A Soft-Network-Coded Multilevel Forwarding Scheme for Multiple-Access Relay Systems

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***Abstract*—This paper proposes the novel technique of multilevel-threshold-based soft quantization (MLT-SQ) for a multiple-access relay system (MARS). The scheme is suitable for systems using binary phase-shift keying (BPSK) and network coding at the relay. In the proposed MLT-SQ protocol, the relay evaluates the reliabilities, which are expressed as log-likelihood ratios (LLRs), of the received signals from the two sources. It then computes the LLRs of the network-coded packet and quantizes these using a set of optimized multilevel thresholds, forwarding the resulting "*quantized soft symbols*" to the destination. We provide the derivation for the bit error rate (BER) at the destination, and based on this, we optimize the multilevel thresholds to minimize the BER. Simulation results are provided for the proposed MLT-SQ system, both without coding and for the case where low-density parity-check (LDPC) coding is employed. The proposed system achieves full diversity order. Compared with competing schemes, the performance of our system is superior in terms of BER when the same amount of channel state information (CSI) is exploited.**

***Index Terms*—Cooperative communications, low-density parity-check coding, network coding, relaying.**

I. Introduction

COOPERATIVE communication for wireless networks promises improved transmit diversity and increased spectral efficiency [1], [2]. A judiciously designed signal forwarding technique at the relay and an accurate detection technique at the destination can greatly enhance the system performance. Two classical relaying protocols are in use: amplify-and-forward (AF) and decode-and-forward (DF). With the AF strategy, the relay transmits an amplified version of its received signal to the destination. AF does not perform any noise suppression; therefore, it suffers from severe noise propagation and power inefficiency issues. By use of a detector/decoder at the relay, the DF protocol is able to regenerate the transmitted signal so that the noise propagation can be avoided. However, any decoding error in the regenerated signal can cause a performance degradation at the destination.

Link-adaptive solutions are proposed in [17]–[19], which seek to avoid the error propagation in the conventional DF. The works of [17]–[19] also propose novel network coding schemes to achieve full diversity and assume that frame errors at the relay can be detected by using cyclic-redundancy-check codes. In this scenario, if an error is detected by the relay, then it will be discarded when the network coding takes place at the relay. However, when the extra check information is transmitted, it introduces an extra delay in the transmission. Moreover, when the erroneous signal is discarded at the relay, some useful information inside the frame is also discarded.

Distributed coding schemes such as distributed low-density parity-check (LDPC) codes [4], [5] and distributed turbo codes (DTCs) [6] have been proposed in recent years to improve the coding gain, quality, and reliability of wireless links. Moreover, a recently proposed and promising relay protocol called *soft information relaying* (SIR) has gained significant attention [7]–[16] as a potential method to overcome the principal drawbacks of AF and DF. In [9], the implementation of SIR was studied in conjunction with DTC. In fact, this method leads to the reliability of the recursively soft re-encoded bits depending strongly on the least reliable input bits, causing a decaying log-likelihood ratio (LLR) profile as shown in [10]. In [9], the effective noise introduced by the relay is modeled as Gaussian noise. In [11], it is shown that the Gaussian assumption made in [9] is not very accurate in general, by numerically demonstrating the LLR distribution at the destination for the case of DTC. Moreover, in [12], it is shown that in the uncoded scenario, the SIR protocol maximizes the SNR at the destination and thus possesses a better error performance relative to the AF and DF protocols in the one-way single-relay channel.

Recently, a soft decode–compress–forward scheme was proposed in [16]; this work featured a new model, referred to as the *soft scalar model*, to facilitate the LLR computation at the destination. A soft forwarding technique based on symbolwise mutual information was investigated in [14] using physical-layer network coding (PLNC) in the two-way relay channel. Schemes using *soft network coding*, i.e., the incorporation of reliability information into the network-coded relay transmission, were introduced in [20] and [21]. In particular, the method in [21] presented a network coding scheme for the two-way relay channel where the network coding operation (XOR operation) takes place in the soft (continuous) domain and could be

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considered as a form of estimate-and-forward relaying where the estimate is of the network-coded symbol. A drawback of all of the aforementioned unquantized soft forwarding schemes is that a heuristic and not quite accurate model must be adopted for the equivalent noise (comprising contributions from both channel and relay operations), in order to form LLRs at the destination. This is an inherent problem that originates due to the unquantized nature of the signal transmitted from the relay.

An LLR-threshold-based forwarding protocol was presented in [23]–[27]. In these works, the relay evaluates the reliabilities of the received symbols (from each source) and accordingly selects the corresponding symbol to send to the destination. When the bit LLR is sufficiently large (i.e., the symbol decision is deemed to be sufficiently reliable), the relay transmits the hard decision for the symbol; otherwise, it is silent. Therefore, these works [23]–[27] may be regarded as a soft forwarding scheme based on three-level LLR quantization in cooperative relay networks. Moreover, in [27], a mutual-information-based soft information forwarding scheme was proposed, but since it is based on the maximization of the mutual information between the LLR and its quantized value, it cannot guarantee the optimal error rate performance at the destination. In [22], a power scaling scheme for the one-way relay channel was introduced, and in [26], this was extended to multisource relay channels.

In this paper, we propose a new framework for designing a multilevel-threshold-based soft quantization (MLT-SQ) protocol using multiple thresholds, which are optimized for minimum overall BER at the destination in a multiple-access relay system (MARS) using network coding. In contrast to the methods of [23]–[27], the quantization levels do not represent "decisions" but represent true reliability information, and all quantization levels are taken into account by the destination. Furthermore, in contrast to the SIR schemes of [9]–[16], the proposed scheme allows *exact* calculation of the LLRs at the destination without the need for a complex and approximate model for the effective noise (and while maintaining almost the same precision of forwarded reliability information). Simulation results, both with and without channel coding, are presented, which compare the performance of the proposed MLT-SQ scheme to that of competing schemes. We compare with three-level soft forwarding, uncoded DF, and a "genie-aided" scheme as benchmarks; as another competing scheme, we also include the link-adaptive regeneration (LAR) protocol, as proposed in [26]. The simulation results demonstrate that the proposed MLT-SQ scheme efficiently mitigates error propagation in a power-efficient manner when compared with the benchmark schemes.

II. System Model

In this paper, we consider a four-terminal topology as shown in Fig. 1. It is assumed that there is a direct transmission from the sources to the destination. In the first time slot,[1] source S_1

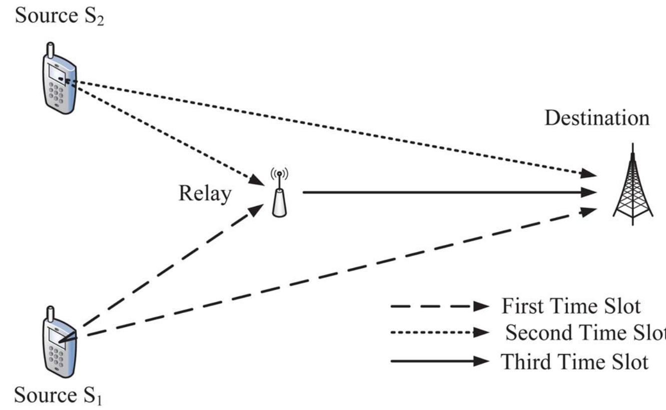

Fig. 1. The proposed multiple access relay system in half-duplex mode.

broadcasts an uncoded frame, of length N, of binary phase-shift keying (BPSK) modulated symbols (source S_2 being silent); this transmission is received both by the relay and by the destination. In the second time slot, source S_2 broadcasts its uncoded data frame using BPSK, with source S_1 being silent. In the third time slot, the relay aids the destination by transmitting a (soft quantized) network-coded message based on the signals received in the first and second time slots. We assume that all nodes have only one antenna working in a half-duplex mode.

The system model considered here has previously appeared in the context of vehicular communications; for example, [30] and [31] consider a single-relay scenario in which source vehicle, relay vehicle, and destination vehicle operate in half-duplex mode. In [30], cooperative diversity for intervehicular communications based on cascaded Rayleigh fading is investigated, assuming an aggregate channel model that takes into account both the long-term path loss and short-term fading (this allows to explicitly consider the effects of the relay location in the system model). In [31], a similar system model for vehicular communication is used, but it provides the optimal power allocation through maximizing source-to-destination channel capacity.

We denote[2] by h_{iR}, h_{iD}, and h_{RD}, where $i \in \{S_1, S_2\}$, the channel coefficients between i and R, between i and D, and between R and D, respectively. The corresponding distances between nodes are denoted by d_{iR}, d_{iD}, and d_{RD}, respectively. We assume that h_{iR}, h_{iD}, and h_{RD} are independent and identically Rayleigh distributed. The channel gains are related to the corresponding distances by the attenuation exponent γ, i.e., $\lambda_{iR} = 1/(d_{iR})^\gamma$, $\lambda_{iD} = 1/(d_{iD})^\gamma$, and $\lambda_{RD} = 1/(d_{RD})^\gamma$, respectively. We consider quasi-static fading channels, i.e., the channel coefficients are constant during one transmission phase (time slot) and change independently from one phase to another. In each of the first two time slots, in the jth symbol interval, the source bit $u_{i,j} \in \{0, 1\}$ is mapped to a BPSK symbol $x_{i,j} \in \{-1, 1\}$ via the mapping $0 \mapsto +1$, $1 \mapsto -1$. The received signals at the relay and destination corresponding to source i in the jth symbol interval are given by

$$\begin{aligned} y_{iR,j} &= \sqrt{P_i} h_{iR} x_{i,j} + n_{iR,j} \\ y_{iD,j} &= \sqrt{P_i} h_{iD} x_{i,j} + n_{iD,j} \end{aligned} \tag{1}$$

[1]Unless otherwise stated, in this paper, $S, R,$ and D stand for source, relay, and destination, respectively. Throughout this paper, all vectors are taken to be row vectors. Moreover, vectors are denoted by bold letters and the ith element by an italic letter. We use regular letters to denote scalars (including random variables). For a random variable x, we use $\mathbb{E}[x]$ to denote the expected value of x. The soft information corresponding to symbol a is represented by $\tilde{a}$. The notation $\mathrm{sgn}(\cdot)$ indicates the sign of the variable in the bracket.

[2]Unless otherwise stated, in this paper, we assume $i \in \{S_1, S_2\}$ and $j \in \{1, 2, \ldots, N\}$.

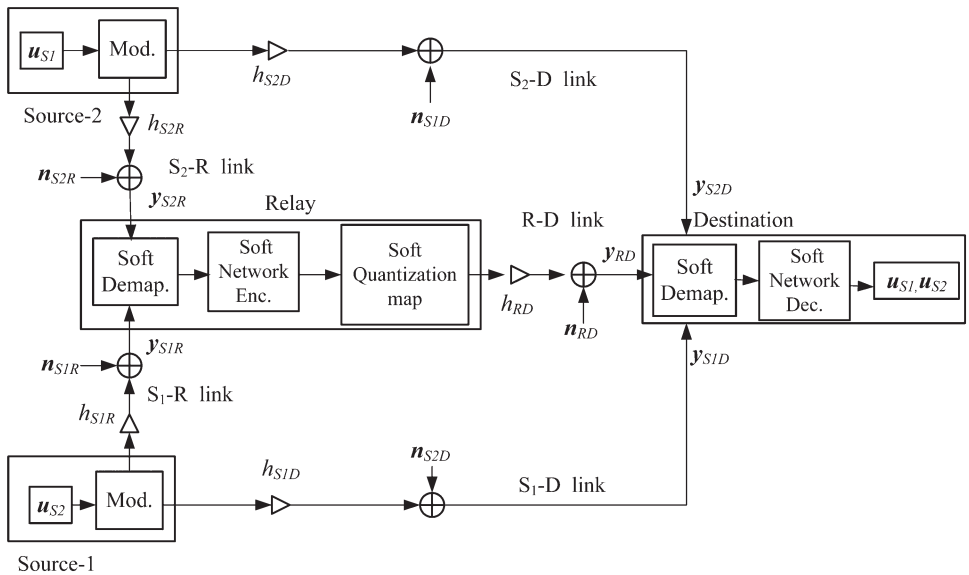

Fig. 2. Proposed half-duplex relaying system, featuring soft-domain network coding and quantize-and-forward multilevel relaying.

where $n_{iR,j}$ and $n_{iD,j}$ are independent and identically distributed real Gaussian random variables, each having zero mean and the same variance $\sigma^2 = N_0/2$. Moreover, P_i is the transmit power constraint from node i (here, we assume $P_1 = P_2 = 1$).

The source, relay, and destination processing for the proposed soft MLT-SQ scheme is shown in Fig. 2.

As the network coding operation in the hard decision domain, i.e., XOR, between two bits is equivalent to the multiplication of the corresponding BPSK symbols, the network-coded symbol $x_{R,j}$ can be obtained via $x_{R,j} = \hat{x}_{1,j}\hat{x}_{2,j}$, where $\hat{x}_{i,j}$ is the hard decision of $x_{i,j}$ at the relay. The relay may then transmit these network-coded symbols to the destination in order to achieve diversity (BPSK modulation being assumed for retransmission), at a power of P_R. However, at low source–relay SNR, $x_{i,j}$ is often detected incorrectly by the relay, and forwarding hard decisions can result in erroneous symbols being propagated to the destination. Instead of simply checking the polarity of the relay received signal $y_{iR,j}$, in our proposed MLT-SQ scheme, the relay performs a soft decision. More specifically, it extracts the appropriate soft information by computing each LLR $L_{i,j} = \ln((p(x_{i,j}=+1|y_{iR,j})/p(x_{i,j}=-1|y_{iR,j}))) = (2h_{iR}/\sigma^2)y_{iR,j}$ for $i \in \{S_1, S_2\}$. The relay then uses the principle of "soft network coding," which is based on the result that the LLRs of the network-coded bits $x_{R,j}$, defined by

$$L_{R,j} = \ln\left(\frac{p(x_{R,j} = +1|y_{S_1R,j}, y_{S_2R,j})}{p(x_{R,j} = -1|y_{S_1R,j}, y_{S_2R,j})}\right), \tag{2}$$

can be deduced from the LLRs of the users' bits via

$$L_{R,j} = 2\tanh^{-1}\left(\tanh\left(\frac{L_{S_1,j}}{2}\right)\tanh\left(\frac{L_{S_2,j}}{2}\right)\right) \tag{3}$$

assuming that the two users' data bits are statistically independent [21]. The relay computes the LLR value $L_{R,j}$ for each network-coded symbol $x_{R,j}$ after detection at the relay, using (3). This may be considered to be the analog of the XOR operation in the "soft" domain.

As an attempt to achieve diversity, if the LLR value in (3) shows that the confidence regarding the decision is high, i.e., the absolute LLR value is larger than the lowest preset optimal threshold, then a corresponding soft-quantized value $\tilde{x}_{R,j} = f(L_{R,j})$ is forwarded to the destination, where the function $f(\cdot)$ will be elucidated in Section III.

III. Multilevel-Threshold-Based Soft Quantization Scheme

In what follows, we will focus on the relay processing, i.e., MLT-SQ and relay–destination transmission, particularly the soft-message preparation and soft network coding. The LLR $L_{R,j}$ of the jth soft-network-coded bit as given by (3) is quantized according to

$$\tilde{x}_{R,j} = \begin{cases} s_1 \operatorname{sgn}(L_{R,j}) & |L_{R,j}| \geq L_1 \\ s_2 \operatorname{sgn}(L_{R,j}) & L_2 \leq |L_{R,j}| < L_1 \\ s_3 \operatorname{sgn}(L_{R,j}) & L_3 \leq |L_{R,j}| < L_2 \\ \vdots & \vdots \\ s_k \operatorname{sgn}(L_{R,j}) & L_k \leq |L_{R,j}| < L_{k-1} \\ \vdots & \vdots \\ s_n \operatorname{sgn}(L_{R,j}) & L_n \leq |L_{R,j}| < L_{n-1} \\ 0 & L_{R,j} < L_n. \end{cases} \tag{4}$$

Here, we have $2n+1$ symmetrical quantization levels (n positive, n negative, and the zero level), comprising the set $\mathcal{A} = \{-s_1, -s_2, -s_3, \ldots, -s_n, 0, s_n, \ldots, s_3, s_2, s_1\}$. Moreover, we assume $s_k = ((n-(k-1)/n))$ for every k, so that there is a uniform spacing of $1/n$ between adjacent levels. The set of positive threshold values $\{L_k\}$, $k = 1, 2, \ldots, n$ will be chosen to optimize the overall BER, as will be shown later.

The mapping presented in (4) may be viewed as a soft symbol mapping that acts as a substitute for the symbol expectation mapping $\tilde{x}_{R,j} = \tanh(L_{R,j}/2)$ as used in [9]–[16]. The principal advantage of the proposed soft symbol mapping is that there is a finite number of possible transmit levels rather than an infinite number as would be produced by the symbol expectation (tanh function) mapping; this facilitates exact LLR computation at the destination. The signal transmitted by the relay to the destination is given by

$$y_{RD,j} = \sqrt{P_R}\beta h_{RD}\tilde{x}_{R,j} + n_{RD,j} \tag{5}$$

where $n_{RD,j}$ is a Gaussian noise with zero mean and variance $\sigma^2 = N_0/2$; P_R is the relay transmit power (here, we set $P_R = 1$); and the factor β is chosen to satisfy the transmit power constraint at the relay, i.e., $\beta = \sqrt{N/\sum_{j=1}^{N}|\tilde{x}_{R,j}|^2}$. The instantaneous channel state information (CSI) of h_{iD} and h_{RD} are assumed to be available at the relay when the relay performs its optimization of quantization levels.

A. Derivation of Optimal Multilevel Thresholds

Here, we derive the optimal individual thresholds in order to minimize the BER at the destination. We remark that the approach proposed here is different from existing approaches reported in the literature, which use only a single positive threshold (three levels) [23]–[27]. We denote by $\varepsilon_{c,k}$ the event that the magnitude of bit LLR $|L_{R,j}|$ lies above the kth threshold L_k and $\tilde{x}_{R,j}$ has the *correct* sign, i.e., $\text{sgn}(\tilde{x}_{R,j}) = \text{sgn}(x_{R,j})$, where we define $x_{R,j} = x_{1,j}x_{2,j}$. Similarly, we denote by $\varepsilon_{e,k}$ the event that the magnitude of bit LLR $|L_{R,j}|$ lies above the kth threshold and $\tilde{x}_{R,j}$ has the *incorrect* sign, i.e., $\text{sgn}(\tilde{x}_{R,j}) \neq \text{sgn}(x_{R,j})$. Finally, the event ε_s represents the event that $|L_{R,j}|$ is smaller than the smallest threshold L_n, i.e., the relay is silent. These events are illustrated as follows:

$$\begin{array}{lccc}
\varepsilon_{c,1} & : & |L_{R,j}| \geq L_1, & \text{sgn}(\tilde{x}_{R,j}) = \text{sgn}(x_{R,j}) \\
\varepsilon_{e,1} & : & |L_{R,j}| \geq L_1, & \text{sgn}(\tilde{x}_{R,j}) \neq \text{sgn}(x_{R,j}) \\
\varepsilon_{c,2} & : & L_2 \leq |L_{R,j}| < L_1, & \text{sgn}(\tilde{x}_{R,j}) = \text{sgn}(x_{R,j}) \\
\varepsilon_{e,2} & : & L_2 \leq |L_{R,j}| < L_1, & \text{sgn}(\tilde{x}_{R,j}) \neq \text{sgn}(x_{R,j}) \\
\varepsilon_{c,3} & : & L_3 \leq |L_{R,j}| < L_2, & \text{sgn}(\tilde{x}_{R,j}) = \text{sgn}(x_{R,j}) \\
\varepsilon_{c,3} & : & L_3 \leq |L_{R,j}| < L_2, & \text{sgn}(\tilde{x}_{R,j}) \neq \text{sgn}(x_{R,j}) \\
\vdots & & \vdots & \\
\varepsilon_{c,k} & : & L_k \leq |L_{R,j}| < L_{k-1}, & \text{sgn}(\tilde{x}_{R,j}) = \text{sgn}(x_{R,j}) \\
\varepsilon_{e,k} & : & L_k \leq |L_{R,j}| < L_{k-1}, & \text{sgn}(\tilde{x}_{R,j}) \neq \text{sgn}(x_{R,j}) \\
\vdots & & \vdots & \\
\varepsilon_{c,n} & : & L_n \leq |L_{R,j}| < L_{n-1}, & \text{sgn}(\tilde{x}_{R,j}) = \text{sgn}(x_{R,j}) \\
\varepsilon_{e,n} & : & L_n \leq |L_{R,j}| < L_{n-1}, & \text{sgn}(\tilde{x}_{R,j}) \neq \text{sgn}(x_{R,j}) \\
\varepsilon_s & : & |L_{R,j}| < L_n. &
\end{array} \tag{6}$$

Consequently, the average BER at the destination $P_{\text{error},i}$ for source i is expressed as

$$P_{\text{error},i} = \sum_{k=1}^{n}\left[P_{i,k}^{(c)}\Pr(\varepsilon_{c,k}) + P_{i,k}^{(e)}\Pr(\varepsilon_{e,k})\right] + P_i^{(s)}\Pr(\varepsilon_s) \tag{7}$$

where $P_{i,k}^{(c)}$, $P_{i,k}^{(e)}$, and $P_i^{(s)}$, respectively, indicate the BER at the destination: where the relay transmits the kth quantization level and this has the *correct* sign, where the relay transmits the kth quantization level and this has the *incorrect* sign, and where the relay stays silent. The average BER for the two sources at the destination is denoted by $P_{\text{error}} = (1/2) \times (P_{\text{error},1} + P_{\text{error},2})$. Now, we concentrate on determining $\{\Pr(\varepsilon_{c,k})\}$ and $\{\Pr(\varepsilon_{e,k})\}$ for $k = 1, 2, 3, \ldots, n$ and $\Pr(\varepsilon_s)$. We begin by investigating the probability density function (pdf) of $L_{R,j}$ at the relay node. For a given channel realization, the pdf of $L_{R,j}$, conditioned on the underlying BPSK symbol being equal to $+1$, can be approximated to a Gaussian random variable having the following pdf:

$$P_{L_{R,j}}(L) = \frac{1}{\sqrt{2\pi\sigma_L^2}}\exp\left(-\frac{(L-\mu_L)^2}{2\sigma_L^2}\right) \tag{8}$$

where the relationship described in [28] holds, i.e., that the variance is twice the mean ($\sigma_L^2 = 2\mu_L$). It is straightforward to show that these properties hold *exactly* for the individual LLRs $L_{i,j}$, where $i \in \{S_1, S_2\}$; the assumption that the LLR for the XOR of these bits as given by (2) also possesses these properties is a widely used one, and has been used in many previous studies, e.g., in [4] and [24]. Moreover, it is useful to note that the expression in (3) can be regarded as a special case of the LLR combination at the check node of an LDPC code (the special case being that of the check node having degree two) and that the Gaussian approximation (together with the assumption that the variance equals twice the mean) underpins the well-known technique of *density evolution*, a powerful tool known for analyzing the asymptotic performance of an LDPC code ensemble [28].

Next, the probabilities we seek may be expressed in terms of the pdf $P_{L_{R,j}}(L)$ and the multilevel thresholds L_k, i.e.,

$$\Pr(\varepsilon_{c,1}) = \int_{L_1}^{+\infty} P_{L_{R,j}}(L)dL, \tag{9}$$

$$\Pr(\varepsilon_{e,1}) = \int_{-\infty}^{-L_1} P_{L_{R,j}}(L)dL, \tag{10}$$

and for $k = 2, 3, \ldots, n$,

$$\Pr(\varepsilon_{c,k}) = \int_{L_k}^{L_{k-1}} P_{L_{R,j}}(L)dL, \tag{11}$$

$$\Pr(\varepsilon_{e,k}) = \int_{-L_{k-1}}^{-L_k} P_{L_{R,j}}(L)dL, \tag{12}$$

and finally

$$\Pr(\varepsilon_s) = \int_{-L_n}^{L_n} P_{L_{R,j}}(L)dL. \tag{13}$$

Note also that

$$\Pr(\varepsilon_s) = 1 - \sum_{k=1}^{n}\left[\Pr(\varepsilon_{c,k}) + \Pr(\varepsilon_{e,k})\right]. \tag{14}$$

Considering both sources, the overall average BER at the destination is then given by $P_{\text{error}} = (1/2)(P_{\text{error},1} + P_{\text{error},2})$, each term here being given by (7). This yields

$$P_{\text{error}} = \sum_{k=1}^{n} \left[P_k^{(c)} \Pr(\varepsilon_{c,k}) + P_k^{(e)} \Pr(\varepsilon_{e,k}) \right] + P^{(s)} \Pr(\varepsilon_s) \quad (15)$$

where $P_k^{(c)} = \frac{1}{2}(P_{1,k}^{(c)} + P_{2,k}^{(c)})$, $P_k^{(e)} = \frac{1}{2}(P_{1,k}^{(e)} + P_{2,k}^{(e)})$, and $P^{(s)} = \frac{1}{2}(P_1^{(s)} + P_2^{(s)})$.

The optimum thresholds, i.e., those which jointly minimize this BER, are provided in the following theorem.

Theorem 1: The set of optimal thresholds $\{L_k^*\}$, which minimize the overall BER at the destination, can be expressed as

$$L_k^* = \ln \left[\frac{P_k^{(e)} - P_{k+1}^{(e)}}{P_{k+1}^{(c)} - P_k^{(c)}} \right], \qquad \text{for } k = 1, 2, 3, \ldots, n-1$$

$$L_n^* = \ln \left[\frac{P_n^{(e)} - P^{(s)}}{P^{(s)} - P_n^{(c)}} \right].$$

Proof: The proof of this theorem is given in the Appendix. ■

Note that, in the special case of a single positive threshold, this theorem reduces to

$$L_1^* = \ln \left[\frac{P_1^{(e)} - P^{(s)}}{P^{(s)} - P_1^{(c)}} \right]. \quad (16)$$

The probabilities $P_k^{(c)}$, $P_k^{(e)}$, and $P^{(s)}$, which appear in Theorem 1, are calculated in Section III-C.

B. Destination LLR Formation

In most SIR schemes reported in the literature, LLR computation at the destination can be very difficult to perform exactly, and heuristic modeling of the overall channel experienced by the constellation symbol is required in order to provide a means of estimating the LLR [9], [16]. However, in the present system, we may perform exact LLR computation at the destination by considering all possible relay-transmitted levels, these being finite in number and known to the destination. Using Bayes' theorem, we may write

$$L_{RD,j} = \ln \left(\frac{\sum_{s>0} p(y_{RD,j}|s) p(s)}{\sum_{s>0} p(y_{RD,j}|-s) p(s)} \right) \quad (17)$$

where $p(s) = p(-s)$ denotes the probability of the transmission of quantization level $s \in \mathcal{A}$ by the relay, with these values being estimated at the destination. Moreover, from Gaussianity of the channel noise, we have $p(y_{RD}^j|s) = (1/\sqrt{2\pi\sigma^2}) \times \exp(-((y_{RD}^j - s)^2/2\sigma^2))$ for any $s \in \mathcal{A}$.

The LLR values at the destination corresponding to the source transmissions are $L_{iD,j} = (2h_{iD}/\sigma^2) y_{iD,j}$. The extrinsic LLR for bit $x_{i,j}$, determined from the network coding operation between[3] $x_{\bar{i},j}$ and $\tilde{x}_{R,j}$, is represented by

$$L_{iD,j}^E = 2 \tanh^{-1} \left(\tanh \left(\frac{L_{\bar{i}D,j}}{2} \right) \tanh \left(\frac{L_{RD,j}}{2} \right) \right). \quad (18)$$

[3]The subscript $\bar{i}$ refers to the opposite source when source i is under consideration.

The combined LLR at the destination, which is denoted by $L_{D,j}$, is computed as $\tilde{L}_{iD,j} = L_{iD,j} + L_{iD,j}^E$.

C. Error Probability Analysis

As we can see from (6), the optimal thresholds L_k^* are based on $P_{i,k}^{(c)}$, $P_{i,k}^{(e)}$, and $P_i^{(s)}$, which in turn are based on the channel realizations h_{1D}, h_{2D}, and h_{RD}. Now, we will determine these probabilities when perfect CSI (i.e., knowledge of h_{1D}, h_{2D}, and h_{RD}) is available at the relay. The received LLRs at the destination, i.e., $L_{iD,j}$, $L_{RD,j}$, and $L_{iD,k,j}^E$, given $h_{i,D}$ and h_{RD}, are approximately Gaussian distributed with their variances being twice the absolute value of their means [25], [28]. The mean of $L_{iD,j}$ can be approximated as $m_{L_{iD}} = \mathbb{E}(L_{iD,j}) \triangleq (2h_{iD}^2 x_{i,j}/\sigma^2)$, and the mean value of $L_{RD,j}$ conditioned on the transmission of level s_k by the relay can be approximated as $m_{L_{RD,k}} = \mathbb{E}(L_{RD,j}|s_k) \triangleq (2h_{RD}^2 s_k^2 \text{sgn}(x_{R,j})/\sigma_{RD}^2)$.

Next, we define the following function $\phi(z)$, first introduced in [28], which will be useful in our analysis:

$$\phi(z) = \begin{cases} 1 - \frac{1}{\sqrt{4\pi z}} \int_{-\infty}^{\infty} \tanh\left(\frac{u}{2}\right) \exp\left(-\frac{(u-z)^2}{4z}\right) du, & z > 0 \\ 1, & z = 0. \end{cases} \quad (19)$$

It is easy to check that $\phi(z)$ is a continuous and monotonically decreasing function on $z \in (0, \infty]$, with $\phi(0) = 1$ and $\phi(\infty) = 0$. Then, it can be shown (see [28] for details) that the mean value of the extrinsic LLR $L_{iD,k,j}^E$, which is denoted by $m_{L_{iD,k}^E}$, may be expressed as

$$m_{L_{iD,k}^E} = x_{i,j} \text{sgn}(\tilde{x}_{R,j}) \phi^{-1} \Big(\phi\left(\left| m_{L_{\bar{i}D,j}^E} \right| \right) + \phi\left(\left| m_{L_{RD,k}^E} \right| \right) - \phi(|m_{L_{iD}}|) \phi\left(|m_{L_{RD,k}}| \right) \Big).$$

It was also shown in [28] that, for $z > 0$, the function $\phi(\cdot)$ is bounded by $\sqrt{(\pi/z)} \exp(-(z/4))(1 - (3/z)) < \phi(z) < \sqrt{(\pi/z)} \exp(-(z/4))(1 + (1/7z))$ and that when z is sufficiently large, the upper and lower bounds converge to $\sqrt{(\pi/z)} \exp(-(z/4))$. Therefore, when z_1 and z_2 are both sufficiently large, we have

$$\phi(z_1) + \phi(z_2) - \phi(z_1)\phi(z_2) \approx \max(\phi(z_1), \phi(z_2)). \quad (20)$$

In a similar manner, we can approximate the mean $m_{L_{iD,k}^E}$ in the high SNR regime as

$$m_{L_{iD,k}^E} \approx x_{i,j} \text{sgn}(\tilde{x}_{R,j}) \phi^{-1} \left(\max\left(\phi(m_{L_{iD,j}}), \phi(m_{L_{RD,k,j}}) \right) \right) \quad (21)$$

and this can be approximated to

$$m_{L_{iD,k}^E} = \frac{x_{i,j} \text{sgn}(\tilde{x}_{R,j})}{\sigma^2} \min\left(h_{iD}^2, h_{RD}^2 s_k^2 \right). \quad (22)$$

The combined LLR $L_{D,j}$ can be considered approximately Gaussian distributed with mean $m_{L_{D,k}} = m_{L_{iD}} + m_{L_{iD,k}^E}$ and variance $\sigma_{L_{D,k}}^2 = 2(|m_{L_{iD,k}}| + |m_{L_{iD,k}^E}|)$. The instantaneous error probabilities can be obtained by utilizing the $Q(\cdot)$ function, i.e., $Q(z) = 1/\sqrt{2\pi} \int_z^{\infty} \exp\left(-\frac{u^2}{2}\right) du$. In the case of $\varepsilon_{c,k}$, we have $\tilde{x}_{R,j} = \tilde{x}_{\bar{i}j} \tilde{x}_{ij}$. In this case, $m_{L_{iD}}$ and $m_{L_{iD,k}^E}$ have the same signs; thus, $|m_{L_{iD}} + m_{L^E_{iD,k}}| = |m_{L_{iD}}| + |m_{L^E_{iD,k}}|$. Therefore, we obtain the error probability of x_i as

$$P^{(c)}_{i,k} = Q\left(\sqrt{\frac{|m_{L_{iD}}| + \left|m_{L^E_{iD,k}}\right|}{2}}\right). \tag{23}$$

In the event of incorrect information forwarding from the relay, i.e., when $\varepsilon_{e,k}$ occurs, we have $\text{sgn}(\tilde{x}_{R,j}) = -x_{R,j}$. In this case, $m_{L_{iD}}$ and $m_{L^E_{iD,k}}$ have opposite signs; thus, we have $|m_{L_{iD}} + m_{L^E_{iD,k}}| = ||m_{L_{iD}}| - |m_{L^E_{iD,k}}||$. The value of $P^{(e)}_{i,k}$ is then

$$\begin{cases} Q\left(\sqrt{\dfrac{\left(|m_{L_{iD}}| - \left|m_{L^E_{iD,k}}\right|\right)^2}{2\left(|m_{L_{iD}}| + \left|m_{L^E_{iD,k}}\right|\right)}}\right), & |m_{L_{iD}}| > \left|m_{L^E_{iD,k}}\right| \\ 1 - Q\left(\sqrt{\dfrac{\left(|m_{L_{iD}}| - \left|m_{L^E_{iD,k}}\right|\right)^2}{2\left(|m_{L_{iD}}| + \left|m_{L^E_{iD,k}}\right|\right)}}\right), & |m_{L_{iD}}| \le \left|m_{L^E_{iD,k}}\right|. \end{cases} \tag{24}$$

When the relay is silent, i.e., when ϵ_s occurs, we have $P^{(s)}_i = Q(\sqrt{|m_{L_{x_iD}}|/2})$. The relevant mean values of the LLRs are estimated on a frame-by-frame basis. If needed, these means can be updated adaptively according to the rate of fade of the channel. Using (23), (24), and $P_{i,s}$, we can compute the optimum values of the n positive thresholds $\{L^*_k\}$ according to Theorem 1.

D. Use With Higher Order Modulation

Here, we explain how the proposed scheme may be adapted in a useful way for the situation where the sources transmit using M-ary pulse amplitude modulation (PAM). First, the relay uses a standard soft demapper that extracts the $\log_2 M$ LLRs of the bits underlying the transmitted PAM symbol. Define the *most significant bit* (MSB) to be the bit position (in the constellation label) which changes *most frequently* when moving from one PAM symbol to an adjacent one (this may be interpreted as the bit which is most vulnerable to noise). Then, the relay computes the LLR for the network-coded combination of the MSBs of the two users and transmits this to the destination using the $2n + 1$-level MLT-SQ relaying scheme. The destination processing will then be as described earlier for the MSBs of the users, whereas the other (non-MSB) bit LLRs are determined from the source transmission *only* using a standard soft demapper. This allows for high-data-rate transmission while leveraging the gains due to the proposed soft-quantize-and-forward network-coded relay cooperation. For this scenario, the investigation of the optimum power level at which to transmit the network-coded symbol for various PAM constellation sizes, mappings, and link SNRs forms an interesting problem for study, but lies outside the scope of the this paper.

IV. Simulation Results and Discussion

Here, simulation results are provided to demonstrate the effectiveness of the proposed MLT-SQ system. We first present simulation results for the uncoded scenario and then for an LDPC coded system. In the uncoded scenario, we use BPSK signaling with a frame length of $N = 10\,000$. All channels are assumed to exhibit quasi-static fading, i.e., the channel coefficients h_{S_1D}, h_{S_2D}, h_{RD}, h_{S_1R}, and h_{S_2R} are constant for each transmission phase and change independently from one phase to the next. First, we consider a symmetric relay setup where the two sources S_1 and S_2 have the same distance to the destination, and where the two sources, the relay, and the destination are aligned in the same horizontal line. The distances between the sources and the destination are normalized to unity, i.e., $d_{S_1D} = d_{S_2D} = 1$. The attenuation exponent was chosen to be $\gamma = 2$.

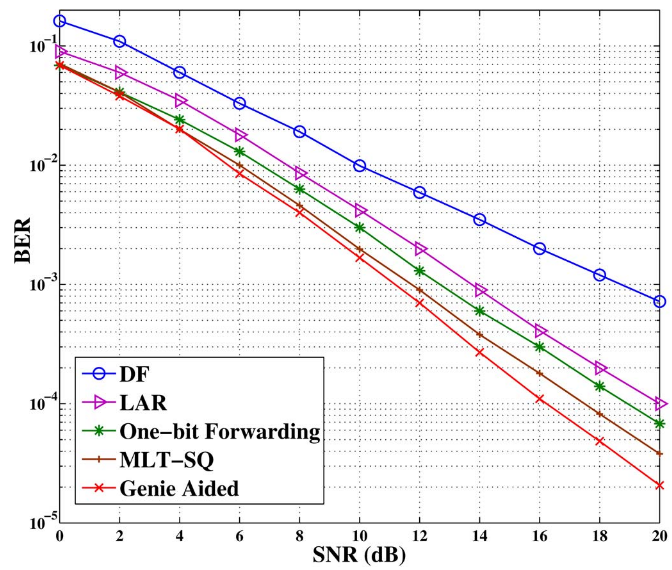

Fig. 3. Comparison of the BER performance of the proposed network-coded MLT-SQ system with other competing schemes using MARS for Case 1. The simulations took place over quasi-static fading channel links.

In this paper, we consider three cases, corresponding to three different locations of the relay. In Case 1, we have considered a strong source–relay link scenario, where $d_{S_1R} = d_{S_2R} = 0.3$; $d_{RD} = 0.7$. In Case 2, we have placed the relay in the center of the source–destination line, i.e., $d_{S_1R} = d_{S_2R} = 0.5$; $d_{RD} = 0.5$. Case 3 considers a weak source–relay link scenario, i.e., $d_{S_1R} = d_{S_2R} = 0.7$; $d_{RD} = 0.3$. For the MLT-SQ system, we have implemented seven soft quantization levels at the relay (i.e., $n = 3$) – $\{0, \pm L^*_1, \pm L^*_2, \pm L^*_3\}$.

We evaluate the BER performance of the proposed system in the absence of channel coding (simulation results for the proposed MLT-SQ scheme in conjunction with LDPC coding will be presented in Fig. 7). Figs. 3–5 compare the BER for the proposed uncoded MLT-SQ scheme with a number of benchmark schemes for Cases 1–3, respectively; these benchmark schemes will be explained in the following.

The first benchmark scheme is that of conventional network-coded DF; here, the relay makes hard decisions on the source bits and transmits the corresponding network-coded symbol.

As another competing scheme, we have simulated the LAR protocol as proposed in [26]; this is a power scaling scheme where the relay-located power scaling factor is given by $w = \min((\min(\gamma_{S_1R}, \gamma_{S_2R}))/\gamma_{RD}), 1))$, where γ_{iR} and γ_{RD} are the channel SNR of the $i - R$ and $R - D$ links, respectively ($i \in \{S_1, S_2\}$). We have adopted it according to the proposed MARS with physical-layer network coding

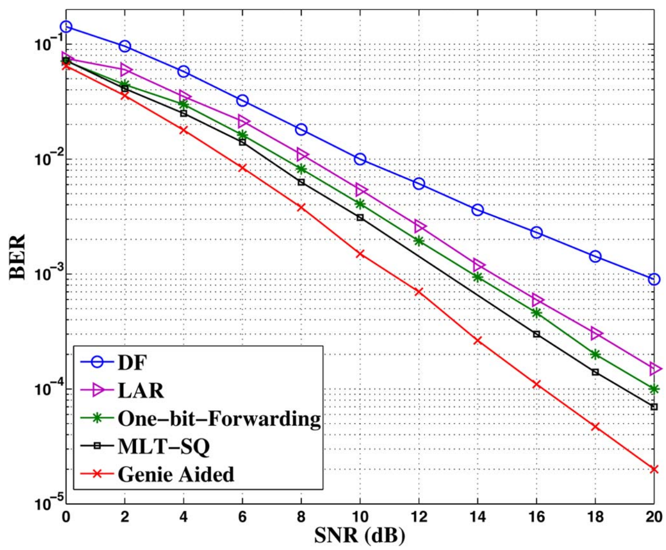

Fig. 4. Comparison of the BER performance of the proposed network-coded MLT-SQ system with other competing schemes using MARS for Case 2. The simulations took place over quasi-static fading channel links.

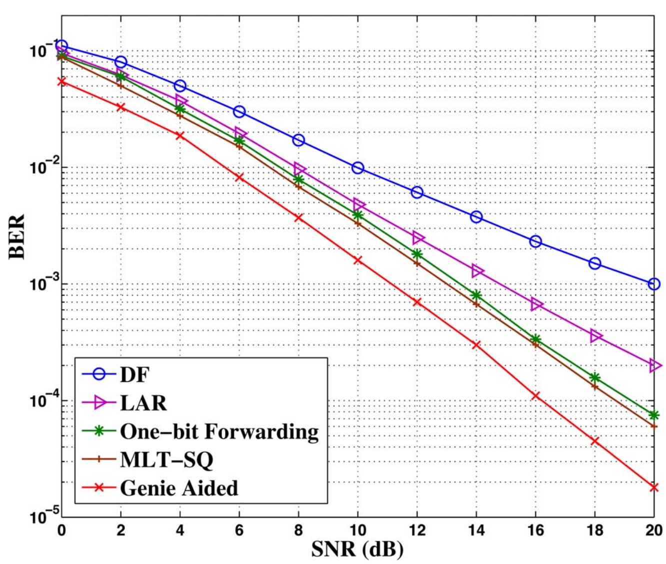

Fig. 5. Comparison of the BER performance of the proposed network-coded MLT-SQ system with other competing schemes using MARS for Case 3. The simulations took place over quasi-static fading channel links.

as $w = \min((\min(h^2_{S_1R}, h^2_{S_2R})/h^2_{RD}), 1)$. This scheme adapts the power for each transmitted block according to the channel information. Moreover, note that the LAR protocol has lower computational complexity than our proposed scheme MLT-SQ. It requires only one multiplication operation for each network-coded symbol at the relay.

Another benchmark known as the "genie-aided" protocol, which forms a lower bound on performance of the all of these schemes, assumes that for any given frame, the relay transmission is error free. In addition, we have also simulated MLT-SQ with three levels (which we call "one-bit forwarding"). Note that in this case, the relay either transmits the symbol $\mathrm{sgn}(L_{x_{R,j}})$ (i.e., $+1$ or -1) or stays silent, according to the level of the LLR $L_{x_{R,j}}$. It may be seen that one-bit forwarding always has improved BER performance over uncoded DF and LAR.

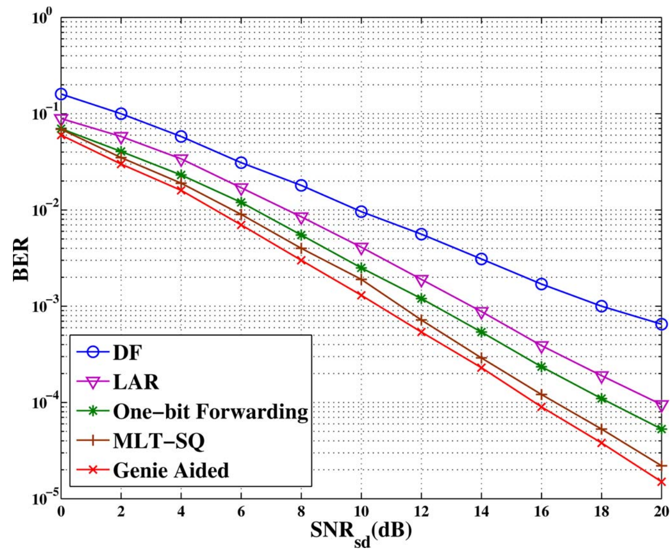

Fig. 6. Comparison of the BER performance of the proposed soft-network-coded MLT-SQ system with other competing schemes using asymmetric MARS. The simulations took place over quasi-static fading channel links.

We can observe from Fig. 3 that the proposed MLT-SQ scheme outperforms the other benchmark schemes, providing an error rate performance closer to that of the "genie-aided" bound. Moreover, the one-bit forwarding scheme and the MLT-SQ scheme have universally better BER performances over LAR and DF in this study. The reason is that our one-bit forwarding and MLT-SQ schemes are optimized to minimize the system BER, whereas LAR is not designed for optimality in this sense. We also note that as the number of quantization levels increases, the error rate performance improves. Finally, note that all schemes, except for the DF protocol, can achieve the full diversity order, i.e., 2.

We next consider an uncoded asymmetric scenario (Case 4), where one source is closer to the relay and destination than the other. Here, $d_{S_1R} = 0.45$, $d_{S_2R} = 0.15$, $d_{RD} = 0.7$, $d_{S_1D} = 1.15$, and $d_{S_2D} = 0.85$. Comparative performance results with the previous benchmark schemes are shown in Fig. 6. From this figure, as we can see, our proposed MLT-SQ scheme outperforms DF, LAR, and one-bit forwarding. Moreover, here the proposed MLT-SQ system achieves a BER gain of 2 dB over the one-bit forwarding scheme at a BER of 10^{-4}.

It may be seen in Figs. 3–5 that in the uncoded scenario, the gain due to the proposed scheme diminishes as the relay moves closer to the destination and away from the sources. However, this gain can be reinstated by using channel coding. First, note that although the derivation of the optimal thresholds for the proposed MLT-SQ scheme was given for the uncoded scenario, the scheme itself can easily be employed in the presence of LDPC channel coding—here, the LLRs for the network-coded symbols are computed from the *a posteriori* LLRs resulting from LDPC decoding at the relay. In the following, we investigate the BER performance of the MLT-SQ system when LDPC coding is employed at both sources. The LDPC code used at both sources is a regular Gallager code[4] having a block length of 816 and a code rate of 1/2.

[4]This code is code 816.3.134 of the listing at http://www.inference.phy.cam.ac.uk/mackay/codes/data.html.

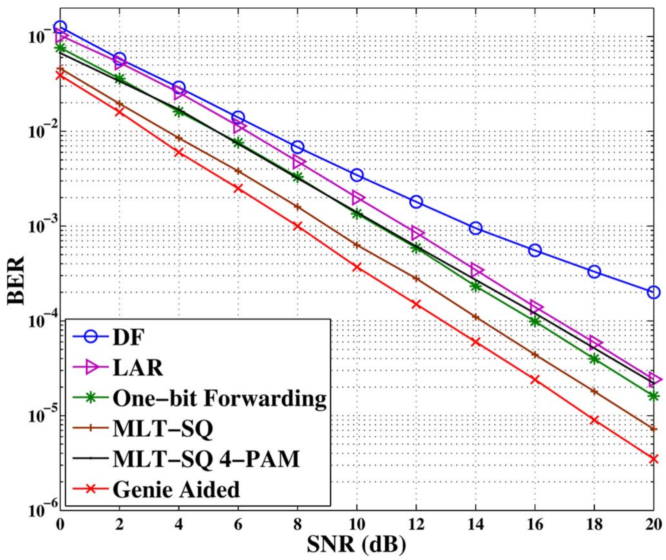

Fig. 7. Comparison of the BER performance of the proposed LDPC network-coded MLT-SQ system with other competing schemes using MARS for Case 3. The simulations took place over quasi-static fading channel links.

Fig. 7 presents the simulation results for the proposed MLT-SQ system with LDPC coding; the topology of the system nodes is that given by Case 3, and we have assumed LDPC coded cooperation for all the benchmarks present in Fig. 7. From the figure, we can observe that again the DF scheme only achieves a diversity order of one while all other schemes achieve the full diversity order of two. Moreover, here the proposed MLT-SQ system achieves a BER gain of 2 dB over the one-bit forwarding scheme at a BER of 10^{-4} and also outperforms the DF and LAR schemes.

Finally, we provide a simulation result demonstrating the performance of the proposed MLT-SQ scheme where higher order modulation is employed at the sources, as explained in Section III-D. Here, the sources both use 4-PAM modulation according to the following bit pair to symbol mapping $(a, b) \rightarrow x$:

$$\begin{array}{lcl} (0,0) \rightarrow +3/\sqrt{5} & ; & (0,1) \rightarrow +1/\sqrt{5} \\ (1,1) \rightarrow -1/\sqrt{5} & ; & (1,0) \rightarrow -3/\sqrt{5} \end{array} \tag{25}$$

so that bit a determines the sign of the 4-PAM symbol x, and bit b determines its magnitude. Then, bit b is the mapping's MSB as defined in Section III-D; the relay computes the LLR for the network-coded XOR of the "b" bits of both users and forwards this to the destination using multilevel soft network coding (the destination's processing of information relating to these "b" bits is the same as in the BPSK case of MLT-SQ). On the other hand, standard soft demapping is used at the destination to form LLRs for the "a" bits for the two sources, as the relay transmission carries no information about these bits. It may be seen from the simulation results that there is a gap of approximately 2 dB between the performance curves of the BPSK case and the 4-PAM case at a BER of 10^{-4}; however, in the 4-PAM case, the system operates at double the spectral efficiency.

V. Conclusion

A novel optimized soft-quantize-and-forward scheme has been presented, based on cooperative network coding in a MARS. Instead of forwarding hard decisions, our proposed scheme forwards soft-quantized values based on the magnitude of the network-coded LLRs. The quantization levels of the thresholding scheme were optimized to minimize the overall BER at the destination. Although the derivation of the proposed scheme considers only the uncoded scenario, simulation results for the case of an LDPC coded system show that the scheme provides significant improvement of error rate performance when compared with other relevant competing schemes.

Appendix
Proof of Theorem 1

Substituting (14) into (15), we may express the overall average BER as

$$\sum_{j=1}^{n}\left[\left(P_j^{(c)}-P^{(s)}\right)\Pr(\varepsilon_{c,j})+\left(P_j^{(e)}-P^{(s)}\right)\Pr(\varepsilon_{e,j})\right]+P^{(s)}. \tag{26}$$

To find the optimum set of levels $\{L_k\}$, we take the partial derivative of the overall average BER given by (26) with respect to each L_k ($k \in \{1, 2, \ldots, n\}$) and set the result in each case equal to zero. This yields

$$\sum_{j=1}^{n}\left(P_j^{(c)}-P^{(s)}\right)\frac{\partial \Pr(\varepsilon_{c,j})}{\partial L_k}=\left(P^{(s)}-P_j^{(e)}\right)\frac{\partial \Pr(\varepsilon_{e,j})}{\partial L_k}. \tag{27}$$

Next we note that, for $k \in \{2, 3, \ldots, n\}$

$$\begin{aligned}\frac{\partial \Pr(\varepsilon_{c,k})}{\partial L_k} &= \frac{\partial}{\partial L_k}\int_{L_k}^{L_{k-1}} P_{L_{R,j}}(L)dL \\ &= -\frac{\partial}{\partial L_k}\int_{L_{k-1}}^{L_k} P_{L_{R,j}}(L)dL \\ &= -P_{L_{R,j}}(L_k)\end{aligned}$$

where in the first line, we have used (11), and in the final line, we have used the fundamental theorem of calculus.[5] This result holds also for $k = 1$; the proof can be handled similarly [using (9) in place of (11)]. Similarly, it can be shown that

$$\frac{\partial \Pr(\varepsilon_{e,k})}{\partial L_k} = -P_{L_{R,j}}(-L_k), \qquad \text{for } k=1,2,\ldots,n, \tag{28}$$

$$\frac{\partial \Pr(\varepsilon_{c,k+1})}{\partial L_k} = P_{L_{R,j}}(L_k), \qquad \text{for } k=1,2,\ldots,n-1, \tag{29}$$

$$\frac{\partial \Pr(\varepsilon_{e,k+1})}{\partial L_k} = P_{L_{R,j}}(-L_k), \qquad \text{for } k=1,2,\ldots,n-1. \tag{30}$$

[5]The fundamental theorem of calculus states that for a continuous real-valued function f and a real constant a, $(\partial/\partial x)\int_a^x f(t)\mathrm{d}t = f(x)$. Note that $P_{L_{R,j}}(L)$ [as given by (8)] is continuous for all $L \in \mathbb{R}$.

Since the levels $\{L_k\}$ are considered independent variables, all partial derivatives $(\partial \Pr(\varepsilon_{c,j})/\partial L_k)$ and $(\partial \Pr(\varepsilon_{e,j})/\partial L_k)$ are zero for $j \notin \{k, k+1\}$. Therefore, (27) simplifies to the following [retaining only the terms $j = k$ and $j = k+1$ in the sum and using (28)–(30)]:

$$\left(P_{k+1}^{(c)} - P_k^{(c)}\right) P_{L_{R,j}}(L_k) = \left(P_k^{(e)} - P_{k+1}^{(e)}\right) P_{L_{R,j}}(-L_k). \tag{31}$$

Substituting for $P_{L_{R,j}}(L)$ from (8) yields

$$\ln\left[\frac{P_k^{(e)} - P_{k+1}^{(e)}}{P_{k+1}^{(c)} - P_k^{(c)}}\right] = \frac{1}{2\sigma_L^2}\left([-L_k - \mu_L]^2 - [L_k - \mu_L]^2\right)$$
$$= \frac{4L_k\mu_L}{2\sigma_L^2} = L_k$$

where in the final line we have used the assumption that $\sigma_L^2 = 2\mu_L$. This proves that the optimal thresholds L_k^* are as stated in Theorem 1 for $k = 1, 2, \ldots, n-1$. The optimal threshold L_n^* may be derived in an analogous manner (here, only the term $j = n$ is retained in (27); otherwise, the proof proceeds similarly to the above). This completes the proof.

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