

Successive Interference Cancellation using LSTM in MIMO

Raushan Kumar
Research scholar

Sarvepalli Radhakrishnan University,
Bhopal, M.P, India
raushanr2@gmail.com

Dr. Nikhil Ranjan
Associate Professor

Sarvepalli Radhakrishnan University,
Bhopal, M.P, India

Dr. Bharti Chourasia
Associate Professor

Sarvepalli Radhakrishnan University,
Bhopal
bharti.chourasia27@gmail.com

Abstract: In this paper, we suggest LSTMSIC, a data-driven multiple user MIMO recipient architectural work. We used the iterative SIC algorithm to produce LSTMSIC, which really is a model depending Multiple Input Multiple Output that involves measuring, can be easily adapted to include machine learning approach, and has a manageable computational effort. By replacing the model-based basic components of iterative SIC with committed compressed DNNs, we were able to formulate the data-driven LSTMSIC receiver. LSTMSIC is channel model independent and can be trained to implement interference cancellation in non-linear configurations with non-additive interference, unlike its model-based counterpart. In this study, the performance was evaluated using Matlab, and the results were discussed.

Keywords: LSTMSIC, MIMO, DNN, TDM, WDM, FDM, SIC, I-SIC,

I. INTRODUCTION

Signal analysis refers to the process of condensing measured data in order to retrieve data about a distanced natural condition. Signal processing can indeed be interpreted in a number of ways. It is a method used by acousticians to convert signals into relevant information. Multiplexing, also known as muxing, is a method of simultaneously transmitting various signals or flows of data over a shared channel in the form of a specific, complicated signal.

Time slotting the line of communication and allowing so every subscription sole use of the line for a specified amount of time is an extended version of the TDM idea. Analog electrical impulses, usually voltage levels, from detectors or transducers are being sent in parallel to a multiplexer or commutator that emits a single flow of voltage spikes, a practice known as time division multiplexing (TDM). A multiplexing is utilized at the near end of the fibre in a WDM system to launch various channels at various wavelengths with one fibre. WDM (wavelength division multiplexing) is a methodology for combining optical signals. A multitude of distinct visible light share the sample fiber-optic transmission in WDM.

Multiplexing, also known as muxing, is a method of simultaneously sending a bunch of signals or waterways of data over a communication network in the consisting of a

specific, complex signal. Whenever the signal achieves its goal, a process known as demultiplexing, or demuxing, recuperates the independent signals and sends them to separate tracks.



Figure 1 Multiplexing

Multiplexing methodologies are used in a number of ways in network infrastructure, and they often operate in the same way conceptually. Individual system signals are fed into a multiplexer (mux), which further manages to combine those into a composite signal that is sent over a shared medium. A demultiplexer (demux) splits the composite feedback signal into its component signals and output values them into separate tracks for usage by different processes once it arrives at its destination.

5G intends to usage a massive MIMO unit including a beam-forming medium of communication to specific customers, minimizing interference and streamlining transfer of information. MIMO (Multiple-Input Multiple-Output) is a communication device that leads to enhanced of a radio link by using multiple transmitter and receiver antennas. In simplistic terms, it is a transceiver with multiple radio antennas to facilitate a wide selection of signal paths (one for each antenna) to thereby using via multipath.

OFDM is a multi-carrier modulation technique in which the modulation is done in parallel with the input streaming data using a gathering of sub - carriers. In the temporal domain, the transmitter needs a sufficient frequency range to arrange orthogonally the modulated signals, however in the frequency response, the signals of various routes may coincide. This interlaced data spectral range produces a waveform that enhances spectrum utilization by utilising the given bandwidth

variety. As a result, any channel with a time domain and frequency domain can conveniently use OFDM.

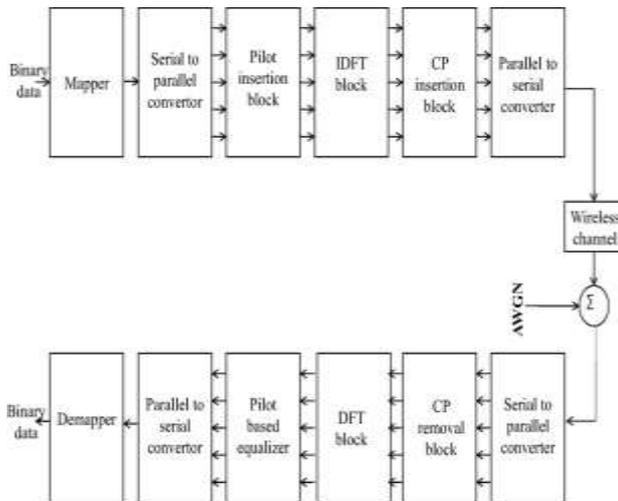


Figure 2 Typical OFDM

Beamforming is a method for obtaining a specific antenna trend at the transmitter with the proper stage and gain greater weight so that the signal power at the recipient is exceeded. Smart transmitters, which can be partitioned into multispectral systems or term weighting systems, are used to achieve beamforming. Beamforming has the advantage of reducing multipath fading by allowing signals from multiple antennas to pile up constructive manner at the receiver, increasing the received signal gain. When the receiver has multiple antennas, modulation scheme is required to maximize the benefit with multiple streams. Precoding necessitates CSI understanding at both the transmitter and receiver.

II. LITERATURE REVIEW

(Koc & Le-ngoc, 2021) [1] For full-duplex mm Wave massive-MIMO systems, an innovative angular depending combined hybrid precoding/combining (AB-CHPC) has been suggested. The proposed AB-JHPC technique's primary goals are to (i) enhance the effectiveness of self-interference cancellation (SIC), (ii) maximise the authority of the desired or intended signal, (iii) minimise the channel estimation occupancy dimension, and (iv) mitigate equipment cost and complexity by using a small number of RF chains. To begin, the Radiofrequency stage of the AB-JHPC was built using delayed time-varying AoD/AoA data, with the transmit or receive Radiofrequency beamformers aiming to maximise the preferred signal power while cancelling the powerful Signal Interference power. As a result, a joint Radiofrequency beamformer framework was created to generate orthogonal data transmission beams that covered AoD/AoA assistance of the intentional channel of excluding AoD/AoA support of the SI channel.

Digital networked programming protocol to improve bit rate for the second loop in an fundamental cognitive radio environment (Duy et al., n.d.) [2]. A foremost sender and a foremost recipient, respectively, employ transmitting antenna

choice and choice of combining technologies to enhance achievement for a network operator in the suggested technique. In a second loop, two additional sources communicate information with the aid of a commonly involved relay, which uses an interference cancellation technique to save one timeframe when compare to conventional digital communication programming procedure. The suggested technique improves the supplementary network's achievement in terms of information rate and power failure probability.

(Zhan et al., 2021) [3] for downlink mm Wave multi-user huge Multiple Input Multiple Output systems, a non-linear hybrid beamforming architecture with interference cancellation was initiated. Three Soft Interference Cancellation aided hybrid beamforming methods relying on the supremacy of inter-user interference, intra-user interference, or both have been suggested based on the suggested approach. The suggested hybrid beamforming techniques have been shown to have a SE that is similar to completely digital beamforming and outcompete their conventional distribution equivalents at the expense of increased computational effort for the SIC process. Besides that, using 2-bit finite pixel density phase shifters, the suggested hybrid beamforming techniques can achieve over 91 percent SE of infinite resolution phase shifters.

2021 (Huang et al.) In a full duplex MIMO transmitter or receiver, self-interference at co-located received signals by recipient antenna can be inhibited by employing transmission beamforming in the dissemination realm with a carefully chosen sub-space aspect. Multi-beam interactions with distant transmitters and receivers can be attained in the meantime by pre-coding the data circulates in the similar sub-space, the aspect of that which defines the precoding mistake. Besides transceiver beamforming with recognised eigenvector distributions of the interference streams, an analysis balance to evaluating the ISR is developed. To appraise the ISR with unidentified eigenvalue distributions and concoct trade-off curves between both the ISR and the precoding erroneous, a uniformly distributed estimation is suggested.

(Kusaladharna et al., 2021) [5] Non-orthogonal multiple access (NOMA) is used to enhance the efficiency of cell-free huge multiple-input multiple-output (MIMO) systems for future networks with probability entry point and user locations. Poisson point procedures are used to design the node places in this frame of reference. Uplink streams are approximated domestically employing uplink pilots, and time division duplexing (TDD) is used. To strike the right balance here between learning overhead and the cluster centers, distinctive pilot patterns are used among Non-orthogonal multiple access groupings, whilst also pilot reusability happens inside every cluster. For downlink transmitting, paired pre-coding is used. The impulse response component and simplifications via moment trying to match are used to characterise the accumulated received signal mathematically.

III. METHODOLOGY

In this section, we present a data-driven approach to iterative Soft Interference Cancellation. We first create the LSTMSIC receiver framework, which is depending on learning algorithms, in order to create the suggested receiver. Then we'll go over how to train the receiver's DNNs, as well as the advantages and disadvantages.

We assume an uplink architecture wherein D single antenna users connect across a memory-less static channel having a receiver configured with N_r antennas. The d th user,

$$d \in \{1,2,3 \dots, D\} \triangleq \mathcal{D}$$

Broadcasts a symbol $S_d(i)$ taken out of a constellation S of size m, i.e.,

$|S|= m$, at every time instance i .

Every symbol is dispersed equally across S, and the symbols communicated by various users are conditionally independent. The channels outputs at time index i is denoted by

$$Y[i] \in R^{N_r}.$$

Although we concentrate on real-valued networks, the modelling approach may be modified to complicated valued channels since complicated vectors can be expressed in the same way as actual vectors with expanded dimensionality. As a result, the constellation set S is not restricted to actual values, and the receivers structures described in the sequel, that are defined for real-valued networks, can be used in complicated channels. Because the channel has no storage, $Y[i]$ is determined via a stochastic mapping of,

$$S[i] \triangleq [S_1[i]S_2[i] \dots \dots S_D[i]]^T$$

The conditionally distributions parameter $V_{Y[i]S[i]}(\cdot | \cdot)$ is used to represent this. The feature that the channel is stable means that this conditional distribution is independent of the index i and so is represented by $V_{Y[i]S[i]}(\cdot | \cdot)$. Figure 1 shows a representation of the system.

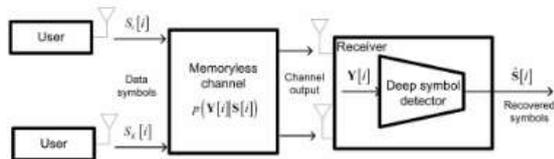


Figure 3 Architecture of the System

The issue of starting to recover the transmitted data $S[i]$ from the channel output $Y[i]$ is the subject of this section. The MAP sensor is an ideal sensing rule that reduces the probability of error provided a channel output realization $Y[i]= y$. The MAP rule is provided by letting $V_{Y[i]S[i]}(\cdot | \cdot)$ be the conditional distribution of $S[i]$ given $Y[i]$ is represented as:

$$\widehat{s}_M[i] \triangleq \arg \max_{s \in S^D} V_{S|Y}(s|y)$$

Whenever the amount of users D expands, the MAP sensor is becoming impracticable because it searches more than a collection of MD various possible input combinations to restore the representations of all consumers. For simply $D = 20$ users, the variety of distinct channel inputs is greater than 10^6 while binary constellations are utilized, i.e., $m = 2$. Moreover, the MAP sensor necessitates a thorough understanding of the channel estimation.

Interference cancellation is a popular approach for implementing combined identification with a low computing complexity that is appropriate for channels wherein $Y[i]$ is provided by a linear transition of $S[i]$ manipulated by additive noise. Interference cancellation is a subcategory of joint detection systems that restore a subset of $S[i]$ dependent on channel output and an approximate of the residual interfering signs in an iterative manner. These methods make it easier to retrieve the subset of $S[i]$ from the channel output by cancelling the impact of approximate interference employing channel variables and, in particular, how another interfering symbol relates to the channel outcome.

a. Iterative Soft Interference Cancellation (I-SIC)

In general, the detection approach is iterative, with each iterative process generating a forecast of the conditional distribution of $S_d[i]$ provided the channel output $Y[i] = y$ for each user $d \in D$ employing the respective forecasts of the interfering symbols $\{S_L[i]\}_{L \neq d}$ acquired in the early iteration. The conditional distribution forecasts are streamlined by iteratively following the above steps, enabling for precise recovery of every symbol out from outcome of the last layer employing difficult call. The iterative process is depicted in Figure 2.

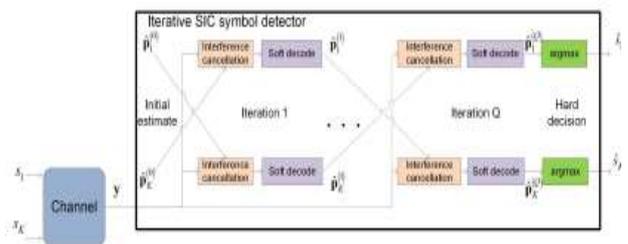


Figure 4 Soft Interference Cancellation (SIC) –Iterative

To establish the method, we regard a channel for whom outcome is acquired as a linear transformation of its input manipulated by additive white Gaussian noise (AWGN), i.e., a broadcaster for whom outcome is procured as a linear conversion of its input manipulated by additive white Gaussian noise (AWGN).

$$Y[i] = CS[i] + M[i]$$

However,

$C \in R^{N_r \times D}$ is a channel matrix that is recognized ahead of time.

And $M[i] \in R^{N_r}$ is a self-reliant of $S[i]$ zero-mean multivariate Gaussian vector having covariance $\sigma_o^2 ID$.

There are G iterations in iterative SIC, with every iteration listed $g \in \{1,2,3 \dots, G\} \triangleq \mathcal{G}$ created D distributions vectors, $\hat{v}_D^{(g)} \in R^m, d \in D$.

The distribution vectors achieved in the earlier iteration, and also the channel outcome y , are used to calculate these vectors as given below, in a detailed sequential form.

$$\{\hat{v}_D^{(g-1)}\}_{d=1}^D$$

The entries of $\hat{v}_D^{(g)}$ are estimates of the distribution of $S_d[i]$ and assuming that the interfering symbols $\{S_L[i]\}_{L \neq d}$ are distributed through $\{\hat{v}_D^{(g-1)}\}_{L \neq d}$

Each iteration involves two stages: interference cancellation and soft detection, which are performed simultaneously for every user. The interference cancellation phase calculates the predicted values and variance of $\{S_L[i]\}_{L \neq d}$ which is depending on $\{\hat{v}_D^{(g-1)}\}_{L \neq d}$ for the d th user and the g th iteration initially.

The variances and expected values are calculated using,

$$E_L^{(g-1)} = \sum_{\gamma_n \in S} \gamma_n \{\hat{v}_L^{(g-1)}\}_n,$$

$$\delta_L^{(g-1)} = \sum_{\gamma_n \in S} (\gamma_n - E_L^{(g-1)})^2 \{\hat{v}_L^{(g-1)}\}_n$$

While, $\gamma_{n=1}^m$ are indexed elements of constellation set S .

The symbols are detected well after completion by selecting the symbol that enhances the approximated conditional distribution for every user, i.e.

$$\hat{s}_d = \underset{n \in \{1,2,3 \dots m\}}{\operatorname{argmax}} \{\widehat{V}_d^{(G)}\}_n$$

We introduce a data-driven deployment of iterative SIC in this segment. To create the suggested receiver, we initially create the LSTMSIC receiver architectural style, which is focused on machine learning. Whereupon, we explain the advantages and disadvantages of various methodologies for training the Deep Neural Networks (LSTM) implanted in the receiver.

LSTM - Recurrent neural networks (RNNs) are considered a type of supervised learning algorithm. They can model consecutive information for estimation and recognition. RNNs consist of higher dimensional hidden layers made of artificial

neurons with feedback loops containing non-linear dynamics. Consequently, RNNs have two inputs, the current and the recent past sample, as shown in Figure 5, where the recent input is the non-looping input to each neuron and the recent past is the output that loops back into the network.

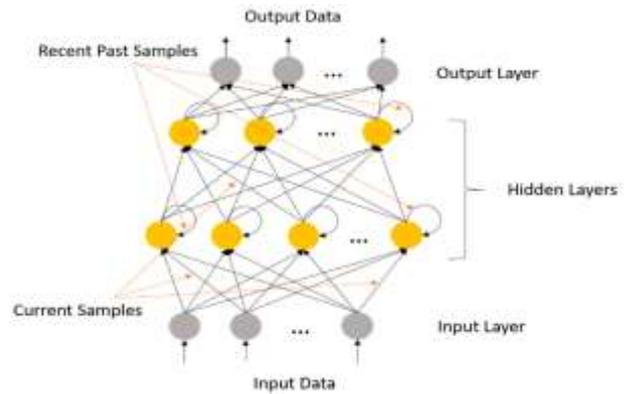


Figure 5 LSTM Network

The traditional RNN using backpropagation through time suffers from the vanishing gradient problem and slow learning. In order to resolve this limitation, Sepp Hochreiter and Jürgen Schmidhuber proposed long-short term memory (LSTM) neural networks, since LSTMs are able to model selective dependencies between different portions of the received signal with a small number of neurons and without learning problems. Moreover, they accept vector-based sequence data (where each time step has a vector of measurements), thus incorporating the magnitude and phase parts of the received signal simultaneously. LSTMs introduce memory cells, which are able to store and access data over longer periods of time through their distinct structural design, and preserve the error from back-propagating, unlike the conventional RNN.

IV. Result And Discussion

LSTMSIC is focused on implementing the iterative SIC algorithm. As a result, once trained, it shares the model-based algorithm's major benefits: LSTMSIC is predicted to encounter the performance of the optimal MAP detector in scenarios where iterative SIC is likely to apply, such as linear channels of the form (2).LSTMSIC's computational complexity expands linearly with the quantity of customers, equivalent to the model-based iterative SIC algorithm from that which is derived. LSTMSIC can now be used in MIMO scenarios where traditional MAP detection is impossible. Moreover, because LSTMSIC is made up of a network of relatively small DNNs, it shares the inference performance gain of DNN-based receivers over iterative model-based receivers. Owing to the intrinsic complexity in measuring the complex nature of training and implementing DNNs, which is strongly depends on the quantity of variables and the learning algorithm, expressly characterizing the complexity of LSTMSIC is challenging.

LSTMSIC has two important benefits over through the model-based algorithm from that which is derived, in addition to the ability to incorporate iterative SIC without foreknowledge of the channel model and its variables: First, because LSTMSIC realises to postpone training-induced interference rather than assuming that its participation is complementary, it can be used in non-linear channels. In non-linear channels, iterative SIC, which is trying to cancel interference by removing its guesstimate from the channel output, leads to increased inconsistencies. Moreover, iterative SIC's performance is highly sensitive to unreliable CSI, even now in linear scenarios where it would be likely to apply.

We mathematically evaluate LSTMSIC across several applicable multiuser MIMO detection scenarios in the subsequent sections. 1. We look at linear Gaussian channels, which seem to be suitable for both traditional model-based iterative SIC and the large percentage of initially proposed DNN-based MIMO detectors. Then we show how LSTMSIC provides better performance in two non-linear scenarios: quantized Gaussian setups and Poisson channels. The methodologies for training LSTMSIC are then compared.

With such a comparatively small training dataset of 5000 training instances, we given training LSTMSIC employing the ADAM optimizer and evaluated over 2000 symbols. The goal with using small training sets is to show that LSTMSIC can train with a sample set of the order of a preamble sequential, implying that it is possible to adjust in changing environments by exploiting the framework stimulated by communication channels.

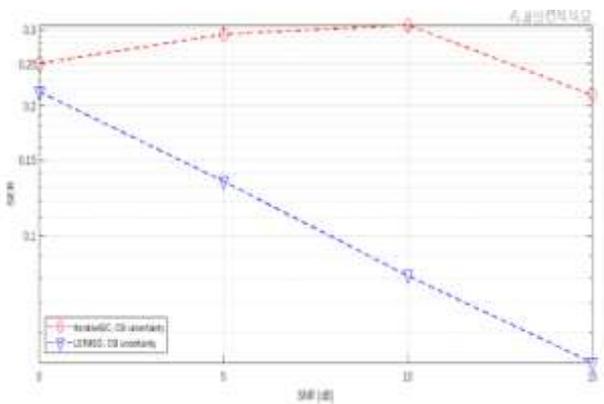


Figure 6 SER Analysis for 2*2 MIMO

The above graph shows the comparison between two different techniques namely iterative SIC and Proposed technique LSTMSIC used in channel state information uncertainty in 2×2 MIMO. It can be seen clearly that the performance of LSTMSIC is better as symbol error rate gradually reduces.

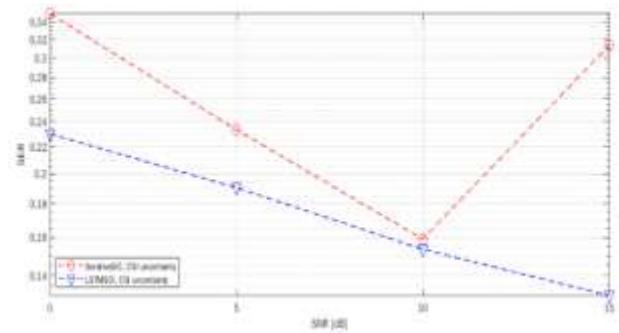


Figure 7 SER Analysis for 4*4 MIMO

The above graph shows the comparison between two different techniques namely iterative SIC and Proposed technique LSTMSIC used in channel state information uncertainty in 4×4 MIMO. It can be seen clearly that the performance of Iterative SIC is not effective as symbol error rate reduces initially and then it begins to raise. Thus, LSTMSIC outperforms on comparison.

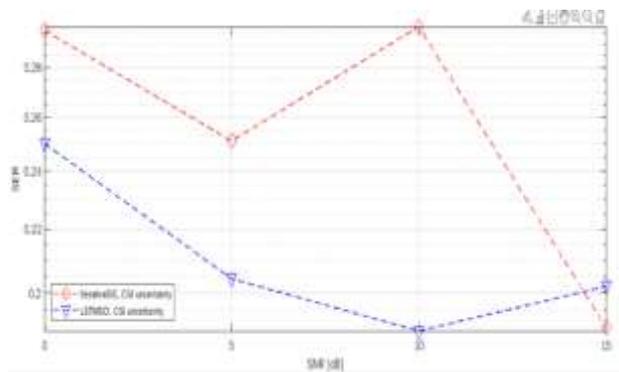


Figure 8 SER Analysis for 6*6 MIMO

The above graph shows the comparison between two different techniques namely iterative SIC and Proposed technique LSTMSIC used in channel state information uncertainty in 6×6 MIMO. It can be seen clearly that the performance of Iterative SIC is not effective as symbol error rate reduces initially and then it begins to raise and then reduces, it fluctuates. Whereas, LSTMSIC outperforms on comparison because gradually reduces initially then it can be observed that it raises slightly.

We employed different network architectural styles for every training technique of DeepSIC in the parametric simulations mentioned in previous subcategories: E2E DeepSIC utilised two fully-connected layers in incorporating the machine learning relying building blocks of Fig. 1, whereas Seq. DeepSIC employed three layers.

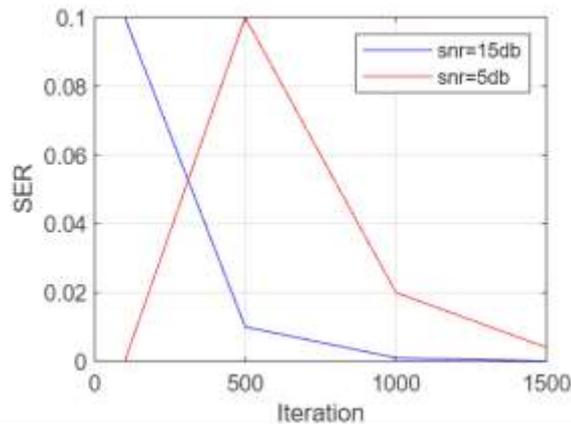


Figure 9 SER Analysis for Training

The above graph shows that symbol error rate decreases with high signal to noise ratio and Symbol error rate increases with low signal to noise ratio on specific number of iterations.

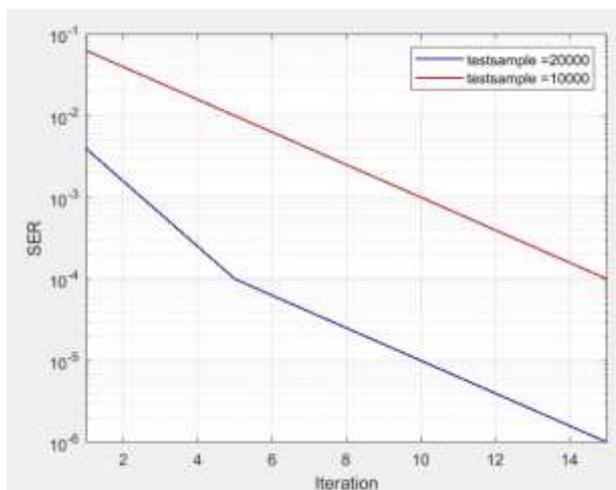


Figure 10 SER Analysis for Testing

The above graph shows that symbol error rate decreases with increase in test samples and Symbol error rate increases with reduced testing samples on specific number of iterations.

V. CONCLUSION

LSTMSIC, a data-driven multiuser MIMO receiver architectural style, was suggested in this research work. We used the iterative SIC algorithm to create LSTMSIC, that is a model-based MIMO involves measuring that can be obviously prolonged to include machine learning techniques and is precise and computational complexity workable. By substituting the model-based basic components of iterative SIC with committed compressed DNNs, we were able to create the data-driven LSTMSIC receiver. LSTMSIC, apart from its model-based counterpart, is self reliant of the channel model and can train to enforce interference cancellation in non-linear configurations with non-additive interference. We proposed two methods for training LSTMSIC: an end-to-end approach and a sequential scheme, where the latter is more suitable for

small training sets and can thus be used to quickly adapt in dynamic environments. Our numerical results demonstrate that for conventional linear channels, LSTMSIC approaches the MAP performance, outperforming previously proposed DNN-based receivers while demonstrating improved robustness to CSI uncertainty.

REFERENCES

- [1] Koc, A., & Le-ngoc, T. H. O. (2021). Full-Duplex mmWave Massive MIMO Systems : A Joint Hybrid Precoding / Combining and. 2(March).
- [2] Duy, T. T., Son, P. N., Truong, S. N., Truong, P. Q., Phan, V., & Hovan, K. (n.d.). Outage Probability of Interference Cancellation Based Two-Way Relaying Cognitive Radio Protocol with Primary MIMO Communication. 481–486.
- [3] Zhan, J., Member, G. S., Dong, X., & Member, S. (2021). Beamforming for mmWave Multi-User Massive MIMO Systems. 70(3), 2322–2336.
- [4] Huang, X., Member, S., Le, A. T., & Guo, Y. J. (2021). Transmit Beamforming for Communication and Self-Interference Cancellation in Full Duplex MIMO Systems : A Trade-Off Analysis. <https://doi.org/10.1109/TWC.2021.3053542>
- [5] Kusaladharma, S., Zhu, W., Member, S., Ajib, W., & Member, S. (2021). Achievable Rate Characterization of NOMA-Aided Cell-Free Massive MIMO With Imperfect Successive Interference Cancellation. 69(5), 3054–3066.
- [6] Righini, D., & Tonello, A. M. (2021). MIMO In-Band-Full-Duplex PLC : Design , Analysis and First Hardware Realization of the Analog Self-Interference Cancellation Stage. *IEEE Open Journal of the Communications Society*, 2(April), 1344–1357. <https://doi.org/10.1109/OJCOMS.2021.3085830>
- [7] Yu, X., Ye, J., Yan, L., Member, S., Zhou, T., & Zou, X. (2021). Photonic-Assisted Multipath Self-Interference Cancellation for Wideband MIMO Radio- over-Fiber Transmission. 8724(c), 1–8. <https://doi.org/10.1109/JLT.2021.3080833>
- [8] Mandloi, M., & Gurjar, D. S. (2021). Low-complexity interference cancellation algorithms for detection in media-based modulated uplink massive-MIMO systems. *Telecommunication Systems*, 77(1), 129–142. <https://doi.org/10.1007/s11235-020-00745-y>
- [9] Shlezinger, N., Fu, R., & Eldar, Y. C. (2020). Deep Soft Interference Cancellation for MIMO Detection. *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 8881–8885.
- [10] Wu, J., Lin, D., Li, G., Liu, Y., & Yin, Y. (2019). Distributed Link Scheduling Algorithm Based on Successive Interference Cancellation in MIMO Wireless Networks. 2019.
- [11] Askar, R., Baum, F., Keusgen, W., & Haustein, T. (2018). Decoupling-Based Self-Interference Cancellation in MIMO Full-Duplex Wireless Transceivers. *2018 IEEE International Conference on Communications Workshops (ICC Workshops)*, 1–6.
- [12] Chen, Y., & Tech, V. (2018). A General Model for DoF-based Interference Cancellation in MIMO Networks with Rank-deficient Channels. *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, 9, 900–907.
- [13] Aref, M. A., Member, S., Jayaweera, S. K., & Memeber, S. (2020). Deep Learning-aided Successive Interference Cancellation for MIMO-NOMA. 1–5.
- [14] Lee, W., Kim, M., & Song, H. (2017). Inter-Relay Interference Cancellation Using MIMO Detection. *Wireless Personal Communications*. <https://doi.org/10.1007/s11277-017-4951-3>
- [15] Ghaedi, N., Ali, M., Shirazi, M., & Ali, R. (2018). Spatial Interference Cancellation in MIMO Systems Using Side Lobe Canceller Structure.

Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 0123456789. <https://doi.org/10.1007/s40998-018-0050-z>

- [16] Cancellation, B. S., Dastjerdi, M. B., Member, S., Jain, S., & Member, S. (2019). Analysis and Design of a Full-Duplex Two-Element MIMO Circulator-Receiver With High TX Power Handling Exploiting MIMO RF and Shared-Delay. *IEEE Journal of Solid-State Circuits*, 54(12), 3525–3540. <https://doi.org/10.1109/JSSC.2019.2945303>
- [17] Tong, J., Guo, Q., Xi, J., Yu, Y., & Schreier, P. J. (2018). REGULARIZED LATTICE REDUCTION-AIDED ORDERED SUCCESSIVE INTERFERENCE CANCELLATION FOR MIMO DETECTION Jun Tong , Qinghua Guo , Jiangtao Xi , Yanguang Yu University of Wollongong SST Group University of Paderborn. 2018 IEEE Statistical Signal Processing Workshop (SSP), 2, 717–721. <https://doi.org/10.1109/SSP.2018.8450791>
- [18] Adcs, L. (2019). Energy Efficiency of Massive MIMO Systems With Interference Cancellation. 18(8), 3987–4002.
- [19] Sun, B., Zhou, Y., Yuan, J., & Shi, J. (2020). for Massive MIMO Systems with Time Shifted Pilots. XX(XX), 1–18. <https://doi.org/10.1109/TWC.2020.3006208>
- [20] Le, A. T., Tran, L. C., Member, S., Huang, X., & Member, S. (2020). Beam-Based Analog Self-Interference Cancellation in Full-Duplex MIMO Systems. XX(XX), 1–12. <https://doi.org/10.1109/TWC.2020.2965441>