A Stacked Autoencoder-based Decode-and-Forward Relay Networks with I/Q Imbalance

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Abstract

We propose a stacked autoencoder (AE) that stacks a novel bit-wise denoising AE and a bit-wise AE for decode and forward (DF) relay network impacted by the I/Q imbalance (IQI) at all the nodes. Within the stacked AE framework, we propose block-coded modulation (BCM) and differential-BCM (d-BCM) designs depending on the availability of the channel state information (CSI) knowledge. Moreover, IQI estimation increases feedback overhead, thus, we design the stacked AE without utilizing the IQI parameters information that can generalize well on varying levels of IQI and signal-to-noise ratio, completely removing the IQI estimation overhead. By extensive evaluation, we show that the proposed stacked AE framework can remove the deteriorating impact of IQI performing similar to ideal relay networks without IQI.

Keywords

Autoencoder, block coded modulation, decode-and-forward, deep learning, I/Q imbalance, relay networks.

1. Introduction

With the advent of internet-of-everything (IoE) in the sixth-generation (6G) networks, relay networks will play a pivotal role by enhancing network reliability, data coverage, and spectral efficiency. The decode-and-forward (DF) [1] relaying outperforms amplify-and-forward (AF) [2] relaying, but suffers from error propagation due to imperfect signal decoding and re-encoding.

Further, future applications of the IoE mandate low-latency requirements. Thus, designing block coded modulation (BCM) for short block lengths (n) has gained considerable industry traction, but remains a difficult problem because (1) it becomes extremely difficult to fit 2^k (for any k input bits) for short block lengths, and (2) bit-labeling requires solving a $2^k!$ combinatorial problem, that becomes NP-hard for larger values of k. Further, estimating channel state information (CSI) knowledge increases the feedback overhead, that will increase exponentially in the future IoE-based 6G networks. Thus, we propose to design both the BCM and differential BCM (d-BCM) with and without the CSI knowledge for the DF relay networks, respectively.

Autoencoder (AE) has appeared as a promising solution for performing BCM and d-BCM designs [3]–[4]. We can broadly classify the AE as symbol-wise AE and bit-wise AE based on the maximized symbol-wise mutual information (MI) and bit-wise MI, respectively. While

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Table 1
Comparison of proposed work versus state-of-the-art AE-based DF relay works [7]–[10].

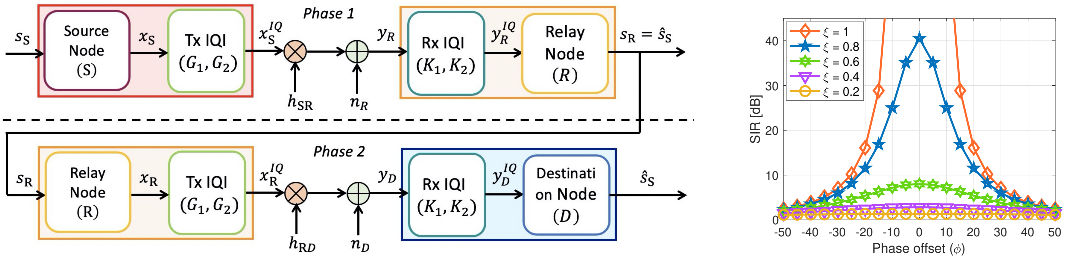
Ref No.	Bit-wise AE	Denoising Bit-wise AE	BCM design	d-BCM design	I/Q Imbalance	Rate R_T [bits/channel-reuse]
[7]	✗	✗	✗	✓	✗	4/14
[8]	✗	✗	✗	✗	✗	N/A
[9]	✗	✗	✗	✓	✗	4/14
[10]	✓	✗	✗	✗	✗	N/A
Ours	✓	✓	✓	✓	✓	8/14

symbol-wise AE needs to perform bit-labeling separately by solving a $2^k!$ combinatorial problem, bit-wise AE performs automatic bit-labeling possibly in a Gray-coded format [5], [6].

A handful works have analyzed AE for DF relaying networks in [7, 8, 9, 10]. While [7, 8, 9] consider a symbol-wise AE, [10] consider bit-wise AE for cooperative non-orthogonal multiple access. All works [7]–[10] consider a separate AE for each phase, where the hard decision decoding (HDD) is performed on the soft probabilistic output of the first phase's AE before passing it as input to the second phase's AE. Directly, the chances of incorrectly decoding the soft outputs lying close to the hard decision threshold increases, thus biggest disadvantage of conventional DF relay networks, i.e., the problem of error propagation, still remains unsolved in AE works. Further, [7] proposed a better two-step training policy compared to an iterative two-step training policy in [9]. Only [7, 9] considered a symbol-wise AE-based d-BCM design.

In practice, the DF relay networks are compromised by the hardware impairments, e.g., in-phase (I) and quadrature-phase (Q) imbalance (IQI), deteriorating the network performance [11, 12, 13]. All prior works [7]–[10] consider an ideal case of I/Q matching, where the signal-to-interference-ratio (SIR) becomes *infinity*, while [11] show that even small IQI can deteriorate the SIR. Any IQI compensation algorithm [11], [12] requires the IQI parameters estimation [13], increasing the feedback overhead. However, none of prior signal processing [11]–[13] nor AE [3]–[10] works have performed BCM/d-BCM without estimating IQI parameters. We summarize our comparison in Table 1. The major contributions of this work are as follows:

- We propose stacked AE-based BCM and d-BCM designs for the DF relay network with IQI at all the nodes. We propose a bit-wise AE for the first phase and a novel denoising bit-wise AE for the second phase, where we directly utilize the soft probabilistic outputs as the input of denoising AE. Further, we propose a two-step training, where we propose new training for denoising AE using the input of the first phase's AE. Thus, even though the AE in first-phase produces erroneous soft-outputs, the denoising AE can denoise these outputs, while encoding-decoding the signal. Thereby, denoising AE helps in correctly decoding the bits close to hard decision threshold, reducing the error propagation.
- We propose BCM and d-BCM that remove the necessity of IQI estimation, reducing the feedback overhead. We focus on generalizability, the trained stacked AE can generalize well on any testing IQI and signal-to-noise-ratio (SNR). Under a low SIR regime, we show that stacked AE completely removes the IQI, performing similarly to ideal relay networks.



(a) System model. (b) Impact of IQI on the SIR.

Figure 1: DF relay networks with IQI at each node and impact of IQI on each hop in DF relay networks.

2. System Model

Now, we detail the DF relay network with IQI at all the nodes, as shown in Fig. 1a. Each node has a single antenna and the direct link is absent because of large scale shadowing and path-loss. The effective transmission rate $R_T = k/2n$ [bits/channel reuse], where k bits are transmitted in 2 phases using n transmissions. For explanation, we keep $n = 1$.

2.1. Modelling the I/Q Imbalance (IQI)

We can model the IQI effects at the complex local oscillator (LO) signals, operating with angular frequency ω_L, at transmitter (Tx) and receiver (Rx) sides as [11]:

$$z_T(t) = G_1 e^{j\omega_L t} + G_2 e^{-j\omega_L t}, \qquad z_R(t) = K_1 e^{-j\omega_L t} + K_2 e^{j\omega_L t} \tag{1}$$

Let $\{\xi_T, \phi_T\}$ and $\{\xi_R, \phi_R\}$ represent the effective amplitude and phase imbalances of the Tx and Rx sides, respectively. Using (1) we can obtain the IQI parameters at Tx and Rx sides as $G_1 = (1+\xi_T e^{j\phi_T})/2, G_2 = (1-\xi_T e^{-j\phi_T})/2, K_1 = (1+\xi_R e^{-j\phi_R})/2, K_2 = (1-\xi_R e^{j\phi_R})/2$. In the ideal without IQI scenario, the IQI parameters at Tx and Rx sides becomes $\xi_T = \xi_R = 1$ (or $G_1 = K_1 = 1$) and $\phi_T = \phi_R = 0°$ (or $G_2 = K_2 = 0$), respectively.

2.2. Signal Transmission–Reception

We detail the steps for signal transmission–reception between the Tx node $\Gamma = \{S, R\}$ and Rx node $\Upsilon = \{R, D\}$, where $\Gamma \neq \Upsilon$, in two phases of DF relay network, as below:

Firstly, the Tx node Γ maps intended bits $\mathbf{s}_\Gamma \in \{0,1\}^k$ to a complex symbol $x_\Gamma \in \mathbb{C}$, such that $\mathbb{E}\{|x_\Gamma|^2\} = 1$. The up-converted signal in presence of Tx IQI becomes x_Γ^{IQ}, as

$$x_\Gamma^{IQ} = G_1 x_\Gamma + G_2^\star x_\Gamma^\star \tag{2}$$

where $(\cdot)^\star$ denotes conjugate operation. *Secondly*, Tx node Γ transmits signal to Rx node Υ, as $y_\Upsilon = \sqrt{P_\Gamma} h_{\Gamma\Upsilon} x_\Gamma^{IQ} + n_\Upsilon$, where P_Γ is Γ's transmit power, $h_{\Gamma\Upsilon} \sim \mathcal{CN}(0,1)$ is fading channel between Γ, Υ, and $n_\Upsilon \sim \mathcal{CN}(0, \sigma_\Upsilon^2)$ is AWGN at Υ. *Thirdly*, the received signal at Υ with the Rx side IQI, becomes

$$y_\Upsilon^{IQ} = K_1 y_\Upsilon + K_2 y_\Upsilon^\star \tag{3}$$

$$y_{\Upsilon}^{IQ} = \underbrace{\sqrt{P_\Gamma}\left(K_1 G_1 h_{\Gamma\Upsilon} + K_2 G_2 h_{\Gamma\Upsilon}^{\star}\right) x_\Gamma}_{\text{Desired signal, } \Lambda(\Gamma,\Upsilon)x_\Gamma} + \underbrace{\sqrt{P_\Gamma}\left(K_1 G_2^{\star} h_{\Gamma\Upsilon} + K_2 G_1^{\star} h_{\Gamma\Upsilon}^{\star}\right) x_\Gamma^{\star}}_{\text{Self-interference signal, } \Omega(\Gamma,\Upsilon)x_\Gamma^{\star}} + \underbrace{K_1 n_\Upsilon + K_2 n_\Upsilon^{\star}}_{\text{Noise, } \tilde{n}_\Upsilon(\Gamma,\Upsilon)}$$

Thus, IQI leads to signal distortion, $\Lambda(\Gamma,\Upsilon)x_\Gamma$, and causes self-interference, $\Omega(\Gamma,\Upsilon)x_\Gamma^{\star}$. *Fourthly*, we apply traditional zero-forcing (ZF)-based IQI compensation at the Rx node as follows

$$\begin{aligned}\begin{bmatrix} y_\Upsilon^{IQ} \\ y_\Upsilon^{IQ\star} \end{bmatrix} &= \begin{bmatrix} \Lambda(\Gamma,\Upsilon) & \Omega(\Gamma,\Upsilon) \\ \Omega(\Gamma,\Upsilon)^{\star} & \Lambda(\Gamma,\Upsilon)^{\star} \end{bmatrix} \begin{bmatrix} x_\Gamma \\ x_\Gamma^{\star} \end{bmatrix} + \begin{bmatrix} K_1 & K_2 \\ K_2^{\star} & K_1^{\star} \end{bmatrix} \begin{bmatrix} n_\Upsilon \\ n_\Upsilon^{\star} \end{bmatrix} \\ \mathbf{y}_\Upsilon^{IQ} &= \mathbf{A}(\Gamma,\Upsilon)\mathbf{x}_\Gamma + \mathbf{B}(\Gamma,\Upsilon)\mathbf{n}_\Upsilon \end{aligned} \tag{4}$$

We perform ZF-based IQI compensation to get $\hat{y}_\Upsilon^{IQ}$, as $[\hat{y}_\Upsilon^{IQ}, \hat{y}_\Upsilon^{IQ\star}] = (\mathbf{A}(\Gamma,\Upsilon))^{-1} \times \mathbf{y}_\Upsilon^{IQ}$. Please note in ZF-based IQI compensation, we know IQI parameters, but in its absence, we only have $\hat{y}_\Upsilon^{IQ} = y_\Upsilon^{IQ}$. *Fifthly*, we perform maximum likelihood decoding (MLD) as $\hat{\mathbf{s}}_\Gamma = \arg\min_{x\in\mathcal{C}} ||\hat{y}_\Upsilon^{IQ} - \sqrt{P_\Gamma} h_{\Gamma\Upsilon} x||^2$, where $\mathcal{C}$ denotes all possible symbols and $\hat{\mathbf{s}}_\Gamma$ is decoded bits.

2.3. Impact of IQI on DF Relay Networks

Considering there are no noise terms $n_\Upsilon = 0$, the SIR for each phase can be given as

$$\text{SIR (in dB)} = \frac{\mathbb{E}\{|\Lambda(\Gamma,\Upsilon)x_\Gamma|^2\}}{\mathbb{E}\{|\Omega(\Gamma,\Upsilon)x_\Gamma^{\star}|^2\}} = \frac{|K_1|^2|G_1|^2 + |K_2|^2|G_2|^2}{|K_1|^2|G_2|^2 + |K_2|^2|G_1|^2} \tag{5}$$

In Fig. 1b, we analyze the impact of IQI on SIR. In the ideal without IQI scenario, SIR becomes *infinity*, whereas, even a small phase/amplitude offset (IQI) can deteriorate SIR significantly.

3. Proposed Stacked AE-based DF Relay Networks with IQI

In this section, we propose a stacked AE-based DF relay network with IQI. We consider each phase in the DF relay network as a separate AE-based transmission because the direct link is absent and the relay node operates in DF mode. For the first phase, we consider a bit-wise AE with its NN encoder at the source node S and its NN decoder at the relay node R. Now, for the first time, we introduce the bit-wise denoising AE, defined as below.

Definition 1. *A bit-wise denoising AE is a bit-wise AE with the difference that the input at the NN encoder is the soft probabilistic values lying between* $[0,1]$ *instead of bits* $\{0,1\}$.

In the second phase, we employ the bit-wise denoising AE with its NN encoder at the relay node R and its NN decoder at the destination node D because the NN decoder (of bit-wise AE) at the relay node R produces soft outputs, which can be directly fed as an input to the denoising AE. Thus, we remove the HDD on the soft outputs of the bit-wise AE in the first phase as [7]–[10], which suffers from error propagation because the wrongly decoded bits are fed for re-transmission. Further, the probability of erroneous bit decoding is highest for soft outputs close to HDD threshold due to the ambiguity. Instead, by directly utilizing soft outputs as input to the bit-wise denoising AE, we can remove noise from input and decode soft probabilities close to HDD threshold correctly. Note stacked AE mimics the operations of conventional DF mode that employs decoding and re-encoding, with additional denoising of decoded signal. Thus, processing requirements of stacked AE remains same as conventional DF relay network.

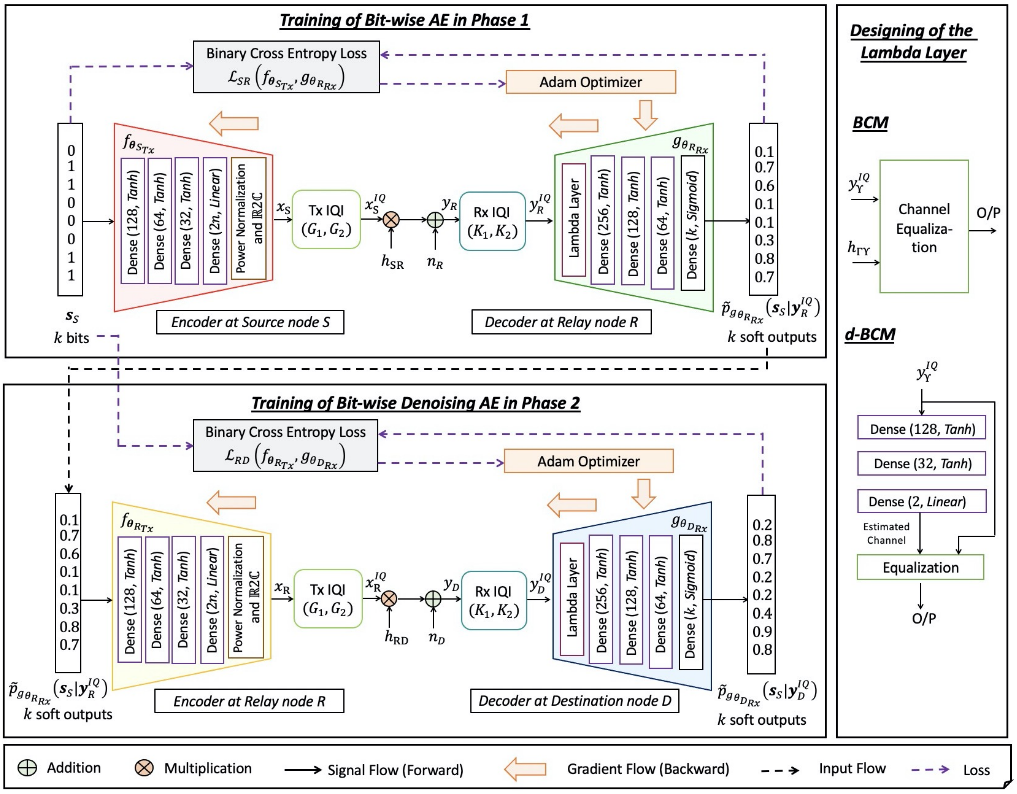


Figure 2: Proposed stacked AE framework for DF relay networks with IQI.

3.1. Designing of the Bit-wise AE for Phase 1

In this work, we utilize dense layers in the NN architectures, where any l^{th} dense layer in a NN can be represented as $\boldsymbol{\omega}_l(\mathbf{x}_l) = \sigma_l\left(\mathbf{W}_l\mathbf{x}_l + \mathbf{b}_l\right)$ where δ_l is number of neurons, $\mathbf{x}_l \in \mathbb{R}^{\delta_l}$ is input, $\mathbf{W}_l \in \mathbb{R}^{\delta_l \times \delta_{l+1}}$ is weight matrix between the l^{th} and $(l+1)^{\text{th}}$ dense layers, $\mathbf{b}_l \in \mathbb{R}^{\delta_l}$ is bias vector, and σ_l is activation function. We denote $\boldsymbol{\theta}_{(\cdot)_{Tx/Rx}}$ as the weight and bias terms of the Tx or Rx at the $(\cdot)$ node with constituent M or N, respectively.

The source node S takes k bits $\mathbf{s}_S \in \{0,1\}^k$ as input and maps to n complex symbols $\mathbf{x}_S \in \mathbb{C}^n$ using the mapping function, given as

$$f_{\boldsymbol{\theta}_{S_{Tx}}}\left(\mathbf{s}_S, \mathbf{x}_S\right) = \mathbf{P_N}\left(\boldsymbol{\omega}_M\left(...\boldsymbol{\omega}_1(\mathbf{s}_S)...\right)\right) \tag{6}$$

where $\mathbf{P_N}$ is the power normalization layer that mandates $||\mathbf{x}_S||_2^2 = n$. Then, symbol-by-symbol transmission takes place using (2)–(3) with $\Gamma, \Upsilon = S, R$ to obtain n symbols $\mathbf{y}_R^{IQ} \in \mathbb{C}^n$ at NN decoder of relay node, that obtains k soft probabilistic outputs $\tilde{p}_{g_{\boldsymbol{\theta}_{R_{Rx}}}}(\mathbf{s}_A|\mathbf{y}_R^{IQ}) \in [0,1]^k$, using the de-mapping function, given as

$$g_{\boldsymbol{\theta}_{R_{Rx}}}(\mathbf{y}_R^{IQ}, \tilde{p}_{g_{\boldsymbol{\theta}_{R_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_R^{IQ})) = \boldsymbol{\omega}_N(...\boldsymbol{\omega}_1(\mathbf{L_L}(\mathbf{y}_R^{IQ}))...) \tag{7}$$

where $\mathbf{L_L}$ denotes the Lambda layer with no trainable NN parameters.

Table 2
Training data and hyper-parameter settings.

Comments	Parameters	Values
Training dataset creation parameters	SNR E_b/N_0	$\mathcal{S} = \{3, 8, 13, 23, 33, 43, 53, 63\}$ dB
	Phase offset ϕ	$\mathcal{P} = \{25^\circ, 35^\circ, 40^\circ, 45^\circ\}$
	Amplitude offset ξ	$\mathcal{A} = \{0.4, 0.5, 0.6, 0.7\}$
NN Settings	Optimizer	Adam
	Weight initializer	Glorot
	Batch size	$B = 6000$
Step decay for learning rate (LR)	Initial LR	$\tau_0 = 0.002$
	Drop	$\eta = 0.5$
	Step size	$D_E = 25$
	Minimum LR	$\tau_{\min} = 10^{-5}$

3.2. Designing of the Bit-wise Denoising AE for Phase 2

The relay node R takes the k soft probabilistic outputs $\tilde{p}_{g_{\boldsymbol{\theta}_{R_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_R^{IQ}) \in [0,1]^k$ as input and maps to n complex symbols $\mathbf{x}_R \in \mathbb{C}^n$ using mapping function, given as

$$f_{\boldsymbol{\theta}_{R_{Tx}}}(\tilde{p}_{g_{\boldsymbol{\theta}_{R_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_R^{IQ}), \mathbf{x}_R) = \mathbf{P_N}(\boldsymbol{\omega}_M(...\boldsymbol{\omega}_1(\tilde{p}_{g_{\boldsymbol{\theta}_{R_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_R^{IQ}))...)) \quad (8)$$

where $\mathbf{P_N}$ ensures $||\mathbf{x}_R||_2^2 = n$. Then, symbol-by-symbol transmission takes place using (2)–(3) with $\Gamma, \Upsilon = R, B$ to obtain n symbols $\mathbf{y}_D^{IQ} \in \mathbb{C}^n$ at the NN decoder of destination node, that obtains k soft probabilistic outputs $\tilde{p}_{g_{\boldsymbol{\theta}_{D_{Rx}}}}(s_S^m|\mathbf{y}_D^{IQ}) \in [0,1]$, for all m, using de-mapping function, (where $\mathbf{L_L}$ denotes the Lambda layer), given as

$$g_{\boldsymbol{\theta}_{D_{Rx}}}(\mathbf{y}_D^{IQ}, \tilde{p}_{g_{\boldsymbol{\theta}_{D_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_D^{IQ})) = \boldsymbol{\omega}_N(...\boldsymbol{\omega}_1(\mathbf{L_L}(\mathbf{y}_D^{IQ}))...) \quad (9)$$

3.3. Proposed AE-based BCM and d-BCM Designs

We propose stacked AE-based BCM and d-BCM, where for generalizability, we employ same NN architecture for BCM/d-BCM, except Lambda layer $\mathbf{L_L}$ in the NN decoders is designed as

- *BCM* – Herein, we assume the CSI knowledge and perform channel equalization in Lambda layer with $h_{\Gamma\Upsilon}$.
- *d-BCM* – Herein, we assume absence of CSI knowledge and employ a radio transformer network (RTN), widely employed to estimate the CSI knowledge [3]. However, we propose an RTN that also helps in removing the IQI from the received signal at the Rx node Υ.

Remark 1. *Unlike the conventional networks performing ZF-based IQI compensation (in Sec. 2.2) using IQI parameters, we do not utilize the IQI parameter information. Thus, removing the feedback overhead for IQI estimation.*

3.4. Training of the Proposed Stacked AE

Both AEs are optimized by minimizing binary cross-entropy loss, $\mathcal{L}_{\Gamma\Upsilon}(\mathbf{s}_S, \tilde{p}_{g_{\boldsymbol{\theta}_{\Upsilon_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_{\Upsilon}^{IQ}))$, denoted as $\mathcal{L}_{\Gamma\Upsilon}$ for clarity, solving the multi-label binary classification problem, as

$$\mathcal{L}_{\Gamma\Upsilon} = \sum_{m=1}^{k} -(1 - s_S^m) \log_2(\tilde{p}_{g_{\boldsymbol{\theta}_{\Upsilon_{Rx}}}}(s_S^m|\mathbf{y}_{\Upsilon}^{IQ})) - s_S^m \log_2(1 - \tilde{p}_{g_{\boldsymbol{\theta}_{\Upsilon_{Rx}}}}(s_S^m|\mathbf{y}_{\Upsilon}^{IQ})) \tag{10}$$

Note that minimization of (10) only takes place during training (offline phase), once the stacked AE is trained we can deploy the trained NNs (testing phase). The NN architectures for encoder, decoder, and RTN are generalizable for both the AEs, as shown in Fig. 2. We assume $\xi_T = \xi_R = \xi$ and $\phi_T = \phi_R = \phi$. We create a training dataset (using simulations) with 2^{k+2} blocks of data for each combinations of E_b/N_0, phase offsets and amplitude offsets from the sets $[\mathcal{S}, \mathcal{P}, \mathcal{A}]$ detailed in Table 2. Using this training set we train both the AEs individually by estimating the expected loss in (10) with mini-batch training, using the hyper-parameter settings detailed in Table 2. Specifically, we employ Adam optimizer and Glorot initializer for weight initialization. Dependence on different weight initializations is left for future work. We utilize the step-decay method to update the learning rate and reduce overfitting [14]. The distinct advantages are:

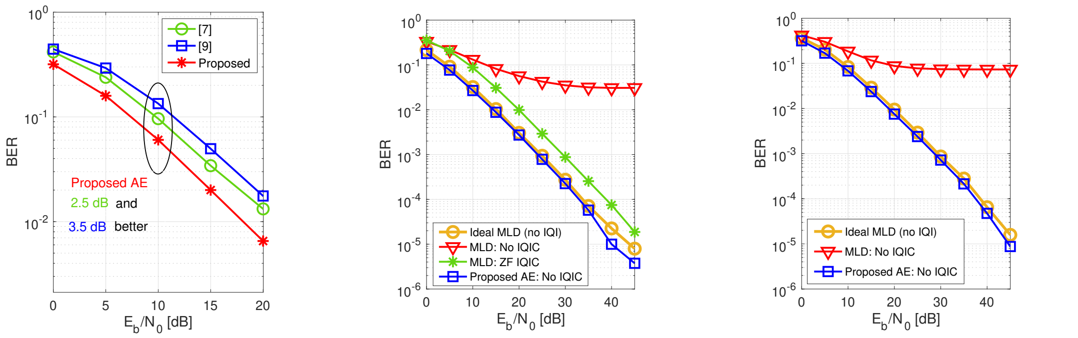
- We create a single training dataset such that a single trained stacked AE framework can generalize well for varying levels of testing E_b/N_0 and IQI.
- For the bit-wise denoising AE we utilize the input bits at source node and soft outputs of NN decoder for minimizing the loss in (10), with $\Gamma, \Upsilon = R, B$, as shown in Fig. 2. Thus, NN decoder of bit-wise denoising AE learns the distribution $\tilde{p}_{g_{\boldsymbol{\theta}_{D_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_D^{IQ})$, learning the soft outputs for input bits at source node. If end-to-end training between the input-output of the bit-wise denoising AE have been performed, then the NN decoder of would have learnt the distribution $\tilde{p}_{g_{\boldsymbol{\theta}_{D_{Rx}}}}(\tilde{p}_{g_{\boldsymbol{\theta}_{R_{Rx}}}}(\mathbf{s}_S|\mathbf{y}_R^{IQ})|\mathbf{y}_D^{IQ})$, learning the soft outputs of the NN decoder of bit-wise AE in first phase, propagating the errors made in first phase.

During deployment, we can monitor the decoding performance, if it falls below a threshold due to varying environmental conditions, we can re-train the NN using transfer learning [14].

4. Performance Evaluation

In this section, we evaluate the proposed stacked AE under Rayleigh block fading channels with $R_T = 8/7$ [bits/channel reuse], where the channel remains constant for $n = 7$ symbols and then changes randomly. For the conventional scenarios, we utilize QPSK (with CSI)/d-QPSK (without CSI) with $(7, 4)$ Hamming codes and consider the following as benchmarks – (1) MLD without any IQI compensation (*MLD: No IQIC*), (2) MLD with ZF-based IQI compensation (*MLD: ZF IQIC*), and (3) MLD in ideal relay network without IQI (*Ideal MLD*).

In Fig. 3a, we compare the proposed staked AE with state-of-the-art AE works in [7], [9] for an ideal relay network without IQI because no prior works consider IQI. Also, we can't compare with [10] because it considers a NOMA scenario. Proposed stacked AE-based d-BCM design outperforms [7], [9] by $2.5, 3.5$ dB, showing the merits of proposed stacked AE framework.



(a) d-BCM - Stacked AE versus [7], [9].

(b) BCM design (with CSI) for $\phi, \xi = 45°, 0.7$.

(c) d-BCM design (without CSI) for $\phi, \xi = 30°, 0.8$.

Figure 3: Performance evaluation of the proposed stacked AE-based BCM and d-BCM designs.

In Fig. 3b, 3c, we analyze the stacked AE-based BCM and d-BCM designs for DF relay networks with varying IQI levels. In Fig. 3b, we analyze the BCM design for SIR < 3 dB. In Fig. 3c, we analyze the d-BCM design for SIR < 6 dB. We can see that the MLD with ZF-based IQI compensation (MLD: ZF IQIC) is always able to decode the signals because of the presence of IQI parameters, while MLD without any IQI compensation (MLD: No IQIC) is unable to decode the signals because of absence of IQI parameters. Also, the proposed stacked AE is always able to decode the signal, even without utilizing the IQI parameters information. In fact, stacked AE performs similar to MLD for an ideal relay network without IQI (Ideal MLD: No IQI), indicating stacked AE completely removes the impact of IQI, without utilizing the IQI parameters information (reducing feedback overhead), even under low SIR regimes, due to:

- Bit-wise AE in the first phase forms 2^k codewords in $2n$-dimensional space with kurtosis as 1, indicating that spherical codes are formed, which are optimal for small block lengths. Also, it maximizes the minimum Euclidean distance between codewords to 1.5 and 1.2 for BCM and d-BCM designs compared to 1.4 and 0.76 in QPSK and d-QPSK, respectively.
- Bit-wise denoising AE in the second phase takes soft probabilistic outputs as input, thus it learns almost a slightly different codeword for different soft outputs, helping in removing the noise in the input soft probabilistic outputs while decoding the signal at NN decoder.

5. Conclusion

In this work, we propose stacked AE-based BCM and d-BCM designs for the DF relay network with IQI at all the nodes. We propose to employ bit-wise AE in the first phase and a novel bit-wise denoising AE in the second phase, with a new training policy for bit-wise denoising AE. The proposed stacked AE generalizes well on any testing IQI and SNR. Under a low SIR regime, we show that stacked AE performs similar to ideal DF relay network without IQI, even without utilizing the IQI parameters, thereby saving bandwidth and computational resources, highly suitable for IoE applications that mandates low latency. Further, stacked AE can be directly re-utilize for low-density parity-check (LDPC) codes as the outer codes, similar to the work [15].

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