DeepRISBeam: A deep machine learning approach for improvement of Beam Management in RISs for channel estimation

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1 Introduction

Beam management in Reconfigurable Intelligent Surfaces (RISs) is an important aspect of wireless communication systems, as it can greatly improve the overall system performance. RISs are made up of multiple reflecting elements that can be reconfigured to change the propagation direction of incoming signals, thus enabling beamforming and beam steering. To improve beam management in RISs, the authors have proposed a BRNN-LSTM (Bidirectional Recurrent Neural Network- Long Short-Term Memory) approach for channel estimation. The basic idea is to use a deep neural network to estimate the channel between the RIS and the user equipment (UE), which can be used to optimize beamforming and beam steering.

- CONTRIBUTION

The rest of the paper is structured as follows. Section 2 provides some background information on the , , . It also provides related work on approaches addressing . The assumptions, terms, problem description and formulation, including an overview on how the investigated approaches are associated with the optimisation objective , are elaborated in Section 3. Additionally, the enhanced implementations are provided in Section **??**. The efficiency of the investigated approaches is examined, evaluated and compared in Section 5. Finally, Section 6 includes concluding remarks and our future directions.

2 Background Knowledge and Related Work

2.1 Background Knowledge

Within this section, the necessary context and pertinent studies regarding beam management in (RISs), particularly in the realm of machine learning (ML) techniques that aim to establish a proper channel between the RIS and the user equipment (UE), which can further be used to optimize beamforming and beam-steering are furnished. Subsequent to the examination of related work, a concise depiction and comparative analysis of the methodologies employed has been finalized, juxtaposed with select papers from the aforementioned related work.

[1] investigates a wireless system in a single-cell scenario, where a reconfigurable intelligent surface (IRS) is deployed to enhance communication between a multi-antenna access point (AP) and multiple single-antenna users. Minimizing the overall transmit power at the AP is achieved by jointly optimizing the transmit beamforming from the active antenna array at the AP and the reflect beamforming from the passive phase shifters at the IRS.

A joint design of transmit beamforming matrix at the base station and the phase shift matrix is investigated using a deep reinforcement learning (DRL) based algorithm in [2]. The joint design is achieved by engaging in trial-and-error interactions with the environment while observing predefined rewards.

In [3] the authors propose two computationally efficient algorithms for obtaining the RIS phase shift coefficients and optimal power allocation. One algorithm utilizes gradient descent to determine the phase coefficients of the (RIS) and employs fractional programming to allocate the optimal transmit power. In contrast, the second algorithm utilizes sequential fractional programming to optimize the phase shifts of the RIS.

In [4] a millimeter wave (mmWave) communication system with the assistance of an intelligent reflecting surface (IRS) is introduced. A hybrid precoding architecture is employed which consists of baseband digital and analog RF precoding. This is achieved by using a subarray-connected structure at the base station.

[5] analyzes a multi-user multiple-input single-output (MISO) communication system aided by an RIS under imperfect channel state information (CSI). In this work, the researchers leverage prior knowledge of large-scale fading statistics at the base station (BS) to derive Bayesian minimum mean squared error (MMSE) channel estimates. These estimates are obtained through a protocol where the IRS applies a set of optimal phase shift vectors across multiple channel estimation sub-phases. Both analytical and numerical evaluations demonstrate that the resulting mean squared error (MSE) is lower compared to the MSE achieved by LS estimates.

2.2 Related Work

This section provides a brief review of the open literature approaches related to improvement of beam management in RISs for channel estimation.

2.2.1 Related Work on using channel prediction in mMIMO Systems

[6] has shown that the optimum technique to improve the performance of mMIMO systems by reducing complexity and raising accuracy is RNN-based CSI prediction. When processing time series data, recurrent neural networks (RNNs)

are particularly efficient. We see mMIMO channel prediction using RNNs as a technology with enormous future potential that will significantly impact wireless technology since channel response data is strongly related to time series data. The novelty of the work includes a a low cost mMIMO RNN-based CSI predictor and the comparison the complexity and cost of using RNN-based predictors to more traditional CSI predictors in terms of performance measures.

2.2.2 Related Work on LSTM based channel estimation schemes

[7]Due to the doubly-dispersive nature of vehicle channels, accurate channel prediction is essential for system performance in vehicular communications. The IEEE 802.11p standard does not assign enough pilots for precise channel tracking. As a result, traditional IEEE 802.11p estimators have a significant performance reduction, particularly in high mobility settings. Thus an estimator which uses a temporal averaging (TA) processing step as a noise reduction method is used after applying an LSTM unit to estimate the channel. Additionally, the noise mitigation ratio is calculated analytically, verifying the effectiveness of TA processing in raising overall performance. The performance of the suggested schemes is superior than the recently proposed DL-based estimators, according to simulation findings, which also show a significant reduction in computational cost.

2.2.3 Related Work on LSTM based energy efficient communication

[8] suggests a decision-making system based on Long Short-Term Memory utilizing dynamic wireless network data to account for channel complexity and RIS energy harvesting to boost energy efficiency. The suggested LSTM model predicts the ideal RIS configuration for each transmission after being trained in a real-time context. Users in various parts of the relevant wireless network are the target audience for the transmissions under consideration. The RIS-aided downlink system model is constructed using the LSTM model and Adam optimizer, and its energy effectiveness and robustness are investigated. According to the findings of numerous simulations, the LSTM framework increases energy efficacy to 35.42% while increasing the RIS elements from 9 to 25. The model also attained a net data rate of above 100 bps/Hz.

3 Problem Description, Formulation and Investigated Associated Approaches to the Optimisation Objective

In this research, the primary goal is to tackle the

3.1 Assumptions and Terms

The investigation considers the following assumptions:

1. a

3.2 System Description

Considering a RIS enabled wireless communication system, the objective is to devise a solution which optimizes the energy conservation of the downlink power transmission.

$$max_{T_p,\omega,\rho} min_t FO_t(T_p, \omega, \rho)$$

such that

$$\sum_t T_p < T_{max}$$

$$SU_t \leq SE_t \forall t$$

where T_p denotes the transmission power, ρ is used for assessing achievable data rates and $FO_t = t_r(F * \omega * A * W * W^H * A^H * \omega^H * F^H) + \gamma^2 * K$ estimates the energy conservation as the energy of the received signal Equation (7) shows the total captured energy that the BS uses for decision-making in order to maximise the minimum amount of conserved power in each gearbox and achieve energy efficacy. Equation (8) illustrates the restriction that the total transmission power must be less than the maximum transmission power currently in use. Equation (9) shows that the amount of energy used by the RIS element during each gearbox must be less than the total amount of energy preserved, which was determined using equation (6). The Base Station cannot directly compute the optimisation function since it lacks knowledge of the channel status information. In practise, the base station is aware of its broadcast power and the users are required to submit feedback regarding the received data rate.

In order to comprehend the impact of each value on the system's overall communication and energy efficacy, the phase shift and ON/OFF state of the RIS elements are also evaluated. Input variables for the objective function are Tp (the transmission power), (the phase shift at the RIS element), and (the on-off state of the RIS elements). The problem space is discontinuous and non-smooth, making analytical computation-based optimisation impossible. The problem here can therefore be framed as one of sequential data prediction. Intricate relationships between input-output can be found using DL-based methods like LSTM, where input is the transmission power, the distance between the user device and the RIS, and the related RIS setup to maximise energy conservation.

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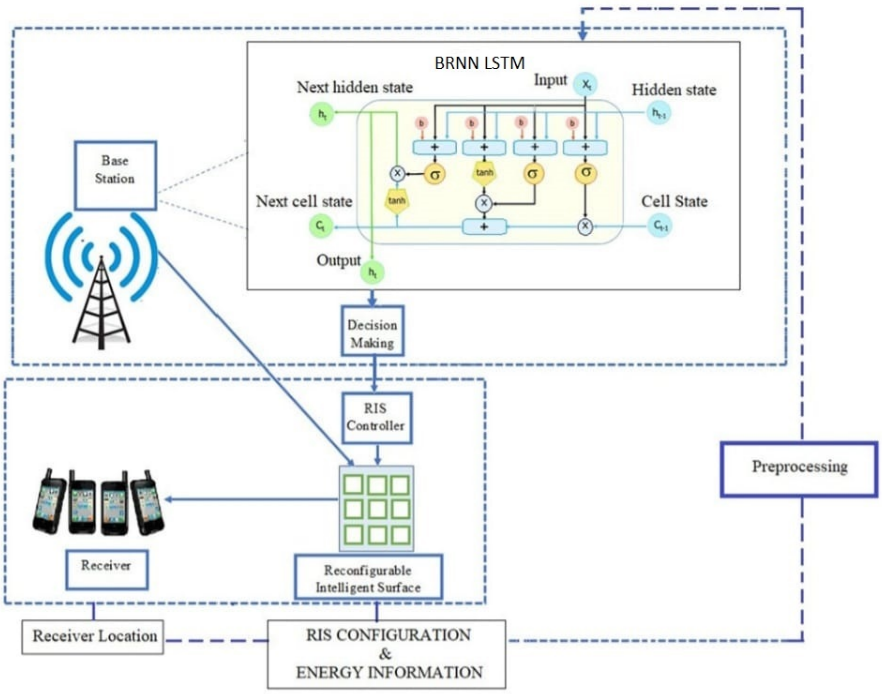
4 Methodology



A BRNN-LSTM network is used as the beam prediction algorithm, composed of two stages. The first stage being the outer processing stage between the layers, and the input state inside the LSTM cell. The input data is first processed by the bidirectional forward and backward layers for the outer stage between the layers in order to identify the hidden states. The context of the beam indices and associated power levels is reflected in these statistics. The concealed states are then fused to create the output layer after this phase. As opposed to standard LSTM, the bidirectional property in this case allows LSTM to retrieve additional beam index contextual information by retrieving the present and future time steps by switching between the backward and forward states.Each bidirectional LSTM unit's backward and forward processes are comparable because each LSTM cell has a state that includes g_t^{in}, input modulation g_t^{mod}, forget g_t^f, and output g_t^{out} gates that control the information entering the cell state. Think about the information in the LSTM cell.

For the inner stage of the LSTM unit, initially, g_t^f in the sigmoid layer placed beneath it modifies the cell state c_t at time t, specifying the information transported to the next sequence. g_t^{mod} is then altered by g_t^f, delivering the new candidate cell state. The inputs to the forget gate g_t^f are the input vector at time step t, xt, and the hidden-state vector η_{t-1}(output vector of the LSTM unit) at time step $t-1$. The output of this gate is then a number between 0 and 1 for each number in the cell state of the preceding time step $t-1$, c_{t-1}. By multiplying 0 by a location in the matrix, the output of g_t^f tells the cell state which information to forget or delete. The information is maintained in the cell state, where a sigmoid function, σ_g, is applied to the weighted input and prior concealed state, if the output of g_t^f is 1. Equations (7)–(11) represent the c_t, g_t^f, g_t^{in}, g_t^{mod}, g_t^{out} formulations at the time step t.

$$c_t = g_t^f c_{t1} + g_t^{in} g_t^{mod}$$

$$g_t^f = \sigma_g(W_f[\eta_{t-1}, x_t] + \beta^f)$$
$$g_t^{in} = \sigma_g(W_{in}[\eta_{t-1}, x_t] + \beta^{in})$$
$$g_t^{mod} = tanh(W_c[\eta_{t-1}, x_t] + \beta^c)$$
$$g_t^{out} = \sigma_g(W_{out}[\eta_{t-1}, x_t] + \beta^{out})$$

The weight matrices are W_f, W_{in}, W_{out}, and W_c and the bias vectors for c_t, g_t^f, g_t^{in}, g_t^{out} are β_c, b_f, β_{in}, β_{out} respectively after training. η_t, the hidden state layer output is modeled as $\eta_t = g_t^{out}.\tanh(c_t)$. The logistic sigmoid and the hyperbolic tanh nonlinear activation function for each gate to predict probability of the output are the model's main parameters, it should be noted. g_t^{in} is a sigmoid function that can only add memory, and its range is $\in$ [0,1]. Because the cell state equation sums together the past cell states, it should be noted that the sigmoid function cannot forget or clear memory. In order to enable the cell state to forget memory, g_t^{mod} is activated with a tanh activation function with a [1, 1] range. Overall, there are four layers and one thick layer in the model's training parameters.

The weight of the hidden layers is controlled by the dropout layer, with a dropout regularisation rate of 0.2 applied to each regularizer layer. Over the course of two weeks, 350 epoches are used to train the model. Since LSTM cells maintain long-term memory state, a data structure is formed with 60 time steps, each lasting 10 minutes, and a single output is produced. As a result, for each sample that is taken, there are 60 elements from the previous training set in each training stage. In order to accurately determine the next best beam index during testing, the first 60 samples are required. The overall goal of training is to create bias and weight matrices that reduce the loss function over all training time steps.

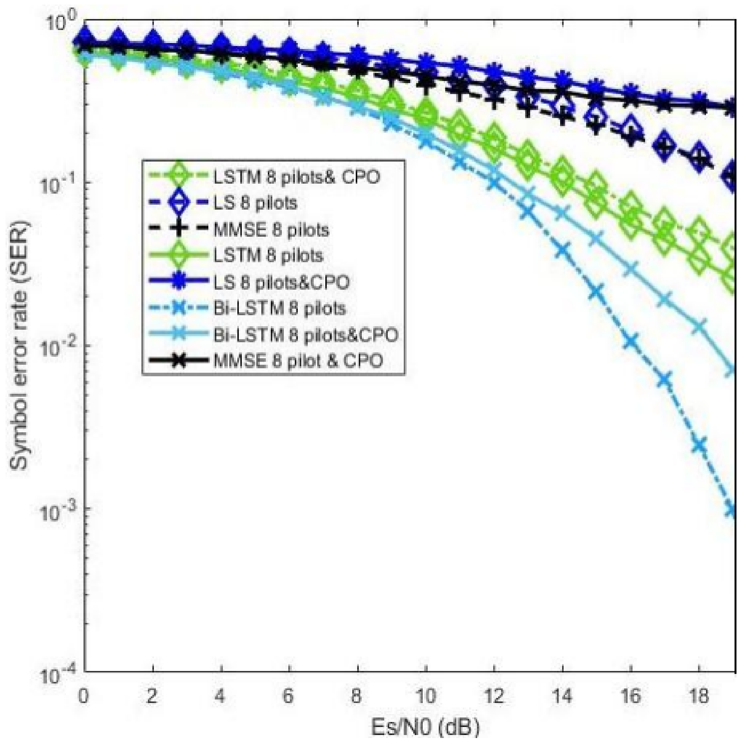
4.1 Emulation/Simulation Environment

5 Performance Evaluation

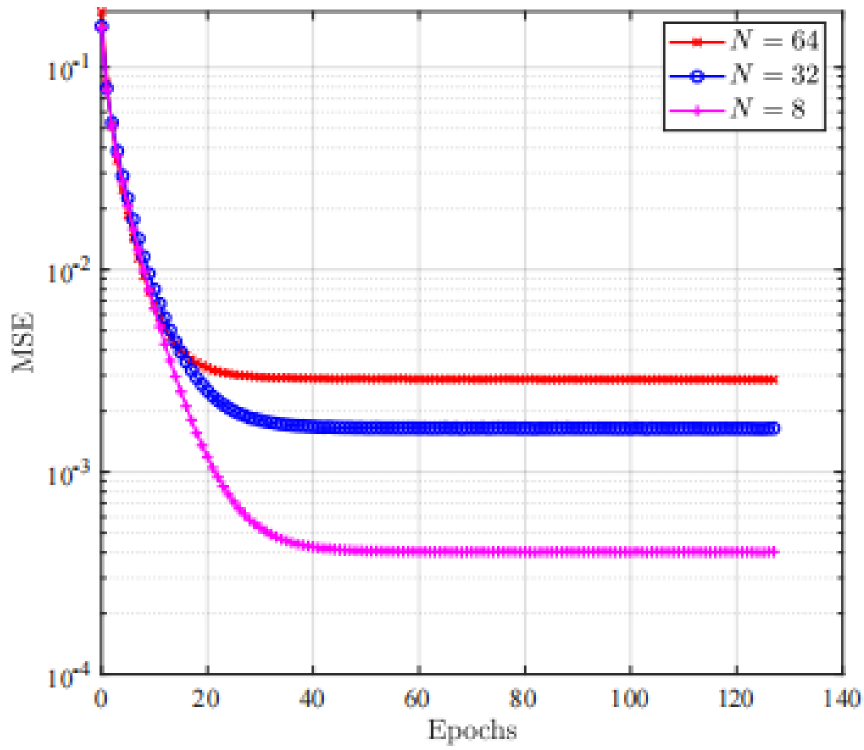
This section examines, evaluates, and compares the efficiency of

5.1 Results

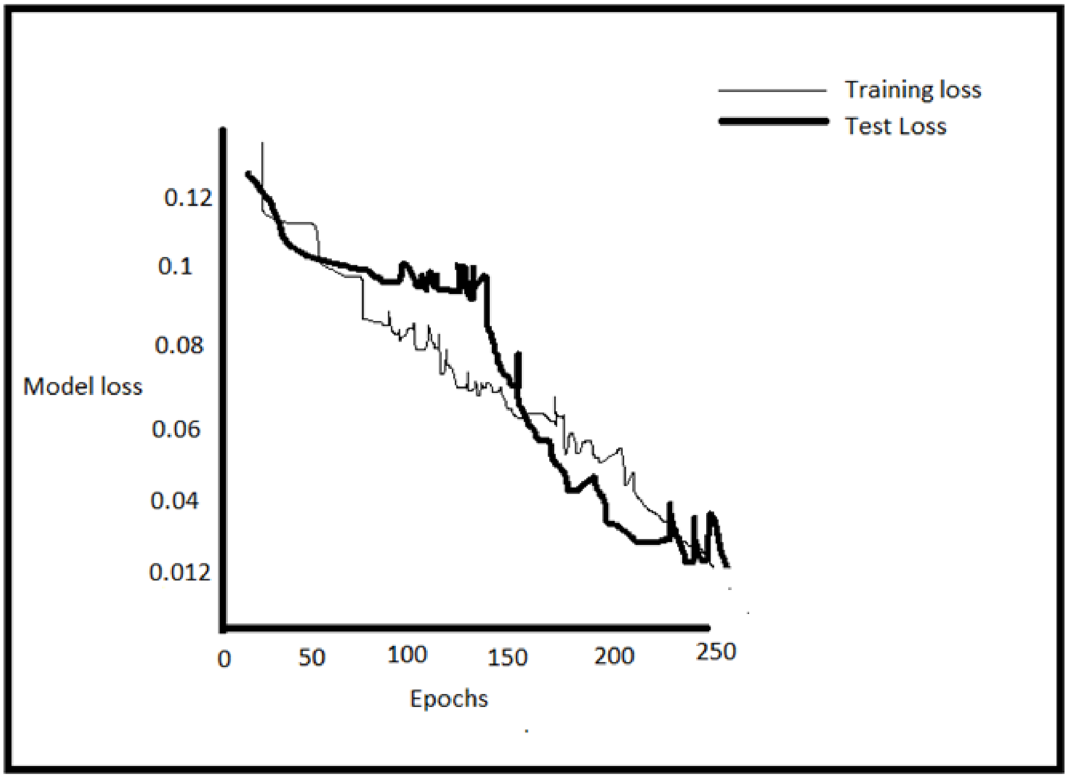
In this section, the comparison is done after the wireless system has been implemented in MATLAB and various plots show the improvement in results. With the system model presented in Section 2, the optimization problem formulated for the proposed work can only be evaluated with real-life network conditions. The BRNN-LSTM scheme here recursively processes beam sequences at every time step of the input. It then maintains a hidden state which is a function of the previous state and the current input. The symbol error rate is much less for the Bi-LSTM enabled channel compared to the MMSE enabled channel as the figure below depicts.



The MSE reduces rapidly until it reaches convergence at the 40th epoch. The number of elements in the RIS also play a major role in reaching convergence faster as the higher the number of elements, the faster it is achieved as depicted in the figure below.



The training loss achieved by the model is very minimal as seen in the figure below. Thus, the BRNN LSTM can be modeled in such a way to have high convergence with minimal MSE providing an overall improvement of beam management for channel estimation.



5.1.1 Overall Remarks

6 Conclusions and Future Work