

**Massive MIMO System using Machine Learning and Channel Estimation  
Technique: A Review**

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**Abstract:** - Massive Multiple-Input Multiple-Output (MIMO) technology is a fundamental component of next-generation wireless communication systems, offering improved spectral efficiency, higher data rates, and enhanced network reliability. However, the performance of massive MIMO systems heavily depends on accurate channel estimation, which remains a significant challenge due to pilot contamination, hardware impairments, and computational complexity. Traditional channel estimation techniques, such as Least Squares (LS) and Minimum Mean Square Error (MMSE), often struggle to provide optimal performance in large-scale antenna systems. To overcome these limitations, machine learning (ML)-based approaches have emerged as promising solutions, enabling efficient channel estimation and system optimization through data-driven models. This review paper provides an in-depth analysis of various machine learning techniques applied to channel estimation in massive MIMO systems, including supervised learning, deep learning, and reinforcement learning-based methods. We discuss the advantages, limitations, and computational trade-offs of these techniques while comparing them with conventional estimation methods. Additionally, we explore hybrid approaches that integrate traditional and ML-based methods to enhance estimation accuracy and reduce processing complexity. Through a comprehensive survey of recent advancements, this paper highlights key research challenges, open issues, and future directions in the field. The findings indicate that machine learning-driven channel estimation can significantly improve the efficiency and adaptability of massive MIMO systems, paving the way for intelligent and self-optimizing wireless networks.

**Keywords:** - MIMO, OFDM, Machine Learning (ML), Channel Estimation

## **I. INTRODUCTION**

In recent years, Internet usage has increased in leaps and bounds and has billions of users. Internet usages like VOD-Video on Demand, E-Mail, Browsing, Contacts etc. Demand high speed Internet that leads to a need for broadband adoption. At the same time, cellular systems have made it possible for people to stay connected with the world from almost anywhere, resulting in a concept while On The Move. With the increase in users and their demands, the broadband market continues to grow, which in turn leads to development of new technologies like Wimax [1], LTE, LTE-advanced for broadband wireless. These technologies provide usage flexibility, high throughput and more coverage. Wireless channel [2] is the main barrier for these new technologies. It causes impairments like noise addition, interference, multipath fading effects etc. in the transmitted signal. This demands very complex algorithms in the wireless receiver to overcome these impairments. Previous technologies like GSM [3] use FDM (Frequency Division Multiplexing), while CDMA uses orthogonal codes and spread spectrum to overcome channel impairments. These systems have their own limitations. For example, FDM requires guard band for separation to overcome interference between two consecutive users. Similarly, CDMA [4] needs to generate orthogonal sequences with zero correlation which is difficult to achieve if the number of users increases indefinitely. This leads to OFDM [5] (Orthogonal Frequency Division Multiplexing). The concept is equivalent to dividing the channel frequency response into smaller orthogonal sub-bands. Since each adjacent frequency is orthogonal to each other, it eliminates the need of guard band for separation. Simultaneously, OFDM divides high data rate signal into multiple small data rate signals. Moreover, it can be implemented by simple FFT/IFFT techniques, leading to ease in implementation.

**First-Generation Systems (1G):-** In 1970, 1G (First generation) was introduced for voice communication. 1G was an analog system with frequency modulation technique for radio transmission using Frequency Division Multiple Access (FDMA). 1G system was Advanced Mobile Phone System (AMPS), Total Access Communication Systems (TACS) and Nordic Mobile Telephone (NMT). In North America, two 25 MHz bands were allocated to AMPS, one for downlink transmission from the base station to the mobile unit (869- 894 MHz) and the other for uplink transmission from the mobile to the base station (824-849 MHz) [5].

In 1985, the Federal Communications Commission (FCC) enabled the commercial development of wireless LANs (WLAN) by authorizing the public use of the Industrial, Scientific, and Medical (ISM) frequency bands for wireless LAN products.

**Second Generation Systems (2G):-** The 2nd generation system was accomplished in 1990's. The 2G mobile communication system is a digital system. Today in different parts of the world, it is used for voice communication and other services such as SMS and e-mail. In this generation Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA) are used with frequency band 850-1900 MHz. Also in this age, GSM technology uses eight channels per carrier with a gross data rate of 22.8 kbps (a net rate of 13 kbps) in full rate channel and a frame of 4.6 milliseconds (ms) duration. The 2.5G and 2.75G are enhancement of this generation. 2G standards are GPRS, Enhanced Data Services for GSM Evolution (EDGE), Interim Standard (IS) as IS-54 and IS-136 systems currently provide data rates of 40-60 Kbps. The IS-95 systems support higher data using a time-division technique called High Data Rate (HDR) [6].

**Third Generation Systems (3G):-** Third generation (3G) services combine high speed mobile access with Internet Protocol (IP)-based services. The 3G technology supports both for packet and circuit switched data transmission which is compatible to 2G. The 3G technology includes the services such as wireless web base access, email, video conferencing and multimedia services. The 3G devices may share the same wireless network and be connected to internet anytime, anywhere. 3G provides different data rates from 384 kbps for pedestrian use, 144 kbps for vehicular use and 2 Mbps for indoor office use depending on mobility and environment. The frequency band is 1.8 - 2.5 GHz [7]. Different versions of wireless LAN (WLAN) standards exist in the 2.4 GHz and 5 GHz bands [8].

**Fourth Generation Systems (4G):-** 4G is an enhanced version of 2G and 3G. Recently 3GPP (third Generation Project Partner) has introduced LTE Advanced version as 4G standard. A 4G system provides a comprehensive and secure IP based services. 4G gives the facilities such as voice, streamed multimedia and data to users at anytime, anywhere with much higher data rates than earlier generations. 4G can provide larger demanding requirements in terms of QoS. 4G applications are wireless broadband access, video chat, Multimedia Messaging Service (MMS), mobile TV, HDTV and Digital Video Broadcasting (DVB) etc. The 4G wireless system is for Global and seamless roaming between different wireless systems, hot spots and pedestrian environments data rate 100M~1Gbps, vehicular environments rate up to 100 Mbps

and high spectrum efficiency. MIMO technology is used in 4G to get high data rate and reliability [9].

### **Fifth Generation System (5G)**

5G networks are digital cellular networks, in which the service area covered by providers is divided into small geographical areas called *cells*. Analog signals representing sounds and images are digitized in the phone, converted by an analog to digital converter and transmitted as a stream of bits. All the 5G wireless devices in a cell communicate by radio waves with a local antenna array and low power automated transceiver (transmitter and receiver) in the cell, over frequency channels assigned by the transceiver from a pool of frequencies which are reused in other cells. The local antennas are connected with the telephone network and the Internet by a high bandwidth optical fiber or wireless backhaul connection. As in other cell networks, a mobile device crossing from one cell to another is automatically "handed off" seamlessly to the new cell [10].

There are plans to use millimeter waves for 5G. Millimeter waves have shorter range than microwaves, therefore the cells are limited to smaller size; The waves also have trouble passing through building walls. Millimeter wave antennas are smaller than the large antennas used in previous cellular networks. They are only a few inches (several centimeters) long. Another technique used for increasing the data rate is massive MIMO (multiple-input multiple-output). Each cell will have multiple antennas communicating with the wireless device, received by multiple antennas in the device, thus multiple bit streams of data will be transmitted simultaneously, in parallel. In a technique called beamforming the base station computer will continuously calculate the best route for radio waves to reach each wireless device, and will organize multiple antennas to work together as phased arrays to create beams of millimeter waves to reach the device.

The new 5G wireless devices also have 4G LTE capability, as the new networks use 4G for initially establishing the connection with the cell, as well as in locations where 5G access is not available [11].

## **II. MIMO TECHNOLOGY**

The framework which has one antenna at input and single antenna at destination may be supposed as SISO framework in the arena of communication. This endures a few issues of

capacity, as a result of technologist Shannon Nyquist rule. The current day telecommunication framework requirements enhanced quality, more prominent system and higher data rate. Keeping in mind to achieve exceptional demand, its data transfer capacity and power of transfer should be expanded. Advancements In current day technology demonstrate that utilization of MIMO framework in inaccessible communication enhance the capacity without increase in bandwidth and transfer power. To improve the capacity of framework signal with multiple paths is employed. Now in wireless communication, MIMO has become an essential element and includes:

- 1) Long Term Evolution (4G)
- 2) WIMAX (4G)
- 3) HSPA+ (3G)
- 4) IEEE 802.11ac

Digital communication utilizing numerous input output antennas has been viewed as a standout amongst the foremost specialized breakthrough current communications. Before the explaining of —Why MIMO System, it is important to quickly deliberate the meaning of MIMO. MIMO stances for multiple inputs and multiple output system. A method where signals are transmitted by means of numerous antennas rather than just one antenna as in FDM. Like several different communication systems, MIMO-OFDM system has numerous elements of antennas at the input and destination.

Mathematically MIMO system can be represented as:

$$Y(t) = X(t) * H(t) + n(t) \quad (1)$$

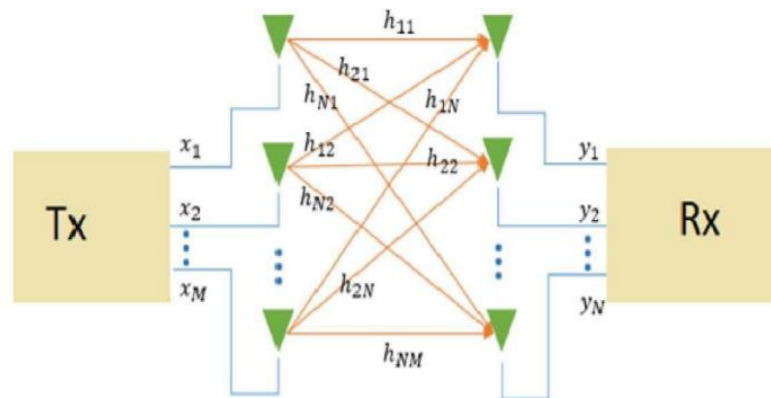
In this equation

$Y(t)$  = signal at the destination

$H(t)$  = matrix of channel

$X(t)$  = signal at the input signal

$n(t)$  = noise



**Figure 1: General Concept of MIMO**

### III. RELATED WORK

**Zhitong Xing et al. [1]**, massive MIMO is one of the cornerstones of 5G technology. MIMO scaled up to hundreds or even thousands of antenna terminals can result in an extensive increase in the capacity at reduced computational complexity. Channel State Information (CSI) estimation has an indispensable role in the deployment of massive MIMO. Since the spatial information is important for the massive MIMO phase component to have higher significance as compared to the magnitude component in CSI. If the phase estimation of the channel can be made accurate, we can ensure efficient estimation of channel gains as well. Thereby ensuring the error-free transmission of massive data. The proposed multi-layer perceptron model for massive MIMO takes the beamformed signal with higher directivity as its input and learns the features of different channel conditions and predict the direction of arrival (DoA) or Angle of Arrival (AoA) of the received signal. This accurate prediction of DoA helps in the estimation of channel conditions much better than the time domain counterpart especially with a reduced number of iterations. The proposed system has better metrics about the accuracy, mean squared error (MSE) performance, and bit error rate (BER) performance. The number of epochs required for training is less implies computational complexity is less, which is a significant improvement comparing with other data-driven techniques

**Mustafa S. et al. [2]**, hybrid Beamforming has been used in wireless communications for many years. With the fifth generation of wireless communications or (5G) and beyond networks, the need for beamforming is ever increasing because of the use of higher frequencies and the need to provide better coverage and better spectral utilization. Although many designs have been suggested to build hybrid beamforming, the Machine Learning (ML) based designs have



attracted much attention recently because of the flexibility in coping with the wireless channel variations and user mobility they can attain when directing the transmission to the right direction during the communication process. In this paper, we describe the extended design of machine learning based hybrid beamforming for multiple users in systems that use millimeter waves (mmWaves) and massive MIMO architectures. The simulation results show that with the right amount of training data samples (channel feedback), the ML based hybrid beamforming architecture can achieve the same spectral efficiency (bits/sec/Hz) as the fully digital beamforming designs with negligible error for both single user and multi-user Massive-MIMO scenarios.

**Ebubekir et al. [3]**, reliable data connectivity is vital for the ever increasingly intelligent, automated, and ubiquitous digital world. Mobile networks are the data highways and, in a fully connected, intelligent digital world, will need to connect everything, including people to vehicles, sensors, data, cloud resources, and even robotic agents. herefore, this article discusses technologies that will evolve wireless networks toward a sixth generation (6G) and which we consider as enablers for several potential 6G use cases. We provide a fullstack, system-level perspective on 6G scenarios and requirements, and select 6G technologies that can satisfy them either by improving the 5G design or by introducing completely new communication paradigms.

**Farzana et al. [4]**, device to Device and Cooperative communication are the two new emerging technologies in the new era of communication technology which differ from the existing cellular technology. In review article we have enlisted different technologies which play a very important role in third Generation Partnership Project (3GPP). In this paper we have studied the various techniques of resource allocation, Mode selection for underlay communications in terms of device to device and cooperative communication techniques in terms of Long Term Evolution and Long Term Evolution-Advanced platform. A new technique LTE-Advanced Pro has also been introduced by 3GPP. Various simulators including Vienna LTE-Advanced have also been discussed. Better utilization of the spectrum is also depicts which is done on the basis of analysis if proper resource allocation whether it is power, frequency or time and mode selection is done in the programmed manner which would result in the reduction of interference and it will also lead to the secure system.

**Osama I. et al. [5]**, communications over millimeter-wave (mm-Wave) frequencies are considered as a new revolution of wireless communications, specifically with the official launching of 5G. Typically, mm-Wave with massive multiple-input multiple-output (MIMO) can be implemented by using the hybrid beamforming transceivers that consists of massive number of analog phase shifters and smaller number of RF chains. The power consumption and cost are reduced when the hybrid beamforming architecture is implemented by combining the digital and analog beamforming. The main motivation for this paper is to introduce a deep learning-based hybrid beamforming design to join optimization of the precoder and combiner in massive MIMO mm- Wave communication systems. Specifically, the joint optimization of the precoder and combiner is carried out by means of two convolutional neural networks (CNN) and through going into two stages of operation, namely training and prediction stages. The MATLAB simulation results show that the deep learning-based hybrid beamforming approach for the mm-Wave massive MIMO outperforms the legacy optimization-based hybrid beamforming approaches in terms of spectrum efficiency.

**Amirashkan F. et al. [6]**, in line-of-sight massive MIMO, the downlink channel vectors of few users may become highly correlated. This high correlation limits the sum-rates of systems employing linear precoders. To constrain the reduction of the sum-rate, few users can be dropped and served in the next coherence intervals. The optimal strategy for selecting the dropped users can be obtained by an exhaustive search at the cost of high computational complexity. To alleviate the computational complexity of the exhaustive search, a correlation based dropping algorithm (CDA) is conventionally used, incurring a sum-rate loss with respect to the optimal scheme. In this paper, we propose a dropping algorithm based on neural networks (DropNet) to find the set of dropped users. We use appropriate input features required for the user dropping problem to limit the complexity of DropNet. In particular, for a 64-antenna base station and 10 single-antenna users: (i) DropNet reduces the computational complexity of the exhaustive search by a factor of 46 and 3 for CB and ZF, respectively, (ii) DropNet improves the 5th percentile sum-rate of CDA by 0.86 and 2.33 bits/s/Hz for CB and ZF, respectively.

**Ismayil et al. [7]**, beamforming with antenna arrays has been considered as an enabling technology in future wireless communication systems. To conduct beamforming, one has to know the angle-of-departure (AoD) or angle-of-arrival (AoA). For data detection, the receiver also has to know channel response. In this paper, we propose a new joint AoD, AoA, and channel estimation scheme for pilot-assisted MIMO-OFDM systems. First, a compressive-



sensing technique is employed to estimate the channel impulse response, exploiting the sparsity property of wireless channels. Then, AoA and AoD are jointly estimated for each detected path by the maximum likelihood method. The Cramér-Rao lower bound (CRLB) is also derived and a transmit beamforming scheme is proposed accordingly. In the scenario of available prior information, a maximum a posteriori estimation is proposed. The Bayesian CRLB (BCRLB) for the problem is also derived and a transmit beamforming scheme is further proposed. It turns out that only two training OFDM symbols are required for the estimation. Simulation results show that the proposed methods can approach the CRLB/BCRLB in both scenarios and achieve the same spectral efficiency as that obtained with the ideal channel in millimeter-wave communications.

#### **IV. MACHINE LEARNING**

Uproarious information is available in the heap of substance that will be identified through the anomaly strategies. The information can be spatial or can be a transient method spatial connected with the geological conditions and worldly connected with the time perspectives [14, 15]. The principle point of exception identification is to deal with the loud information that is introduced in the heap of text. Different methods for recognizing abnormalities in Text are specified in below:

##### **Learning**

The main property of an ML is its capability to learn. Learning or preparing is a procedure by methods for which a neural system adjusts to a boost by making legitimate parameter modifications, bringing about the generation of wanted reaction. Learning in an ML is chiefly ordered into two classes as [16].

- Supervised learning
- Unsupervised learning

##### **Supervised Learning**

Regulated learning is two stage forms, in the initial step: a model is fabricated depicting a foreordained arrangement of information classes or ideas. The model developed by investigating database tuples portrayed by traits. Each tuple is expected to have a place with a predefined class, as dictated by one of the qualities, called to have a place with a reclassified

class, as controlled by one of the traits called the class name characteristic. The information tuple are dissected to fabricate the model all things considered from the preparation dataset [17].

### **Unsupervised learning**

It is the kind of learning in which the class mark of each preparation test isn't knows, and the number or set of classes to be scholarly may not be known ahead of time. The prerequisite for having a named reaction variable in preparing information from the administered learning system may not be fulfilled in a few circumstances.

Data mining field is a highly efficient techniques like association rule learning. Data mining performs the interesting machine-learning algorithms like inductive-rule learning with the construction of decision trees to development of large databases process. Data mining techniques are employed in large interesting organizations and data investigations. Many data mining approaches use classification related methods for identification of useful information from continuous data streams.

### **Nearest Neighbors Algorithm**

The Nearest Neighbor (NN) rule differentiates the classification of unknown data point because of closest neighbor whose class is known. The nearest neighbor is calculated based on estimation of  $k$  that represents how many nearest neighbors are taken to characterize the data point class. It utilizes more than one closest neighbor to find out the class where the given data point belong termed as KNN. The data samples are required in memory at run time called as memory-based technique. The training points are allocated weights based on their distances from the sample data point. However, the computational complexity and memory requirements remained key issue. For addressing the memory utilization problem, size of data gets minimized. The repeated patterns without additional data are removed from the training data set [18].

### **Naive Bayes Classifier**

Naive Bayes Classifier technique is functioned based on Bayesian theorem. The designed technique is used when dimensionality of input is high. Bayesian Classifier is used for computing the possible output depending on the input. It is feasible to add new raw data at

runtime. A Naive Bayes classifier represents presence (or absence) of a feature (attribute) of class that is unrelated to presence (or absence) of any other feature when class variable is known. Naïve Bayesian Classification Algorithm was introduced by Shinde S.B and Amrit Priyadarshi (2015) that denotes statistical method and supervised learning method for classification. Naive Bayesian Algorithm is used to predict the heart disease. Raw hospital dataset is employed. After that, the data gets preprocessed and transformed. Finally by using the designed data mining algorithm, heart disease was predicted and accuracy was computed.

### **Support Vector Machine**

SVM are used in many applications like medical, military for classification purpose. SVM are employed for classification, regression or ranking function. SVM depends on statistical learning theory and structural risk minimization principal. SVM determines the location of decision boundaries called hyper plane for optimal separation of classes as described in figure 3. Margin maximization through creating largest distance between separating hyper plane and instances on either side are employed to minimize upper bound on expected generalization error. Classification accuracy of SVM not depends on dimension of classified entities. The data analysis in SVM is based on convex quadratic programming. It is expensive as quadratic programming methods need large matrix operations and time-consuming numerical computations.

### **v. CONCLUSION**

Massive MIMO technology plays a crucial role in next-generation wireless communication systems, but its performance heavily depends on accurate and efficient channel estimation. Traditional methods such as LS and MMSE, while widely used, face limitations in terms of computational complexity, pilot contamination, and sensitivity to noise in large-scale antenna deployments. This review explored the integration of machine learning techniques for channel estimation in massive MIMO systems, highlighting the advantages of data-driven approaches in improving estimation accuracy, reducing computational overhead, and enhancing overall system performance. Supervised learning, deep learning, and reinforcement learning methods have shown significant potential in addressing the challenges of conventional estimation techniques. Additionally, hybrid models that combine traditional and ML-based approaches offer a promising direction for further optimization. Despite these advancements, challenges

such as real-time implementation, data availability, and model interpretability remain key research areas. Future studies should focus on developing lightweight, adaptive ML models that can operate efficiently in dynamic wireless environments. The insights from this review suggest that machine learning-driven channel estimation can significantly enhance the performance of massive MIMO systems, paving the way for more intelligent and self-optimizing wireless networks in the era of 5G and beyond.

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