Optimal Pilot Pattern Design for Dynamic Spectrum Access MIMO Multicarrier Systems

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Abstract—One of the serious challenges, which hamper application of multiple-input multiple-output (MIMO) multicarrier (MC) transmission systems in the cognitive radio (CR) environments, is the synthesis of reliable pilot signals, which can be used for the CR channel sounding. This paper addresses design of the optimal pilot pattern for MIMO-MC CRs. The principal novelty of this work in contrast to the previous ones is that the proposed solution is optimal from both performance and receiver complexity standpoint. To be more specific, we consider pilot sequence precoding, which leads to the best channel estimation accuracy, ensured by the optimal pilot power distribution and joint estimation of the second-order channel response statistics.

Keywords—channel estimation; MIMO; multicarrier; pilot pattern

I. INTRODUCTION

Multiple-input multiple-output (MIMO) multicarrier (MC) systems represent a ubiquitous concept adopted in a variety of existing and emerging wireless communication interfaces, which target increased spectral efficiency levels – up to 10bps/Hz. At present there is a growing interest in extending their functionality to the dynamic spectrum access channels, which are characterised by frequency and time varying availability of the spectrum holes suitable for transmission [1].

It is known that the best spectral efficiency is achieved only by coherent systems, which rely on the availability of channel state information (CSI) at the receiver. Pilot-assisted transmission is recognised as a reliable and efficient way to acquire CSI. During the last decade optimal pilot signal design has been an active research area [2]. In particular, there have been several investigations of the optimal pilot structure for the classic MIMO orthogonal frequency division multiplexing (OFDM) systems [3]-[5], where the recommendations of the equipaced and equipowered pilot symbols in the frequency-time grid and the independent pilot patterns for different transmit (Tx) antennas have been made to achieve the best filtering performance in the white Gaussian noise (WGN) channel. Apart from the optimal performance, such a pilot pattern (PP) is simple for practical implementation.

WGN and non-restricted subcarrier placement are traditional assumptions for the non-cognitive communication system models. In the dynamic spectrum access scenarios these conditions may not hold. The problem is aggravated by several factors. First, for each cognitive radio (CR) channel scenario there is a unique optimal PP. Second, this optimal PP might lead to a complex channel estimator implementation. Effective pilot symbols positioning to account for CR interference has been investigated in [6][7]. Referring to these research findings as a starting point, our work develops the optimal PP corresponding to the pre-allocated pilot subcarrier positions in the band. PP optimisation is carried out through the linear precoding of the reference pilot sequence. It is shown that a solution exists, which is concurrently optimal in both performance and complexity sense.

The rest of the paper is organised as follows. System and channel model aspects are described in Section II. The new PP design method is formulated and described in detail in Section III. Recommendations with regard to the power distribution of the reference pilot sequence are given in Section IV. Sections V and VI present a numerical example and main conclusions.

II. SYSTEM AND CHANNEL MODEL

In this paper, a general discrete-time baseband MIMO-MC system model is considered. It includes transmitter with \( N_\text{tx} \) antennas, receiver with \( N_\text{rx} \) \( (N_\text{tx} \geq N_\text{rx}) \) antennas and an equivalent bandlimited channel model specified for each Tx-Rx antenna link termed subsequently as spatial layer (SL). Each Tx antenna transmits blocks of \( N \) complex-valued signal symbols \( x_{n,m} \), \( n \in [0, N-1] \) from the inverse discrete Fourier transform (IDFT) processor output, where \( m \) denotes the serial index of the block \( (m \geq 0) \). Before transmission, the blocks are prepended with a cyclic prefix (CP) of a length \( N_\text{cp} \) to eliminate inter-block interference. It is assumed that the channel remains constant during one block, so there is no loss of orthogonality between subcarriers.

The channel is spatially homogenous and time-frequency selective, being described by the sampled wide-sense stationary uncorrelated scattering (WSSUS) \( K \)-path response model [8], which specifies \((i, j)\) th SL’s channel impulse response (CIR) with the energy enclosed within \( L \) samples \((L \leq N_\text{cp}+1)\) according to the formula:

\[
\mathbf{h}_{n}(j,i) = [\mathbf{h}_{L,n}(j,i)]_{x_{K}} = \mathbf{\Sigma \alpha}_{n}(j,i), \quad l \in [0, L-1],
\]

where the path gains \( \mathbf{\alpha}_{n}(j,i) = [\alpha_{L,n}(j,i)]_{x_{K}} \), \( k \in [0, K-1] \) represent zero-mean complex Gaussian random variables (CGRVs) produced by lowpass-filtered independent identical stochastic processes (the covariance matrix...
\( \mathbf{R}_{nn} = \text{E}[\mathbf{a}_n(j,i)\mathbf{a}_n(j,i) \dagger] \) is diagonal, and the elements of the band-limiting matrix \( \Sigma \) are
\[
[\Sigma]_{i,j} = [\sin \pi(l - B \tau_j)]/[\pi(l - B \tau_j)].
\]
Here \( B = (N + N_{op})/T \) is the effective bandwidth, \( T \) is the block duration (including CP), and \( \tau_j \) is the excess delay associated with the \( j \)th path. The excess delays \( \tau_j \) in (2) are considered to be SL-independent that is stipulated by small antenna spacings inside the Tx and Rx arrays in comparison with propagation distance. Thus, the CIR covariance matrix \( \mathbf{R}_{hh} = \text{E}[\mathbf{h}_n(j,i)\mathbf{h}_n(j,i) \dagger] = \Sigma \mathbf{R}_{nn} \Sigma^H \) is identical for all SLs, and CIRs at different SLs are mutually uncorrelated due to the homogeneity assumption [8].

At the receiver side, the block at the output of each Rx antenna is separated from the CP and is DFT-transformed after that. The resultant \( N_{tx} \) sets of symbols are parallel-forwarded for processing in the channel estimator and MIMO detector. Since the MC system can be interpreted as \( N \) parallel narrowband channels, which do not interfere with each other in frequency, the received symbol on the \( n \)th subcarrier at the \( j \)th antenna within the \( m \)th block is described as
\[
y_{n,m}(j) = \sum_{i=0}^{N_{tx}-1} x_{n,m}(i) h_{n,m}(j,i) + w_{n,m}(j),
\]
where \( h_{n,m}(j,i) \) is the channel frequency response (CFR) gain (to be estimated), corresponding to the \( (i,j) \)th SL, and \( w_{n,m}(j) \) is the noise sample, which represents a realisation of the zero-mean CGRV.

III. PILOT-ASSISTED ESTIMATION OF CHANNEL RESPONSE

The optimal pilot symbol sequence in the MC systems is known to be decoupled from the data symbol transmissions by means of assignment to a separate subcarrier set [9]. Let \( \mathbf{p} = [p_0, p_1, \ldots, p_{N_{tx}-1}]^T \) denote a vector of selected positioning indices associated with the pilot subcarriers, and let \( \mathbf{x}^p = [x_{p_0}, x_{p_1}, \ldots, x_{p_{N_{tx}-1}}]^T \) denote a reference sequence of the pilot symbol values. Assume that the length of this vector is \( L N_{tx} \), where \( N/N_{tx} \) is an integer and \( L \geq N/N_{tx} \); later on this assumption will be justified.

A. Linear Model of Pilot Transmission

The linear model of the frequency-multiplexed pilot transmission in the DFT-based, CP-assisted block MC system has the following mathematical description [10], specifying received symbol observations at the pilot positions at the \( j \)th Rx antenna output in the form of
\[
y_p^m(j) = N^{-1} \mathbf{C} \mathbf{F} \sum_{i=0}^{N_{tx}-1} \mathbf{H}_m(j,i) \mathbf{F}^H \mathbf{C}^H \mathbf{Z}(i) \mathbf{x}^p + \mathbf{C} \mathbf{w}_m(j),
\]
where \( m, i \) and \( j \) denote block, Tx antenna and Rx antenna indices respectively; vector \( \mathbf{w}_m(j) = [w_{p_0,m}(j) \ w_{p_1,m}(j) \ \cdots \ w_{p_{N_{tx}-1},m}(j)]^T \) contains \( N \) Gaussian noise samples at the output of the DFT processor associated with the \( j \)th Rx antenna (let the noise covariance matrix be identical for all receiver inputs and equal to \( \mathbf{R}_{ww} = \text{E}[\mathbf{w}_m(j)\mathbf{w}_m(j) \dagger] \); \( \mathbf{C} \) is the \( (L N_{tx}) \times N \) pilot selection matrix with the elements \( [\mathbf{C}]_{k,n} = \begin{cases} 1, & \text{if } n = p_k \\ 0, & \text{otherwise} \end{cases} \), \( k \in [0, L N_{tx} - 1] \); \( \mathbf{F} \) is the \( N \times N \) non-scaled DFT matrix with the elements \( [\mathbf{F}]_{m,n} = \exp(-j 2 \pi m n / N) \), \( m, n \in [0, N - 1] \); \( \mathbf{Z}(i) \) is the \( (L N_{tx}) \times (L N_{tx}) \) precoding matrix; \( \mathbf{H}_m(j,i) \) is the \( N \times N \) circular convolution matrix, having the column-wise circulant property
\[
\mathbf{H}_m(j,i) = \left[ \begin{array}{c} \mathbf{h}_m(j,i) \\ \mathbf{0}_{(N_{tx}-1 \times 1)} \end{array} \right] \cdots \left[ \begin{array}{c} \mathbf{h}_m(j,i) \\ \mathbf{0}_{(N_{tx}-1 \times 1)} \end{array} \right] \mathbf{0}_{(N_{tx}-1 \times 1)} N - 1, \right]
\]

(5)

where \( \mathbf{c}_s[\cdot] \) denotes cyclic shift downward by the specified number of elements, \( \mathbf{h}_m(j,i) = \mathbf{F}^H \mathbf{h}_m(j,i) \) is CCRF of the \( (i,j) \)th SL, and \( \mathbf{B} = \mathbf{I}_{N \times L} \) is the zero-padding matrix (\( \mathbf{I}_{N \times L} \) denotes \( N \times L \) identity matrix).

It is worth noting that \( \mathbf{H}_m(j,i) \) has only \( L \) non-zero elements in each column. The other \( N - L \) entries, originally occupied by zeros, could be assigned virtual values to bring \( \mathbf{H}_m(j,i) \) to a more compact linear form. Filling \( L N_{tx} \) arbitrary entries in the column of \( \mathbf{H}_m(j,i) \) with CIR samples from all \( N_{tx} \) Tx antennas ensures algebraic separation of the channel responses at different SLs. The question is what the precoding matrices \( \mathbf{Z}(i) \) should be equal to for this separation to be realised.

Let the matrix \( \mathbf{D}(i) \) denote cyclic shift upward by delta rows, specified by the expression,
\[
\mathbf{D}(i) = \text{cs}[\mathbf{I}_{N \times L - N_{tx}}, -\Delta(i)],
\]
then the permuted \( \mathbf{H}_m(j,i) \mathbf{D}(i)^H \) could be expressed as \( \mathbf{H}_m(j,i) \mathbf{D}(i)^H \), and the corresponding precoding matrix to encode this permutation at the transmitter is
\[
\mathbf{Z}(i) = \mathbf{C} \mathbf{F} \mathbf{D}(i)^H \mathbf{F}^H \mathbf{C}^H
\]

(7)
in (4). From here it becomes clear that the rank of \( \mathbf{Z}(i) \) (and the length of the reference pilot sequence \( \mathbf{x}^p \)) must be equal to at least \( L N_{tx} \) for the precoding to be realisable.

Introduction of the substitute matrix
\[
\mathbf{H}_m(j) = \sum_{i=0}^{N_{tx}-1} \mathbf{H}_m(j,i) \mathbf{D}(i)^H,
\]
which contains all CIR components of the MIMO channel ending at the \( j \)th Rx antenna (i.e. \( L N_{tx} \) non-zero components in each column of \( \mathbf{H}_m(j) \)), allows re-expressing (4) in a much simpler form:
\[
y_p^m(j) = N^{-1} \mathbf{C} \mathbf{F} \mathbf{H}_m(j) \mathbf{F}^H \mathbf{C}^H \mathbf{x}^p + \mathbf{C} \mathbf{w}_m(j)
\]
Equation (8) is recognised as the classic linear model, from where the maximum likelihood (ML) estimate of the virtual CIR \( \vec{h}_n(j) = [\vec{h}_n(j,0)\, \vec{h}_n(j,1)\, \ldots \, \vec{h}_n(j,N_m-1)]^T \) is known to be equal to [11]

\[
\vec{h}_n(j) = (X^*CFA)^H R_{\text{ww}}^{-1} X^*CFA]^{-1} (X^*CFA)^H R_{\text{ww}}^{-1} y_n^p(j),
\]

(9)

where \( R_{\text{ww}} = C \) is the pilot noise covariance matrix, which can be assumed diagonal in the practical case of pilot subcarriers being scattered in the band. From here one can obtain ML CIR estimates for the individual SLs as \( \vec{h}_n(j,i) = K(i) \vec{h}_n(j), \) where the product with the matrix

\[
K(i) = \left[ \begin{array}{c} 0_{L \times (i-1)} \\ I_{L 	imes L} \\ 0_{L 	imes (N_m-i-1)} \end{array} \right]
\]

selects \( \vec{h}_n(j,i) \) samples from the vector \( \vec{h}_n(j). \)

By substitution of \( y_n^p(j) \) into (9), one can express:

\[
\vec{h}_n(j,i) = \vec{h}_n(j,i) + K(i)(X^*CFA)^H C w_n(j),
\]

(10)

i.e. the signal at the output of the ML estimator is damped into the additive Gaussian noise, which is uncorrelated with \( \vec{h}_n(j,i) \) and has the covariance

\[
\Sigma_{\vec{h}_n(i)} = E[(\vec{h}_n(j,i) - \vec{h}_n(j,i))^H(\vec{h}_n(j,i) - \vec{h}_n(j,i))^H] = K(i) S K(i)^H,
\]

(11)

where

\[
S = (X^*CFA)^{-1} R_{\text{ww}}^{-1} (X^*CFA)^{-H}.
\]

C. Optimal Extension to MMSE Scheme

The ML estimates (10) can be subject to further smoothing by taking into account the CIR and noise covariance. However, a variety of the estimation error covariance matrices \( \Sigma_{\vec{h}_n(i)} \) associated with different Tx antennas complicate the necessary receiver enhancements. An optimal low-complexity secondary filtering with identical filter design for all SLs would be possible if \( \Sigma_{\vec{h}_n(i)} \) could be the same for all \( i \).

It can be that the persymmetric hermitean matrix \( S \), partitioned into \( N_m \times N_m \) square \((L \times L)\) submatrices, has the property of equal submatrices on the main diagonal yielding identical \( \Sigma_{\vec{h}_n(i)} \) for all \( i \) if and only if

\[
A = \begin{bmatrix}
I_{(N_m/N_s) \times L} & 0_{(N_m/N_s) \times L} \\
0_{(N_m/N_s) \times L} & I_{(N_m/N_s) \times L} \\
\vdots & \vdots \\
0_{(N_m/N_s) \times L} & 0_{(N_m/N_s) \times L} \\
\end{bmatrix},
\]

(13)

where \( 0_{(N_m/N_s) \times L} \) denotes \((N_m/N_s) \times L\) zero matrix.

To conform to the constraint (13), affecting the virtual CFR \( \vec{h}_n(j) = FA \vec{h}_n(j) \) and hence the circular convolution matrix \( \vec{h}_n(j) \), the individual CIR vectors comprising the columns of \( \vec{h}_n(j) \) have to be equally cycle-shifted by \( N_m/N_s \) elements with respect to each other. Mathematically, this corresponds to the following definition of the optimal shift value in (6):

\[
\Delta(i) = iN_m/N_s, \quad i = [0, N_m-1].
\]

(14)

Thus, equality of the channel estimation error covariance matrix across SLs associated with different Tx antennas (and hence secondary filtering complexity reduction) is ensured by the optimal parameters (13) and (14), which are used in the estimator (9) and the PP precoder (7) respectively.

The secondary linear filtering based on the minimum mean square error (MMSE) criterion is realised by extending the ML estimator \( \vec{h}_n(j,i) = K(i) \vec{h}_n(j) \) to smooth out the noise effect in (10). According to the Gauss-Markov theorem [11], the MMSE CIR estimates are computed as

\[
\hat{h}_n(j,i) = (R_{hh} + R_{\text{ee}}^{-1})^{-1} K(i) \tilde{h}_n(j),
\]

(15)

where \( R_{\text{ee}} = R_{\text{ee}}(0) = K(0) S K(0)^H \) (due to \( R_{\text{ee}}(i) \) being the same for all \( i \)) and \( R_{hh} = R_{hh} + R_{\text{ee}} \).

D. Recursive Operation Mode

The estimator (15) relies on the a priori known CIR covariance matrix \( R_{hh} \) and the noise covariance matrix \( R_{\text{ww}} \). Coupling of the linear filtering with the covariance estimation yields adaptive channel estimator architecture, adjusting itself to the channel. In this work, an earlier proposed recursive MMSE (RMMSE) algorithm [12] is adopted for improving estimation performance in the channels with arbitrary response covariance.

Let the instantaneous estimate of the precision matrix \( T_{hh} = (R_{hh} + R_{\text{ee}}^{-1})^{-1} \) of CIR-plus-error mixture be denoted as \( \hat{T}_{hh} \). It can be shown that the precision matrix estimate can be updated recursively block-by-block [10][12]:

\[
\hat{T}_{hh} = \frac{1}{1 - \alpha_{ss}} \hat{T}_{hh} - \frac{V_m}{N_m N_s (1 - \alpha_{ss} / \alpha_{pp} + tr(V_m))},
\]

(16)
where $\alpha_{FF}$ ($0 < \alpha_{FF} < 1$) is the forgetting factor (FF) preset or adapted according to the channel variability, 
\[
V_n = \left[ \sum_{i = 0}^{L N - 1} \sum_{j = 0}^{L R - 1} K(i) \tilde{h}_m(i, j) \tilde{h}_m(j, H) H \right] T_{bbm}^{-1} - I
\]
with the recommended setting $t \rightarrow \infty$. It should be noted here that channel response measurements from all $N_L N_R$ independent SLs are aggregated to produce the $\hat{T}_{bbm}$ estimate. Thus, apart from reduced receiver complexity via identical SL filtering modules, channel estimation performance is expected to be improved due to the joint response covariance estimation.

Based on (16) and the noise covariance matrix $R_m$ (which is assumed to be acquired by external means), the RMMSE CIR estimates are computed as
\[
\hat{h}_{m}^{\text{RMMSE}}(j, i) = (I_{L R N} - R_m \hat{T}_{bbm}^{-1}) K(i) \tilde{h}_m(j).
\]

Comparing equations (15) and (17), it can be seen that the RMMSE estimator becomes MMSE-optimal if the CIR-plus-error precision matrix is estimated perfectly, i.e. when $\hat{T}_{bbm} \rightarrow T_{bbm}$.

IV. OPTIMAL DISTRIBUTION OF PILOT SYMBOLS POWER

In the preceding section it has been shown that PP precoding, yielding the complexity-optimal channel estimator design, can be realised for any reference pilot sequence $x^p$. Additionally, the reference pilot sequence can be selected to guarantee the least sum of square errors (SSE) of the ML CIR estimation, i.e.
\[
x_{PP}^{opt} = \arg \min z^T R z,
\]
subject to the total pilot power constraint $x^p H x^p = \sigma_j^2$. Here $z = [x_{\pi_1} \cdots x_{\pi_{L R N - 1}}]^T$, $R = (CFA^{H} F^{H} C^{H})^{-1} \otimes R_{xx}^{opt} \cdot \text{tr}(\cdot)$, $(\cdot)^*$ and $\otimes$ denote matrix trace, complex conjugate and element-wise product respectively.

It can be shown that $\text{tr}(S) \geq \sigma_j^2 \text{tr}(S R_{opt} L x^{1/2})$, with the equality if and only if $x^p = [\text{tr}(R_{opt} L x^{1/2})]^{-1/2} R_{opt}^{1/2} 1_{(L R N, 1)}$, where $1_{(L R N, 1)}$ is the vector of all ones, and the phase of the pilot symbols is specified to be constant as it does not affect the channel estimation SSE.

V. NUMERICAL ANALYSIS

A. System Configuration

Let the example configuration represent a discrete-time fully synchronised baseband MIMO-MC system with the processing block length $N = 64$. The modelled CIR length is $L = 6$ samples. The number of Tx antennas is 2, and the number of Rx antennas is 4. 12 subcarriers in each transmitted block are dedicated to serve as pilots and their locations are specified for 3 different scenarios:

PP1. $p = [1 \ 4 \ 7 \ 10 \ 13 \ 16 \ 45 \ 48 \ 51 \ 54 \ 57 \ 60]^T$ (a wide section in the middle of the bandwidth between the subcarriers #16 and #45 is unavailable for transmission);

PP2. $p = [1 \ 6 \ 11 \ 16 \ 19 \ 30 \ 33 \ 36 \ 44 \ 49 \ 54 \ 59]^T$ (two narrow band sections #20-#29 and #37-#43 are unavailable for transmission);

PP3. $p = [3 \ 8 \ 13 \ 18 \ 23 \ 28 \ 33 \ 38 \ 43 \ 48 \ 53 \ 58]^T$ (pilot subcarriers are uniformly spaced in the band).

The multipath channel model for each SL is constituted by $K = 3$ equipowered independent identically distributed components with the non-sample-spaced excess delays $\tau_0 = 1.5 B^{-1}$, $\tau_1 = 2.2 B^{-1}$ and $\tau_2 = 3.7 B^{-1}$. The interblock channel variation is modelled as a white stochastic process.

There is no need to simulate the ML and MMSE estimators as their performance can be determined using MSE formulas:
\[
\sigma_{\text{mle}}^2 = \text{tr}(R_{m}),
\]
\[
\sigma_{\text{mmse}}^2 = \text{tr}(R_{m}(R_{bbm} + R_{m})^{-1} R_{m}) \label{21}
\]

The RMMSE estimator is simulated with parameters $\alpha_{FF} = 0.01$ and $t = 10^5$. It should be noted that since no specific model is adopted to describe channel response time variation, the choice of the forgetting factor does not play a significant role. In this example, we do not aim to compare RMMSE performance with any other algorithm. This problem has already been investigated in detail previously [10][12].

The convergence behaviour of the RMMSE estimator is monitored by block-wise computation of the normalised sum of square errors (NSSE):
\[
\text{NSSE}_{m} = \frac{1}{N_L N_R} \sum_{i = 0}^{L N - 1} \sum_{j = 0}^{L R - 1} \left[ (\hat{h}_{m}(j, i) - h_{m}(j, i))^H (\hat{h}_{m}(j, i) - h_{m}(j, i)) \right] \label{22}
\]
that is averaged over 10 realisations of the channel process.

B. Performance Evaluation

Performance of the RMMSE estimator’s initialisation stage is illustrated in Fig.1. Due to the equality of the ML estimation error covariance matrices at different SLs, the actual MIMO array dimensions do not matter. In our example assuming $N_L = 4$, increase of the number of Tx antennas from 1 to 2 corresponds to the transition from “4 SLs” to “8 SLs” curve in the figure. This is possible only if the CIR-plus-error covariance matrix is estimated jointly on all SLs associated with different Tx antennas, and the proposed pilot precoding should be regarded as the enabling scheme for that. The achievable gain of the estimator convergence speed-up from doubling the number of aggregated CIR-plus-error measurements is clearly visible: the average NSSE difference at some transient points (e.g., $m = 20$ for comparison between “4 SLs” and “8 SLs”, $m = 10$ for comparison between “8 SLs” and “16 SLs”, etc.) reaches an order of the magnitude.
Analysis of the channel estimation MSE with different PPs (Fig.2 and Fig.3) shows that certain pilot subcarrier positioning schemes fundamentally limit performance and this effect cannot be compensated by other means, e.g., via optimal distribution of the pilot symbol power. In fact, for a variety of investigated PPs the MSE improvement after pilot power loading optimisation has been found marginal and tending to disappear if the MMSE (or RMMSE) channel estimator is employed. The experimental scenarios illustrated in Fig.2 and Fig.3 included both the WGN channel model (PP2 and PP3 cases) and the channel model characterised by the exponential noise variance distribution with the peak in the band centre and the exponent’s factor being equal to 12 (PP1 case). It should be noted that the power-optimised PP noticeably differs from the equipowered PP only in the case of the exponential noise model and PP1 scheme, in other scenarios (PP2 and PP3) optimal and equipowered PP shapes are close to each other.

A more interesting finding (Fig.3) is that with some pilot arrangements and noise variance profiles, the MMSE estimator can gain more than an order of the MSE magnitude with respect to ML (see the PP1 case). This observation emphasises the RMMSE algorithm’s potential as an adaptive MMSE implementation suitable for practical deployments.

VI. CONCLUSION

The distinctive feature of the developed CR MIMO-MC PP solution is the concurrent optimality property from both channel estimation and receiver complexity standpoint. Simulation examples have shown the advantages of the MMSE-type channel estimation algorithms specifically for the opportunistic pilot positioning in the band, which is necessitated by the CR channel limitations. The RMMSE scheme is particularly attractive from the practical standpoint as its design does not rely on the a priori known channel response covariance unlike the optimal MMSE counterpart.

REFERENCES