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Robust Linear Transceiver Design for Multi-Hop Non-Regenerative MIMO Relaying Systems

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Abstract—In this paper, optimal linear transceiver designs for multi-hop amplify-and-forward (AF) Multiple-input Multiple-output (MIMO) relaying systems with Gaussian distributed channel estimation errors are investigated. Some commonly used transceiver design criteria are unified into a single matrix-variate optimization problem. With novel applications of majorization theory and properties of matrix-variate function, the optimal structure of robust transceiver is first derived. Based on the optimal structure, the original transceiver design problems are reduced to much simpler problems with only scalar variables whose solutions are readily obtained by iterative water-filling algorithms. The performance advantages of the proposed robust designs are demonstrated by the simulation results.

Index Terms—Amplify-and-forward (AF), MIMO relay, majorization theory, robust transceiver design

I. INTRODUCTION

In order to satisfy the emerging requirements for high speed ubiquitous wireless communications, MIMO cooperative communication has become one of the key parts in the future wireless standards such as LTE, IMT-Advanced, Winner project, etc. Transceiver design for amplify-and-forward (AF) MIMO relaying systems has been reported in [1]–[6]. There are various design criteria with different goals. The most common criteria are capacity maximization [1], [2], [5] and data mean-square-error (MSE) minimization [3]–[5]. In most of the previous works on transceiver design, most of the designs are restricted for dual-hop AF MIMO relaying systems as special cases. There is one source with $N_1$ antennas wants to communicate with the destination with $M_K$ antennas through $K – 1$ relays. For the $k^{th}$ relay, it has $M_k$ receive antennas and $N_{k+1}$ transmit antennas. It is obvious that the dual-hop AF MIMO relaying systems is one of its special cases when $K = 2$.

At the source, a $N \times 1$ data vector $s$ with covariance matrix $R_s = E\{ss^H\} = I_N$ is transmitted through a precoder matrix $P_1$. The received signal $x_1$ at the first relay is

$$x_1 = H_1 P_1 s + n_1$$

where $H_1$ is the MIMO channel matrix between the source and the first relay, and $n_1$ is the additive Gaussian noise vector at the first relay with zero mean and covariance matrix $R_{n_1} = \sigma^2 I_{M_1}$.

At the first relay, the received signal $x_1$ is first multiplied by a forwarding matrix $P_2$ and then the resultant signal is transmitted to the second relay. The received signal $x_2$ at the second relay is given by

$$x_2 = H_2 P_2 x_1 + n_2 = H_2 P_2 H_1 P_1 s + H_2 P_2 n_1 + n_2,$$

where $\sigma^2 I_{M_1}$ denotes an $M \times M$ identity matrix.

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where $\mathbf{H}_2$ is the MIMO channel matrix between the first relay and the second relay, and $\mathbf{n}_2$ is the additive Gaussian noise vector at the second relay with zero mean and covariance matrix $\mathbf{R}_{n_2} = \sigma_n^2 \mathbf{I}_{M_2}$. Similarly, the received signal at $k^{th}$ relay can be written as

$$\mathbf{x}_k = \mathbf{H}_k \mathbf{P}_k \mathbf{x}_{k-1} + \mathbf{n}_k$$  \hspace{1cm} (3)

where $\mathbf{H}_k$ is the channel for the $k^{th}$ hop, and $\mathbf{n}_k$ is the additive Gaussian noise with zero mean and covariance matrix $\mathbf{R}_{n_k} = \sigma_n^2 \mathbf{I}_{M_k}$.

Finally, for a $K$-hop AF MIMO relaying system, the received signal at the destination is
taken to be

$$\mathbf{y} = \left[ \prod_{k=1}^{K} \mathbf{H}_k \mathbf{P}_k \right] \mathbf{s} + \sum_{k=1}^{K-1} \left[ \prod_{j=k+1}^{K} \mathbf{H}_j \mathbf{P}_j \right] \mathbf{n}_k + \mathbf{n}_K,$$  \hspace{1cm} (4)

where $\prod_{k=1}^{K} \mathbf{Z}_k$ denotes $\mathbf{Z}_K \times \cdots \times \mathbf{Z}_1$. In order to guarantee the transmitted data $\mathbf{s}$ can be recovered at the destination, it is assumed that $N_k$ and $M_k$ are greater than or equal to $N$.

In practical systems, because of limited length of training sequences, channel estimation errors are inevitable. With channel estimation errors, we can write

$$\mathbf{H}_k = \bar{\mathbf{H}}_k + \Delta \mathbf{H}_k,$$  \hspace{1cm} (5)

where $\bar{\mathbf{H}}_k$ is the estimated channel in the $k^{th}$ hop and $\Delta \mathbf{H}_k$ is the corresponding channel estimation error whose elements are zero mean Gaussian random variables. Moreover, the $M_k \times N_k$ matrix $\Delta \mathbf{H}_k$ can be decomposed using the widely used Kronecker model $\Delta \mathbf{H}_k = \Sigma^{1/2}_k \bar{\mathbf{H}}_k \Psi_k^{1/2}$ [7, 8]. The elements of the $M_k \times N_k$ matrix $\bar{\mathbf{H}}_k$ are independent and identically distributed (i.i.d.) Gaussian random variables with zero mean and unit variance. The specific formulas of the row correlation matrix $\Sigma_k$ and the column correlation matrix $\Psi_k$ are determined by the training sequences and channel estimators being used [7, 8].

At the destination, a linear equalizer $\mathbf{G}$ is employed to detect the desired data vector $\mathbf{s}$. The resulting data MSE matrix equals to $\Phi(\mathbf{G}) = \mathbb{E}\{[\mathbf{Gy} - \mathbf{s}][\mathbf{Gy} - \mathbf{s}]^H\}$, where the expectation is taken with respect to random data, channel estimation errors, and noise. Following a similar derivation in dual-hop systems [8], the MSE matrix is derived to be

$$\Phi(\mathbf{G}) = \mathbb{E}\{[\mathbf{Gy} - \mathbf{s}][\mathbf{Gy} - \mathbf{s}]^H\} = \mathbf{G}[\bar{\mathbf{H}}_K \mathbf{P}_K \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_K^H \bar{\mathbf{H}}_K^H] \mathbf{G}^H + \mathbb{E}\{\mathbf{R}_{n_K} \mathbf{G}^H\} + \mathbb{E}\{\mathbf{I}_N \mathbf{G}^H\},$$

where the received signal covariance matrix $\mathbf{R}_{\mathbf{x}_K}$ at the $k^{th}$ relay satisfies the following recursive formula

$$\mathbf{R}_{\mathbf{x}_K} = \bar{\mathbf{H}}_K \mathbf{P}_K \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_K^H \bar{\mathbf{H}}_K^H + \mathbb{E}\{\mathbf{G} \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_K^H \mathbf{G}^H\} \Sigma_K + \mathbb{E}\{\mathbf{R}_{n_K}\},$$  \hspace{1cm} (7)

and $\mathbf{R}_{\mathbf{x}_0} = \mathbf{R}_s = \mathbf{I}_N$ represents the signal covariance matrix at the source.

### III. Transceiver Design Problems

#### A. Objective Functions

There are various performance metrics for transceiver designs. In the following, we focus on two widely used metrics.

1. In general, for balancing the performance across different data streams, (e.g., minimizing the worst data stream MSE), the objective function is written as [9]

$$\text{Obj 1: } \psi_1[\mathbb{d}(\Phi(\mathbf{G}))]$$  \hspace{1cm} (8)

where $\psi_1(\bullet)$ is an increasing Schur-convex function\(^2\) and $\mathbb{d}(\Phi(\mathbf{G})) = [\Phi(\mathbf{G})]_{1,1} [\Phi(\mathbf{G})]_{2,2} \cdots [\Phi(\mathbf{G})]_{K, K}^H$, with the symbol $(i, j)$ representing the $(i, j)^{th}$ entry of $\mathbf{Z}$.

2. On the other hand, if a preference is given over a certain data streams, (e.g., loading more resources to the data streams with better channel state information), the objective function can be written as

$$\text{Obj 2: } \psi_2[\mathbb{d}(\Phi(\mathbf{G}))]$$  \hspace{1cm} (9)

where $\psi_2(\bullet)$ is an increasing Schur-concave function.

#### B. Problem Formulation

Although the above two criteria aim at different designs, the transceiver design optimization problem can be unified into a single form:

$$\min_{\mathbf{P}_k, \mathbf{G}} f(\Phi(\mathbf{G}))$$

s.t. $\text{Tr}(\mathbf{P}_k \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_k^H) \leq P_k, \quad k = 1, \ldots, K$  \hspace{1cm} (10)

where the objective function $f(\bullet)$ is a real-valued matrix-variate function with $\Phi(\mathbf{G})$ as its argument. Notice that for all the two objectives described above, $f(\bullet)$ is a matrix-monotone increasing function.

For (10), there is no constraint on the equalizer $\mathbf{G}$. We can differentiate the trace of (6) with respect to $\mathbf{G}$ and obtain the LMMSE equalizer

$$\mathbf{G}_{\text{LMMSE}} = \left[ \prod_{k=1}^{K} \bar{\mathbf{H}}_k \mathbf{P}_k \right]^H \left[ \bar{\mathbf{H}}_K \mathbf{P}_K \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_K^H \bar{\mathbf{H}}_K^H \right] + \text{Tr}(\mathbf{P}_K \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_K^H \mathbf{G}^H \Sigma_K + \mathbf{R}_{n_K})^{-1},$$  \hspace{1cm} (11)

with the property [10]

$$\Phi(\mathbf{G}_{\text{LMMSE}}) \preceq \Phi(\mathbf{G}).$$  \hspace{1cm} (12)

Because $f(\bullet)$ is a matrix-monotone increasing function, (12) implies that $\mathbf{G}_{\text{LMMSE}}$ minimizes the objective function in (10). Substituting the optimal equalizer of (11) into $\Phi(\mathbf{G})$ in (6), $\Phi(\mathbf{G})$ equals to

$$\Phi_{\text{MSE}} = \mathbf{I}_N - \left[ \prod_{k=1}^{K} \bar{\mathbf{H}}_k \mathbf{P}_k \right]^H \left[ \bar{\mathbf{H}}_K \mathbf{P}_K \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_K^H \bar{\mathbf{H}}_K^H \right] + \text{Tr}(\mathbf{P}_K \mathbf{R}_{\mathbf{x}_{K-1}} \mathbf{P}_K^H \mathbf{G}^H \Sigma_K + \mathbf{R}_{n_K})^{-1} \left[ \prod_{k=1}^{K} \bar{\mathbf{H}}_k \mathbf{P}_k \right]^H,$$  \hspace{1cm} (13)

\(^2\)The detailed introduction of Schur-convex/convex functions, and majorization theory is given in [11].
For multi-hop AF MIMO relaying systems, the received signal at the \( k \)'th relay depends on the forwarding matrices at all preceding relays, making the power allocations at different relays couples with each other (as seen in the constrains of (10)), and thus the problem (10) difficult to solve. In order to simplify the problem, we define the following new variable in terms of \( P_k \):

\[
F_k \triangleq P_k K_k^{1/2} \times \left( K_k^{-1/2} \tilde{H}_{k-1} F_{k-1}^H K_k^{-1/2} H_{k-1} + I_{M_{k-1}} \right)^{1/2} Q_{k-1}^{-1/2},
\]

where \( K_F \triangleq \text{Tr}(F_k F_k^H \Psi_k) \Sigma_k + \sigma_n^2 I_{M_k} \) and \( Q_k \) is an unknown unitary matrix. The introduction of \( Q_k \) is due to that fact that for a positive semi-definite matrix \( M \), its square roots has the form \( M^{1/2} Q \) where \( Q \) is an unitary matrix. Notice that if \( F_1 = P_1 \). With the new variable, the MSE matrix \( \Phi_{\text{MSE}} \) is reformulated as

\[
\Phi_{\text{MSE}} = I_N - \left[ \prod_{k=1}^{K} Q_k \Pi_{k}^{-1/2} K_F^{1/2} \tilde{H}_k F_k \right]^H \times \left[ \prod_{k=1}^{K} Q_k \Pi_{k}^{-1/2} K_F^{1/2} \tilde{H}_k F_k \right],
\]

\[
= I_N - A_1^H \cdots A_K^H A_K \cdots A_1.
\]

Meanwhile, with the new variables \( F_k \), the corresponding power constraint in the \( k \)'th hop can now be rewritten as

\[
\text{Tr}(F_k F_k^H) \leq P_k.
\]

It is obvious that with the new variables \( F_k \), the constraints become independent of each other. Putting (15) and (16) into (10), the transceiver design problem can be reformulated as

\[
P_1: \min_{F_k, Q_k} \quad f(I_N - \Theta)
\]

s.t. \( \text{Tr}(F_k F_k^H) \leq P_k, \quad k = 1, \ldots, K \)
\[
\Theta = A_1^H \cdots A_K^H A_K \cdots A_1
\]
\[
Q_k^H Q_k = I_{M_k}
\]

**Property 1:** At the optimal value of \( P_1 \), \( \Theta \) must have the structure of

\[
\Theta = U_\Omega \text{diag}[\lambda(\Theta)] U_\Omega^H
\]

where the vector \( \lambda(\Theta) = [\lambda_1(\Theta), \cdots, \lambda_N(\Theta)]^T \) with \( \lambda_n(\Theta) \) being the \( n \)'th largest eigenvalue of \( \Theta \), and

\[
U_\Omega = \begin{cases} 
Q_F & \text{for Obj 1} \\
I_N & \text{for Obj 2} 
\end{cases}
\]

In (19), the unitary matrix \( U_W \) is defined from the eigen-decomposition \( W = U_W \Lambda_W U_W^H \) with \( \Lambda_W \) \( \succ \) the matrix \( U_{\text{Arb}} \) is an arbitrary unitary matrix, and \( Q_F \) is the unitary matrix which makes \( Q_F \text{diag}[\lambda(\Theta)] Q_F^H \) having identical diagonal elements. Furthermore, with this optimal structure, the objective function of \( P_1 \) simplifies to

\[
f(I_N - U_\Omega \text{diag}[\lambda(\Theta)] U_\Omega^H) = g[\lambda(\Theta)]
\]

where \( g(\bullet) \) is a monotonically decreasing and Schur-concave function with respective to \( \lambda(\Theta) \).

**Proof:** See Appendix A. \( \blacksquare \)

Based on Property 1, the objective function of (17) can be directly replaced by \( g[\lambda(\Theta)] \) and thus the optimization problem is simplified as

\[
P_2: \min_{F_k, Q_k} \quad g[\lambda(\Theta)]
\]

s.t. \( \Theta = A_1^H \cdots A_K^H A_K \cdots A_1 \)
\[
\text{Tr}(F_k F_k^H) \leq P_k, \quad Q_k^H Q_k = I_{M_k}
\]
\[
\Theta = U_\Omega \text{diag}[\lambda(\Theta)] U_\Omega^H
\]

where \( A_k \)'s are defined in (15). In order to further simplify the optimization problem, we make use of the following two additional properties.

**Property 2:** As \( g(\bullet) \) is a decreasing and Schur-concave function and \( \lambda(\Theta) \prec_w \gamma(\Theta) \), the objective function in \( P \) 2 satisfies

\[
g[\lambda(\Theta)] \geq g[\gamma_1(\Theta) \cdots \gamma_N(\Theta)]^T\]

\[
\triangleq g(\gamma(\Theta))
\]

with \( \gamma_i(\Theta) \triangleq \lambda_i(A_K^H A_K) \lambda_i(A_{K-1}^H A_{K-1}) \cdots \lambda_i(A_1^H A_1) \),

\[
\text{where the equality in (22) holds when the neighboring } A_k \text{'s satisfy}
\]
\[
V_{A_k} = U A_{k-1}, \quad k = 2, \cdots, K
\]

with unitary matrices \( U_{A_k} \) and \( V_{A_k} \) being defined based on the following singular value decomposition \( A_k = U_{A_k} A_{k} V_{A_k}^H \) with \( A_{k-1} \) \( \prec \).

**Property 3:** As \( g(\bullet) \) is a monotonically decreasing function with respective to its vector argument, the optimal solutions of the optimization problem always occur on the boundary:

\[
\text{Tr}(F_k F_k^H) = P_k.
\]

\( ^3 \)The specific expressions of \( g(\bullet) \) are given in Appendix A, but they are not important for the derivation of the optimal structures.
Furthermore, defining
\[
\eta_{f_k} \triangleq \text{Tr}(F_k F_k^H \Psi_k) + \sigma^2_{n_k}
\]  
with \( \alpha_k = \text{Tr}(\Sigma_k)/M_k \) which is a constant, (25) is equivalent to
\[
\text{Tr}[F_k F_k^H (\alpha_k P_k \Psi_k + \sigma^2_{n_k} I_{N_k})]/\eta_{f_k} = P_k.
\]  

Based on Properties 2 and 3, the optimal solution of the optimization problem (21) is exactly the optimal solution of the following new optimization problem with different constraints
\[
P 3: \min_{F_k, Q_k} \quad g[\gamma(\Theta)]
\]
\[
\text{s.t.} \quad \text{Tr}[F_k F_k^H (\alpha_k P_k \Psi_k + \sigma^2_{n_k} I_{N_k})]/\eta_{f_k} = P_k
\]
\[
\Theta = A_1^H \cdots A_K^H A_K \cdots A_1
\]
\[
Q_k \geq I_{M_k}, \quad \Theta = U_{\Omega} \text{diag}[\gamma(\Theta)] U_{\Omega}^H
\]
\[
V_{A_k} = U_{A_{k-1}}, \quad k = 2, \ldots, K.
\]  

Noticing that \( g(\bullet) \) is a monotonically decreasing function, solving P 3 gives the following structure for the optimal solution.

**Conclusion 1:** Defining unitary matrices \( U_{\mathcal{H}_k} \) and \( V_{\mathcal{H}_k} \) based on the following singular value decomposition
\[
(K_{F_k}/\eta_{f_k})^{-1/2} \tilde{H}_k (\alpha_k P_k \Psi_k + \sigma^2_{n_k} I_{N_k})^{-1/2} = U_{\mathcal{H}_k} \Lambda_{\mathcal{H}_k} V_{\mathcal{H}_k}^H
\]  
with \( \Lambda_{\mathcal{H}_k} \preceq \) and \( U_{\mathcal{H}_0} = U_{\Omega} \),
\[
(29)
\]
when \( \Psi_k \propto I \) or \( \Sigma_k \propto I \), the optimal solutions of the optimization problem (28) have the following structure
\[
F_{k,\text{opt}} = \sqrt{\xi_k(\Lambda_{\mathcal{H}_k})} (\alpha_k P_k \Psi_k + \sigma^2_{n_k} I_{N_k})^{-1/2} \times \Psi_k (\alpha_k P_k \Psi_k + \sigma^2_{n_k} I_{N_k})^{-1/2} V_{\mathcal{H}_k,\text{N}} \Lambda_{\mathcal{H}_k,\text{N}} V_{\mathcal{H}_k,\text{N}}^H
\]
\[
Q_{k,\text{opt}} = I_{M_k},
\]  
where \( V_{\mathcal{H}_k,\text{N}} \) and \( U_{\mathcal{H}_k,\text{N}} \) are the matrices consisting of the first \( N \) columns of \( V_{\mathcal{H}_k} \) and \( U_{\mathcal{H}_k} \), respectively, and \( \Lambda_{\mathcal{H}_k} \) is a \( N \times N \) unknown diagonal matrix. The scalar \( \xi_k(\Lambda_{\mathcal{H}_k}) \) is a function of \( \Lambda_{\mathcal{H}_k} \) and equals to
\[
\xi_k(\Lambda_{\mathcal{H}_k}) = \eta_{f_k}
\]
\[
= \sigma^2_{n_k}/[1 - \alpha_k \text{Tr}[V_{\mathcal{H}_k,\text{N}} (\alpha_k P_k \Psi_k + \sigma^2_{n_k} I_{N_k})^{-1/2} \times \Psi_k (\alpha_k P_k \Psi_k + \sigma^2_{n_k} I_{N_k})^{-1/2} V_{\mathcal{H}_k,\text{N}} \Lambda_{\mathcal{H}_k,\text{N}} V_{\mathcal{H}_k,\text{N}}^H]}.\]
\[
(31)
\]

In the optimal structure given by (30), the scalar variable \( \xi_k(\Lambda_{\mathcal{H}_k}) \) is only a function of the matrix \( \Lambda_{\mathcal{H}_k} \) and therefore the only unknown variable in (30) is \( \Lambda_{\mathcal{H}_k} \). The remaining unknown diagonal elements of \( \Lambda_{\mathcal{H}_k} \) can be obtained by water-filling alike solution as discussed in the next section.

**V. Computations of \( \Lambda_{\mathcal{H}_k} \)**

The remaining unknown variables in (30) are only \( \Lambda_{\mathcal{H}_k} \). Substituting the optimal structures given by Conclusion 1 into P 3 and defining \( [\Lambda_{\mathcal{H}_k}]_{i,i} = h_{k,i} \) and \( [\Lambda_{\mathcal{F}_k}]_{i,i} = f_{k,i} \) for \( i = 1, \ldots, N \), the optimization problem for computing \( \Lambda_{\mathcal{F}_k} \) becomes
\[
\min_{f_{k,i}} \quad g[\gamma(\Theta)]
\]
s.t.
\[
\sum_{i=1}^{N} f_{k,i}^2 = P_k
\]
\[
\gamma(\Theta) = [\gamma_1(\Theta) \ldots \gamma_N(\Theta)]^T
\]
\[
\gamma_i(\Theta) = \frac{\prod_{k=1}^{K} (f_{k,i}^2, h_{k,i}^2)}{\prod_{k=1}^{K} (f_{k,i}^2, h_{k,i}^2 + 1)}.
\]

The specific methods for finding \( f_{k,i} \) depend on the expressions of \( g(\bullet) \). In the following, we discuss the solution of (32) in more detail. The design criterion of MAX-MSE minimization is taken as example to show how to compute \( \Lambda_{\mathcal{F}_k} \).

MAX-MSE minimization is a special case of Object 1 in (8) and in this case, \( \psi_1(\Phi_{\text{MSE}}) = \max \Phi_{\text{MSE}} \). Furthermore, in Appendix A it is proved that \( g(\lambda(\Theta)) = \psi_1[1 - \sum_{i=1}^{N} \lambda_i(\Theta) \otimes 1_N] \). The symbol \( \otimes \) denotes the Kronecker product. Therefore, \( g[\gamma(\Theta)] \) equals to
\[
g[\gamma(\Theta)] = \max \left( 1_N - \sum_{i=1}^{N} \gamma_i(\Theta) \otimes 1_N \right)
\]
\[
= 1 - \frac{1}{N} \sum_{i=1}^{N} \gamma_i(\Theta)
\]

(33)
based on which the optimization problem (32) becomes
\[
\min_{f_{k,i}} \quad 1 - \frac{1}{N} \sum_{i=1}^{N} \prod_{k=1}^{K} (f_{k,i}^2, h_{k,i}^2 + 1)
\]
s.t.
\[
\sum_{i=1}^{N} f_{k,i}^2 = P_k.
\]

(34)
The optimization problem (34) can be solved by using iterative water-filling algorithm.

**VI. SIMULATION RESULTS AND DISCUSSIONS**

In this section, the performance of the proposed robust designs are evaluated by simulations. For the purpose of comparison, the algorithms based on the estimated channel only (without taking the channel estimation errors into account) are also simulated. In the following, we consider a three-hop AF MIMO relaying system where all nodes are equipped with 4 antennas. Furthermore, the estimation error correlation matrices are chosen as the popular exponential model [8] i.e., \( \Psi_k \circ \psi_{1} = \sigma^2_{e} \alpha^{[1-t]} \) and \( \Sigma_{k} \circ \psi_{1} = \beta^{[1-t]} \), and \( \sigma^2_{e} \) denotes the estimation error variance. The estimated channels \( \tilde{H}_k \)'s, are generated based on the following complex Gaussian distributions [8]
\[
\tilde{H}_k \sim \mathcal{CN}_M(0_{M_k, N_k}, (1 - \sigma^2_{e}) \Sigma_k \otimes \Psi_k^T).
\]

(35)
such that channel realizations \( H_k = \tilde{H}_k + \Delta H_k \) have unit variance. We define the signal-to-noise ratio (SNR) for the
with equality holds if and only if $|\Theta|_{i,i} = \sum_{i=1}^{N} \lambda_i(\Theta)/N$. Therefore, $\Theta$ must have the following structure [9]

$$\Theta = Q_F \text{diag}(\lambda(\Theta)) Q_F^H.$$  

(38)

where $Q_F$ is a unitary matrix such that $\Theta$ has identical diagonal elements.

Based on the definition that $\psi_1(\bullet)$ is a decreasing and Schur-convex function, based on 3.4.A.6.**Lemma** and 3.4.A.8.**Theorem** in [11] it can be directly proved that $g(\lambda(\Theta))$ is a decreasing and Schur-concave function of $\lambda(\Theta)$.

**Obj 2:** Notice that for the positive semi-definite matrix $\Phi_{\text{MSE}} = I_N - \Theta$, $d(I_N - \Theta) \preceq \lambda(I_N - \Theta)$ [9]. Furthermore $\psi_2(\bullet)$ is Schur-concave, we have

$$\psi_2(d(I_N - \Theta)) \geq \psi_2(I_N - \lambda(\Theta)).$$

(39)

In order to make the equality in (39) hold, we need $|\Theta|_{i,i} = \lambda_i(\Theta)$, which means that $\Theta$ is a diagonal matrix. Therefore, we can write

$$\Theta = I_N \text{diag}(\lambda(\Theta)) I_N.$$  

(40)

Since $\psi_2(\bullet)$ is increasing and Schur-concave, based on 3.4.A.6.**Lemma** and 3.4.A.8.**Theorem** in [11] it is obvious that $\psi_2(I_N - \lambda(\Theta))$ is decreasing and Schur-concave with respect to $\lambda(\Theta)$.

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