Energy Efficient Antenna Selection in Massive MIMO System Under Imperfect Channel State Information

Nega Lemma Zewude

A Thesis Submitted to

The Department of Electronics and Communication Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Electronics and Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

June, 2023

Adama, Ethiopia

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Major Advisor: Dr. Dereje Takilu

Co-Advisor: Dr. Shanko Chura

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APPROVAL PAGE FOR M.SC THESIS

As advisors for the thesis titled " **Energy Efficient Antenna Selection in Massive MIMO System Under Imperfect Channel State Information** " authored by Nega Lemma Zewad, we confirm that the final version of the thesis has appropriately integrated the recommendations and suggestions provided by the examining board.

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As members of the examining board for the thesis titled " **Energy Efficient Antenna Selection in Massive MIMO System Under Imperfect Channel State Information** " authored by Nega Lemma Zewude, we have carefully reviewed and assessed the thesis and also observed the candidate during the open defense. We hereby confirm that the thesis is accepted as a partial fulfillment of the requirements for the degree of Master of Science in Electronics and Communication Engineering.

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The final submission of the thesis to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC) is necessary for the approval and acceptance of the thesis

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School Dean	Signature	Date
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Office of Postgraduate Studies, Dean	Signature	Date

DECLARATION

I certify that my Master's Thesis, titled " Energy Efficient Antenna Selection in Massive MIMO System Under Imperfect Channel State Information" is my original work and has not been submitted for academic credit at any other university. All materials used in this thesis were properly acknowledged through citation.

Nega Lemma Zewude	____________________	_________________
Name of the Student	Signature	Date

RECOMMENDATION

As advisors of this thesis titled " Energy Efficient Antenna Selection in Massive MIMO System Under Imperfect Channel State Information " we confirm that we have reviewed the revised version of the thesis prepared by Nega Lemma Zewude under our guidance, which is submitted in partial fulfillment of the requirements for the degree of Masters of Science in Electronics and Communication Engineering. We recommend the submission of the revised version of the thesis to the department in accordance with the applicable procedures.

Dr. Dereje Takilu	______________________	______________
Major Advisor	Signature	Date
Dr.Shanko Chura	______________________	______________
Co-advisor	Signature	Date

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ABSTRACT

Massive MIMO systems have gained significant attention in recent years due to their potential to provide high data rates in wireless communication systems. However, the large number of antennas used in such systems results in high power consumption and decreased energy efficiency. Therefore, effective antenna selection schemes are required to reduce the number of active antennas and improve energy efficiency. Several antenna selection techniques have been proposed by researchers in the past few years, broadly classified into two categories: deterministic and stochastic. Deterministic algorithms aim to find the optimal subset of antennas by iteratively searching for the best combination of antennas using mathematical optimization techniques, while stochastic algorithms select a subset of antennas using a random search approach. Both techniques have limitations in terms of computational complexity and accuracy under rapidly changing channels. To overcome these limitations, this study proposes a deep learning-based approach that uses a deep neural network (DNN) for antenna selection. The proposed scheme in this thesis selects the antenna by taking into account the effect of imperfections in the channel state information and selects the antenna based on the factor less sensitive to channel imperfection. In the study, the impact of the distance between the user and the base station antenna and corresponding path losses on the energy efficiency of the system is evaluated. Then using this information as input to a deep learning scheme that considers the effect of SNR and channels the optimal number of antennas is determined. Finally, the accuracy of the proposed scheme is compared with some traditional machine learning techniques. The proposed scheme aimed to enhance the energy efficiency of massive MIMO systems while maintaining a certain level of performance.

Keywords: *Massive MIMO, antenna selection, Imperfect channel state information, deep learning*

LIST OF ACRONYMS AND ABBREVIATIONS

AE	Auto Encoders
AI	Artificial Intelligence
ANN	Artificial Neural Network
AS	Antenna Selection
BS	Base Station
CSI	Channel State Information
CBPSO	Capacity Based Binary Particle Swarm Optimization
COAS	Capacity-Optimized Antenna Selection
CNN	Convolutional Neural Network
CSI	Channel State Information
DLEE	Deep Learning Energy Efficient Scheme
DNN	Deep Neural Network
EDAS	Euclidean Distance-Optimized Antenna Selection
EE	Energy Efficiency
ESA	Exhaustive Search Algorithms
GSM	Generalized Spatial Modulation
JASPD	Joint Antenna Selection and Precoding Design
L-ASPA	Learning-Based Antenna Selection and Precoding Design
MDP	Markov Decision Process
ML	Machine Learning
MT	Mobile Terminals
QoS	Quality Of Service
PLE	Path Loss Exponent
RAS	Random Antenna Selection
RF	Radio Frequency
RNN	Recurrent Neural Networks
SE	Spectral Efficiency
SINR	Signal-To-Interference-Plus-Noise Ratio
SVM	Support Vector Machine
UE	User Equipment

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CHAPTER ONE

1 INTRODUCTION

1.1 Back Ground of the Study

Wireless communication systems are designed to provide a wide range of services to users with varying needs and expectations. These services can include voice, data, and video, and users may require different levels of reliability, speed, and quality of service (QoS). The varying and diverse nature of user expectations can raise the functionality demands for wireless communication systems. making it necessary to constantly improve their performance(FAWAD AHMAD 2022). 5G mobile broadband systems are designed to improve system functionality, capacity, and coverage. Massive multiple input multiple output (Ma-MIMO) technologies are critical to achieve these goals. It utilizes a significant number of antennas at both the transmitter and receiver, resulting in improved reliability, spectral efficiency, and energy efficiency. Spectral efficiency (SE) serves as a crucial metric for evaluating MIMO system performance. Studies have demonstrated that increasing the number of antennas in a MIMO system can lead to an overall improvement in SE (Asaad et al., 2018; Busari et al., 2018; Chan; De Mi, 2017; Li et al., 2019; Srivastava et al., 2019; Tai et al., 2015). However, the usage of a high number of antennas might leads to efficiency (EE) reduction. As a result, the subject of how to optimize EE in a multiple antenna system has gained increased attention. (Chan; Chang et al., 2017; De Mi, 2017; Marinello et al., 2020; Olyaee et al., 2018; Tai et al., 2015).

Optimizing the number of selected antennas is crucial for a massive MIMO system. Antenna selection (AS) methods in massive MIMO systems offer improved performance while utilizing the same number of radio frequency (RF) chains as conventional systems. AS plays a significant role in enhancing system performance by reducing the number of active antennas and mitigating the impact of imperfect channel state information. Numerous antenna selection algorithms have been proposed by researchers for massive MIMO systems, addressing the challenges posed by imperfect CSI.(Hongyuan Gao, 2019; Jin et al., 2019; Li & Li, 2018; Shenko Chura, 2022a). Initially, simple methods like random antenna selection (RAS) were used for antenna selection. However, these methods did not take into account the channel conditions and did not provide optimal performance(Sayeb, 2012). Next, more sophisticated methods like greedy antenna selection (GAS) and orthogonal matching pursuit (OMP) were developed (Barry et al., 2021; Leite & Lamare, 2021; Zhang et al., 2020). These methods selected antennas based on their correlation with the channel or their sparsity, respectively. However, these methods still did not fully leverage the potential of massive MIMO systems, especially when operating in environments with imperfect channel state information (CSI). Recently, more optimized and advanced antenna selection methods have been proposed, such as COAS and EDAS. These methods aim to select the best subset of antennas for transmission based on their capacity or Euclidean distance from the receiver, respectively. However, these methods may still have limitations in terms of complexity and flexibility(Aydin, 2019; Aydın, 2019), which is where machine learning-based approaches come into play.

Machine learning-based techniques can learn the underlying relations between the channel and the selected antennas, and can predict the best subset of antennas for transmission in real-time. Overall, the evolution of antenna selection has been driven by the need to improve system performance in complex channel environments, while minimizing complexity and maximizing flexibility. Antenna selection techniques have evolved from simple heuristic methods to more sophisticated and optimized approaches, and now towards machine learning-based methods that hold great promise for improving the efficiency and effectiveness of wireless communication systems(Naeem, 2020; Yu et al., 2021). For further improvement of performance, deep learning-based antenna selection is implemented which can learn the complex nonlinear relationship between the channel state information and optimal antenna selection than traditional machine learning. And it can handle a complex number of channels and a large number of antennas. Therefore, it is suitable for modern communication with massive MIMO at imperfect channel state information. And also it can adopt a new scenario by fine-tuning the pre-trained model by training the new model on new data (Lin et al., 2021; Scarpa Giulia & Carol, 2019).

The implementation of deep learning-based antenna selection for imperfect channel state information is a significant contribution of this work. The challenge of imperfect channel state information was addressed by first estimating the channel and considering the effects of channel errors. This ensured the robustness of the antenna selection process to channel imperfections. The antenna selection process was divided into two phases to reduce computational complexity. In the first phase, the optimal number of antennas was determined based on a threshold value of the channel condition. This reduced the computational complexity of the antenna selection process. In the second phase, the optimal antenna element was selected using deep learning, which learned the optimal selection policy from training data. Overall, the study is expected to have a significant impact on reducing the computational complexity of antenna selection processes and the model can be used to select an optimal antenna that maximizes energy efficiency and enhance the energy by selecting the channel that has the best channel condition.

1.2 Statement of the Problem

This thesis addresses the energy efficiency of massive MIMO systems by proposing a deep learning-based approach for antenna selection. The existing antenna selection techniques are either computationally complex or require more computation time and also effected by channel imperfection error to achieve the desired performance. To overcome these limitations, the proposed approach uses a deep neural network for antenna selection. However, imperfect channel state information can reduce the system's accuracy, so the study selects the antenna based on a factor less sensitive to channel imperfections and considers channel imperfection errors. The proposed scheme evaluates the impact of user distance, and path loss, and determines the optimal number of antennas required for different channel conditions. By using a deep learning scheme that considers input factors such as SNR, path loss, and channel gain, the study identifies the antenna element that maximizes energy efficiency. Finally, the proposed scheme's accuracy is compared with traditional machine learning techniques, with the aim of contributing to improving the energy efficiency of massive MIMO systems while maintaining a certain level of performance.

1.3 Objectives

1.3.1 General Objective

- To select energy efficient antennas in massive MIMO system under imperfect channel state information

1.3.2 Specific Objectives

- To evaluate the effect of distance between the user and base station antenna and cross ponding pathlosses on the energy efficiency of a system
- To find optimal number of antennas required at different channel condition of the system
- To determine the optimal number of antennas required to optimize energy efficiency by taking into account the effect of channel imperfection and based on the factor less sensitive to channel imperfection

- To select those antennas elements that maximizes energy efficiency at a given channel condition using deep learning and compare its accuracy with some machine learning techniques

1.4 Significance of the System

Deep learning algorithms can learn complex patterns in the channel data, enabling them to identify the best antenna configuration for a given channel state. This leads to higher spectral efficiency and better utilization of the available frequency spectrum. The algorithms eliminate the need for exhaustive search algorithms, which can be computationally expensive, particularly in large-scale MIMO systems. This leads to a significant reduction in the computational complexity of the system. And it can adapt to changes in the channel conditions in real-time, enabling the system to quickly respond to changing network conditions. In addition, that algorithm can optimize the antenna selection process to improve the quality of service for users by maximizing the signal-to- noise ratio (SNR). And also, it can reduce the power consumption of the system, leading to improved energy efficiency.

1.5 Thesis Contribution

The contributions of this thesis are as follows:

- We evaluate the system's path loss under suitable models, providing valuable insights into its real-world performance.
- We determine the optimal number of antennas under different conditions, offering practical guidance for system designers and reducing power consumption.
- Our proposed antenna selection scheme achieves high performance while minimizing complexity.
- Our use of deep learning for antenna selection has significant implications for the application of machine learning in wireless communication research.
- We enhance the system's energy efficiency and demonstrate its effectiveness in cases of imperfect channel state information.

1.6 Scope and Limitation of the Study

The scope this thesis is to improve the energy efficiency of a single base station in a massive MIMO system by implementing a deep learning-based antenna selection scheme. The study will primarily focus on evaluating the impact of distance between the user and base station antennas and responding path losses on the energy efficiency of the system. Then, by considering the effect of channel state information imperfection and based on the channel condition such as user distribution, and user mobility within a given radius, the optimal number of antennas required to optimize energy efficiency will be determined. Finally Deep learning will be used to select the optimal antennas based on pre-trained optimal conditions, using path loss, channel gain, and SNR as inputs. The accuracy of the proposed scheme will be evaluated against some conventional machine learning techniques. Overall, the study aims to optimize the antenna selection model by analyzing the propagation behavior of the wireless channel.

1.7 Organization of the Thesis

The thesis has been organized into five chapters.

Chapter 1: briefly discusses the background of the study. The problem statement, thesis objectives, significance of the study, and scope of the study are briefly discussed.

Chapter 2: starts by discussing a brief Introduction to the massive MIMO system Massive MIMO at imperfect channel state information is briefly discussed, introduction to machine learning and deep learning and its algorithms is briefly discussed. And also, an overview of antenna selection as well as deep learning-based antenna selection is briefly discussed,

Chapter 3: presents the research method that has been used in the thesis and the system models for channel estimation for imperfect channel state information, signal modeling, antenna selection, and dataset analysis are briefly discussed

Chapter 4: includes the results and discussion of massive MIMO antenna selection. The effect of path losses and distance as well as imperfection of channel state information on energy efficiency and the number of antennas to be selected and the element selection of the antenna by machine learning is briefly discussed.

Chapter 5: Finally, the conclusion and recommendation of the study are briefly discussed

CHAPTER TWO

2 LITERATURE REVIEW AND RELATED WORK

2.1 Introduction to Massive MIMO System

Massive MIMO, also known as large-scale MIMO, is a promising technique that has the potential to greatly improve spectral efficiency. By increasing the number of antennas at the base station to hundreds or even thousands, large-scale statistical effects can be used to eliminate small-scale fading, interference, and noise from the communication system. This allows the transmitted energy to be concentrated solely on the desired target, allowing for the scheduling of many more user terminals and greatly enhancing overall spectral efficiency. The assumption of hundreds of antennas is not ridiculous, as a typical 4G/LTE-A base station has 240 antenna components at maximum size. As a result, the scientific community has given Massive MIMO a lot of attention and is researching its potential. The basic premise has been made more plausible by a number of methods. For instance, progress has been made in solving the problem of estimating channel state information (CSI) for all of the associated channels, i.e., from each base station antenna to each user antenna. Additionally, efforts are being made to reduce the computational cost of precoding approaches.

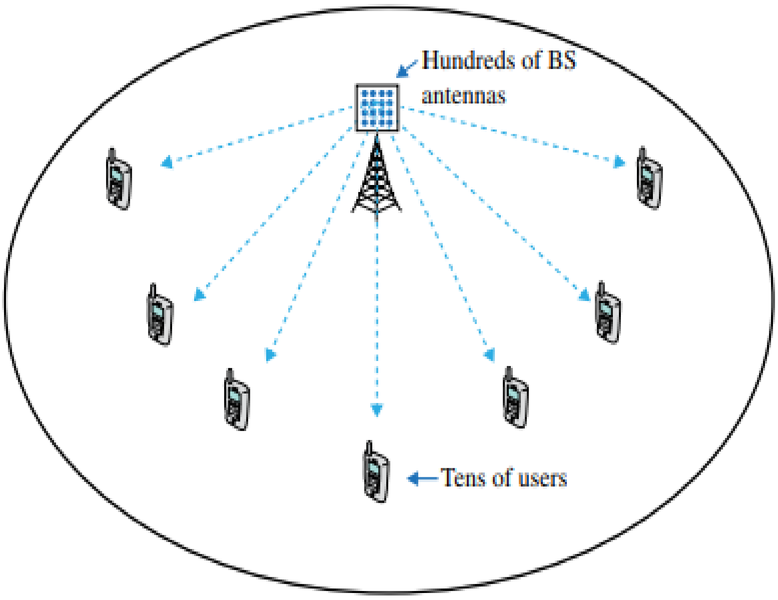

Figure 2. 1:Basic concept of massive MIMO system(Yao et al., 2018).

Various aspects of Massive MIMO systems' energy efficiency are being researched. These researches also take into account hardware flaws, which have a considerable impact on lowering the price per transceiver, especially when using hundreds of them. (Deshpande, 2018).

2.2 Massive MIMO at Imperfect Channel State Information

The effect of channel imperfection on massive MIMO system performance can be significant. Inaccurate CSI can lead to suboptimal beamforming and antenna selection, resulting in reduced system capacity and increased power consumption. It can also lead to increased interference, leading to reduced signal quality and higher error rates. To address the issue of channel imperfection in massive MIMO systems, researchers are investigating various techniques such as channel estimation refinement, feedback delay reduction, and quantization error mitigation. Deep learning-based approaches are also being explored to improve the accuracy of CSI by learning the underlying patterns and relationships in the data and using them to estimate the channel. These approaches can help reduce the impact of channel imperfection on the performance of massive MIMO systems, leading to more efficient and reliable wireless communication. Overall, channel imperfection is a significant challenge in massive MIMO systems that can have a significant impact on system performance. To address this issue, researchers are exploring various techniques to improve the accuracy of CSI and mitigate the effects of channel imperfection, including deep learning-based approaches. These techniques have the potential to significantly improve the energy efficiency and performance of massive MIMO systems, leading to more sustainable and cost-effective wireless networks. For further improvements of the system, it's better to estimate the channel and include it in the deep learning system (Chataut & Akl, 2020; Indrajeet Kumara, 2019; Nguyen et al., 2020).

2.3 Fundamentals of Deep Learning

A subfield of computer science called artificial intelligence (AI) focuses on to creating machines that can respond logically to outside input. The ultimate goal of AI is to build tools that can perform tasks that now need human intelligence. AI is now widespread in daily life because to applications like virtual assistants, search prediction technology, and ride-hailing services. Machine learning is a type of artificial intelligence application where a machine or computer learns from the past (input data) to forecast the future. It is expected that the system will perform at least as well as a human. The system gains knowledge from a given dataset to carry out a certain task. Artificial intelligence is created using deep learning, a subset of machine learning. The figure below provides a visual depiction of these ideas for a better understanding. (Jeyaraj et al., 2022; Sarker, 2021).

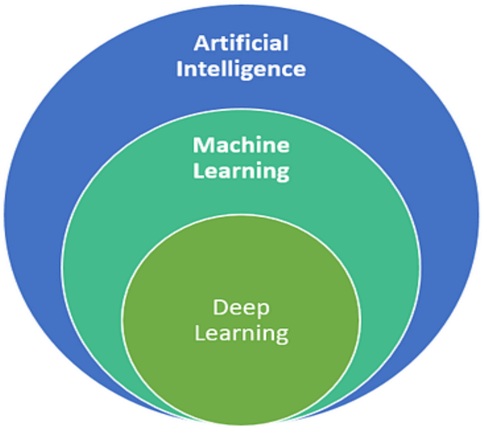

Figure 2. 2: Subfield of machine AI (Alzubaidi et al., 2021)

2.3.1 Machine Learning

Artificial Intelligence (AI) refers to the ability of computers to mimic human cognitive behavior. Achieving this requires researching how the human brain thinks, learns, makes decisions, and solves problems. AI encompasses any technique that enables computers to simulate human behavior by programming them explicitly for tasks such as speech recognition, image recognition, and natural language understanding. Machine Learning (ML) is a version of AI where machines can learn without being explicitly programmed and without the need for hard coding. In machine learning, a dataset is typically divided into training and testing data. The machine is trained using the training data, and its accuracy is then tested. Once trained, the machine can receive input data and compare it to its learned information to determine the outcome. There are three types of machine learning(R, 2015; Sihombing, 2018).

2.3.1.1 Supervised Learning

Every training example in supervised learning has a label attached to it, making it a form of machine learning. The objective is to train a learning model using a collection of known optimal solutions to a set of problem instances, and then use the learned model to predict optimal solutions for new data. A dataset of instances (also known as the training set, examples, samples, or objects) and their accompanying labels (also known as y) are used to formulate the issue in supervised learning. The algorithm, represented by $\alpha\theta$ (for instance, decision tree, linear model, neural network, etc.), must find a function $\alpha\theta(x) \rightarrow y$ to map instances to actions. The algorithm utilizes a loss function L $(y, \alpha\theta(x))$ to evaluate the predictor's performance. The primary objective of supervised learning is to develop a model that can accurately predict the correct label for new, unseen instances based on the labeled training data. Supervised learning is widely utilized in various fields, such as speech recognition, natural language processing, and computer vision, enabling machines to learn from past experiences and make accurate predictions on new data.(Shenko Chura, 2022b).

2.3.1.2 Unsupervised Learning

Unsupervised learning involves training machine learning algorithms on a set of unlabeled features, represented by the symbols x_1, x_2 and etc. To locate subgroups of variables that naturally share particular characteristics, use the function x_n to. Finding patterns and linkages in datasets is a particular strength of this approach. Since it does this job automatically, the approach is not designed to find linked attribute groupings But the algorithm can be instructed on how many clusters are required in a certain situation. Edge devices in a mobile network can be successfully aggregated using clustering, a well-liked machine learning technique. Autoencoders (AEs) have been used for a long time in neural networks for dimensionality reduction or feature learning. If the concept of AEs is applied to the physical layer of a communication system as an end-to-end optimal machine learning activity, input signal reconstruction within a neural network can be evaluated as a specific example of an AE. Researchers have been trying to optimize a large nonlinear neural network with many degrees of freedom for a simple high-level objective. They faithfully replicated a random input message that was sent and received across a channel at the receiver's output. (Shenko Chura, 2022b).

2.3.1.3 Reinforcement Learning

Wireless networks operate stochastically in uncertain situations like those with variable node locations and power levels. A mathematical framework known as a Markov decision process (MDP) can be utilized to model the system dynamics in order to optimize desired objectives under these circumstances. During each decision time, an agent, or learning entity, interacts with the environment and chooses an action that is available at the present state. Unlike being explicitly taught, the agent in reinforcement learning (RL) learns by interacting with the environment and understands the consequences of its actions. This includes exploiting past experiences and exploring new choices. (Xinxin Chai, 2020).

2.4 Deep Learning

The primary focus of deep learning, a branch of machine learning, is artificial neural networks, which are algorithms driven by the composition and operation of the brain. These networks are intended to evaluate sensory data and identify patterns through machine perception, clustering, or labeling of unprocessed information. All real-world data, such as images, sounds, text, and time series, are represented by vectors that contain numerical patterns. Due to its ability to handle a huge number of features, deep learning is very successful when processing unstructured data. Additionally, by automating feature engineering, it makes problem-solving simpler. A single end-to-end model can replace complex multistage pipelines and deep learning models can learn all the features in a single pass, removing the requirement for manual feature engineering. The most used antenna selection architecture is DNN. (Alzubaidi et al., 2021; Nikolenko, 2017).

2.4.1 Deep Neural Networks

An artificial neural network (ANN) that has more than two layers between the input and output layers is called a deep neural network (DNN). The precise issue being handled determines the network's size and structure. Regardless of the type, all neural networks include the same fundamental building blocks, including neurons, synapses, weights, biases, and functions, which interact in a similar way to how the human brain does. DNN architectures allow for the creation of compositional models. Things are expressed in these models as layered compositions of primitives. In comparison to a shallow network that operates similarly, the additional layers enable the gathering of features from lower levels, which may enable the modeling of complicated data with fewer units. Deep architectures come in a variety of shapes, and each one has proved effective in a certain area. It might not be workable without assessing the effectiveness of alternative solutions using the same datasets. Since feedforward networks rule in DNNs, information goes straight from the input layer to the output layer. The DNN assigns random integer values or "weights" to the connections between virtual neurons during training. The weights and inputs are multiplied to get an output between 0 and 1. If a particular pattern cannot be accurately identified by the network, an algorithm alters the weights by giving some parameters more weight, and this process continues until the correct mathematical operation for fully processing the data is found. (Durstewitz et al., 2019; Samek et al., 2021).

2.5 Types of Deep Neural Networks

There are three commonly used types of deep neural networks today:

Multi-Layer Perceptron, Convolutional Neural Networks, and Recurrent Neural Networks

2.5.1 Multilayer Perceptron (MLP)

A multilayer perceptron (MLP) is a type of artificial neural network (ANN) that is feedforward and consists of a series of fully connected layers. MLPs are the most fundamental type of deep neural network. Modern deep learning architectures require high computing power, but MLP machine learning methods can be used to overcome this limitation. Each new layer in an MLP is composed of nonlinear functions of a weighted sum of all outputs from the previous layer, resulting in a fully connected network.(Abdelaziz Botalb, 2018).

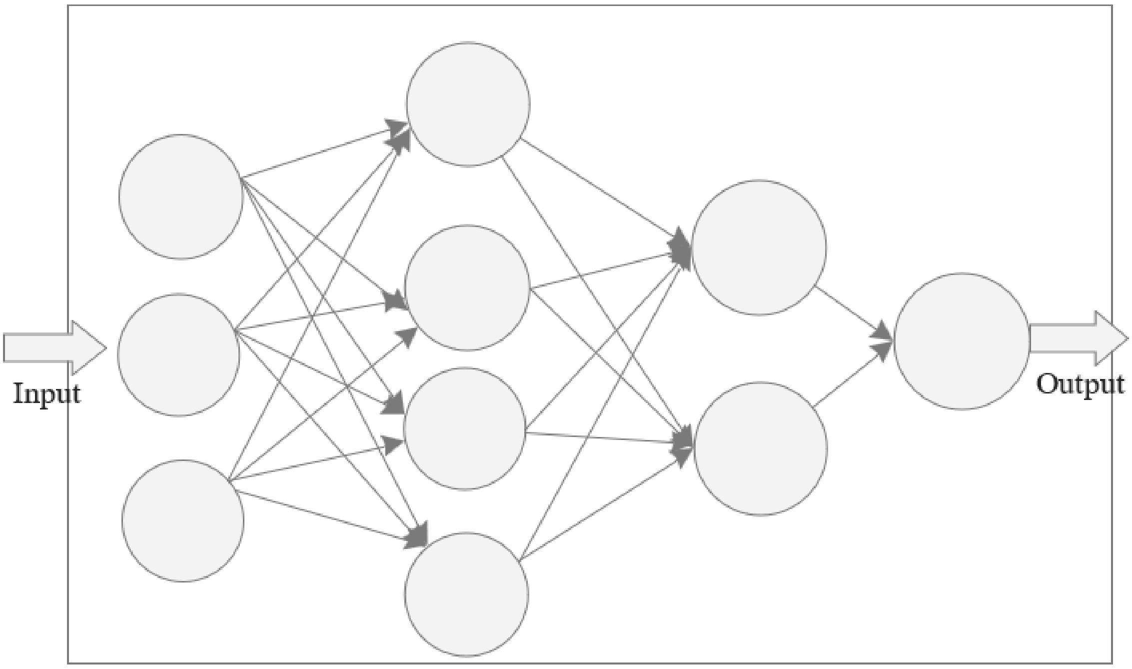

Figure 2. 3: Multilayer perceptron (Alzubaidi et al., 2021)

2.5.2 Convolutional Neural Network (CNN)

Convolutional neural network (CNN), is a typical deep neural network used in computer vision. For specific tasks like face identification, picture classification, and semantic segmentation, a CNN can be trained to automatically extract features from real-world photographs or videos. Convolution operations are employed in one or more convolution layers in CNN models, as opposed to fully linked layers in MLPs, to extract basic properties from input data. Each layer in a CNN is composed of nonlinear functions that weighted sums of spatially nearby subsets of the outputs from the previous layer at different places. Because it can reuse the weights, CNN is better able to recognize and learn complex features from the data.(Abdelaziz Botalb, 2018).

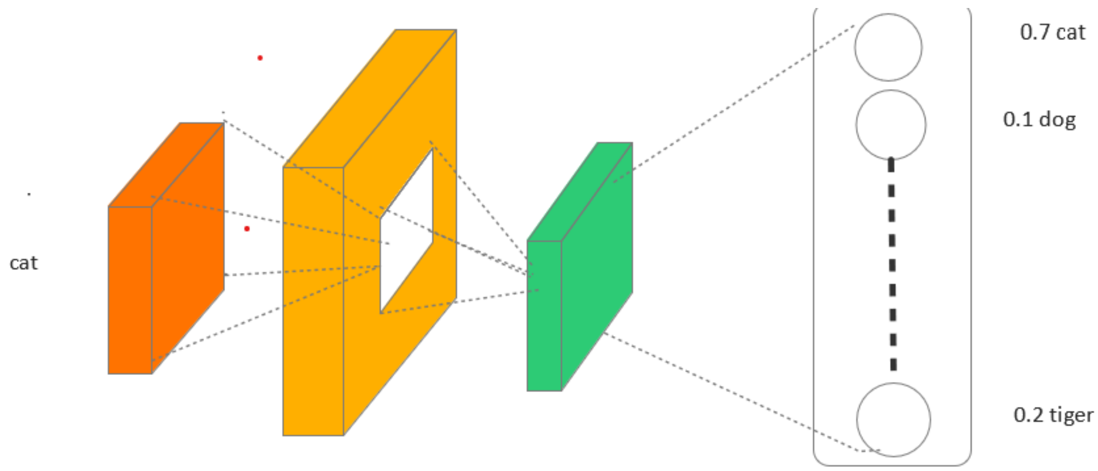

Figure 2. 4: Convolutional Neural Network (Alzubaidi et al., 2021)

2.5.3 Recurrent Neural Network (RNN)

Recurrent neural networks (RNNs), a particular type of artificial neural network, are designed with sequential data in mind. RNNs were created as a solution to the issues with time-series data, where the network is fed both the most recent sample and data from the past. The connections made between the nodes in RNNs as a result create a graph with directions along a temporal sequence. The network can discern temporal correlations and learn from earlier inputs because to the built-in memory that each neuron in an RNN contains.

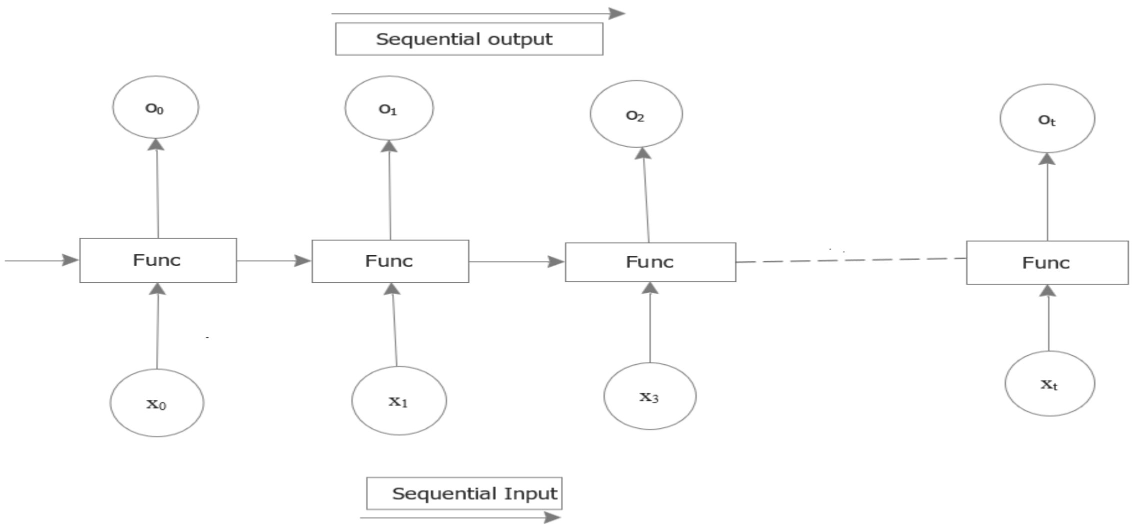

Figure 2. 5: Recurrent neural network (Alzubaidi et al., 2021)

Recurrent neural network (RNN) models are favored for Natural Language Processing (NLP) because they can handle data with a variety of input lengths. In an effort to develop a machine that can comprehend human speech, these models carry out tasks such natural language modeling, word embedding, and machine translation. In RNNs, each additional layer is composed of nonlinear functions based on the outputs' weighted sums and the prior state. The basic unit of an RNN is referred to as a "cell," and a series of cells and layers enables the sequential processing of recurrent neural network models.(WOJCIECH SAMEK, 2020).

2.6 Antenna Selection

A number of base station antennas are used in the wireless communication technology known as massive MIMO to increase performance while reducing system complexity and cost. Antenna selection, which comprises picking a subset of the available antennas for signal transmission and reception, is a crucial part of massive MIMO. The intention is to select a subset of antennas that can offer the best signal quality with the fewest possible antennae. Nevertheless, this procedure adds to the complexity of the system, therefore it is important to properly take into account things like channel conditions, hardware constraints, and system needs. Numerous antenna selection strategies have been put out in the literature in recent years. These techniques can be broadly divided into two groups: deterministic and stochastic. (Huang et al., 2016; J. Roscia Jeya Shiney, G. Indumathi, and A. Allwyn Clarence Asis2, 2020).

2.6.1 Deterministic Antenna Selection Techniques

Deterministic antenna selection techniques are based on a predefined set of rules or algorithms that select a subset of antennas from the available antenna array(Ke Dong1, 2011).

2.6.1.1 Exhaustive Search

The exhaustive search algorithm is a common deterministic technique used to identify the optimal antenna combination that maximizes system performance However, because of this technique's high computational complexity, enormous MIMO designs with several antennas cannot use it. The exhaustive search approach is not practical for large-scale antenna arrays because the computational complexity rises exponentially with the number of antennas.

2.6.1.2 Greedy Algorithm

Other deterministic techniques include greedy algorithms, the greedy algorithm is a simple but effective method for antenna selection. It starts by selecting the antenna with the strongest channel coefficient and then iteratively selects the next antenna that maximizes the capacity of the system, subject to constraints on the total power consumption and the target SNR for each user. This process continues until the desired number of antennas is selected.

It selects antennas based on a certain criterion, such as the highest channel gain or lowest interference, and recursive algorithms, which select antennas based on the correlation between the selected antennas and the remaining ones. These techniques provide near-optimal performance with low computational complexity and are suitable for large-scale antenna arrays. In these cases complexity growth with a number of antennas(J. Roscia Jeya Shiney, G. Indumathi, and A. Allwyn Clarence Asis, 2020; Konar & Sidiropoulos, 2018).

2.6.2 Stochastic Antenna Selection Techniques

Stochastic antenna selection techniques are based on probabilistic methods that select antennas randomly or with a certain probability distribution. These techniques include genetic algorithms, simulated annealing, and particle swarm optimization. Although stochastic techniques provide suboptimal performance, they are suitable for large-scale antenna arrays and offer good trade-offs between performance and computational complexity.

2.6.2.1 Genetic Algorithm

The genetic algorithm is a metaheuristic optimization algorithm that draws inspiration from the natural selection process. It involves generating a population of candidate antenna selections and applying genetic operators such as mutation and crossover iteratively to create new candidate solutions. The fitness of each solution is then assessed based on its energy consumption and capacity, and the top solutions are selected for the next generation. While this approach can tackle complex optimization problems, it can be computationally expensive. (Rao & Malleswara Rao, 2019).

2.6.3 Particle Swarm Optimization

Particle swarm optimization is another metaheuristic optimization algorithm that is inspired by the behavior of social insects such as bees and birds. It involves creating a population of particles that move through the search space and adjust their position based on the best solution found so far. The fitness of each particle is evaluated based on its capacity and energy consumption, and the best particles are selected for the next generation. This approach can handle complex optimization problems and can be more computationally efficient than the genetic algorithm. Overall, the choice of algorithm depends on the specific requirements and constraints of the wireless communication system. The greedy algorithm is a simple and efficient method that can achieve good performance for many systems, while convex optimization, genetic algorithms, and particle swarm optimization can handle more complex optimization problems but may require more computation (Ahmad et al., 2022).

2.6.4 Deep Learning-Based Antenna Selection

With regard to the multi-class classification issue, machine learning techniques can be used to solve the antenna selection problem. The performance and complexity of optimization-driven and data-driven AS approaches were compared by the authors. The best antenna for optimizing secrecy performance can be chosen using ML The authors suggested a brand-new transmit antenna grouping strategy to improve the performance of generalized spatial modulation (GSM) in massive MIMO (Ma-MIMO) systems. GSM outperforms spatial multiplexing when the ideal antenna configuration is used. although the effectiveness of linked channels and channel estimates can affect the system. In terms of bit error rate (BER), deep learning (DL) techniques beat the ideal AS method in suboptimal transmission conditions. While the proposed DL-based algorithms show higher error performance, the EDAS method still works well for channels with perfect knowledge and high signal-to-noise ratios (SNR). Using simulations and accuracy tests, the authors verified their findings. (Cong Shen, 2022; Ke He, 2021; Singh & Kishoreraja, 2021; Zhong et al., 2020).

2.7 Related Work

Hu et al. (2014), proposed an algorithm based on convex optimization for energy-efficient antenna selection in large MIMO wireless communication systems. The algorithm optimizes the number of transmit antennas, the specific set of transmit antennas, and servable mobile terminals (MTs) to increase energy efficiency while ensuring that the cell's channel capacity exceeds a predetermined threshold. The authors conducted a detailed analysis of the joint optimization problem and recommended a solution. Analysis and numerical simulations confirmed that the proposed algorithm significantly improved energy efficiency compared to using no antenna selection. However, the optimal solution requires an exhaustive search, which can be computationally challenging, especially for systems with many antennas.

Du et al. (2022) proposed a method for antenna selection and power allocation (GA-AS+PA) in the downlink of a MIMO system constrained by the sum-rate of users. The authors used a genetic algorithm to identify the active transmitting antenna of each base station (BS), followed by a convex optimization method to allocate transmission power across all users. The system's energy efficiency (EE) was optimized based on the number of active antennas and the optimal transmit power of the BS. Simulation results demonstrated that the GA-AS+PA technique satisfied user sum-rate requirements while improving the system's EE. The proposed method outperformed other approaches, including equal power allocation (EPA), random antenna selection + equal power allocation (RAS+EPA), random antenna selection + power allocation (RAS+PA), and genetic algorithm-based antenna selection with equal power allocation (GA-AS+EPA). The simulation results showed that the proposed GA-AS+PA method improved EE by 33.3% compared to the EPA strategy

Konar & Sidiropoulos. (2018) proposed an approach for selecting transmit antennas in the downlink of a single-cell, multi-user massive MIMO system, which increases the system's sum-rate capacity with fixed user power allocation under various RF switching constraints. Most previous research on this topic utilized convex relaxation-based methods, which can be computationally expensive and lack theoretical performance guarantees. The authors of this paper introduced a new approach that formulates RF switching constraints as independent sets of a Metroid while demonstrating that the objective function of the antenna selection problem is monotone and satisfies sub modularity. As a result, a simple greedy algorithm can guarantee a constant-factor approximation for all instances of the problem. Simulation results revealed that the greedy selection approach achieved a significant portion of the overall downlink channel capacity at a much lower complexity than convex relaxation-based methods, even with the smallest RF chains. This discovery could lead to a considerable reduction in the hardware complexity of large MIMO systems by implementing more straightforward procedures.

Vu et al. (2021) Optimizing the downlink sum-rate capacity for a single-cell, multi-user massive MIMO system's transmit antenna selection in the presence of various RF switching constraints is a known NP-hard problem. Previous solutions to this problem have utilized convex relaxation-based methods that are computationally taxing and lack theoretical performance guarantees. However, this study takes a different approach. The authors demonstrate that the problem's objective function is monotone and satisfies submodularity, and RF switching constraints can be formulated as independent sets of a Metroid. As a result, a simple greedy algorithm can guarantee a constant-factor approximation for all instances of the problem. Simulation results indicate that the greedy selection approach produces a solution that is practically nearly optimal and effectively utilizes a significant proportion of the downlink channel capacity, even with few RF chains. The greedy method is also much simpler than convex relaxation-based methods, suggesting the possibility of reducing hardware complexity in massive MIMO systems by using straightforward algorithms.

Ahmad et al. (2022) This study proposes a low-complexity method for simultaneously selecting broadcast antennas and constructing hybrid precoders in multi-user millimeter-wave (mm Wave) massive MIMO communication systems. The proposed method takes into account a partially connected hybrid architecture and employs a deep neural network (DNN) for analog precoder design and binary particle swarm optimization for transmit antenna selection. Simulation results show that the proposed method achieves a spectrum efficiency that is nearly as good as the best exhaustive search-based antenna selection and singular value decomposition-based precoder design, but with lower computational complexity. Furthermore, the proposed method enhances the system's energy efficiency and is less vulnerable to channel imperfections.

TRV. Anandharajan. (2019) This study proposes a novel Deep Learning Energy Efficient (DLEE) scheme for serving multiple users in a massive MIMO system with many antennas. The DLEE technique aims to establish the relationship between the spatial beamforming pattern and base station power consumption. The authors introduce a unique learning approach that employs the spatial correlation between user equipment antennas as input features and outputs the base station's energy efficiency. Unlike other methods that focus solely on energy efficiency through bit rate and power required for efficient throughput due to multipath propagation, this paper presents the unsupervised algorithm DLEE, which resembles an autoencoder and integrates the power consumed during beamforming and the DL framework. The proposed DLEE approach has the potential to improve base station energy efficiency by up to 12%.

Vu et al. (2021) This paper proposes a method for jointly selecting transmit antennas and designing hybrid precoders in MIMO communication systems. The method employs a deep neural network (DNN) and binary particle swarm optimization for transmit antenna selection and constructs an analog precoder while considering a partially connected hybrid architecture. Simulation results demonstrate that the proposed method achieves a spectrum efficiency that is nearly equivalent to the best exhaustive search-based antenna selection and singular value decomposition-based precoder design, with the added benefit of being computationally less demanding. Moreover, the proposed solution enhances the system's energy efficiency and is less susceptible to channel imperfections.

Cai et al.(2019)This study proposes a novel antenna selection method centered around deep learning. The authors optimize channel capacity to generate labels that are used to train the antenna systems. The channel matrices are then processed through a deep convolutional neural network (CNN) to capture the significant latent signals of attenuation coefficients, which provide the class label and determine the optimal antenna subset. Experimental results indicate that the proposed method outperforms previous data-driven antenna selection approaches. However, the proposed method does not account for incomplete channel state information.

Shen et al. (2020) This article proposes a receive antenna selection method based on deep neural networks (DNNs), leveraging recent advances in deep learning. The authors utilize numerical simulations to define the neural network's structure and evaluate its performance, demonstrating that the data-driven approach achieves near-optimal mutual information in simple scenarios. However, the proposed method does not scale naturally with the problem size. To address this limitation, the authors suggest hybrid greedy techniques for practical applications where the number of selected antennas is uncertain at the outset. These techniques employ a DNN-based approach for a fixed dimension and then use a greedy algorithm to either increase or decrease the number of antennas to approximate the optimal solution of the new problem dimension. The effectiveness of the hybrid approaches is demonstrated through numerical simulations.

Table 2. 1: Summary of related and gap of related work

Authors name	**Year**	**Title**	**Contribution**	**Weakness**
Chongjun Ouyang	2018	Massive MIMO antenna selection Asymptotic Upper capacity bound and partial CSI	The proposed approach in this study is an adaptive antenna selection method that can attain a significant portion of the transmission rate while utilizing less channel state information (CSI).	Computational complexity compared increase linearly with the number of antennas. In case imperfect channel state information the system has no sense

Cong Shen Donghao	2020	MIMO receives antenna selection via deep learning and greedy adaptation	The effectiveness of the hybrid solution is demonstrated in this study by combining the DNN-based approach for a specific problem dimension with a greedy algorithm, resulting in hybrid greedy solutions.	It depends on channel state information
Hindavi KishorJadhavVinoth BabuKumaravelu	2022	Transmit antenna selection for spatial modulation based on machine learning	enhance SM's performance in terms of average bit error rate.	It has no sense in case of imperfect channel state information
Hao Li; Julian Cheng ; Zhigang Wang; Houjun Wang	2019	Joint Antenna Selection and Power Allocation for an Energy-efficient Massive MIMO System	A method that solves problems iteratively until convergence is reached is developed to identify the ideal number of transmit antennas and power distribution. The numerical findings show that the suggested approach works as intended.	Complexity problem
Salman Khalid, Waqaas bin abbas, Farhan Khalid	2021	Deep Learning based Joint Precoder Design and Antenna Selection for Partially Connected Hybrid Massive MIMO Systems	In a partially linked massive MIMO hybrid system, the authors provide a computationally effective combined deep convolutional neural network technique for precoder design and antenna selection.	not very sensitive to channel irregularities
Jia-xin CaiI, Ranxu Zhong2, Yan Li	2019	Antenna selection for multiple-input multiple-output systems based on deep convolutional neural networks	The deep convolutional neural network (CNN) was applied to the channel matrices by the authors in order to better use the important latent cues of attenuation coefficients.	They didn't consider the effect of channel imperfection

2.8 Summary of the Gap and Proposed and Implemented Solution

The task of antenna selection in a massive Mimeo system is very important to serve the user. Since massive MIMO antenna selection has a very high performance than conventional massive MIMO systems many conventional antenna selections in massive MIMO systems are implemented by the researcher. The application of the system in real-world scenarios is restricted by computational complexity and flexibility requirements. At this point, deep learning-based antenna selection is implemented by the researcher but until this, the system has no sense in case of imperfect channel state information. To address this issue this work proposes an adapted antenna selection algorithm, we model the imperfect channel estimates using a Gauss-Markov uncertainty model. And take into account the effect of it. And by using a high dataset based on the three important channel conditions the accuracy of antenna selection is improved.

CHAPTER THREE

3 MATERIAL AND METHODOLOGY

3.1 Overview

This thesis reviews various papers and articles related to massive MIMO antenna selection, sourced from reputable journals such as IEEE, Springer, and Elsevier, as well as relevant books. The proposed methods and techniques are designed and simulated by the methodology outlined in section 3.3, which takes into account the insights gained from the literature review and the problem statement.

3.2 Materials

The MATLAB/R2022a software tools were used to run the simulations for this thesis. An effective language for technical computing is called MATLAB, which stands for Matrix Laboratory. This software set consists of Simulink, a graphical programming environment for modeling, simulating, and analyzing dynamic systems, as well as technical computing tools.

3.3 Methodology

To meet the above-mentioned objectives of the thesis the following formal methodologies are followed.

Literature Review: This thesis is closely tied to prior research conducted by experts and scholars in the field. Accordingly, it is crucial to study the works of these individuals to gain pertinent and valuable knowledge on the topic. A literature review is conducted by examining a range of sources, including papers, books, journals, and online resources, to identify relevant information. As such, the literature review in this thesis involves reading articles, conference proceedings, papers, books, and journals, and conducting online searches to identify relevant information on deep learning-based antenna selection for massive MIMO systems.

Problem Identification: based on the paper reviewed from different journals, articles and Conferences of the problem (research gaps) are identified for a research study.

System Designing: After the identification of the research gap the systems are designed for the proposed work.

Simulation of Designed System Using MATLAB: after modeling the proposed system the simulation is done using MATLAB tools.

Result and Discussion: Discussions of the outcomes are conducted based on the simulation results, and performance assessments of suggested strategies are also conducted.

Documentation: After examining the outcomes of the created system, the research study's overall work is ended by outlining an implicit recommendation and additional work that has to be done in the relevant fields.

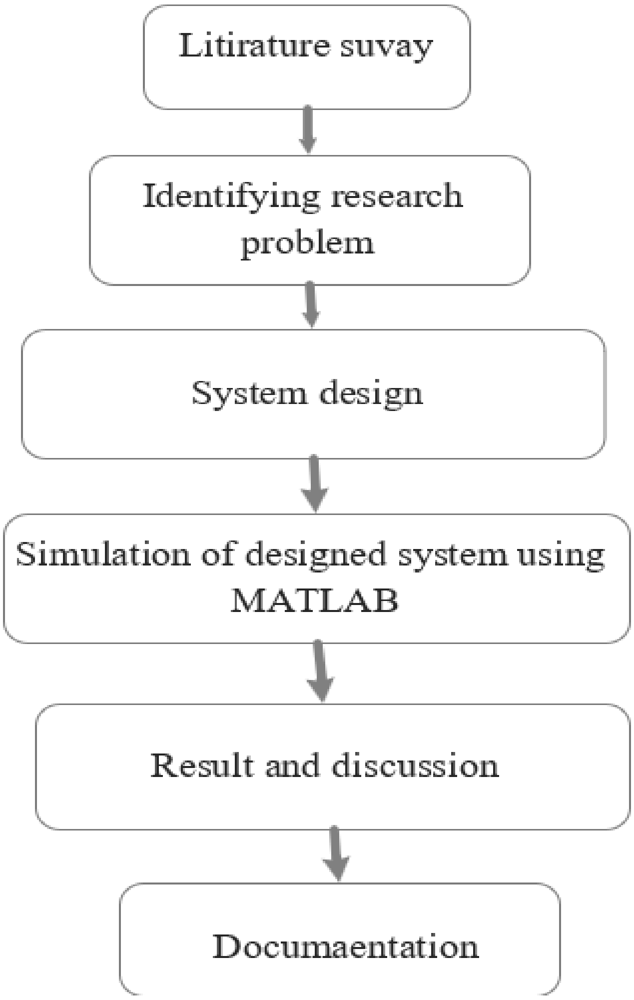

Figure 3. 1: Methodology

3.4 System Model for Down Link Massive MIMO System

A base station outfitted with many antennas connects with numerous users who are present inside its service area in a downlink massive MIMO system. This system uses N single reception antenna users and one transmitter with M antennas, where M is much more than K. The system pre-processes and pre-codes MIMO data using the base station (BS) to map the data stream.

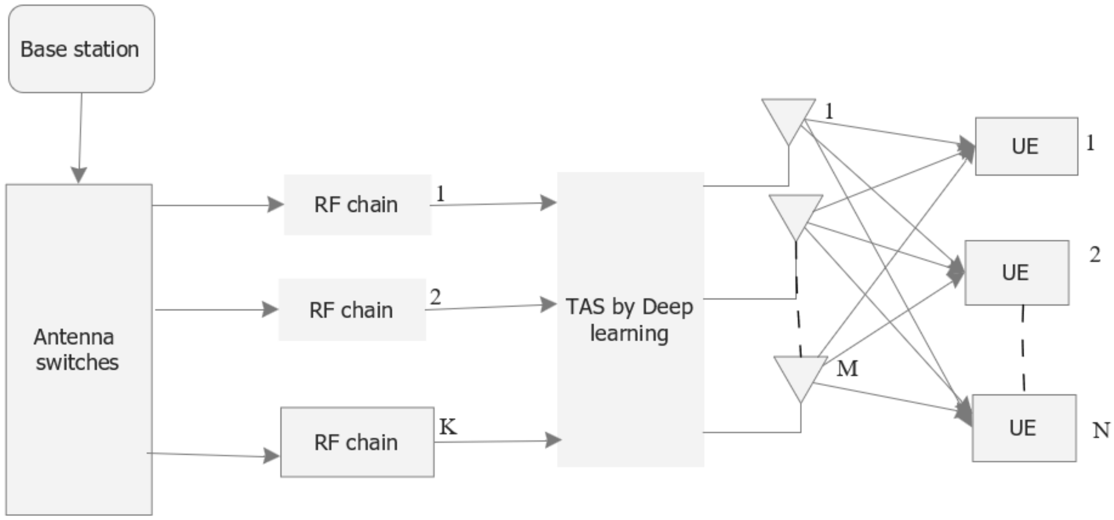

Figure 3. 2: system model downlink massive MIMO system

The processed data is then sent through a large set of radio frequency (RF) chains, which can increase the hardware complexity of the system and lead to power dissipation. Which leads to a degradation in energy efficiency. To improve energy efficiency, the system can use a massive MIMO system with transmit antenna selection (TAS). The number of antennas to be chosen is determined amount of transmit power available during the communication process. In the system, the base station is transmitting a signal to the user equipment the antenna selection can be performed at the base station (BSAS) or transmitter antenna selection (TAS). In the BSAS base station select the best subset of the antenna to transmit the signal to the UE based on estimated CSI. In our system, the TAS selection is based on maximizing energy efficiency. Antenna selection in a downlink massive MIMO system can be optimized for energy efficiency by considering factors such as SNR, path loss, and channel gain. The goal of energy-efficient antenna selection is to maximize the system throughput while minimizing energy consumption. One approach of energy efficient antenna selection is considering the channel condition and selecting the antenna that provides the highest channel gain and lowest path loss to ensure that the transmitted signal is directed toward the intended devices with the highest qualities which improves the overall system performance and reduces the need for retransmission. Therefore to obtain the above channel condition proper channel estimation and path loss modeling are required Before going to the antenna selection let us discuss the channel condition, path loss modeling, and channel estimation effect of the system(Ahmad et al., 2022).

3.5 Channel Estimation

To achieve optimal system performance, it is crucial to have accurate channel estimation. Accurate channel estimation has a significant impact on antenna selection, which, in turn, affects the overall system performance. In the model studied channel coefficients are initially estimated at the users and then broadcasted. However, in practical scenarios, errors are introduced in the transmitter's channel estimates due to the estimation and feedback processes. This issue affects both the antenna selection and precoding processes. To tackle this problem and develop an adapted antenna selection algorithm, the authors use a Gauss-Markov uncertainty model to represent the imperfect channel estimates.

$$H_k = \sqrt{1-\sigma}\widehat{H}_k + \sqrt{\sigma}e_k \quad (3.1)$$

where H_k is the true part of the kth user channel vector, $\widehat{H}_k$ is the imperfect observation of the kth user channel vector, The i.i.d. estimation error term is represented by ek, and σ represents the estimation accuracy, where a value of $\sigma = 0$ indicates perfect channel estimation, while $\sigma = 1$ indicates that the channel estimation is entirely erroneous. (Benmimoune et al., 2016).

3.6 Path Loss Model

The path loss model can provide essential information about the wireless channel, including the distance between the transmitter and receiver, the frequency of the signal, and the surrounding environment. By incorporating the path loss model as an input factor, the deep learning system can learn to select antennas that are optimal for the specific channel conditions, including the path loss. This can enhance the system's overall performance, including energy efficiency, spectral efficiency, and throughput.

3.6.1 Close in (CI) Path Loss Model

The selection of the path loss model is dependent on the specific scenario and the environment's characteristics. In deep learning-based antenna selection for massive MIMO systems with imperfect CSI, the closed-in path loss model can be used as it provides a more accurate description of the wireless channel in short-range communication scenarios. By integrating the closed-in path loss model into the input factor, the deep learning system can select antennas that are optimal for specific channel conditions, including effects from multipath propagation and shadowing.

The Constant of Proportionality (CI), which is used to characterize the route loss as a function of the environment, is a key component of the path loss model based on the fundamental radio propagation ideas proposed by Friis and Bullington. It is advised to use the CI 1m reference distance to translate the actual transmit power or Path Loss (PL) to a distance of one meter because base station towers are tall and inter-site distances for particular frequency bands can be several kilometers. Standardizing to a 1m reference Standardizing to a 1m reference distance makes it easier to compare dimensions and models, gives a consistent description of the Path Loss Exponent (PLE), and enables rapid and simple path loss estimations without the aid of a calculator. In order to reduce interference and ensure fairness, power control systems distribute less power to user terminals that are near the base station than to those that are farther away. The CI path loss model is a general frequency model that provides a context-specific explanation for large-scale route loss at all relevant frequencies. However, the dynamic range of signals perceived by users in a commercial system becomes significantly lower than the equation for the CI model, which is formulated as a constant plus the product of the PLE and the logarithm of the distance between the transmitter and receiver.

$$PL\_\{CI\}_{\{dB\}} = PL_{\{FS\}} + 10n\log10(d) + x_a^{\{ci\}} \tag{3.2}$$

An empirical value, the path loss exponent is represented by n. Path loss is defined by the PLE in terms of long distances starting at one meter, with path loss being defined by 10n in terms of dB. The following formula is used to calculate the free space path loss at a distance of 1 m from a station at carrier frequency f:

$$PL_{FS}(f, 1m)[dB] = 20\log10(4\pi/\lambda) \tag{3.3}$$

Where λ is the wavelength of the signal. x_σ^{cl} Is large-scale signal fluctuations due to the CI path loss model(Chura, 2022).

3.7 Signal Modeling

Antenna selection is a signal processing method that improves the performance of MIMO systems. MIMO systems, also known as multiple-antenna systems, are used to enhance the reliability and capacity of radio communication. However, the use of multiple RF chains with multiple antennas can be costly in terms of hardware, power, and size. In a massive MIMO system with M transmit and N receive antennas $Mand\ N\ where\ N \ll M$) an input and output relationship are illustrated as.

$$y(t) = \sqrt{\frac{\rho}{M}} Hx(t) + W(t) \tag{3.4}$$

Where: $y(t)$ is the received signal.

$x(t)$ Is the transmit signal and

$w(t)$ Denote the white Gaussian noise. ρ Is the average signal-to-noise ratio and $H \in C^{M\times N}$is a channel matrix. In the absence of instantaneous channel state information (CSI), the transmitter must distribute its power equally to all the Mt antennas.

3.8 Channel capacity

The channel capacity of the MIMO system for the channel matrix H can be represented as follows.

$$C(H) = log_2\, det(\, I_M + \frac{\rho}{M} H^H H) \tag{3.5}$$

The entire set of transmitter antennas can be used if M_s transmit antennas are chosen from the M_t available antennas, where M_t =M_s,. When there is a tiny time variation in the channel, the receiver can get instantaneous CSI with some uncertainty. As a result, antenna selection at the receiver can be done fairly accurately. The chosen antenna indices are transmitted to the transmitter via the constrained feedback channel once the antenna selection process is complete. As a result, the channel capacity following the selection of the transmit antenna (TAS) can be represented as(Ahmad et al., 2022).

$$C(H_{sel}) = log_2\, det(\, I_M + \frac{\rho}{M_{sel}} {H_{sel}}^H H_{sel}) \tag{3.6}$$

3.9 Total Power Consumption

When analyzing the energy efficiency of a cellular network, it is crucial to model power consumption accurately. In a massive MIMO system, power consumption can be categorized into two main types: circuit power consumption and static power consumption. Circuit power consumption refers to the energy consumed by the active components in the system, including the power amplifier and local oscillator. This type of power consumption is directly proportional to the amount of data being transmitted and the number of active components in the system. On the other hand, static power consumption refers to the energy consumed by the passive components in the system, such as antennas, RF filters, and transmission lines. Unlike circuit power consumption, static power consumption is not dependent on the amount of data being transmitted and is primarily determined by the size and number of passive components in the system. In the downlink of a massive MIMO system, the antennas used to transmit the signal over the air dominates static power consumption.

The total power before and after low-resolution DAC and selection can be expressed as follows:

Before selection:

$$P_{total} = P_{LO} + P_{PA} + M(2P_{DAC} + 2P_M + 2P_{LF} + P_{HB}) \tag{3.7}$$

After selection:

$$P_{total} = P_{LO} + P_{PA} + M_s(2P_{DAC} + 2P_M + 2P_{LF} + P_{HB}) \quad (3.8)$$

Where P_{LO} andP_{PA}, respectively, stand for the power used by the local oscillator and power amplifier. The power used by the mixer, low pass filter, and hybrid with buffer are each represented by the letters P_M, P_{LF}, and P_{HB} respectively. It is clear from examining Equations 3.7 and 3.8 that $P_{DAC}, P_M, P_{LF} and P_{HB}$ depend substantially on the quantity of massive antenna elements M. As a result, choosing every available antenna element will considerably increase power consumption and hence decrease the system's total energy efficiency.(Aredo et al., 2022; Singh & Kishoreraja, 2021; Tai et al., 2015).

3.10 Energy Efficiency of the System

In this work energy efficiency is defined as the achievable downlink sum-rate total power consumption based on 3.5 and 3.7 the energy efficiency can be given as.

$$EE = \left(\frac{C}{ptotal}\right)_M \approx \frac{log_2\, det(I_M + \frac{\rho}{M} H^H H)}{P_{LO}+P_{PA}+M(2P_{DAC}+2P_M+2P_{LF}+P_{HB})} \quad (3.9)$$

3.10.1Energy Efficiency of Massive MIMO at Imperfect Channel State Information

In a massive MIMO system with imperfect CSI, the channel is estimated using pilot symbols, and the estimated channel matrix is used for data transmission. The estimation error in the channel matrix can affect the energy efficiency of the system. The energy efficiency of a massive MIMO system with imperfect CSI can be expressed as

$$EE = \frac{B\log_2\left(\det(I + \frac{P_{tx}}{NoB}))\frac{H_{\mathrm{mod}} H_{\mathrm{mod}}{}^{H}}{H_{est} H_{est}{}^{H} + \Delta}\right)}{P_{LO}+P_{PA}+M(2P_{DAC}+2P_M+2P_{LF}+P_{HB})} \quad (3.10)$$

We can modify the channel matrix to take into account the SNR, channel gain, and path loss, and it is used in the estimation of the true channel matrix and the pilot contamination parameter.

The modified channel matrix can be expressed as:

$$H_{\mathrm{mod}} = \sqrt{\rho} G H \sqrt{PL} \quad (3.11)$$

Where ρ is the transmit power scaling factor, G is the channel gain matrix, H is the true channel matrix and PL is the path loss scaling factor

$$EE = \frac{B\log_2\left(\det(I + \frac{P_{tx}}{NoB}))\frac{H_{\mathrm{mod}} H_{mod}{}^{H}}{H_{est} H_{est}{}^{H} + \Delta}\right)}{P_{LO}+P_{PA}+M(2P_{DAC}+2P_M+2P_{LF}+P_{HB})} \quad (3.12)$$

3.11 Antenna Selection

The overall antenna selection process can be divided into two phases: number selection and element selection. The number selection phase involves determining the optimal number of antennas to use in a massive MIMO system, depending on the system requirements and operating conditions. The element selection phase involves selecting a subset of antennas from the total number of antennas available in the system.

3.11.1 Number Selection

During the selection phase, the transmit power that will be broadcast through each antenna is managed to determine the required number of antennas. Trilateration is used to determine the positions of the users in order to reduce leakage and make it possible for the primary beam to just focus on the desired area. In order to take mobility-related changes in user position into account, the transmit power is also adjusted. Only a small number of transmit antennas are adaptively utilized when user nodes get close to the base station (BS) center. the minimal Signal-to-Noise Ratio (SNR) at the cell edge is used as a threshold value to achieve this. The BS distributes power proportionally to the shorter distance rather than depending on maximum transmit power allocation at the edge. As a result, fewer antennas are activated, conserving resources.

Hence, for cell-edge users, the initial ideal number of antennas. Consequently, the following is chosen as the initial ideal number of antennas for cell-edge users, M^O is. Therefore, the first optimal number of antennas for cell-edge users

$$M^O = \max_{l \in M, \zeta \in |\zeta_{th} \max|} \rightarrow EE\big(M(l)\big) \tag{3.13}$$

Where $EE\big(M(l)\big)$ is given in equation (3.12)

Next, adaptive selection follows as the users move from the cell edge to the cell center or the outskirts and given by:

$$M_s^O = \frac{\left(\sum pl(r)/_k\right) M^O}{pl(d_{\max})} \tag{3.14}$$

Where The CI path loss of users is denoted by $\alpha(r)$ and $\alpha(D_{Max})$ for any arbitrary distance and maximum distance, respectively. whereas M represents the overall number of antennas. The number of RF chains N equals the number of antennas to be selected, which is $M_s$in the event of changes in channel condition or user position. With regard to digital beam former technology, this is especially true.(Aredo et al., 2022).

3.11.2 Element Selection Algorithm

There are various antenna selection algorithms, including Exhaustive Search Algorithms (ESA), conventional Binary Particle Swarm Optimization (BPSO), Cooperative Binary Particle Swarm Optimization (CBPSO), and Random Search (RS) methods. ESA is an optimal antenna selection approach that calculates and evaluates all possible combinations to identify the optimal performance. However, ESA has a high computational complexity and is not practical for real-time scenarios when the channel changes rapidly. Therefore, heuristic algorithms like BPSO and CBPSO, which are based on swarm intelligence, are commonly used for antenna selection in practical systems. These algorithms can provide a near-optimal solution with a lower computational cost than ESA. However, these algorithms may not always achieve the optimal antenna selection solution. And also, in case of an exhaustive search to select M_S^o number of antennas from M number of antenna by using factorial permutation as

$$\frac{M^O}{M_S^o} = \frac{M^O!}{M^o!(M^O - M_S^o} \tag{3.15}$$

A deep learning-based antenna selection approach is suggested in this study to further reduce selection complexity. The suggested algorithm seeks to achieve the specified level of service quality while maximizing the system's energy efficiency. Out of all the available antennas in the system, the algorithm is made to choose a subset of them. The decision is made using a deep learning model that has been trained on a sizable dataset to identify the best antenna subset for various operating scenarios.(Aredo et al., 2022).

3.12 Deep Learning-Based Antenna Selection for Massive MIMO System

Antenna selection (AS) is a challenging problem in massive MIMO systems due to the large number of antennas, making an exhaustive search approach computationally prohibitive. For instance, if there are M antennas and K users, the number of possible subsets is $\binom{N}{K}$, which is typically too large for practical implementation. Even if an exhaustive search's performance can be improved, the complexity of the search exponentially grows with the number of antennas and the number of antennas chosen. An alternative to AS is branch and bound (BnB), although it is not capable of removing the worst-case exponential complexity because its complexity depends on the channel realizations and is constrained by the difficulty of the problem. Classification issues have been successfully resolved using deep learning. It is possible to think of this as a problem of multi-class classification, where each class corresponds to a subset of antennas. So, it seems sense to investigate whether a deep neural network (DNN) may be trained to offer a nearly ideal substitute for the exhaustive search and BnB approaches. The best antenna selection policy can be taught to the DNN using a large dataset of channel realizations. The advantage of this strategy is that the DNN, as opposed to the exhaustive search or BnB approaches, can offer a nearly optimal solution with significantly less complexity. (FAWAD AHMAD 2022).

3.13 Dataset Generation

In our system we make the selection depending on the path loss, snr, and channel gain between each of the base station antenna and user antenna the data is prepared by simulating the desired massive MIMO system with various channel conditions and antenna configuration.

Here are the steps we have flowed:

Step 1: we define the system parameters such as the number of users, base station antennas, and samples, as well as the transmit power, noise power, channel variance, and path loss parameters.

Step 2: Generate random antenna positions on a circle around the base station within 100m and randomly distribute user locations near the base station within the 400m radius.

By fixing the base station antenna at the first position and randomly distributing the user located near the given radius for every iteration we have generated a random channel matrix and added noise to simulate imperfect CSI and calculated their distance.

The channel matrix is considered a data sample. Initially, the complex channel matrix H is transformed into a real-value matrix by replacing the (i, j)th element h_{ij} with its amplitude $|h_{ij}|$

$$|h_{ij}| \rightarrow \left||h_{ij}|\right|, \quad for \quad all, ij \tag{3.16}$$

Since each row of H represents a transmitting antenna, normalization must be performed on each row vector. Thus, the channel matrix is normalized to obtain a scale-invariant feature using the following equation:

$$h_{ij} \rightarrow \frac{h_{ij} - \min\{h_j\}}{\max\{h_j\} - \min\{h_j\}} \quad for \quad all \quad i, j \tag{3.17}$$

Here h_j denotes the jth column vector of H.

The distance between each antenna and the user is calculated by using the Euclidean formula

Step 3: based on the above information (channel matrix and distance between each base station antenna and user antennas) we calculate the path loss for each user antenna to base station antenna using the CI path loss model which is suitable for imperfect channel state information since we have going to select the transmitter antenna which has lower path loss for energy efficiency optimization to reduce the complexity we can calculate the average path loss of every single antenna to each user to use as input for deep learning

Step 4: we have calculated the SNR for the user antenna to each base station antenna using the channel matrix and we calculate the average SNR for every single base station antenna to each user antenna for understanding purposes to use the result as input feature for deep learning

Step 5: we have calculated the channel gain for the user antenna to each base station antenna using the channel matrix and calculated the average channel gain for every single base station antenna to each user antenna for understanding purposes to use the result as an input feature for deep learning

Step 6: Repeat step 1to 5 for further improvement of the performance for increasing the size of the dataset

Step 7: based on the above three features we can predict for each element of the antenna that maximizes the energy efficiency of the system. We can obtain the optimal antenna that maximizes the energy.

Step 8: Labeling

In a massive MIMO system for energy efficiency, the goal is to select the antenna set that maximizes energy efficiency while maintaining a certain level of performance. The labeling process for antenna selection can be done using the following three features of the channel condition:

Path loss: The path loss between each user antenna and base station antenna can be calculated using a CI path loss model. The path loss reflects the attenuation of the signal power as it travels from the transmitter to the receiver. Antennas with lower path loss will have better signal quality and can be selected for transmission. To achieve K values of Energy efficiency we can determine the threshold values of path loss

Signal-to-Noise Ratio (SNR): The SNR for each user antenna to the base station antenna can be calculated using the channel matrix and the noise power. The SNR reflects the quality of the received signal relative to the noise level. Antennas with higher SNR will have better signal quality and can be selected for transmission. Based on the Gaussian model of energy efficiency in the massive MIMO we have identified the threshold values of SNR required to achieve the energy efficiency

Channel gain: The channel gain for each user antenna to the base station antenna can be calculated using the channel matrix. The channel gain reflects the strength of the received signal. Antennas with higher channel gain will have stronger received signals and can be selected for transmission. Based on the Gaussian energy efficiency model the threshold values of the channel gain can be determined

Based on these three features, the labeling process can be done as follows:

1. Calculate the path loss, SNR, and channel gain for each user antenna to the base station antenna.
2. For each single base station antenna to each user pair, calculate the sum of the path loss, SNR, and channel gain. The weights can be determined based on the specific requirements and constraints of the system
3. Select the top k antennas with the highest scores as the labeled set. The value of k can be determined based on the specific requirements and constraints of the system.
4. Assign a label of 1 to the selected antennas and a label of 0 to the remaining antennas.
5. Repeat the above process for each sample in the dataset.

The resulting labeled dataset can then be used to train a deep learning model for antenna selection in a massive MIMO system for energy efficiency. The model can predict the optimal antenna set for a given channel condition based on the learned patterns in the dataset. In our system, by assuming every user in the given base station can access every antenna in the system the connection of each user antenna and each single base station we have considered the massive MIMO system which has 64 base station antenna and 10 single antenna users. By randomly distributing the user antenna within the radius of 400m and the base station antenna is distributed within 100m, the position of a base station is at the center. We have calculated the average of the above three features each single base station antenna to the user antenna. And based on the three features the values of the antenna which has SNR greater than 480, channel gain greater than 7.5, and path loss less than 430 are mapped to class 1 and the reverse is class 0. As the following table

Table 3. 1: Dataset Labeling

Base station antenna index	Average of the channel gain for each user antenna to every single antenna	Average of SNR for each user antenna to every single antenna	average of path loss for each user antenna to every single antenna	Selected class
1	8.24444	461.7243	-406.24	1
2	6.8476	468.6856	-408.956	0
⋮	⋮	⋮	⋮	⋮
63	8.4380	-454.5945	-408.218	1
64	8.4380	457.9988	-404.058	0

In this example table, the labeled dataset includes 64 base station antennas and 10 single antenna users. For each combination of a single base station antenna and every user antenna, the table lists the SNR, channel gain, and path loss (PL). Based on the calculated values of these three features, the selected antennas are mapped to class 1 and the rejected antenna are mapped to class 0. The resulting labeled dataset can be used to train a deep learning model for antenna selection in a massive MIMO system for energy efficiency.

3.14 DNN Design

A deep neural network (DNN) can be utilized for antenna selection in a massive MIMO system. The DNN takes three input features – signal-to-noise ratio (SNR), channel gain, and path loss – from a labeled dataset. The input layer of the DNN has three nodes, one for each input feature. Hidden layers can have varying numbers of nodes, depending on the complexity of the problem and the size of the dataset. Typically, multiple hidden layers with a moderate number of nodes, such as 64 or 128 nodes per layer, are used. This study uses a DNN with two hidden layers, the first of which has 1000 nodes and the second of which has 500 nodes. The hidden layers employ the rectified linear unit (ReLU) activation function, which outputs the input value if it is positive and 0 otherwise. Batch normalization (BN) is used to normalize the input to the next layer and enhance the stability and convergence of the network. The output layer has one node that represents the binary classification (i.e., selected or rejected) for the antenna combination, with a binary classifier used as the activation function.

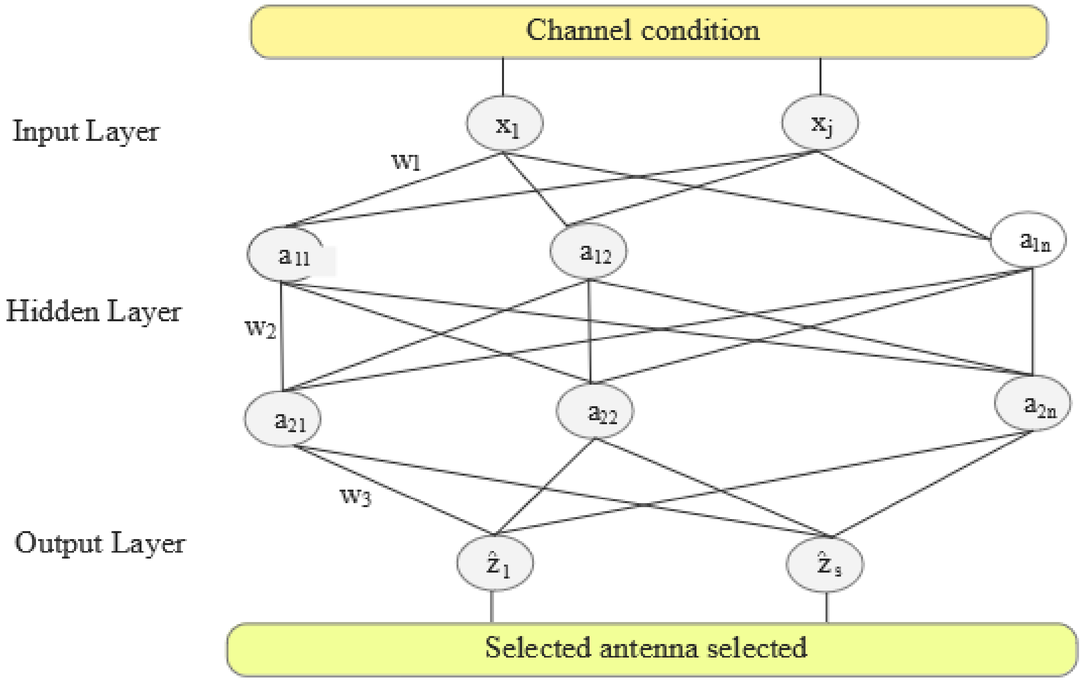

Figure 3. 3:DNN architecture (Zhong et al., 2020)

To learn the optimal antenna selection policy that maximizes energy efficiency (EE), a deep neural network (DNN) is trained on a vast dataset of channel realizations. The EE is calculated based on the received signal from the users and the selected antennas. The DNN is optimized using backpropagation, which adjusts the weights and biases of the network to minimize the loss function between the predicted and actual antenna selection.

CHAPTER FOUR

4 RESULT AND DISCUSSION

4.1 Effect of Path Loss on Energy Efficiency

Figure 4.1 below depicts the effect of path loss on the energy efficiency of a massive MIMO system. The plot shows that as the path loss increases the energy efficiency of the system decreases. i.e. when the path loss increases from 40 to 58 dB the energy efficiency decreases from 9 to 7.8 for a sum-rate equal to100Mbs, from 4.5 to 3.9 for a sum rate equal to 50 and it decreases for a sum rate equal to 1 to 1.9 for 10Mbs this is because the received signal strength decreases with increasing path losses and the base station needs to increase its transmit power to compensate for this loss this increasing power leads to decrease the energy efficiency because of extra power consumption for three constant values of sum rate. Furthermore, the plot also shows the effect of different values of the sum rate on energy efficiency. It demonstrates that at a constant path loss, higher sum rates lead to higher energy efficiency. This is because the rate is directly proportional to energy efficiency Energy efficiency can also be improved by adapting the system to the path loss conditions. For example, in cellular networks, base stations can be designed to dynamically adjust their transmit power based on the path loss to the user's device. This can reduce unnecessary power consumption and improve overall energy efficiency.

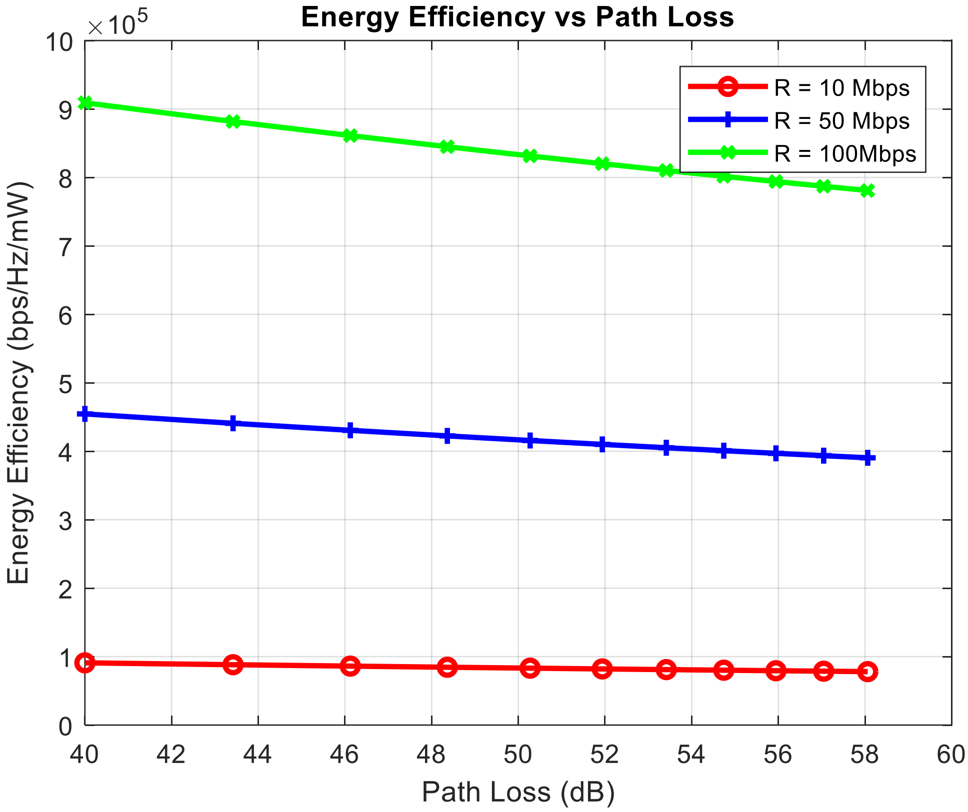

Figure 4. 1: Path loss vs energy efficiency

4.2 Distance vs Energy Efficiency

Figure 4.2 shows the relationship between distance and energy efficiency in a massive MIMO system. In the plot, three different constant values of the sum rate are considered for a specific number of users and transmitter antennas. As the plot demonstrates, when the distance between the user and transmitter increases, the energy efficiency of the system decreases. This is because the received signal quality decreases with distance, and the base station needs to increase it's transmitted power to maintain a certain level of signal quality. This increase in transmit power leads to higher energy consumption and reduces the energy efficiency of the system. Furthermore, as the distance between the user and the base station increases, the channel becomes more prone to interference from other signals, which can further reduce the overall signal quality and lead to a decrease in energy efficiency. The plot also highlights the effect of the sum rate on system performance. In general, higher sum rates lead to higher energy efficiency because they require less transmit power to achieve a certain level of signal quality.

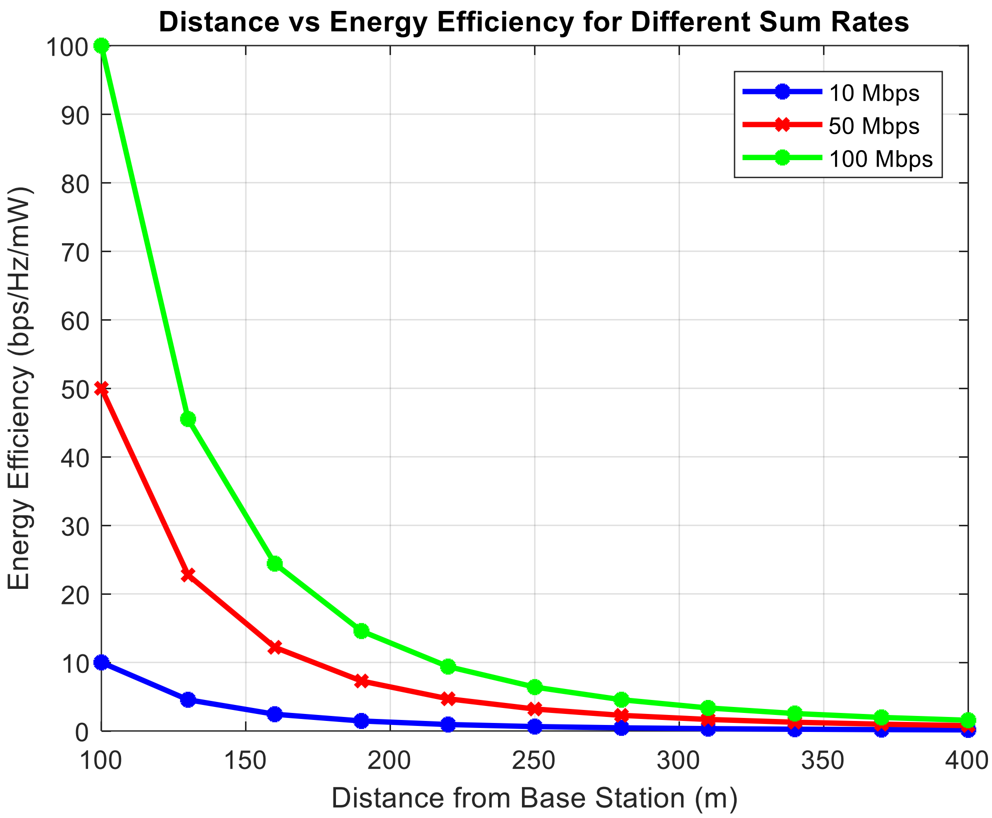

Figure 4. 2:Effect of distance on EE

Table 4 1: Effect of increasing distance on energy efficiency

Sum rate	The change in energy efficiency as the distance increases from 100m to 400m
10Mbs	Decrease from 10 to 0
50Mbs	Decrease from 50 to 0.2
100Mbs	Decrease from 100 to 0.4

4.3 Number of Antennas Required Vs Path Loss

Figure 4.3 illustrates the relationship between the number of antennas to be selected and the path loss of a system. The graph plots the number of antennas in a massive MIMO system against path loss for three different distances. This visualization is a helpful tool for understanding the impact of antenna numbers on signal strength and system performance. As the graph indicates, increasing the number of antennas in a massive MIMO system can reduce path loss, leading to better signal strength at the receiver. This is because a large number of antennas at the transmitter and receiver can exploit spatial diversity, mitigating the effects of path loss and enhancing the quality of the received signal. The optimal number of antennas for a given massive MIMO system depends on the path loss. In systems with high path loss, a larger number of antennas may be necessary to achieve the desired energy efficiency and signal quality. This is because a greater number of antennas can help compensate for the increased path loss and improve the quality of the received signal.

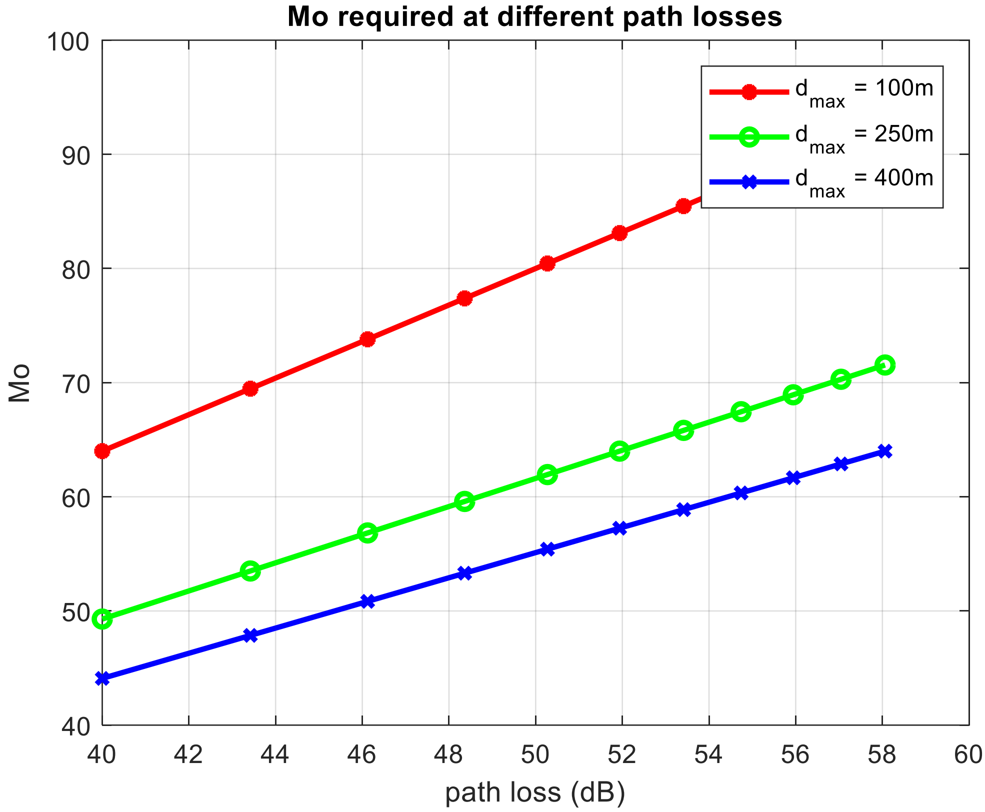

Figure 4. 3:Number of antennas required vs path loss

4.4 Effect of Increasing Number of Antennas on the Number of Users Served for the Limited Power

A Massive MIMO system's relationship between the number of antennas and the number of users is shown in Figure 4.4, along with how transmit power affects this relationship. With more antennas, the system can accommodate more concurrent users, resulting in enhanced spectral efficiency and channel capacity. However, due to the transmit power restriction, practical limitations place a limit on the number of antennas. The transmit power is distributed among the antennas in a Massive MIMO system, and as the number of antennas rises, the power per antenna falls. The number of concurrent users that can be serviced may be limited if the transmit power is fixed. Due to the constrained power budget, as the number of antennas increases, the number of users begins to decline. Because there is a trade-off between these variables, it is crucial to balance the number of antennas and users based on the particular needs and limitations of the application.

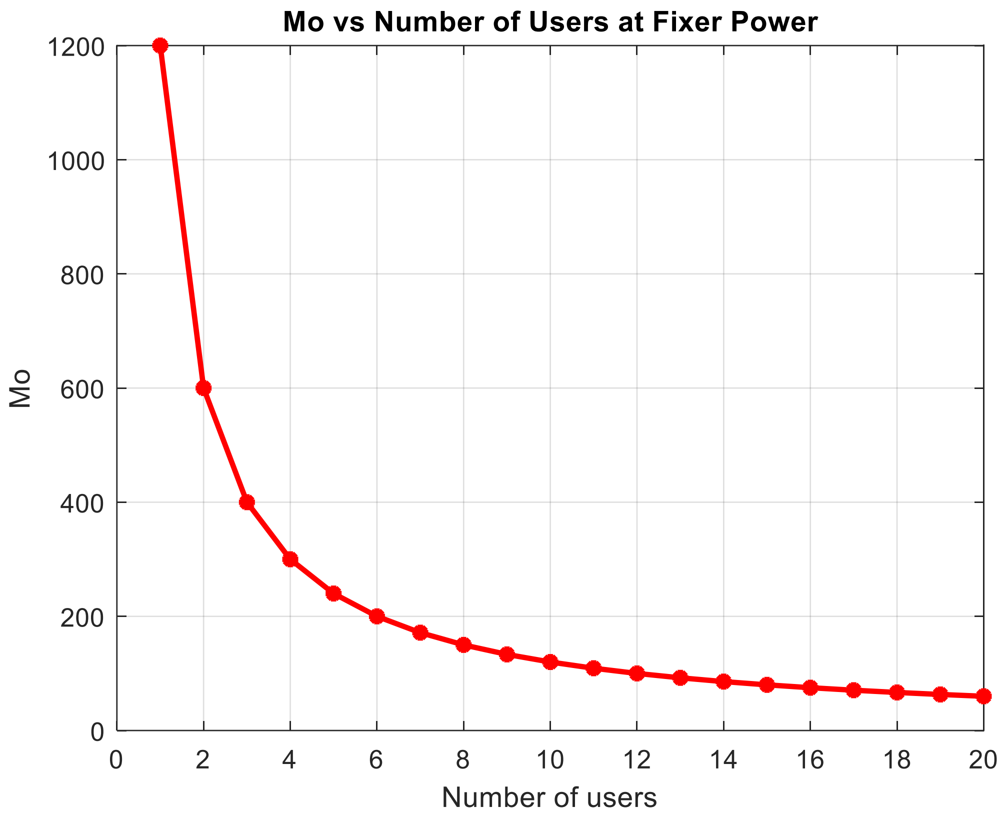

Figure 4. 4: Number of antennas required vs number of users

4.5 Distribution of User and Its Effect on the Number of Antennas Selected

Figure 4.5 shows the distribution of users within a given radius near the base station antenna provides important insights into the impact of user distribution on the number of antennas required in a massive MIMO system. As the plot demonstrates, when users are distributed closer to the base station, fewer antennas are required to achieve the desired level of signal quality. This is because the users are closer to the antennas, and the signal strength is typically higher, which can reduce the need for a large number of antennas. On the other hand, when users are located farther away from the base station, more antennas may be required to achieve the desired level of signal quality. This is because the signal strength decreases with distance, and a larger number of antennas may be needed to compensate for the increased path loss and interference. Furthermore, if users move randomly within a given radius, the number of antennas required may change over time as the user distribution changes. This highlights the importance of designing a flexible system that can adapt to changes in user distribution and other system parameters.

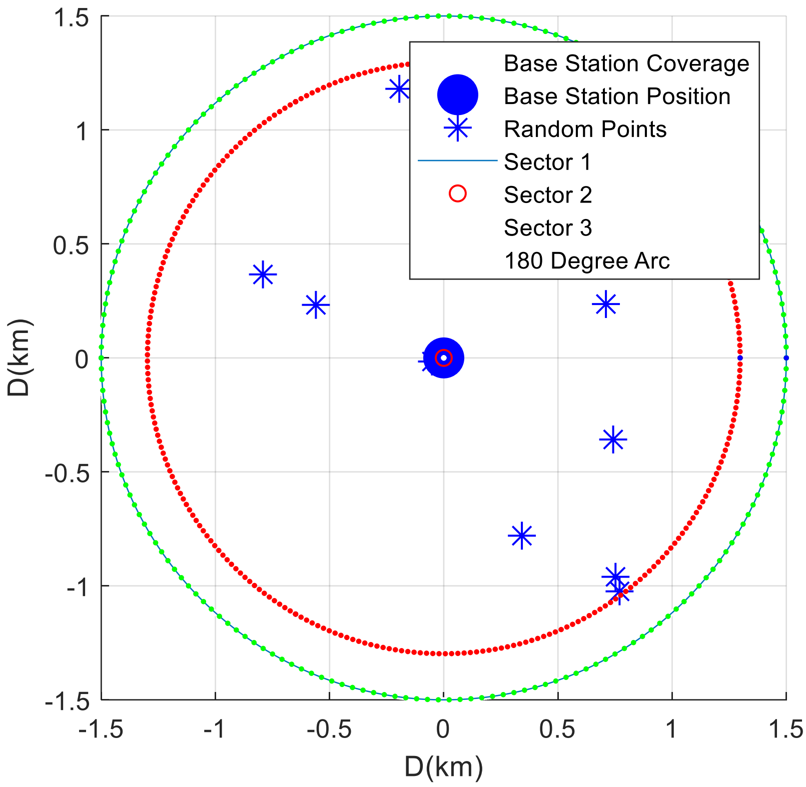

Figure 4. 5:Distribution of users on a given radius

4.6 Effect of User Mobility on the System

Figure 4.6 illustrates how the number of antennas needed to provide a required quality of service to users can be affected by their mobility and distribution within a certain radius of a base station in a massive MIMO system. The plot highlights that the required number of antennas can vary depending on the user distribution and mobility patterns. When users move randomly within the radius, the number of antennas required may change over time as the user distribution changes. It is important to note that the number of antennas required to achieve a certain level of signal quality can be less than the number of antennas installed in the system. This is because the system is typically installed with a consideration of the possible maximum distance for each user, which is the outer radius. However, specific user distribution and mobility patterns may enable the system to achieve the desired level of signal quality with fewer antennas than those installed. Additionally, systems designed to cover smaller radii may require relatively fewer antennas compared to those designed to cover larger radii

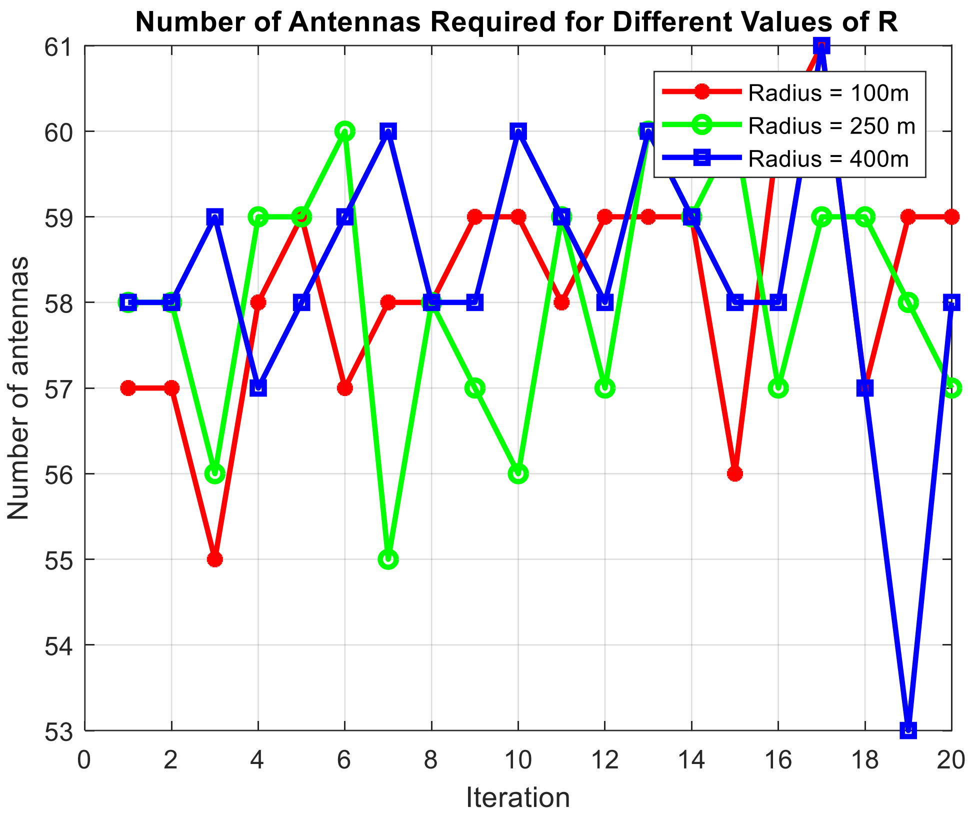

Figure 4. 6:Effect of user motion on the number of antennas selected

4.7 Energy Efficiency vs Number of Transmit Antenna

Figure 4.7 which depicts the relationship between energy efficiency and the number of transmit antennas in a massive MIMO system for variable and fixed SNR levels provides important insights into the impact of antenna numbers on system performance. As the plot shows, increasing the number of antennas can improve energy efficiency up to a certain threshold value. This is because more antennas can allow for better spatial diversity and interference mitigation, which can lead to improved signal quality and higher energy efficiency. However, beyond this threshold value, increasing the number of antennas can lead to a decrease in energy efficiency. This is because the additional antennas may not be serving any useful purpose and are simply wasting power, which can degrade the overall energy efficiency of the system. The optimal number of antennas for a given system depends on factors such as the number of users, signal-to-noise ratio (SNR), and available resources. As can be understood from the diagram of the following plot the system is installed with 64 transmit antennas but, the maximum energy efficiency is achieved at 23 antennas for fixed SNR, while in the variable SNR case, the maximum energy efficiency is achieved at 61 antennas. Therefore, in the case of fixed, 41 antennas are wasting energy efficiency without serving the user in the case of fixed SNR and 3 antennas in the case of a variable.

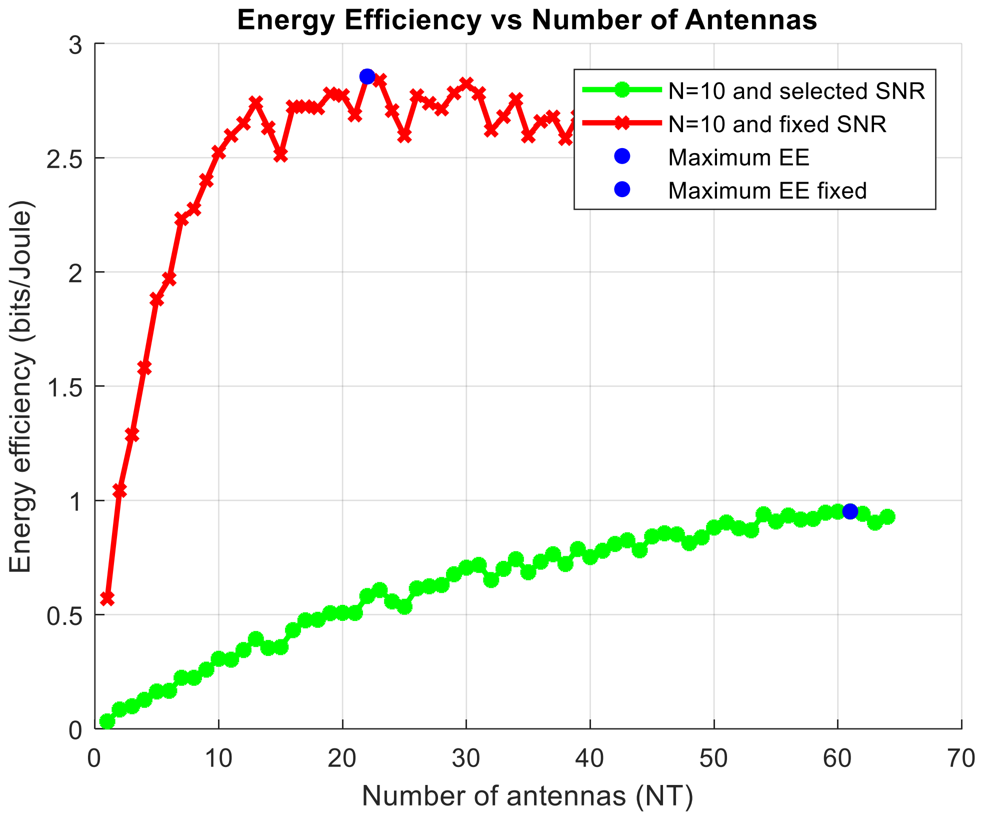

Figure 4. 7:Number of antennas required vs number of users

4.8 Element Selection by Deep Learning

Our system is designed to use deep learning for transmitter selection in massive MIMO systems, to select the optimal base station antenna based on important features such as SNR, path loss, and channel gain to optimize energy efficiency. By adjusting the channel matrix using these features, it is possible to select the antenna that maximizes energy efficiency without having to calculate every possible combination. To achieve a target threshold value of energy efficiency, our system selects the antenna by adjusting the features based on their mathematical relationship. We use a DNN with one input and output layer and two hidden layers, with 1000 and 500 nodes respectively. The input layer has three nodes, and the output layer has one node representing a binary number that indicates whether the antenna element is selected or not. We use the ReLU activation function at hidden layers and SoftMax at the output layer. We collected over 4000 data for each feature through measurement and used this to train the DNN. The DNN achieved an accuracy of 0.95. By using our system, we can reduce the computational complexity of the transmitter selection process and maximize energy efficiency. In our system, we select the optimal antenna for energy efficiency by choosing the antenna with the highest values of SNR and channel gain and the lowest value of path loss. We focus on two similar behavior vectors and one different behavior vector in our system. Specifically, we set the threshold value for SNR greater than 480, path loss less than -430, channel gain greater than 7.5 to 1, and reverse to 0. As can be seen from the table only one value has the error

Table 4 2: Test for the proposed study

SNR (dB)	Path loss(dB)	Channel gain	Actual value	Predicted value
458.0981	-409.641	13.48381	1	1
463.5514	-422.783	9.514818	1	1
477.43	-409.724	10.192	1	1
445.5708	-387.475	13.36753	1	1
459.9645	-410.06	9.764323	1	1
454.2756	-389.611	8.276884	1	0
500.0622	-381.306	6.223357	0	0
488.0136	-410.706	7.174434	0	0
444.3866	-406.303	12.61877	1	1
442.5778	-407.255	11.41109	1	1

4.9 Accuracy of the Designed Model

Our proposed system can achieve a high accuracy of 0.95, which indicates that the system can predict the optimal antenna with a high level of precision. This suggests that the system can be able to make accurate predictions and select the optimal antenna for each user by assigning optimal antenna for each user in can be able to achieve higher energy efficiency. Our system takes into account both path loss and minimum required receiver power for each antenna to each user which is a very important feature of antenna to determine the best combination. The fore the robust and simple antenna selection system is achieved by the system. Which is effective for the antenna section method for improving energy efficiency. Overall, the performance of the system appears to be very promising, and it has the potential to significantly improve the energy efficiency of the wireless massive MIMO system. As it can be understood from the following output increasing the number of epochs or iterations will increase the performance of the system since the machine is trained repeatedly to get the optimal antenna of the system. In addition to that the system can reduce the complexity problem. The following table is directly copped from the output

Table 4 3: Accuracy of the designed model

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch accuracy	Validation accuracy	Mini-batch loss	Validation loss	Base Learning Rate
1	1	00:00:04	78.12%	21.95%	4.1699	168.6992	0.0010
50	1850	00:00:43	92.19%	96.13%	0.1851	0.0874	0.0010
100	3700	00:01:39	92.19%	96.01%	0.1703	0.0956	0.0010

Training finished: Max epochs completed.

Accuracy on test set: 0.95761

4.10 Accuracy vs Epoch for DNN

As the number of epochs increased the accuracy of the system increased. According to the plot when the epoch is increased from 0 to 4000 the accuracy of the model becomes to approach 1. That means the system can able to select the antenna with almost all percent correct. So, by using the proposed method it can select the optimal antenna and allocate it for the user it is possible to optimize the energy efficiency however when making antenna selection by the proposed method channel condition are very carefully considered as the number of epochs increases the accuse become asymptote to 1.

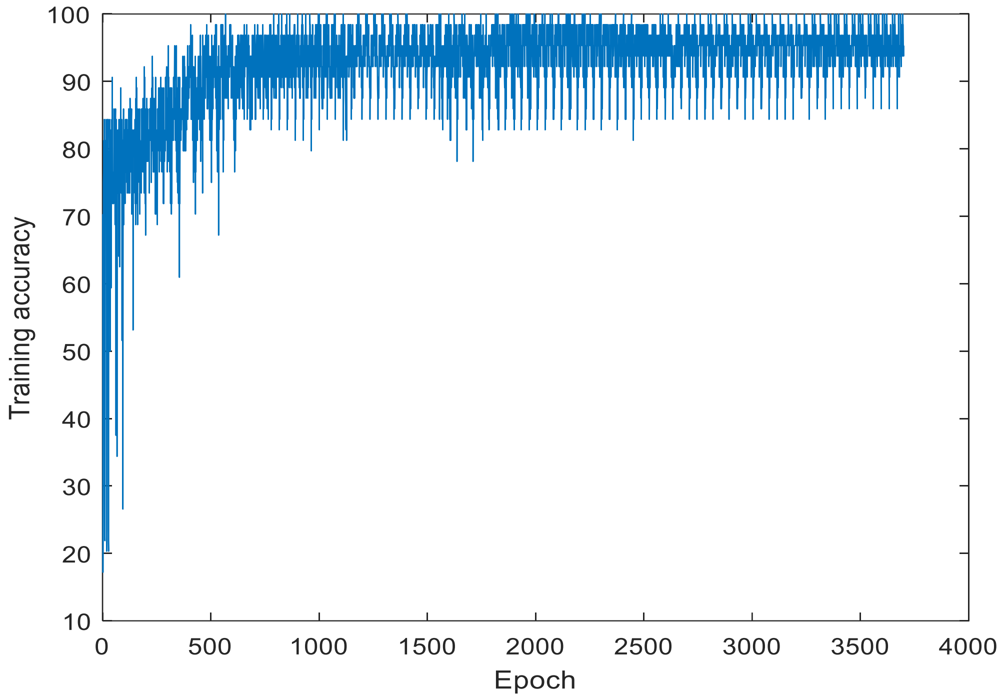

Figure 4. 8:Accuracy of the proposed model

4.11 Comparison with KNN and SVM

Two methods, KNN and SVM, were used for comparison. In the KNN classification experiment, the metric measurement employed was the Euclidean distance. The parameter K was optimized by thorough searching, and the KNN classifier allocates the query sample to the class with the highest frequency among its K nearest neighbors. The test set's classification results were noted in order to find the best antenna selection options. The radial basis function (RBF) was used as the kernel function for SVM, and grid searching was used to improve the parameters cost and gamma. The one-vs-rest technique was used to convert the binary-class classification problem into a multi-class problem.

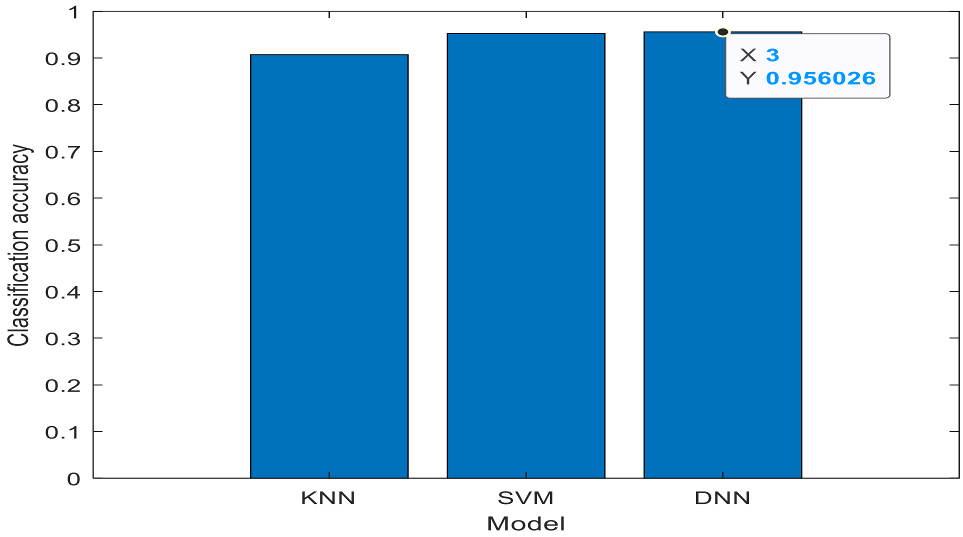

Figure 4. 9:Are diagram for classification accuracy

Based on the information given in the question, the accuracy of the DNN is 0.95603, which is greater than the accuracy of both KNN (0.90717) and SVM (0.95277) on the same dataset. Therefore, it can be concluded that the DNN has a better performance than KNN and SVM on this particular dataset.

5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This thesis proposes a deep learning-based antenna selection scheme for a massive MIMO system operating under imperfect channel state information. The scheme is composed of two phases: the number selection phase and the element selection phase. During the number selection phase, the optimal number of antennas required under different conditions, such as: user mobility, distance between users and antennas, path loss, and SNR, is determined. In the element selection phase, the deep learning scheme selects the best antenna elements to achieve the desired energy efficiency level. The scheme also takes into account the effect of channel imperfection by using Markov uncertainty, and selects antennas based on the parameter that is less sensitive to channel imperfection. By considering the above factors, the optimal number of antennas is determined, and those optimal antennas are selected by deep learning using path loss, SNR, and channel gain as input features. Finally, the performance of the proposed scheme is compared with other well-known machine learning techniques

5.2 Recommendation

For a huge MIMO system with incomplete channel state information, we suggested a deep learning-based antenna selection strategy in this thesis. The method optimizes the antenna selection by taking into account the path loss and distance between users and base station antennas. Future study can further enhance the system's performance by considering the impact of other channel performance measures including SNR, directivity, and beamforming The system can be improved to attain even greater performance and energy efficiency by taking these aspects into account. After choosing antennas, future researchers can investigate the usage of preprocessing methods based on deep learning. By offering extra optimization and augmentation of the signals prior to transmission, this can help the system function better still. The system's overall performance and effectiveness can be greatly increased by integrating deep learning-based preprocessing and antenna selection.

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