Machine learning-enabled joint antenna selection and precoding

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ABSTRACT

Joint antenna selection (AS) and precoding design is essential for improving spectral efficiency and energy efficiency in multi-antenna wireless communication systems. However, conventional optimization-based solutions rely on exhaustive search and iterative processing, leading to high computational complexity that limits real-time applicability. This work proposes a machine learning-enabled framework that shifts the computational burden from online operation to offline training. Optimal AS and precoding decisions are first generated offline using model-based optimization under diverse channel conditions. A supervised machine learning model is then trained to learn the relationship between channel state information (CSI) and optimal transmission configurations. During online operation, the trained model enables fast and efficient AS with significantly reduced processing time. Numerical results demonstrate that the proposed approach achieves near-optimal system performance while substantially lowering computational complexity, making it well suited for real-time and next-generation wireless communication systems.

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1. INTRODUCTION

Multiple-input multiple-output (MIMO) is an essential technology that meets the rapidly increasing demand for data-intensive applications in both present and future mobile networks. A MIMO base station (BS) employs a significant number of antennas to simultaneously transmit multiple information streams to different users, all while ensuring minimal interference between users. The advantages of MIMO systems, when implemented with suitable beamforming techniques, encompass improved spectral efficiency and increased energy efficiency [1]. With the substantial increase in the number of antennas in MIMO systems, the implementation of antenna selection (AS) can improve performance in terms of both hardware costs and technological factors [2]. This happens due to the fact that the radio frequency (RF) chains generally involve much greater expenses in comparison to antenna elements. An effective AS strategy can notably achieve complete spatial diversity while significantly lowering the energy consumption of RF chains, thus improving the overall energy efficiency of the system [3]. AS is categorized as a nondeterministic polynomial (NP)-hard problem, and the sole method to guarantee an optimal solution is via exhaustive search, which entails evaluating all potential combinations of antennas. The significant complexity of AS may limit its practical use, especially in 5G services that usually require stringent latency and real-time decision-making abilities [4]. Effective solutions are crucial for making AS practically attainable, especially for BSs that are outfitted with a medium to large array of antennas. An algorithm utilizing block diagonalization is presented in [5] for multiuser MIMO systems, concentrating on the selection of optimal antennas to either minimize the symbol error rate (SER) upper bound or improve the minimum capacity. This method methodically eliminates one antenna at a time, concentrating on the one that has the greatest impact on energy consumption within the pertinent orthogonal beamformers. Wang *et al.* [6] introduce a collaborative method for beamforming design and an AS algorithm focused on minimizing transmit power for multicasting. Employing group sparsity-promoting $1_{1,2}$ norms instead of the 1_0 norm facilitates the extraction of specific antennas and beamformers via an iterative algorithm. The application of $1_{1,2}$ norms is employed in massive MIMO to minimize transmit power [7] and in cell-free MIMO downlink setups for the combined selection of access points and power allocation [8]. An AS algorithm employing mirror-prox successive convex approximation (SCA) is presented in [9] aimed at maximizing the minimum rate in multiple-input single-output (MISO) broadcasting systems. A similar methodology grounded in SCA is proposed in [10], [11] to enhance energy efficiency.

Recently, the use of machine learning in communication systems has attracted considerable attention [12]–[14]. The main advantage of employing machine learning in communications lies in its capacity to discern relationships between system parameters and desired outcomes, facilitating the shift of computational requirements from real-time processing to the offline training phase. Xia *et al.* [15] present a beamforming neural network (BNN) designed to minimize transmit power in multiuser MISO systems. This method employs convolutional neural networks (CNN) in conjunction with a supervised-learning technique to predict both the magnitude and direction of the beamforming vectors. This method is elaborated upon in references [16]–[18] for unsupervised learning aimed at optimizing the weighted sum-rate of the system. A transmission strategy enhanced by deep learning is introduced for a single-user MIMO system with constrained feedback, focusing on pilot-aided training and the selection of channel codes. Lin and Zhu [19] introduce a deep learning approach to beamforming design that focusses on maximizing the spectral efficiency of a single-user millimeter wave (mmWave) MISO system, showing enhanced spectral efficiency in comparison to conventional hybrid beamforming designs. The application of Q-learning is elaborated in [20] to tackle the combinatorial complexity associated with choosing the optimal channel impulse response for vehicle to infrastructure communications. A similar approach utilizing Q-learning is introduced in [21] to tackle the integrated design of beamforming, power control, and interference coordination within cellular networks. Mismar *et al.* [22] introduce a deep reinforcement learning framework aimed at autonomously optimizing broadcast beams in MIMO broadcast systems, leveraging measurements from users. A commonly utilized data set for training mmWave MIMO networks is detailed in [23]–[25], considering various performance metrics. The incorporation of machine learning into the design of the physical layer offers a compelling strategy to tackle the challenges linked to adaptive systems. A collaborative design for AS and hybrid beamformers for single-user mmWave MIMO is presented in [26], employing two sequential CNNs. One CNN is focused on predicting the chosen antennas, whereas the other CNN is aimed at estimating the hybrid beamformers. Jadhav and Kumaravelu [27] propose a multi-class classification approach to tackle the AS problem in single-user MIMO systems, employing two classification methods: multiclass k-nearest neighbors and support vector machine (SVM). A neural network (NN)-based method is presented in [28] to reduce the computational complexity of AS for broadcasting. The NN is employed to directly predict the selected antennas that enhance the minimum signal to noise ratio among the users. Khurana [29] present a learning-based method for selecting transmit antennas designed to improve security in the wiretap channel. This study explores two learning-based methodologies, namely SVM and naïve Bayes schemes. The potential to improve secrecy performance while reducing feedback overhead is clear; however, the configuration analyzed in [29] is limited to a single AS.

2. METHOD

This section presents a novel approach that leverages recent advancements in machine learning to address the significant high-complexity challenge associated with the selection process. A learning-based AS and precoding design (L-ASPD) algorithm was proposed to enhance efficiency. The proposed L-ASPD algorithm is designed to utilize machine learning predictions to assist the optimal algorithm in addressing the most challenging and time-intensive aspects of the optimization process. A deep neural network (DNN) is employed as the learning model in order to develop latent relationships between the system parameters (inputs) and the antenna subset that has been chosen. There are three primary components that make up the DNN, which are as follows: one input layer, one output layer, and hidden layers, as shown in Figure 1. The learning parameters, such as the cost function, are optimized by the DNN based on the labeled data in order to reduce the amount of error that is associated with the prediction. There are three stages involved in the implementation of the L-ASPD algorithm: i) offline training data creation, ii) creating the learning model, and iii) real-time prediction are the stages.

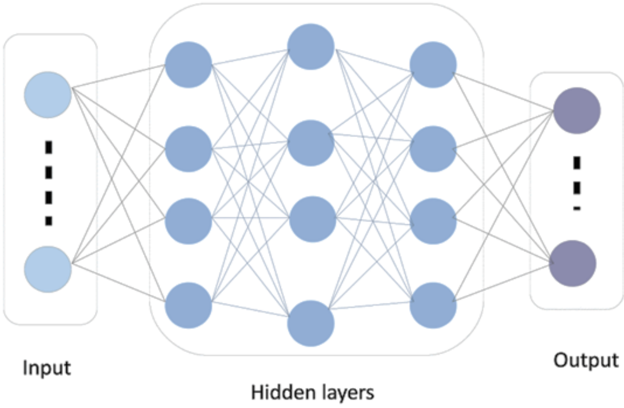

Figure 1. DNN with three hidden layers

3. RESULTS AND DISCUSSION

This section evaluates the effectiveness of the proposed algorithms through numerical results. The distribution of users is uniform across a distance spanning from 50 to 300 meters from the BS. The WINNER II line-of-sight pathloss model is employed, resulting in a pathloss that ranges uniformly from -59.4 dB to -74.6 dB. Every wireless channel undergoes Rayleigh fading. The bandwidth of the channel is 1 MHz, with a noise spectral density of -140 dBm/Hz. The long-term evolution (LTE) requirements are employed, indicating that one code unit (c.u.) lasts for one symbol, which corresponds to 66.7 μs, while a block duration comprises 200 c.u. The BS is anticipated to utilize 0.2 computational units for the resolution of a single convex optimization problem. As a result, implementing the proposed L-ASPD method necessitates 0.2 kilo-symbols (KS) c.u., with KS representing the expected number of subsets. A DNN featuring two hidden layers is employed to train the learning model for the L-ASPD algorithm, with each layer comprising 100 nodes. SVM offer a quick training phase; however, their performance tends to be inferior when compared to DNN. This occurs because SVM creates hyperplanes to distinguish data, whereas DNN utilizes more intricate functions to achieve the same goal. The DNN undergoes training utilizing the scaled conjugate gradient method.

The outcomes are based on 200 random realizations of channel fading coefficients and user positions. For each instance, algorithms are implemented until convergence is reached. Figure 2 depicts the total rate attained by the two proposed algorithms as a function of the iteration count. Both algorithms demonstrate swift convergence, accomplishing this in under 10 iterations, thus highlighting the effectiveness of the suggested iterative methods. Figure 3 illustrates the relationship between sum-rate and simulation time, providing valuable insights into the computational performance of the developed algorithms.

Figure 4 demonstrates the performance-complexity tradeoff of the proposed L-ASPD algorithm, employing M =4 RF chains and a total of N =8 antennas. The L-ASPD algorithm achieves over 96% of the optimal sum rate obtained via exhaustive search, all while decreasing complexity by more than 95%. The L-ASPD algorithm achieves 86% optimal performance while consuming merely 2% of the computational time, thus confirming its efficacy. The L-ASPD algorithm demonstrates a reduction of more than 13% in computational time when compared to the heuristic solution, all while upholding a target performance gain of 95%. Figure 5 demonstrates the comparative effectiveness of the L-ASPD algorithm in real-time prediction based on the quantity of training samples utilized. The relative performance is expressed as the ratio of the sum rate achieved by the L-ASPD algorithm compared to that obtained by the joint AS and precoding design (JASPD) algorithm. Every training sample is produced randomly, capturing the diversity in both channel small-scale fading and user positioning. Typically, augmenting the number of training samples improves prediction accuracy, as the L-ASPD algorithm gains a more profound comprehension of the inherent relationship between the chosen antennas and the input features. The L-ASPD algorithm shows that 200,000 training samples are sufficient to achieve more than 94% of optimal performance.

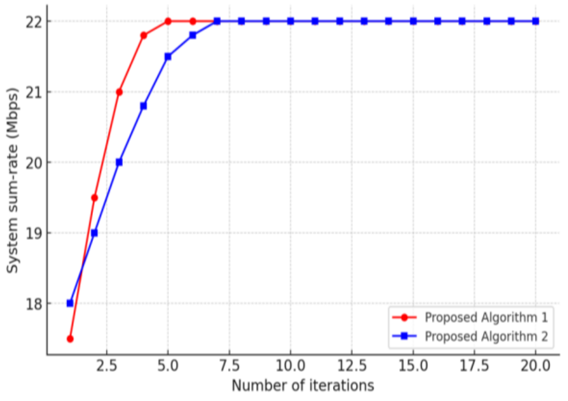

Figure 2. Performance comparison of the proposed algorithm

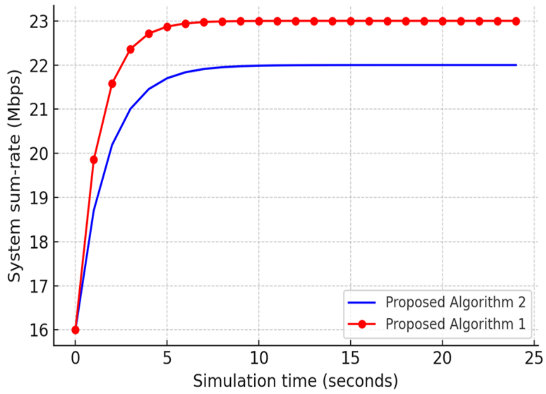

Figure 3. Performance comparison of the proposed algorithm, both algorithms converge in less than 10 iterations

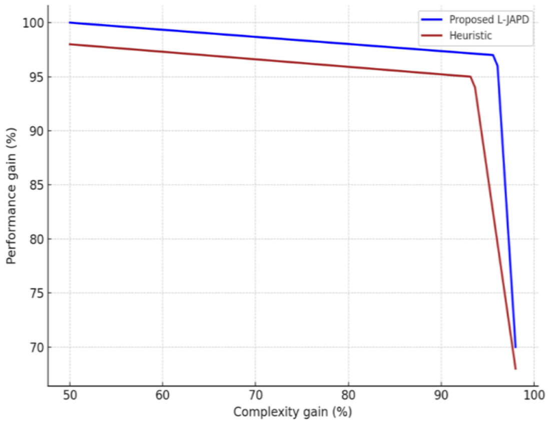

Figure 4. The offered L-ASPD's performance-complexity tradeoff

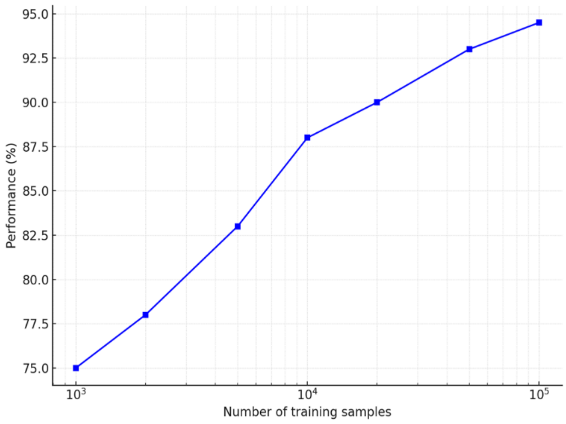

Figure 5. Learning performance as a function of training sample size

Figure 6 demonstrates the achievable sum rate in relation to KS, emphasizing the most promising subsets identified through the proposed L-ASPD algorithm. To illustrate the benefits of the proposed beamforming design, a curve that employs zero-forcing based power control on the antenna subsets identified by the algorithm was presented. The curve is labelled as proposed-zero forcing in the figures. The L-ASPD algorithm shows enhanced performance relative to all other schemes across the various KS values examined.

Figure 7 presents the effective sum rate associated with different total antenna counts, N. To guarantee a fair evaluation, the total transmit power is set at 30 dBm, taking into account the entire overhead related to channel estimation and computation. In the former scenario, obtaining the channel state information (CSI) demands 8 c.u. with a total of 6, 7, or 8 antennas, while it requires 12 c.u. when the antenna count increases to 9 or 10. Upon analysis, it becomes clear that the L-ASPD algorithm limits its search to the 10 most promising candidates, while the JASPD algorithm assesses all (NM) antenna subsets. The findings indicate that a higher number of antennas results in a better effective sum rate across all schemes, thus confirming the benefits of AS. The proposed L-ASPD algorithm exhibits exceptional performance, especially for large N, challenging the traditional notion that exhaustive search methods provide the optimal outcomes. The comparison takes into account the computation time, as illustrated. The comprehensive search approach thus dedicates considerable time to pinpointing the best subset, particularly when N is substantial, resulting in reduced effective rates. When N equals 10, the exhaustive search method requires a computation time that is 21 times more than that of the L-ASPD algorithm.

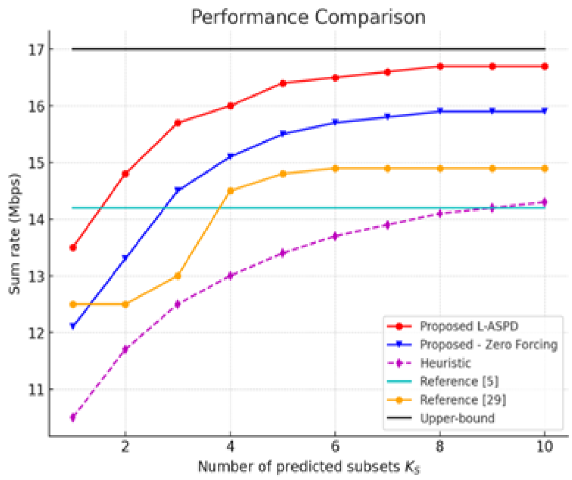

Figure 6. The relationship between the number of anticipated subgroups and the sum rate performance of the methods that were proposed

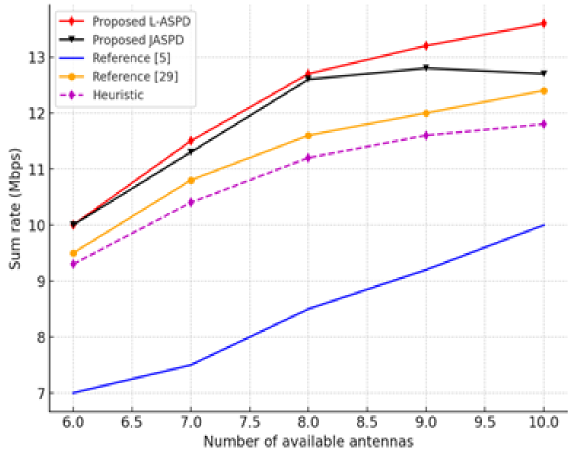

Figure 7. Comparison of effective sum rates for different total antenna numbers

The obtained experimental results are consistent with and well supported by existing studies on joint AS and precoding in multi-antenna wireless systems. Prior optimization-based works have demonstrated that jointly selecting antennas and designing precoders significantly improves spectral efficiency compared to separate or heuristic designs, but at the cost of prohibitive computational complexity that limits real-time applicability. Recent machine learning-assisted approaches reported in the literature show that learning-based models can effectively approximate optimal AS decisions by capturing the underlying relationship between channel conditions and transmission strategies. In line with these findings, the proposed method achieves performance close to optimal benchmark solutions while drastically reducing execution time. Similar trends have been observed in learning-assisted beamforming and AS studies, where offline training enables fast online inference without noticeable performance degradation. Therefore, the results presented in this work not only validate the effectiveness of the proposed approach but also reinforce the growing consensus that machine learning provides a practical and scalable alternative to exhaustive optimization for next-generation wireless communication systems.

4. CONCLUSION

This study examines the integrated design of AS and precoding vectors in multi-user, multi-antenna systems to optimize spatial diversity utilization. A (near) optimal joint AS and precoding algorithm is initially introduced to maximizing the system sum rate, while adhering to users' quality of service (QoS) requirements and constraints on transmit power. The proposed joint design optimizes the precoding vectors through two iterative optimization algorithms, utilizing semidefinite relaxation and SCA methods. To enhance optimization efficiency, a machine learning-based solution is developed for timely and accurate antenna predictions. The proposed learning-based algorithm demonstrates robustness concerning user quantity and distribution, BS transmit power, and channel fading effects. Simulation results demonstrate that the proposed learning-based solution significantly surpasses current selection schemes and the exhaustive search-based solution. This work suggests several potential research directions. Improving the efficiency of the training phase presents a significant challenge, particularly when dealing with a large number of available antennas. A low-complexity precoding design, such as zero-forcing, can be employed to efficiently acquire adequate training samples. The second issue pertains to managing network dynamics, necessitating the learning model to be frequently and promptly adapted. Transfer learning and reinforcement learning present effective approaches to circumvent the necessity of retraining the entire network.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding the publication of this paper.

ETHICAL APPROVAL

This research does not involve any studies with human participants or animals performed by any of the authors.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [LDR], upon reasonable request.

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