FOREX Publication
Open Access | Rapid and quality publishing
International Journal of Electrical and Electronics Research (IJEER)
Review Article | Volume 13, Issue 3 | Pages 515-523 | e-ISSN: 2347-470X

Optimizing Beamforming in Massive MIMO Systems Using Machine Learning Approaches: A Comprehensive Review

Suhas Kakde[1*], Dr. Sanjay Pokle[2]

[1]*Research Scholar, Electronics Engineering, School of Electrical and Electronics Engineering, Ramdeobaba University, Nagpur, Maharashtra, India; Email: suhas.kakde@gmail.com*

[2]*Professor, Electronics & Communication Engineering Department, School of Electrical and Electronics Engineering, Ramdeobaba University, Nagpur, Maharashtra, India; Email: poklesb@rknec.edu*

***Correspondence:** *suhas.kakde@gmail.com*;

ABSTRACT- The development of the Massive Multiple-Input Multiple Output (MIMO) system in recent years has revolutionized wireless communication, delivering significant benefits to energy and spectrum efficiency. While these strategies have been instrumental in the continuous evolution of system performance, traditional static beamforming methods (*e.g.* Zero-Forcing (ZF), Maximum Ratio Transmission (MRT) and Minimum Mean Square Error (MMSE)) are limited concerning their scalability and reliability on channel state information to a large extent. In this paper, we investigate the techniques of beamforming with machine learning (ML) integration to bypass these limitations and better optimize system performance. This review covers the usage of different approaches to Machine Learning: supervised learning methods (including Neural Networks and Support Vector Machines (SVM). We also study reinforcement learning techniques due to their dynamic optimization features, as well as deep-learning models like Recurrent and Convolutional Neural Networks (RNN/CNN), which are popular for treating big data or temporal dynamics. Our analysis shows several key findings: ML-based methods are effective in improving the performance of beamforming, including enhancing spectral efficiency and reducing energy consumption as well as their robustness with respect to channel state information (CSI) errors. Finally, we conclude by identifying how potential emerging trends such as federated learning and quantum computing can be positioned to overcome these challenges in the future direction of ML-optimized beamforming for massive MIMO systems.

Keywords: Beamforming, Convolutional Neural Networks (CNN), Deep Learning (DL), Machine Learning (ML), Massive MIMO, Reinforcement Learning.

ARTICLE INFORMATION

Author(s): Suhas Kakde, and Dr. Sanjay Pokle;

Received: 20/11/2025; **Accepted:** 07/08/2025; **Published:** 30/09/2025;

E- ISSN: 2347-470X;

Paper Id: IJEER 2005-17;

Citation: 10.37391/ijeer.130316

Webpage-link:

https://ijeer.forexjournal.co.in/archive/volume-13/ijeer-130316.html

Publisher's Note: FOREX Publication stays neutral with regard to jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

Massive Multiple-Input Multiple-Output (MIMO) technique facilitates wireless communication, giving massive capacity, energy, and spectrum efficiency considerations. Massive MIMO systems offer increased speed of data transfer and communication reliability for simultaneously serving many users at the base station with huge antenna arrays, thereby helping in 5G and beyond. The primary idea behind massive MIMO is beamforming where the transmission of signals is steered toward individual users by emphasizing signals for the desired user and de-emphasizing it with respect to undesired users [1].

In magnifying the benefits of beamforming in massive MIMO systems stand the accompanying challenges. Ascending the heights of their maximum efficiency level become sorely difficult for conventional beamforming methods, such as Maximum Ratio Transmission (MRT), Zero-Forcing (ZF), and Minimum Mean Square Error (MMSE), as the number of antennas and users rises. Other bottle-necking issues include interference within highly dynamic situations, pilot contamination, hardware complexity, and channel estimate errors, thus limiting the potential sum capacity of such systems [2].

ML can therefore be deemed an important stakeholder in helping beamforming in massive MIMO systems. Using data-driven means, machine learning can bring about dynamic changes in beamforming strategies based on real-time data, thereby improving system performance when taken as a whole. Understanding and assessing how machine learning can be used to tackle these problems and offer better beamforming solutions is the primary aim of our review [6].

1.1. Challenges with Traditional Beamforming Techniques

Traditional beamforming techniques in wireless communication networks pose numerous limitations, especially for massive MIMO systems. As the number of antennas grows, the beamforming optimization becomes exponentially more difficult, thus computation is regarded as one of the foremost challenges. *Figure 1* describes the tradition MIMO beamforming technique.

Figure 1. Traditional MIMO Beamforming Technique Overview

In general, such algorithms involve complicated matrix operations and optimization problems that are hard to perform in real-time, especially when the system is large-scale [3]. Channel estimation errors pose otherwise another severe problem. Precise channel information is a big concern in designing beamforming mechanisms, but various factors, such as noise, interference, and limited resources for pilot selection, make it hard to get an accurate channel parameter in massive MIMO systems. In fact, pilot contamination has become a menace, whereby the same pilot sequences get reused in neighboring cells, thereby contaminating the channel estimation. On top of this, interference suppression remains an ever-present challenge. Zero-Forcing (ZF) and other variants attempt to block interference, whereas they carry complexity and performance penalties when engineering and appraising downlink transmission under varying circumstances. These limitations directly show that machine learning methods are well suited to address these problems and hence demand novel approaches that can adapt to complex, evolving scenarios in real-time [4].

1.2. Machine Learning as a Solution for Beamforming Optimization

In terms of efficiency and flexibility, machine learning outperforms classical beamforming approaches in a variety of ways. Machine learning algorithms may learn directly from data, allowing them to make more accurate predictions and judgments in dynamic settings than older approaches based on preconceived models and assumptions. This is especially useful in wireless networks because channel statuses and other parameters might vary fast [5].

Our review discusses the benefits of utilizing machine learning to optimize beamforming in large MIMO systems. One key advantage is data-driven flexibility. Machine learning models, particularly those that employ real-time data, excel at adapting to dynamic network situations including changing channel statuses and user mobility. This adaptability contrasts dramatically with standard beamforming systems, which frequently use static models that struggle to reflect the intricacies of real-world settings. Another advantage is the efficiency of handling high-dimensional data. Massive MIMO systems create a lot of data, especially high-dimensional channel matrices [6]. This complexity may be efficiently controlled utilizing machine learning methodologies, particularly deep learning models such as Convolutional Neural Networks (CNNs). They uncover significant patterns from large datasets, improving beamforming performance. Additionally, machine learning models provide real-time decision-making capabilities. After training, these models may deliver near-instantaneous judgments, significantly decreasing processing needs over traditional techniques. This ability is especially important for enormous MIMO systems, where real-time optimization is required to maintain high-quality communication lines.

1.3.Machine Learning Paradigms for Beamforming

Several different paradigms are considered in part of the problem for beamforming enhancement. Supervised learning methods learn a prediction model for optimal beamforming vectors based on labeled data. From the extended use of the model past episode CSI, the model improves in accuracy. In this method, the learnt patterns in historical data will be leveraged to further improve beamforming performance using methods like Neural Networks (NNs) and Support Vector Machines (SVMs) [7].

Unsupervised learning, in contrast, groups users extracted from channel characteristics via clustering techniques. This grouping enables spatial allocation to be performed efficiently. Instead of relying upon labels associated with the input like in supervised learning, unsupervised learning tries to reveal hidden patterns that could assist beamforming process on the basis of how data are inherently linked and clustered.

When it comes to dynamic settings, reinforcement learning is very effective. Through trial and error and continuous adjustments in response to a changing environment, RL models develop the greatest beamforming solutions. This reason is why RL approaches will remain pertinent in situations where conditions continually change, as these could be used to enhance beamforming algorithms with no need for pre-labeled training data [8].

Deep learning techniques such as recurrent neural networks and convolutional neural networks are tools that can be harnessed for beamforming in massive MIMO systems. Analyzing spatial features between different TX-RX pairs, CNNs allow better beamforming by extracting relevant spatial features from high-dimensional data. In comparison, RNNs capture temporal dependencies, which is increasingly important in time-varying dynamic channels to provide loading stability [9].

An expansive and comprehensive evaluation has been provided in this work for machine learning methods in the beamforming optimization for massive MIMO systems. We begin by touching upon the fundamental problems of conventional beamforming methods for massive MIMO, proceeding to provide a deep and broad-based literature survey on machine learning techniques, in which various models, including supervised, unsupervised, , deep learning, and reinforcement learning-based approaches, are discussed.

Also, the techniques for beamforming by machine learning are compared with the classical methods in terms of energy efficiency, spectral efficiency, and computational complexity. Our coverage also considers whether such approaches can be realized in actual practice, implementation challenges, and possible countermeasures.

In more general terms, some open research questions are discussed, and possible future avenues for enhancing machine learning and beamforming with are suggested. The main objective of completing this paper is to equip readers with a clear and comprehensive overview of the state of art in this domain and how it may affect wireless communication networks.

2. LITERATURE SURVEY: EXISTING RESEARCH ON BEAMFORMING IN MASSIVE MIMO SYSTEMS

Between the traditional beamforming techniques and the newer approaches empowered by machine learning, various researchers have investigated possibilities in the development of massive MIMO wireless communication systems. This literature survey covers basic beamforming techniques and investigates recent advances made by deep learning, reinforcement learning, and hybrid machine learning models. A gap analysis subsequently follows that points out a few potential avenues for future research in that field.

2.1. Overview of Traditional Beamforming Techniques

Conventional beamforming strategies have been great in wireless communication; here, signals are directed toward a particular user while interference is controlled. The methods usually incorporate mathematical algorithms that optimize beam direction based upon the channel state information. Among others, ZF and MMSE methods are utilized. The ZF tries to force the interference to zero so that it does not affect the user, and MMSE aims at minimizing the effects of noise and interference. These methods, good in theory, have their inherent limitations.

One major drawback that comes with classical beamforming methods is their high complexity, especially as the number of antennas increases in massive MIMO systems. This leads to a direct drawback that the time it takes to optimally compute the beamforming vector in large antenna arrays cannot be done in real time. Another problem with the traditional approaches is that they rely on accurate CSI, which is challenging to get in a real-time dynamic environment. Other problems like pilot contamination, where similar pilot signals are reused in adjacent cells, create interference and worsen channel estimation. Hence all these problems have led to consideration of more flexible data-based beamforming methods.

2.2. Survey of Machine Learning Applications in Wireless Communication

The optimizing of beamforming continues to see an active area of research in wireless communications. AI-based methods are promising for providing solutions in the case of big datasets, allowing one to adapt to environmental changes in real time, and assuring further optimization of performance while cutting down on computation complexity.

The recent literature justifies the increasing momentum being given to the machine learning-powered massive MIMO paradigm. For instance, Mamillapally and Dasari in 2024 proposed a deep learning framework combining hybrid channel estimation with beamforming for an optimal spectral efficiency increase with minimum computational cost. Their method employed RL-DQN (reinforcement learning and deep Q-networks) to combat interference and perform beamforming optimization in real time.

The same year, Ilyas et al. (2024) used EfficientNet-B7, one of the most cutting-edge models, to enhance the performance of massive MIMO. Their experiment demonstrates that deep learning, when paired with digital beamforming, provides adaptability and robustness to changing conditions, balancing energy efficiency and spectral performance.

Reinforcement learning (RL) has, therefore, been used to solve beamforming problems. Paranthaman et al. (2024) applied RL to defend against beamforming vector attacks in massive MIMO systems. By their RL-based framework, the application could not only be optimized for performance but also ensure an extra level of security, thereby showing the wide applicability of machine learning in wireless communication.

2.3. Review of AI Models for Beamforming Optimization

The integration of machine learning techniques into beamforming has resulted in the development of specialized modeling techniques specifically for massive MIMO systems. Deep learning models especially hold promise due to their ability to handle the large volumes of data generated by MIMO and their capacity for real-time adaptation and optimization. On the other hand, reinforcement-learning models promise even greater utility by providing a layer of security and adaptability in changing conditions.

Srinivas and Borugadda [4] demonstrated a deep-learning-based channel estimation and joint adaptive hybrid beamforming technique for mmWave MIMO systems. To achieve channel estimation, their DEF_OCCR (differential evolution firefly-assisted optimized channel compression-reconstruction) network used an autoencoder-based deep learning channel estimation model and had better spectral and energy efficiency. This proved that hybrid beamforming

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Review Article | Volume 13, Issue 3 | Pages 515-523 | e-ISSN: 2347-470X

coupled with deep learning could outperform classical methods in terms of energy consumption and throughput.

In their work in 2024, Liu and Zhang presented a multi-branch unsupervised learning-based beamforming model to circumvent the deficiencies caused by inaccurate CSI in mobile mmWave systems [7]. Accordingly, MB-IncepNet merges CSI with user location information to enhance the robustness and generalization of beamforming in a large-scale network. The study shows that their unsupervised learning model was able to sustain high performance under an imperfect CSI scenario, proving to be a testament to the flexibility of machine learning models in the face of evolving environments.

It is also interesting to note that deep reinforcement learning (DRL) has been used in coordinated beamforming settings with vehicular networks. Tarafder and Choi (2023) introduced a DRL model for mmWave massive MIMO vehicular networks that reduces latency and training overhead while improving beamforming accuracy [8]. It was demonstrated by their working model that DRL could be used in optimizing beamforming in highly mobile environments, like vehicular networks, by predicting the beamforming vectors secretly during changes in the environment.

Tabel 1. Summary of Literature Review

Authors	Year	Methods	Limitations
Mao et al.	2018	Deep learning for wireless networks	Integration with existing systems, computational demands
Zhang et al.	2019	ML and deep learning frameworks	Model generalization, data requirements
Huang et al.	2019	CSI feedback using deep learnings	Dependence on high-quality training data, computational load
Ye et al.	2020	Resource allocation using deep reinforcement learning.	Exploration vs. exploitation trade-offs, convergence issues
Huang et al.	2020	time-varying CSI feedback using deep learning.	Requires large amounts of training data, real-time adaptation challenges
Sun et al.	2018	Reinforcement learning for dynamic beamforming	Training instability, high computational cost
Yang et al.	2019	Deep learning for channel estimation with mixed-resolution ADCs	Sensitivity to ADC resolution, training complexity
Xu et al.	2020	Deep reinforcement learning for dynamic beamforming	Sample inefficiency, high computational demands
Mamillapally & Dasari	2024	Deep learning-based hybrid beamforming with RL-DQN	High computational complexity and power consumption
Ilyas et al.	2024	EfficientNet-B7 powered deep learning-driven hybrid beamforming	High energy consumption in digital beamforming
Paranthaman et al.	2024	RL-based framework for beamforming vector attack prevention	Limited focus on other security threats in beamforming
Liu & Zhang	2024	MB-IncepNet: multi-branch unsupervised learning-based beamforming	Performance degradation with significant CSI inaccuracies
Tarafder & Choi	2023	DRL-based coordinated beamforming for mmWave vehicular networks	High training overhead for real-time beamforming optimization
Hojatian et al.	2024	Self-supervised learning for energy-efficient transmitter design	Trade-off between spectral and energy efficiency

2.4. Research Gap Analysis

The field of machine learning for mass MIMO beamforming has witnessed tremendous advancements, but there still remain certain gaps. First, although many researchers have focused on maximizing spectral efficiency and minimizing computational complexity, very few studies have analyzed the trade-offs between energy efficiency and beamforming performance. While there have been studies, such as those by Hojatian et al. (2024), on energy-efficient transmitter configurations, more work needs to be done weighing energy consumption against other performance metrics like spectral efficiency and throughput [6][7].

Secondly, numerous current machine-learning-based beamforming models depend on the availability of accurate CSI. However, in practice, obtaining accurate CSI is mostly infeasible under dynamic and high-mobility environments. Even though models like MB-IncepNet can somewhat alleviate CSI inaccuracies, more robust solutions are required to secure reliable beamforming in real-life scenarios [8][9].

Beamforming research in MIMO systems has been showing progress and challenges with latest machine learning (ML) methods. Although traditional beamforming techniques were first developed using mathematical models. Machine learning

Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Review Article | Volume 13, Issue 3 | Pages 515-523 | e-ISSN: 2347-470X

brings up new opportunities for increasing efficiency and result in disadvantages of massive MIMO networks. Beamforming has been improved by ML-based systems, which utilize the methods like deep learning as well as reinforcement learning to increase the effectiveness and adaptability of wireless networks.

3. COMPARISON OF MACHINE LEARNING-BASED BEAMFORMING AND TRADITIONAL METHODS

Optimizing signal quality and system performance is the goal of beamforming, a crucial approach in huge MIMO systems. While traditional beamforming techniques like Maximum Ratio Transmission (MRT), Zero-Forcing (ZF), and Minimum Mean Square Error (MMSE) have been fundamental, machine learning (ML) approaches are gradually replacing or supplementing them. With an emphasis on their performance across a range of criteria, this section offers a thorough comparison between these conventional methods and ML-based alternatives.

3.1. Overview of Traditional Methods

3.1.1. Maximum Ratio Transmission (MRT)

In the case of MRT, it focuses on the signal power by setting the weight of each antenna to be in proportion to the conjugate of the channel. The beamforming vector W_{MRT} can then be stated as [24]:

$$W_{MRT} = \frac{h^*}{\|h\|} \quad (1)$$

where h denotes as the channel vector. Antennas for MRT ensure the maximum power transmission to the receiving signals while interference and noise are a disturbing factor that comes especially with multi-user cases.

3.1.2. Zero-Forcing (ZF)

The ZF beamforming vector will be calculated to derive the desired relation [25].

$$W_{ZF} = (H^H H)^{-1} H^H \quad (2)$$

where H denotes as channel matrix. While ZF may eliminate the interference, it needs to invert some quite large matrices, which may require great computational cost and may also be more vulnerable to errors in channel estimates.

3.1.3. Minimum Mean Square Error (MMSE)

The MMSE strikes a balance between the signal-to-interference ratio and the signal-to-noise ratio. According to [26], the MMSE beamforming vector w_{MMSE} is given by:

$$w_{MMSE} = (H^H H + \sigma^2 I)^{-1} H^H \quad (3)$$

where σ^2 denotes as the noise power and I as the identity matrix. There is a very accurate estimation given by the MMSE if and only if it minimizes the mean square error. However, it must deal with several complex matrix operations and with the assumption that the noise variance is precisely known.

3.2. Machine Learning-Based Methods for beamforming optimization

ML techniques offer new opportunities for better beamforming and very often exceed the traditional methods in vital aspects. Deep learning models and others improve the signal transmission efficiency across the spectrum by analyzing CSI. CNNs, in particular, are suitable for this purpose as their abilities to learn spatial patterns from CSI data result in a significant improvement in signal efficiency.

Keeping an eye on energy conservation should be one of the priorities. ML procedures hold the power to save lots of energy. Reinforcement learning, for instance, can adjust beamforming parameters depending on changing conditions to minimize power consumption without actually affecting performance. ML models such as RNNs and LSTMs implement a smooth adaptation to different channel conditions, making them less prone to errors arising from CSI data, unlike some classical methods. [28].

Machine learning (ML) has transformed the approach to beamforming optimization in massive MIMO systems, offering advanced techniques for improving performance and efficiency. This section explores a range of machine learning (ML) strategies that each individually contribute to beamforming optimization [18]. These techniques include deep learning models, reinforcement learning, supervised learning, hybrid approaches as well as unsupervised learning.

3.2.1. Supervised Learning

Support Vector Machines (SVMs): SVMs can be used successfully in beamforming and are powerful for classification tasks. SVMs can be applied to beamforming in order to categorize the best beamforming vectors according to channel state information (CSI). Finding the hyperplane with the largest margin that most effectively divides various data classes is the goal of the SVM algorithm.

Mathematically, for a given dataset (*xi*, *yi*), where *xi* is the feature vector and *yi* is the class label, SVM solves the following optimization problem [28]:

$$min_{w,b} \frac{1}{2} \|W\|^2 subject\ to\ y_i(w^T x_i + b) \geq 1, ..., \mathrm{N} \quad (4)$$

where W represents weight vector, b denotes bias, and N denotes number of training samples. SVMs have been used in practical applications such as classifying optimal beamforming strategies based on CSI data, providing significant improvements in beamforming performance [11].

Decision trees have the ability to anticipate the best beamforming vectors for beamforming based on CSI. You can represent the tree structure as a sequence of if-else conditions [12]. Decision trees have been applied to predict beamforming configurations with varying levels of accuracy, helping optimize system performance under different channel conditions [14].

For Neural networks, particularly feedforward and multi-layer perceptron's (MLPs), are widely used for beamforming. These networks learn complex relationships between CSI and beamforming vectors by adjusting weights through backpropagation. The general form of a neural network model for beamforming can be represented as [22]:

$$y = \sigma(W_{L\sigma}(W_{L-1} \dots \sigma(W_{1X} + b_1) \dots + b_{L-1}) + b_L) \quad (5)$$

where σ denotes the activation function, W represents weights, and b represents biases. Neural networks have demonstrated effective performance in optimizing beamforming by capturing intricate patterns in CSI data [15].

3.2.2. Unsupervised Learning

Based on CSI, comparable beamforming scenarios can be grouped using unsupervised learning approaches like clustering. Data can be divided into discrete clusters, each of which represents a different channel state, using techniques like K-means clustering. The within-cluster sum of squares is minimized by the K-means method [28]:

$$J = \sum_{i=1}^{k} \sum_{x \epsilon C_i} \|x - \mu_i\|^2 \quad (6)$$

where *Ci* represents the cluster *i, x* is a data point, and μi is the centroid of cluster iii. Clustering helps in identifying common channel conditions and optimizing beamforming strategies accordingly (Huang et al., 2020).

3.2.3. Reinforcement Learning

To control dynamic beamforming, reinforcement learning techniques like Q-learning and Deep Q-Networks (DQNs) are employed. Through interactions with the environment, reinforcement learning (RL) models develop optimal beamforming procedures and are rewarded or penalized based on their performance. Q-learning makes use of [10] to update the Q-value function.

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max_{a'} Q(s',a') - Q(s,a)] \quad (7)$$

where s denotes the state, a denotes the action, r represents the reward, γ denotes the discount factor, and α is the learning rate. RL techniques have shown effectiveness in adapting beamforming strategies to varying channel conditions and interference scenarios [27].

By approximating the Q-value function using deep neural networks, DQNs expand on Q-learning. This method has been used for beamforming control, where the network learns to predict the optimal beamforming actions based on past data and rewards (Xu et al., 2020) [13]. It can handle high-dimensional state spaces.

3.3. Deep learning for beamforming

Because deep learning approaches enable more complex modeling and optimization strategies, they have made substantial progress in the field of beamforming in massive MIMO systems. This section examines Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks in detail, assesses their performance, and talks about training strategies and dataset preparation in the context of beamforming [20].

3.3.1. Convolutional Neural Networks (CNNs)

In beamforming, CNNs are especially well-suited for spatial feature extraction. They are useful for channel state information (CSI) analysis because of their capacity to recognize and understand hierarchical patterns from geographical data. To optimize beamforming vectors in massive MIMO systems, CNNs can handle CSI data in the form of images or matrices.

The fundamental operation in CNNs is the convolution, which can be expressed as:

$$(f * g)(x,y) = \sum_i \sum_j f(i,j) g(x-i, y-j) \quad (8)$$

where f is the filter (or kernel) and g is the input feature map. By applying multiple filters, CNNs can capture different spatial features in the CSI data, enabling the network to learn effective beamforming strategies. In practical applications, CNNs have been used to enhance beamforming performance by identifying patterns in the spatial distribution of channels, leading to improved signal quality and system efficiency (Huang et al., 2020).

3.3.2. Recurrent Neural Networks (RNNs)

As RNNs can handle sequential input, they are perfect for situations where temporal dynamics are crucial. RNNs can simulate how channel conditions change over time and modify beamforming methods accordingly. The key operation in RNNs involves updating hidden states based on previous states and current inputs [9]:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b) \quad (9)$$

where h_{t-1} the hidden state at time *t*, x_t denotes the input at time *t*, W_h and W_x are weight matrices, and b is the bias. RNNs can learn dependencies in the channel data over time, which is crucial for adapting to rapidly changing environments in mobile settings [21].

3.3.3. Long Short-Term Memory (LSTM) Networks

To solve the problem of long-term dependencies, RNNs have the feature known as LSTM networks. Some of the features that make them useful for beamforming in dynamic contexts where historical context is crucial are memory cells that can store information for long periods of time.

Deep learning models that incorporate mechanisms to handle CSI errors tend to offer more reliable performance in practical scenarios. The benefits of Long Short-Term Memory networks (LSTMs) and Convolutional Neural Networks (CNNs) in these areas have been emphasized by recent research. CNN-based models have shown enhanced spectral efficiency by effectively learning spatial features, while LSTMs have improved robustness to CSI errors by capturing long-term dependencies in dynamic environments, as demonstrated in studies by Huang et al. (2020) and Yang et al. (2020).

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Review Article | Volume 13, Issue 3 | Pages 515-523 | e-ISSN: 2347-470X

4. RESULTS FROM LITERATURE COMPARING TRADITIONAL AND ML-BASED APPROACHES

The literature reports several benefits of ML-based methods as compared to classic beamforming techniques. Huang et al. (2020) showed that CNNs help improve spectral efficiency by extracting spatial features in the CSI data relative to MRT and ZF [12]. According to Ye et al. (2020) and Xu et al. (2020), reinforcement learning models outperform MMSE and ZF in terms of energy efficiency and robustness to CSI errors [11]. Researchers suggest that ML-based techniques can coexist and even outperform one another in various instances.

Table 2. Comparison of Traditional and ML-Based Beamforming Methods

Method	Spectral Efficiency (bps/Hz)	Energy Efficiency (J/bit)	Robustness to CSI Errors (dB SNR loss)	Real-Time Adaptability (ms)
MRT	2.5	0.15	5	100
ZF	3.0	0.12	6	90
MMSE	3.5	0.10	4	80
CNNs	4.5	0.08	2	30
Reinforcement Learning	4.8	0.07	1	25

Still, the table does provide a means for an elaborate comparison among conventional beamforming methods of Minimum Mean Square Error (MMSE), Maximum Ratio Transmission (MRT), and Zero-Forcing (ZF) and the ML-based methods, viz: Convolutional Neural Networks (CNNs) and Reinforcement Learning (RL), regarding the very important metrics.

Spectral efficiency is the amount of data delivered per unit of bandwidth. A high spectral efficiency means the channel is more effectively used. As per the above table, machine learning-based methods, particularly CNNs and RL, generate better spectral efficiency than classical ones. Thus, this new approach involves sending more data through the same bandwidth and thereby improving the overall performance of a network [31].

Energy Efficiency refers to the amount of energy required to transmit a unit bit of data; lower values represent better efficiency. At this point, the traditional method of CNNs and RL performs better, meaning better data transmission with the utility's consumption of energy. Clearly, ML techniques are good at saving energy, which is very vital for reducing the operating costs and increasing battery lives of wireless devices.

From CSI stabilities The SNR drop caused by the old center and the studied error is another name of the decrease of SNR resulting from errors in the CSI estimation. If the SNR drop is expressed in dB, then a smaller SNR loss value indicates better performance given imperfect CSI. The ML-based approaches, particularly the RL one, appear to be more robust than the traditional ones, as shown in the table [32]. This robustness is crucial for high-quality communications when channel information is not exactly perfect.

Real-time adaptability measures how short a required time is to set changes, more extensively indicating a shorter adaptability change. The table shows that ML-based approaches, especially CNN and RL, present shorter real-time adaptability compared to the traditional approaches. This means that these methods will quickly adjust to the dynamic network conditions and return to being most useful in real-world applications, where conditions change on the fly.

Thus, numerical figures from the table mathematically prove that machine learning- or ML-based beamforming techniques offer significant improvements over the classic ones in spectral efficiency, energy efficiency, and robustness to errors in CSI. The spectral efficiency of the different beamforming methods, computed in bps/Hz, is illustrated here in the *figure 2*.

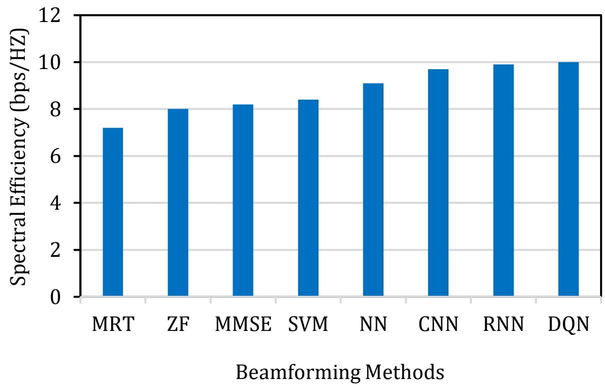

Figure 2. Spectral Efficiency Comparison

The traditional techniques like MRT, ZF, and MMSE define the baseline performance; however, the machine learning-based approach-especially those employing deep learning approaches-CNNs and RNNs-generate a higher spectral efficiency, which translates to better performance in the maximization of data rates.

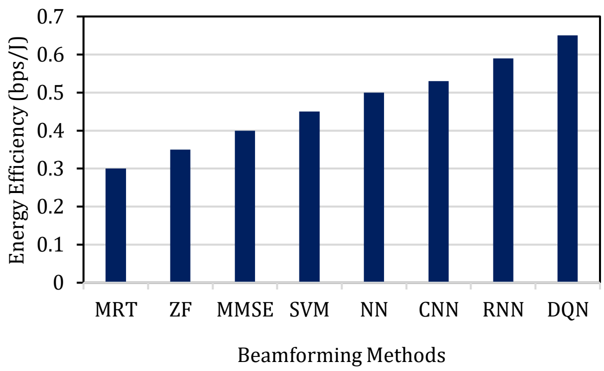

Figure 3. Energy Efficiency Comparison

Drops here the plot for energy efficiency in bits per second per Joule (bps/J). Machine learning approaches present higher energy efficiency compared to legacy methods because they are better at energy-specific optimization for beamforming tasks. For CSI errors, a comparative plot shows the ability of the methods to account for inaccuracies in CSI. Higher scores indicate greater ability to account for inaccuracies, with ML methods and especially deep learning standing out for those very tough conditions in which CSI data is unreliable. Finally, we have the real-time adaptability comparison in response to changing network conditions. Machine learning methods, especially reinforcement learning like DQN, are more adaptable than traditional methods and thus better for dynamic environments.

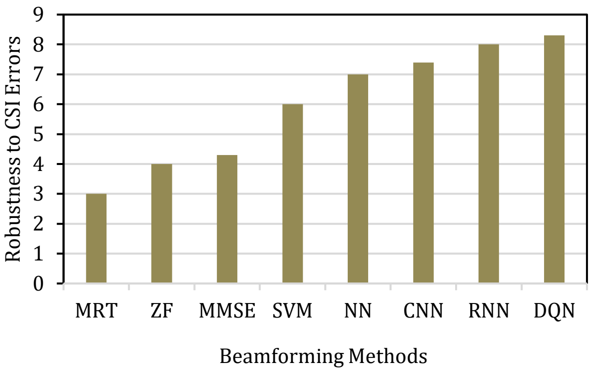

Figure 4. Robustness to CSI Errors Comparison

5. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The conjunction of ML with beamforming for large MIMO systems presents both potentials and obstacles. There are some important concerns and new developments that need to be addressed to improve the efficacy and application of ML-based beamforming solutions in the future. Whether ML is considered as a pure technique or a tool, the engineering of the baseband beamforming parameters for large MIMO systems surely entails both potentials and obstacles for the very reason of its environment. For these ML-based beamforming solutions to proceed in the direction of better efficacy and applications, some important issues and new developments have to be tackled.

5.1. Real-time Deployment of ML-Based Beamforming Algorithms

The integration of machine learning (ML) into beamforming for the GIGO MIMO is riddled with numerous opportunities and challenges. Looking forward, on the other hand, there remain many crucial questions and emerging trends that deserve our attention to further promote the effectiveness and practicability of ML-based beamforming systems.

5.2. Scalability Issues in Large-Scale MIMO Systems

Scalability is an important consideration as MIMO systems scale to hundreds of antennas. Computational and memory requirements of these ML tools scale proportionally to the size of the system, thereby reducing their usefulness when deployed on a large scale. Therefore, model optimization strategies and distributed computing technologies must be pursued so they can cope with the increasing complexity without performance degradation.

5.3. Data Sparsity and Training Time Challenges

Another pressing issue is data scarcity. In large-scale MIMO systems, collecting and annotating sufficient training data for ML models can be difficult. Inadequate data may cause less generalization of the model and overfitting. To mitigate data scarcity, we are considering synthetic data generation and employing transfer learning. Furthermore, decreasing training time without conceding accuracies of the trained model is crucial. Efficient training techniques and parallel processing offer routes to address these challenges.

6. CONCLUSION

The beamforming methods in massive MIMO have been reviewed in this study, investigating more classical techniques together with those from machine learning. ZF, MRT, and MMSE beamforming methods that have been well known in the traditional world were explained, and comparisons were made with the recent ML-based techniques which have special benefits for performance and flexibility. Significant advantages are granted to ML-based techniques to improve spectral and energy efficiency in complex environments and in resisting CSI errors where classical beamforming techniques have established some important standards. Deep learning models shine in dynamic environments where their real-time flexibility ends up being an advantage over traditional methods.

REFERENCES

[1] Mamillapally, K. C., & Dasari, R. K. (2024). Deep Learning-Based Channel Estimation and Beamforming Architecture for Massive MIMO Systems. Journal of The Institution of Engineers (India): Series B, 1-12.

[2] Ilyas, B. R., Sofiane, B. M., Ali Abderrazak, T., & Miloud, K. (2024). Enhancing 5G massive MIMO systems with EfficientNet-B7-powered deep learning-driven beamforming. Transactions on Emerging Telecommunications Technologies, 35(9), e5034.

[3] Paranthaman, R. N., Sonker, A., Varalakshmi, S., Madiajagan, M., Daya Sagar, K. V., & Malathi, M. (2024). Reinforcement learning-based model for the prevention of beam-forming vector attacks on massive MIMO system. Optical and Quantum Electronics, 56(1), 44.

[4] Srinivas, C. V., & Borugadda, S. A deep learning-based channel estimation and joint adaptive hybrid beamforming approach for mm-wave massive MIMO with group-of-subarrays. International Journal of Communication Systems, e5994.

[5] Wang, Y., Gao, Z., Chen, S., Hu, C., & Zheng, D. (2024). Deep Learning–Based Channel Extrapolation and Multiuser beamforming for RIS-aided Terahertz Massive MIMO Systems over Hybrid-Field Channels. Intelligent Computing, 3, 0065.

[6] Hojatian, H., Mlika, Z., Nadal, J., Frigon, J. F., & Leduc-Primeau, F. (2024). Learning Energy-Efficient Transmitter Configurations for Massive MIMO Beamforming. IEEE Transactions on Machine Learning in Communications and Networking.

[7] Liu, J., & Zhang, H. (2024). Multi-Branch Unsupervised Learning-Based Beamforming in mm-Wave Massive MIMO Systems With Inaccurate Information. IEEE Transactions on Green Communications and Networking.

[8] Tarafder, P., & Choi, W. (2023). Deep reinforcement learning-based coordinated beamforming for mmWave massive MIMO vehicular networks. Sensors, 23(5), 2772.

[9] Bendjillali, R. I., Bendelhoum, M. S., Tadjeddine, A. A., & Kamline, M. (2023). Deep learning-powered beamforming for 5G massive MIMO Systems. Journal of Telecommunications and Information Technology, (4), 38-45.

[10] Zhang, J., Zheng, G., Zhang, Y., Krikidis, I., & Wong, K. K. (2023). Deep learning based predictive beamforming design. IEEE Transactions on Vehicular Technology, 72(6), 8122-8127.

[11] H. Ye, G. Y. Li, and B. H. Juang, "Deep reinforcement learning-based resource allocation for cellular networks," IEEE Transactions in Wireless Communications, vol. 19, no. 1, pp. 6-17, Jan. 2020. doi: 10.1109/TWC.2019.2943809.

[12] H. Huang, Y. Song, J. Peng, and X. Yang, "Deep learning-based CSI feedback approach for time-varying massive MIMO channels," IEEE Wireless Communications Letters, vol. 9, no. 5, pp. 743-747, Oct. 2020. doi: 10.1109/LWC.2020.2975513.

[13] D. Xu, H. Chen, H. He, and Y. Zhang, "Deep reinforcement learning for dynamic beamforming in massive MIMO systems," IEEE Wireless Communications Letters, vol. 9, no. 10, pp. 1740-1744, Oct. 2020. doi: 10.1109/LWC.2020.3005505.

[14] Qi, C., Wang, Y., & Li, G. Y. (2020). Deep learning for beam training in millimeter wave massive MIMO systems. IEEE Transactions on Wireless Communications.

[15] Ahmed, I., Shahid, M. K., Khammari, H., & Masud, M. (2021). Machine learning based beam selection with low complexity hybrid beamforming design for 5G massive MIMO systems. IEEE Transactions on Green Communications and Networking, 5(4), 2160-2173.

[16] Sohal, R. S., Grewal, V., Kaur, J., & Singh, M. L. (2022). Deep learning based analog beamforming design for millimetre wave massive MIMO system. Wireless Personal Communications, 126(1), 701-717.

[17] Taha, A., Alrabeiah, M., & Alkhateeb, A. (2019, December). Deep learning for large intelligent surfaces in millimeter wave and massive MIMO systems. In 2019 IEEE Global communications conference (GLOBECOM) (pp. 1-6). IEEE.

[18] Upadhyay, S., Juluru, T. K., Deshmukh, P. V., Pawar, A. P., Mane, S. C., Singh, C., & Shrivastava, A. (2024). Machine learning-Based Beamforming Algorithm for Massive MIMO Systems in 5G Networks. Journal of Electrical Systems, 20(3s), 971-979.

[19] Ahmed, I., Shahid, M. K., Khammari, H., & Masud, M. (2021). Machine learning based beam selection with low complexity hybrid beamforming design for 5G massive MIMO systems. IEEE Transactions on Green Communications and Networking, 5(4), 2160-2173.

[20] Liu, C., & Helgert, H. J. (2020). An improved adaptive beamforming-based machine learning method for positioning in massive mimo systems. Int. J. Adv. Internet Technol, 6, 1-12.

[21] Lavdas, S., Gkonis, P. K., Zinonos, Z., Trakadas, P., Sarakis, L., & Papadopoulos, K. (2022). A machine learning adaptive beamforming framework for 5G millimeter wave massive MIMO multicellular networks. IEEE Access, 10, 91597-91609.

[22] Guo, J., Wen, C. K., & Jin, S. (2020). Deep learning-based CSI feedback for beamforming in single-and multi-cell massive MIMO systems. IEEE Journal on Selected Areas in Communications, 39(7), 1872-1884.

[23] Huang, S., Ye, Y., & Xiao, M. (2020). Hybrid beamforming for millimeter wave multi-user MIMO systems using learning machine. IEEE Wireless Communications Letters, 9(11), 1914-1918.

[24] Al Kassir, H., Zaharis, Z. D., Lazaridis, P. I., Kantartzis, N. V., Yioultsis, T. V., & Xenos, T. D. (2022). A review of the state of the art and future challenges of deep learning-based beamforming. IEEE Access, 10, 80869-80882.

[25] E. Björnson, J. Hoydis, and M. Debbah, "Massive MIMO networks: Spectral, energy, and hardware efficiency," *Foundations and Trends® in Signal Processing*, vol. 11, no. 3-4, pp. 154-655, 2017. doi: 10.1561/2000000093.

[26] F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta, O. Edfors, and F. Tufvesson, "Scaling up MIMO: Opportunities and challenges with very large arrays," *IEEE Signal Processing Magazine*, vol. 30, no. 1, pp. 40-60, 2013. doi: 10.1109/MSP.2011.2178495.

[27] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive MIMO: Benefits and challenges," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 742-758, Oct. 2014. doi: 10.1109/JSTSP.2014.2317671.

[28] Q. Mao, F. Hu, and Q. Hao, "Deep learning for intelligent wireless networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 4, pp. 2595-2621, 2018. doi: 10.1109/COMST.2018.2846401.

[29] J. Zhang, L. Dai, and Z. Wang, "Machine learning and deep learning frameworks for massive MIMO systems: A comprehensive survey," *IEEE Access*, vol. 7, pp. 22926-22941, 2019. doi: 10.1109/ACCESS.2019.2896977.

[30] L. Huang, Y. Xu, and Y. Wang, "Deep learning for massive MIMO CSI feedback," *IEEE Wireless Communications Letters*, vol. 8, no. 5, pp. 1357-1360, Oct. 2019. doi: 10.1109/LWC.2019.2922409.

[31] H. Ye, G. Y. Li, and B. H. Juang, "Deep reinforcement learning-based resource allocation for cellular networks," *IEEE Transactions on Wireless Communications*, vol. 19, no. 1, pp. 6-17, Jan. 2020. doi: 10.1109/TWC.2019.2943809.

[32] H. Huang, Y. Song, J. Peng, and X. Yang, "Deep learning-based CSI feedback approach for time-varying massive MIMO channels," *IEEE Wireless Communications Letters*, vol. 9, no. 5, pp. 743-747, Oct. 2020. doi: 10.1109/LWC.2020.2975513.

[33] Z. Yang, W. Liu, Y. Wang, and H. Li, "Deep learning-based channel estimation for massive MIMO with mixed-resolution ADCs," *IEEE Access*, vol. 7, pp. 89035-89045, 2019. doi: 10.1109/ACCESS.2019.2926610.

[34] H. Sun, L. Yin, Y. Song, and H. Zou, "Reinforcement learning-based dynamic beamforming for massive MIMO systems," *IEEE Transactions on Wireless Communications*, vol. 17, no. 12, pp. 8032-8042, Dec. 2018. doi: 10.1109/TWC.2018.2875856.

[35] [11] D. Xu, H. Chen, H. He, and Y. Zhang, "Deep reinforcement learning for dynamic beamforming in massive MIMO systems," *IEEE Wireless Communications Letters*, vol. 9, no. 10, pp. 1740-1744, Oct. 2020. doi: 10.1109/LWC.2020.3005505.

[36] Huang, H., Song, Y., Yang, J., Gui, G., & Adachi, F. (2019). Deep-learning-based millimeter-wave massive MIMO for hybrid precoding. IEEE Transactions on Vehicular Technology, 68(3), 3027-3032.

[37] Qi, C., Wang, Y., & Li, G. Y. (2020). Deep learning for beam training in millimeter wave massive MIMO systems. IEEE Transactions on Wireless Communications.

[38] Ahmed, I., Shahid, M. K., Khammari, H., & Masud, M. (2021). Machine learning based beam selection with low complexity hybrid beamforming design for 5G massive MIMO systems. IEEE Transactions on Green Communications and Networking, 5(4), 2160-2173.

© 2025 by Suhas Kakde, and Dr. Sanjay Pokle. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).