Joint Information and Energy Transfer in the Spatial Domain with Channel Estimation Error

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Abstract—In this paper, we investigate a new technique for simultaneous information and energy transfer in multiple-input multiple-output (MIMO) networks with radio frequency (RF) energy harvesting (EH) capabilities. The proposed technique exploits the spatial decomposition of the MIMO channel and uses the eigenchannels either to convey information or to transfer energy. In order to generalize our study, we consider channel estimation error in the decomposition process and we model the interference between the eigenchannels. An optimization problem that minimizes the total transmitted power subject to information and energy constraints is formulated as a mixed-integer nonlinear program and solved to optimality by a polynomial complexity algorithm developed by exploiting the special characteristics of the problem. Numerical results show that the imperfect channel estimation is beneficial from RF-EH standpoint and is characterized by an optimal (non-zero) value.

Index Terms—RF energy transfer, MIMO channel, single-value decomposition, channel estimation error, optimization.

I. INTRODUCTION

The integration of renewable energy sources into communication networks is a hot research topic. It provides significant energy gains and is an efficient green communication solution for the expected future data traffic increase. Traditional renewable energy sources such as solar energy and wind depend on the weather conditions and are characterized by a high instability; the integration of these energy sources requires a fundamental re-design of communications systems in all levels of protocol stack in order to ensure robustness and reliability. On the other hand, recently there is a lot of interest to use electromagnetic radiation as a potential renewable energy resource. The key idea of this concept is that electromagnetic waves convey energy, which can be converted to DC energy by using some specific rectenna circuits. This approach achieves a wireless energy transfer, recycling the transmitted RF radiation and is introduced as a fully controlled and continuous renewable energy resource; these characteristics motivate the development of new green wireless applications and services.

Most of the work on RF energy transfer concerns the design of rectenna circuits in different frequency bands, which is a fundamental aspect towards the development of this technology [2]–[4]. From an information theoretic standpoint, evaluating the channel capacity for different network configurations, when RF energy harvesting requirements characterize the receiver nodes, is a challenging problem. The work in [5] discusses the joint transfer of information and energy for a single-input single-output (SISO) channel and is extended in [6] for a set of parallel point-to-point channels; the authors in [7] study the capacity for two baseline multi-user systems with RF energy constraints, namely multiple access and multihop channels. However, information theoretic studies assume that the receivers are able to decode information and harvest energy from the same RF signal without limitations. Although this assumption provides some useful theoretical bounds it cannot be supported by the current practical implementations.

In order to satisfy the above practical limitation, the work in [8] deals with the beamforming design for a basic broadcast MIMO channel, where the source conveys information to one receiver while transfers energy to the other one. In that work, the authors introduce two main practical techniques for simultaneous information/energy transfer: a) “time switching” (TS), where the receiver switches between decoding information and harvesting energy and b) “power splitting” (PS), where the receiver splits the received signal in two parts for decoding information and harvesting energy, respectively. The works in [9]–[11] focus on the TS technique for different network topologies. Specifically, in [9] the authors investigate the optimal switching strategy for a SISO channel in order to achieve various trade-offs between wireless information transfer and energy harvesting with/without CSI knowledge at the transmitter. The work in [10] presents a TDMA-based multiuser broadcast channel where the downlink (broadcast channel) is used for energy harvesting while the uplink for conveying information from the users to the access point. In [11], the authors apply the TS technique for a basic relay channel and investigate the optimal switching rule. On the other hand, in [12] the authors study the performance of a cooperative system, where the relay is powered by employing a PS technique on the received signal. The work in [13] studies the optimal transmitted power for a MISO interference channel with PS where the destinations have both information/energy constraints.

In this work, we propose a simultaneous information and energy transfer in the spatial domain for a basic point-to-point multiple-input multiple-output (MIMO) channel. Based on the single-value decomposition (SVD) of the MIMO channel, the communication link is transformed to parallel channels that can convey either information data or energy; this binary allocation is in respect to the current practical limitations. In order to make our analysis more general (and practical), we
assume an imperfect channel estimation that affects the orthogonality of the eigenchannels (the imperfect channel knowledge generates an interference to the eigenchannels). We study the minimization of the transmitted power when the receiver is characterized by both information rate and energy transfer constraints. The optimization problem requires the assignment of each eigenchannel to information/energy transfer and is solved by using tools from Lagrange optimization theory. An interesting result is that imperfect channel estimation is beneficial for the energy transfer and is characterized by an optimal (non-zero) value.

Notation: Upper case and lower case bold symbols denote matrices and vectors, respectively. $\text{diag}(\cdot)$ represents a diagonal matrix with the vector $\cdot$ in the main diagonal, $\det(\cdot)$ denotes determinant, $\mathbf{I}_n$ is the identity matrix of order $n$, $\log(\cdot)$ denotes the logarithm of base 2, $\mathbb{E}[\cdot]$ represents the expectation operator and the superscript $^H$ denotes the Hermitian transpose operation.

The rest of this paper is organized as follows. In Section II, we present the system model and introduce the spatial domain energy harvesting as well as the associated optimization problem. In Section III, we deal with the solution of the optimization problem considered. Section IV provides simulation results to evaluate the performance of the proposed technique. Finally, Section V concludes the paper.

II. SYSTEM MODEL & PROBLEM FORMULATION

We assume a simple point-to-point MIMO model consisting of one source $S$ with $N_T$ transmit antennas and one destination with $N_R$ receive antennas. The source is connected to a constant power supply while the destination has RF transfer capabilities and can harvest energy from the received electromagnetic radiation. We consider flat fading spatially uncorrelated Rayleigh MIMO channel where $\mathbf{H} \in \mathbb{C}^{N_R \times N_T}$ denotes the channel matrix. The channel remains constant during a transmission time and changes independently from one transmission to the other one. The entries of $\mathbf{H}$ are assumed to be independent, zero-mean circularly symmetric complex Gaussian (ZMCSCEG) random variables with unit variance (which ensures $\text{rank}(\mathbf{H}) = N = \min(N_T,N_R)$). The received signal is described by

$$y = \mathbf{H}x + \mathbf{n}, \quad (1)$$

where $x \in \mathbb{C}^{N_T \times 1}$ denotes the transmitted signal with $\mathbb{E}[xx^H] = \mathbf{Q}$ and $\mathbf{n} \in \mathbb{C}^{N_R \times 1}$ represents the noise vector having ZMCSCEG entries of unit variance. We assume that the channel matrix is subject to a channel estimation error and therefore is imperfectly known at both the transmitter and the receiver with a MMSE estimation error $\mathbf{E} = \mathbf{H} - \hat{\mathbf{H}}$, where the entries of $\mathbf{E}$ are ZMCSCEG with variance $\sigma_e^2$ and the entries of $\hat{\mathbf{H}}$ are also i.i.d. ZMCSCEG with variance $1 - \sigma_e^2$ [14]. The channel estimation is performed at the destination via a downlink pilot/training sequence and is communicated to the source by using an uplink feedback channel; the channel estimation process is beyond the scope of this paper. Based on the estimated channel knowledge $\hat{\mathbf{H}}$, a lower bound of the instantaneous mutual information is given by [14]

$$I(x; y) = \log \det \left( \mathbf{I}_M + \frac{1}{1 + \sigma_e^2 P} \hat{\mathbf{H}} \hat{\mathbf{H}}^H \mathbf{Q} \right). \quad (2)$$

It is worth noting that for $\sigma_e^2 = 0$ (perfect channel knowledge), the above expression gives the exact mutual information of the MIMO channel. By using the SVD of the $\hat{\mathbf{H}}$ channel, it has been proven in [14] that the lower bound of the mutual information is maximized when $\mathbf{Q} = \text{diag}(P_1, \ldots, P_N)$ and takes the form

$$I(x; y) = \sum_{i=1}^{N} \log \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_e^2 P} \right), \quad (3)$$

where $\lambda_i$ is the $i$-th eigenvalue of $\hat{\mathbf{H}} \hat{\mathbf{H}}^H$, $P_i$ is the power allocated to the $i$-th eigenchannel and $P = \sum_i P_i$. The expression in (3) shows that the imperfect channel estimation generates an interference to the $N$ parallel single-input single-output channels (eigenchannels). We assume that the destination is characterized by both information rate and RF energy harvesting requirements; this means that for each transmission the destination requires an instantaneous information rate $C_I$ and an energy $C_{EH}$ as an input to its rectenna circuits (the amount of energy that can be stored depends on the energy conversion efficiency of the specific implementation).

A. Simultaneous information/energy transfer: optimization problem

The proposed scheme exploits the SVD structure of the MIMO channel and achieves simultaneous information and energy transfer in the spatial domain. More specifically, the transformation of the MIMO channel to $N$ parallel SISO channels allows the simultaneous transfer of data traffic and RF energy by using an eigenchannel either to convey information or energy. An eigenchannel cannot be used to convey both information and energy; this limitation refers to practical constraints and is inline with the other approaches proposed in the literature (i.e. power splitting). The proposed technique sacrifices some degrees of freedom in order to satisfy the RF energy harvesting constraint. The receiver can achieve

1This bound can be achieved based on the SVD of the estimated channel matrix and by appropriate precoding and receiver shaping at the source and the destination, respectively.
simultaneous information and energy transfer by having two different circuits at each antenna, one for information decoding and one for energy harvesting. During each transmission an appropriate optimization problem is solved which determines the usage of each antenna and a switching mechanism selects the appropriate circuits.

In this paper, we focus on the minimization of the transmitted power given that both information and energy constraints are satisfied. Based on the notation considered, the proposed technique introduces the following optimization problem

\[
\min_{i=1}^{N} P_i \quad (4)
\]

subject to

\[
\sum_{i=1}^{N} \pi_i \log \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_i^2 P} \right) \geq C_I
\]

\[
\sum_{i=1}^{N} (1 - \pi_i)(P_i \lambda_i + \sigma_i^2 P) \geq C_{EH}
\]

\[
P_i \geq 0
\]

\[
\pi_i \in \{0, 1\},
\]

where the binary variable \( \pi_i \) defines if the \( i \)-th eigenchannel is used for information transfer (\( \pi_i = 1 \)) or energy transfer (\( \pi_i = 0 \)). This mathematical program involves binary and continuous variables, as well as nonlinear functions; hence it belongs to the class of mixed-integer nonlinear optimization problems, which are very hard to solve in the general case.

We note that the energy harvested due to the receiver noise is negligible. The optimization problem can be solved in the source node and then flag bits can be used in each eigenchannel in order to inform the receiver about their “content”. Fig. 1 schematically presents the system model and the transformation of the MIMO channel to \( N \) eigenchannels for potential transfer of information/energy.

III. OPTIMAL SOLUTION

In this section, we deal with the solution of the above optimization problem. We start by finding the optimal power allocation to problem (4) for a given channel assignment towards the satisfaction of the information and energy constraints. We also show that we can obtain the optimal assignment by examining a polynomial number of combinations and develop an algorithm that solves problem (4) optimally.

Assume that a given assignment of channels is made such that \( \pi_{i_1} = 1, i_1 \in \mathcal{I} \) and \( \pi_{i_2} = 0, i_2 \in \mathcal{E} \). Due to this assignment, problem (4) can be written as:

\[
\min \quad P = \sum_{i=1}^{N} P_i
\]

subject to

\[
\sum_{i \in \mathcal{I}} \log \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_i^2 P} \right) \geq C_I
\]

\[
\sum_{i \in \mathcal{E}} (P_i \lambda_i + \sigma_i^2 P) \geq C_{EH}
\]

\[
P_i \geq 0, \quad i \in \{\mathcal{I} \cup \mathcal{E}\}
\]

Because there is no imposed upper bound on the transmitted power in each channel, only one channel with non-zero value will be assigned for EH purposes. If a set of channels \( \mathcal{E} \) are assigned to satisfy the EH constraint, then only at most one channel will have non-zero value; that will be the channel with the largest eigenvalue in the set of energy channels, \( \lambda_e, e \in \mathcal{E} \). Despite the fact that the power assigned to other channels in \( \mathcal{E} \) is zero, they still contribute towards the satisfaction of the EH constraint due to the presence of the term \( \sigma_e^2 P \) in the EH constraint. Another important observation is that channels with \( P_i = 0 \) can only be the channels with the overall smallest eigenvalues as “better” channels can contribute towards the satisfaction of the information rate and EH constraints. Regarding the set of information channels \( \mathcal{I} \), it is easy to see that in the optimal solution, no information channel should have zero power. This is because channels with zero power contribute to the EH constraint but not to the information constraint. The above analysis implies that in order to find the optimal assignment we need two different indices. The first index \( e \) indicates the energy channel with a possibly non-zero value, while the second indicates the channel with the largest eigenvalue with \( P_{i_2} = 0, i_2 \in \mathcal{E} - \{e\} \). Based on the above observations, we can conclude that in order to find the optimal assignment, we only need to examine \( O(N^2) \) different assignment combinations.

Next we show that given a fixed assignment \( \mathcal{I}, \mathcal{E} \) we can obtain the optimal required total power in closed form without explicitly solving the problem. This is a very important result, as it illustrates that to obtain the optimal value of problem (4) one can find the objective for different assignments inexpensively and only solve the problem for the assignment that provides the best objective value. The problem is comprised of two subproblem associated with the satisfaction of the information and EH constraints.

Let us first examine the energy subproblem. Assuming a given power allocation for the information channels we have that:

\[
\min \quad P_e
\]

subject to

\[
P_e \lambda_e + |\mathcal{E}| \sigma^2 e P \geq C_{EH}
\]

\[
P_e \geq 0,
\]

It is easy to see that the optimal solution to the above problem is \( P_e = \max \{0, (C_{EH} - |\mathcal{E}| \sigma^2 e \sum_{i \in \mathcal{I}} P_i)/(\lambda_e + |\mathcal{E}| \sigma^2 e)\} \). Note that the EH constraint is always binding when \( P_e > 0 \), as a non-binding solution is not beneficial neither for the objective nor for the information constraint in problem (5).

The information subproblem can be written as:

\[
\min \quad \sum_{i \in \mathcal{I}} P_i
\]

subject to

\[
\sum_{i \in \mathcal{I}} \ln \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_i^2 P} \right) \geq \ln(2) \cdot C_I
\]

\[
P_i \geq 0, \quad i \in \mathcal{I}.
\]
Applying Lagrange multipliers to the above problem yields:

\[
\min_{\nu \geq 0, \mu_1 \geq 0, \mu_2 \geq 0} \mathcal{L}(P, \nu, \mu_1, \mu_2) = \sum_{i \in \mathcal{I}} P_i + \nu_1 \left[ -\sum_{i \in \mathcal{I}} \ln \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_e^2 P} \right) \right] - \sum_{i \in \mathcal{I}} \lambda_i \nu_i.
\]

The optimal value for this problem can be obtained by setting the derivatives of the Lagrange function with respect to \(P_i\), \(i \in \mathcal{I}\), equal to zero.

\[
\frac{\partial \mathcal{L}(P, \nu, \mu_1, \mu_2)}{\partial P_i} = 1 - \mu_1 \left[ \frac{\lambda_i - \sigma_e^2}{(1 + \sigma_e^2 P)^2} \right] \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_e^2 P} \right)^{-1} \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_e^2 P} \right)^{-1} + \sum_{j \in \mathcal{I} \setminus \{i\}} \frac{-\sigma_e^2}{(1 + \sigma_e^2 P)^2} \left( 1 + \frac{P_j \lambda_j}{1 + \sigma_e^2 P} \right)^{-1} - \nu_i = 0, \quad i \in \mathcal{I}.
\]

(8)

Note that the derivation of the above formula is a result of the fact that the total power \(P\) is also a function of \(P_i\). Straightforward algebraic manipulation of the above formula gives:

\[
\frac{\lambda_i}{(y + P_i \lambda_i)} = \frac{\nu_i y}{\mu_1} + \frac{y \sigma_e^2}{\mu_1 \sum_{i \in \mathcal{I}} \frac{y \sigma_e^2}{(1 + \sigma_e^2 P)^2}} \times \left( 1 + \frac{P_i \lambda_i}{1 + \sigma_e^2 P} \right)^{-1}, \quad i \in \mathcal{I},
\]

(9)

where \(y = 1 + \sigma_e^2 P\). Note that the second and third terms of the right hand side of Eq. (9) are always constant while the first term is constant when \(\nu_i = 0\), which is true when \(P_i > 0\). Nonetheless, we have already explained that this situation occurs for the optimal assignment. Hence we have that:

\[
\frac{\lambda_i}{(y + P_i \lambda_i)} = \frac{1}{K} \Leftrightarrow \frac{y}{\lambda_i} + P_i = K, \quad i \in \mathcal{I}
\]

(10)

Substituting Eqs. (10) into the information constraint, we obtain:

\[
\sum_{i \in \mathcal{I}} \log_2 \left( \frac{K \lambda_i}{y} \right) = \log_2 \left( \prod_{i \in \mathcal{I}} \frac{K \lambda_i}{y} \right) = C_I \Rightarrow K = y \beta,
\]

(11)

where

\[
\beta = \left( \frac{2^{C_I}}{\prod_{i \in \mathcal{I}} \lambda_i} \right)^{\frac{1}{|\mathcal{I}|}}
\]

(12)

Substitution of Eq. (11) into (10) yields

\[
P_i = y(\beta - 1/\lambda_i) > 0 \Rightarrow (\beta - 1/\lambda_i) > 0, \quad i \in \mathcal{I}.
\]

We have already shown that all information channels must have non-zero power; this implies that the above condition is necessary for optimality. Hence, any given assignments that do not satisfy the particular condition can be rejected without any further consideration.

Apart from Eq. (11), we can obtain a second formula that combines variables \(y\) and \(K\) by summing Eqs. (10) for \(i \in \mathcal{I}:

\[
y \sum_{i \in \mathcal{I}} \frac{1}{\lambda_i} + \sum_{i \in \mathcal{I}} P_i = |\mathcal{I}| K = |\mathcal{I}| \beta y.
\]

Substituting in the above expression the fact that \(y = 1 + \sigma_e^2 \left( P_e + \sum_{i \in \mathcal{I}} P_i \right)\) yields the following expression for \(y:\)

\[
y = \sum_{i \in \mathcal{I}} \frac{P_e + \sigma_e^2}{\lambda_i} + |\mathcal{I}| \beta y = \frac{C_EH - (y - 1) \mathcal{E}}{\lambda_e},
\]

(13)

and substitute it into Eq. (13) to obtain:

\[
y = \sum_{i \in \mathcal{I}} \frac{C_EH}{\lambda_e} + \frac{1}{\lambda_e} + \frac{|\mathcal{E}|}{\lambda_e} = |\mathcal{I}| \beta.
\]

(15)

To check for infeasible solutions, we further need to ensure that the obtained solution for \(y\) yields a positive value for \(P_e\) according to Eq. (14). As \(y\) is a monotonically increasing function of \(P\), by finding the best feasible value for \(y\) among all feasible assignments, \(y_{opt}\), we can derive the optimal allocation of power into channels, as outlined in Alg. 1.

It should be emphasized that Alg. 1 has two very attractive characteristics: (a) it solves a nonlinear combinatorial optimization problem involving binary variables, in polynomial time, as it requires the examination of a polynomial number of fixed assignments (approximately \(N^2/2\)), and (b) the optimal power allocation needs to be derived only for the optimal assignment \(\mathcal{I}_{opt}\), \(c_{opt}\), and not for all examined fixed assignments which reduces the execution time of the algorithm. Although each assignment appears to be of computational complexity \(O(N)\) due to the presence of \(\sum_{i \in \mathcal{I}} \frac{1}{\lambda_i}\) and \(\prod_{i \in \mathcal{I}} \lambda_i\), we can reduce the computational complexity to \(O(1)\). This can be achieved by storing the sum and product terms for fixed EH assignment, \(e\), and updating their values for an increasing number of information channels \(i = e + 1, ..., N\). Hence, the total complexity of Alg. 1 is \(O(N^2)\).

IV. NUMERICAL RESULTS

Computer simulations are carried-out in order to evaluate the performance of the proposed RF-EH technique. In order to simplify the demonstration of the results, we assume a MIMO channel with eigenvalues drawn from the uniform distribution in the range \([0, N]\); the simulation setup consists of \(N = 8\)
Algorithm 1: Optimal solution to problem (5)

Initialization: \( y_{\text{opt}} = \infty, \mathcal{I}_{\text{opt}} = \emptyset, \) and \( e_{\text{opt}} = \emptyset. \) Eigenvalues sorted in descending value.

for \( e = 1 \) to \( N \) do
    for \( i = e + 1 \) to \( N \) do
        1. Initialise fixed assignment: \( \mathcal{I} = \{1, \ldots, i - 1\}/e. \)
        if \( (|\mathcal{I}| > 0) \) then
            2. Compute \( \beta \) according to (12).
                //The condition below must be true at the optimal solution; otherwise examine another assignment.
            if \( (\beta - 1/\lambda_j > 0, j = \max(\mathcal{I})) \) then
                3. Compute the value of \( y \) according to Eq. (13) and set \( P_e = 0. \)
                if \( (|\mathcal{E}|(y - 1) < C_{EH}) \) then
                    4. Compute the values of \( y \) and \( P_e > 0 \) according to Eqs. (15) and (14) respectively.
                    end if
                if \( ((y_{\text{opt}} > y) \ \text{AND} \ (y \geq 1) \ \text{AND} \ (P_e > 0)) \) then
                    5. Store the optimal solution found so far:
                        \( y_{\text{opt}} = y, \mathcal{I}_{\text{opt}} = \mathcal{I}, \) and \( e_{\text{opt}} = e. \)
                    end if
                end if
            end if
        end if
    end for
if \( (1 \leq y < \infty) \) then
    6. Having found optimal assignment \( \mathcal{I}_{\text{opt}}, e_{\text{opt}} = e \) and \( y_{\text{opt}} \) compute power allocation as follows:
        Compute \( P_{e_{\text{opt}}} = (\eta_{\text{opt}} - 1)\sigma_{\epsilon}^{-2}, \beta_{e_{\text{opt}}}, K_{e_{\text{opt}}} = \beta_{e_{\text{opt}}}y_{\text{opt}}, \) and finally \( P_i, i \in \mathcal{I}_{\text{opt}} \) according to Eq. (10).
else
    7. Deem problem infeasible.
end if

and \( \sigma_{\epsilon}^2 = 0.1, \) while we run 1000 problem instances for each set of parameters. In Fig. 2, we plot the average normalized transmitted power versus the RF-EH constraint \( (C_{EH}) \) for \( C_I = \{2, 4, 6\}. \) It can be seen the required transmitted power is increased as the information and the RF-EH constraints increase. An interesting observation is that the transmitted power increases linearly in order to give a linear increase in the \( C_{EH} \) threshold. On the other hand, Fig. 3 plots the average normalized transmitted power versus the information threshold \( (C_I) \) for \( C_{EH} = \{2, 6, 10\}. \) The main observations are inline with the the previous figure and thus the transmitted power increases as \( C_I \) and \( C_{EH} \) increase. It is worth noting that the increase is not linear since the information constraint is characterized by the logarithmic function.

Fig. 4 shows the impact of the variance of the channel estimation error \( \sigma_{\epsilon}^2 \) on the required transmitted power for different RF-EH thresholds \( C_{EH} = \{0.1, 0.3, 0.5, 0.7, 0.9, 1.1\}. \) As it can be seen that \( \sigma_{\epsilon}^2 \) significantly affects the total power consumption; the main remark is that this imperfection seems to be beneficial for the total transmitted power. More specifically, a perfect channel estimation results in higher power consumption while a non-zero \( \sigma_{\epsilon}^2 \) improves the energy consumption of the system. In addition, we can see that an optimal value for the \( \sigma_{\epsilon}^2 \) exists that minimizes the total power consumption. The main reason for this behavior is that \( \sigma_{\epsilon}^2 \) affects the orthogonality of the eigenchannels and results in an interference between them, which is useful for the satisfaction of the RF-EH constraint. This result shows that although the imperfect channel estimation degrades the performance in conventional systems, it becomes useful for the proposed spatial domain information/energy transfer. Therefore, the proposed technique is not sensitive to the variance of the channel estimation error; this attribute is attractive to practical implementations. Fig. 5 shows the impact of \( \sigma_{\epsilon}^2 \) for different information rate thresholds. The main results are similar to Fig. 4 and confirm our conclusions.
Fig. 4. Average normalized transmitted power versus the variance of the estimation error for various values of $C_{EH}$; $C_I = 2$ and $N = 8$.

Fig. 5. Average normalized transmitted power versus the variance of the estimation error for various values of $C_I$; $C_{EH} = 0.6$ and $N = 8$.

V. CONCLUSION

We have investigated the simultaneous information and energy transfer in the spatial domain for a MIMO channel with RF-EH capabilities. By using the SVD decomposition of the wireless channel under an imperfect channel knowledge, the proposed technique uses the eigenchannels for conveying either information or energy. To minimize the transmitted power subject to some well-defined information and energy constraints, the problem is formulated as a mixed-integer nonlinear optimization program. A polynomial complexity algorithm that produces the optimal solution to the considered problem is developed with the use of Lagrange multipliers.

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