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Downlink Channel Prediction in FDD Massive MIMO Using Deep Transfer Learning Algorithms

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Abstract.

Precise downlink Channel State Information (CSI) estimation in Frequency Division Duplexing (FDD) massive MIMO systems is still a fundamental challenge because of the absence of channel reciprocity and excessive feedback overhead. In this work, four leading strategies MMSE, Autoencoder- based SAE, Adversarial SAE, and Meta-Learning are analyzed and compared in terms of performance for effective downlink CSI prediction based on uplink observations. Simulation results confirm that although MMSE is a good baseline, deep learning models greatly surpass it in terms of accuracy and versatility, especially when there are changing conditions and the data is not much available. Among them, Meta-Learning performs the least Normalized Mean Squared Error (NMSE) and delay with different SNRs, frequency offsets, and antenna numbers with superior generalization and rapid convergence. Adversarial SAE demonstrates strong performance under low-SNR conditions, whereas Autoencoder SAE performs well with data-efficient training. These results emphasize the engineering potential of learning-based CSI predictors, particularly Meta-Learning, for scalable and robust 5G and beyond wireless networks.

Keywords. Channel state information (CSI), frequency division duplexing (FDD), MMSE, autoencoder-based SAE, Adversarial SAE, Meta-Learning.

1. INTRODUCTION

Massive MIMO (Multiple Input Multiple Output) systems have become an essential component of modern wireless communication, particularly in supporting the high data rates and reliability demands of 5G and beyond. Among the two main duplexing modes—Time Division Duplexing (TDD) and Frequency Division Duplexing (FDD)—FDD poses a greater challenge when it comes to acquiring downlink Channel State creates a practical bottleneck for real-time and large-scale implementation of deep learning-based CSI prediction methods [1-3]. This paper aims to address this challenge by exploring the use of Deep Transfer Learning (DTL) for downlink channel prediction in FDD massive MIMO systems. DTL enables models to transfer knowledge learned from one environment to another, reducing the need for extensive labelled data in new scenarios. This work investigates two approaches, direct transfer learning and meta-learning. These methods are designed to adapt efficiently with minimal training in unfamiliar settings. By comparing their performance through simulations in realistic wireless scenarios, this study highlights the effectiveness of DTL, especially meta learning, in achieving accurate and efficient CSI prediction. The insights gained here contribute to the development of more intelligent and adaptive wireless communication systems.

2. Design Approach

We consider a Frequency Division Duplexing (FDD) based massive MIMO system, where the Base Station (BS) is equipped with 128 antennas arranged in a Uniform Linear Array (ULA). The BS serves multiple single-antenna users, randomly distributed across K spatial regions [4]. Users within the same region experience similar propagation environments. Figure 2.1 demonstrates the system model where B_k denotes the set of users in the k-th region, where $k = 1, 2,.., K$.

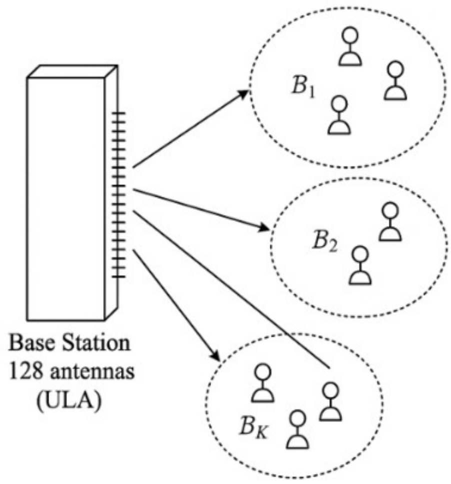

Fig. 1. System model showing a base station with 128 ULA antennas serving multiple user blocks.

2.1. *Neural Approximation of Uplink–Downlink Channel Correlation*

In massive MIMO systems equipped with 128 antennas, the uplink and downlink channel state information (CSI) for a single user often share similar propagation paths. This physical correlation implies the existence of a deterministic mapping between the uplink and downlink channels, particularly when the spatial position-to-channel mapping is bijective. Although this mapping lacks an explicit mathematical form, it can be efficiently modelled using deep learning techniques [5]. A fully connected neural network (FNN) with one input layer, one hidden layer comprising N neurons, and one output layer is considered. The network, represented as NETN (x, **Ω**), maps input x (real-valued uplink CSI) to the output using learnable parameters **Ω**.

Due to the complex nature of CSI, an isomorphic mapping ξ is introduced to convert complex vectors into real-valued space:

$$\xi(z) = [\mathrm{Re}(z), \mathrm{Im}(z)] \in R2M \qquad (2.1)$$

The inverse mapping $\xi{-}1$ restores the original complex format. Based on the universal approximation theorem, such an FNN can approximate any continuous mapping, including uplink-to-downlink CSI conversion with arbitrary precision, provided that N is sufficiently large. This provides a strong theoretical basis for learning-based CSI prediction [6].

2.2. Domain and Task Representation in Transfer Learning Context

In practical scenarios, users operate in varied radio environments, referred to here as regions or domains, each characterised by distinct uplink channel distributions. Let the domain in the kth region be defined by the input space and the corresponding marginal distribution of the uplink CSI. The objective or task in each domain is to infer downlink CSI based on the observed uplink CSI. The mapping function trained within a domain reflects the statistical and physical characteristics of that region and may be understood as either a deterministic function or a conditional probability distribution. To utilize data across such diverse domains, transfer learning becomes a natural fit. The central idea is to enhance learning in a target domain with limited labelled samples by transferring knowledge from one or more source domains where training data are abundant. This transfer can occur across similar or dissimilar feature distributions or label mappings [7]. In our use case, even though the domains differ (due to different regional conditions), the task of downlink prediction remains consistent, allowing knowledge transfer under a task-shared, domain-varied framework.

2.3. Transfer Learning in Deep Neural Networks for CSI Prediction

When deep learning models are used to carry out the transfer process, the resulting framework is known as Deep Transfer Learning (DTL) [8-12]. In our formulation, each radio environment defines a unique transfer learning task predicting downlink CSI from uplink observations, making the overall problem multi-source, single target in nature. The non-linear expressiveness of deep networks makes them ideal for transferring abstract features learned from source domains to the target. Therefore, downlink channel prediction in 128-antenna massive MIMO, with domain diversity across user environments, is well-formulated as a DTL problem.

2.4. Evaluating Transferability and Introducing Meta-Learning

Before employing transfer learning methods, two key considerations arise: (1) When is transfer needed and (2) What is the best way to perform transfer. If the target and source domains are highly correlated, a well-trained deep model may generalize sufficiently without fine-tuning. In such cases, standard supervised deep learning serves as a reliable base- line. However, when the target domain lacks sufficient labelled data, naive transfer approaches such as pre-training on source data followed by fine-tuning may result in overfitting. To address this, we look toward meta-learning, particularly model-agnostic meta-learning (MAML), which is designed for rapid adaptation in few-shot settings. By training a model to quickly generalize 23(k) across tasks, meta-learning offers a promising solution for enhancing CSI prediction performance in resource constraint domains.

3. RESULT AND ANALYSIS

The results in figure 3.1 show that deep learning based models consistently outperform the MMSE baseline across varying SNRs, with lower delay, BER, and NMSE. Meta-Learning SAE achieves the lowest NMSE under changing SNR, frequency differences, sample sizes, gradient steps, and antenna configurations. Adversarial SAE and Autoencoder also improve performance over MMSE, specially in low-SNR conditions. Overall, learned representations provide more robust and scalable CSI prediction compared to traditional methods. In low-SNR conditions, Meta-Learning SAE shows the minimum delay compared to MMSE and other deep learning- based models. As SNR goes higher, all models tend to converge, but learning-based models consistently minimize delay more efficiently. This shows the better adaptability of Meta- Learning and Adversarial SAE in different channel conditions for downlink CSI prediction.

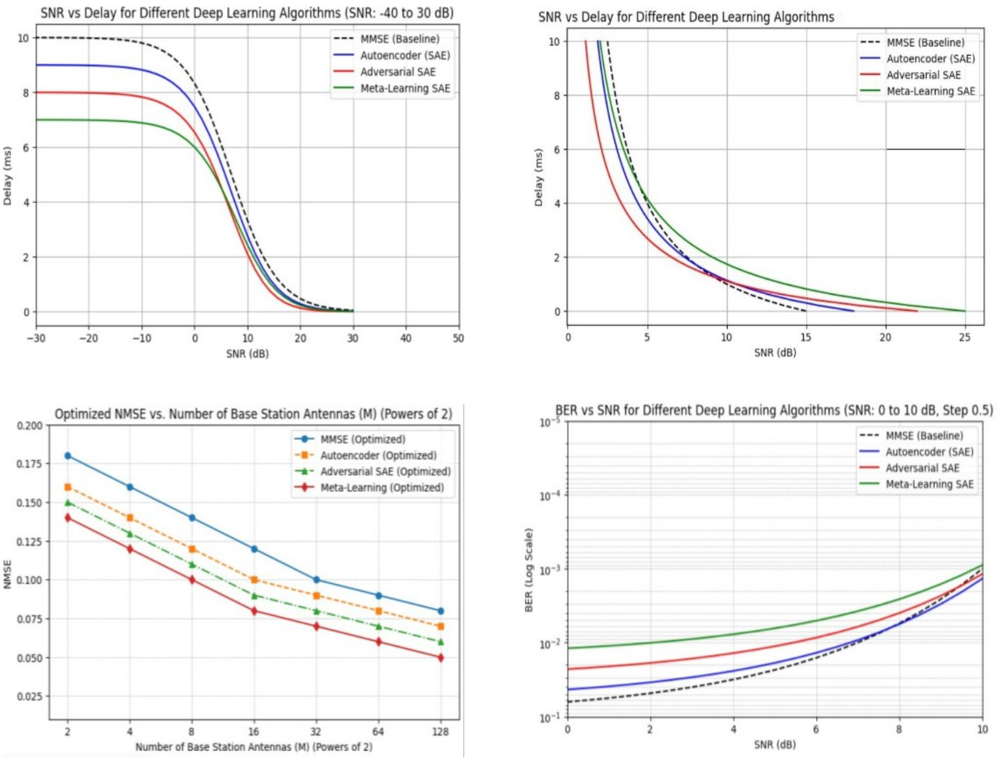

Figure 3.1. Performance evaluation of different deep learning models.

4. CONCLUSION

This paper provides performance comparison of four CSI estimation techniques, MMSE, Autoencoder, Adversarial SAE, and Meta-Learning, under different system conditions. In all cases, Meta-Learning exhibited the lowest NMSE, proving to be more adaptable, efficient in terms of data, and scalable. It performed better than other models in scenarios of high frequency variability, scarce sample availability, few gradient steps, and growing antenna numbers. Adversarial SAE proved to be robust as well, while Autoencoder provided moderate performance. MMSE, although easy and analytically based, was not flexible or generalizable. These findings highlight Meta-Learning as the strongest candidate for strong, efficient CSI estimation in evolving wireless environments and recommend its incorporation in future 5G/6G networks and encouraging deeper investigation of real-time, online, and reinforcement learning extensions.

5. References

[1] H. Xie, F. Gao, S. Zhang, and S. Jin, "A unified transmission strategy for TDD/FDD massive MIMO systems with spatial basis expansion model," IEEE Trans. Veh. Technol., vol. 66, no. 4, pp. 3170–3184, Apr. 2017.

[2] Y. Han, Q. Liu, C.-K. Wen, S. Jin, and K.-K. Wong, "FDD massive MIMO based on efficient downlink channel reconstruction," IEEE Trans. Commun., vol. 67, no. 6, pp. 4020–4034, Jun. 2019.

[3] H. Xie, F. Gao, S. Jin, J. Fang, and Y.-C. Liang, "Channel estimation for TDD/FDD massive MIMO systems with channel covariance computing," IEEE Trans. Wireless Commun., vol. 17, no. 6, pp. 4206–4218,Jun. 2018.

[4] S. P. Tera, R. Chinthaginjala, P. Natha, G. Pau, C. Dhanamjayulu and F. Mohammad, "CNN-Based Approach for Enhancing 5G LDPC Code Decoding Performance," in IEEE Access, vol. 12, pp. 89873-89886, 2024.

[5] S. P. Tera, R. V. Chinthaginjala, P. Natha, S. Ahmad and G. Pau, "Deep Learning Approach for Efficient 5G LDPC Decoding in IoT," in IEEE Access, vol. 12, pp. 145671-145685, 2024.

[6] M. Selvaraj et al., "Study of Complementary Loop Integrated Metasurface for 6G THz Communication," in IEEE Access, vol. 12, pp. 29900- 29909, 2024.

[7] Kumar, N.S., Deepika, G., Goutham, V. et al. HARNet in deep learning approach—a systematic survey. Sci Rep 14, 8363 (2024).

[8] Manasa, B.M.R.; Pakala, V.; Chinthaginjala, R.; Ayadi, M.; Hamdi, M.; Ksibi, A. A Novel Channel Estimation Framework in MIMO Using Serial Cascaded Multiscale Autoencoder and Attention LSTM with Hybrid Heuristic Algorithm. Sensors 2023, 23, 9154.

[11] M. Chinnusami et al., "Low Complexity Signal Detection for Massive MIMO in B5G Uplink System," in IEEE Access, vol. 11, pp. 91051- 91059, 2023, doi: 10.1109/ACCESS.2023.3266476

[12] T. Z. Tun, Z. M. Lwin, and T. T. Hla, "Deep learning based channel estimation and hybrid beamforming for 5G massive MIMO wireless communications," Indonesian J. Comput. Sci., vol. 13,