Experimental Studies about Eigenbeamforming in Standardization MIMO Channels

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Abstract— **Recently, the 3GPP standardization body for future mobile communication systems proposed four realistic channel models for propagation channels in a communication system with several transmit and several receive antennas.**
In this paper we apply the eigenbeamforming approach to these standardization MIMO channel models to investigate this system setup with respect to the *bit-error-rate* (BER).

I. Introduction

For the last years much effort has been spent to extend existing mobile communication systems with respect to an increased performance, not only because of the growing number of subscribers, but also due to the increasing demands regarding *quality of service* (QoS) and data rate. Thereby, the use of multiple receive antennas as well as multiple transmit antennas has attracted worldwide attention. Such systems are denoted as *multiple-input-multiple-output* (MIMO) systems.
The proposals to exploit the potentialities of MIMO systems are very variegated (e.g. BLAST [1] and Eigenbeamforming [2] in various versions). However, just as various as the system proposals are the required properties for the MIMO propagation channel [3]. A possibility to obtain an insight into basic properties of real propagation channels are MIMO channel measurements [4]. A first consensus about basic temporal and spatial features of a MIMO channel was defined in a proposal in the standardization discussions [5].

Section II describes the model of the MIMO propagation channel proposed in the standardization, Section III describes the system setup of our communication link and Section IV gives some simulation results of the performance, i.e. the BER of the investigated system.

II. The MIMO Channel Models in Standardization

The MIMO channel models proposed in the standardization were defined to be applicable for link level simulations of different MIMO schemes. Moreover, the MIMO channel models are backward compatible with the existing ITU channel profiles, which only define the power-delay profile. The channel model is given as a general tap-delay line model (FIR), where the number of taps, their power and their delay is fixed. The time-variant behavior is implicitly specified via the Doppler spectrum. All these properties are already given by the standardized ITU models [6]. With this starting point, the only additional input parameters to the MIMO channel model compared to the ITU *single-input-single-output* (SISO) models are the spatial correlation matrices for the transmitter and receiver side. These correlation matrices are defined by the *power-azimuth spectrum* (PAS) with a certain *azimuth-spread* (AS), *angle-of-arrival* (AoA) and array configuration. Note, that different combinations of PAS, AS and AoA can result in almost identical correlation matrices. Therefore, only four cases are specified:

Case 1	Uncorrelated Rayleigh Channel
Case 2	Macrocell Pedestrian Type A
Case 3	Macrocell Vehicular Type A
Case 4	Microcell/Bad-urban Pedestrian Type B

The mathematical representation of the channel impulse response $\boldsymbol{H}(t', t)$ for a system with M transmit antennas and N receive antennas can be written as

$$\boldsymbol{H}(t', t) = \sum_{k=1}^{K} \boldsymbol{H}_k(t') \delta(t - \tau_k), \qquad (1)$$

where K denotes the number of temporal taps, each with delay τ_k and the corresponding weighting $\boldsymbol{H}_k(t') \in \mathbb{C}^{N \times M}$. Thereby, the tap weights $\boldsymbol{H}_k(t')$ are time variant and have to be chosen such, that the desired antenna correlations are fulfilled. We assume block fading such, that all $\boldsymbol{H}_k(t')$ are constant within a block of L transmissions. In the following we will focus on the downlink.

III. System Model

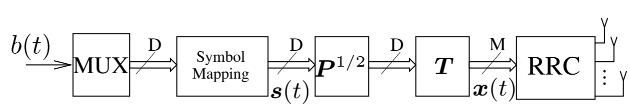

Fig. 1. System diagram for the transmitter (Base station)

At the transmitter the bit stream $b(t)$ is multiplexed into D substreams and mapped onto complex modulation symbols $\boldsymbol{s}(t)$. Each substream is given an individual power by multiplying with a diagonal matrix $\boldsymbol{P}^{1/2}$ and then a unitary beamforming matrix $\boldsymbol{T}$ according to the eigenbeamforming concept is applied [2]. The resulting signal $\boldsymbol{x}(t)$ is pulse shaped with a *root-raised cosine* (RRC) impulse with roll-off factor $\alpha = 0,22$. Note, that the beamforming $\boldsymbol{T}$ has no FIR structure.

At the receiver the received signal $\boldsymbol{y}(t)$ is matched filtered with

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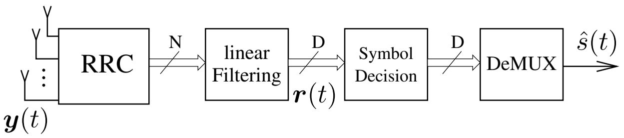

Fig. 2. System diagram for the receiver (User equipment)

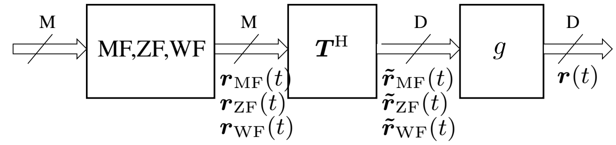

Fig. 3. System diagram of the linear receive filter.

a RRC pulse and then processed by a linear filter to combat *inter-symbol-interference* (ISI) due to the frequency selective channel $\boldsymbol{H}(t', t)$. This linear filter is one of the following: *matched filter* (MF), *zero-forcing filter* (ZF), or *Wiener filter* (WF). The resulting signal $\boldsymbol{r}(t)$ is basis for a *maximum likelihood* (ML) symbol decision of the actual transmit signal, disregarding transmit signals at other time instants (hard decision)[1]. Both parts, transmitter and receiver, are connected by the MIMO propagation channel from Eq. (1). If we include the transmit RRC ($\alpha = 0.22$) filter into the channel as

$$\boldsymbol{H}_{\mathrm{RRC}}(t', t) = \sum_{k=1}^{K} \boldsymbol{H}_k(t') \cdot RRC(t - \tau_k), \tag{2}$$

we can write

$$\boldsymbol{y}(t) = \boldsymbol{H}_{\mathrm{RRC}}(t', t) \star \boldsymbol{x}(t) + \boldsymbol{n}(t), \tag{3}$$

where '$\star$' denotes convolution and $\boldsymbol{n}(t)$ is assumed to be additive Gaussian noise, temporally and spatially white with power σ_n^2.
To adjust the desired correlations [5] at the *base station* (NB) and at the *user equipment* (UE) for each temporal tap k we compute the weighting $\boldsymbol{H}_k(t')$ as

$$\boldsymbol{H}_k(t') = \boldsymbol{C}_{k,\mathrm{UE}} \boldsymbol{\mathcal{Z}}(t') \boldsymbol{C}_{k,\mathrm{NB}}^{\mathrm{H}}, \tag{4}$$

where $(\bullet)^{\mathrm{H}}$ denotes conjugate transpose and $\boldsymbol{\mathcal{Z}}(t')$ is a $N \times M$ zero-mean complex Gaussian matrix with unit variance realizing the time variant fading, i.e. the Doppler spectrum. The matrices $\boldsymbol{C}_k$ emerge from the eigenvalue decomposition of the desired correlation matrices $\boldsymbol{R}_k = \boldsymbol{U}_k \boldsymbol{\Lambda}_k \boldsymbol{U}_k^{\mathrm{H}}$ as

$$\boldsymbol{C}_k = \boldsymbol{U}_k \boldsymbol{\Lambda}_k^{1/2}. \tag{5}$$

Since the temporal structure of the MIMO standardization channels has taps at delay times, which are no multiples of the symbol duration, the MIMO channel as well as the two RRC pulse filters and the linear receive filter have to operate at continuous time, while the other parts in the communication link are time discrete, i.e. work at symbol rate T.

Since it is possible to transmit less data streams than the number of antennas ($D < M$), the signals lie in a D-dimensional subspace. In the following we will perform the linear filtering at the receiver in the full, M-dimensional space to estimate the modulation symbols $\boldsymbol{x}(t)$. Thereafter we will reduce the dimension to D by applying the reverse beamforming with $\boldsymbol{T}^{\mathrm{H}}$ and perform a scalar Wiener Filter g to recover the amplitude before we perform the symbol decision (see also Figure 3).

[1]Note, that the optimum receiver would be a maximum likelihood sequence estimator. However, our suboptimum approach combats the time dispersion of the frequency selective channel and accounts for the additive noise of the channel while simultaneously keeping the computational effort low.

Additionally we assume unit transmit power per transmission

$$\mathrm{tr}\,(\boldsymbol{P}) = 1. \tag{6}$$

A. Matched Filter Receiver

As stated above, the matched filter has to operate at continuous time. The output $\boldsymbol{r}_{\mathrm{MF}}(t)$ of the matched filter can be sampled at symbol rate T.
The continuous convolution of the channel $\boldsymbol{H}_{\mathrm{RRC}}(t', t)$ with the matched filter $\boldsymbol{H}_{\mathrm{RRC}}^{\mathrm{H}}(t', -t)$ reads as

$$\begin{aligned} \boldsymbol{H}_{\mathrm{MF}}(t', t) &= \boldsymbol{H}_{\mathrm{RRC}}^{\mathrm{H}}(t', -t) \star \boldsymbol{H}_{\mathrm{RRC}}(t', t) = \\ &= \sum_{k=1}^{K} \sum_{k'=1}^{K} \boldsymbol{H}_k^{\mathrm{H}}(t') \cdot \boldsymbol{H}_{k'}(t') \cdot RC(t - \tau_{k'} + \tau_k), \end{aligned} \tag{7}$$

where $RC(t)$ denotes the raised-cosine impulse $RRC(t) \star RRC(t)$. Assuming block processing at the receiver we can combine the transmit signals $\boldsymbol{x}(t)$ from L time instances into one big space-time vector

$$\boldsymbol{x} = \mathrm{vec}\left[\boldsymbol{x}(0),\ \boldsymbol{x}(T),\ \boldsymbol{x}(2T), \ldots, \boldsymbol{x}((L-1) \cdot T)\right]. \tag{8}$$

The same applies for the output of the MF $\boldsymbol{r}_{\mathrm{MF}}(t)$ to produce a space-time vector $\boldsymbol{r}_{\mathrm{MF}}$. The space-time beamforming matrices are

$$\boldsymbol{T}_{\mathrm{st}} = \boldsymbol{1}^{L \times L} \otimes \boldsymbol{T}, \qquad \boldsymbol{P}_{\mathrm{st}} = \boldsymbol{1}^{L \times L} \otimes \boldsymbol{P}. \tag{9}$$

This produces the functional connection between $\boldsymbol{s}$ and $\boldsymbol{r}_{\mathrm{MF}}$ as

$$\begin{aligned} \boldsymbol{r}_{\mathrm{MF}} &= \boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}} \cdot \boldsymbol{x} + \boldsymbol{n}_{\mathrm{MF}} \\ &= \boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}} \boldsymbol{T}_{\mathrm{st}} \boldsymbol{P}_{\mathrm{st}}^{1/2} \boldsymbol{s} + \boldsymbol{n}_{\mathrm{MF}}, \end{aligned} \tag{10}$$

where $\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}$ denotes a space-time block Toeplitz matrix comprising the whole time-continuous transmission elements. The (j, k)-th block of $\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}$ reads as

$$\begin{aligned} &\left[\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\right]_{(i,j)} = \\ &= \sum_{k=1}^{K} \sum_{k'=1}^{K} \boldsymbol{H}_k^{\mathrm{H}}(t') \cdot \boldsymbol{H}_{k'}(t') \cdot RC\left((i-j)T - \tau_{k'} + \tau_k\right) \end{aligned} \tag{11}$$

The noise $\boldsymbol{n}_{\mathrm{MF}}$ from Eq. (10) is the sampled complex noise after the receive matched filter. The noise $\boldsymbol{n}_{\mathrm{MF}}$ is now spatially and temporally correlated. For one time instant t this can be written as

$$\begin{aligned} \boldsymbol{n}_{\mathrm{MF}}(t) &= \boldsymbol{H}_{\mathrm{RRC}}^{\mathrm{H}}(t', -t) \star \boldsymbol{n}(t) \\ &= \sum_{k=1}^{K} \boldsymbol{H}_k^{\mathrm{H}}(t') \cdot \boldsymbol{n}(t) \star RRC(\tau_k + t). \end{aligned} \tag{12}$$

The filtered and sampled space-time noise vector reads then as

$$\boldsymbol{n}_{\mathrm{MF}} = \mathrm{vec}\left[\boldsymbol{n}_{\mathrm{MF}}(0),\ \boldsymbol{n}_{\mathrm{MF}}(T),\ \ldots, \boldsymbol{n}_{\mathrm{MF}}((L-1)\cdot T)\right]. \quad (13)$$

We will denote the space-time noise covariance matrix as

$$\boldsymbol{R}_{nn}^{\mathrm{st,MF}} = \mathrm{E}\left\{\boldsymbol{n}_{\mathrm{MF}}\boldsymbol{n}_{\mathrm{MF}}^{\mathrm{H}}\right\} = \sigma_n^2 \boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}. \quad (14)$$

The output $\boldsymbol{r}_{\mathrm{MF}}$ of the MF is dimensional reduced

$$\begin{aligned} \tilde{\boldsymbol{r}}_{\mathrm{MF}} &= \boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{r}_{\mathrm{MF}} \\ &= \boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\boldsymbol{T}_{\mathrm{st}}\boldsymbol{P}_{\mathrm{st}}^{1/2}\boldsymbol{s} + \tilde{\boldsymbol{n}}_{\mathrm{MF}} \end{aligned} \quad (15)$$

with the new noise covariance matrix

$$\boldsymbol{R}_{\tilde{n}\tilde{n}}^{\mathrm{st,MF}} = \mathrm{E}\left\{\tilde{\boldsymbol{n}}_{\mathrm{MF}}\tilde{\boldsymbol{n}}_{\mathrm{MF}}^{\mathrm{H}}\right\} = \sigma_n^2 \boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\boldsymbol{T}_{\mathrm{st}} \quad (16)$$

and weighted with the scalar WF (see Figure 2)

$$g_{\mathrm{MF}} = \frac{\mathrm{tr}\left(\boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\boldsymbol{T}_{\mathrm{st}}\boldsymbol{P}_{\mathrm{st}}^{1/2}\right)}{\mathrm{tr}\left(\boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\underbrace{\boldsymbol{T}_{\mathrm{st}}\boldsymbol{P}_{\mathrm{st}}\boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}}_{:=\boldsymbol{R}_{xx}^{\mathrm{st}}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st,H}}\boldsymbol{T}_{\mathrm{st}} + \boldsymbol{R}_{\tilde{n}\tilde{n}}^{\mathrm{st,MF}}\right)}. \quad (17)$$

The result $\boldsymbol{r}(t)$ is then fed into a ML estimator which provides an estimate $\hat{\boldsymbol{s}}(t)$ of the originally transmitted modulation symbol $\boldsymbol{s}(t)$. The ML-estimation is only performed in the space domain, only one time instant is considered. Consequently, only the (k,k)-th block $\boldsymbol{R}_{\tilde{n}\tilde{n}}$ of the space-time noise covariance matrix $\boldsymbol{R}_{\tilde{n}\tilde{n}}^{\mathrm{st,MF}}$ applies as noise statistic for the ML estimate

$$\hat{\boldsymbol{s}}(kT) = \arg\min_{\boldsymbol{s}} \left\|\boldsymbol{r}(kT) - g_{\mathrm{MF}}\boldsymbol{T}^{\mathrm{H}}\boldsymbol{H}_{\mathrm{MF}}^{0}\boldsymbol{T}\boldsymbol{P}^{1/2}\boldsymbol{s}\right\|_{\boldsymbol{R}_{\tilde{n}\tilde{n}}^{-1}}^{2}, \quad (18)$$

with $\boldsymbol{H}_{\mathrm{MF}}^{0} = \boldsymbol{H}_{\mathrm{MF}}(t', t=0)$.

B. Zero-Forcing Filter Receiver

Also the ZF filter has to operate at continuous time, just as the MF. It has been shown, that the analog ZF filter can be decomposed into an analog MF, followed by a time-discrete ZF stage [7] working at symbol rate T.
With this insight, we can take the time-discrete output of the MF (see Section III-A) as input for a subsequent ZF stage. Right after the ZF stage we apply the space-time beamforming matrix from Eq. (9) and a scalar Wiener Filter g_{ZF} to recover the correct signal amplitude. This produces the filter output $\boldsymbol{r}(t)$ (see Figure 2).

Again we are assuming block processing. The output $\boldsymbol{r}_{\mathrm{ZF}}$ of the ZF filter in the space-time domain in analogy to the MF, c.f. Eq. (10), reads as

$$\begin{aligned} \boldsymbol{r}_{\mathrm{ZF}} &= \boldsymbol{G}_{\mathrm{ZF}}^{\mathrm{st}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\cdot\boldsymbol{x} + \boldsymbol{n}_{\mathrm{ZF}} \\ &= \boldsymbol{G}_{\mathrm{ZF}}^{\mathrm{st}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\boldsymbol{T}_{\mathrm{st}}\boldsymbol{P}_{\mathrm{st}}^{1/2}\boldsymbol{s} + \boldsymbol{n}_{\mathrm{ZF}}, \end{aligned} \quad (19)$$

where the zero-forcing stage $\boldsymbol{G}_{\mathrm{ZF}}^{\mathrm{st}}$ computes as

$$\boldsymbol{G}_{\mathrm{ZF}}^{\mathrm{st}} = \boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st},-1} \quad (20)$$

and the noise $\boldsymbol{n}_{\mathrm{ZF}}$ computes as

$$\boldsymbol{n}_{\mathrm{ZF}} = \boldsymbol{G}_{\mathrm{ZF}}^{\mathrm{st}}\mathrm{vec}\left\{\boldsymbol{H}_{\mathrm{RRC}}^{\mathrm{H}}(t', -t)\star\boldsymbol{n}(t)\right\}\Big|_{kT}. \quad (21)$$

The space-time noise covariance matrix consequently reads as

$$\boldsymbol{R}_{nn}^{\mathrm{st,ZF}} = \mathrm{E}\left\{\boldsymbol{n}_{\mathrm{ZF}}\boldsymbol{n}_{\mathrm{ZF}}^{\mathrm{H}}\right\} = \sigma_n^2 \boldsymbol{G}_{\mathrm{ZF}}^{\mathrm{st}}. \quad (22)$$

We again reduce the dimension with

$$\begin{aligned} \tilde{\boldsymbol{r}}_{\mathrm{ZF}} &= \boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{r}_{\mathrm{ZF}} \\ &= \boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{G}_{\mathrm{ZF}}^{\mathrm{st}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\boldsymbol{T}_{\mathrm{st}}\boldsymbol{P}_{\mathrm{st}}^{1/2}\boldsymbol{s} + \tilde{\boldsymbol{n}}_{\mathrm{ZF}} \\ &= \boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{T}_{\mathrm{st}}\boldsymbol{P}_{\mathrm{st}}^{1/2}\boldsymbol{s} + \tilde{\boldsymbol{n}}_{\mathrm{ZF}} \\ &= \boldsymbol{P}_{\mathrm{st}}^{1/2}\boldsymbol{s} + \tilde{\boldsymbol{n}}_{\mathrm{ZF}} \end{aligned} \quad (23)$$

and obtain the new noise covariance matrix

$$\boldsymbol{R}_{\tilde{n}\tilde{n}}^{\mathrm{st,ZF}} = \mathrm{E}\left\{\boldsymbol{n}_{\mathrm{MF}}\boldsymbol{n}_{\mathrm{MF}}^{\mathrm{H}}\right\} = \sigma_n^2 \boldsymbol{T}_{\mathrm{st}}^{\mathrm{H}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st},-1}\boldsymbol{T}_{\mathrm{st}} \quad (24)$$

The output $\tilde{\boldsymbol{r}}_{\mathrm{ZF}}$ is weighted with the scalar Wiener Filter

$$g_{\mathrm{ZF}} = \frac{L}{\mathrm{tr}\left(\boldsymbol{P}_{\mathrm{st}} + \boldsymbol{R}_{\tilde{n}\tilde{n}}^{\mathrm{st,ZF}}\right)} \quad (25)$$

to produce $\boldsymbol{r}$ (see Figure 2 and 3).

The result $\boldsymbol{r}(t)$ is fed into a ML estimator which provides an estimate $\hat{\boldsymbol{s}}(t)$ of the originally transmitted modulation symbol $\boldsymbol{s}(t)$. This reads, in analogy to the MF receiver, as

$$\hat{\boldsymbol{s}}(kT) = \arg\min_{\boldsymbol{s}} \left\|\boldsymbol{r}(kT) - g_{\mathrm{ZF}}\boldsymbol{P}^{1/2}\boldsymbol{s}\right\|_{\boldsymbol{R}_{\tilde{n}\tilde{n}}^{-1}}^{2}, \quad (26)$$

where only the (k,k)-th block $\boldsymbol{R}_{\tilde{n}\tilde{n}}$ of the space-time noise covariance matrix $\boldsymbol{R}_{\tilde{n}\tilde{n}}^{\mathrm{st,ZF}}$ applies as noise statistic for the ML estimate[2].

C. Wiener Filter Receiver

The time continuous space-time Wiener Filter can also be decomposed into an analog MF, followed by a time-discrete WF stage [7] working at symbol rate T.
With block processing the output $\boldsymbol{r}_{\mathrm{WF}}$ of the WF filter in the space-time domain reads as

$$\begin{aligned} \boldsymbol{r}_{\mathrm{WF}} &= \boldsymbol{G}_{\mathrm{WF}}^{\mathrm{st}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\cdot\boldsymbol{x} + \boldsymbol{n}_{\mathrm{WF}} \\ &= \underbrace{\boldsymbol{G}_{\mathrm{WF}}^{\mathrm{st}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\boldsymbol{T}_{\mathrm{st}}}_{\boldsymbol{H}_{\mathrm{WF}}^{\mathrm{st}}}\boldsymbol{P}_{\mathrm{st}}^{1/2}\boldsymbol{s} + \boldsymbol{n}_{\mathrm{WF}}, \end{aligned} \quad (27)$$

where the WF stage $\boldsymbol{G}_{\mathrm{WF}}^{\mathrm{st}}$ computes as

$$\boldsymbol{G}_{\mathrm{WF}}^{\mathrm{st}} = \boldsymbol{R}_{xx}^{\mathrm{st}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st,H}}\left(\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\boldsymbol{R}_{xx}^{\mathrm{st}}\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st,H}} + \sigma_n^2\boldsymbol{H}_{\mathrm{MF}}^{\mathrm{st}}\right)^{-1}. \quad (28)$$

The noise $\boldsymbol{n}_{\mathrm{WF}}$ computes as

$$\tilde{\boldsymbol{n}}_{\mathrm{WF}} = \boldsymbol{G}_{\mathrm{WF}}^{\mathrm{st}}\mathrm{vec}\left\{\boldsymbol{H}_{\mathrm{RRC}}^{\mathrm{H}}(t', -t)\star\boldsymbol{n}(t)\right\}\Big|_{kT} \quad (29)$$

[2]Note, that $\boldsymbol{T}^{\mathrm{H}}\boldsymbol{T} = \mathbf{1}$, but $\boldsymbol{T}\boldsymbol{T}^{\mathrm{H}} \neq \mathbf{1}$.

with the space-time noise covariance matrix

$$\begin{aligned} \boldsymbol{R}_{nn}^{\text{st,WF}} &= \mathrm{E}\left\{\boldsymbol{n}_{\text{WF}}\boldsymbol{n}_{\text{WF}}^{\text{H}}\right\} \\ &= \sigma_n^2 \boldsymbol{G}_{\text{WF}}^{\text{st}} \boldsymbol{H}_{\text{MF}}^{\text{st}} \boldsymbol{G}_{\text{WF}}^{\text{st,H}}. \end{aligned} \tag{30}$$

Applying the rank reduction $\boldsymbol{T}_{\text{st}}^{\text{H}}$ and the trivial scalar Wiener filter $g_{\text{WF}} = 1$ produces the filter output

$$\begin{aligned} \boldsymbol{r} = \tilde{\boldsymbol{r}}_{\text{WF}} &= \boldsymbol{T}_{\text{st}}^{\text{H}} \boldsymbol{r}_{\text{WF}} \\ &= \underbrace{\boldsymbol{T}_{\text{st}}^{\text{H}} \boldsymbol{G}_{\text{WF}}^{\text{st}} \boldsymbol{H}_{\text{MF}}^{\text{st}} \boldsymbol{T}_{\text{st}} \boldsymbol{P}_{\text{st}}^{1/2}}_{:= \boldsymbol{H}_{\text{WF}}^{\text{st}}} \boldsymbol{s} + \tilde{\boldsymbol{n}}_{\text{WF}} \end{aligned} \tag{31}$$

with the new space-time noise covariance matrix

$$\boldsymbol{R}_{\tilde{n}\tilde{n}}^{\text{st,WF}} = \sigma_n^2 \boldsymbol{T}_{\text{st}}^{\text{H}} \boldsymbol{G}_{\text{WF}}^{\text{st}} \boldsymbol{H}_{\text{MF}}^{\text{st}} \boldsymbol{G}_{\text{WF}}^{\text{st,H}} \boldsymbol{T}_{\text{st}}. \tag{32}$$

The result $\boldsymbol{r}(t)$ of the WF is fed into a ML estimator to provide an estimate $\hat{\boldsymbol{s}}(t)$ of the originally transmitted modulation symbol $\boldsymbol{s}(t)$ as

$$\hat{\boldsymbol{s}}(kT) = \arg\min_{\boldsymbol{s}} \|\boldsymbol{r}(kT) - \boldsymbol{H}_{\text{WF}}(k)\boldsymbol{s}\|^2_{\boldsymbol{R}_{\tilde{n}\tilde{n}}^{-1}}, \tag{33}$$

where only the (k,k)-th block $\boldsymbol{R}_{\tilde{n}\tilde{n}}$ of the space-time noise covariance matrix $\boldsymbol{R}_{\tilde{n}\tilde{n}}^{\text{st,WF}}$ applies as noise statistic for the ML estimate and $\boldsymbol{H}_{\text{WF}}(k)$ denotes the (k,k)-th block of the combined space-time transfer function $\boldsymbol{H}_{WF}^{\text{st}}$.

D. Transmitter Knowledge

The unitary beamforming matrix $\boldsymbol{T}$ is chosen according to the eigenbeamforming concept [2]. Since the frequency selective channel $\boldsymbol{H}(t',t)$ is experiencing block fading with given average values

$$\boldsymbol{R}_{k,\text{UE}} = \mathrm{E}\left\{\boldsymbol{H}_k(t')\boldsymbol{H}_k^{\text{H}}(t')\right\} \tag{34}$$

and

$$\boldsymbol{R}_{k,\text{NB}} = \mathrm{E}\left\{\boldsymbol{H}_k^{\text{H}}(t')\boldsymbol{H}_k(t')\right\} \tag{35}$$

it is possible to perform the eigenbeamforming on two different time scales:

- on a short-term basis by computing the strongest eigenvectors of $\boldsymbol{H}_{\text{MF}}^{0}\boldsymbol{H}_{\text{MF}}^{0,\text{H}}$ (instantaneous knowledge), or
- on a long-term basis by computing the strongest eigenvectors of $\sum_k \boldsymbol{R}_{k,\text{NB}}$ (knowledge on average).

The eigen spectrum of each of the two approaches also allows to choose the rank D of the transmission. More explicitly: if the channel offers only one dominant eigenvalue, it is reasonable to transmit only one, scalar data stream. To maintain a constant data rate it is necessary to simultaneously increase the modulation level while decreasing the number of data streams.

It is well-known, that the best possible strategy for allocating the power on the eigenmodes in a MIMO transmission is the water-filling approach [8]. However, this is only valid for Gaussian distributed signals.

To circumvent this difficult problem, we are applying a uniform power distribution on our data streams. In other word, we always choose

$$\boldsymbol{P} = \frac{1}{D} \cdot \boldsymbol{1}^{D\times D}. \tag{36}$$

IV. Simulations

For the simulations we are transmitting at a fixed data rate of 4 bits per channel use over a symmetrical 4×4 system.

A. Channel Case 4

Figure 4 shows the BER of the Eigenbeamforming approach for different receiver structures and different knowledge at the transmitter if we transmit one 16QAM data stream. We transmit $L = 60$ symbols over one channel realization and averaged over 500 channel realizations.

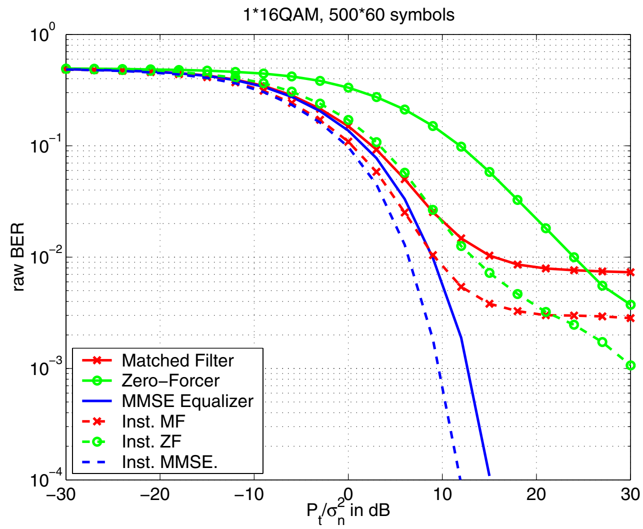

Fig. 4. BER as function of the transmit SNR for Eigenbeamforming with one 16-QAM stream.

Figure 5 shows the BER of the Eigenbeamforming approach for different receiver structures and different knowledge at the transmitter if we transmit two 4QAM data stream.

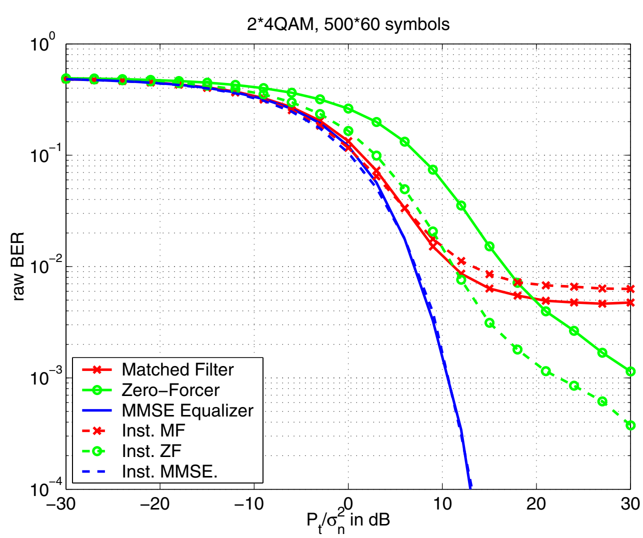

Fig. 5. BER as function of the transmit SNR for Eigenbeamforming with two 4-QAM streams.

From the comparison of Figure 4 and 5 we see, that we gain approximately 3dB SNR if we double the number of data

streams in the long-term WF approach. This is easily explained by the fact, that channel type #4 offers two dominant eigenvalues.
Additionally we can see, that in the case of a WF receiver and two data streams (see Figure 5) there is no substantial difference between short-term and long-term knowledge at the receiver. However, this is a result of the uniform distribution of the data rate and power onto the two dominant eigenvalues. Applying smart power allocation and adaptive modulation would re-establish the difference between short-term and long-term knowledge. However, note that also the long-term approach would gain from smart power allocation and adaptive modulation.

B. Channel Case 3

Figure 6 shows the BER of the Eigenbeamforming approach for different receiver structures and different knowledge at the transmitter if we transmit one 16QAM data stream. We transmit $L = 60$ symbols over one channel realization and averaged over 500 channel realizations.

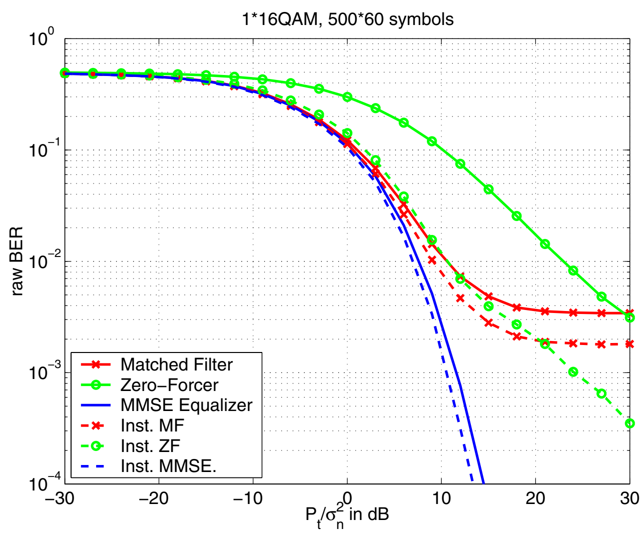

Fig. 6. BER as function of the transmit SNR for Eigenbeamforming with one 16-QAM stream.

Figure 7 shows the BER of the Eigenbeamforming approach for different receiver structures and different knowledge at the transmitter if we transmit two 4QAM data stream.

From the comparison of Figure 6 and 7 we see, that we lose performance if we transmit more than one data stream. This indicates, that the strongest eigenvalue is very dominant. We also see, that in Figure 7 the long-term approach performs better than the short-term approach. The reason is, that in the short-term approach the data is exactly separated into the two eigenspaces. If one eigenspace degrades, one half of the data is lost. In the long-term approach the data is not perfectly separated. Therefore always at least a fraction of every data stream can be recovered from each subspace.

V. Conclusions

In this paper we have applied the Eigenbeamforming approach to two realistic channel models, proposed by the 3GPP

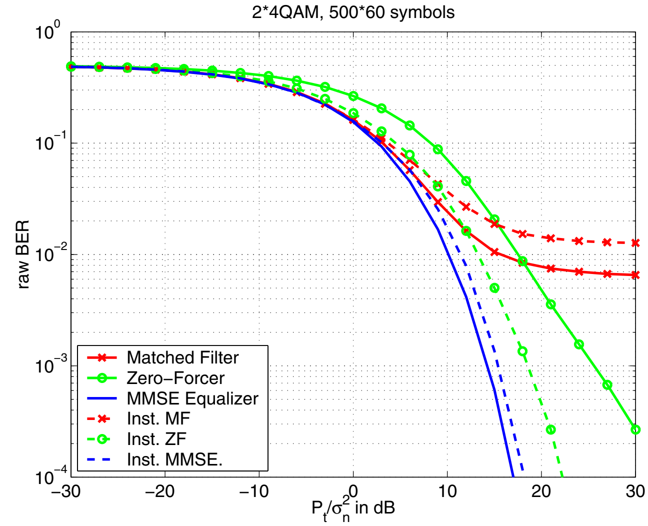

Fig. 7. BER as function of the transmit SNR for Eigenbeamforming with two 4-QAM streams.

standardization body. We have evaluated this transmission concept with respect to the BER for different receiver structures and different number of data streams while keeping the data rate constant. The results show, that for these channel types long-term knowledge at the transmitter achieves high performance, which is close to instantaneous channel knowledge at the transmitter side.

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