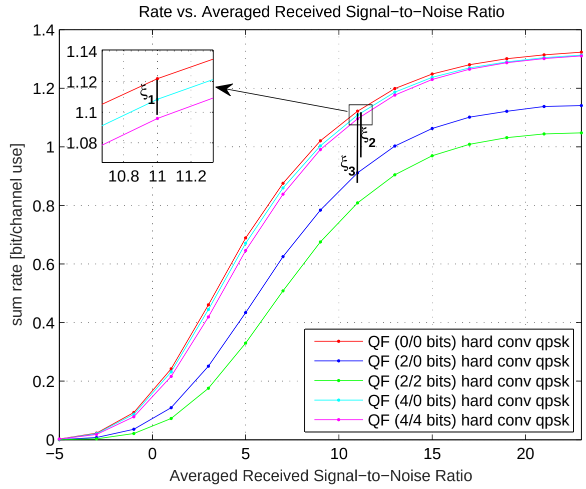


Fig. 10: Sum rates (R_{sum}) for several signal/channel quantization bits over averaged SNR (b_y/b_H bits).

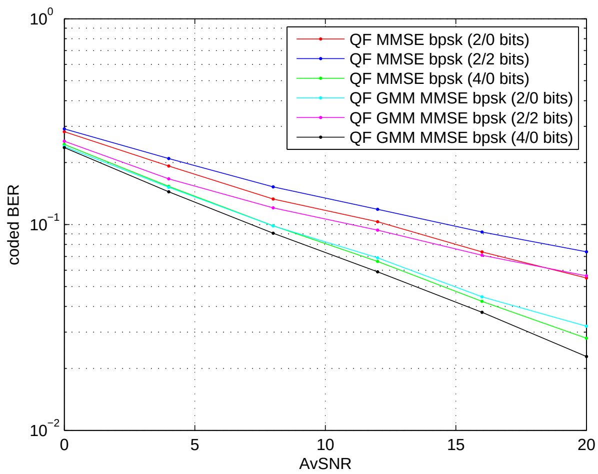


Fig. 11: Bit error rates for MMSE and GMM MMSE estimators (b_y/b_H bits).

b_y \ b_H	0	1	2	3	4	5
0	1.122	0.6387	1.001	**1.077**	**1.103**	**1.112**
1	0.4267	0.1847	0.3633	0.418	0.4203	0.422
2	0.914	0.4767	0.8147	0.8787	0.9047	0.9127
3	**1.056**	0.582	0.948	**1.019**	**1.044**	**1.047**
4	**1.108**	0.6307	0.9853	**1.064**	**1.096**	**1.098**
5	**1.111**	0.636	0.996	**1.079**	**1.101**	**1.105**

TABLE IV: Sum rates (R_{sum}) for several signal/channel quantization bits at 11dB in terms of bits per channel use.

V. Conclusion

In this study, some future physical layer design aspects that could be considered for MTC networks is investigated with two approaches which can be implemented in current physical layer technology. Results should be considered in terms of the tasks of macro base station and mini base station. QF and conventional approach BS are compared with different parameters (like modulation, quantization bit numbers, etc.). For QF approach quantization effects on data rate and equalization are investigated. The improvement of using GMM MMSE estimator is shown for different signal quantization bit numbers and the number of quantization bits that should be spend for signal and channel for some thresholds is also addressed.

Acknowledgement

The authors would like to thank Jan Schreck and Miruna Raceala Motoc for their support and useful discussions.

References

[1] K. R. Rao, Z. S. Bojkovic, and B. M. Bakmaz, *Wireless Multimedia Communication Systems: Design, Analysis, and Implementation*, 1st ed. Boca Raton, FL, USA: CRC Press, Inc., 2014.

[2] M. Hasan, E. Hossain, and D. Niyato, “Random access for machine-to-machine communication in lte-advanced networks: issues and approaches,” *Communications Magazine, IEEE*, vol. 51, no. 6, pp. 86–93, June 2013.

[3] J. Li, Y. Zhang, J. Chen, H. Li, and W. Zhang, “Group key agreement in multimedia service for machine type communication,” in *Services Computing Conference (APSCC), 2014 Asia-Pacific*, Dec 2014, pp. 141–146.

[4] M. Corici, H. Coskun, A. Elmangoush, A. Kurniawan, T. Mao, T. Magedanz, and S. Wahle, “Openmtc: Prototyping machine type communication in carrier grade operator networks,” in *Globecom Workshops (GC Wkshps), 2012 IEEE*, Dec 2012, pp. 1735–1740.

[5] T. Taleb, A. Ksentini, and A. Kobbane, “Lightweight mobile core networks for machine type communications,” *Access, IEEE*, vol. 2, pp. 1128–1137, 2014.

[6] C. Dohler and Antn-HaroMischa, *Machine-To-Machine (M2M) Communications*. Oxford: Woodhead Publishing, 2015.

[7] K. Chang, A. Soong, M. Tseng, and Z. Xiang, “Global wireless machine-to-machine standardization,” *Internet Computing, IEEE*, vol. 15, no. 2, pp. 64–69, March 2011.

[8] A. Aijaz and A. Aghvami, “A prma based mac protocol for cognitive machine-to-machine communications,” in *Communications (ICC), 2013 IEEE International Conference on*, June 2013, pp. 2753–2758.

[9] Y. Qi, A. Ijaz, A. Quddus, M. Imran, P. Navaratnam, Y. Ma, R. Tafazolli, M. Webb, and Y. Morioka, “On the physical layer design for low cost machine type communication in 3gpp lte,” in *Vehicular Technology Conference (VTC Fall), 2014 IEEE 80th*, Sept 2014, pp. 1–5.

[10] B. Nazer and M. Gastpar, “Compute-and-forward: Harnessing interference with structured codes,” in *Information Theory, 2008. ISIT 2008. IEEE International Symposium on*, July 2008, pp. 772–776.

[11] S.-N. Hong and G. Caire, “Compute-and-forward strategies for cooperative distributed antenna systems,” *Information Theory, IEEE Transactions on*, vol. 59, no. 9, pp. 5227–5243, Sept 2013.

[12] E. Hossain and M. Hasan, “5g cellular: key enabling technologies and research challenges,” *Instrumentation Measurement Magazine, IEEE*, vol. 18, no. 3, pp. 11–21, June 2015.

[13] J.-R. Ohm, *Multimedia Communication Technology: Representation,Transmission and Identification of Multimedia Signals*. Springer Berlin Heidelberg, 2004.

[14] J. Flam, S. Chatterjee, K. Kansanen, and T. Ekman, “On mmse estimation: A linear model under gaussian mixture statistics,” *Signal Processing, IEEE Transactions on*, vol. 60, no. 7, pp. 3840–3845, July 2012.

[15] A. Kundu, S. Chatterjee, A. Sreenivasa Murthy, and T. Sreenivas, "Gmm based bayesian approach to speech enhancement in signal / transform domain," in *Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on*, March 2008, pp. 4893–4896.

[16] M. Blaum, P. G. Farrell, and H. C. van Tilborg, *Information, Coding and Mathematics*. Springer, 2002.

[17] J. C. Moreira and P. G. Farrell, *Essentials of Error-Control Coding*. Wiley, Sep. 2006.

[18] D. Tse and P. Viswanath, *Fundamentals of Wireless Communications*. New York: Cambridge University Press, 2005.

[19] S. Buyukcorak, M. Vural, and G. Kurt, "Lognormal mixture shadowing," *Vehicular Technology, IEEE Transactions on*, vol. 64, no. 10, pp. 4386–4398, Oct 2015.

[20] M. Vural, G. Kurt, and C. Schneider, "The effect of shadow fading distributions on outage probability and coverage area," in *Vehicular Technology Conference (VTC Spring), 2015 IEEE 81st*, May 2015, pp. 1–6.

[21] M. Vural, P. Erdem, and O. Agin, "Regression clustering with lower error via em algorithm," in *Signal Processing and Communications Applications Conference (SIU), 2014 22nd*, April 2014, pp. 979–982.