

THE MIMO RADIO CHANNEL

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SUMMARY

The presentation will discuss the important parameters of the MIMO radio channel and describe ways to model this channel, in particular the two principal methods: "propagation-based" and "analytical". The former describes the radio environment independent of antennas, mostly in a double-directional way, and gives the freedom to try out various antenna arrays configurations (number, spacing, polarization). The latter modeling approach starts already with given array configurations, but gives faster results when simulating algorithms and transceiver designs. A recipe to estimate and to interpret the parameters of a new analytical model will be given.

En route I will discuss some less-known facts about MIMO channels (e.g. path loss as an important performance parameter; the role of multipath clusters; too high expectations about MIMO in general). Hopefully, I can clarify some confusion about MIMO modeling and performance without adding new. Although spectacular advances have been made recently in characterizing MIMO radio propagation, particularly in identifying multipath components and their clustering, there are still interesting questions open. Among them is model validation, which is rarely done rigorously.

INTRODUCTION

Scanning the titles of contributions to major radio and communications conferences in the last few years, one could get the impression that MIMO (multiple-input multiple-output) is set to solve the transmission bottleneck in wireless systems for good. While it is true that MIMO systems can, in theory, provide the seemingly paradoxical arbitrary multiplication of Shannon's capacity, and nobody doubts that MIMO will be *the* enabling technology for high-speed wireless data, many questions remain. In particular, the limiting role of the radio channel as to which of the well-known benefits of MIMO can be exploited is not widely appreciated.

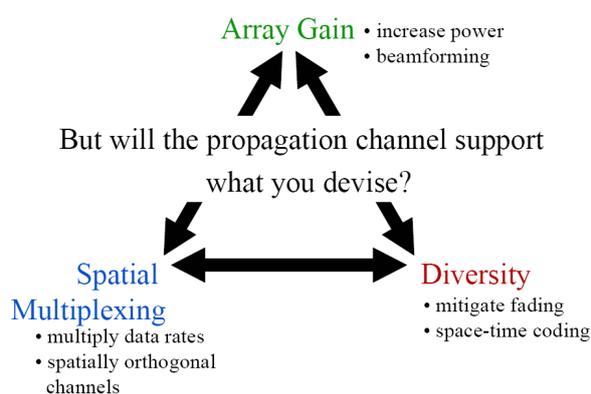


Figure 1. Benefits of MIMO

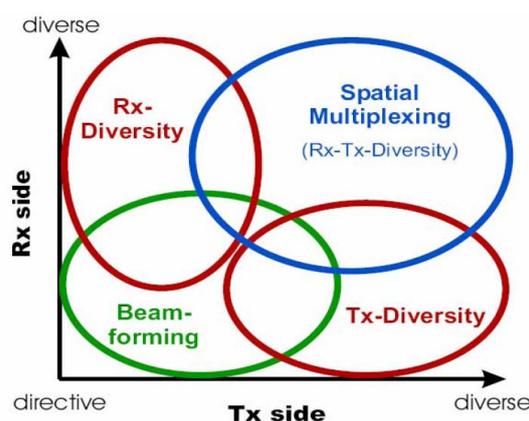


Figure 2. The MIMO radio channel

MIMO may offer three different benefits, namely beamforming gain, spatial diversity, and spatial multiplexing (Fig. 1). By *beamforming*, the transmit and receive antenna patterns can be focused into a specific angular direction by the appropriate choice of complex baseband antenna weights. The more *correlated* the *antenna signals*, the better for beamforming. Under line-of-sight (LOS) channel conditions, the Rx and Tx gains add up, leading to an upper limit of $m \cdot n$ for the beamforming gain of a MIMO system (n and m being the number of antenna elements for the receiver Rx and for the transmitter Tx, respectively).

Multiple replicas of the radio signal from different directions in space give rise to spatial *diversity*, which increases the reliability of the fading radio link. For a spatially white MIMO channel, i.e. completely *uncorrelated antenna signals*, the diversity order is limited to $m \cdot n$. Spatial correlation of the antenna signals will reduce the diversity order and is therefore an important channel characteristic. MIMO channels can support parallel data streams by transmitting and receiving on orthogonal spatial filters ("*spatial multiplexing*"). The number of multiplexed streams depends on the rank of the instantaneous channel matrix H , which, in turn, depends on the spatial properties of the radio environment. The spatial multiplexing gain may reach $\min(m, n)$ in a sufficiently rich scattering environment.

Beamforming, diversity, and multiplexing are rivaling techniques. To highlight the role of the propagation channel, the threefold trade-off between beamforming, diversity, and multiplexing can be broken down into several dichotomous trade-offs [Böl06], see Fig. 2.

The partial overlap of the ellipses in Fig. 2 indicates that there is a gradual transition between the pure realizations of any MIMO benefit. In summary, it is the *propagation environment* that determines what *can* be gained by MIMO techniques; however, this does not mean that it *will* be gained in actual MIMO operation.

MIMO CHANNEL MODELS

How shall we describe or model the MIMO channel? First, this depends what we want to model for. For MIMO system deployment and network planning, we need *site-specific* models, for MIMO algorithm development, and system design and testing, we need *site-independent* models. Then, what kind of model serves our purpose best? Given that the number of MIMO models is huge, and still increasing, this is a difficult question that is not always decided rationally. Systems engineers pressure for models that are "simple", sometimes ridiculously so¹, while radio engineers strive to capture the details of the radio channel. Before adopting a MIMO model, one should have answers ready on these questions:

- _ At which level should the model function? Propagation, channel, link, system?
- _ Which aspect of MIMO shall be modeled? Multiplexing, beamforming or diversity gain?
- _ Has the model been validated, and if yes, how?

Figure 3 tries to provide a compass to navigate through the jungle of MIMO models.

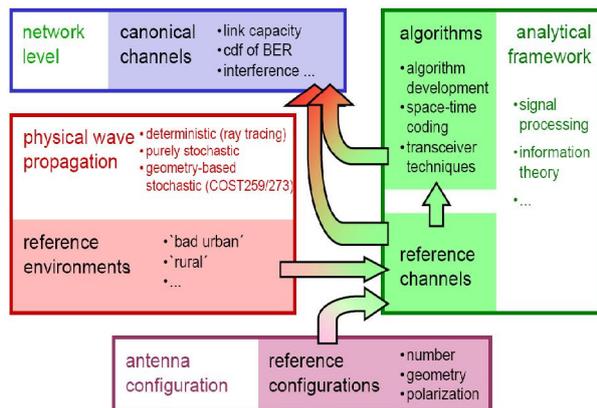


Figure 3. MIMO Models – an Overview

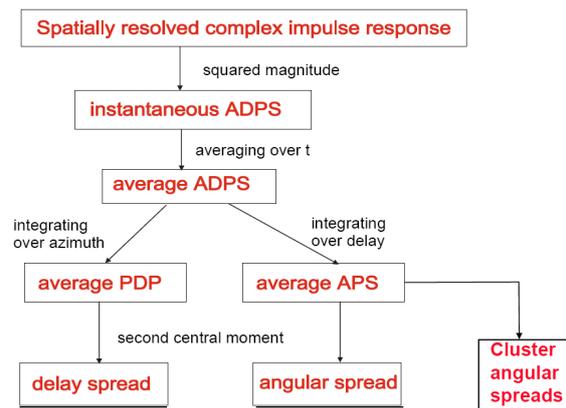


Figure 4. Aggregate parameters of MIMO radio channel models derived from the spatially resolved impulse response. ADPS...Angular Delay Power Spectrum; PDP...Power Delay Profile; APS...Angular Power Spectrum; CAS...Cluster (or Component) Angular Spread

¹ Some companies have even tried to persuade standardization committees to adopt MIMO channel models *without* a spatial component.

Electromagnetic wave propagation provides the basis for *propagation* or *physical models*. The final result of physical modeling is the *characterization of the environment* on the basis of propagation. Reference scenarios² are agreed-on environments that make comparison of models and their performance much easier. Specifying a system *bandwidth* and *antenna arrays* at both link ends by setting the number of antenna elements, their geometrical configuration, and their polarizations turns the propagation model into a MIMO *channel model*. Accounting for mobility of a terminal complements a channel model on link level. Such a model provides MIMO *channel matrices* as an *analytical* framework for designing transmit and receive techniques for a MIMO link, e.g. space-time codes. How MIMO channel models on the link level may be combined to model a MIMO implementation on network level will not be discussed here.

Parameters of the MIMO radio channel

The channel is characterized by a time- and delay-dependent MIMO channel matrix, $\mathbf{H}(t, \tau)$ that contains the impulse responses from each transmit to each receive antenna (for both polarizations), calculated from dual-polarized double-directional wave propagation.

If, for simplicity sake, we assume a narrowband system, adopt complex baseband representation and transform the delay domain (τ) into the frequency domain (ω), the matrix \mathbf{H} is composed of the complex-valued entries $h_{i,j}$, which characterize the transfer function from the j -th transmit to the i -th receive antenna. Of particular interest is the Wishart form, $\mathbf{H}\mathbf{H}^H$, where H means the Hermitian transpose of \mathbf{H} . It determines the mutual information, I ,

$$I = \log_2 \det \left(\mathbf{I}_n + \frac{\text{SNR}}{m} \mathbf{H}\mathbf{Q}\mathbf{H}^H \right) \quad (1)$$

of that particular realization of the MIMO channel. Here, \mathbf{I}_n is the $n \times n$ identity matrix, \mathbf{Q} the signal covariance matrix and SNR the prevalent signal-to-noise ratio. Applying the expectation operator over an ensemble of realizations and optimizing \mathbf{Q} according to the channel statistics (\mathbf{Q} is usually taken to be the identity matrix) yields $\mathbf{H}\mathbf{H}^H$ in (1) as the very popular ergodic capacity formula of the MIMO channel. I hasten to say that capacity is neither the only interesting quantity nor a particularly meaningful one to assess a model's goodness.

Which parameters do we have to consider when we want to model a MIMO radio channel in detail for system design? In delay domain, we are interested in the complex valued impulse response and derived parameters. Its length and temporal clusters will guide our choice of the system's symbol length. As the secret power of MIMO is based upon spatial samples of the spatially varying electromagnetic field, taken or imposed by the array antennas, the *angularly resolved impulse response* is what distinguishes MIMO from conventional channel modeling. Direction of arrival (DOA) and direction of departure (DOD) of multipath components (MPCs) and their clustering in direction are paramount. From this information we can derive number and configuration of Tx and Rx antenna arrays to exploit best what the channel offers. For time-varying channels, we have to model additionally the average duration of fades and a Doppler profile to choose appropriate frame and block lengths and the interleaving depth.

Aggregate parameters are then usually derived in the way of Figure 4.

The parameters of the time domain and the delay domain are well known from the traditional SISO (single-input single-output) radio channel. We will focus here on the spatial domain and note that polarization offers advantages particular in MIMO. In particular, I want to highlight the *cluster angular spread* [Kuc02], because channel situations that will produce widely different MIMO responses may have the same (global) angular spread, derived from the entire environment.

² Why not 'typical' scenarios? A meaningful selection would require many a-priori measurements. Alas, practical procedures are the reverse: from intuition, at best, 'typical' environments are chosen and then only there are quick measurements made. That is the reason why *reference scenarios* should be established by the international research community.

Model Classification

MIMO models appear in a confusing variety of names. Among the *physical* models, we found it convenient to distinguish between

- _ deterministic models (e.g. ray tracing, stored measurements)
- _ geometry-based stochastic models (e.g. the GSCM of COST 259/273[Cor01, Cor06])
- _ stochastic models (without geometrical input, e.g. Hao Xu et al. [Xu04], Zwick[Zwi04]).

Deterministic models boast good agreement with physically existing results (site-specific!) and are easily reproducible. However, they may not be typical, require a large data bases, are expensive to produce, and their parameters cannot be changed easily.

Stochastic models describe the radio channel by (multidimensional) probability density functions of the desired parameters. Simulation runs with them are fast, because of legacy tapped-delay-line realization, but they are difficult to parameterize over large areas. Parameterization can be sped up by feeding in a single site-specific MIMO measurement and randomizing the parameters of the multipath components [Mol02]).

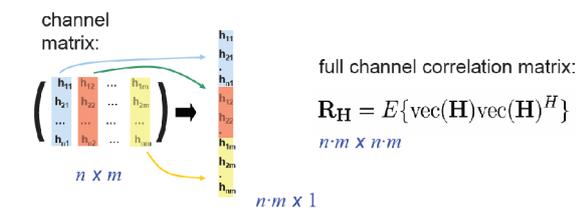
Geometry-based stochastic channel models (GSCM) try to combine the best of the two worlds by starting with geometrical input about the environment and then superimpose statistical information. They excel in simulating both interference and the temporal evolution of the channel when terminals or scatterers move.

Analytical models specify MIMO channel matrices. I see two kinds. One starts from the correlation properties of the channel right away, extracted from MIMO measurement campaigns (IST-METRA or 'Kronecker' model [Ker02], Weichselberger [Wei06]) or theoretical considerations alone, like the 'i.i.d. model' with random Gaussian entries in the \mathbf{H} matrix, very popular with theoreticians. Other analytical models are motivated by propagation principles, e.g. the 'finite scatterers model' [Bur03] or the 'virtual channel representation' [Say02].

Models adopted by standardization bodies like 3GPP and IEEE 802.11n combine elements of both groups (not necessarily in an optimal way) and prescribe temporal and spatial characteristic of the MIMO radio channel rigorously by aggregate parameters (compare Fig. 4).

How to model correlation

Spatial correlation of antenna signals has been early identified as the show-stopper of MIMO systems [Shi00]. To determine the spatial correlation in a specific environment, we have to measure the full MIMO system with specific Tx and Rx arrays in place. Analytical models start from the full channel correlation matrix, \mathbf{R}_H (Figure 5), and become simpler, when making assumptions about propagation³.



- Elements of \mathbf{R}_H describe correlation between any pair of \mathbf{H} elements
- Full description of channel matrix, if channel described by second-order statistics
- Elements of \mathbf{R}_H are difficult to interpret physically
- Full correlation matrix is very large =>
- Find meaningful approximations of \mathbf{R}_H

Figure 5. Full correlation matrix \mathbf{R}_H

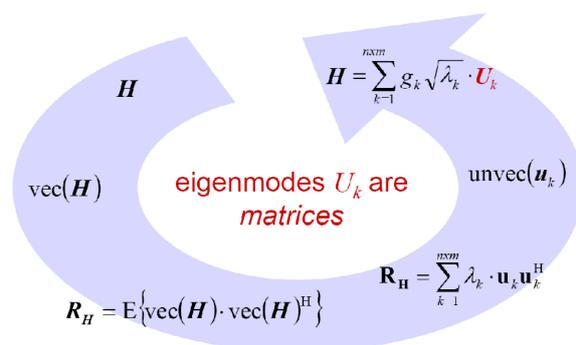


Figure 6. Principle of eigenbasis representation of MIMO channels

³ A hidden assumption of correlation-based models is that they are strictly valid only for Gaussian channels (i.e. that have Rayleigh fading statistics of the $h_{i,j}$).

A popular approach assumes complete independence of the Tx and Rx propagation environments [Ker02]. The MPCs arriving at the receiver have "forgotten" how they have been sent off from the transmitter. Then, the MIMO correlation properties are characterized by separate correlation matrices at the receiver, \mathbf{R}_{Rx} , and the transmitter, \mathbf{R}_{Tx} ,

$$\mathbf{R}_{\text{Rx}} = \text{E}\{\mathbf{H}\mathbf{H}^H\}, \quad (2)$$

$$\mathbf{R}_{\text{Tx}} = \text{E}\{\mathbf{H}^T\mathbf{H}^*\}, \quad (3)$$

giving the full correlation matrix \mathbf{R}_{H} as their Kronecker product; hence the name. However, I want to stress that this approach neglects the correlation terms across the link ("cross correlation", "joint correlation"), which do matter, at least in some indoor scenarios [Özc03a]. This joint correlation makes MIMO to more than just the sum of SIMO and MISO. A surprising result, emphasizing that separate Rx and Tx correlation matrices are not able to completely describe MIMO channels, was recently found in [Oes04]: so-called "diagonal correlations" may boost the ergodic capacity beyond the previously accepted upper limit of – totally uncorrelated - i.i.d. random entries of \mathbf{H} .⁴

The rank of the correlation matrix, i.e. the number of its significant eigenvalues, is interesting because it also gives the maximum achievable degrees of diversity.

AN ANALYTICAL MIMO CHANNEL MODEL (WEICHELBERGER)

The goal was to parameterize a correlation-based model directly from measurements or channel estimates obtained during system operation [Wei06]. The model is a generalization of MISO eigenmode analysis to MIMO (Fig. 6).

The spatial correlation of transmit weights (complex excitation of the Tx array elements) determines how much power is radiated into which directions (and polarizations). The main assumption is: the *spatial eigenbases* are not affected by the transmit weights and, thus, *reflect the radio environment only*, i.e. number, positions, and strengths of the scatterers. The *eigenvalues*, on the other hand, do depend on the transmit weights. They *reflect how the scatterers are illuminated* by the radio waves propagating from the transmitter. Radiating in certain directions, for example, may illuminate only certain scatterers and leave others 'dark'. This will affect, of course, the spatial correlation at the Rx array⁵. The correlation matrices \mathbf{R}_{Rx} and \mathbf{R}_{Tx} are eigendecomposed and enter the model only via their eigenbases \mathbf{U}_{Rx} and \mathbf{U}_{Tx} (Fig.7).

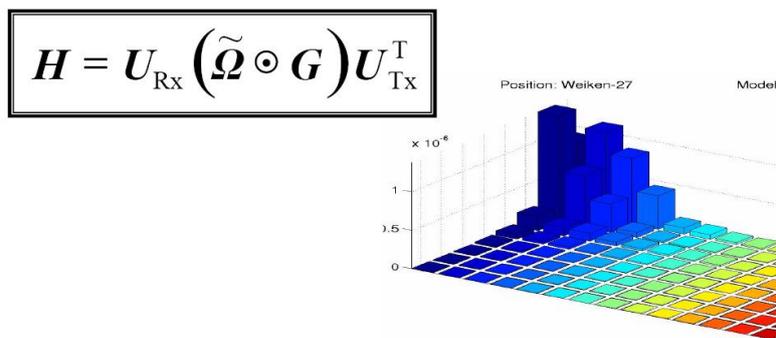


Figure 7. Formal definition of how to generate a realization of the Weichselberger model. The \mathbf{U} 's are the eigenmodes at Tx and Rx, \mathbf{G} is a random i.i.d. matrix, and the dotted circle denotes element-wise multiplication. Also shown is a measured sample of the coupling matrix $\tilde{\mathbf{Q}}$.

Eigenbases have some nice properties: they fade independently, they are orthogonal, the eigendecomposition is unique, the principal eigenmode maximizes power, they provide the smallest number of modes possible, but their number does not exceed $n \cdot m$.

⁴ If one measures, unaware of the limited dynamic range and phase noise of the sounder, noise instead of multipath signals, random entries of \mathbf{H} will also result.

⁵ A shortcoming of the Kronecker model is the assumption that the receive correlation equ.(2) is always the same, irrespective of what the transmitter sends.

Figure 8 shows some examples of structures of Ω and the corresponding physical radio environments. The structure of Ω reflects the spatial arrangement of scattering objects and influences the capacity as well as the degree of diversity that is experienced on spatially multiplexed channels. It tells us how many *parallel data streams* can be multiplexed, which degree of *diversity* is present at side A and at side B, and how much *beamforming* gain can be achieved. In order to aid intuition, think of the eigenmodes as discrete directions (center column of Figure 8). Such an interpretation of eigenmodes is not correct in general, but it facilitates their visualization. The number of eigenmodes present in the channel considered equals the number of resolvable multipath components, which evidently is a lower bound to all multipath components present. The right-hand column of Fig. 8 tells which benefit of MIMO can be exploited in the exemplary channels shown. Figure 7 shows an actual coupling matrix of a channel measured with 15 x 8 arrays. It becomes evident that a 4 x 4 MIMO system would suffice to exploit all the eigenmodes present; the channel is non-Kronecker. Figure 9 demonstrates that, given an ensemble of T time samples of the channel is available, the corresponding coupling matrix is only four clicks in MATLAB away.

Structure of Ω depends on the environment

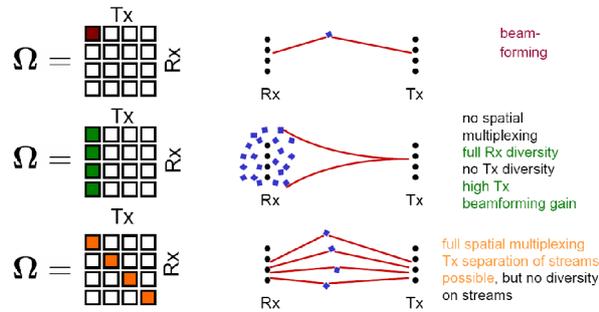


Figure 8. Sample structures of coupling matrix

- A simple estimator $\hat{R}_{R_x} = \frac{1}{T} \sum_{t=1}^T H(t)H^H(t)$
- Eigendecomposition $\hat{R}_{R_x} = \hat{U}_{R_x} \hat{\Lambda}_{R_x} \hat{U}_{R_x}^H$
 $\hat{R}_{T_x} = \hat{U}_{T_x} \hat{\Lambda}_{T_x} \hat{U}_{T_x}^H$
- Auxiliary matrix $K(t) \triangleq \hat{U}_{R_x}^H H(t) \hat{U}_{T_x}^H$
- Coupling matrix $\hat{\Omega} = \frac{1}{T} \sum_{t=1}^T K(t) \odot K^*(t)$

Figure 9. How to derive the coupling matrix from an ensemble of T measured time samples of H .

A GEOMETRY-BASED STOCHASTIC MIMO CHANNEL MODEL

To discuss important features that a *propagation-driven* MIMO channel model should capture in my opinion, I will now sketch a GSCM for indoor wireless broadband packet access in a large US/Japan-style office room [Bon05].

Start with the geometry of the room and information about wall and furniture properties. Scattering objects are modeled as clusters of MPCs in space and delay, and are described by the location of their centers and their size. We consider LOS, wall-reflections, reflections/scattering at interacting objects, up to 2nd order, and diffuse scattering. The coupling between directions-of-departure (DoDs), directions-of-arrival (DoAs), both in azimuth and elevation, and delay of the cluster centers is given implicitly by the geometry of the room and the scattering clusters, and are modeled deterministically by simple three-dimensional ray tracing. In contrast, the MPCs *within* a cluster are modeled stochastically. *Local* scattering clusters are modeled around the link ends, which move, in case of a moving terminal, simultaneously move along the same route. The rms angular spread of MPCs within a cluster (*cluster angular spread*) is determined from their spatial extension by simple geometric considerations. The first and the last cluster of MPCs in the joint angular-temporal domain of a specific propagation path define the actual angular spreads at transmit and receive side, respectively (which are different in general). The rms delay spread is defined to be equal for all clusters [Sal87] and has to be specified as an input parameter to the model. In the delay domain, the MPCs within a cluster are distributed according to a Poisson process. The intra-cluster DoDs and DoAs of the k -th MPC relative to the l -th cluster centre (both in azimuth and elevation) are randomly generated according to a *von Mises distribution* [Abd02] with zero mean. Each interacting object introduces polarisation dependent attenuation of the scattered signal and a depolarisation. Therefore, each MPC carries four random phases and four complex amplitudes. All multipath components of a cluster are superposed *coherently*. So are the contributions from each wall reflection and the LOS component.

Thus, the small scale fading is not modeled explicitly but results from the coherent superposition of all MPCs. We note that we need several coordinate systems, for the room, the polarized ray and for the antenna arrays, which have to be transformed appropriately to each other.

Dense Multipath

In addition to discrete, identifiable MPCs, measurements have shown that there exist typically a large number of MPCs that cannot be modeled discretely. Therefore, an important feature are additional *dense multipath components* (Fig.10) [Ric05], which capture the contributions of diffuse scattering, of higher-order reflections, and of diffraction⁶. We model this experimental observation by superimposing an exponentially decaying, random spatially white i.i.d. channel matrix to the channel matrix resulting from clusters and discrete components. The relative power of this i.i.d. component has to be specified beforehand (between 10% in LOS and 70% in NLOS [Ric05]).

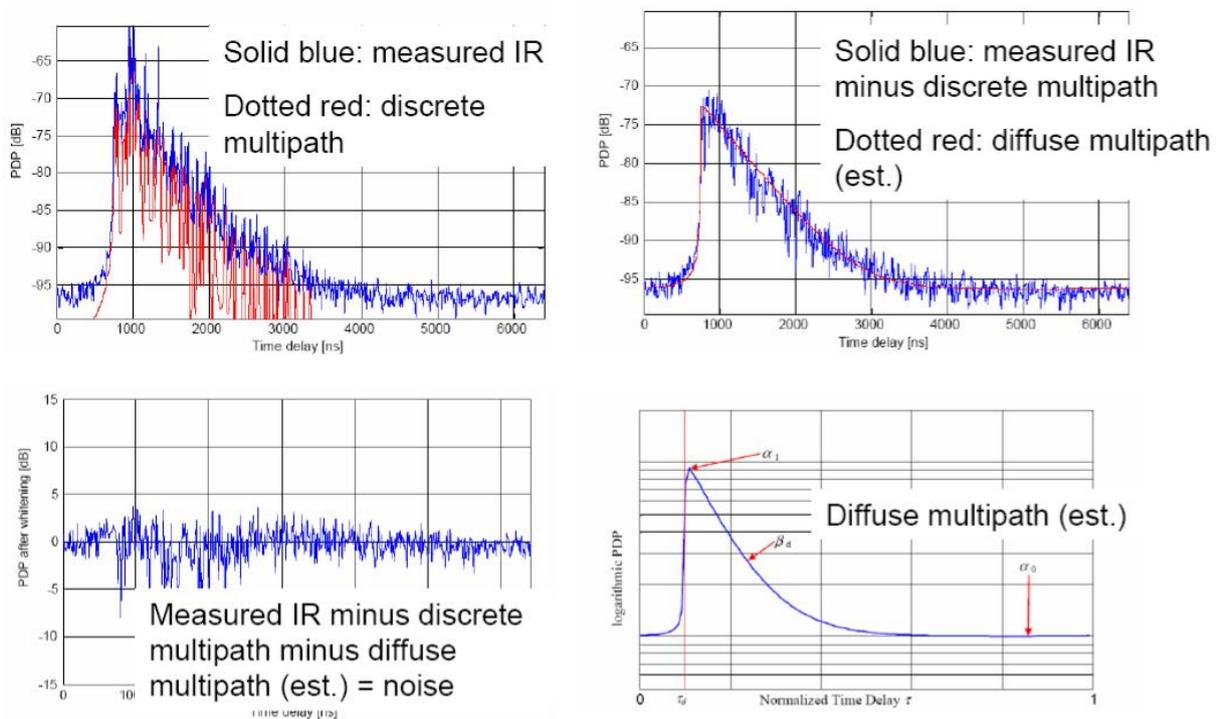


Figure 10. Modeling of the dense multipath of a measured impulse response

Temporal Evolution

To model the temporal evolution of the MIMO channel matrix in a given scenario, we incorporate *correlated* phase variations according to movement/Doppler-shift. The mobile is assumed to be moving with a constant speed but only within a small area, such that the spatial structure of the channel does not change (virtual movement). *Shadowing* due to moving people is implemented as additional random attenuation of specific clusters. In order to create independent channel realizations, the phases of each MPC and polarization are randomly varied within $[-\pi, \pi)$ for each realization [Mol02]. To create large-scale variations, we specify a route of movement through the scenario to obtain the resulting changes in geometry, i.e. DoAs, DoDs, delays, and path loss for each MPC. Figures 11 and 12 show the basic model structure and a schematic of the modeled impulse response. A particular advantage of the geometry-based, mixes deterministic/stochastic approach is its ability o model interference.

⁶ In a furnished room, diffraction cannot be reliably modeled today, and I doubt whether rigorous diffraction modeling is meaningful in non-stationary environments at all.

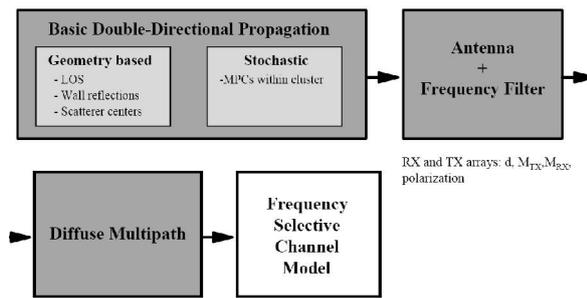


Figure 11. Model structure of a geometry-based stochastic MIMO channel model for packet access.

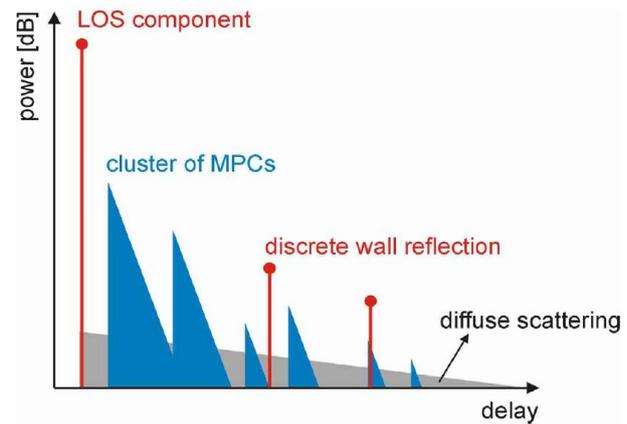


Figure 12. Schematic impulse response obtained with the model of Figure 11.

WHAT IS NEW, WHAT IS LACKING ?

In this section we will review very recent progress in characterizing the MIMO radio channel and point out where gaps in knowledge still need to be filled. Dense multipath modeling (see previous section) has turned out to be a must in MIMO models. This signal component may contribute considerably to the desired multipath richness, in contrast to noise that appears in a similar way in measurements.

Characterization of multipath components

The double-directional characterization of MPCs in the radio channel [Ste01], supported by double-directional channel sounding with multi-element near-omni-directional arrays (Fig. 13), is closely related to MIMO radio channel modeling. A number of groups, notably in Europe and Japan, have taken up the subject [Tho05]. Besides DoDs, DoAs, and delay, even polarization and Doppler of MPCs has been measured. To increase the accuracy of the channel transfer matrix's spatial and temporal structure, high-resolution parameter estimation techniques (MUSIC, ESPRIT, SAGE) have been pushed to their limits [Fle02]. Figure 13 gives a nice example of what has been achieved already.

Identification of scatterers

The illusionary goal of a complete electromagnetic description of the MIMO radio channel has been approached in spectacular ways by a combined assault of double-directional channel sounding, UWB measurements and high-resolution algorithms. The origin of MPCs and the properties of scattering objects in selected environments has been revealed e.g. in [Tsu04] and [Chi06] (Figure 14).

Clustering

Clustering of MPCs has been frowned upon because clusters were identified by 'visual inspection', i.e. the huge processing power of the human brain, but such identification is, of course, subject to individual idiosyncrasy. Very recently, [Czi06] has set up a complete solution to the problem of how to parameterize cluster-based stochastic MIMO channel models from measurement data, *with minimum user intervention*. The method comprises the following steps: (i) identify clusters in measurement data, (ii) identify the optimum number of clusters, (iii) track clusters over consecutive time windows, (iv) estimate cluster parameters. These parameters are given as estimated probability density functions of the cluster power, cluster positions, cluster spreads and the number of paths within a cluster. The method is particularly useful to process the huge amount of data measurement campaigns usually produce.

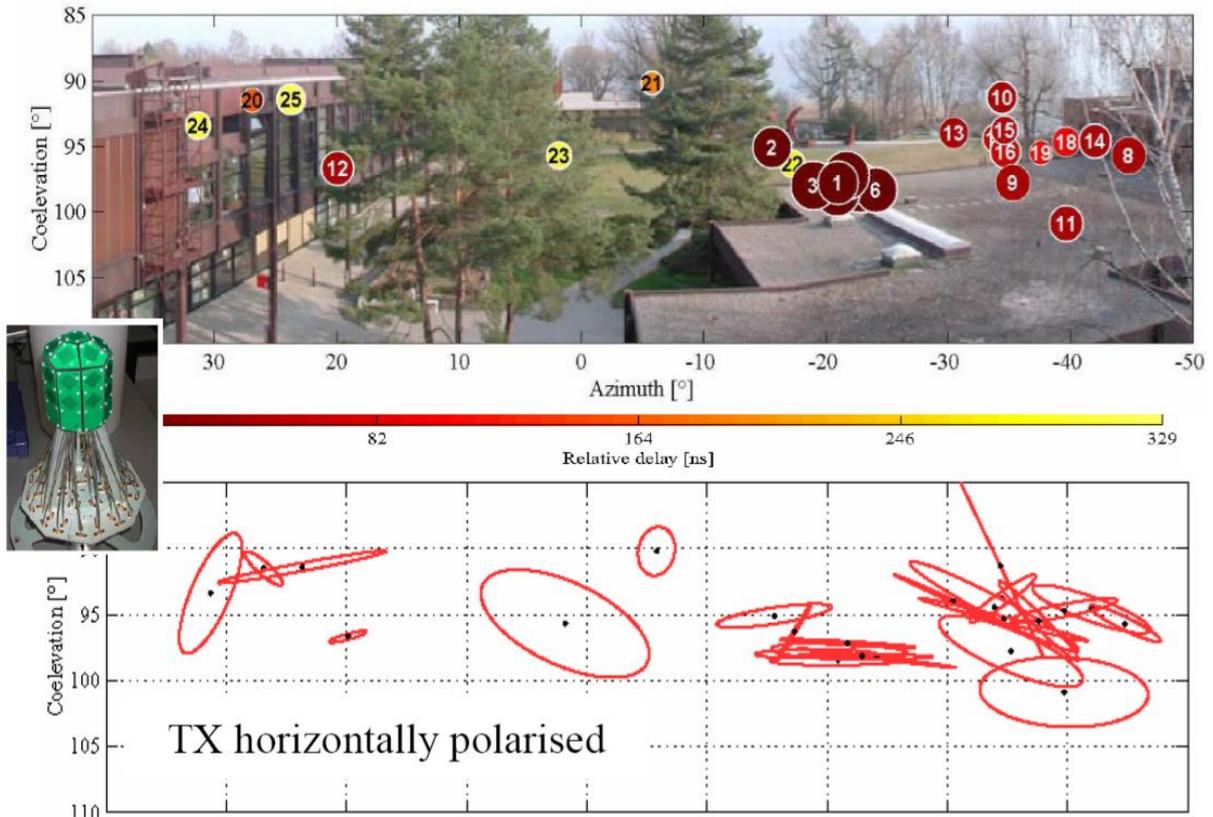


Figure 13. Received depolarized multipath as seen from Rx numbered and colored by delay. Signal strength is indicated by dot size. Courtesy B. Fleury, Aalborg. Antenna insert: Courtesy Elektrobot.

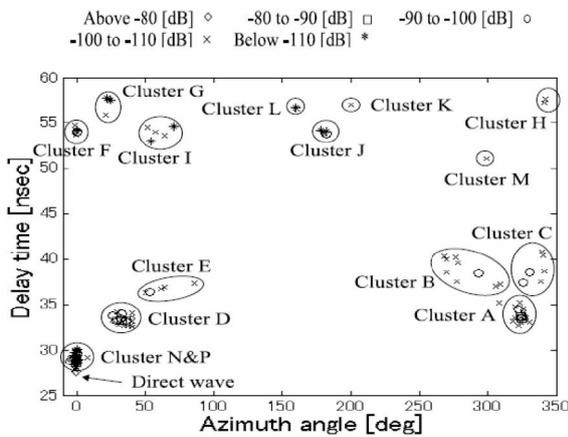
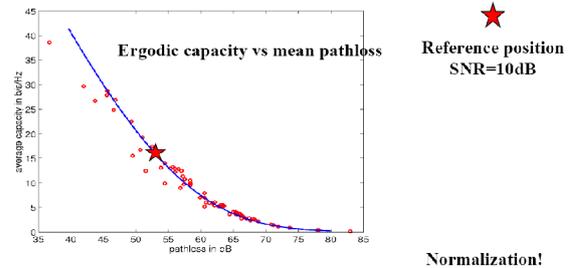


Figure 14. Discrete V-V multipath identified by a UWB MIMO technique and resolved in delay and angle [Tsu04].

Which MIMO System: Constant Tx Power vs. Constant SNR?



$$C = \log \det [I_n + (\text{SNR}/m) \times H_n H_n^H] \quad H_n \text{ normalized channel matrix}$$

$$C = \log \det [I_n + P_t / (\sigma^2 m) \times H H^H] \quad H \text{ for constant TX power}$$

Figure 15. Ergodic capacity vs. mean path loss when H -matrices are normalized to Tx power

Rich multipath or receive power?

There is a discussion ongoing whether a large number of eigenvalues ('rich multipath' in NLOS) or high receive SNR (usually in LOS) are more important⁷. Equation (1) shows that both factors contribute to ergodic capacity. A high SNR may imply a low degree of scattering [Sva03]. On the other hand, it was shown [Her03, Özc03b] that proper normalization of the measured H -matrices reveals the expected variation of capacity with path loss. A key to resolving controversial opinions

⁷ A measure to characterize 'rich multipath' was recently proposed by [And05] in the form of the *richness function*.

could be fact that some, but not all, LOS environments also have rich multipath around the Rx. Also, it makes a significant difference whether one considers a constant-Tx-power or a constant-receive-SNR MIMO system: different normalization of the measured instantiations of the MIMO channel is appropriate for these two totally different MIMO schemes (Figure 15).

Polarization

Polarization is an attractive property of the electromagnetic field to exploit in MIMO systems. It offers a dramatic reduction in the size of arrays, which makes the idea of multiple antennas at handheld terminals feasible. Dual-polarized MIMO systems and electromagnetic vector sensors [Yon05] have been studied. Oestges [Oes06] found that dual-polarization is advantageous in Ricean fading channels, but less so in Rayleigh fading channels, for constant Tx power. Vertically polarized waves persist longer in several environments than horizontally polarized ones. Much more measurements are necessary to clarify these phenomena (as is true for most MIMO ideas!). Proper normalization seems to be also the key to meaningful comparison of dual-polarized MIMO schemes with single-polarized ones.

Model Validation

Creating new models for MIMO has been a popular sport among researchers over the last years. The result is amazing: there seem to be only 'good' models around, if one believes their originators. Have these models been validated? Validation is usually done with far too little measured data, maybe a single campaign in arbitrarily selected environments. Careful model validation requires several campaigns to be performed, preferably by researchers that did not propose the model. Whether a model has specificity, i.e. whether it describes the targeted environment and whether it is closer to that than other, competing models is rarely asked at all. MIMO models are so important because all the rest of signal processing, coding and deployment hinges on good models. Given these facts, the discrepancy between efforts to develop new MIMO models and validating the existing ones is striking. A lot of the scarce work on model validation has been done within COST 273 [Cor06].

Another question is whether aggregate statistical parameters like ergodic capacity and eigenvalue distributions alone are sufficient to judge whether a model is appropriate or not. Aggregate metrics provide necessary but not sufficient conditions for the validation of channel models⁸. But definitely are some models better suited to predict a certain aspect of MIMO system performance than others [Özc05]. Evidence that some *metrics* are more useful than others in describing certain aspects of MIMO models is also gaining ground. *The MIMO model does not exist*. The quest for metrics allowing to assess the specificity of MIMO models must continue.

Channel State Information (CSI) and Stationarity

To what degree we can utilize any MIMO scheme depends largely on the knowledge about the channel we have at the Tx [Jaf05]. There, we might have *instantaneous* CSI (estimated or perfect), *average* CSI, or *no knowledge* at all. Average channel knowledge is advantageous, because we can exploit eigenmodes; however, whether the channel is stationary or not comes into play. [Her05] have proposed a metric of temporal stationarity, called Correlation Matrix Distance. Application to MIMO transmission schemes will show whether this metric is specific enough to allow comparison of such schemes. Again, many more solid measurements of MIMO radio channels need to be taken.

ACKNOWLEDGEMENTS

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⁸ Even the worst-fitting model I have seen is within 10% of true capacity.

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