Joint Linear Receiver Design and Power Allocation Using Alternating Optimization Algorithms for Wireless Sensor Networks

Tong Wang, Rodrigo C. de Lamare, *Senior Member, IEEE*, and Anke Schmeink, *Member, IEEE*

***Abstract*—In this paper, we consider a two-hop wireless sensor network with multiple relay nodes where the amplify-and-forward scheme is employed. We present strategies to jointly design linear receivers and the power allocation parameters via an alternating optimization approach subject to global, individual and neighbour-based power constraints. Two design criteria are considered: the first one minimizes the mean-square error and the second one maximizes the sum-rate of the wireless sensor network. We derive constrained minimum mean-square error and constrained maximum sum-rate expressions for the linear receivers and the power allocation parameters that contain the optimal complex amplification coefficients for each relay node. Computer simulations show good performance of our proposed methods in terms of bit error rate or sum-rate compared to the method with equal power allocation and to a two-stage power allocation technique. Furthermore, the methods with neighbour-based constraints bring flexibility to balance the performance against the computational complexity and the need for feedback information which is desirable for wireless sensor networks to extend their lifetime.**

***Index Terms*—Minimum mean-square error (MMSE) criterion, maximum sum-rate (MSR) criterion, power allocation, wireless sensor networks (WSNs).**

I. Introduction

Recently, there has been a growing research interest in wireless sensor networks (WSNs) because of their unique features that allow a wide range of applications in the areas of defence, environment, health and home [1]. WSNs are usually composed of a large number of densely deployed sensing devices which can transmit their data to the desired user through multihop relays [2]. Low complexity and high energy efficiency are the most important design characteristics of communication protocols [3] and physical layer techniques employed for WSNs. The performance and capacity of these networks can be significantly enhanced by exploiting the spatial diversity with cooperation between the nodes [2]. In a cooperative WSN, nodes relay signals to each other in order to propagate redundant copies of the same signals to the destination nodes. Among the existing relaying schemes, the amplify-and-forward (AF) and the decode-and-forward (DF) are the most popular approaches [4]. In the AF scheme, the relay nodes amplify the received signal and rebroadcast the amplified signals toward the destination nodes. In the DF scheme, the relay nodes first decode the received signals and then regenerate new signals to the destination nodes subsequently.

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Due to the limitations in sensor node power, computational capacity and memory [1], some power allocation methods have been proposed for WSNs to obtain the best possible SNR or best possible quality of service (QoS) [5], [6] at the destinations. The majority of the previous literature considers a source and destination pair, with one or more randomly placed relay nodes. These relay nodes are usually placed with uniform distribution [7], equal distance [8], or in line [9] with the source and destination. The reason for these simple considerations is that they can simplify complex problems and obtain closed-form solutions. A single relay AF system using mean channel gain channel state information (CSI) is analyzed in [10], where the outage probability is the criterion used for optimization. For DF systems, a near-optimal power allocation strategy called the Fixed-Sum-Power with Equal-Ratio (FSP-ER) scheme based on partial CSI has been developed in [7]. This near-optimal scheme allocates one half of the total power to the source node and splits the remaining half equally among selected relay nodes. A node is selected for relaying if its mean channel gain to the destination is above a threshold. Simulation results show that this scheme significantly outperforms two traditional power allocation schemes. One is the 'Constant-Power scheme' where all nodes serve as relay nodes and all nodes including the source node and relay nodes transmit with the same power. The other one is the 'Best-Select scheme' where only one node with the largest mean channel gain to the destination is chosen as the relay node.

The BER performance [11], [12], capacity [13] and outage probability [14], [15] are often used as the optimization criterion for the power allocation performance. In [16], a power allocation method is proposed to maximize the Effective Configuration Duration (ECD) in WSNs. It aims to minimize the signalling overhead for performing relay nodes selection and power allocation which can save the power significantly and thus extend the lifetime. Compared with traditional power allocation schemes, this method jointly considers the residual energy of sensors and the mean channel gains. Therefore, the feedback burden is limited and the stability of the topology is increased.

The alternating minimization procedure under the information geometry framework was proposed by Csiszar and Tusnady in 1984 [17] which have developed a proof for its global convergence in problems involving two variables. It is a very successful technique that has been used for solving optimization problems in applications that include signal processing, information theory, control and finance because of its iterative nature and simplicity. A general set of sufficient conditions for its convergence and correctness were developed in [18] for adaptive problems.

In this paper, we consider a general two-hop wireless sensor network where the AF relaying scheme is employed. Our strategy is to jointly design the linear receivers and the power allocation parameter vector that contains the optimal complex amplification coefficients for each relay node via an alternating optimization approach. Two kinds of receivers are designed, the minimum mean-square error (MMSE) receiver and the maximum sum-rate (MSR) receiver. They can be considered as solutions to constrained optimization problems where the objective function is the mean-square error (MSE) cost function or the sum-rate (SR) and the constraint is a bound on the power levels among the relay nodes. Then, the constrained MMSE or MSR expressions for the linear receiver and the power allocation parameter can be derived. For the MMSE receiver, a closed form solution for the Lagrangian multiplier (λ) that arises in the expressions of the power allocation parameter can be achieved. For the MSR receiver, the novelty is that we make use of the Generalized Rayleigh Quotient [19] to solve the optimization problem in an alternating fashion. Finally, the optimal amplification coefficients are transmitted to the relay nodes through the feedback channel. In this work, we first present the strategies where the power allocation is considered for all of the relay nodes. They are subject to the global or individual power constraints. Next, to reduce the computational complexity for the power allocation, we choose the relay nodes which have good channel coefficients (when a channel power gain is above a threshold) between them and the destination nodes called neighbour relay nodes. Only the power allocation for these nodes are required and the remaining nodes use the equal power allocation method [7]. Therefore, the computational complexity and feedback burden can be reduced. The main contributions of this paper can be summarized as:

1) Constrained MMSE expressions for the design of linear receivers and power allocation parameters. The constraints include the global, individual and neighbour-based power constraints. Some preliminary results of this part have been reported in [20].
2) Constrained MSR expressions for the design of linear receivers and power allocation parameters. The constraints include the global and neighbour-based power constraints.
3) Alternating optimization algorithms that compute the linear receivers and power allocation parameters in 1) and 2) to minimize the mean-square error or maximize the sum-rate of the WSN.
4) Computational complexity and convergence analysis of the proposed optimization algorithms.

The rest of this paper is organized as follows. Section II describes the general two-hop WSN system model. Section III develops three joint MMSE receiver design and power allocation strategies subject to three different power constraints. Section IV develops two joint MSR receiver design and power allocation strategies subject to two different power constraints. Section V contains the analysis of the computational complexity and the convergence. Section VI presents and discusses the simulation results, while Section VII provides some concluding remarks.

II. System Model

Consider a general two-hop wireless sensor network (WSN) with multiple parallel relay nodes, as shown in Fig. 1. The WSN consists of N_s source nodes, N_d destination nodes and N_r relay nodes. We concentrate on a time division scheme with perfect synchronization, for which all signals are transmitted and received in separate time slots. The sources first broadcast the $N_s \times 1$ signal vector $\mathbf{s}$ to all relay nodes. We consider an amplify-and-forward (AF) cooperation protocol in this paper. Each relay node receives the signal, amplifies and rebroadcasts them to the destination nodes. In practice, we need to consider the constraints on the transmission policy. For example, each transmitting node would transmit during only one phase. Let $\mathbf{H}_s$ denote the $N_r \times N_s$ channel matrix between the source nodes and the relay nodes and $\mathbf{H}_d$ denote the $N_d \times N_r$ channel matrix between the relay nodes and the destination nodes as given by

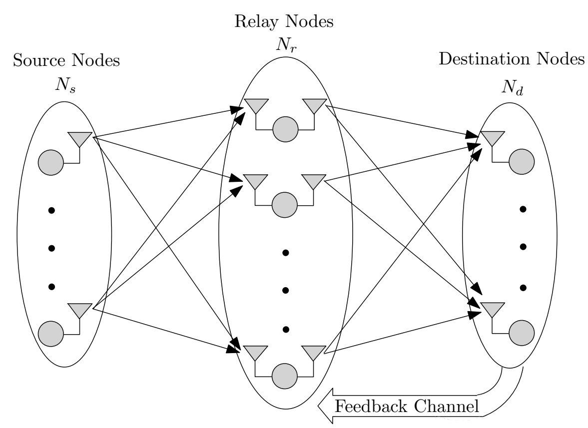

Fig. 1. A two-hop cooperative WSN with N_s source nodes, N_d destination nodes and N_r relay nodes.

$$\mathbf{H}_s = \begin{bmatrix} \mathbf{h}_{s,1} \\ \mathbf{h}_{s,2} \\ \vdots \\ \mathbf{h}_{s,N_r} \end{bmatrix}, \qquad \mathbf{H}_d = \begin{bmatrix} \mathbf{h}_{d,1} \\ \mathbf{h}_{d,2} \\ \vdots \\ \mathbf{h}_{d,N_d} \end{bmatrix}, \tag{1}$$

where $\mathbf{h}_{s,i} = [h_{s,i,1}, h_{s,i,2}, ..., h_{s,i,N_s}]$ for $i = 1, 2, ..., N_r$ denotes the channel coefficients between the source nodes and the ith relay node, and $\mathbf{h}_{d,i} = [h_{d,i,1}, h_{d,i,2}, ..., h_{d,i,N_r}]$ for $i = 1, 2, ..., N_d$ denotes the channel coefficients between the relay nodes and the ith destination node. The received signal at the relay nodes can be expressed as

$$\mathbf{x} = \mathbf{H}_s\mathbf{s} + \mathbf{v}_r, \tag{2}$$

$$\mathbf{y} = \mathbf{F}\mathbf{x}, \tag{3}$$

where $\mathbf{v}$ is a zero-mean circularly symmetric complex additive white Gaussian noise (AWGN) vector with covariance matrix $\sigma_n^2\mathbf{I}$, and $\mathbf{F} = \text{diag}\left\{(\sigma_s^2|\mathbf{h}_{s,1}|^2+\sigma_n^2),(\sigma_s^2|\mathbf{h}_{s,2}|^2+\sigma_n^2),...,(\sigma_s^2|\mathbf{h}_{s,N_r}|^2+\sigma_n^2)\right\}^{-\frac{1}{2}}$ denotes the normalization matrix which can normalize the power of the received signal for each relay node. At the destination nodes, the received signal can be expressed as

$$\mathbf{d} = \mathbf{H}_d\mathbf{A}\mathbf{y} + \mathbf{v}_d, \tag{4}$$

where $\mathbf{A} = \text{diag}\{a_1, a_2, ..., a_{N_r}\}$ is a diagonal matrix whose elements represent the amplification coefficient of each relay node. Please note that the property of the matrix vector multiplication $\mathbf{Ay} = \mathbf{Ya}$ will be used in the next section, where $\mathbf{Y}$ is the diagonal matrix form of the vector $\mathbf{y}$ and $\mathbf{a}$ is the vector form of the diagonal matrix $\mathbf{A}$. In our proposed designs, the full CSI of the system is assumed to be known at all the destination nodes. In practice, a fusion center [21] which contains the destination nodes is responsible for gathering the CSI, computing the optimal linear filters and the optimal amplification coefficients. The fusion center also recovers the transmitted signal of the source nodes and transmits the optimal amplification coefficients to the relay nodes via a feedback channel.

III. Proposed Joint MMSE Design of the Receiver and Power Allocation

In this section, three constrained optimization problems are proposed to describe the joint design of the MMSE linear receiver ($\mathbf{W}$) and the power allocation parameter ($\mathbf{a}$) subject to a global, individual and neighbour-based power constraints.

A. MMSE Design with a Global Power Constraint

We first consider the case where the total power of all the relay nodes is limited to P_T. The proposed method can be considered as the following optimization problem

$$\begin{aligned}[\mathbf{W}_{\text{opt}}, \mathbf{a}_{\text{opt}}] &= \arg\min_{\mathbf{W},\mathbf{a}} E[\|\mathbf{s} - \mathbf{W}^H\mathbf{d}\|^2], \\ &\text{subject to } N_d\mathbf{a}^H\mathbf{a} = P_T.\end{aligned} \tag{5}$$

where $(\cdot)^H$ denotes the complex-conjugate (Hermitian) transpose. To solve this constrained optimization problem, we modify the MSE cost function using the method of Lagrange multipliers [22] which yields the following Lagrangian function

$$\begin{aligned}\mathcal{L} =& E[\|\mathbf{s} - \mathbf{W}^H\mathbf{d}\|^2] + \lambda(N_d\mathbf{a}^H\mathbf{a} - P_T) \\ =& E(\mathbf{s}^H\mathbf{s}) - E(\mathbf{d}^H\mathbf{W}\mathbf{s}) - E(\mathbf{s}^H\mathbf{W}^H\mathbf{d}) + E(\mathbf{d}^H\mathbf{W}\mathbf{W}^H\mathbf{d}) \\ &+ \lambda(N_d\mathbf{a}^H\mathbf{a} - P_T).\end{aligned} \tag{6}$$

By fixing $\mathbf{a}$ and setting the gradient of $\mathcal{L}$ in (6) with respect to the conjugate of the filter $\mathbf{W}^*$ equal to zero, where $(\cdot)^*$ denotes the complex-conjugate, we get

$$\begin{aligned}\mathbf{W}_{\text{opt}} &= [E(\mathbf{d}\mathbf{d}^H)]^{-1}E(\mathbf{d}\mathbf{s}^H) \\ &= \left[\mathbf{H}_d\mathbf{A}E(\mathbf{y}\mathbf{y}^H)\mathbf{A}^H\mathbf{H}_d^H + \sigma_n^2\mathbf{I}\right]^{-1}\mathbf{H}_d\mathbf{A}E(\mathbf{y}\mathbf{s}^H).\end{aligned} \tag{7}$$

The optimal expression for the power allocation vector $\mathbf{a}$ is obtained by equating the partial derivative of $\mathcal{L}$ with respect to $\mathbf{a}^*$ to zero

$$\begin{aligned}\frac{\partial\mathcal{L}}{\partial\mathbf{a}^*} =& -E\left(\frac{\partial\mathbf{d}^H}{\partial\mathbf{a}^*}\mathbf{W}\mathbf{s}\right) + E\left(\frac{\partial\mathbf{d}^H}{\partial\mathbf{a}^*}\mathbf{W}\mathbf{W}^H\mathbf{d}\right) + N_d\lambda\mathbf{a} \\ =& -E(\mathbf{Y}^H\mathbf{H}_d^H\mathbf{W}\mathbf{s}) + E[\mathbf{Y}^H\mathbf{H}_d^H\mathbf{W}\mathbf{W}^H(\mathbf{H}_d\mathbf{Y}\mathbf{a} + \mathbf{v}_d)] \\ &+ N_d\lambda\mathbf{a} \\ =& \mathbf{0}.\end{aligned} \tag{8}$$

Therefore, we get

$$\begin{aligned}\mathbf{a}_{\text{opt}} =& [E(\mathbf{Y}^H\mathbf{H}_d^H\mathbf{W}\mathbf{W}^H\mathbf{H}_d\mathbf{Y}) + N_d\lambda\mathbf{I}]^{-1}E(\mathbf{Y}^H\mathbf{H}_d^H\mathbf{W}\mathbf{s}) \\ =& [\mathbf{H}_d^H\mathbf{W}\mathbf{W}^H\mathbf{H}_d \circ E(\mathbf{y}\mathbf{y}^H)^* + N_d\lambda\mathbf{I}]^{-1} \\ &* [\mathbf{H}_d^H\mathbf{W} \circ E(\mathbf{y}\mathbf{s}^H)^*\mathbf{u}]\end{aligned} \tag{9}$$

where $\circ$ denotes the Hadamard (element-wise) product and $\mathbf{u} = [1, 1, ..., 1]^T$. The expressions in (7) and (9) depend on each other. Thus, it is necessary to iterate them with an initial value of $\mathbf{a}$ to obtain the solutions.

The Lagrange multiplier λ can be determined by solving

$$N_d\mathbf{a}_{\text{opt}}^H\mathbf{a}_{\text{opt}} = P_T. \tag{10}$$

Let

$$\boldsymbol{\phi} = E(\mathbf{Y}^H\mathbf{H}_d^H\mathbf{W}\mathbf{W}^H\mathbf{H}_d\mathbf{Y}) \tag{11}$$

and

$$\mathbf{z} = E(\mathbf{Y}^H\mathbf{H}_d^H\mathbf{W}\mathbf{s}). \tag{12}$$

Equation (10) becomes

$$N_d\mathbf{z}^H(\boldsymbol{\phi} + N_d\lambda\mathbf{I})^{-1}(\boldsymbol{\phi} + N_d\lambda\mathbf{I})^{-1}\mathbf{z} = P_T. \tag{13}$$

Using an eigenvalue decomposition (EVD), we have

$$\boldsymbol{\phi} = \mathbf{Q}\boldsymbol{\Lambda}\mathbf{Q}^{-1} \tag{14}$$

where $\boldsymbol{\Lambda} = \text{diag}\{\alpha_1, \alpha_2, ..., \alpha_M, 0, ..., 0\}$ consists of eigenvalues of $\boldsymbol{\phi}$, and $M = \min\{N_s, N_r, N_d\}$. Then, we get

$$\boldsymbol{\phi} + N_d\lambda\mathbf{I} = \mathbf{Q}(\boldsymbol{\Lambda} + N_d\lambda\mathbf{I})\mathbf{Q}^{-1}. \tag{15}$$

Therefore, (13) can be expressed as

$$N_d\mathbf{z}^H\mathbf{Q}(\boldsymbol{\Lambda} + N_d\lambda\mathbf{I})^{-2}\mathbf{Q}^{-1}\mathbf{z} = P_T. \tag{16}$$

Using the properties of the trace operation, (16) can be written as

$$N_d tr\left\{(\boldsymbol{\Lambda} + N_d\lambda\mathbf{I})^{-2}\mathbf{Q}^{-1}\mathbf{z}\mathbf{z}^H\mathbf{Q}\right\} = P_T. \tag{17}$$

Defining $\mathbf{C} = \mathbf{Q}^{-1}\mathbf{z}\mathbf{z}^H\mathbf{Q}$, (17) becomes

$$N_d\sum_{i=1}^{N_r}(\boldsymbol{\Lambda}(i,i) + N_d\lambda)^{-2}\mathbf{C}(i,i) = P_T. \tag{18}$$

Since $\boldsymbol{\phi}$ is a matrix with at most rank M, only the first M columns of $\mathbf{Q}$ span the column space of $E(\mathbf{Y}^H\mathbf{H}_d^H\mathbf{W}\mathbf{s})^H$ which causes the last $(N_r - M)$ columns of $\mathbf{z}^H\mathbf{Q}$ to become zero vectors, and thus the last $(N_r - M)$ diagonal elements of $\mathbf{C}$ are zero. Therefore, we obtain the $\{2M\}$th-order polynomial in λ

$$N_d \sum_{i=1}^{M} (\alpha_i + N_d \lambda)^{-2} \mathbf{C}(i,i) = P_T. \quad (19)$$

B. MMSE Design with Individual Power Constraints

Secondly, we consider the case where the power of each relay node is limited to some value $P_{T,i}$. The proposed method can be considered as the following optimization problem

$$[\mathbf{W}_{\text{opt}}, a_{1,\text{opt}}, ..., a_{N_r,\text{opt}}] = \arg\min_{\mathbf{W}, a_1, ..., a_{N_r}} E[\|\mathbf{s} - \mathbf{W}^H \mathbf{d}\|^2], \\ \text{subject to } P_i = P_{T,i},\ i = 1, 2, ..., N_r, \quad (20)$$

where P_i is the transmitted power of the ith relay node, and $P_i = N_d a_i^* a_i$. Using the method of Lagrange multipliers, we have the following Lagrangian function

$$\mathcal{L} = E[\|\mathbf{s} - \mathbf{W}^H \mathbf{d}\|^2] + \sum_{i=1}^{N_r} \lambda_i (N_d a_i^* a_i - P_{T,i}). \quad (21)$$

Following the same steps as described in Section III.A, we get the same optimal expression for the $\mathbf{W}$ as in (7), and the optimal expression for the a_i

$$a_{i,\text{opt}} = [\boldsymbol{\phi}(i,i) + N_d \lambda_i]^{-1} [\mathbf{z}(i) - \sum_{l \in I, l \neq i} \boldsymbol{\phi}(i,l) a_l] \quad (22)$$

where $I = \{1, 2, ..., N_r\}$, $\boldsymbol{\phi}$ and $\mathbf{z}$ have the same expression as in (11) and (12). The Lagrange multiplier λ_i can be determined by solving

$$N_d a_{i,\text{opt}}^* a_{i,\text{opt}} = P_{T,i} \quad i = 1, 2, ..., N_r. \quad (23)$$

C. MMSE Design with a Neighbour-based Power Constraint

In order to reduce the computational complexity for power allocation and the need for feedback, we choose the relay nodes which have good channel coefficients between them and the destination nodes called neighbour relay nodes. Only the power allocation for these nodes are required and the remaining nodes employ the equal power allocation method. Therefore, the computational complexity and feedback burden can be reduced. The received signal at the destination nodes can be rewritten as

$$\begin{aligned} \mathbf{d} &= \mathbf{H}_d \mathbf{A} \mathbf{y} + \mathbf{v}_d \\ &= \mathbf{H}_N \mathbf{A}_N \mathbf{y}_N + \mathbf{H}_o \mathbf{A}_o \mathbf{y}_o + \mathbf{v}_d, \end{aligned} \quad (24)$$

where $\mathbf{A}_N$ and $\mathbf{y}_N$ denote the amplification matrix and normalized signal for the neighbour relay nodes, $\mathbf{A}_o$ and $\mathbf{y}_o$ denote the amplification matrix and normalized signal for the non-neighbour relay nodes, respectively.

We consider the case where the total power of all the neighbour relay nodes is limited to P_N and $P_N + N_d \mathbf{a}_o^H \mathbf{a}_o = P_T$. The proposed method can be considered as the following optimization problem

$$[\mathbf{W}_{\text{opt}}, \mathbf{a}_{N,\text{opt}}] = \arg\min_{\mathbf{W}, \mathbf{a}_N} E[\|\mathbf{s} - \mathbf{W}^H \mathbf{d}\|^2], \\ \text{subject to } N_d \mathbf{a}_N^H \mathbf{a}_N = P_N. \quad (25)$$

Using the method of Lagrange multipliers, we have the following Lagrangian function

$$\mathcal{L} = E[\|\mathbf{s} - \mathbf{W}^H \mathbf{d}\|^2] + \lambda_N (N_d \mathbf{a}_N^H \mathbf{a}_N - P_N). \quad (26)$$

Following the same steps as described in Section III.A, we get the same optimal expression for $\mathbf{W}$ as in (7). Substituting (24) into (26), equating the partial derivative of $\mathcal{L}$ with respect to $\mathbf{a}_N^*$ to zero gives

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \mathbf{a}_N^*} =& - E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{s}) + E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{W}^H \mathbf{H}_N \mathbf{Y}_N) \mathbf{a}_N \\ &+ E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{W}^H \mathbf{H}_o \mathbf{Y}_o \mathbf{a}_o) + N_d \lambda_N \mathbf{a}_N \\ =& \mathbf{0}. \end{aligned} \quad (27)$$

Therefore, we obtain the optimal expression for $\mathbf{a}_N$

$$\begin{aligned} \mathbf{a}_{N,\text{opt}} =& [E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{W}^H \mathbf{H}_N \mathbf{Y}_N) + N_d \lambda_N \mathbf{I}]^{-1} \\ &* [E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{s}) - E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{W}^H \mathbf{H}_o \mathbf{Y}_o \mathbf{a}_o)]. \end{aligned} \quad (28)$$

The Lagrange multiplier λ_N can be determined by solving

$$N_d \mathbf{a}_{N,\text{opt}}^H \mathbf{a}_{N,\text{opt}} = P_N. \quad (29)$$

Let

$$\boldsymbol{\phi}_N = E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{W}^H \mathbf{H}_N \mathbf{Y}_N) \quad (30)$$

and

$$\mathbf{z}_N = E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{s}) - E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{W}^H \mathbf{H}_o \mathbf{Y}_o \mathbf{a}_o). \quad (31)$$

Equation (29) becomes

$$N_d \mathbf{z}_N^H (\boldsymbol{\phi}_N + N_d \lambda_N \mathbf{I})^{-1} (\boldsymbol{\phi}_N + N_d \lambda_N \mathbf{I})^{-1} \mathbf{z}_N = P_N. \quad (32)$$

Using an EVD,

$$\boldsymbol{\phi}_N = \mathbf{Q}_N \boldsymbol{\Lambda}_N \mathbf{Q}_N^{-1} \quad (33)$$

where $\boldsymbol{\Lambda}_N = \text{diag}\{\alpha_1, \alpha_2, ..., \alpha_M, 0, ..., 0\}$ consists of the eigenvalues of $\boldsymbol{\phi}_N$, and $M_N = \min\{N_s, N_N, N_d\}$ (N_N is the number of neighbour relay nodes), we get

$$\boldsymbol{\phi}_N + N_d \lambda_N \mathbf{I} = \mathbf{Q}_N (\boldsymbol{\Lambda}_N + N_d \lambda_N \mathbf{I}) \mathbf{Q}_N^{-1}. \quad (34)$$

Therefore, (32) can be expressed as

$$N_d \mathbf{z}_N^H \mathbf{Q}_N (\boldsymbol{\Lambda}_N + N_d \lambda_N \mathbf{I})^{-2} \mathbf{Q}_N^{-1} \mathbf{z}_N = P_N. \quad (35)$$

Using the properties of the trace operation, (35) can be written as

$$N_d tr \left\{ (\boldsymbol{\Lambda}_N + N_d \lambda_N \mathbf{I})^{-2} \mathbf{Q}_N^{-1} \mathbf{z}_N \mathbf{z}_N^H \mathbf{Q}_N \right\} = P_N. \quad (36)$$

Defining $\mathbf{C}_N = \mathbf{Q}_N^{-1} \mathbf{z}_N \mathbf{z}_N^H \mathbf{Q}_N$, (36) becomes

$$N_d \sum_{i=1}^{N_N} (\boldsymbol{\Lambda}_N(i,i) + N_d \lambda_N)^{-2} \mathbf{C}_N(i,i) = P_N. \quad (37)$$

Since $\boldsymbol{\phi}_N$ is a matrix with at most rank M_N, only the first M_N columns of $\mathbf{Q}_N$ span the column space of $E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{s})^H$ and $E(\mathbf{Y}_N^H \mathbf{H}_N^H \mathbf{W} \mathbf{W}^H \mathbf{H}_o \mathbf{Y}_o \mathbf{a}_o)^H$ which cause the last $(N_N - M_N)$ columns of $\mathbf{z}_N^H \mathbf{Q}_N$ to become zero vectors and thus the last $(N_N - M_N)$ diagonal elements of $\mathbf{C}_N$ are zero. Therefore, we can obtain the $\{2M\}$th-order polynomial in λ_N

$$N_d \sum_{i=1}^{M_N} (\alpha_i + N_d \lambda_N)^{-2} \mathbf{C}_N(i,i) = P_N. \quad (38)$$

We notice from the equations in this section that when all the relay nodes are chosen as the neighbour relay nodes, the MMSE design with a neighbour-based power constraint is equivalent to the MMSE design with a global power constraint. Therefore, the global approach can be considered as a specific case of the neighbour-based approach. Table I shows a summary of our proposed MMSE design with global, individual and neighbour-based power constraints which will be used for the simulations. If the quasi-static fading channel (block fading) is considered in the simulations, we only need two iterations.

IV. Proposed Joint Maximum Sum-Rate Design of the Receiver and Power Allocation

In this section, two constrained optimization problems are proposed to describe the joint MSR design of the linear receiver ($\mathbf{w}$) and power allocation parameter ($\mathbf{a}$) subject to a global and neighbour-based power constraints. By the MSR designs, the best possible SNR and QoS can be obtained at the destinations. They will improve the spectrum efficiency which is desirable for the WSNs with the limitation in the sensor node computational capacity. The individual power constraints are not considered here, because of the MSR receiver we make use of the Generalized Rayleigh Quotient which is only suitable to solve the optimization problems for the vectors.

A. MSR Design with a Global Power Constraint

We first consider the case where the total power of all the relay nodes is limited to P_T. By substituting (2) and (3) into (4), we get

$$\mathbf{d} = \mathbf{H}_d \mathbf{A} \mathbf{F} \mathbf{H}_s \mathbf{s} + \mathbf{H}_d \mathbf{A} \mathbf{F} \mathbf{v}_r + \mathbf{v}_d. \quad (39)$$

We focus on a system with one source node for simplicity. Therefore, the expression of the SR in terms of bps/Hz for our two-hop WSN is

$$\mathrm{SR} = \frac{1}{2}\log_2\left[1 + \frac{\sigma_s^2}{\sigma_n^2} \frac{\mathbf{w}^H \mathbf{H}_d \mathbf{A} \mathbf{F} \mathbf{H}_s \mathbf{H}_s^H \mathbf{F}^H \mathbf{A}^H \mathbf{H}_d^H \mathbf{w}}{\mathbf{w}^H (\mathbf{H}_d \mathbf{A} \mathbf{F} \mathbf{F}^H \mathbf{A}^H \mathbf{H}_d^H + \mathbf{I}) \mathbf{w}}\right] \text{ (bps/Hz)}, \quad (40)$$

where $\mathbf{w}$ is the linear receiver, and $(\cdot)^H$ denotes the complex-conjugate (Hermitian) transpose. Let

$$\mathbf{\Phi} = \mathbf{H}_d \mathbf{A} \mathbf{F} \mathbf{H}_s \mathbf{H}_s^H \mathbf{F}^H \mathbf{A}^H \mathbf{H}_d^H, \quad (41)$$

and

$$\mathbf{Z} = \mathbf{H}_d \mathbf{A} \mathbf{F} \mathbf{F}^H \mathbf{A}^H \mathbf{H}_d^H + \mathbf{I}. \quad (42)$$

Equation (40) becomes

$$\mathrm{SR} = \frac{1}{2}\log_2\left(1 + \frac{\sigma_s^2}{\sigma_n^2}\frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}}\right) = \frac{1}{2}\log_2(1 + ax), \quad (43)$$

where

$$a = \frac{\sigma_s^2}{\sigma_n^2} \quad (44)$$

and

$$x = \frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}}. \quad (45)$$

Since $\frac{1}{2}\log_2(1+ax)$ is a monotonically increasing function of x ($a > 0$), the problem of maximizing the sum-rate is equivalent to maximizing x. Therefore, the proposed method can be considered as the following optimization problem:

$$\begin{aligned}[\mathbf{w}_{\mathrm{opt}}, \mathbf{a}_{\mathrm{opt}}] &= \arg\max_{\mathbf{w},\mathbf{a}} \frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}}, \\ &\text{subject to } N_d \mathbf{a}^H \mathbf{a} = P_T.\end{aligned} \quad (46)$$

We note that the expression $\frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}}$ in (46) is the Generalized Rayleigh Quotient. Thus, the optimal solution of our maximization problem can be solved [19]: $\mathbf{w}_{\mathrm{opt}}$ is any eigenvector corresponding to the dominant eigenvalue of $\mathbf{Z}^{-1}\mathbf{\Phi}$.

In order to obtain the optimal power allocation vector $\mathbf{a}_{\mathrm{opt}}$, we rewrite $\frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}}$ and the expression is given by

$$\frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}} = \frac{\mathbf{a}^H \mathrm{diag}\{\mathbf{w}^H \mathbf{H}_d \mathbf{F}\} \mathbf{H}_s \mathbf{H}_s^H \mathrm{diag}\{\mathbf{F}^H \mathbf{H}_d^H \mathbf{w}\} \mathbf{a}}{\mathbf{a}^H \mathrm{diag}\{\mathbf{w}^H \mathbf{H}_d \mathbf{F}\} \mathrm{diag}\{\mathbf{F}^H \mathbf{H}_d^H \mathbf{w}\} \mathbf{a} + \mathbf{w}^H \mathbf{w}}. \quad (47)$$

Since the multiplication of any constant value and an eigenvector is still an eigenvector of the matrix, we express the receive filter as

$$\mathbf{w} = \frac{\mathbf{w}_{\mathrm{opt}}}{\sqrt{\mathbf{w}_{\mathrm{opt}}^H \mathbf{w}_{\mathrm{opt}}}}. \quad (48)$$

Hence, we obtain

$$\mathbf{w}^H \mathbf{w} = 1 = \frac{N_d \mathbf{a}^H \mathbf{a}}{P_T}. \quad (49)$$

By substituting (49) into (47), we get

$$\frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}} = \frac{\mathbf{a}^H \mathrm{diag}\{\mathbf{w}^H \mathbf{H}_d \mathbf{F}\} \mathbf{H}_s \mathbf{H}_s^H \mathrm{diag}\{\mathbf{F}^H \mathbf{H}_d^H \mathbf{w}\} \mathbf{a}}{\mathbf{a}^H (\mathrm{diag}\{\mathbf{w}^H \mathbf{H}_d \mathbf{F}\} \mathrm{diag}\{\mathbf{F}^H \mathbf{H}_d^H \mathbf{w}\} + \frac{N_d}{P_T}\mathbf{I}) \mathbf{a}}. \quad (50)$$

Let

$$\mathbf{M} = \mathrm{diag}\{\mathbf{w}^H \mathbf{H}_d \mathbf{F}\} \mathbf{H}_s \mathbf{H}_s^H \mathrm{diag}\{\mathbf{F}^H \mathbf{H}_d^H \mathbf{w}\}, \quad (51)$$

and

$$\mathbf{N} = \mathrm{diag}\{\mathbf{w}^H \mathbf{H}_d \mathbf{F}\} \mathrm{diag}\{\mathbf{F}^H \mathbf{H}_d^H \mathbf{w}\} + \frac{N_d}{P_T}\mathbf{I}. \quad (52)$$

Equation (50) becomes

$$\frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}} = \frac{\mathbf{a}^H \mathbf{M} \mathbf{a}}{\mathbf{a}^H \mathbf{N} \mathbf{a}}. \quad (53)$$

Likewise, we note that the expression $\frac{\mathbf{a}^H \mathbf{M} \mathbf{a}}{\mathbf{a}^H \mathbf{N} \mathbf{a}}$ in (53) is the Generalized Rayleigh Quotient. Thus, the optimal solution of our maximization problem can be solved: $\mathbf{a}_{\mathrm{opt}}$ is any eigenvector corresponding to the dominant eigenvalue of $\mathbf{N}^{-1}\mathbf{M}$, and satisfying $\mathbf{a}_{\mathrm{opt}}^H \mathbf{a}_{\mathrm{opt}} = \frac{P_T}{N_d}$. The solutions of $\mathbf{w}_{\mathrm{opt}}$ and $\mathbf{a}_{\mathrm{opt}}$ depend on each other. Thus, it is necessary to iterate them with an initial value of $\mathbf{a}$ to obtain the optimum solutions.

B. MSR Design with a Neighbour-based Power Constraint

Similar to the steps described in Section III.C, we separate the relay nodes into neighbour relay nodes and non-neighbour nodes in the expressions of the system model. Therefore, (2)

TABLE I
SUMMARY OF THE PROPOSED MMSE DESIGN WITH GLOBAL, INDIVIDUIAL AND NEIGHBOUR-BASED POWER CONSTRAINTS

Global Power Constraint	Individual Power Constraints	Neighbour-based Power Constraint
Initialize the algorithm by setting: $\mathbf{A}=\sqrt{\frac{P_T}{N_r N_d}}\mathbf{I}$ For each iteration: 1. Compute $\mathbf{W}_{\text{opt}}$ in (7). 2. Compute $\boldsymbol{\phi}$ and $\mathbf{z}$ in (11) and (12). 3. Calculate the EVD of $\boldsymbol{\phi}$ in (14). 4. Solve λ in (19). 5. Compute $\mathbf{a}_{\text{opt}}$ in (9).	Initialize the algorithm by setting: $a_i=\sqrt{\frac{P_{T,i}}{N_d}}$ for $i=1,2,...,N_r$ For each iteration: 1. Compute $\mathbf{W}_{\text{opt}}$ in (7). 2. Compute $\boldsymbol{\phi}$ and $\mathbf{z}$ in (11) and (12). 3. For $i=1,2,...,N_r$ a) Solve λ_i in (23). b) Compute $a_{i,\text{opt}}$ in (22).	Initialize the algorithm by setting: $\mathbf{A}=\sqrt{\frac{P_T}{N_r N_d}}\mathbf{I}$ For each iteration: 1. Compute $\mathbf{W}_{\text{opt}}$ in (7). 2. Compute $\boldsymbol{\phi}_N$ and $\mathbf{z}_N$ in (30) and (31). 3. Calculate the EVD of $\boldsymbol{\phi}_N$ in (33). 4. Solve λ_N in (38) 5. Compute $\mathbf{a}_{N,\text{opt}}$ in (28).

and (3) can be rewritten as

$$\mathbf{x}_N=\mathbf{H}_{s,N}\mathbf{s}+\mathbf{v}_N, \tag{54}$$

$$\mathbf{x}_o=\mathbf{H}_{s,o}\mathbf{s}+\mathbf{v}_o, \tag{55}$$

$$\mathbf{y}_N=\mathbf{F}_N\mathbf{x}_N, \tag{56}$$

$$\mathbf{y}_o=\mathbf{F}_o\mathbf{x}_o, \tag{57}$$

where the subscript N is denoted for the neighbour relay nodes and the subscript o is used for the non-neighbour relay nodes. By substituting (54)-(57) into (24), we get

$$\begin{aligned}\mathbf{d}=&(\mathbf{H}_N\mathbf{A}_N\mathbf{F}_N\mathbf{H}_{s,N}+\mathbf{H}_o\mathbf{A}_o\mathbf{F}_o\mathbf{H}_{s,o})\mathbf{s}+\mathbf{H}_N\mathbf{A}_N\mathbf{F}_N\mathbf{v}_N\\&+\mathbf{H}_o\mathbf{A}_o\mathbf{F}_o\mathbf{v}_o+\mathbf{v}_d.\end{aligned} \tag{58}$$

We focus on the system which consists of one source node. Therefore, the expression of the SR in terms of bps/Hz for our two-hop WSN is

$$\text{SR}=\frac{1}{2}\log_2\left(1+\frac{\sigma_s^2}{\sigma_n^2}\frac{\mathbf{w}^H\boldsymbol{\Phi}\mathbf{w}}{\mathbf{w}^H\mathbf{Z}\mathbf{w}}\right)\ \text{(bps/Hz)}. \tag{59}$$

where

$$\begin{aligned}\boldsymbol{\Phi}=&(\mathbf{H}_N\mathbf{A}_N\mathbf{F}_N\mathbf{H}_{s,N}+\mathbf{H}_o\mathbf{A}_o\mathbf{F}_o\mathbf{H}_{s,o})\\&*(\mathbf{H}_N\mathbf{A}_N\mathbf{F}_N\mathbf{H}_{s,N}+\mathbf{H}_o\mathbf{A}_o\mathbf{F}_o\mathbf{H}_{s,o})^H,\end{aligned} \tag{60}$$

and

$$\mathbf{Z}=\mathbf{H}_N\mathbf{A}_N\mathbf{F}_N\mathbf{F}_N^H\mathbf{A}_N^H\mathbf{H}_N^H+\mathbf{H}_o\mathbf{A}_o\mathbf{F}_o\mathbf{F}_o^H\mathbf{A}_o^H\mathbf{H}_o^H+\mathbf{I}. \tag{61}$$

We consider the case where the total power of all the neighbour relay nodes is limited to P_N and $P_N+N_d\mathbf{a}_o^H\mathbf{a}_o=P_T$. Following the same steps as described in Section IV.A, the proposed method can be considered as the following optimization problem

$$\begin{aligned}[\mathbf{w}_{\text{opt}},\mathbf{a}_{N,\text{opt}}]\ &=\arg\max_{\mathbf{w},\mathbf{a}_N}\frac{\mathbf{w}^H\boldsymbol{\Phi}\mathbf{w}}{\mathbf{w}^H\mathbf{Z}\mathbf{w}},\\ &\text{subject to } N_d\mathbf{a}_N^H\mathbf{a}_N=P_N.\end{aligned} \tag{62}$$

We note that the expression $\frac{\mathbf{w}^H\boldsymbol{\Phi}\mathbf{w}}{\mathbf{w}^H\mathbf{Z}\mathbf{w}}$ in (62) is the Generalized Rayleigh Quotient. Thus, the optimal solution of our maximization problem can be solved: $\mathbf{w}_{\text{opt}}$ is any eigenvector corresponding to the dominant eigenvalue of $\mathbf{Z}^{-1}\boldsymbol{\Phi}$.

In order to obtain the optimal power allocation vector for the neighbour relay nodes $\mathbf{a}_{N,\text{opt}}$, we rewrite $\frac{\mathbf{w}^H\boldsymbol{\Phi}\mathbf{w}}{\mathbf{w}^H\mathbf{Z}\mathbf{w}}$

$$\frac{\mathbf{w}^H\boldsymbol{\Phi}\mathbf{w}}{\mathbf{w}^H\mathbf{Z}\mathbf{w}}=\frac{\mathbf{a}_N^H\mathbf{M}_1\mathbf{a}_N+\mathbf{a}_N^H\mathbf{M}_2\mathbf{a}_o+\mathbf{a}_o^H\mathbf{M}_3\mathbf{a}_N+\mathbf{a}_o^H\mathbf{M}_4\mathbf{a}_o}{\mathbf{a}_N^H\mathbf{N}_1\mathbf{a}_N+\mathbf{w}^H\mathbf{N}_2\mathbf{w}} \tag{63}$$

where

$$\mathbf{M}_1=\text{diag}\{\mathbf{w}^H\mathbf{H}_N\mathbf{F}_N\}\mathbf{H}_{s,N}\mathbf{H}_{s,N}^H\text{diag}\{\mathbf{F}_N^H\mathbf{H}_N^H\mathbf{w}\}, \tag{64}$$

$$\mathbf{M}_2=\text{diag}\{\mathbf{w}^H\mathbf{H}_N\mathbf{F}_N\}\mathbf{H}_{s,N}\mathbf{H}_{s,o}^H\text{diag}\{\mathbf{F}_o^H\mathbf{H}_o^H\mathbf{w}\}, \tag{65}$$

$$\mathbf{M}_3=\text{diag}\{\mathbf{w}^H\mathbf{H}_o\mathbf{F}_o\}\mathbf{H}_{s,o}\mathbf{H}_{s,N}^H\text{diag}\{\mathbf{F}_N^H\mathbf{H}_N^H\mathbf{w}\}, \tag{66}$$

$$\mathbf{M}_4=\text{diag}\{\mathbf{w}^H\mathbf{H}_o\mathbf{F}_o\}\mathbf{H}_{s,o}\mathbf{H}_{s,o}^H\text{diag}\{\mathbf{F}_o^H\mathbf{H}_o^H\mathbf{w}\}, \tag{67}$$

$$\mathbf{N}_1=\text{diag}\{\mathbf{w}^H\mathbf{H}_N\mathbf{F}_N\}\text{diag}\{\mathbf{F}_N^H\mathbf{H}_N^H\mathbf{w}\}, \tag{68}$$

$$\mathbf{N}_2=\mathbf{H}_o\mathbf{A}_o\mathbf{F}_o\mathbf{F}_o^H\mathbf{A}_o^H\mathbf{H}_o^H+\mathbf{I}. \tag{69}$$

Since the multiplication of any constant value and an eigenvector is still an eigenvector of the matrix, we express the receive filter as

$$\mathbf{w}=\frac{\mathbf{w}_{\text{opt}}}{\sqrt{\mathbf{w}_{\text{opt}}^H(\mathbf{H}_o\mathbf{A}_o\mathbf{F}_o\mathbf{F}_o^H\mathbf{A}_o^H\mathbf{H}_o^H+\mathbf{I})\mathbf{w}_{\text{opt}}}}. \tag{70}$$

Therefore, we obtain

$$\mathbf{w}^H\mathbf{N}_2\mathbf{w}=1=\frac{N_d}{P_N}\mathbf{a}_N^H\mathbf{a}_N. \tag{71}$$

By substituting (71) into (63), we obtain

$$\frac{\mathbf{w}^H\boldsymbol{\Phi}\mathbf{w}}{\mathbf{w}^H\mathbf{Z}\mathbf{w}}=\frac{\mathbf{a}_N^H\mathbf{M}_1\mathbf{a}_N+\mathbf{a}_N^H\mathbf{M}_2\mathbf{a}_o+\mathbf{a}_o^H\mathbf{M}_3\mathbf{a}_N+\mathbf{a}_o^H\mathbf{M}_4\mathbf{a}_o}{\mathbf{a}_N^H\mathbf{N}\mathbf{a}_N}, \tag{72}$$

where

$$\mathbf{N}=\mathbf{N}_1+\frac{N_d}{P_N}\mathbf{I}. \tag{73}$$

The expression in (72) can be divided into four terms and only the first term is the Generalized Rayleigh Quotient. In order to make use of the Generalized Rayleigh Quotient to solve the optimization problem, our aim is to transform the remaining three terms into the Generalized Rayleigh Quotient. For the fourth term, we have

$$\begin{aligned}\mathbf{a}_o^H\mathbf{M}_4\mathbf{a}_o&=\mathbf{a}_o^H\mathbf{M}_4\mathbf{a}_o\frac{N_d\mathbf{a}_N^H\mathbf{a}_N}{P_N}\\&=\mathbf{a}_N^H\left(\frac{N_d\mathbf{a}_o^H\mathbf{M}_4\mathbf{a}_o}{P_N}\mathbf{I}\right)\mathbf{a}_N.\end{aligned} \tag{74}$$

For the second and third terms, we can achieve the Generalized Rayleigh Quotient by solving the following optimization problem:

$$[\mathbf{T}_{\text{opt}}, \mathbf{a}_{N,\text{opt}}] = \arg\min_{\mathbf{T},\mathbf{a}_N} (\mathbf{a}_N^H \mathbf{M}_2 \mathbf{a}_o + \mathbf{a}_o^H \mathbf{M}_3 \mathbf{a}_N - \mathbf{a}_N^H \mathbf{T} \mathbf{a}_N)^2, \quad \text{subject to } N_d \mathbf{a}_N^H \mathbf{a}_N = P_N. \tag{75}$$

By fixing $\mathbf{a}_N$, we obtain

$$\mathbf{T} = \frac{N_d}{P_N} (\mathbf{M}_2 \mathbf{a}_o \mathbf{a}_N^H + \mathbf{a}_N \mathbf{a}_o^H \mathbf{M}_3) \tag{76}$$

which satisfies the following equation

$$\mathbf{a}_N^H \mathbf{M}_2 \mathbf{a}_o + \mathbf{a}_o^H \mathbf{M}_3 \mathbf{a}_N = \mathbf{a}_N^H \mathbf{T} \mathbf{a}_N \tag{77}$$

for any value of $\mathbf{a}_N$. Let us define

$$\mathbf{M} = \mathbf{M}_1 + \mathbf{T} + \frac{N_d \mathbf{a}_o^H \mathbf{M}_4 \mathbf{a}_o}{P_N} \mathbf{I}. \tag{78}$$

Then, equation (72) becomes

$$\frac{\mathbf{w}^H \mathbf{\Phi} \mathbf{w}}{\mathbf{w}^H \mathbf{Z} \mathbf{w}} = \frac{\mathbf{a}_N^H \mathbf{M} \mathbf{a}_N}{\mathbf{a}_N^H \mathbf{N} \mathbf{a}_N}, \tag{79}$$

which is a Generalized Rayleigh Quotient. Therefore, the optimal solution of our maximization problem can be solved: $\mathbf{a}_{N,\text{opt}}$ is any eigenvector corresponding to the dominant eigenvalue of $\mathbf{N}^{-1}\mathbf{M}$ and satisfies $\mathbf{a}_{N,\text{opt}}^H \mathbf{a}_{N,\text{opt}} = \frac{P_N}{N_d}$.

In this section, two methods are employed to calculate the dominant eigenvectors. The first one is the QR algorithm [23] which calculates all the eigenvalues and eigenvectors of a matrix. We can choose the dominant eigenvector among them. The second one is the power method [23] which only calculates the dominant eigenvector of a matrix. Hence, the computational complexity can be reduced. Table II shows a summary of our proposed MSR design with global and neighbour-based power constraints which will be used for the simulations. If the quasi-static fading channel (block fading) is considered in the simulations, we only need two iterations.

V. Analysis of the Proposed Algorithms

In this section, an analysis of the computational complexity and a convergency of the algorithms are developed.

A. Computational Complexity Analysis

Table III and Table IV list the computational complexity per iteration in terms of the number of multiplications, additions and divisions for our proposed joint linear receiver design (MMSE and MSR) and power allocation strategies. For the joint MMSE designs, we use the QR algorithm to perform the eigendecomposition of the matrix. We set $M = \min\{N_s, N_r, N_d\} = 1$ and $M_N = \min\{N_s, N_N, N_d\} = 1$ to simplify the processing of solving the equations in (19) and (38). Please note that in this paper the QR decomposition by Householder transformation [23], [24] is employed by the QR algorithms. n_Q and n_P denote the number of iterations of the QR algorithm and the power method, respectively. Because the multiplication dominates the computational complexity, in order to compare the computational complexity of our proposed joint MMSE and MSR deigns, the number of multiplications versus the number of relay nodes for each iteration are displayed in Fig. 2 and Fig 3. For the purpose of illustration, we set $N_s = 1$, $N_d = 2$ and $n_Q = n_P = 10$. R denotes the averaged ratio of the number of neighbour relay nodes to the number of relay nodes. It can be seen that our proposed MMSE and MSR receivers with a neighbour-based power constraint have a significant complexity reduction compared with the proposed receivers with a global power constraint. Obviously, a lower R will lead to a lower computational complexity. For the MMSE design, when the individual power constrains are considered, the computational complexity is lower than other constraints because there is no need to compute the eigendecomposition for it. For the MSR design, employing the power method to calculate the dominant eigenvectors has a lower computational complexity than employing the QR algorithm.

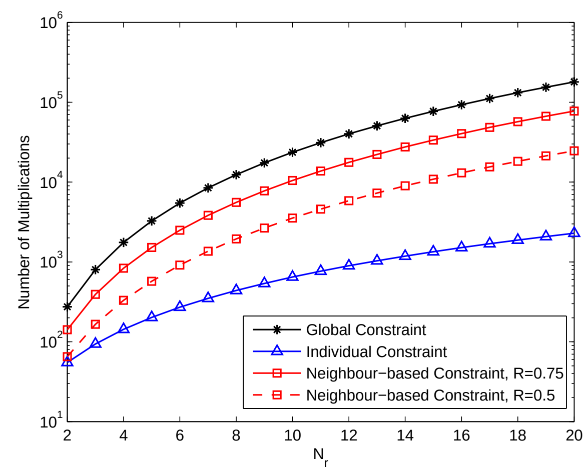

Fig. 2. Number of multiplications versus the number of relay nodes of our proposed joint MMSE design of the receiver and power allocation strategies.

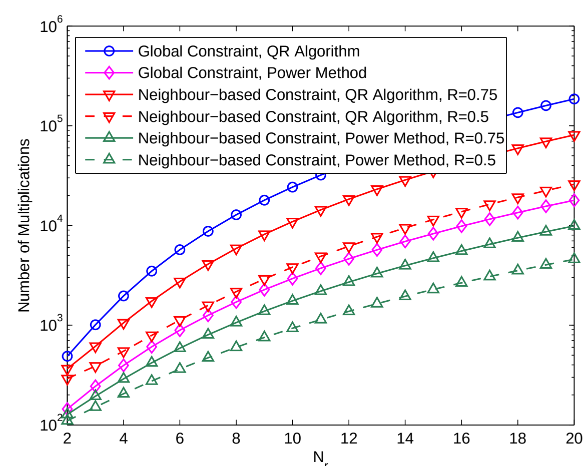

Fig. 3. Number of multiplications versus the number of relay nodes of our proposed joint MSR design of the receiver and power allocation strategies.

TABLE II

SUMMARY OF THE PROPOSED MSR DESIGN WITH GLOBAL AND NEIGHBOUR-BASED POWER CONSTRAINTS

Global Power Constraint	Neighbour-based Power Constraint
Initialize the algorithm by setting: $\mathbf{A}=\sqrt{\frac{P_T}{N_rN_d}}\mathbf{I}$ For each iteration: 1. Compute $\boldsymbol{\Phi}$ and $\mathbf{Z}$ in (41) and (42). 2. Use the QR algorithm or the power method to compute the dominant eigenvector of $\mathbf{Z}^{-1}\boldsymbol{\Phi}$, denoted as $\mathbf{w}_{\rm opt}$. 3. Compute $\mathbf{M}$ and $\mathbf{N}$ in (51) and (52). 4. Use the QR algorithm or the power method to compute the dominant eigenvector of $\mathbf{N}^{-1}\mathbf{M}$, denoted as $\mathbf{a}$. 5. To ensure the power constraint $\mathbf{a}_{\rm opt}^H\mathbf{a}_{\rm opt}=\frac{P_T}{N_d}$, compute $\mathbf{a}_{\rm opt}=\sqrt{\frac{P_T}{N_d\mathbf{a}^H\mathbf{a}}}\mathbf{a}$.	Initialize the algorithm by setting: $\mathbf{A}=\sqrt{\frac{P_T}{N_rN_d}}\mathbf{I}$ (include $\mathbf{a}_N$ and $\mathbf{a}_o$) For each iteration: 1. Compute $\boldsymbol{\Phi}$ and $\mathbf{Z}$ in (60) and (61). 2. Use the QR algorithm or the power method to compute the dominant eigenvector of $\mathbf{Z}^{-1}\boldsymbol{\Phi}$, denoted as $\mathbf{w}_{\rm opt}$. 3. Compute $\mathbf{T}$ in (76). 4. Compute $\mathbf{M}$ and $\mathbf{N}$ in (78) and (73). 5. Use the QR algorithm or the power method to compute the dominant eigenvector of $\mathbf{N}^{-1}\mathbf{M}$, denoted as $\mathbf{a}_N$. 6. To ensure the power constraint $\mathbf{a}_{N,\rm opt}^H\mathbf{a}_{N,\rm opt}=\frac{P_N}{N_d}$, compute $\mathbf{a}_{N,\rm opt}=\sqrt{\frac{P_N}{N_d\mathbf{a}_N^H\mathbf{a}_N}}\mathbf{a}_N$.

TABLE III

COMPUTATIONAL COMPLEXITY PER ITERATION OF THE JOINT MMSE DESIGNS

Parameter	Power Constraint Type	Multiplications	Additions	Divisions
$\mathbf{W}$	All	$N_d(N_d-1)(4N_d+1)/6$ $+(N_s+N_r)N_d^2+N_r^2N_d+N_sN_rN_d$ $+N_rN_d$	$N_d(N_d-1)(4N_d+1)/6$ $+(N_s+N_r)N_d^2+N_r^2N_d+N_sN_rN_d$ $-(N_d^2+2N_sN_d+N_rN_d)+N_d$	$N_d(3N_d-1)/2$
λ	Global	$n_Q(\frac{13}{6}N_r^3+\frac{3}{2}N_r^2+\frac{1}{3}N_r-2)$ $-N_r^3+3N_sN_r^2+N_sN_rN_d$ $+N_r^2+N_sN_r+1$	$n_Q(\frac{13}{6}N_r^3-N_r^2-\frac{1}{6}N_r+1)$ $-N_r^3+3N_sN_r^2+N_sN_rN_d$ $-N_r^2-2N_sN_r-N_r+1$	$n_Q(N_r-1)+1$
	Individual	$N_sN_r^2+N_sN_rN_d+2N_r^2+N_sN_r+N_r$	$N_sN_r^2+N_sN_rN_d-N_sN_r$	N_r
	Neighbour-based	$n_Q(\frac{13}{6}N_N^3+\frac{3}{2}N_N^2+\frac{1}{3}N_N-2)$ $-N_N^3+2N_sN_N^2+N_sN_rN_d+N_sN_rN_N$ $-N_N^2+2N_rN_N+N_sN_N+1$	$n_Q(\frac{13}{6}N_N^3-N_N^2-\frac{1}{6}N_N+1)$ $-N_N^3+2N_sN_N^2+N_sN_rN_d+N_sN_rN_N$ $-N_N^2-N_sN_N-N_sN_r-2N_N+2$	$n_Q(N_N-1)+1$
$\mathbf{a}$	Global	$N_r(N_r-1)(4N_r+1)/6+N_r^2+1$	$N_r(N_r-1)(4N_r+1)/6+N_r^2$	$N_r(3N_r-1)/2$
	Individual	$2N_r$	N_r	N_r
	Neighbour-based	$N_N(N_N-1)(4N_N+1)/6+N_N^2+1$	$N_N(N_N-1)(4N_N+1)/6+N_N^2$	$N_N(3N_N-1)/2$

B. Sufficient Conditions for Convergence

To develop the analysis and proofs, we need to define a metric space and the Hausdorff distance that will extensively be used. A metric space is an ordered pair $(\mathcal{M},d)$, where $\mathcal{M}$ is a nonempty set, and d is a metric on $\mathcal{M}$, i.e., a function $d:\mathcal{M}\times\mathcal{M}\rightarrow\mathbb{R}$ such that for any $x,y,z\in\mathcal{M}$, the following conditions hold:

1) $d(x,y)\geq 0$.
2) $d(x,y)=0$ iff $x=y$.
3) $d(x,y)=d(y,x)$.
4) $d(x,y)\leq d(x,y)+d(y,z)$.

The Hausdorff distance measures how far two subsets of a metric space are from each other and is defined by

$$d_H(X,Y)=\max\left\{\sup_{x\in X}\inf_{y\in Y}d(x,y),\sup_{y\in Y}\inf_{x\in X}d(x,y)\right\}. \tag{80}$$

The proposed joint MMSE designs can be stated as an alternating minimization strategy based on the MSE defined in (5) and expressed as

$$\mathbf{W}_n\in\arg\min_{\mathbf{W}\in\underline{\mathbf{W}}_n}\mathrm{MSE}(\mathbf{W},\mathbf{a}_{n-1}) \tag{81}$$

$$\mathbf{a}_n\in\arg\min_{\mathbf{a}\in\underline{\mathbf{a}}_n}\mathrm{MSE}(\mathbf{W}_n,\mathbf{a}) \tag{82}$$

where the sets $\underline{\mathbf{W}},\underline{\mathbf{a}}\subset\mathcal{M}$, and the sequences of compact sets $\{\underline{\mathbf{W}}_n\}_{n\geq 0}$ and $\{\underline{\mathbf{a}}_n\}_{n\geq 0}$ converge to the sets $\underline{\mathbf{W}}$ and $\underline{\mathbf{a}}$, respectively.

Although we are not given the sets $\underline{\mathbf{W}}$ and $\underline{\mathbf{a}}$ directly, we have the sequence of compact sets $\{\underline{\mathbf{W}}_n\}_{n\geq 0}$ and $\{\underline{\mathbf{a}}_n\}_{n\geq 0}$. The aim of our proposed joint MMSE designs is to find a sequence of $\mathbf{W}_n$ and $\mathbf{a}_n$ such that

$$\lim_{n\rightarrow\infty}\mathrm{MSE}(\mathbf{W}_n,\mathbf{a}_n)=\mathrm{MSE}(\mathbf{W}_{\rm opt},\mathbf{a}_{\rm opt}) \tag{83}$$

where $\mathbf{W}_{\rm opt}$ and $\mathbf{a}_{\rm opt}$ correspond to the optimal values of $\mathbf{W}_n$ and $\mathbf{a}_n$, respectively. To present a set of sufficient conditions under which the proposed algorithms converge, we need the so-called three-point and four-point properties [17], [18]. Let

TABLE IV
COMPUTATIONAL COMPLEXITY PER ITERATION OF THE JOINT MSR DESIGNS

Parameter	Power Constraint Type	Multiplications	Additions	Divisions
$\mathbf{w}$	Global/Neighbour-based QR Algorithm	$n_Q(\frac{13}{6}N_d^3+\frac{3}{2}N_d^2+\frac{1}{3}N_d-2)$ $+N_d(N_d-1)(4N_d+1)/6$ $+N_rN_d^2+N_d^2+3N_rN_d$	$n_Q(\frac{13}{6}N_d^3-N_d^2-\frac{1}{6}N_d+1)$ $+N_d(N_d-1)(4N_d+1)/6$ $+N_rN_d^2-N_d^2+N_rN_d$	$n_Q(N_d-1)$ $+N_d(3N_d-1)/2$
	Global/Neighbour-based Power Method	$n_PN_d^2$ $+N_d(N_d-1)(4N_d+1)/6$ $+N_d^3+N_rN_d^2+N_d^2+3N_rN_d$	$n_PN_d(N_d-1)$ $+N_d(N_d-1)(4N_d+1)/6$ $+N_d^3+N_rN_d^2-2N_d^2+N_rN_d$	$N_d(3N_d-1)/2$
$\mathbf{a}$	Global QR Algorithm	$n_Q(\frac{13}{6}N_r^3+\frac{3}{2}N_r^2+\frac{1}{3}N_r-2)$ $+N_r(N_r-1)(4N_r+1)/6$ $+N_r^2+N_rN_d+4N_r+N_d$	$n_Q(\frac{13}{6}N_r^3-N_r^2-\frac{1}{6}N_r+1)$ $+N_r(N_r-1)(4N_r+1)/6$ $+N_rN_d+N_r+N_d-2$	$n_Q(N_r-1)$ $+N_r(3N_r-1)/2$ $+N_d+1$
	Global Power Method	$n_PN_r^2$ $+N_r(N_r-1)(4N_r+1)/6$ $+N_r^3+N_r^2+N_rN_d+4N_r+N_d$	$n_PN_r(N_r-1)$ $+N_r(N_r-1)(4N_r+1)/6$ $+N_r^3-N_r^2+N_rN_d+N_r+N_d-2$	$N_r(3N_r-1)/2$ $+N_d+1$
	Neighbour-based QR Algorithm	$n_Q(\frac{13}{6}N_N^3+\frac{3}{2}N_N^2+\frac{1}{3}N_N-2)$ $+N_N(N_N-1)(4N_N+1)/6$ $-N_N^3+N_rN_N^2+2N_r^2+2N_N^2+N_d^2$ $+N_rN_d-2N_rN_N+2N_r+2N_N+N_d+1$	$n_Q(\frac{13}{6}N_N^3-N_N^2-\frac{1}{6}N_N+1)$ $+N_N(N_N-1)(4N_N+1)/6$ $-N_N^3+N_rN_N^2+N_r^2+2N_N^2+N_d^2$ $+N_rN_d-2N_rN_N-N_r+3N_N-3$	$n_Q(N_N-1)$ $+N_N(3N_N-1)/2$ $+N_d+1$
	Neighbour-based Power Method	$n_PN_N^2$ $+N_N(N_N-1)(4N_N+1)/6$ $+N_rN_N^2+2N_r^2+2N_N^2+N_d^2$ $+N_rN_d-2N_rN_N+2N_r+2N_N+N_d+1$	$n_PN_r(N_r-1)$ $+N_N(N_N-1)(4N_N+1)/6$ $+N_rN_N^2+N_r^2+N_N^2+N_d^2$ $+N_rN_d-2N_rN_N-N_r+3N_N-3$	$N_N(3N_N-1)/2$ $+N_d+1$

us assume that there is a function $f:\mathcal{M}\times\mathcal{M}\rightarrow\mathbb{R}$ such that the following conditions are satisfied.

1) *Three-point property* $(\mathbf{W},\widetilde{\mathbf{W}},\mathbf{a})$:
For all $n\geq 1$, $\mathbf{W}\in\underline{\mathbf{W}}_n$, $\mathbf{a}\in\underline{\mathbf{a}}_{n-1}$, and
$\widetilde{\mathbf{W}}\in\arg\min_{\mathbf{W}\in\underline{\mathbf{W}}_n}\text{MSE}(\mathbf{W},\mathbf{a})$, we have

$$f(\mathbf{W},\widetilde{\mathbf{W}})+\text{MSE}(\widetilde{\mathbf{W}},\mathbf{a})\leq\text{MSE}(\mathbf{W},\mathbf{a}) \tag{84}$$

2) *Four-point property* $(\mathbf{W},\mathbf{a},\widetilde{\mathbf{W}},\tilde{\mathbf{a}})$:
For all $n\geq 1$, $\mathbf{W},\widetilde{\mathbf{W}}\in\underline{\mathbf{W}}_n$, $\mathbf{a}\in\underline{\mathbf{a}}_n$, and
$\tilde{\mathbf{a}}\in\arg\min_{\mathbf{a}\in\underline{\mathbf{a}}_n}\text{MSE}(\widetilde{\mathbf{W}},\mathbf{a})$, we have

$$\text{MSE}(\mathbf{W},\tilde{\mathbf{a}})\leq\text{MSE}(\mathbf{W},\mathbf{a})+f(\mathbf{W},\widetilde{\mathbf{W}}) \tag{85}$$

These two properties are the mathematical expressions of the sufficient conditions for the convergence of the alternating minimization algorithms which are stated in [17] and [18]. It means that if there exists a function $f(\mathbf{W},\widetilde{\mathbf{W}})$ with the parameter $\mathbf{W}$ during two iterations that satisfies the two inequalities about the MSE in (83) and (84), the convergence of our proposed MMSE designs that make use of the alternating minimization algorithm can be proved by the theorem below.

Theorem: Let $\{(\underline{\mathbf{W}}_n,\underline{\mathbf{a}}_n)\}_{n\geq 0}$, $\underline{\mathbf{W}},\underline{\mathbf{a}}$ be compact subsects of the compact metric space $(\mathcal{M},d)$ such that

$$\underline{\mathbf{W}}_n\overset{d_H}{\rightarrow}\underline{\mathbf{W}}\qquad\underline{\mathbf{a}}_n\overset{d_H}{\rightarrow}\underline{\mathbf{a}} \tag{86}$$

and let MSE : $\mathcal{M}\times\mathcal{M}\rightarrow\mathbb{R}$ be a continuous function. Let conditions 1) and 2) hold. Then, for the proposed algorithms, we have

$$\lim_{n\rightarrow\infty}\text{MSE}(\mathbf{W}_n,\mathbf{a}_n)=\text{MSE}(\mathbf{W}_{\text{opt}},\mathbf{a}_{\text{opt}}) \tag{87}$$

A general proof of this theorem is detailed in [17] and [18]. The proposed joint MSR designs can be stated as an alternating maximization strategy based on the SR defined in (40) that follow a similar procedure to the one above.

VI. SIMULATIONS

In this section, we numerically study the performance of our proposed joint designs of the linear receiver and the power allocation methods and compare them with the equal power allocation method [7] which allocates the same power level for all links between relay nodes and destination nodes. For the purpose of fairness, we assume that the total power for all relay nodes in the network is the same which can be indicated as $\sum_{i=1}^{N_r}P_{T,i}=P_T$. We consider a two-hop wireless sensor network. The number of source nodes (N_s), relay nodes (N_r) and destination nodes (N_d) are 1, 4 and 2 respectively. We consider an AF cooperation protocol. The quasi-static fading channel (block fading channel) is considered in our simulations whose elements are Rayleigh random variables (with zero mean and unit variance) and assumed to be invariant during the transmission of each packet. In our simulations, the channel is assumed to be known at the destination nodes. For channel estimation algorithms for WSNs and other low-complexity parameter estimation algorithms, one refers to [26] and [27]. During each phase, the source transmits the QPSK modulated packets with 1500 symbols. The noise at the relay and destination nodes is modeled as circularly symmetric complex Gaussian random variables with zero mean. A perfect (error free) feedback channel between the destination nodes and the relay nodes is assumed to transmit the amplification coefficients.

For the MMSE design, it can be seen from Fig. 4 that our three proposed methods achieve a better BER performance than the equal power allocation method. Among them, the method with a global constraint has the best performance. This result is what we expected because a global constraint provides the largest degrees of freedom for allocating the power among the relay nodes. For the method with a neighbour-based constraint, we introduce a bound B, which is set to 0.6, for the channel power gain between the relay nodes and the destination nodes to choose the neighbour relay nodes. Although it has a higher BER compared to the method with a global constraint, the averaged ratio of the number of neighbour relay nodes to the number of relay nodes (R) is 0.7843 which indicates a reduced computational complexity. For the MSR design, it can be seen from Fig. 5 and Fig. 6 that our proposed methods achieve a better sum-rate performance than the equal power allocation method. Using the power method to calculate the dominant eigenvector yields a very similar result to the QR algorithm but requires a lower complexity. For the method with a neighbour-based constraint, when we introduce a bound B = 0.6, a similar performance to the method with a global constraint can be achieved with a reduced R (0.7830).

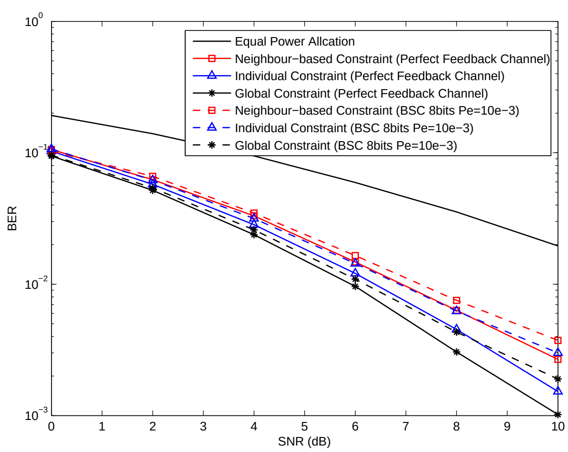

Fig. 4. BER performance versus SNR of our proposed joint MMSE design of the receiver and power allocation strategies, compared to the equal power allocation method.

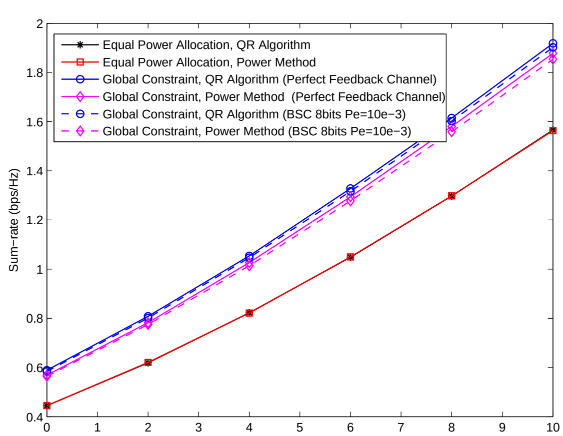

Fig. 5. Sum-rate performance versus SNR of our proposed joint MSR design of the receiver and power allocation strategies with a global constraint, compared to the equal power allocation method.

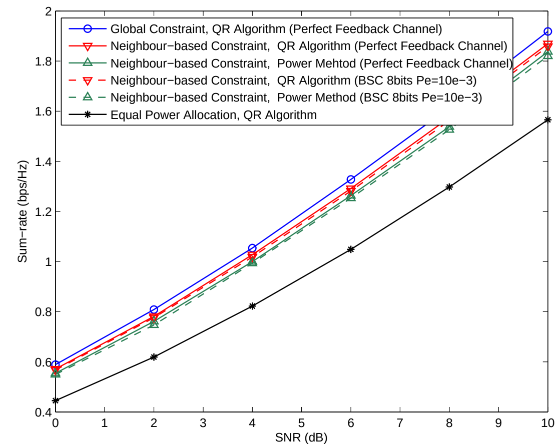

Fig. 6. Sum-rate performance versus SNR of our proposed joint MSR design of the receiver and power allocation strategies with a neighbour-based constraint, compared to the equal power allocation method.

To show the performance tendency for other values of B, we fix the SNR at 10 dB and choose B ranging form 0 to 1.5. The performance curves are shown in Fig. 7 and Fig. 8, which include the BER and sum-rate performance versus B and R versus B of the MMSE design and MSR design respectively with a neighbour-based power constraint. It can be seen that along with the increase in B, their performance becomes worse, and the R becomes lower. It demonstrates that for our joint designs of the receivers with a neighbour-based power constraint, the value of B can be varied to trade off achievable performance against computation complexity.

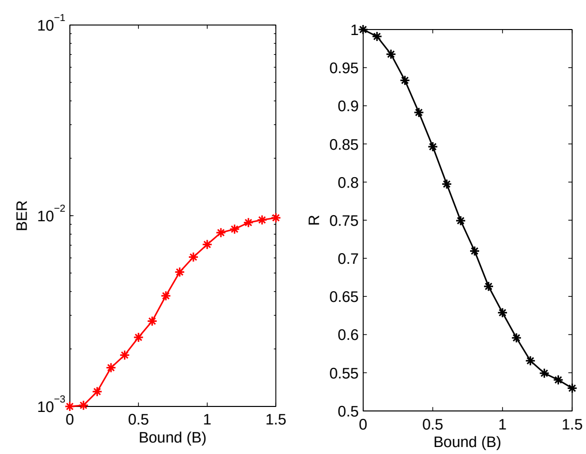

Fig. 7. (a) BER performance versus the bound and (b) R versus the bound of the MMSE design with a neighbour-based power constraint.

Besides the equal power allocation scheme, the two-stage power allocation scheme reported in [25] has also been used for comparison. It can be seen from Fig. 9 that our proposed MMSE and MSR designs outperform the two-stage power allocation scheme. Note that in order to have a fair comparison for which the sum power of all the relay nodes is constrained (global constraint), we only employ the second stage of the two-stage power allocation scheme in the simulations.

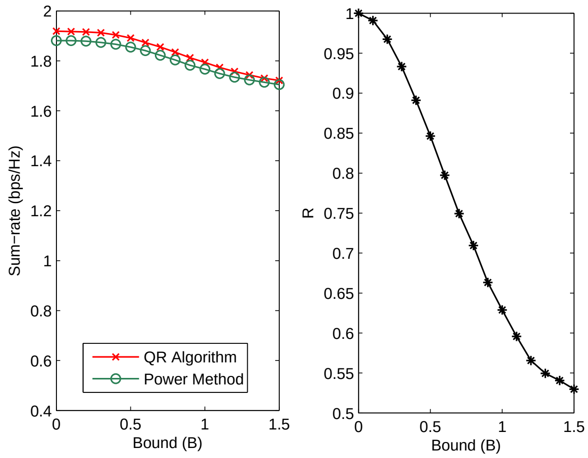

Fig. 8. (a) Sum-rate performance versus the bound and (b) R versus the bound of the MSR design with a neighbour-based power constraint.

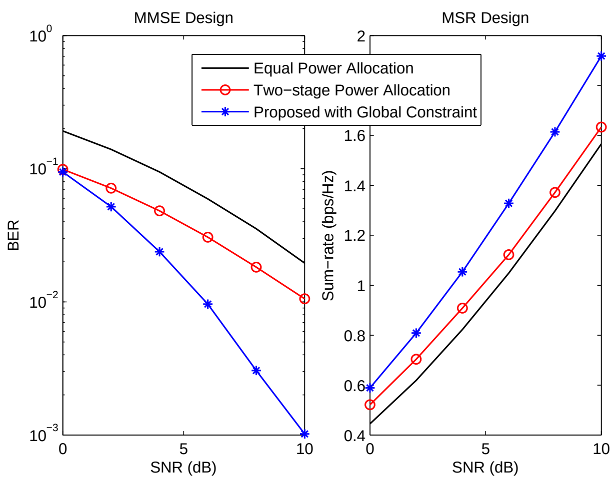

Fig. 9. (a) BER performance versus SNR of our proposed MMSE design (b) Sum-rate performance versus SNR of our proposed MSR design with a global power constraint and compare with the two-stage power allocation and equal power allocation schemes.

In practice, the feedback channel cannot be error free. In order to study the impact of feedback channel errors on the performance, we employ the binary symmetric channel (BSC) as the model for the feedback channel and quantize each complex amplification coefficient to an 8-bit binary value (4 bits for the real part, 4 bits for the imaginary part). The error probability (Pe) of the BSC is fixed at 10^{-3}. The dashed curves in Fig. 4, Fig. 5 and Fig. 6 show the performance degradation compared to the performance when using a perfect feedback channel. To show the performance tendency of the BSC for other values of Pe, we fix the SNR at 10 dB and choose Pe ranging from 0 to 10^{-2}. The performance curves are shown in Fig. 10, which illustrate the BER and the sum-rate performance versus Pe of our two proposed joint designs of the receivers with neighbour-based power constraints. It can be seen that along with the increase in Pe, their performance becomes worse.

Next, we replace the perfect CSI with the estimated channel coefficients to compute the receive filters and power allocation parameters at the destinations. We employ The BEACON channel estimation which is proposed in [26]. Fig. 11 illustrates the impact of the channel estimation on the performance of our proposed MMSE and SMR design with a global power constraint by comparing to the performance of perfect CSI. The quantity n_t denotes the number of training sequence symbol per data packet. Please note that in these simulations perfect feedback channel is considered and the QR algorithm is used in the MSR design. For both the MMSE and MSR designs, it can be seen that when n_t is set to 10, the BEACON channel estimation leads to an obvious performance degradation compared to the perfect CSI. However, when n_t is increased to 50, the BEACON channel estimation can achieve a similar performance to the perfect CSI. Other scenarios and network topologies have been investigated and the results show that the proposed algorithms work very well with channel estimation algorithms and a small number of training symbols.

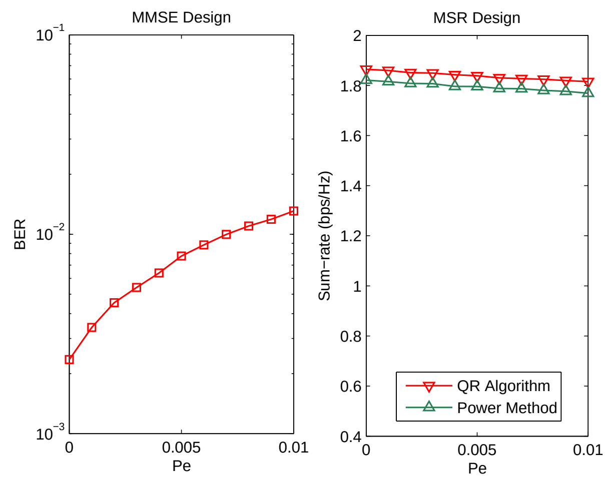

Fig. 10. (a) BER performance versus Pe of our proposed MMSE design (b) Sum-rate performance versus Pe of our proposed MSR design with a neighbour-based power constraint when employing the BSC as the model for the feedback channel. B = 0.6.

Finally, as the extension of our work about the complexity analysis displayed in Fig. 1 and Fig. 2, we show Fig. 12 which indicates the performance/complexity tradeoff of our proposed MMSE and MSR designs when the global constraint is considered. We set $N_s = 1$, $N_d = 2$. The range of N_r is from 1 to 10. The SNR is fixed at 10dB. It can be seen that along with increasing the number of relay nodes, our proposed algorithms can achieve a better performance, which requires a higher number of multiplications and consequently a higher complexity.

VII. Conclusions

Two kinds of joint receiver design and power allocation strategies have been proposed for two-hop WSNs. It has been shown that our proposed strategies achieve a significantly better performance than the equal power allocation and two-stage power allocation. Moreover, when the neighbour-based constraint is considered, it brings a feature to balance the

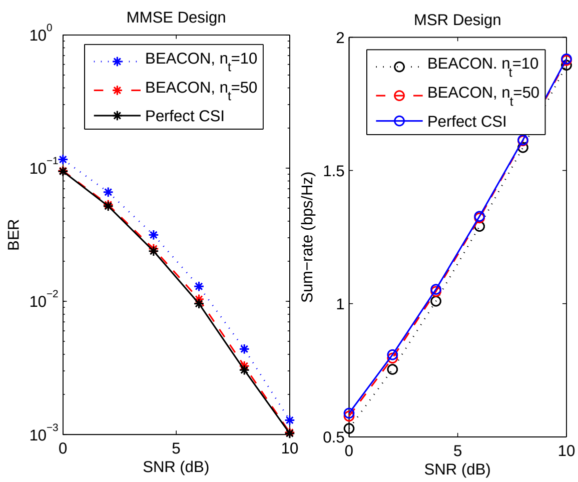

Fig. 11. (a) BER performance versus SNR of our proposed MMSE design (b) Sum-rate performance versus SNR our proposed MSR design with a global power constraint when employing the BEACON channel estimation, compared to the performance of perfect CSI

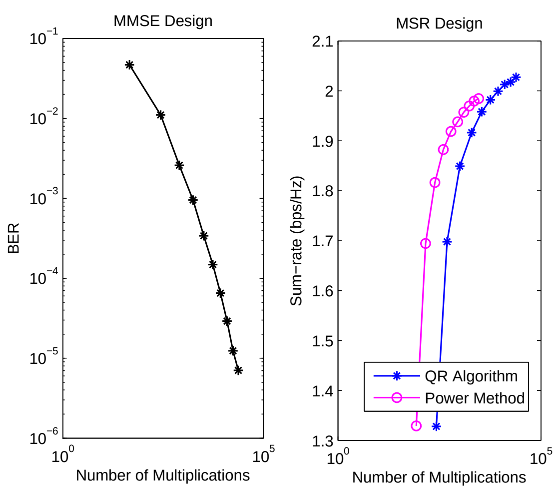

Fig. 12. (a) BER performance versus number of multiplications of our proposed MMSE design (b) Sum-rate performance versus number of multiplications of our proposed MSR design with a global power constraint.

performance against the computational complexity and the need for feedback information which is desirable for WSNs to extend their lifetime. Possible extensions to this work may include the development of these joint strategies in the general multihop WSNs which can provide larger coverage than the two-hop WSNs. Also, low-complexity adaptive algorithms can be used to compute the the linear receiver and power allocation parameters.

References

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A Survey on Sensor Networks," *IEEE Commun. Mag.*, vol. 40, pp. 102-114, Aug. 2002.

[2] J. N. Laneman, D. N. C. Tse and G. W. Wornell, "Cooperative diversity in wireless networks: Efficient protocols and outage behavior," *IEEE Trans. Inf. Theory*, vol. 50, no. 12, pp. 3062-3080, Dec. 2004.

[3] H. Li and P. D. Mitchell, "Reservation packet medium access control for wireless sensor networks," *in Proc. IEEE PIMRC*, Sep. 2008.

[4] Y. W. Hong, W. J. Huang, F. H. chiu, and C. C. J. Kuo, "Cooperative Communications in Resource-Constrained Wireless Networks," *IEEE Signal Process. Mag.*, vol. 24, pp. 47-57, May 2007.

[5] T. Q. S. Quek, H. Shin, and M. Z. Win, "Robust Wireless Relay Networks: Slow Power Allocation With Guaranteed QoS," *IEEE J. Sel. Topics Signal Process.*, vol. 1, no. 4, pp. 700-713, Dec. 2007.

[6] K. Vardhe, D. Reynolds, and B. D. Woerner "Joint Power Allocation and Relay Selection for Multiuser Cooperative Communication" *IEEE Trans. Wireless Commun.*, vol. 9, no. 4, pp. 1255-1260, Apr. 2010.

[7] J. Luo, R. S. Blum, L. J. Cimini, L. J. Greenstein, and A. M. Haimovich "Decode-Forward Cooperative Diversity with Power Allocation in Wireless Networks" *IEEE Trans. Wireless Commun.*, vol. 6, no. 3, pp. 793-799, Mar. 2007.

[8] W. Su, A. K. Sadek, and K. J. R. Liu, "Ser performance analysis and optimum power allocation for decode and forward cooperation protocol in wireless networks," *in Proc. IEEE WCNC*, pp. 984-989, Mar. 2005.

[9] D. Gunduz and E. Erkip, "Opportunisti cooperation by dynamic resource allocation," *IEEE Trans. Wireless Commun.*, vol. 6, pp. 1446-1454, Apr. 2007.

[10] X. Deng and A. Haimovich, "Power allocation for cooperative relaying in wireless networks," *IEEE Trans. Commun.*, vol. 50, no. 12, pp. 3062-3080, Jul. 2005.

[11] Y. Li, B. Vucetic, Z. Zhou, and M. Dohler, "Distributed Adaptive Power Allocation for Wireless Relay Networks," *IEEE Trans. Wireless Commun.*, vol. 6, no. 3, pp. 948-958, March 2007.

[12] J. Adeane, M. R. D. Rodrigues, and I. J. Wassell, "Centralised and distributed power allocation algorithms in cooperative networks" *in Proc. IEEE SPAWC*, pp. 333-337, 2005.

[13] G. Yu, Z. Zhang, Y. Chen, and P. Qiu, "Adaptive Power Allocation for Cooperative Relaying System in Fading Wireless Channel" *Int. Conf. Wireless Communi., Networking and Mobile Computing*, 2007.

[14] Y. Zhao, R. Adve, and T. J. Lim, "Improving amplify-and-forward relay networks: optimal power allocation versus selection," *IEEE Trans. Wireless Commun.*, vol. 6, no. 8, pp. 3114 - 3123, Aug. 2007.

[15] X. Deng and A. M. Haimovich, "Power Allocation for Cooperative Relaying in Wireless Network," *IEEE Commun. Lett.*, vol. 9, no. 11, pp. 994 - 996, Nov. 2005.

[16] C. Yang, W. Wang, G. Yuan and M. Peng, "A Power Allocation Method with Maximum Effective Configuration Duration in Wireless Sensor Networks" *Int. Conf. BROADNETS*, 2008.

[17] I. Csiszar and G. Tusnady, "Information geometry and alternating minimization procedure," *Statist. Decis.-Supplement Issue*, no. 1, pp. 205-237, 1984.

[18] U. Niesen, D. Shah, and G. W. Wornell, "Adaptive alternating minimization algorithms," *IEEE Trans. Inf. Theory*, vol. 55, no. 3, pp. 1423-1429, Mar. 2009.

[19] R. D. Juday, "Generalized Rayleigh quotient approach to filter optimization" *J. Opt. Soc.*, vol. 15, no. 4, pp. 777-790, Apr. 1998.

[20] T. Wang and R. C. de Lamare, "Joint Receiver Design and Power Allocation Strategies for Wireless Sensor Networks," *Sensor Signal Processing for Defence(SSPD)*, Sep. 2011.

[21] P. K. Varshney, Distributed Detection and Data Fusion, Springer-Verlag, 1997.

[22] S. Haykin, *Adaptive Filter Theory*, 4th ed. Englewood Cliffs, NJ: Prentice-Hall, 2002.

[23] D. S. Watkins, *Fundamentals of Matrix Computations*, 2nd ed. John Wiley & Sons, New York, 2002.

[24] G. H. Golub and C. F. V. Loan, *Matrix Computations*, 3rd ed. Baltimore, MD: Johns Hopkins Univ. Press, 1996.

[25] H. -S. Chen, W. -H. Fang, Y. -T. Chen, "Relaying Through Distributed GABBA Space-Time Coded Amplify-and-Forward Cooperative Networks With Two-Stage Power Allocation," *IEEE Vehicular Technology Conference (VTC)*, May 2010.

[26] T. Wang, R. C. de Lamare, and P. D. Mitchell, "Low-Complexity Set-Membership Channel Estimation for Cooperative Wireless Sensor Networks," *IEEE Trans. Veh. Technol.*, vol. 60, no. 6, May, 2011.

[27] R. C. de Lamare and P. S. R. Diniz, "Set-Membership Adaptive Algorithms based on Time-Varying Error Bounds for CDMA Interference Suppression," *IEEE Trans. Veh. Technol.*, vol. 58, no. 2, Feb. 2009.

Tong Wang received the B.Eng. degree in electrical engineering and automation from Beijing University of Aeronautics and Astronautics (BUAA), Beijing, China, in 2006, the M.Sc. degree (with distinction) in communications engineering and Ph.D. degree in electronic engineering from University of York, York, U.K., in 2008 and 2012, respectively.

He is currently a research associate in the UMIC Research Centre, RWTH Aachen University, Aachen, Germany. His research interests include sensor networks, cooperative communications, adaptive filtering and resource optimization.

Rodrigo C. de Lamare (S'99 M'04 SM'10) received the Diploma in electronic engineering from the Federal University of Rio de Janeiro (UFRJ) in 1998 and the M.Sc. and PhD degrees, both in electrical engineering, from the Pontifical Catholic University of Rio de Janeiro (PUC-Rio) in 2001 and 2004, respectively. Since January 2006, he has been with the Communications Research Group, Department of Electronics, University of York, where he is currently a Reader. His research interests lie in communications and signal processing, areas in which he has published over 250 papers in refereed journals and conferences. Dr. de Lamare serves as an associate editor for the EURASIP Journal on Wireless Communications and Networking. He is a Senior Member of the IEEE and has served as the general chair of the 7th IEEE International Symposium on Wireless Communications Systems (ISWCS), held in York, UK in September 2010, and will serve as the technical programme chair of ISWCS 2013 in Ilmenau, Germany.

Anke Schmeink received her Diploma degree in mathematics with a minor in medicine and the PhD degree in electrical engineering and information technology from RWTH Aachen University, Germany, in 2002 and 2006, respectively. She worked as a research scientist for Philips Research before joining RWTH Aachen University as Assistant Professor in 2008. Anke Schmeink spent several research visits at the University of Melbourne, Australia, and at the University of York, England. She received diverse awards, in particular the Vodafone young scientist award. Anke Schmeink is also a member of the Young Academy at the North Rhine-Westphalia Academy of Science. Her research interests are in information theory, systematic design of communication systems and bio-inspired signal processing, particularly using game theory and optimization.