Machine Learning Techniques for Optimizing Sub-6GHz Patch-Based MIMO Antennas: A Review for 5G Applications

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Abstract

The rapid advancement of fifth-generation (5G) communication technologies necessitates the development of efficient Multiple Input Multiple Output (MIMO) antenna system to support low latency, enhanced reliability and high data rates. Among various antenna designs, patch antennas have emerged as a promising solution due to their small size, low cost, and its seamless integration into contemporary devices. Operating in the Sub-6GHz spectrum, these antennas must meet stringent performance metrics, including optimized gain, bandwidth, and radiation efficiency, while adhering to physical and operational constraints. Traditional optimization techniques for MIMO antenna design often struggle with multi-parameter trade-offs and computational inefficiencies. This review explores the integration of machine learning (ML) techniques into the development and enhancement of patch-based MIMO antennas, with a focus on Sub-6GHz 5G applications. Key algorithms, including Support Vector Regressor (SVR), Logistic Regression, k-Nearest Neighbors (kNN), and Random Forest Regressor are analysed for their effectiveness in enhancing critical performance parameters. The paper discusses challenges such as data acquisition, computational overhead, and model generalizability, while highlighting the potential of ML-driven approaches to overcome these limitations.

Keywords. Sub-6 GHz, MIMO, 5G, Machine Learning, SVM

1. Introduction

The swift advancement of wireless communication has driven the creation of fifth-generation (5G) networks, which promise enhanced data rates, low latency, and reliable connectivity for various applications, such as mobile broadband, smart city development, and the Internet of Things (IoT). A key driver of these innovations is the implementation of sophisticated antenna systems tailored to satisfy the rigorous performance demands of 5G networks. Among these systems, **Multiple Input Multiple Output (MIMO)** technology has become a cornerstone, allowing for the concurrent transmission and reception of multiple data streams, thus enhancing spectral efficiency and increasing network capacity.[1]

Patch antennas are favoured for sub-6 GHz MIMO applications due to their compact design, easy manufacturing, and compatibility with modern devices. However, optimization challenges include reducing mutual coupling, ensuring uniform radiation patterns, and balancing compactness with performance.[2]

Challenges in MIMO Antenna Design

Designing sub-6 GHz MIMO antennas presents challenges like minimizing mutual coupling, balancing bandwidth and gain, and maintaining compactness without efficiency loss. Impedance matching is crucial to reduce signal reflection and ensure stability in high-interference environments. Fabrication precision and material selection impact efficiency, while optimizing multiple parameters increases computational load, requiring hybrid design methods and advanced materials for modern wireless communication.[3]

Traditional design techniques, including iterative simulations and empirical methods, have been instrumental in the development of MIMO systems. However, they are often time-consuming and may not efficiently explore the vast design space. This limitation has spurred interest in leveraging emerging tools and techniques to accelerate and improve antenna design processes.[4]

Objective and Scope of This Study

This paper focuses on the design and optimization of patch-based MIMO antennas operating in the Sub-6GHz spectrum for 5G applications. It provides an overview of key considerations in antenna design, highlights advancements in achieving efficient and compact structures, and discusses optimization strategies to enhance performance metrics such as gain, bandwidth, and efficiency. Furthermore, the study examines the role of innovative design approaches in addressing the challenges faced by MIMO systems in 5G and beyond.

2. COMPARISON OF TECHNIQUES USED TO REDUCE THE SIZE OF THE ANTENNA

From the (Table. I) for compactness-focused designs, [5] is the top choice, followed by [6], due to their optimized size and performance.

Smallest Footprint: At 19 × 43 × 0.5 mm, this antenna is the smallest among its peers. Its 0.5 mm thickness keeps it nearly flat, making it ideal for space-constrained applications like smartphones, wearables, and IoT devices. **Excellent Use of Space:** Despite its small size, it achieves >13 dB isolation, suppressing mutual coupling in MIMO systems. Its 3–6 dB peak gain is competitive and sufficient for reliable sub-6 GHz 5G communication. **Advanced Design Techniques:** Parasitic patches and stubs enhance compactness, reduce coupling, and extend bandwidth without increasing size. The Surrounding Technique with FSS cells optimizes gain and efficiency without performance loss. **Practical Applications:** The ultra-thin profile and small area make it ideal for:

i. Smartphones: Fits within tight internal spaces and supports modern 5G standards.
ii. Wearables: Its compact size allows for seamless integration into smartwatches, fitness bands, and other body-worn devices.
iii. IoT Devices: Useful for sensors and compact electronics where minimal space is available.[5]

3. COMPARISON OF MACHINE LEARNING TECHNIQUES USED

From the (Table. II) the most effective machine learning approach for sub-6 GHz MIMO antenna optimization is a hybrid method integrating HGNN, ANN, KBNN, CNN, and Random Forest, ensuring strong performance in spectral efficiency, impedance matching, gain optimization, and feature selection. [9]-[12]

TABLE I. COMPARISON OF SIZE

Ref No.	Dimensions (mm²)	Material Used	Isolation (dB)	Band-width	Peak Gain	Technique Used	Remarks
[5]	19 x 43 x 0.5	Rogers 4350B, 3.66	>13	3 - 6	7.96	Parasitic patches and stubs reduce coupling and size, while the "Surrounding Technique" removes extra FSS cells to boost gain.	The design ensures high gain, strong isolation, and compact size for sub-6 GHz 5G, optimized with parasitic elements and FSS.
[6]	31.5 x 45 x 1.6	FR-4, 4.4	>17, >26	3.45 – 4.7, 5.45 - 9	2.5 – 3.4, 3.5 - 4	The antenna uses a Squared Shape Modified Monopole with a partially Defected Ground fed by a Co-Planar Waveguide with defects and an I-shaped strip. A Double T-shaped strip acts as a band-stop filter for decoupling.	The antenna provides excellent MIMO diversity for portable wireless use, with a compact, easy-to-fabricate design, dual-band support, and good isolation and gain.
[7]	48 x 48	FR-4, 4.4	-15	1.5 – 2.3, 3.7 – 4.2	4, 2	Etching F-shaped and circular slots reduced the radiating area, leading to a smaller size without significant performance loss.	Compact sub-6 GHz 5G design with excellent impedance matching, high radiation efficiency, and strong MIMO port isolation.

[8]	120 x 60	FR-4, 4.4	-10	0.94 – 4.45	1.06 – 2.97	Planar Inverted-F Antennas was chosen for its compact size, wide bandwidth, and easy integration.	Compact, multiband design with reconfigurable frequency and radiation patterns, ideal for 5G terminals.

Heterogeneous Graph Neural Network: HGNN excels in large-scale system optimization, hybrid beamforming, and spectral efficiency. Its ability to process graph-structured data makes it ideal for analyzing antenna interactions, while its low computational complexity supports scalable sub-6 GHz MIMO designs. It is well-suited for beamforming, spectral efficiency, and 5G base station optimization.[12]

Artificial Neural Network: ANN excels in predicting and optimizing antenna parameters like resonant frequency, S11, and gain. Its accuracy with smaller datasets complements HGNN's large-scale optimization, making it ideal for fine-tuning parameters and reducing simulation time.[9]

Knowledge-Based Neural Network: KBNN provides accurate S-parameter optimization with lower computational costs, ensuring optimal impedance matching and reducing reflection losses in sub-6 GHz MIMO antennas.[11]

Random Forest: RF is strong in classification and regression with mixed data types, providing insights into feature importance and parameter interactions. It's useful for feature selection and guiding more complex models like ANN or CNN.[10]

In addition, **Support Vector Regressor:** It is effective for small to medium datasets, handling linear and nonlinear problems with kernels, and robust to outliers. It optimizes impedance matching and models gain/efficiency but is computationally expensive for large datasets and requires complex hyperparameter tuning.[13]

TABLE. II COMPARISON OF ML ALGORITHMS

Ref No.	ML Algorithm	Feature Engineering	Dataset Used	Task Performed	Performance Metric	Advantages	Limitations
[9]	Artificial Neural Network (ANN)	Manual extraction of key antenna parameters: resonant frequency, gain, and S11.	Dataset generated using CST simulation software with 201 records and 1009 features	Prediction of optimal antenna parameters such as resonant frequency and impedance matching	Mean Square Error and R-square scores for regression tasks	Efficient regression for non-linear datasets; significantly reduces simulation time for antenna design	Computational cost increases with more features and dataset size
[10]	Linear Regression, Random Forest, Decision Tree, XGBoost	Manual selection of antenna parameters: slot length, stub dimensions, feedline size	203 samples simulated using CST MWS software	Prediction of antenna gain and efficiency	Linear Regression: 99.79%, XGBoost: 98.63%, RF: 96.68%, DT: 93.93%	Efficient gain and efficiency validation; Linear Regression predicts accurately, near simulations.	Data-intensive; simulated data requires further validation for real-world generalization.
[11]	Ridge Regression, Artificial Neural Network, Knowledge-Based Neural Network	Manual parametric tuning for antenna dimensions; automated learning for S11 optimization	3888 simulated samples generated via Ansys HFSS.	Optimization of antenna S-parameters (reflection coefficient S11)	R^2 Score: KBNN: 0.9688, RR: 0.962, ANN: 0.94. Accuracy for KBNN was 96.88%	Reduced computational time; accurate S-parameter predictions; efficient resource utilization	Requires a large dataset; real-world performance depends on fabrication tolerances.
[12]	Heterogeneous Graph Neural Network (HGNN)	Node and edge features from sub-6GHz and partial mmWave CSI, including	DeepMIMO dataset for sub-6GHz and mmWave	Hybrid beamforming optimization for mmWave base stations	Achieved near-optimal spectral efficiency;close to traditional	Low computational complexity and scalability; robust to noisy	Needs large datasets; real-world validations for hardware

		beamforming info, noise power, and power constraints.	CSI with 11,000 samples		optimization methods	CSI inputs; supports partial mmWave CSI	constraints and overheads

Logistic Regression: Ideal for binary/multi-class classification, efficient on small datasets, and interpretable. It classifies decoupling and validates impedance matching (S11<-10 dB) but struggles with nonlinear problems and is limited to linear decision boundaries.[14]

k-Nearest Neighbors: Simple and intuitive, kNN enables localized predictions without training. It predicts gain, isolation, and minimizes coupling but is computationally heavy for large datasets and sensitive to neighbor selection and distance metrics.[15]

4. CONCLUSION

The rapid evolution of fifth-generation (5G) communication networks has introduced both significant challenges and opportunities in antenna design. This paper reviews the design and optimization of patch-based MIMO antennas for Sub-6 GHz applications, with a focus on key performance metrics such as gain, bandwidth, and radiation efficiency. Patch antennas are particularly favored for their compact size, low cost, and ease of integration into modern wireless systems, making them ideal for 5G applications. The study highlighted the challenges in designing MIMO antennas, including reducing mutual coupling, achieving impedance matching, and balancing trade-offs between size and efficiency. It discussed various optimization techniques, ranging from traditional heuristic methods to emerging hybrid approaches, aimed at enhancing antenna performance. The role of innovative materials and design strategies, such as defected ground structures and parasitic elements, was also explored to improve isolation and bandwidth. While machine learning techniques are starting to influence antenna design, their application remains exploratory and complementary to traditional methods, primarily due to data and computational limitations at this stage. Future work should focus on refining optimization frameworks to strike a balance between performance and practical implementation. This includes enhancing mutual coupling mitigation techniques, improving fabrication processes for design consistency, and exploring hybrid approaches that combine conventional methods with data-driven insights. As 5G technology continues to evolve, these advancements will ensure antenna systems can meet the increasing demands for high data rates, low latency, and reliable connectivity. By addressing these challenges and leveraging emerging technologies, the development of high-performance MIMO antennas for Sub 6 GHz 5G applications will pave the way for next-generation wireless communication systems.

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