On Some Physical Layer Design Approaches for MTC in Existing and Near-Future Small-Cell Networks

(Extended Abstract)

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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 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.

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).

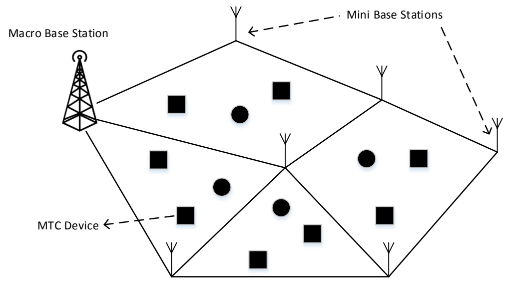
Implementing MTC applications in wireless networks comes with some fundamental challenges. For example, MTC networks have much larger number of devices than human-to-human or human-to-machine networks [5], [6]. That may cause large delays, undesirable power consumption, network congestion and system overload. In order to prevent this kind of shortcomings, optimizations are needed. There are some other challenges to employ and update 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.

Representation of the considered network architecture consisting of mini base stations, MTC devices and macro base station is shown in Fig. 1a. Considering here the system architecture 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

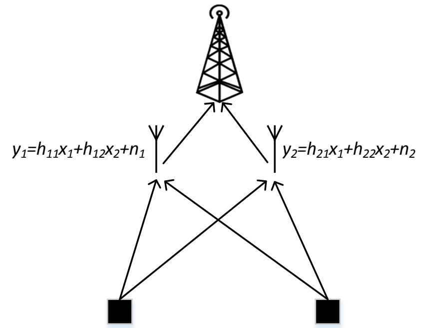
$$y = Hx + n, \tag{1}$$

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 $(k = 1, 2, ..., K)$. 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



(a) Considered network architecture.



(b) Standard scenario with $L = 2$ user devices, $K = 2$ mini basestations and a single macro basestation.

Fig. 1: Considered network architecture and standard scenario

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 goal of this categorization is to evaluate the gains using the insight (A) only since this can be implemented already now with existing technologies. In this contribution, 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. 1b). 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 device (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 are compared, approach A1 and A2.

Approach A1

For approach A1, 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. Considered protocol is CF here. Both, the receive signal y_k and channel coefficients are quantized at each mini base station k:

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

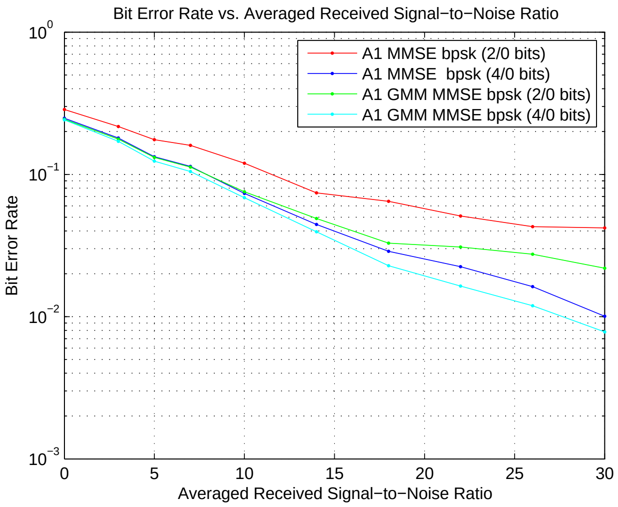
and then transmitted as a message of $\bar{N} \geq LN$ bits.

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 $y^{(\mathrm{Q})} = (y_1^{(\mathrm{Q})}, \ldots, y_K^{(\mathrm{Q})})$ (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:

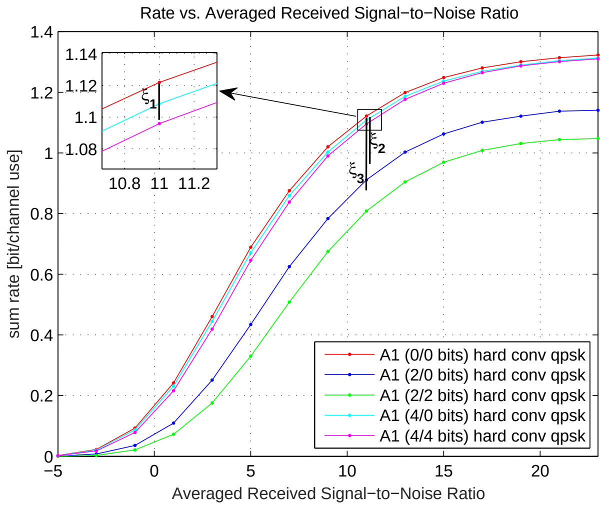
$$y^{(\mathrm{Q})} = Ax + \underbrace{\underbrace{(H-A)}_{n_H}x + \underbrace{(y^{(\mathrm{Q})}-y)}_{n_y} + n}_{n^{\mathrm{eff}}}, \tag{3}$$

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 algorithm.



(a) Bit error rates for equalization.



(b) Sum rates (R_{sum}) with some thresholds (ξ) for several signal/channel quantization bits.

Fig. 2: Quantization effects on equalization and sum rate for A1.

After obtaining the estimate:

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

demodulation and decoding of the information bits can be done.

For A1, the log-likelihood decision for convolutional coding depends also on the quantization errors. This dependency will be indicated for the standard scenario of 2 devices and 2 mini base stations.

Approach A2

Contrary to (A1), 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 (A1) in terms of total energy. The received signals are here already decoded at the mini base stations and then forwarded as LN information bits.

Preliminary Conclusion

To sum up, in this work, 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. A1 and conventional approach A2 are compared with different parameters (like modulation, quantization bit numbers, etc.). For A1 approach quantization effect on data rate and equalization is investigated. The improvement of using GMM MMSE estimator is shown for different signal quantization bit numbers (Fig. 2a, 0 represents no channel quantization, 2 and 4 bits for signal quantization), and the number of quantization bits that should be spend for signal and channel for some thresholds (ξ) is also addressed (Fig. 2b).

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