On Simulating Propagation for OFDM/MIMO Systems with the MR-FDPF Model

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Abstract—**Radio propagation tools are needed to help operators to find the best setting of their network, including but not limited to access points positioning, radiated power optimization, and channel selection. Hence, different approaches proposed in the literature deal with this issue. Empirical models suffer from an unacceptable lack of accuracy while deterministic models have to cope with exponential computational complexity. Geometric models like ray tracing [1], [2] have been extensively developed as they offer a good trade-off between computational load and accuracy but they fail in simulating properly severe environments where multiple diffractions and numerous reflections hold. Second, more accurate methods based on the resolution of the Maxwell's equations have been implemented [3], [4] but they suffer from a high computational load. The MR-FDPF (Multi-Resolution Frequency Domain Partial Flows) approach [5] was proposed to fill in the gap by developing a multi-resolution preprocessing for the frequency domain TLM approach. However, the current challenge for radio propagation tools not relies on providing signal power levels but beyond on providing a realistic prediction of the system performance, e.g. bit error rate (BER) or throughput estimation. From a snapshot of the current main standards, it can be highlighted that most of them exploit OFDM and MIMO principles. Any system level simulator should rely with OFDM and MIMO prediction requirements. This paper investigates the appropriateness of the MR-FDPF approach for such task.**

I. Introduction

Last years, a technological shift in wireless communications has been observed. After few years with a major interest on direct spreading and CDMA based radio access technologies, OFDMA and MIMO are the two key technologies exploited everywhere especially in Indoor like environments [6]. The former successfully exploits frequency diversity while the later exploits spatial diversity. These two technologies all together allow approaching the Shannon's capacity limit, even in strong fading conditions. However, the practical capacity of these networks is not known yet for two main reasons: First, the optimal bound can be approximated only if the transmitter exploits a feedback channel to obtain good channel state information . Second, as wireless networks are densely deployed, interference plays a crucial role. Predicting and managing interference locally while achieving a global optimization is still an open problem [7]–[9]. Simulations and models are very important to validate distributed algorithms for resource allocation, but classical signal strength predictions are not sufficient. A system level simulation is much more complex because some signal features are needed. This question arises especially when MIMO and OFDM are used because they require a very fine resolution in space and frequency domains respectively. It is obviously impossible to derive an exact determinist approach as many uncertainties are present in complex environments. It is therefore more significant to predict some statistical parameters in addition to the classical signal strength. Practically speaking, frequency, spatial and time statistics are needed. Concerning OFDM, the bandwidth is divided in several sub-channels, each one having its own channel response h_i. To evaluate OFDM transmission performance, three kinds of information are mandatory: (i) the average channel gain, (ii) the channel statistics, and (iii) the sub-channels intercorrelation. Average channel gains are predictable with classical simulation approaches but the channel statistics are more difficult to obtain. The objective is for instance to determine the Rice parameter - if the channel is ricean -. This problem was investigated in [10]. However the extension to the case of wideband systems may generate a high computational load. This question is discussed in section IV by deriving an approach that exploits the specific structure of MR-FDPF. Concerning MIMO, the system level performance still relies on predicting the same three components. But the channels are now spatially distributed. A deterministic simulation cannot predict accurately the difference between two antennas separated from only few centimeters. Still, a statistical approach is preferred to derive an estimation of the inter-channel correlation strength.

In [5], we detailed a new method based on a recursive implementation of a frequency domain finite element approach, referred to as MR-FDPF. This approach was designed for simulating radio coverage maps from steady-state simulations. At a first glance, this approach seems adequate neither for wideband systems nor for MIMO systems. Albeit, we will discuss in this paper how this method can be adapted to this context. Further, some specific features of MR-FDPF reveal to be even very powerful.

II. MR-FDPF approach

In this section we provide the necessary background on the MR-FDPF approach. The early version of the MR-FDPF method has been derived for indoor like environments [5], [11] but we also proved in [12] that it can be extended is some cases to large urban scales, if a fake simulation frequency is used. From our opinion however, the major interest of the method is when hard propagation conditions occur such as in Indoor. As described in an associated paper [13], we guess that coupling MR-FDPF with a ray-tracer is the most promising issue for large scale simulations. For this reason, we mostly focus in this paper on Indoor like environments.

A. Frequency domain method

The initial ParFlow method relies on a TLM like formalism [14]. Flows are defined on edges between nodes in a regular grid. The waves propagate along the edges and transmissions and reflexions are tuned with linear equations that are associated with each node. From a general point of view, this system can be expressed under a general equation:

$$F(t + dt) = W \cdot F(t) + S(t) \tag{1}$$

where F(t) is a state vector that contains all propagating flows on the edges, and S(t) is the source vector. The matrix M is the transmission matrix. In the frequency domain, the steady-state problem turns into a linear system according to:

$$(I_d - W) \cdot F = S \tag{2}$$

where I_d refers to the identity matrix, and F to the harmonic flows vector. We showed previously how this system can be solved in a recursive manner, exploiting a recursive dividing procedure as represented in Fig.1. In practice, MR-FDPF

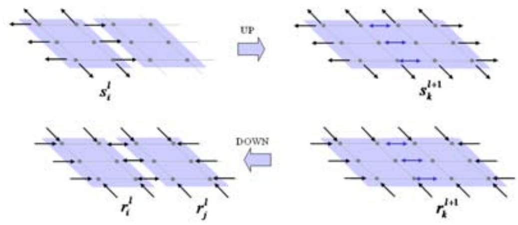

Fig. 1. father and children node flows are related with linear operations in steady-state

approach runs in two steps:

- During the first step, 'vertical' propagation matrices are recursively computed. These matrices allow to update boundary flows from children nodes to father and inversely. The computational cost of this part is the highest part and is in $O(n^3)$ [5] but the interesting property is that this preprocessing is node once whatever the source position. This computational complexity order is further identical to that of computing the coverage of one source with a time domain implementation.
- During the second step, the propagation is performed 'vertically' in the multi-resolution structure. This phase exhibits the advantages of the method: the computational load is only in $O(n^2)$ per source and the exact steady-state result is obtained while all propagation paths are accounted for. In addition, the descending propagation process can be stopped at a certain block size, and statistic parameters can be estimated from inward flows as illustrated in Fig.2. This principle is detailed in next subsection.

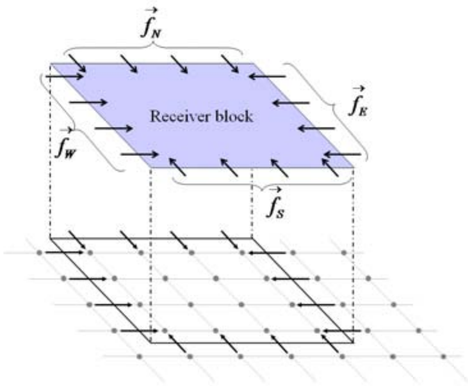

Fig. 2. This figure represents a block with inward flows from which local statistics can be derived.

B. Statistic estimations

The MR-FDPF method provides a sub-wavelength resolution. The simulations are extremely fine but strictly not exact since many artifacts in the real world are not taken into account and affect the exact value of the predicted field. Such a fine estimation is however very interesting to estimate local statistics because it provides a possible picture of what the field could be in any area. For example, we presented in [10], a study on signal strength statistics in some blocks and comparison with measurements exhibited a good agreement. The principle was to measure signal strength variations in a free-space block as represented in Fig.2. From a given block, for which the inward flows have been estimated from the rest of the environment, we can proceed to a local analysis of the incoming flows because they are directly related to the field values inside the block. In a block, the incoming flows allow to characterize the complete field inside.

$$\Psi = W_d \cdot F_{in} \tag{3}$$

where F_{in} is the vector of incoming flows, Ψ the vector field containing all field in the block and W_d is the downward matrix. Thus, the field values are obtained by linear combinations of the incoming flows. In a block, the first meaningful parameter is the average SNR, proportional to the average received power $\bar{\Gamma} = \langle |\Psi|^2 \rangle$ easily derived as:

$$\bar{\Gamma} = \frac{1}{N_x \cdot N_y} F_{in}^{\perp} \cdot W_d^{\perp} \cdot W_d \cdot F_{in} \tag{4}$$

where N_x and N_y are the block dimensions. Let be considered the standard value decomposition (SVD) $W_d = U^{\perp} \Sigma V$ where U and V are unitary matrices and Σ is a diagonal matrix. Note that we have also $W_d^{\perp} W_d = V^{\perp} \cdot \Lambda \cdot V$, wigth $\Lambda = \Sigma^{\perp} \cdot \Sigma$. Then, the inward flows can be projected in the eigenspace $G_{in} = V \cdot F_{in}$ leading to a very efficient computation of the average power in a block:

$$\bar{\Gamma} = \frac{1}{N_x \cdot N_y} G_{in}^{\perp} \cdot \Lambda \cdot G_{in} \tag{5}$$

The SVD decomposition is also very interesting to determine the main mode of the block, i.e. the inward flows that penetrate the most efficiently in the block. Indeed, the inward flow vector aligned to the highest singular value corresponds to the most efficient solution. However, the SVD decomposition cannot be used directly for computing higher order moments and the mean amplitude field. In [10], we explained how the fading strength can be estimated with the k parameter from the first and second moments of the envelope distribution. The envelope first moment A is given by:

$$\bar{A} = \frac{1}{N_x \cdot N_y} \sum_j |\Psi(j)| = \frac{1}{N_x \cdot N_y} \sum_j |u_j \cdot \Sigma \cdot G_{in}| \quad (6)$$

where u_i is the i^{th} eigen vector of U. Then, according to [10] the fading parameter is estimated with:

$$k = \frac{\sqrt{1 - \frac{\Gamma - \bar{A}^2}{\Gamma^2}}}{1 - \sqrt{1 - \frac{\Gamma - \bar{A}^2}{\Gamma^2}}} \quad (7)$$

III. MIMO CHANNEL PREDICTIONS

MIMO systems are now very usual in high rate wireless communications [6], [15]. They proved being very efficient in many context especially in Indoor like environment as they increase the diversity degree of radio links. However, the MIMO gain depends on the fading strength and inter-channel correlation [16]. The fading strength of each channel can be estimated as described above, while the intercorrelation can be characterized with the intercorrelation matrix defined as:

$$R_{hh} = E\langle h.h^{\perp} \rangle \quad (8)$$

where h is the steady-state channel vector. Predicting this correlation is a hard issue in simulation as wide and short scales phenomna have to be considered simultaneously because the different antennas are put together in a very close space. We know discuss how MR-FDP offers a good framework for such task.

A. Integration in MR-FDPF

To obtain a simple but efficient approach we use the matricial nature of the MR-FDPF engine. Let a transmitter be located in a block B_s and a receiver in a boc B_r. In MR-FDPF, directive radiation patterns can be generated with a set of multiple point source fitting with a reference radiation pattern $r(\theta)$ [17]:

$$r(\theta) = \sum_{k \in B_s} s_k \cdot e^{-j\beta\delta(k,\theta)} \quad (9)$$

where $s_k; k \in B_s$ correspond to the complex values of the equivalent sources in the k^{th} point in B_s. Then, the source beamforming vector $V_b(s) = \{s_k; k \in B_s\}$ is derived from the discretized radiation pattern Z_θ in association with a smoothing constraint represented by a matrix Sm, leading to :

$$V_b(s) = \frac{H^{\perp}}{H^{\perp}H + \mu Sm} Z_\theta \quad (10)$$

Whatever the radiation pattern, the same radiated field can be also obtained from the boundary outgoing flows of B_s, noted $F_{out}(s)$ and defined by :

$$F_{out}(s) = W_u \cdot V_b(s) \cdot S_0 \quad (11)$$

where W_u is the reverse matrix of W_d and S_0 is the complex coefficient of the source.

Let us now switch to the receiver block. Thanks to the reciprocity theorem, the beamforming vector in reception can be derived in a similar way, allowing to express the received field by using the beamforming vector (10) of the receiving antenna:

$$\Psi = V_b(r)^{\perp} \cdot \Psi(d) \quad (12)$$

where $\Psi(d)$ is the field vector in the block B. As above, we can also simplify the computation by exploiting the linear relation between boundary incoming flows and filed values leading to:

$$\Psi = V_b(r)^{\perp} \cdot W_d \cdot F_{in}(d) \quad (13)$$

Then, MIMO simulations can be derived by exploiting (11) and (13) and defining different beamforming vectors for transmission and reception $V_S = \{V_{b1}(s), V_{b2}(s), \ldots, V_{bN}(s)\}$ and $V_R = \{V_{b1}(r), V_{b2}(r), \ldots, V_{bN}(r)\}$ respectively. To compute the correlation matrix with (8), the expectation requires different realization. We propose to use a wide set of beamforming antennas, and the expectation can be performed over random selections of antennas in these sets. To avoid a high increase of the computational load, each outgoing flow from s, $f_k(s)$ is propagated solely in the multi-resolution structure to obtain the incoming flows in the destination block. Then, the linear relationship between the source and destination flows are obtained by the propagation matrix $W_P(s,d)$ which relates each source flow to each destination flow:

$$F_{in}(d) = W_P(s,d) \cdot F_{out}(s) \quad (14)$$

Therefore, the computational complexity of this approach is independent on the beamforming vectors set, but only proportional to the source block size. This approach allows simulating partially correlated MIMO channels that take into account the real environment.

IV. WIDEBAND PREDICTIONS

A. Wideband characteristics

In, OFDMA, the bandwidth is subdivided into sub-channels [8], [18]. The fading in each sub-channel is supposed flat and therefore the carrier spacing represents the maximal frequency resolution required for measuring the frequency response. In practice however, this resolution is often much fine than the experimental frequency correlation, and in practice, several adjacent channels are affected with a correlated fading. In $802.11a$ for instance, the channel width of $20MHz$ is divided into 52 sub-channels spacing with a carrier spacing equal to $312.5kHz$. Full resolution frequency response estimation would require 52 samples. The optimal frequency resolution can be also estimated from the channel time spreading with $\Delta f < 1/T_s$ where T_s is the channel time spreading. In usual

Indoor environments, time spreading is in the order of few hundred nanoseconds around $2.4GHz$. This led us considering a frequency resolution of $1MHz$. A full bandwidth estimation of the frequency response thus needs about 20 samples in the frequency domain.

From such simulation, we need a statistical estimation of the channel characteristics. The fading strength is still important for each sub-channel, but the frequency channels inter-correlation is of primary importance. Let us note h_j, the channel associated with carrier j,and $h = [h_j]^t$, the channel vector. The inter-correlation can be represented with the correlation matrix defined in (8), where the channel coefficients h_i now correspond to the frequency carriers.

B. Implementation in MR-FDPF

Wideband simulation is a very challenging issue for MR-FDPF since this approach is based on a steady-state study. Therefore, the complete propagation mechanism detailed in section II should be done several times. The main drawback of this approach is that the high computational load of the pre-processing phase is repeated as many times as the number of independent carriers. Therefore, the main limit for this wideband approach is related to the need of developing the whole preprocessing for each carrier frequency. This generates a large computational overload but also a large increase of memory resource needs, since all vertical propagation matrices have to be stored and maintained in the random access memory. if the bandwidth is very small compared to the carrier frequency, an approximated computation may appear efficient. Let us note the solution at the central frequency:

$$F(f_0) = (I_d - W(f_0))^{-1} \cdot S \tag{15}$$

where $W(f_0)$ is the propagation matrix, noted W_0 in the following. The same expression can be derived for another frequency according to:

$$F(f_0 + \delta_f) = (I_d - W(f_0 + \Delta f))^{-1} \cdot S \tag{16}$$

Note that $W(f_0 + \Delta f) = e^{(-j2\pi\Delta f \Delta t)} W(f_0)$. Δt relies on the inverse of the carrier frequency, while Δf on the system bandwidth. Then one have $\Delta t \cdot \Delta f << 1$, which allows to write (16) as:

$$F(f_0 + \delta_f) = (I_d - W_0 + W_{\delta f})^{-1} \cdot S \tag{17}$$

where $W_{\delta f} \approx -j2\pi\Delta f \Delta t \cdot W_0$ and verifies $||W_{\delta f}|| << 1$. Now, introducing $F(f_0)$ into (17) provides:

$$F(f_0 + \delta_f) = \left(I_d + (Id - W_0)^{-1} \cdot W_{\delta f}\right)^{-1} \cdot F(f_0) \tag{18}$$

which can be expanded with a Taylor series as:

$$\begin{aligned} F(f_0 + \delta_f) = \big(&I_d - (Id - W_0)^{-1} \cdot W_{\delta f} + \\ &\left((Id - W_0)^{-1} \cdot W_{\delta f}\right)^2 + \dots\big) \cdot F(f_0) \end{aligned} \tag{19}$$

At first order, one obtain:

$$F(f_0 + \delta_f) \approx F(f_0) + F^{(1)}(\delta f) \tag{20}$$

with

$$F^{(1)}(\delta f) = -(Id - W_0)^{-1} \cdot W_{\delta f} \cdot F(f_0) \tag{21}$$

This approach is very promising as it becomes possible to compute and keep in memory the matrices computed for a unique frequency. Further, the computational overload for the propagation phase is acceptable. The solution flows at f_0 are used as sources, then propagated locally to their first neighbors with $W_{\delta f}$ and finally propagated vertically in the multi-resolution structure over the whole space. If the first order approximation appears not sufficient, a second order approximation can be assessed by adding a third term equal to

$$F^{(2)}(\delta f) = -(Id - W_0)^{-1} \cdot W_{\delta f} \cdot F^{(1)}(\delta f) \tag{22}$$

which can be generalized to higher order terms:

$$F^{(n+1)}(\delta f) = -(Id - W_0)^{-1} \cdot W_{\delta f} \cdot F^{(n)}(\delta f) \tag{23}$$

At each step, the computational cost is constant.

V. Conclusion

In this paper, we discussed three important contributions to adapt MR-FDPF to OFDM/MIMO systems. The first contribution concerns the estimation of a fading channel model, that was already presented in a previous paper [17]. We here improve this approach by considering an eigen decomposition of inward flows in a homogeneous receiving block. The second contribution is the extension to MIMO simulations by considering radiation patterns in source and reception blocks. The third contribution concerns wideband systems: MR-FDPF was optimized to compute a frequency domain impulse response. Then we derived a Taylor series based approximation to overcome the computational overload associated with a multiple harmonic approach.

This paper exhibits the good properties of MR-FDPF for MIMO/OFDM systems. In a near future, we will have to validate these new features with experimental measurements.

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