Distributed MMSE Relay Strategies for Wireless Sensor Networks

Nima Khajehnouri and Ali H. Sayed, *Fellow, IEEE*

***Abstract*—A fundamental task in a wireless sensor network is to broadcast some measured data from an origin sensor to a destination sensor. Since the sensors are typically small, power limited, and low cost, they are only able to broadcast low-power signals. As a result, the propagation loss from the origin to the destination nodes can attenuate the signals beyond detection. One way to deal with this problem is to pass the transmitted signal through relay nodes. In this paper we propose and study two-hop multisensor relay strategies that achieve minimum mean-square-error (mse) performance subject to either local or global power constraints. The capacity of the resulting relay link and its diversity order are studied. The effect of channel uncertainties on system performance is examined and a modified relay scheme is proposed.**

***Index Terms*—Amplify-and-forward scheme, cooperative networks, relay networks, relay strategy, sensor networks, spatial diversity.**

I. Introduction

A wireless sensor network is a distributed communication network containing geographically separated sensor nodes [1], [2]. A fundamental task in a wireless sensor network is to broadcast some measured data from an origin sensor to a destination sensor. Since the sensors are typically small, power limited, and low cost, they are only able to broadcast very low-power signals. This means that the propagation loss from the origin to the destination sensor can attenuate the signals beyond detection. One way to deal with this problem is to pass the transmitted signal through one or more relay sensors [1]. This option is attractive for at least two reasons. First, shorter-range communication is generally cheaper than longer-range communication and, therefore, it is convenient to transmit information using multihopping among sensors. Second, relay channels add spatial diversity, which helps combat the fading effect of wireless links.

As a result, relay networking has received considerable attention in the literature, with several works dealing with information-theoretic aspects and other works dealing with signal processing and communication aspects. For example, an early study of relay networks appears in [3] where two fundamental coding strategies for the relay channel were introduced. An achievable rate region over additive white Gaussian noise channels appeared later in [4] and [5], with several other information-theoretic studies appearing in [6]–[11]. On the communication side, some works proposed methods to minimize energy consumption and reduce communication cost at the expense of computation. For instance, the contributions [12], [13] proposed approaches that reduce the volume of data through some aggregation techniques. Other works focused on power efficient broadcast scheduling algorithms [6], [14]–[16], and on approaches to overcome the propagation and path loss effect of channels and to achieve higher data rate over relay links [17]. A comparative study of various relay schemes and a discussion on the diversity gain of cooperative relay networks can be found in [18] and [19]. Cooperative networks are also studied in [20]–[22].

Relay schemes can be broadly categorized into three general groups: amplify-forward, compress-forward, and decode-forward. In the amplify-forward scheme, the relay nodes amplify the received signal and rebroadcast the amplified signals toward the destination node [4], [7], [19]. In the compress-forward method, the relay nodes compress the received signals by exploiting the statistical dependencies between the signals at the nodes [3], [23], [24]. In the decode-forward scheme, the relay nodes first decode the received signals and then forward the decoded signals toward the destination node [8], [25], [26]. The minimum mean-square error (mmse) formulation of this paper will lead to relay strategies of the amplify-forward type.

Usually, in conventional amplify-forward relay schemes [see [3], [4], [7], [11], [19], and (15) later] the relay nodes compensate for the phase of the incoming signal in order to result in coherent signal combination at the receiver. In such schemes, each node generally utilizes its maximum allowable power. In contrast, the schemes proposed in this paper will allow the relay nodes to adjust their power in order to attain a certain target signal-to-noise ratio (SNR). In addition, the mmse relay strategies will help increase the transmit range (by compensating for free space loss), the diversity gain and the power efficiency of the source-destination link. The relay nodes will not need to share information about the received signals and, as the number of relay sensors (N) increases, the average power usage per sensor node and the total average power will drop as $O(1/N^2)$ and $O(1/N)$, respectively. We also develop relay strategies that incorporate local and global power constraints.

II. Relay Network Model

Consider a sensor network with N relay nodes between a source sensor and a destination sensor. The relay nodes are labelled from 1 to N—see Fig. 1. Let $\boldsymbol{h}_s$ denote the $N \times 1$ (column) channel vector between the source sensor and the relay nodes, and let $\boldsymbol{h}_t$ denote the $1 \times N$ (row) channel vector between the relay sensors and the destination sensor. A quasi-static fading condition is assumed for each channel gain so that the

Manuscript received June 14, 2005; revised March 1, 2006. This work was supported in part by the National Science Foundation by awards CCF–0208573, ECS-0401188, and ECS-0601266. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. C.-Y. Chi.

The authors are with the Department of Electrical Engineering, University of California, Los Angeles, CA 90095 USA (e-mail: nimakh@ee.ucla.edu; sayed@ee.ucla.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSP.2007.894410

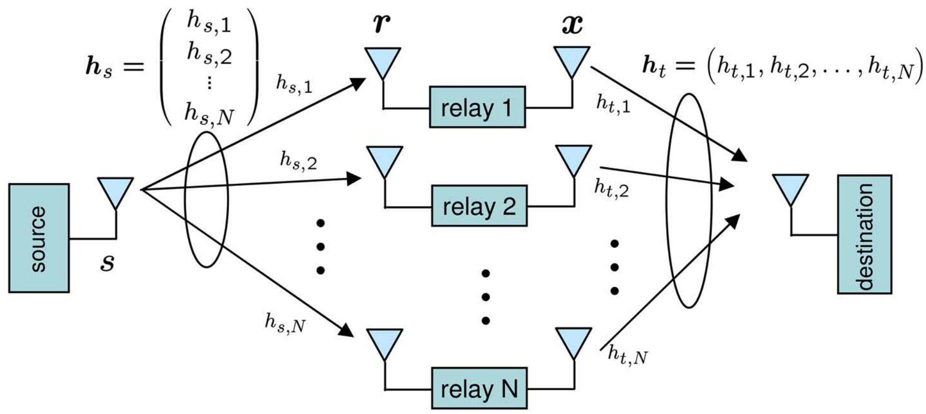

Fig. 1. A relay network with N relay nodes, one source, and one destination.

channel realizations stay fixed for the duration of a single frame of data. Let $h_{s,i}$ denote the ith element of $\boldsymbol{h}_s$, which stands for the channel coefficient from the source sensor to the ith relay node. Likewise, let $h_{t,i}$ denote the ith element of $\boldsymbol{h}_t$, which stands for the channel coefficient from the ith relay node to the destination sensor. A simple two-phase (two-hop) protocol is used to transmit data from the source sensor to the receiver. The first phase (hop) is the broadcasting phase, during which the source sensor broadcasts a signal s towards the relay sensors. The second phase (hop) is the relaying phase, during which the relay sensors transmit their signals to the destination sensor. We assume synchronous transmission and reception at relays nodes, so that the relay nodes relay their data at the same time instant. Using the above formulation, the received vector at the relay sensors is given by

$$\boxed{\boldsymbol{r} = \boldsymbol{h}_s s + \boldsymbol{v}_s} \tag{1}$$

where

$$\boldsymbol{h}_s = [h_{s,1}, h_{s,2}, \ldots, h_{s,N}]^T \text{ (a column vector)} \tag{2}$$

and $\boldsymbol{v}_s$ is $N \times 1$ zero-mean complex noise with covariance matrix $\sigma_{v_s}^2 \boldsymbol{I}$. We assume the relay nodes are far enough from each other such that their noises can be assumed to be uncorrelated. At the second phase of the relaying protocol, the relay sensors rebroadcast a *transformed* signal vector that is given by

$$\boxed{\boldsymbol{x} = \boldsymbol{F}\boldsymbol{r}} \tag{3}$$

where $\boldsymbol{F}$ is an $N \times N$ linear transformation matrix to be determined in order to enforce some optimal performance, as explained later. The received scalar signal at the destination sensor is then given by

$$\boxed{t = \boldsymbol{h}_t \boldsymbol{x} + v_t} \tag{4}$$

where

$$\boldsymbol{h}_t = [h_{t,1}, h_{t,2}, \ldots, h_{t,N}] \text{ (a row vector)}$$

and v_t is a zero-mean scalar noise with variance $\sigma_{v_t}^2$. Substituting (3) into (4) and using (1) we have

$$\boxed{t = \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{h}_s s + \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{v}_s + v_t}. \tag{5}$$

We are interested in choosing the relay matrix $\boldsymbol{F}$ such that the received signal at the destination sensor before corruption by the destination sensor noise (i.e., the term $\boldsymbol{h}_t\boldsymbol{x}$) is a least-mean-squares (lms) estimate of the transmitted signal s or a scaled multiple of it as we now explain.

III. MMSE Relay Strategy

Initially, we select $\boldsymbol{F}$ to minimize the mean-square error (mse) between the uncorrupted received signal $\boldsymbol{h}_t\boldsymbol{x}$ and a scaled multiple of the transmitted signal s, i.e.,

$$\hat{\boldsymbol{F}} = \arg\min_{\boldsymbol{F}} J(\boldsymbol{F}) \tag{6}$$

where

$$\begin{aligned} J(\boldsymbol{F}) &= E|\eta s - \boldsymbol{h}_t \boldsymbol{x}|^2 \\ &= E|\eta s - \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{h}_s s - \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{v}_s|^2 \end{aligned} \tag{7}$$

for some positive scalar η chosen by the designer. For example, the choice $\eta = 1$ would minimize the mse between $\boldsymbol{h}_t\boldsymbol{x}$ and s itself. More generally, the choice

$$\eta = \sqrt{\text{SNR}_t \frac{\sigma_{v_t}^2}{\sigma_s^2}} \tag{8}$$

where

$$\sigma_s^2 = E|s|^2 \tag{9}$$

would ensure a certain a target SNR at the destination node, as remarked after (16). Now expanding (7) leads to

$$\begin{aligned} J = \sigma_s^2 \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{h}_s \boldsymbol{h}_s^* \boldsymbol{F}^* \boldsymbol{h}_t^* + \sigma_{v_s}^2 \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{F}^* \boldsymbol{h}_t^* \\ - \eta \sigma_s^2 \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{h}_s - \eta \sigma_s^2 \boldsymbol{h}_s^* \boldsymbol{F}^* \boldsymbol{h}_t^* + \eta^2 \sigma_s^2. \end{aligned} \tag{10}$$

Introduce the variable $\boldsymbol{z} = \boldsymbol{h}_t \boldsymbol{F}$. Then (10) becomes

$$J = \sigma_s^2 \boldsymbol{z} \boldsymbol{h}_s \boldsymbol{h}_s^* \boldsymbol{z}^* + \sigma_{v_s}^2 \boldsymbol{z}\boldsymbol{z}^* - \eta \sigma_s^2 \boldsymbol{z} \boldsymbol{h}_s - \eta \sigma_s^2 \boldsymbol{h}_s^* \boldsymbol{z}^* + \eta^2 \sigma_s^2.$$

Minimizing J over $\boldsymbol{z}$ gives

$$\left.\frac{dJ}{dz}\right|_{z=\hat{z}} = \sigma_s^2 \boldsymbol{h}_s \boldsymbol{h}_s^* \hat{\boldsymbol{z}}^* + \sigma_{v_s}^2 \hat{\boldsymbol{z}}^* - \eta \sigma_s^2 \boldsymbol{h}_s = 0$$

i.e.

$$\hat{\boldsymbol{z}}^* = \eta \left(\boldsymbol{h}_s \boldsymbol{h}_s^* + \frac{\sigma_{v_s}^2}{\sigma_s^2} \boldsymbol{I} \right)^{-1} \boldsymbol{h}_s \tag{11}$$

and we can use the matrix inversion equality [27] to rewrite (11) as

$$\hat{\boldsymbol{z}}^* = \eta \left(\frac{\sigma_s^2}{\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2} \right) \boldsymbol{h}_s.$$

Recalling that $\boldsymbol{z} = \boldsymbol{h}_t \boldsymbol{F}$, we are reduced to choosing a relay matrix $\boldsymbol{F}$ that satisfies

$$\boxed{\hat{\boldsymbol{F}}^* \boldsymbol{h}_t^* = \eta \left(\frac{\sigma_s^2}{\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2} \right) \boldsymbol{h}_s}. \tag{12}$$

Expression (12) provides N independent equalities for N^2 unknown elements in $\hat{\boldsymbol{F}}$. In other words, the relation provides several degrees of freedom that can be exploited advantageously as we now explain.

IV. Relay Matrix Selection

Note first that a wireless sensor network is a fundamentally distributed communications network. As a result, we shall assume that each node only has access to local channel information. Specifically, every node i will only have access to the channel gains $h_{s,i}$ and $h_{t,i}$ that connect it to the source and the destination. This structure motivates us to seek a diagonal matrix $\hat{\boldsymbol{F}}$ that satisfies (12). Thus we shall select *diagonal* entries $\{\hat{f}_i\}$ such that

$$\hat{f}_i^* h_{t,i}^* = \eta \left(\frac{\sigma_s^2}{\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2} \right) h_{s,i} \tag{13}$$

i.e.,

$$\boxed{\hat{f}_i = \eta \left(\frac{\sigma_s^2}{\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2} \right) \frac{h_{s,i}^* h_{t,i}^*}{|h_{t,i}|^2}}. \tag{14}$$

It is assumed that the source sensor node provides the relay nodes with the value of $\|\boldsymbol{h}_s\|^2$. Alternatively, $\|\boldsymbol{h}_s\|^2$ could be approximated by $N\sigma_{h_s}^2$ (by using an argument similar to the one used in the Appendix).

It is worth noting that the conventional amplify-forward relay scheme employs instead (e.g., [3], [4], [7], [11], [19])

$$\hat{f}_i = \left(\frac{\sigma_r}{\sqrt{\sigma_{v_s}^2 + \sigma_s^2 |h_{s,i}|^2}} \right) \frac{h_{s,i}^*}{|h_{s,i}|} \frac{h_{t,i}^*}{|h_{t,i}|} \tag{15}$$

where σ_r^2 denotes the desired transmit power for each relay node. The differences with (14) are clear, e.g., (14) uses $\|\boldsymbol{h}_s\|^2$ instead of $|h_{s,i}|^2$. Moreover, since the relay factor in (14) is scaled down by the number of relay sensors (i.e., by $\approx N\sigma_{h_s}^2$), unlike (15), we will note that the average power consumption per node drops as the number of relay sensor increases. We will show later that the conventional scheme (15) can be derived by imposing power constrains on each relay node.

As it can be observed from (14), each relay node needs its local channel state information $h_{s,i}$ and $h_{t,i}$, as well as a single common term $\left(\sigma_s^2/\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2\right)$ for all nodes. Thus, the transmission process can be implemented in two phases. First, a training phase provides the relay nodes with channel estimation and, second, a transmission phase relays the signal toward the destination node. The relay nodes can use training sequences to estimate the broadcast or backward channels, $\{h_{s,i}\}$, while the destination node can estimate the individual relay node channels $\{h_{t,i}\}$ and feed them back.

A. Equalization

Continuing with (14), the signal received at the destination sensor is given by (4), which in view of (7) would tend to be

$$t \approx \eta s + v_t \tag{16}$$

with an SNR level that is equal to SNR_t. We still need to equalize t in order to remove the effect of v_t and recover s. To do so, we now choose a scalar α so as to minimize

$$\alpha = \arg\min_{\alpha} J(\alpha) \tag{17}$$

where using (5)

$$\begin{aligned} J(\alpha) &= E|s - \alpha t|^2 \\ &= E|s - \alpha \boldsymbol{h}_t \hat{\boldsymbol{F}} \boldsymbol{h}_s s - \alpha \boldsymbol{h}_t \hat{\boldsymbol{F}} \boldsymbol{v}_s - \alpha v_t|^2. \end{aligned} \tag{18}$$

The optimal α provides the mmse estimate of s given t. Expanding (18) we get

$$\begin{aligned} J(\alpha) &= |\alpha|^2 \sigma_s^2 \boldsymbol{h}_t \hat{\boldsymbol{F}} \boldsymbol{h}_s \boldsymbol{h}_s^* \hat{\boldsymbol{F}}^* \boldsymbol{h}_t^* + |\alpha|^2 \sigma_{v_s}^2 \boldsymbol{h}_t \hat{\boldsymbol{F}} \hat{\boldsymbol{F}}^* \boldsymbol{h}_t^* \\ &\quad - \alpha \sigma_s^2 \boldsymbol{h}_t \hat{\boldsymbol{F}} \boldsymbol{h}_s - \alpha^* \sigma_s^2 \boldsymbol{h}_s^* \hat{\boldsymbol{F}}^* \boldsymbol{h}_t^* + |\alpha|^2 \sigma_{v_t}^2 + \sigma_s^2 \end{aligned} \tag{19}$$

and the optimal scalar α is found to be

$$\hat{\alpha} = \frac{\sigma_s^2 \boldsymbol{h}_s^* \hat{\boldsymbol{F}}^* \boldsymbol{h}_t^*}{\sigma_s^2 |\boldsymbol{h}_t \hat{\boldsymbol{F}} \boldsymbol{h}_s|^2 + \sigma_{v_s}^2 \|\boldsymbol{h}_t \hat{\boldsymbol{F}}\|^2 + \sigma_{v_t}^2}. \tag{20}$$

Substituting $\hat{\boldsymbol{F}}$ from (12) into (20) leads to

$$\boxed{\hat{\alpha} = \frac{\eta \sigma_s^4 \|\boldsymbol{h}_s\|^2 \left(\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2\right)}{\eta^2 \sigma_s^6 \|\boldsymbol{h}_s\|^4 + \eta^2 \sigma_{v_s}^2 \sigma_s^4 \|\boldsymbol{h}_s\|^2 + \sigma_{v_t}^2 \left(\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2\right)^2}}. \tag{21}$$

Clearly, $\hat{\alpha}$ is a real scalar so that the equalizer does not change the phase of the received signal—see Fig. 2.

To get a better insight into the result, let us assume that

$$\sigma_{v_s}^2 + \sigma_s^2 \|\boldsymbol{h}_s\|^2 \approx \sigma_s^2 \|\boldsymbol{h}_s\|^2 \tag{22}$$

which is a realistic assumption as the number of relay sensors increases. Then (21) becomes

$$\hat{\alpha} \approx \frac{\eta \sigma_s^2}{\eta^2 \sigma_s^2 + \frac{\eta^2 \sigma_{v_s}^2}{\|\boldsymbol{h}_s\|^2} + \sigma_{v_t}^2}. \tag{23}$$

If we further ignore $\eta^2 \sigma_{v_s}^2 / \|\boldsymbol{h}_s\|^2$ in comparison with σ_s^2 and $\sigma_{v_t}^2$, we get

$$\boxed{\hat{\alpha} \approx \frac{\eta \sigma_s^2}{\eta^2 \sigma_s^2 + \sigma_{v_t}^2}} \text{(for large } N\text{)}. \tag{24}$$

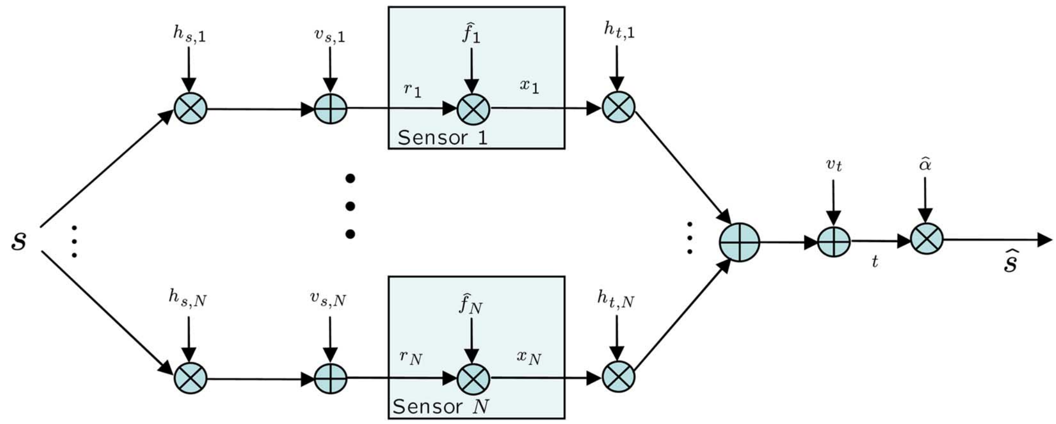

Fig. 2. The relay network scheme.

This expression indicates that when the number of relay sensors increases, the destination node does not need the power of the broadcast channel $\|\boldsymbol{h}_s\|^2$ in order to perform equalization.

B. MSE Behavior

We now examine how the resulting mmse $J(\hat{\alpha})$ varies as a function of the number of relay sensors for large N. Substituting (12) and (20) into (19) gives

$$\begin{aligned}J_{\min} \triangleq J(\hat{\alpha}) = &\frac{\eta^2|\hat{\alpha}|^2\sigma_s^6\|\boldsymbol{h}_s\|^4}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2} + \frac{\eta^2|\hat{\alpha}|^2\sigma_s^4\sigma_{v_s}^2\|\boldsymbol{h}_s\|^2}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2}\\ &- \frac{\eta\hat{\alpha}\sigma_s^4\|\boldsymbol{h}_s\|^2}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2} - \frac{\eta\hat{\alpha}^*\sigma_s^4\|\boldsymbol{h}_s\|^2}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2}\\ &+ |\hat{\alpha}|^2\sigma_{v_t}^2 + \sigma_s^2.\end{aligned}$$

Using (22) again gives

$$\begin{aligned}J_{\min} \approx \eta^2|\hat{\alpha}|^2\sigma_s^2 + &\frac{\eta^2|\hat{\alpha}|^2\sigma_s^2\sigma_{v_s}^2}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2}\\ &-\eta\hat{\alpha}\sigma_s^2 - \eta\hat{\alpha}^*\sigma_s^2 + |\hat{\alpha}|^2\sigma_{v_t}^2 + \sigma_s^2.\end{aligned}$$

Averaging this result over different channel realizations and using the approximation (see the Appendix)

$$E\left(\frac{1}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2}\right) \approx \frac{1}{\sigma_s^2\left(N\sigma_{h_s}^2\right)} \tag{25}$$

we get

$$\boxed{EJ_{\min} \approx (\eta\hat{\alpha}-1)^2\sigma_s^2 + \hat{\alpha}^2\sigma_{v_t}^2 + \frac{\eta^2|\hat{\alpha}|^2\sigma_{v_s}^2}{N.\sigma_{h_s}^2}}. \tag{26}$$

Using the simplified expression (24) for $\hat{\alpha}$ gives

$$\boxed{E\,J_{\min} \approx \left(\frac{\sigma_s^2}{\eta^2\sigma_s^2+\sigma_{v_t}^2}\right)\sigma_{v_t}^2 + \frac{\eta^4\sigma_s^2\sigma_{v_s}^2}{N.\sigma_{h_s}^2\left(\eta^2\sigma_s^2+\sigma_{v_t}^2\right)}}. \tag{27}$$

It follows that increasing the number of relay nodes decreases the mse and it converges to the steady-state value

$$\boxed{EJ_{\min} \approx \left(\frac{\sigma_s^2}{\eta^2\sigma_s^2+\sigma_{v_t}^2}\right)\sigma_{v_t}^2}\ \text{(for large } N\text{)}. \tag{28}$$

In contrast, for the conventional relaying strategy (15), the mse tends to zero as $N \to \infty$; this, however, occurs at the expense of increased total power consumption (it increases with N). One advantage of the proposed scheme is that the network adjusts its power usage based on the required target SNR, so that the desired quality of service can be obtained by adjusting the target SNR or η.

Summary: Asymptotic results for a large number of relay nodes N:

$$\begin{aligned}\hat{f}_i &\approx \eta\left(\frac{\sigma_s^2}{\sigma_{v_s}^2+N\sigma_s^2}\right)\frac{h_{s,i}^*h_{t,i}^*}{|h_{t,i}|^2}\\ \hat{\alpha} &\approx \frac{\eta\sigma_s^2}{\eta^2\sigma_s^2+\sigma_{v_t}^2}\\ EJ_{\min} &\approx \left(\frac{\sigma_s^2}{\eta^2\sigma_s^2+\sigma_{v_t}^2}\right)\sigma_{v_t}^2.\end{aligned}$$

V. Power Efficiency

We can also examine the power consumption of the proposed relay method. The transmitted signal from the ith relay sensor is given by

$$x_i = r_i\hat{f}_i \tag{29}$$

where r_i and $\hat{f}_i$ are the received signal from (1) and the relay factor (14) at the ith sensor, respectively. Then the average power at the ith relay sensor is given by

$$\begin{aligned}P_i &= E|x_i|^2\\ &= E\left(|r_i|^2|\hat{f}_i|^2\right)\\ &= E\left(\frac{\eta^2\sigma_s^4}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2}\frac{|h_{s,i}|^2}{|h_{t,i}|^2}|h_{s,i}s+v_{s,i}|^2\right).\end{aligned} \tag{30}$$

A simple protocol can be used to control the peak power usage by a sensor. A sensor will be allowed to participate in the relay process if $(|h_{s,i}|^2/|h_{t,i}|^2) < \gamma$, where γ is a threshold that determines the maximum allowed peak power. Using this protocol we simply ignore relay sensors with weak forward (from relay to destination) channels. Then the power usage per sensor will be upper bounded by[1]

$$\begin{aligned} P_i &< E\left(\frac{\gamma\eta^2\sigma_s^4}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2}|h_{s,i}s+v_{s,i}|^2\right) \\ &\approx \gamma\eta^2 E\left(\frac{\sigma_s^4}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2}\right)E|h_{s,i}s+v_{s,i}|^2 \\ &\approx \frac{\gamma\eta^2}{N^2\sigma_{h_s}^4}\left(\sigma_s^2E|h_{s,i}|^2+\sigma_{v_s}^2\right) \\ &= \frac{\gamma\eta^2}{N^2\sigma_{h_s}^4}\left(\sigma_s^2\sigma_{h_s}^2+\sigma_{v_s}^2\right) \\ &\approx O\left(\frac{1}{N^2}\right) \end{aligned}$$

where, as argued in the Appendix, we are employing the approximation

$$E\left(\frac{1}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2}\right)\approx\frac{1}{N^2\sigma_s^4\sigma_{h_s}^4}. \tag{31}$$

Thus the power usage per sensor is upper bounded by

$$\boxed{P_i<\frac{\gamma\eta^2}{N^2\sigma_{h_s}^4}\left(\sigma_s^2\sigma_{h_s}^2+\sigma_{v_s}^2\right)\approx O\left(\frac{1}{N^2}\right)}. \tag{32}$$

In this way, increasing the number of sensors not only improves the mse performance, but it also decreases power consumption per sensor. The total power used in the relay network is then

$$\begin{aligned} P_{\text{Total}} &= \sum_{i=1}^{N}P_i \\ &< \sum_{i=1}^{N}\frac{\gamma\eta^2}{N^2\sigma_{h_s}^4}\left(\sigma_s^2\sigma_{h_s}^2+\sigma_{v_s}^2\right) \\ &= \frac{\gamma\eta^2}{N\sigma_{h_s}^4}\left(\sigma_s^2\sigma_{h_s}^2+\sigma_{v_s}^2\right) \\ &\approx O\left(\frac{1}{N}\right) \end{aligned} \tag{33}$$

so that the total power consumption in the network drops by $O(1/N)$.

VI. Capacity of the Relay Network

Due to the two-phase protocol scheme, the relay sensors are busy receiving data during the first phase and relaying data during the second phase. Thus the source sensor is able to transmit only at half of the time. As a result we shall scale the capacity of the channel by a factor of two. According to (5), the received signal at the destination node is given by

$$\begin{aligned} t &= \boldsymbol{h}_t\hat{\boldsymbol{F}}\boldsymbol{r}+v_t \\ &= \underbrace{\boldsymbol{h}_t\hat{\boldsymbol{F}}\boldsymbol{h}_s}_{h}s+\underbrace{\boldsymbol{h}_t\hat{\boldsymbol{F}}\boldsymbol{v}_s+v_t}_{v} \end{aligned} \tag{34}$$

and the capacity of the resulting source-destination links is (assuming v is Gaussian) [28]

$$C=\frac{1}{2}E\left[\log_2\left(1+\frac{\sigma_s^2|h|^2}{\sigma_v^2}\right)\right] \text{ (b/Hz/s)} \tag{35}$$

where $1/2$ is due to transmitting only at half of the times and the expectation is over the distribution of h. Now, using (12) and (34):

$$\begin{aligned} \sigma_v^2 &= E|\boldsymbol{h}_t\hat{\boldsymbol{F}}\boldsymbol{v}_s+v_t|^2 \\ &= \sigma_{v_t}^2+\frac{\eta^2\sigma_s^4\|\boldsymbol{h}_s\|^2}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2}\sigma_{v_s}^2 \end{aligned} \tag{36}$$

and

$$|h|^2=\frac{\eta^2\sigma_s^4\|\boldsymbol{h}_s\|^4}{\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2}. \tag{37}$$

Substituting into (35) gives

$$C=\frac{1}{2}E\left[\log_2\left(1+\frac{\eta^2\sigma_s^6\|\boldsymbol{h}_s\|^4}{\sigma_{v_t}^2\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2+\eta^2\sigma_s^4\sigma_{v_s}^2\|\boldsymbol{h}_s\|^2}\right)\right]. \tag{38}$$

Assuming again $\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\approx\sigma_s^2\|\boldsymbol{h}_s\|^2$, (38) is approximated by

$$C\approx\frac{1}{2}E\left[\log_2\left(1+\frac{\eta^2\sigma_s^2}{\sigma_{v_t}^2+\frac{\eta^2\sigma_{v_s}^2}{\|\boldsymbol{h}_s\|^2}}\right)\right]. \tag{39}$$

This result shows that when the target SNR of η is small, the capacity of the relay link converges to the capacity of a SISO channel between the source sensor and the destination sensor, i.e.,

$$\begin{aligned} \lim_{N\to\infty}C &\approx \frac{1}{2}E\log_2\left(1+\frac{\eta^2\sigma_s^2}{\sigma_{v_t}^2}\right) \\ &= \frac{1}{2}\log_2\left(1+\text{SNR}_t\right)(\eta\ \text{small}). \end{aligned} \tag{40}$$

On the other hand, when the target SNR is large, the dominant noise term will be the relay noise, $\boldsymbol{v}_s$, and the asymptotic capacity will be

$$\begin{aligned} \lim_{\eta\to\infty}C &\approx \frac{1}{2}E\log_2\left(1+\frac{\sigma_s^2\|\boldsymbol{h}_s\|^2}{\sigma_{v_s}^2}\right) \\ &\approx O(\log(N))\,(\eta\ \text{large}) \end{aligned} \tag{41}$$

which is similar to the capacity scaling law for amplify-forward relay schemes [4], [7]. In order to compare the capacity results for the case of small target SNR with the capacity that would

[1]One could deploy a strategy that adjusts the gain of $h_{s,i}$ in order to use the weak $h_{t,i}$, as well. However, this gain adjustment requires inter relay cooperation. If the maximum allowed power consumption per sensor is some value σ_r^2, then (32) further ahead could be used to find what value to use for γ. It will follow from (32) that γ varies as $N^2\sigma_r^2$, so that the more sensors we have the larger γ should be.

result from the conventional scheme (15), let us define the power efficiency of a relay network as the ratio between the capacity and the average power spent at the relay nodes. Using (40) and (33), the power efficiency for a large number of relay nodes can be written as

$$P_{\text{eff}} = \frac{C}{P_{\text{Total}}} \approx \frac{\frac{1}{2}\log_2\left(1+\frac{\eta^2\sigma_s^2}{\sigma_{v_t}^2}\right)}{\frac{\gamma\eta^2}{N\sigma_{h_s}^4}\left(\sigma_s^2\sigma_{h_s}^2+\sigma_{v_s}^2\right)} \approx \frac{O(1)}{O\left(\frac{1}{N}\right)} = O(N)$$

while for the conventional relay scheme (15), the capacity scales by $O(\log(N))$[4], [7] and the power scales as $O(N)$, so that the power efficiency scales as $O(\log(N)/N)$, which decreases as N increases.

VII. Pairwise Error Probability

In order to examine the diversity order of the relay scheme, we proceed to evaluate its bit-error-rate (BER) performance. An upper bound on the BER can be obtained by using the union bound over the pairwise error probabilities [29]:

$$\text{BER} \leq \frac{1}{M\cdot L^2}\sum_{i\in L}\sum_{j\in L, i\neq j} q(s_i,s_j)P(s_i\rightarrow s_j) \tag{42}$$

where $P(s_i \rightarrow s_j)$ denotes the probability that a transmitted symbol s_i is mistaken for a different symbol s_j, L is the number of elements in the codebook, $q(s_i,s_j)$ denotes the number of bits that are different in s_i and s_j, and M is the number of information bits per transmission. In the above BER expression, we are assuming equal probable symbols so that $1/L^2$ denotes the probability of each pair of symbols. Assuming Gaussian distribution for v in (34), the pairwise probability of error, $P(s_i \rightarrow s_j)$, can be written in terms of the Euclidean distance between the transmitted symbols s_i and s_j as

$$\begin{aligned} P(s_i\rightarrow s_j) &= Q\left(\sqrt{\frac{|(s_i-s_j)h|^2}{2\sigma_v^2}}\right) \\ &= Q\left(\sqrt{\frac{|d_{i,j}|^2\sigma_s^2|h|^2}{2\sigma_v^2}}\right) \end{aligned} \tag{43}$$

using h and σ_v^2 from (37) and (36), respectively, and where

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-x^2/2}dx \tag{44}$$

and $d_{i,j}$ is defined via

$$|s_i-s_j|^2 = |d_{i,j}|^2\sigma_s^2, \quad 0\leq |d_{i,j}|\leq 2. \tag{45}$$

Thus

$$P(s_i\rightarrow s_j) = Q\left(\sqrt{\frac{|d_{i,j}|^2\eta^2\sigma_s^6\|\boldsymbol{h}_s\|^4}{\sigma_{v_t}^2\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2+\eta^2\sigma_s^4\sigma_{v_s}^2\|\boldsymbol{h}_s\|^2}}\right). \tag{46}$$

Averaging over channel realizations gives

$$E_h[P(s_i\rightarrow s_j)] = E_h\left[Q\left(\sqrt{\frac{d_{i,j}^2\eta^2\sigma_s^6\|\boldsymbol{h}_s\|^4}{\sigma_{v_t}^2\left(\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2\right)^2+\eta^2\sigma_s^4\sigma_{v_s}^2\|\boldsymbol{h}_s\|^2}}\right)\right]. \tag{47}$$

Assuming again $\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2 \approx \sigma_s^2\|\boldsymbol{h}_s\|^2$,

$$E_h[P(s_i\rightarrow s_j)] \approx E_h\left[Q\left(\sqrt{\frac{d_{i,j}^2\eta^2\sigma_s^2}{\sigma_{v_t}^2+\frac{\eta^2\sigma_{v_s}^2}{\|\boldsymbol{h}_s\|^2}}}\right)\right]. \tag{48}$$

We consider two cases:

- *small* η so that

$$\sigma_{v_t}^2+\frac{\eta^2\sigma_{v_s}^2}{\|\boldsymbol{h}_s\|^2} \approx \sigma_{v_t}^2 \tag{49}$$

  and then

$$\begin{aligned} E_h[P(s_i\rightarrow s_j)] &\approx E_h\left[Q\left(\sqrt{\frac{d_{i,j}^2\eta^2\sigma_s^2}{\sigma_{v_t}^2}}\right)\right] \\ &= Q\left(\sqrt{d_{i,j}^2\text{SNR}_t}\right) \end{aligned} \tag{50}$$

  where we used (8). It follows that increasing the number of relay nodes does not improve diversity in this case (small target SNR). This is because increasing the number of relay nodes compensates for the effect of the relay noise, v_s. But since the target SNR is not large, the effect of v_t still remains.
- *large* η so that

$$\sigma_{v_t}^2+\frac{\eta^2\sigma_{v_s}^2}{\|\boldsymbol{h}_s\|^2} \approx \frac{\eta^2\sigma_{v_s}^2}{\|\boldsymbol{h}_s\|^2} \tag{51}$$

  and then

$$E_h[P(s_i\rightarrow s_j)] \approx E_h\left[Q\left(\sqrt{\frac{d_{i,j}^2\sigma_s^2\|\boldsymbol{h}_s\|^2}{\sigma_{v_s}^2}}\right)\right]. \tag{52}$$

  Now recall that the Chernoff bound for a Gaussian random variable [29] is

$$Q(\sqrt{x}) \leq e^{-x/2}. \tag{53}$$

  Using this bound gives

$$E_h[P(s_i\rightarrow s_j)] < E_h\left[e^{-\left(d_{i,j}^2\sigma_s^2\|\boldsymbol{h}_s\|^2/2\sigma_{v_s}^2\right)}\right]. \tag{54}$$

But since $\chi = \|\boldsymbol{h}_s\|^2$ has a chi-square distribution with $2N$ degrees of freedom [27], the above expectation can be written as

$$E_h[P(s_i\rightarrow s_j)] < E_\chi\left[e^{-\left(d_{i,j}^2\sigma_s^2\chi/2\sigma_{v_s}^2\right)}\right] \tag{55}$$

where the pdf of the random variable χ is given by

$$p(\chi) = \frac{1}{\sigma_{h_s}^{2N}\Gamma(N)}\chi^{N-1}e^{-\chi/\sigma_{h_s}^2}$$

and $\Gamma(.)$ denotes the Gamma function. It follows that:

$$\begin{aligned} E_h[P(s_i \to s_j)] &< \int_0^\infty e^{-\left(d_{i,j}^2\sigma_s^2\chi/2\sigma_{v_s}^2\right)}p(\chi)d\chi \\ &= \int_0^\infty \frac{1}{\sigma_{h_s}^{2N}\Gamma(N)}\chi^{N-1} \\ &\quad \times e^{-\left(\left(d_{i,j}^2\sigma_s^2/2\sigma_{v_s}^2\right)+\left(1/\sigma_{h_s}^2\right)\right)\chi}d\chi \\ &= \left(\frac{d_{i,j}^2\sigma_s^2\sigma_{h_s}^2}{2\sigma_{v_s}^2}+1\right)^{-N} \propto \text{SNR}^{-N} \end{aligned} \tag{56}$$

where $\text{SNR} = \left(\sigma_s^2\sigma_{h_s}^2/\sigma_{v_s}^2\right)$ denotes the received SNR. It follows that in the case of large η, the proposed relay scheme guarantees a diversity order N.

VIII. Channel Uncertainties

Each relay sensor needs to know its local channels to the source and destination to form the relay factor $\hat{f}_i$ given by (14). Due to channel estimation errors, the estimated channels at the relay nodes are not accurate. In order to compensate for the expected degradation in performance, we shall modify the design of the relay matrix $\hat{\boldsymbol{F}}$. Let $\hat{\boldsymbol{h}}_s$ and $\hat{\boldsymbol{h}}_t$ denote the available estimates of $\boldsymbol{h}_s$ and $\boldsymbol{h}_t$, respectively, i.e.,

$$\begin{aligned} \hat{\boldsymbol{h}}_s &= \boldsymbol{h}_s - \delta_s \\ \hat{\boldsymbol{h}}_t &= \boldsymbol{h}_t - \delta_t. \end{aligned} \tag{57}$$

The elements of δ_s and δ_t will be assumed to be complex independent identically distributed (i.i.d.) zero-mean Gaussian random variables with variances $\sigma_{\delta_s}^2$ and $\sigma_{\delta_t}^2$, respectively. The received signal at the destination sensor will then be given by

$$\begin{aligned} t &= \boldsymbol{h}_t\boldsymbol{F}\boldsymbol{r} + v_t \\ &= \boldsymbol{h}_t\boldsymbol{F}\boldsymbol{h}_s s + \boldsymbol{h}_t\boldsymbol{F}\boldsymbol{v}_s + v_t \\ &= (\hat{\boldsymbol{h}}_t + \delta_t)\boldsymbol{F}(\hat{\boldsymbol{h}}_s + \delta_s)s + (\hat{\boldsymbol{h}}_t + \delta_t)\boldsymbol{F}\boldsymbol{v}_s + v_t \\ &= \hat{\boldsymbol{h}}_t\boldsymbol{F}\hat{\boldsymbol{h}}_s s + \hat{\boldsymbol{h}}_t\boldsymbol{F}\delta_s s + \delta_t\boldsymbol{F}\hat{\boldsymbol{h}}_s s + \delta_t\boldsymbol{F}\delta_s s \\ &\quad + \hat{\boldsymbol{h}}_t\boldsymbol{F}\boldsymbol{v}_s + \delta_t\boldsymbol{F}\boldsymbol{v}_s + v_t. \end{aligned} \tag{58}$$

Using the same approach we used for the case of perfect channel information, we want to choose $\boldsymbol{F}$ in order to minimize

$$\begin{aligned} J &= E|\eta s - \boldsymbol{h}_t\boldsymbol{x}|^2 \\ &= E|\hat{\boldsymbol{h}}_t\boldsymbol{F}\hat{\boldsymbol{h}}_s s + \hat{\boldsymbol{h}}_t\boldsymbol{F}\delta_s s + \delta_t\boldsymbol{F}\hat{\boldsymbol{h}}_s s \\ &\qquad + \delta_t\boldsymbol{F}\delta_s s + \hat{\boldsymbol{h}}_t\boldsymbol{F}\boldsymbol{v}_s + \delta_t\boldsymbol{F}\boldsymbol{v}_s - \eta s|^2. \end{aligned} \tag{59}$$

Since each relay sensor only has access to its received signal, we are interested in a local relaying strategy and we again choose $\boldsymbol{F}$ to be a diagonal matrix. Let the $1 \times N$ vector $\boldsymbol{f} = \text{diag}(\boldsymbol{F})$ denote the diagonal elements of $\boldsymbol{F}$. Note that for an $N \times N$ diagonal matrix $\boldsymbol{A}$ and an $1 \times N$ vector $\boldsymbol{b}$ we have

$$\boldsymbol{b}\boldsymbol{A} = \text{diag}(\boldsymbol{A})\text{diag}(\boldsymbol{b})$$

where $\text{diag}(\boldsymbol{A})$ is an $1\times N$ vector that consists of the diagonal elements of $\boldsymbol{A}$ and $\text{diag}(\boldsymbol{b})$ is an $N \times N$ diagonal matrix whose diagonal entries are $\boldsymbol{b}$. Then, neglecting second-order noise terms

$$\begin{aligned} J &\approx E|\boldsymbol{f}\text{diag}(\hat{\boldsymbol{h}}_t)\hat{\boldsymbol{h}}_s s + \boldsymbol{f}\text{diag}(\hat{\boldsymbol{h}}_t)\delta_s s \\ &\qquad + \boldsymbol{f}\text{diag}(\delta_t)\hat{\boldsymbol{h}}_s s + \boldsymbol{f}\text{diag}(\hat{\boldsymbol{h}}_t)\boldsymbol{v}_s - \eta s|^2 \\ &= \sigma_s^2\boldsymbol{f}\text{diag}(\hat{\boldsymbol{h}}_t)\hat{\boldsymbol{h}}_s\hat{\boldsymbol{h}}_s^*\text{diag}(\hat{\boldsymbol{h}}_t^*)\boldsymbol{f}^* \\ &\quad + \sigma_s^2\sigma_{\delta_s}^2\boldsymbol{f}\text{diag}(\hat{\boldsymbol{h}}_t)\text{diag}(\hat{\boldsymbol{h}}_t^*)\boldsymbol{f}^* \\ &\quad + \sigma_s^2\sigma_{\delta_t}^2\boldsymbol{f}\hat{\boldsymbol{h}}_s\hat{\boldsymbol{h}}_s^*\boldsymbol{f}^* + \sigma_{v_s}^2\boldsymbol{f}\text{diag}(\hat{\boldsymbol{h}}_t)\text{diag}(\hat{\boldsymbol{h}}_t^*)\boldsymbol{f}^* \\ &\quad - \eta\sigma_s^2\boldsymbol{f}\text{diag}(\hat{\boldsymbol{h}}_t)\hat{\boldsymbol{h}}_s - \eta\sigma_s^2\hat{\boldsymbol{h}}_s^*\text{diag}(\hat{\boldsymbol{h}}_t)^*\boldsymbol{f}^* + \eta^2\sigma_s^2 \end{aligned} \tag{60}$$

so that setting

$$\begin{aligned} \frac{dJ}{d\boldsymbol{f}} &= \sigma_s^2\text{diag}(\hat{\boldsymbol{h}}_t)\hat{\boldsymbol{h}}_s\hat{\boldsymbol{h}}_s^*\text{diag}(\hat{\boldsymbol{h}}_t^*)\boldsymbol{f}^* \\ &\quad + \sigma_s^2\sigma_{\delta_s}^2\text{diag}(\hat{\boldsymbol{h}}_t)\text{diag}(\hat{\boldsymbol{h}}_t^*)\boldsymbol{f}^* \\ &\quad + \sigma_s^2\sigma_{\delta_t}^2\hat{\boldsymbol{h}}_s\hat{\boldsymbol{h}}_s^*\boldsymbol{f}^* \\ &\quad + \sigma_{v_s}^2\text{diag}(\hat{\boldsymbol{h}}_t)\text{diag}(\hat{\boldsymbol{h}}_t^*)\boldsymbol{f}^* \\ &\quad - \eta\sigma_s^2\text{diag}(\hat{\boldsymbol{h}}_t)\hat{\boldsymbol{h}}_s = 0 \end{aligned} \tag{61}$$

gives

$$\begin{aligned} \hat{\boldsymbol{f}} = \eta\hat{\boldsymbol{h}}_s^*\text{diag}\left(\hat{\boldsymbol{h}}_t^*\right)^{-1}&\left[\sigma_{\delta_t}^2\text{diag}(\hat{\boldsymbol{h}}_t)^{-1}\hat{\boldsymbol{h}}_s\hat{\boldsymbol{h}}_s^*\text{diag}(\hat{\boldsymbol{h}}_t)^{-*}\right. \\ &\left. + \left(\hat{\boldsymbol{h}}_s\hat{\boldsymbol{h}}_s^* + \left(\sigma_{\delta_s}^2 + \frac{\sigma_{v_s}^2}{\sigma_s^2}\right)\boldsymbol{I}\right)\right]^{-1} \end{aligned} \tag{62}$$

with the corresponding relay matrix $\hat{\boldsymbol{F}}$ given by

$$\hat{\boldsymbol{F}} = \text{diag}(\hat{\boldsymbol{f}}). \tag{63}$$

It can be verified that (63) reduces to (14) in the case of no channel uncertainty.

A. Equalization

In order to remove the effect of the receiving noise v_t and recover s, we use the same approach we used before and choose a scalar α so as to minimize

$$\alpha = \arg\min_\alpha J(\alpha)$$

where now

$$\begin{aligned} J(\alpha) &= E|s - \alpha t|^2 \\ &= E|s - \alpha(\hat{\boldsymbol{h}}_t + \delta_t)\hat{\boldsymbol{F}}(\hat{\boldsymbol{h}}_s + \delta_s)s \\ &\qquad - \alpha(\hat{\boldsymbol{h}}_t + \delta_t)\hat{\boldsymbol{F}}\boldsymbol{v}_s - \alpha v_t|^2. \end{aligned} \tag{64}$$

Expanding the above cost function gives

$$\begin{aligned} J(\alpha) &= |\alpha|^2\sigma_s^2\hat{\boldsymbol{h}}_t\hat{\boldsymbol{F}}\hat{\boldsymbol{h}}_s\hat{\boldsymbol{h}}_s^*\hat{\boldsymbol{F}}^*\hat{\boldsymbol{h}}_t^* + |\alpha|^2\sigma_{v_s}^2\hat{\boldsymbol{h}}_t\hat{\boldsymbol{F}}\hat{\boldsymbol{F}}^*\hat{\boldsymbol{h}}_t^* \\ &\quad - \alpha\sigma_s^2\hat{\boldsymbol{h}}_t\hat{\boldsymbol{F}}\hat{\boldsymbol{h}}_s - \alpha^*\sigma_s^2\hat{\boldsymbol{h}}_s^*\hat{\boldsymbol{F}}^*\hat{\boldsymbol{h}}_t^* + |\alpha|^2\sigma_{v_t}^2 + \sigma_s^2 \\ &\quad + |\alpha|^2\sigma_s^2\sigma_{\delta_t}^2\hat{\boldsymbol{h}}_s^*\hat{\boldsymbol{F}}^*\hat{\boldsymbol{F}}\hat{\boldsymbol{h}}_s + |\alpha|^2\sigma_s^2\sigma_{\delta_s}^2\hat{\boldsymbol{h}}_t\hat{\boldsymbol{F}}\hat{\boldsymbol{F}}^*\hat{\boldsymbol{h}}_t^* \end{aligned}$$

and the optimal α is given by (65), shown at the bottom of the page. It can again be verified that (65) reduces to (20) in the case of no channel uncertainty.

IX. Power Constrained Relay Network

In the previous mmse relay scheme defined by (7), we did not impose any constraint on the power usage of the individual relay nodes or the entire network. Still, we showed that the power usage decreases as we increase the number of relay nodes. Now, we consider two additional relay strategies that incorporate power constraint.

A. Local Power Constraints

We first consider the case where the power of each relay node is limited to p_k. We again assume a diagonal relay matrix $\boldsymbol{F}$ with diagonal elements f_i. Since the power usages within the relay network are fixed, we design the relay factors in order to achieve the maximum possible target SNR. So, the power constrained relay matrix can be found by solving

$$\hat{\boldsymbol{F}} = \arg \max_{\boldsymbol{F}:E|f_k r_k|^2 = p_k} J(\boldsymbol{F}), \quad k = 1, \ldots, N \tag{66}$$

where the power of the received signal at the destination can be written as

$$\begin{aligned} J(\boldsymbol{F}) &= E|\boldsymbol{h}_t \boldsymbol{x}|^2 \\ &= E|\boldsymbol{h}_t \boldsymbol{F} \boldsymbol{h}_s s + \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{v}_s|^2 \end{aligned} \tag{67}$$

and

$$E|f_k r_k|^2 = |f_k|^2 \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right), \quad k = 1, \ldots, N. \tag{68}$$

Expanding (67) and using the fact that $\boldsymbol{F}$ is $N \times N$ diagonal leads to

$$J(\boldsymbol{F}) = \sigma_s^2 \left(\sum_{i=1}^N h_{t,i} f_i h_{s,i}\right) \left(\sum_{i=1}^N h_{t,i}^* f_i^* h_{s,i}^*\right) + \sigma_{v_s}^2 \left(\sum_{i=1}^N h_{t,i}^* f_i^* f_i h_{t,i}\right).$$

Using Lagrange multipliers allows us to consider instead

$$\begin{aligned} \hat{\boldsymbol{F}} &= \arg \max_{\boldsymbol{F}} J' \\ &= J(\boldsymbol{F}) - \sum_{k=1}^N \lambda_k \left(|f_k|^2 \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) - p_k\right) \end{aligned} \tag{69}$$

where the second expression is due to the power constraints for each relay node. Maximizing (69) over f_k and λ_k for $k = 1, \ldots, N$ gives

$$\begin{aligned} \frac{dJ'}{df_k} &= \sigma_s^2 h_{t,k} h_{s,k} \underbrace{\left(\sum_{i=1}^N h_{t,i}^* f_i^* h_{s,i}^*\right)}_{a} + \sigma_{v_s}^2 f_k^* |h_{t,k}|^2 \\ &\quad - \lambda_k f_k^* \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) = 0 \\ \frac{dJ'}{d\lambda_k} &= |f_k|^2 \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) - p_k = 0 \\ k &= 1, 2, \ldots, N. \end{aligned} \tag{70}$$

The first expression in (70) gives

$$\hat{f}_k^* = \frac{\sigma_s^2 h_{t,k} h_{s,k} a}{\lambda_k \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) - \sigma_{v_s}^2 |h_{t,k}|^2}. \tag{71}$$

In order to find λ_k, we first assume that λ_k and a are real and later show that the resulting expressions make this assumption feasible. Substituting (71) into the second expression in (70), we find that one solution for λ_k is

$$\lambda_k = \frac{\sigma_s^2/\sqrt{p_k}\sqrt{\sigma_s^2|h_{s,k}|^2 + \sigma_{v_s}^2}\,|h_{t,k}||h_{s,k}|a + \sigma_{v_s}^2 |h_{t,k}|^2}{\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2}. \tag{72}$$

Substituting (71) and (72) into the definition of a gives

$$a = \sum_{k=1}^N \frac{\sqrt{p_k}|h_{t,k}||h_{s,k}|}{\sqrt{\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2}} \tag{73}$$

where it can be seen that the obtained a is real. Now, in order to find the relay factors, we substitute (72) and (73) into (71) to get

$$\boxed{\hat{f}_k = \frac{\sqrt{p_k}}{\sqrt{\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2}} \frac{h_{t,k}^*}{|h_{t,k}|} \frac{h_{s,k}^*}{|h_{s,k}|}}. \tag{74}$$

When $p_k = \sqrt{\sigma_r^2} =$ constant for all k, this result coincides with the conventional relay factor from (15). In the prior works in the literature, this amplify-forward scheme is motivated by the desire to normalize the power at the relay nodes and to compensate for the phase effect of the forward and backward channels by matching the received signal to $h_{t,k}^*/|h_{t,k}|$ and $h_{s,k}^*/|h_{s,k}|$, respectively. Our argument has now shown that this scheme solves a constrained mmse estimation problem.

B. Global Power Constraint

In the second scenario, we assume that the total power usage by the network is limited to some value P, and the relay nodes are allowed to allocate the available power P in order to achieve the mmse estimation of the transmitted signal at the destination node. We again assume a diagonal relay matrix $\boldsymbol{F}$ with diagonal elements f_i. Again, we design the relay factors in order to

$$\hat{\alpha} = \frac{\sigma_s^2 \hat{\boldsymbol{h}}_s^* \hat{\boldsymbol{F}}^* \hat{\boldsymbol{h}}_t^*}{\sigma_s^2 |\hat{\boldsymbol{h}}_t \hat{\boldsymbol{F}} \hat{\boldsymbol{h}}_s|^2 + \left(\sigma_s^2 \sigma_{\delta_s}^2 + \sigma_{v_s}^2\right) \|\hat{\boldsymbol{h}}_t \hat{\boldsymbol{F}}\|^2 + \sigma_s^2 \sigma_{\delta_t}^2 \|\hat{\boldsymbol{F}} \hat{\boldsymbol{h}}_s\|^2 + \sigma_{v_t}^2}. \tag{65}$$

achieve the maximum possible target SNR given the constrained power. So, the power constrained relay matrix can be found by solving

$$\hat{\boldsymbol{F}} = \arg \max_{\boldsymbol{F}:\sum_{k=1}^{N} E|f_k r_k|^2 = P} J(\boldsymbol{F}), \quad k = 1, \ldots, N \tag{75}$$

where, as before, the power of the received signal at the destination can be written as

$$J(\boldsymbol{F}) = E|\boldsymbol{h}_t \boldsymbol{x}|^2 = E|\boldsymbol{h}_t \boldsymbol{F} \boldsymbol{h}_s s + \boldsymbol{h}_t \boldsymbol{F} \boldsymbol{v}_s|^2 \tag{76}$$

and the total power constraint amounts to

$$\sum_{k=1}^{N} E|f_k r_k|^2 = \sum_{k=1}^{N} |f_k|^2 \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) = P. \tag{77}$$

Expanding (76) gives again (69) and using a Lagrange multiplier we can write Lagrangian optimization as

$$\begin{aligned}\hat{\boldsymbol{F}} &= \arg\max_{\boldsymbol{F}} J' \\ &= J(\boldsymbol{F}) - \lambda \left(\sum_{k=1}^{N} |f_k|^2 \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) - P \right).\end{aligned} \tag{78}$$

The optimization problem (78) can be solved numerically. However, in order to find a closed form solution for the relay factors, we shall assume high SNR. Then maximizing (78) over f_k and λ for $k = 1, \ldots, N$ gives

$$\begin{aligned}\frac{dJ'}{df_k} &= \sigma_s^2 h_{t,k} h_{s,k} \underbrace{\left(\sum_{i=1}^{N} h_{t,i}^* f_i^* h_{s,i}^* \right)}_{b} + \sigma_{v_s}^2 f_k^* |h_{t,k}|^2 \\ &\quad - \lambda f_k^* \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) = 0 \\ \frac{dJ'}{d\lambda} &= \sum_{k=1}^{N} |f_k|^2 \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) - P = 0.\end{aligned} \tag{79}$$

Using the first expression in (79) we have

$$\hat{f}_k^* = \frac{\sigma_s^2 h_{t,k} h_{s,k} b}{\lambda \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) - \sigma_{v_s}^2 |h_{t,k}|^2} \tag{80}$$

where we have assumed that λ and b are real, we will obtain a solution that satisfies this condition. Substituting (80) into the second expression in (79) gives

$$\sum_{k=1}^{N} \frac{\left|\sigma_s^2 h_{t,k} h_{s,k} b\right|^2}{\left|\lambda \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right)\right|^2 - \sigma_{v_s}^2 |h_{t,k}|^2} \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) = P. \tag{81}$$

In order to find a closed form solution for λ, we assume low noise relay nodes so that

$$\lambda \left(\sigma_s^2 |h_{s,k}| + \sigma_{v_s}^2\right) - \sigma_{v_s}^2 |h_{t,k}|^2 \approx \lambda \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right). \tag{82}$$

Using (82) and (81) we have

$$\lambda \approx \frac{\sigma_s^2 b}{\sqrt{P}} \sqrt{\sum_{k=1}^{N} \frac{|h_{t,k}|^2 |h_{s,k}|^2}{\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2}}. \tag{83}$$

Substituting (83) into (80), the relay factor can be approximated as

$$\boxed{\hat{f}_k \approx \frac{\sqrt{P} h_{t,k}^* h_{s,k}^*}{\sqrt{\sum_{i=1}^{N} \frac{|h_{t,i}|^2 |h_{s,i}|^2}{\sigma_s^2 |h_{s,i}|^2 + \sigma_{v_s}^2}} \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right)}}. \tag{84}$$

In order to check how the approximation in (82) affects the power constraint, we can calculate the total power usage using the relay factors in (84)

$$\begin{aligned}&\text{Total power usage} \\ &= \sum_{k=1}^{N} |f_k|^2 \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) \\ &= \sum_{k=1}^{N} \frac{P |h_{t,k}|^2 |h_{s,k}|^2}{\sum_{i=1}^{N} \frac{|h_{t,i}|^2 |h_{s,i}|^2}{\sigma_s^2 |h_{s,i}|^2 + \sigma_{v_s}^2} \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right)^2} \\ &\quad \times \left(\sigma_s^2 |h_{s,k}|^2 + \sigma_{v_s}^2\right) \\ &= P\end{aligned} \tag{85}$$

and it follows that total average constraint is satisfied. It can be seen that the total power P is allocated between different nodes in proportion to the product magnitude of the forward and backward channels. As a result, the stronger the forward and backward channels, the more power will be allocated for the relay node.

X. Simulation Results

The performance of the proposed schemes are investigated for a relay network with one source and one destination. We assume that all relay sensors are essentially at the same distance from the source and destination sensors. Using this assumption, the channels from the source sensor to the relay sensors have the same second moment statistics as the channels from the relay sensors to the destination sensor, i.e., $E(\boldsymbol{h}_s \boldsymbol{h}_s^*) = E(\boldsymbol{h}_t^* \boldsymbol{h}_t)$. Moreover, we use zero-mean unit variance complex Gaussian channel models for $\boldsymbol{h}_s$ and $\boldsymbol{h}_t$, and the transmitted signal from the source sensor is assumed to be QPSK with unit power. Since we minimize the mse, the BER is a good criterion to evaluate the performance of the proposed schemes.

First, we consider two different scenarios to compare BER performances that show the effect of different target SNR, and different number of relay sensors. In the first scenario, we assume that all sensors have the same noise variances and the target SNR, or η is not large. The second scenario assumes larger target SNR, which results in more diversity as the number of the relay nodes increases. Fig. 3 shows the BER performance of the first scheme (14) when all sensors have the same noise power $\sigma_{v_t}^2 = \sigma_{v_s}^2$. The SNR in this figure refers to the ratio

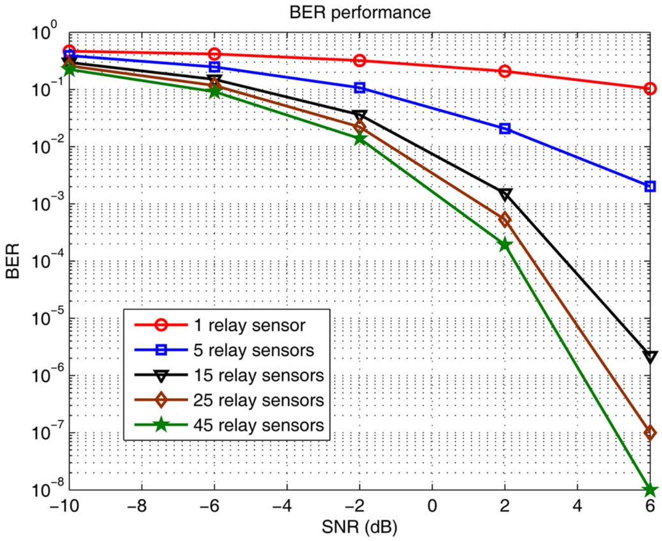

Fig. 3. BER performance of the mmse scheme (14) when the sensors are assumed to have *similar* noise power and the relay sensors are placed such that they have the same distance from the source and destination sensors and $\eta = 1$.

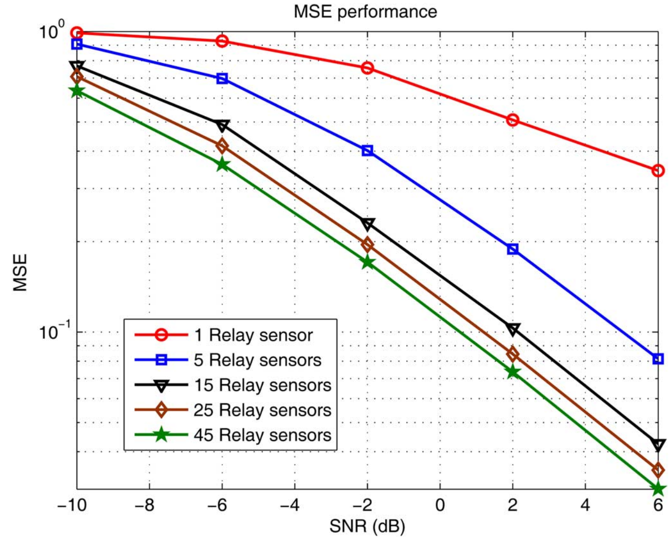

Fig. 5. mse performance of the relay scheme (14) when the relay sensors are assumed to have the *same* noise power as the destination sensor. The relay sensors are placed such that they have the same distance from the source and destination sensors.

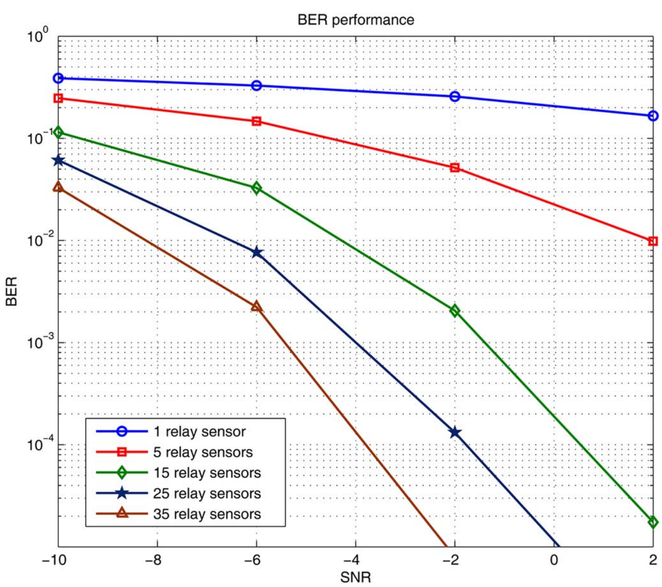

Fig. 4. BER performance of the mmse relay scheme (14) when the relay sensors are assumed to have *more* noise power than the destination sensor so the target SNR is large. The relay sensors are placed such that they have the same distance from the source and destination sensors.

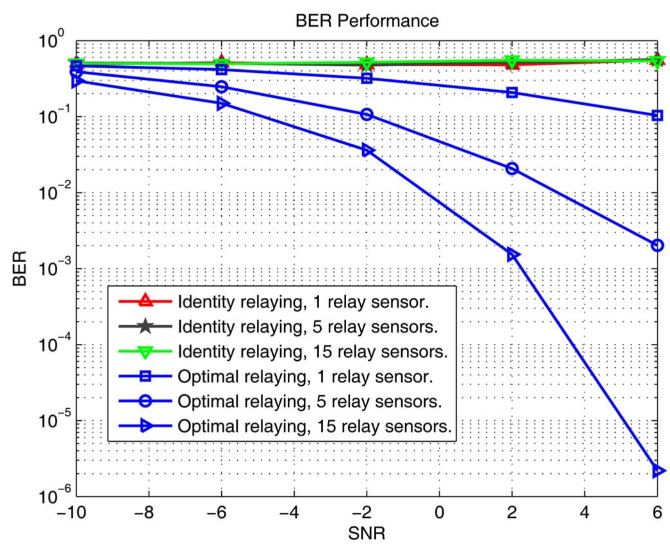

Fig. 6. BER performance of the relay scheme (14) versus the BER performance of a relay network that rebroadcasts the received signals without any modification.

$\sigma_s^2\sigma_{h_s}^2/\sigma_{v_s}^2 = \sigma_s^2\sigma_{h_t}^2/\sigma_{v_t}^2$ with $\eta = 1$. The performance is seen to improve as the number of relay sensors grows for the same target SNR. But since the target SNR is not large, increasing the number of relay nodes only compensates for the effect of relay node noises. Fig. 4 shows the BER performance of the same scheme (14) when the target SNR is large (20 dB) and the SNR in this figure stands for the receiving SNR at the relay node. Figs. 3 and 4 illustrate the derived analytical expressions in (50) and (56), respectively. As a result, for less power consumption, we could achieve better BER performance when more relay nodes are used. Fig. 5 shows the mse performance of the proposed scheme in (14). In this simulation, we have chosen the same parameters as Fig. 3. It can be seen that, as the number of relay nodes increases, the mse performance improves for the same target SNR or η value. Fig. 6 shows how the relay network performs if the relay nodes rebroadcast the received signals without any modification. In this case, increasing the number of relay nodes and increasing the SNR do not improve the BER performance. Fig. 7 shows the power usage per sensor and the total power usage by the relay network versus the number of relay sensor nodes for scheme (14). It can be seen that the power usage per sensor and the total power both drop as we increase the number of relay nodes, and that the power usage per sensor decreases faster than the total power. We also simulate the case when there is uncertainty in the channels. Fig. 8 illustrates the performance of the relay network when we use the modified relay scheme from (62). The channel uncertainty is modelled as white Gaussian noise added to the channel values.

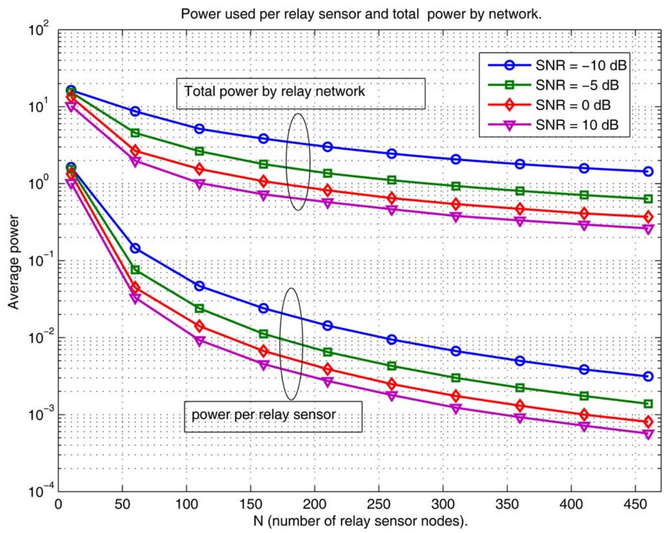

Fig. 7. The power usage per relay sensor node and the total power usage for all relay sensors versus number of relay nodes using the mmse relay scheme (14).

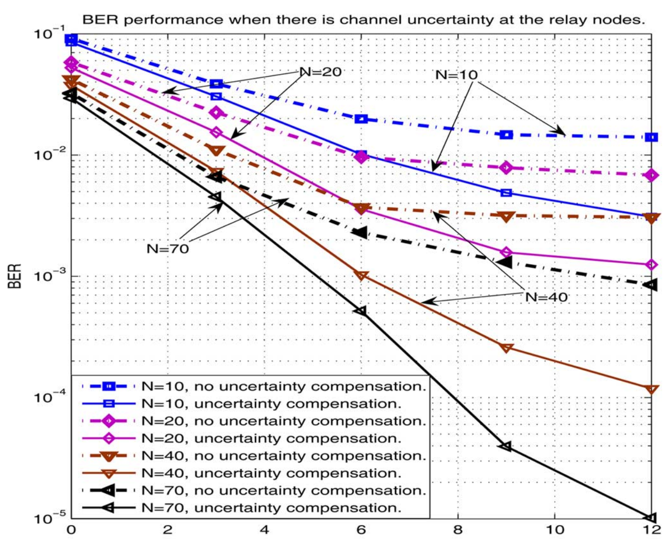

Fig. 8. BER comparison when the channel uncertainty compensation scheme (62) is used versus the mmse relay scheme (14) assuming $10\log\sigma_{\delta_s}^2/\sigma_{h_s}^2 = 10\log\sigma_{\delta_t}^2/\sigma_{h_t}^2 = -10$ dB uncertainty.

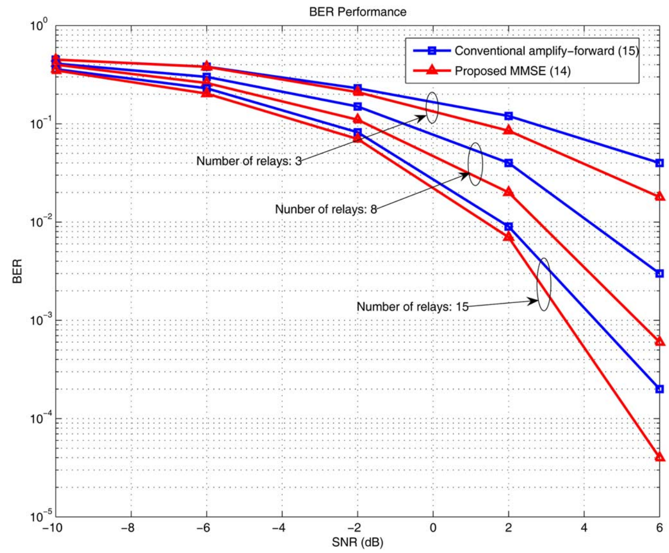

Fig. 9. BER performance of the proposed mmse relay scheme (14) versus the BER performance of conventional amplify-forward relay scheme (15) when both schemes are forced to use almost the same average power per node by adjusting the threshold γ in (32).

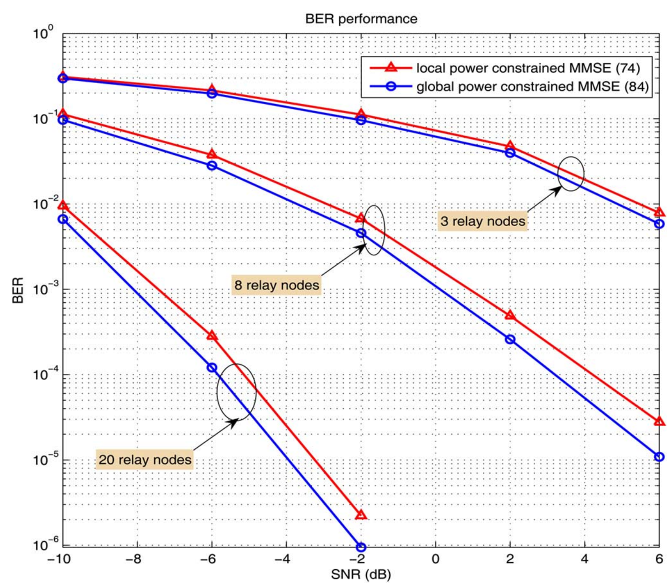

Fig. 10. BER performance of the proposed power constrained mmse scheme (74) versus the BER performance of a relay network that uses the global power constraint mmse solution (84).

The variance of the errors for the backward and forward channels are chosen as $10\log\sigma_{\delta_s}^2/\sigma_{h_s}^2 = 10\log\sigma_{\delta_t}^2/\sigma_{h_t}^2 = -10\,\mathrm{dB}$. Fig. 9 compares the BER performance of the conventional amplify-forward scheme (15) versus the relay scheme in (14) when both schemes are forced to use almost the same average power per node by adjusting the threshold γ in (32). It can be seen that the scheme in (14) outperforms the conventional relay scheme since it assigns different power allocation for different relay nodes. Fig. 10 compares the BER performance of the power constrained amplify-forward scheme (74) when power is allocated uniformly and when it is optimized and allocated globally (84). It can be observed that global power allocation performs better than uniform power allocation.

XI. Conclusion

In this paper, we proposed and analyzed two-hop multisensor relaying strategies that increase the transmit range. In the proposed distributed schemes, the relay sensors do not need to share information about the received signals. An optimal mse design is pursued and the performance is shown to improve as the number of relay sensors increases. Both the power consumption and the link capacity are evaluated. The effect of channel uncertainty is also discussed and addressed, along with the requirement of limited power consumption by the individual nodes and by the network as a whole. We have proposed three general relay methods:

1) *MSE strategy with no power constraints:* In this method, relays can have different power usage in order to achieve the desired QoS at the destination node. This method brings two advantages:
   a. Guarantees a certain QoS when QoS has the highest priority, e.g., in emergency applications.

b. Since the power is adjusted in order to achieve a certain QoS, then it will avoid spending more than necessary amount of power in applications with low QoS requirements.

2) *Relay schemes with local power constraints:* This method is useful when the power budget of each relay is fixed and we want to get the best possible SNR or best possible QoS at the destination by spending this power budget. The solution structure turns out to be similar to (15).

3) Relay schemes with global power constraints: This method is useful when we are given a global power budget and we can allocate different power shares to different relays as long as their total power usage does not aexceed the global power constraint.

A relay strategy for Alamouti space–time-coded networks appears in [32].

APPENDIX

Assuming i.i.d. Gaussian complex entries $h_{s,i}$, then $\|\boldsymbol{h}_s\|^2$ has a chi-square distribution with $2N$ degrees of freedom [27]. Using the probability density function of a chi-square random variable we have

$$E\left(\frac{1}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2}\right)=\int_0^\infty\left(\frac{1}{\sigma_{v_s}^2+\sigma_s^2 x}\right)p(x)dx$$

where

$$p(x)=\frac{1}{\sigma_{h_s}^{2N}\Gamma(N)}x^{N-1}e^{-x/\sigma_{h_s}^2}$$

and $\Gamma(.)$ denotes the Gamma function. Assume $\sigma_{v_s}^2+\sigma_s^2 x\approx\sigma_s^2 x$. Then[2]

$$\begin{aligned}E\left(\frac{1}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2}\right)&\approx\int_0^\infty\frac{1}{\sigma_s^2\sigma_{h_s}^{2N}\Gamma(N)}x^{N-2}e^{-x/\sigma_{h_s}^2}dx\\&=\frac{1}{\sigma_s^2\sigma_{h_s}^{2N}\Gamma(N)}\int_0^\infty x^{N-2}e^{-x/\sigma_{h_s}^2}dx\\&=\frac{1}{\sigma_s^2\sigma_{h_s}^{2N}\Gamma(N)}\Gamma(N-1)\left(\sigma_{h_s}^2\right)^{N-1}\\&=\frac{1}{\sigma_s^2\sigma_{h_s}^{2N}(N-1)!}\\&\quad\times(N-2)!\left(2\sigma_{h_s}^2\right)^{N-1}\\&=\frac{1}{\sigma_s^2(N-1)\sigma_{h_s}^2}\end{aligned}\tag{86}$$

where we assumed $N-1\approx N$. Then

$$\boxed{E\left(\frac{1}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2}\right)\approx\frac{1}{\sigma_s^2 N\sigma_{h_s}^2}}.\tag{87}$$

In a similar manner

$$\boxed{E\left(\frac{1}{\sigma_{v_s}^2+\sigma_s^2\|\boldsymbol{h}_s\|^2}\right)^2\approx\frac{1}{\left(\sigma_s^2 N\sigma_{h_s}^2\right)^2}}.\tag{88}$$

[2]In order to evaluate the expectation, we use $\int_0^\infty t^n e^{-at}dt=(\Gamma(n+1)/a^{n+1})$, where $\Gamma(n+1)=n!$ when n is an integer.

REFERENCES

[1] G. J. Pottie and W. J. Kaiser, "Wireless integrated network sensors," *Commun. ACM*, vol. 43, no. 5, pp. 51–58, May 2000.

[2] D. Estrin, L. Girod, G. J. Pottie, and M. Srivastava, "Instrumenting the world with wireless sensor networks," in *Proc. IEEE Int. Conf. Acoustics, Speech, Signal Processing (ICASSP)*, Salt Lake City, UT, May 2001, pp. 2033–2036.

[3] T. Cover and A. E. Gamal, "Capacity theorems for the relay channel," *IEEE Trans. Inf. Theory*, vol. 25, pp. 572–584, Sep. 1979.

[4] G. Kramer, M. Gastpar, and P. Gupta, "Capacity theorems for wireless relay channels," in *Proc. 41st Annu. Allerton Conf. Commun., Control, Comput.*, Allerton, IL, Oct. 2003, pp. 1074–1083.

[5] M. Gastpar and M. Vetterli, "On the capacity of large Gaussian relay networks," *IEEE Trans. Inf. Theory*, vol. 51, pp. 765–779, Mar. 2005.

[6] ——, "Power, spatio-temporal bandwidth, and distortion in large sensor networks," in *IEEE J. Sel. Areas Commun.*, Apr. 2005, vol. 23, pp. 745–754.

[7] ——, "On the capacity of wireless networks: The relay case," in *Proc. IEEE INFOCOM*, New York, Jun. 2002, pp. 1577–1586.

[8] P. Gupta and P. R. Kumar, "Towards an information theory of large networks: An achievable rate region," *IEEE Trans. Inf. Theory*, vol. 49, pp. 1877–1894, Aug. 2003.

[9] M. A. Khojastepour, A. Sabharwal, and B. Aazhang, "On the capacity of cheap relay networks," in *Proc. 37th Annu. Conf. Inf. Sci. Syst.*, Baltimore, MD, Mar. 2003, pp. 1776–1780.

[10] L.-L. Xie and P. R. Kumar, "A network information theory for wireless communication: Scaling laws and optimal operation," *IEEE Trans. Inf. Theory*, vol. 50, pp. 748–767, May 2004.

[11] H. Bolcskei, R. U. Nabar, O. Oyman, and A. J. Paulraj, "Capacity scaling laws in mimo relay networks," presented at the Allerton Conf, Monticello, IL, Oct. 2003.

[12] C. Intanagonwiwat, D. Estrin, R. Govindan, and J. Heidemann, "Impact of network density on data aggregation in wireless sensor networks," in *Proc. Int. Conf. Distribut. Comput. Syst. (ICDCS)*, Vienna, Austria, Jul. 2002, pp. 457–458.

[13] S. Madden, M. J. Franklin, J. M. Hellerstein, and W. Hong, "A tiny aggregation service for ad hoc sensor networks," presented at the OSDI Conf., Boston, MA, Dec. 2002.

[14] C. Schurgers, S. Ganeriwal, and M. Srivastava, "Optimizing sensor networks in the energy-latency-density design space," *IEEE Trans. Mobile Comput.*, pp. 70–80, Jan. 2002.

[15] W. Ye, J. Heidemann, and D. Estrin, "An energy-efficient MAC protocol for wireless sensor networks," in *Proc. INFOCOM*, New York, Jun. 2002, pp. 1567–1576.

[16] U. Cetintemel, A. Flinders, and Y. Sun, "Power-aware data dissemination in wireless sensor networks," in *Proc. 3rd ACM Int. Workshop on Data Eng. Wireless Mobile Access*, San Diego, CA, Sep. 2003, pp. 1–8.

[17] R. Pabst *et al.*, "Relay-based deployment concepts for wireless and mobile broadband radio," *IEEE Commun. Mag.*, vol. 42, no. 9, pp. 80–89, Sep. 2004.

[18] P. Herhold, E. Zimmermann, and G. Fettweis, "On the performance of cooperative amplify-and-forward relay networks," presented at the 5th Int. ITG Conf. Source and Channel Coding (SCC), Erlangen, Germany, Jan. 2004.

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

[20] L. Venturino, W. Xiaodong, and M. Lops, "Multiuser detection for cooperative networks and performance analysis," in *Proc. IEEE Workshop Signal Processing Advanced Wireless Communications (SPAWC)*, Jun. 2005, pp. 940–944.

[21] I. Maric and R. D. Yates, "Cooperative multihop broadcast for wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 22, no. 6, pp. 1080–1088, Aug. 2004.

[22] Y. Hong and A. Scaglione, "Energy-efficient broadcasting with cooperative transmission in wireless sensory ad hoc networks," presented at the Allerton Conf., Monticello, IL, Oct. 2003.

[23] M. Gastpar, G. Kramer, and P. Gupta, "The multiple-relay channel: Coding and antenna-clustering capacity," in *Proc. IEEE Int. Symp. Inf. Theory*, Lausanne, Switzerland, Jun. 2002, pp. 136–136.

[24] B. Schein and R. G. Gallager, "The Gaussian parallel relay network," in *Proc. IEEE Int. Symp. Inf. Theory*, Sorrento, Italy, Jun. 2000, pp. 22–22.

[25] J. N. Laneman and G. W. Wornell, "Distributed space-time coded protocols for exploiting cooperative diversity in wireless networks," *Trans. Inf. Theory*, vol. 49, no. 10, pp. 2415–2425, Oct. 2003.

[26] G. Kramer, M. Gastpar, and P. Gupta, "Capacity theorems for wireless relay channels," presented at the Allerton Conf. Commun., Control Comput., Monticello, IL, Oct. 2003.
[27] A. H. Sayed, *Fundamentals of Adaptive Filtering*. New York: Wiley, 2003.
[28] T. M. Cover and J. A. Thomas, *Elements of Information Theory*. New York: Wiley, 1991.
[29] J. Proakis, *Digital Communications*. New York: McGraw-Hill, 2000.
[30] C. E. Shannon, "A mathematical theory of communication," *Bell Syst. Tech. J.*, vol. 27, pp. 379–423–623–656, Jul.-Oct. 1948.
[31] S. Verdu, "Spectral efficiency in the wideband regime," *IEEE Trans. Inf. Theory*, vol. 48, pp. 1319–1343, Jun. 2002.
[32] N. Khajehnouri and A. H. Sayed, "Alamouti space–time coded relay strategy for wireless networks," in *Proc. IEEE Workshop Statistical Signal Processing (SSP)*, Bordeaux, France, Jul. 2005, pp. 83–88.

Nima Khajehnouri received the B.Sc. degree in electrical engineering from Sharif University of Technology, Tehran, Iran, in 2001, and the M.Sc. and Ph.D. degrees in electrical engineering from the University of California, Los Angeles (UCLA), in 2002 and 2006, respectively.

His research focuses on signal processing techniques for communication systems, including multiuser MIMO communications, relay networks, and signal processing for sensor networks.

Ali H. Sayed (F'01) received the Ph.D. degree in electrical engineering from Stanford University, Stanford, CA, in 1992.

He is Professor and Chairman of Electrical Engineering with the University of California, Los Angeles (UCLA). He is also the Principal Investigator of the UCLA Adaptive Systems Laboratory (http://www.ee.ucla.edu/asl). He has more than 280 journal and conference publications. He is the author of *Fundamentals of Adaptive Filtering* (New York: Wiley, 2003), coauthor of the research monograph *Indefinite Quadratic Estimation and Control* (Philadelphia, PA: SIAM, 1999) and of the graduate-level textbook *Linear Estimation* (Englewood Cliffs, NJ: Prentice-Hall, 2000). He is also coeditor of the volume *Fast Reliable Algorithms for Matrices with Structure* (Philadelphia, PA: SIAM, 1999). He has contributed several articles to engineering and mathematical encyclopedias and handbooks and has served on the program committees of several international meetings. His research interests span several areas, including adaptive and statistical signal processing, filtering and estimation theories, signal processing for communications, interplays between signal processing and control methodologies, system theory, and fast algorithms for large-scale problems.

Dr. Sayed received the 1996 IEEE Donald G. Fink Award, 2002 Best Paper Award from the IEEE Signal Processing Society, 2003 Kuwait Prize in Basic Science, 2005 Frederick E. Terman Award, and is coauthor of two Best Student Paper awards at international meetings (1999, 2001). He is also a member of the Technical Committees on Signal Processing Theory and Methods (SPTM) and on Signal Processing for Communications (SPCOM), both of the IEEE Signal Processing Society. He is a member of the editorial board of the IEEE *Signal Processing Magazine*. He has also served twice as an Associate Editor of the IEEE TRANSACTIONS ON SIGNAL PROCESSING, and as Editor-in-Chief of the same journal during 2003-2005. He is serving as Editor-in-Chief of the *EURASIP Journal on Advances in Signal Processing* and as General Chairman of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2008. He sits on the Board of Governors of the IEEE Signal Processing Society.