The Impact of Beamforming in ISAC: A Deep Learning Approach

Helitha Nimnaka
Department of Electronic and Telecommunication Engineering
University of Moratuwa
Katubedda, Sri Lanka
nimnakakwh.20@uom.lk

Samiru Gayan
Department of Electronic and Telecommunication Engineering
University of Moratuwa
Katubedda, Sri Lanka
samirug@uom.lk

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I. Introduction

Integrated Sensing and Communication (ISAC) has emerged as a transformative paradigm in modern wireless networks, facilitating the seamless integration of sensing and communication functionalities within a shared spectrum and hardware framework. Unlike conventional frequency-division ISAC (FDSAC) techniques that allocate dedicated resources separately for sensing and communication, ISAC aims to enhance spectral and energy efficiency through advanced signal processing algorithms. The same beamforming vector is used for both communication and extracting information from targets [1].

Beamforming plays a crucial role in ISAC, significantly impacting both the communication rate (CR) and the sensing rate (SR). However, achieving an optimal trade-off between these two competing objectives presents a formidable challenge. Recent advances in Machine Learning (ML) have shown great potential in addressing complex optimization problems in wireless communications [2], [3], motivating us to compare the Deep Learning (DL)-based approach with the analytical approach to evaluate how DL can solve analytically complex problems in real time within communication systems.

II. LITERATURE REVIEW

Integrated Sensing and Communication (ISAC) has emerged as a key enabler for next-generation wireless networks, improving hardware, spectral and energy efficiency. Traditional ISAC designs rely on model-based algorithms, which can be degraded under hardware impairments. To address these limitations, deep learning-based approaches have been introduced to enhance adaptability and performance.

Mateos-Ramos et al. (2024) propose a semi-supervised learning framework for ISAC, which optimizes beamforming while mitigating hardware impairments [2]. Their method introduces an unsupervised loss function that reduces reliance on labeled data, achieving near-supervised performance with 98.8% fewer labeled samples. This demonstrates the viability of semi-supervised learning as an alternative to fully supervised techniques, significantly improving efficiency while maintaining high performance.

Qi et al. (2024) investigate ISAC in the uplink of 6G wireless networks, where both sensing echo signals and communication signals are received simultaneously at the base station [3]. To address mutual interference caused by shared spectrum and hardware resources, they formulate a non-convex optimization problem aimed at maximizing the weighted sum of normalized sensing and communication rates. Due to the computational complexity of traditional optimization techniques, they develop a deep learning-based scheme that enhances ISAC performance while reducing design complexity. Their results demonstrate the effectiveness and robustness of deep learning for real-time ISAC optimization.

These studies highlight the growing role of deep learning in ISAC, particularly in beamforming optimization, impairment mitigation, and joint sensing-communication trade-offs. However, despite the promising results of these deep learning models, a critical question remains largely unexplored: how closely do these data-driven approaches approximate analytical solutions in real-world ISAC scenarios? In this paper, we aim to bridge this gap by evaluating how well our proposed DNN model aligns with analytically optimal solutions. By comparing the results of deep learning-based beamforming with traditional optimization techniques, we provide valuable insights into the practical reliability, efficiency, and trade-offs of data-driven ISAC solutions.

III. Methodology

We use the system setup from [4], where a dual functional radar communication (DFRC) base station (BS) serves a single antenna communication user (CU) while simultaneously sensing a single target. The BS is configured with M transmit antennas and N receive antennas. Within this ISAC framework,

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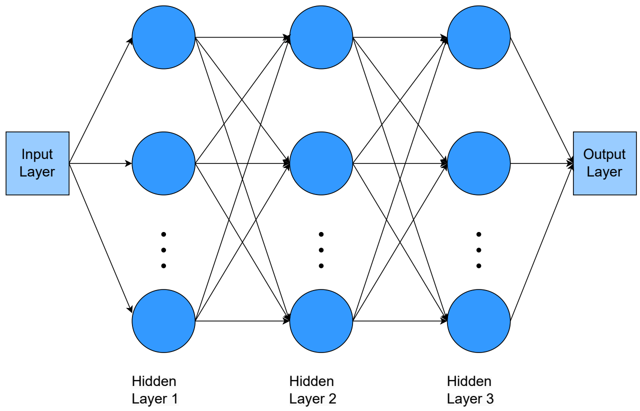

Fig. 1. The architecture of the deep learning model.

we analyze its sensing and communication (S&C) performance based on the communication rate (R_c) and the sensing rate (R_s). Both rates depend on the beamforming vector $\mathbf{w}$, making it challenging to optimize them simultaneously.

$$\mathcal{L} = -\left((1-\alpha)\cdot R_c + \alpha \cdot R_s\right) \quad (1)$$

To address this challenge, we propose a deep neural network (DNN) model, as shown in Figure 1. The DNN is trained using backpropagation to optimize the beamforming vector $\mathbf{w}$, balancing the communication rate R_c and sensing rate R_s. The proposed DNN architecture consists of fully connected layers with ReLU activation functions. We use the Adam optimizer and tune hyperparameters via cross-validation to ensure model convergence and stability. For training, we randomly generate Rayleigh fading channel data and adopt an **unsupervised learning approach**. The objective function used is defined in Equation 1. The parameter α, which balances communication and sensing performance, is treated as a hyperparameter. The model continuously refines the beamforming vector $\mathbf{w}$ without explicit knowledge of the optimal solution. To evaluate the effectiveness of our approach, we compare the DNN's performance against the analytical solution provided in [4].

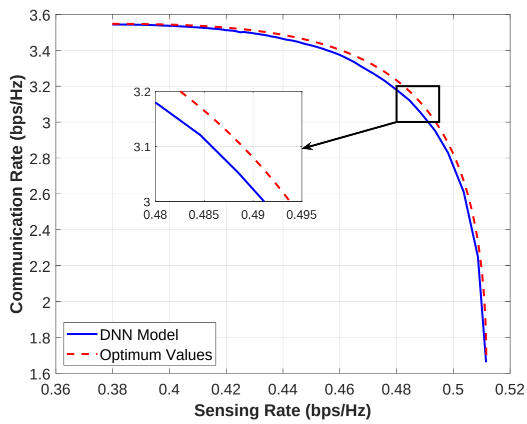

Fig. 2. Pareto Boundary Comparison.

IV. Results and Discussion

We experiment with the results of the DNN model and observe how maximizing one rate affects the reduction of the other rate. Rate tuples on this boundary can be obtained using the rate profile-based method [5] [6].

Figure 2 illustrates that the Pareto boundary obtained using the DNN model is closely aligned with the results derived from the optimum values [4]. We tested different random seed values and variations of the channel to ensure the reliability of the Pareto boundary results. These results show that the unsupervised learning approach can be extended to solve complex optimization problems without knowing the optimum solution. It can be extended to beamforming in **real time applications**, leading to higher performance in telecommunication systems.

V. Conclusion

This paper investigates the role of beamforming in ISAC and proposes a deep learning-based approach to optimize beamforming vectors, balancing both communication and sensing performance. The DNN model effectively learns an adaptive strategy using unsupervised learning to optimize the communication rate (CR) and sensing rate (SR). Experimental results confirm that the model closely approximates the Pareto-optimal boundary and demonstrates robustness under varying channel conditions. These findings highlight the potential of deep learning for real-time beamforming optimization in ISAC systems and show that deep models can closely approximate analytical solutions. Notably, this approach demonstrates the practical advantage of using a pre-trained model to predict beamforming solutions, enabling faster, scalable deployment and eliminating the need for costly real-time optimization. Future work will explore integrating reinforcement learning to support real-time adaptation to dynamic channel environments.

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