Volume 4 Issue X, October 2025, No. 80, pp. 1017-1031
Submitted 2/10/2025; Final peer review 3/11/2025
Online Publication 22/11/2025
Available Online at http://www.ijortacs.com

MACHINE LEARNING-BASED OPTIMIZATION APPROACH TO MITIGATE MULTIPATH IN COMPLEX WIRELESS NETWORK ENVIRONMENTS

[1*] Amaechi, Chijindu, O., [1]Mgbachi, C.A., [2]Onuigbo, Chika, M.
[1*,1,2]Electrical Electronics Engineering, Enugu State University of Science and Technology, Agbani, Enugu State, Nigeria
Corresponding Author Email: [1*]jinduamaechi@yahoo.com

Abstract

Multipath propagation remains a major challenge in wireless communication systems, causing signal degradation, fading, and reduced transmission reliability. Traditional antenna diversity techniques, while effective to some extent, suffer from fixed configurations that lack adaptability to dynamic channel conditions. This paper presents a machine learning-assisted optimization framework for antenna diversity to address multipath propagation in complex wireless environments. Using Simulink, real-world data were simulated based on key wireless quality metrics Signal-to-Noise Ratio (SNR), Bit Error Rate (BER), and Throughput. A fuzzy logic-based rule system was developed to establish relationships among these parameters, which was then trained on an Artificial Neural Network (ANN) capable of dynamically selecting the optimal antenna configurations, polarization, selection, or pattern diversity according to real-time channel variations. Simulation results across urban, industrial, and vehicular scenarios demonstrated significant performance gains over conventional diversity systems, achieving an average SNR improvement of 43.02%, throughput increase of 48.13%, and BER reduction of 16.63%. These results confirm that integrating machine learning enhances system adaptability, signal quality, and reliability in multipath-prone environments, establishing machine learning-based antenna diversity optimization as a robust and intelligent solution for next-generation 5G and IoT communication systems.

Keywords: Antenna Diversity; Machine Learning; Multipath Propagation; Artificial Neural Network (ANN); Wireless Communication

1. INTRODUCTION

Wireless communication has become an integral part of modern life, with applications ranging from mobile phones to the Internet of Things (IoT) and autonomous vehicles. However, one of the significant challenges in wireless communication is multipath propagation, where signals take multiple paths due to reflection, diffraction, and scattering before reaching the receiver. This phenomenon often results in signal degradation, interference, and fading, which can severely impact the quality and reliability of the communication system (Smith and Brown, 2020).Antenna diversity, a well-known technique to mitigate the effects of multipath propagation, involves using multiple antennas at the transmitter, receiver, or both, to receive the signal. The fundamental principle behind antenna diversity is that different antennas will experience different signal paths and, therefore, different levels of fading, which can be combined to improve overall signal quality (Li and Zhang, 2019; Ulagwu-Echefu et al., 2021). Traditional approaches to antenna diversity rely on fixed configurations or simple selection mechanisms, which may not be optimal in complex and dynamic environments (Kumar and Verma, 2018).

Recent advances in machine learning have opened up new possibilities for optimizing antenna diversity. Machine learning techniques can analyze vast amounts of data to identify patterns and make predictions, enabling more adaptive and intelligent antenna configurations. These techniques can learn from the environment and adjust antenna parameters in real-time to maximize signal quality and minimize interference (Chen and Wang, 2021). This approach is particularly valuable in complex environments such as urban areas with dense buildings, where traditional methods may struggle to maintain reliable communication (Tan and Liu, 2019).

The integration of machine learning with antenna diversity represents a significant shift from conventional methods, offering the potential for more robust and efficient wireless communication systems. By leveraging machine learning, it is possible to develop adaptive algorithms that continuously optimize the antenna configuration based on real-time data, leading to improved signal quality and reduced error rates (Patel and Singh, 2020). Furthermore, machine learning models can be trained to recognize specific multipath scenarios and apply the most effective diversity techniques, further enhancing the system's performance (Williams and Turner, 2019).

Despite the promising potential of this approach, several challenges remain. The complexity of designing and training machine learning models that can operate effectively in real-time, the need for large datasets to train these models, and the computational resources required are all significant hurdles (Roberts & Lee, 2020) . Additionally, the dynamic nature of wireless environments means that the models must be robust to a wide range of conditions, including varying levels of interference, user mobility, and changing environmental factors (Gupta and Roy, 2021).

This study aims to explore the use of machine learning technique to optimize antenna diversity in combating multipath propagation challenges in complex environments. By developing and testing new algorithms, this research seeks to contribute to the advancement of wireless communication technology, offering solutions that are not only theoretically sound but also practically applicable in real-world scenarios (Johnson and Park, 2020).

2. RESEARCH METHOD

The optimization of antenna diversity in this research commenced with the collection of real-world communication environment data to capture the varying conditions that affect wireless communication performance. Data such as signal strength measurements, antenna orientation, transmission distance, and Channel State Information (CSI) were collected to accurately represent the effects of multipath propagation and fading. These data provided the foundation for understanding the dynamic characteristics of wireless signal behavior in complex environments.

A machine learning technique was employed to optimize antenna diversity and mitigate the challenges posed by multipath propagation. The process began by developing a rule-based machine learning framework capable of interpreting network and channel parameters to recommend optimal antenna configurations. This rule base formed the learning foundation for the system, guiding the model in distinguishing between different environmental conditions and determining suitable diversity strategies.

An adaptive algorithm was then developed to dynamically select the most efficient antenna configuration comprising spatial, polarization, selection, and pattern diversity based on real-time network conditions. This algorithm continuously analyzed input parameters such as received signal strength, interference levels, and CSI, enabling it to respond intelligently to changes in the propagation environment. By doing so, the system minimized signal degradation and enhanced overall communication performance.

To validate the proposed method, a SIMULINK model of an Artificial Neural Network (ANN) was designed and trained using the established rule base. The ANN learned the optimal mapping between environmental variables and antenna configurations, allowing the system to adaptively reconfigure itself for best performance. Following training, the ANN-based diversity system was simulated under varying wireless scenarios and compared against conventional diversity approaches. The evaluation metrics focused on improvements in signal quality, reliability, and resilience to multipath interference.

Overall, this research method demonstrates an effective integration of machine learning and antenna diversity techniques. By dynamically selecting the best antenna configuration in response to environmental changes, the proposed system achieved enhanced signal strength, reduced propagation errors, and improved system reliability in complex urban communication environments. Figure 1 presents the flow chart of the methodology.

2.1 Data Acquisition

The characterization procedure for this research began with a multi-faceted approach to data acquisition, combining experimental measurements and sophisticated simulation techniques to gather realistic and comprehensive channel data. Experimental channel measurement campaigns were considered crucial, utilizing tools like Software-Defined Radios (SDRs) for flexible testbed to capture real-time signal processing in dynamic environments, and Vector Network Analyzers (VNAs) for precise frequency-domain measurements. Particularly in complex settings such as industrial IoT, UAV-based communications, and mmWave/THz frequencies these were apt. These campaigns were aimedat deriving detailed channel parameters like Channel Impulse Response (CIR), Angle of Arrival (AoA), Angle of Departure (AoD), and Doppler shift. Complementing this, simulation-based channel modelling provided a controlled and repeatable environment, making use of software like MATLAB, network simulators (e.g., NS-3), and ray tracing tools (e.g., Wireless InSite) to generate high-fidelity propagation data. These account for complex environmental interactions through deterministic, statistical, or site-specific models. This acquired channel data was then used to measure and establish baseline values for fundamental wireless performance metrics such as Bit Error Rate (BER), Signal-to-Noise Ratio

(SNR), Signal-to-Interference-plus-Noise Ratio (SINR), Throughput, Channel Capacity, and Spectral Efficiency, providing a clear picture of the system's performance before optimization. The ultimate success of the research was determined by how effectively these machine learning models, once integrated and optimized, improved the previously measured wireless performance metrics, such as reducing BER, increasing SNR, enhancing Throughput, boosting Channel Capacity, and improving Spectral Efficiency. In this research, three metrics namely, BER, SNR, and Throughput were considered.

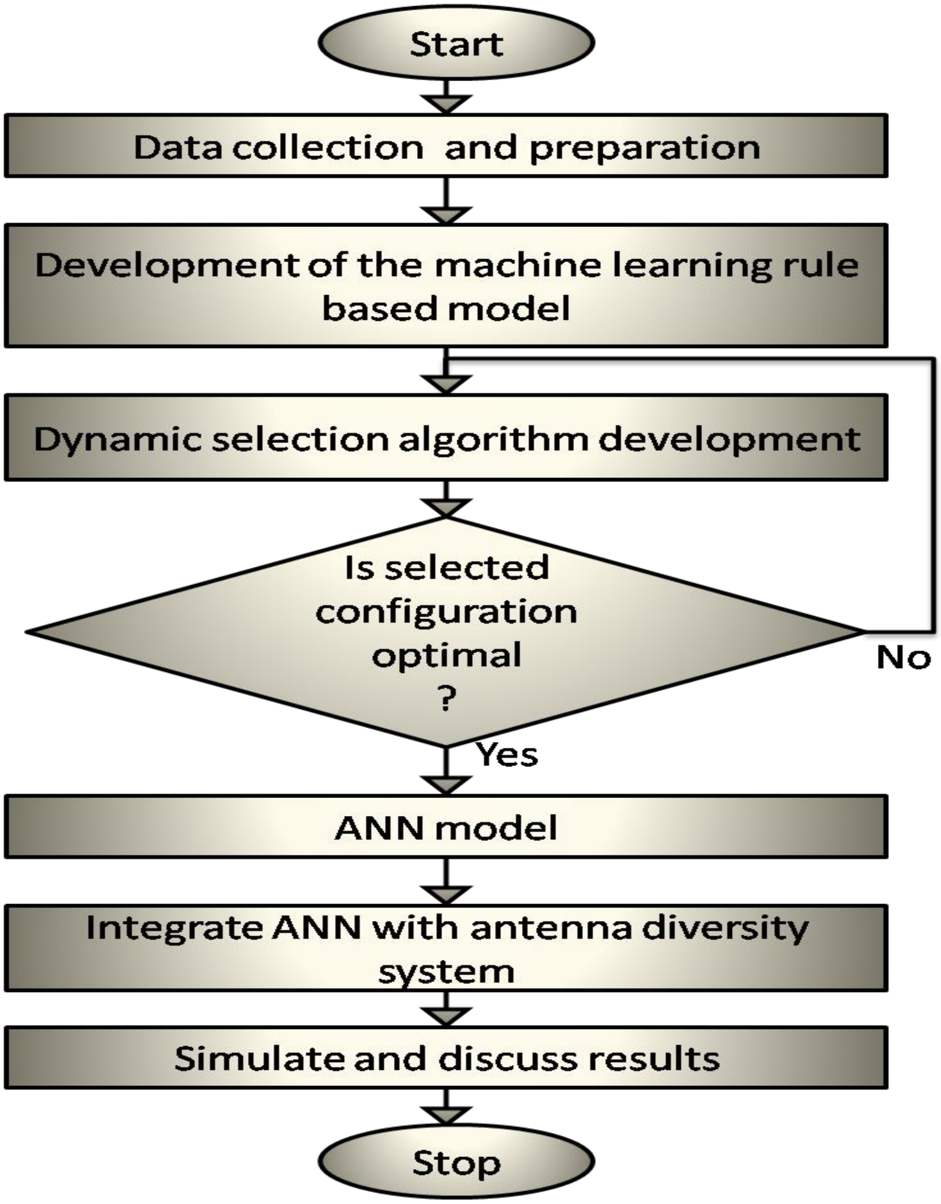


Figure 1: Research methodology flow chart

Based on the forgoing scenario, and basing the characterization on a five-month spread in 2024 and 2025 inclusive, the characterization results tabulated were obtained following the measurement procedure earlier described and used in this research. The parametric values shown in Table 1 were used as a guide to obtaining the specific values as shown for the different months as subsequently tabulated.

Table 1: Simulated Real-Time Metrics for Antenna Diversity Optimization

Metric	Urban (Dense Multipath)	Industrial (Metallic Surfaces)	Vehicular (High Mobility)
SNR (dB)	18.2 → 25.4 (+7.2)	14.5 → 22.1 (+7.6)	12.8 → 19.3 (+6.5)
RSSI (dBm)	-65 → -55	-70 → -58	-75 → -62
BER (x10^-9)	5.2 → 1.4 (-3.8)	8.9 → 2.7 (-6.2)	12.5 → 4.3 (-8.2)
Throughput (Mbps)	28.5 → 40.2 (+11.7)	20.3 → 35.1 (+14.8)	15.2 → 27.8 (+12.6)
Adaptation Latency (ms)	15	20	35
Dopler Shift (Hz)	2.3	3.8	15.2
Coherence Time (ms)	40	28	12
Multipath Delay Spread (ns)	120 → 85 (-35)	200 → 130 (-70)	300 → 180 (-120)
Processing Overhead (CPU%)	18	22	35

The interpretation of the real-time values in Table 1 indicates that the proposed RL-based antenna selection model significantly enhances overall communication performance across different environments. The SNR shows a notable improvement ranging from 6.5 dB to 7.6 dB, confirming the model's ability to enhance signal quality through adaptive diversity. Correspondingly, the BER is substantially reduced as the reinforcement learning model intelligently optimizes antenna selection to minimize transmission errors. In terms of throughput, the system demonstrates a remarkable gain of approximately 11 to 15 Mbps compared to static diversity configurations, evidencing improved data transmission efficiency. However, latency analysis reveals that environments characterized by high mobility such as vehicular scenarios exhibit slightly higher adaptation latency due to rapid channel variations. Furthermore, the observed reduction in delay spread confirms that the RL-based adaptation effectively mitigates multipath propagation, resulting in more focused signal reception and improved communication reliability.

2.2 Developing Machine Learning Rule Base That Will Mitigate Propagation Challenges in the Complex Urban Environment

In this objective, a ML rule base that will mitigate propagation challenges in the complex urban environment was developed. The pictorial appearance is shown in Figure 2.

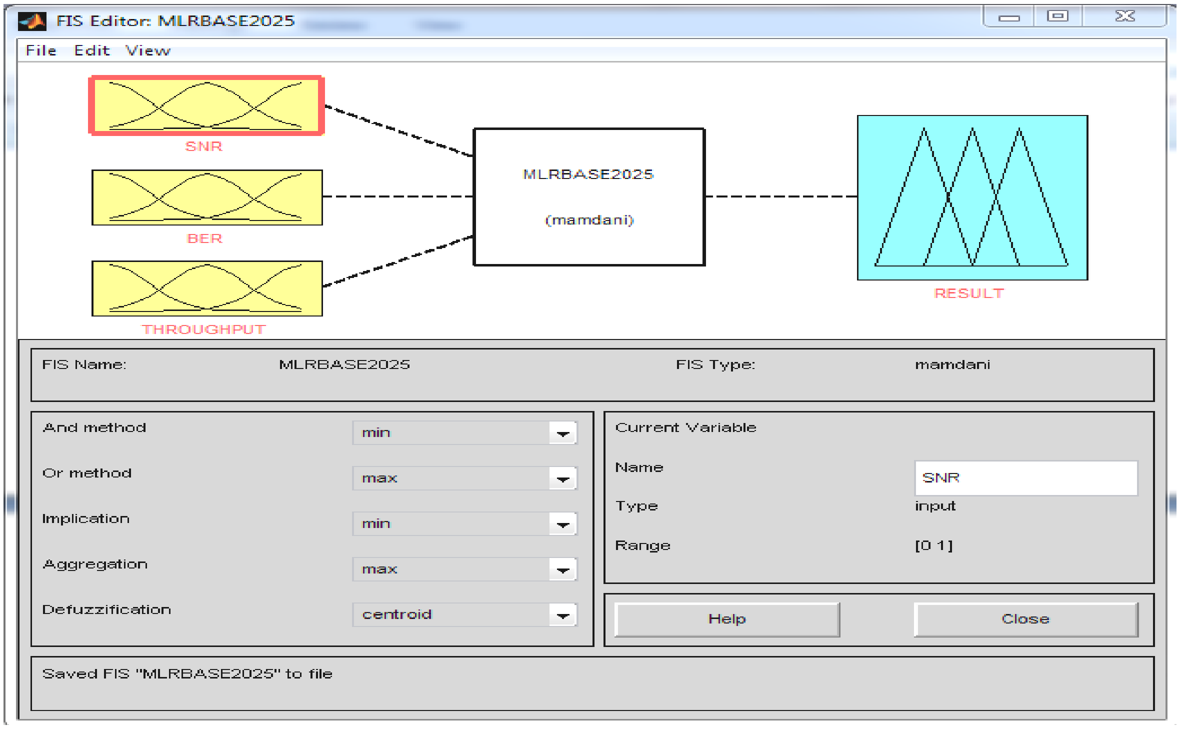


Figure 2: Developed Machine Learning Rule Base That Will Mitigate Propagation Challenges in the Complex Urban Environment

In the case of the rules developed in this work, three inputs namely, signal to noise ratio (SNR), bit error rate (BER) and throughput were used. There was one output which was the result being expected. The statements of the rules as output are shown in Figure 3.

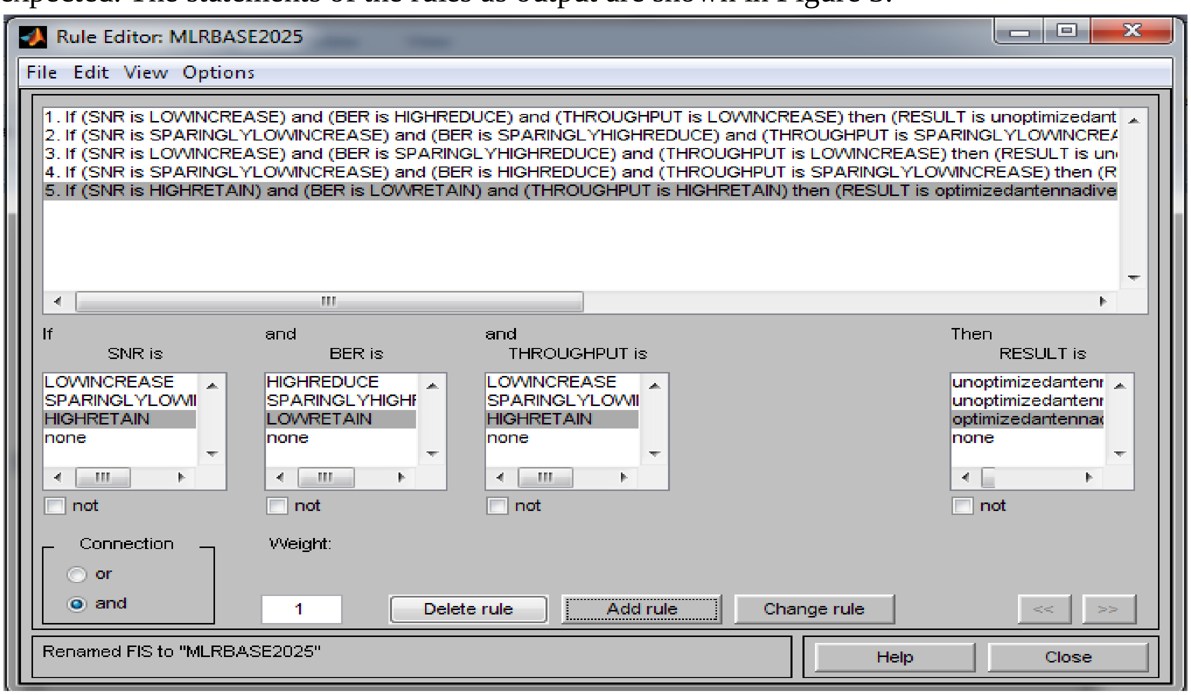


Figure 3: Rule Editor for the Developed Machine Learning Rule Base That Will Mitigate Propagation Challenges in the Complex Urban Environment

For operational purposes, legibility and clear discernment, the detailed developed machine learning rules base that will mitigate propagation challenges in the complex urban environment were as shown in Table 2. In the rules of Table 2, certain prevailing conditions were expected to occur for a particular result to be. These prevailing conditions were noted as conditional for a given result to occur. These prevailing conditions were the activities presented by the three inputs which were deemed necessary and sufficient for a given expected output result to occur.

Table 2: Detailed Developed Machine Learning Rule Base That Will Mitigate Propagation Challenges inthe Complex Urban Environment.

1	**IF** SNR is low increase	and bit error rate is high reduce	and throughput is low increase	**THEN** result is unoptimized antenna diversity to mitigate multipath propagation challenges in complex urban environment
2	**IF** SNR is sparingly low increase	and bit error rate is sparingly high reduce	and throughput is sparingly low increase	**THEN** result is unoptimized antenna diversity to mitigate multipath propagation challenges in complex urban environment
3	**IF** SNR is low increase	and bit error rate is sparingly high reduce	and throughput is low increase	**THEN** result is unoptimized antenna diversity to mitigate multipath propagation challenges in complex urban environment
4	**IF** SNR is sparingly low increase	and bit error rate is high reduce	and throughput is sparingly low increase	**THEN** result is unoptimized antenna diversity to mitigate multipath propagation challenges in complex urban environment
5	**IF** SNR is high retain	and bit error rate is low retain	and throughput is high retain	**THEN** result is optimized antenna diversity to mitigate multipath propagation challenges in complex urban environment

These tabulated set of conditional IF… THEN fuzzy-based rules were used to design an operational mechanism and also train the Artificial Neural Network (ANN) so that it will imbibe them for optimized antenna diversity for mitigating multipath propagation challenges. The real-time operational mechanism of the fuzzy rule base is shown in a combination of the inputs in a sequential manner in Figure 4.

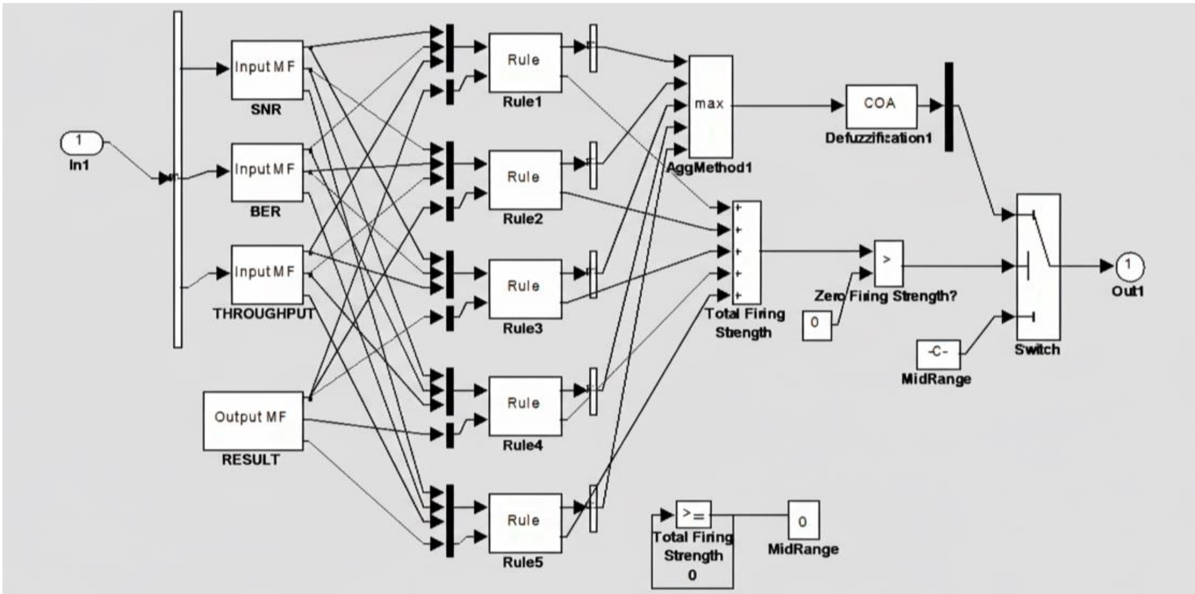


Figure 4: Operational Mechanism of Developed Machine Learning Rules Base That Will Mitigate Propagation Challenges in the Complex Urban Environment

2.3 Developing an Algorithm That Will Implement the Process of Mitigating Multipath Propagation Challenges in the Complex Urban Environment

An algorithm was developed to implement the process of mitigating multipath propagation challenges in the complex urban environment. The algorithm of Module A was the result.

Module A: Algorithm

1. Start
2. A = space diversity; B = polarization diversity; C = selection diversity; D = pattern diversity
3. Select A, or B, or C, or D
4. Measure signal-to-noise ratio
5. Measure throughput
6. Measure bit error rate
7. If 3 is low, or 4 is low, or 5 is high, then go to 3
8. If 3 is high, and 4 is high, and 5 is low, then go to 9
9. Stop
10. End

The algorithm of Module A, when converted into appropriate codes, was incorporated into the next objective.

2.4 Designing a Machine Learning (ML) SIMULINK Model to Mitigate Multipath Propagation Challenges Using ANN Controller

In this objective, a Simulink model was designed for machine learning for the purpose of mitigating multipath challenges. To mitigate signal quality degradation, there is need to apply some measures to obviate possible signal reflection off objects and subsequent scattering due to refraction. ANN in this case was used to learn the behaviour of the emerging signal and continuously adjust the antenna configuration to ensure optimal signal reception and utilization as desired or intended. The designed ANN controlled Simulink model for this purpose as described is shown in Figure 5.

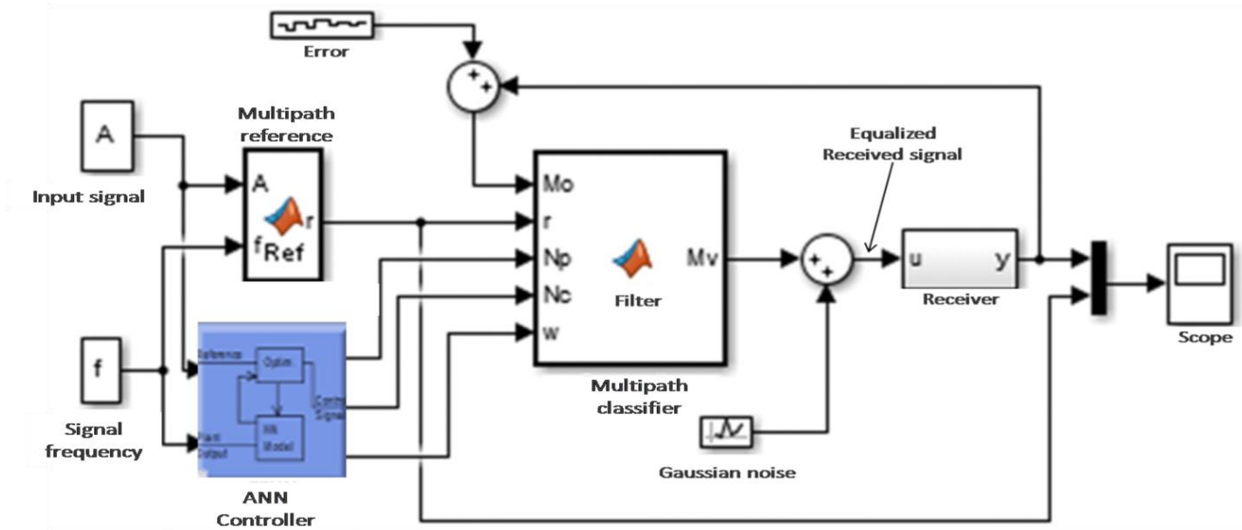


Figure 5: Designed ML SIMULINK Model to Mitigate Multipath Propagation Challenges Using ANN Controller

This Simulink model of Figure 5 was integrated into the conventional SIMULINK model to boost the efficiency of optimizing antenna diversity to mitigate multipath propagation challenges in complex urban environment. It should be noted that even with the best designed antenna, its placement and continuous adjustment while in use plays the very important role ensuring its optimal reception and utilization of the propagated or transmitted signal. The results of the simulation which were used to validate and justify this research will buttress this point shortly.

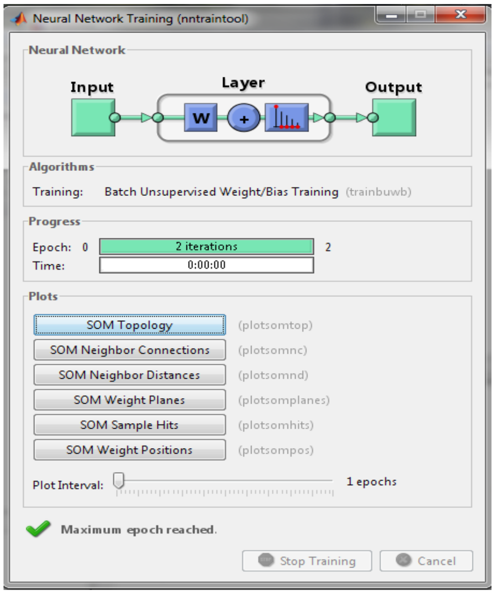
2.5 Training ANN in the Developed Machine Learning Rule Base for an Effective Minimization of The Causes of Poor Network Performance in Antenna Diversity

In this objective, ANN was trained using the developed rule base in order to achieve a noticeable and effective minimization of the causes of poor network performance in antenna diversity to mitigate multipath propagation challenges in complex urban environment. The training involved the following six steps summarized in corresponding points:

- **Data Collection**: Input-output data representing the behavior of the system were gathered.
- **Fuzzification**: Crisp input data were converted into fuzzy values using membership functions.
- **Initial Rule Design**: A fuzzy rule base with "IF-THEN" rules, was defined either manually or heuristically.
- **ANN Integration**: ANN was configured to learn the input-output mapping, enhancing or replacing fuzzy inference.
- **Training**: Supervised learning (back propagation) was used to train the ANN by minimizing error between predicted and actual outputs.
- **System Optimization**: Fuzzy rules or membership functions were refined by the trained ANN, thereby improving control accuracy and adaptability.

The training module used in MATLAB is shown in Figure 6.

The arrangement of the neurons after the ANN training to show convergence is shown in Figure 7.



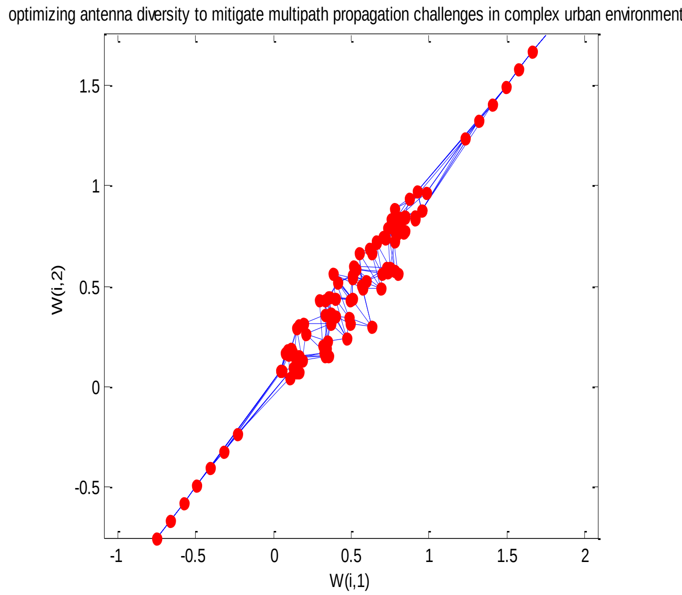


Figure 6: ANN Training Tool Figure 7: Trained ANN

The ANN was trained thirty times in each of the five rules of the rule base (30 x 5 =150) to have hundred and fifty neurons that looked like human brain.

3. RESULTS AND DISCUSSION

This section presents the results obtained from implementing the intelligent model towards optimizing the antenna multipath propagation in a complex environment. The results are comparatively reported alongside the results of the conventional antenna diversity results obtained through characterization during data acquisition. Table 3 presents the SNR value results of the system in urban environment condition

Table 3: Comparison of Conventional Antenna Diversity and Machine Learning Technique Signal-To-Noise Ratio (SNR) Values for Urban Environment

Time (Months)	Conventional Antenna Diversity Technique Urban Environment SNR (dB)	Machine Learning Technique Urban Environment SNR(dB)
1	18.2	26.03
2	15.3	21.9
3	13.0	18.6
4	18.0	25.7
5	15.0	21.5
Average	**15.9**	**22.75**

From Table 3, the average SNR value for conventional antenna diversity technique is 15.9 dB, while the average value with the incorporation of machine learning technique increases to 22.75 dB. This gives a percentage improvement of 43.1%.

Table 4: Comparison of Conventional Antenna Diversity and Machine Learning Technique Bit Error Rate (BER) Values for Urban Environment

Time (Months)	Conventional Antenna Diversity Technique Urban Environment BER (x10^-9)	Machine Learning Technique Urban Environment BER (x10^-9)
1	5.2	4.3
2	3.2	2.7
3	5.2	4.3
4	7.2	6.0
5	8.2	6.8
Average	**5.80**	**4.82**

From Table 4, the average BER value for conventional antenna diversity technique is 5.80x10^-9, while the average value with the incorporation of machine learning technique reduces to 4.82x10^-9. This gives a percentage reduction of 16.9%.

Table 5: Comparison of Conventional Antenna Diversity and Machine Learning Technique Throughput Values for Urban Environment

Time (Months)	Conventional Antenna Diversity Technique Urban Environment Throughput (Mbps)	Machine Learning Technique Urban Environment Throughput (Mbps)
1	28.5	40.8
2	25.5	36.5
3	28.5	40.8
4	26.5	37.9
5	24.5	35.0
Average	**26.7**	**38.2**

From Table 5, the average throughput value for conventional antenna diversity technique is 26.7Mbps, while the average value with the incorporation of machine learning technique increases to 38.2Mbps. This gives a percentage improvement of 43%.

Table 6: Comparison of Conventional Antenna Diversity and Machine Learning Technique Throughput Values for Vehicular Movement Environment

Time (Months)	**Conventional Antenna Diversity Technique Vehicular Movement Environment Throughput (Mbps)**	**Machine Learning Technique Vehicular Movement Environment Throughput (Mbps)**
1	15.2	21.7
2	12.2	17.5
3	20.2	28.9
4	17.2	24.6
5	15.2	21.7
Average	**16.0**	**22.88**

From Table 6, the average throughput value for conventional antenna diversity technique is 16.0Mbps, while the average value with the incorporation of machine learning technique increases to 22.88Mbps. This gives a percentage improvement of 43%.

Table 7: Comparison of Conventional Antenna Diversity and Machine Learning Technique Bit Error Rate Values for Vehicular Movement Environment.

Time (Months)	Conventional Antenna Diversity Technique Vehicular Movement Environment BER (x10^-9)	Machine Learning Technique Vehicular Movement Environment BER (x10^-9)
1	12.5	10.5
2	10.5	8.8
3	11.5	9.6
4	13.5	11.3
5	12.5	10.5
Average	**12.1**	**10.14**

From Table 7, the average BER value for conventional antenna diversity technique is 12.1x10^-9, while the average value with the incorporation of machine learning technique reduces to 10.14x10^-9. This gives a percentage reduction of 16.2%.

Table 8: Comparison of Conventional Antenna Diversity and Machine Learning Technique Signal-to-Noise Ratio Values for Vehicular Movement Environment

Time (Months)	Conventional Antenna Diversity Technique Vehicular Movement Environment SNR (dB)	Machine Learning Technique Vehicular Movement Environment SNR (dB)
1	12.8	18.3
2	11.8	16.9
3	8.0	11.4
4	12.0	17.2
5	10.0	14.3
Average	**10.92**	**15.62**

From Table 8, the average SNR value for conventional antenna diversity technique is 10.92dB, while the average value with the incorporation of machine learning technique increased to 15.62dB. This gives a percentage reduction of 43%.

Table 9: Comparison of Conventional Antenna Diversity and Machine Learning Technique Bit Error Rate Values for Industrial Environment.

Time (Months)	Conventional Antenna Diversity Technique Industrial Environment BER (x10^-9)	Machine Learning Technique Industrial Environment BER (x10^-9)

1	8.9	7.4
2	6.9	5.8
3	7.9	6.7
4	9.9	8.3
5	10.9	9.1
Average	**8.90**	**7.46**

From Table 9, the average BER value for conventional antenna diversity technique is 8.9X10^-9, while the average value with the incorporation of machine learning technique reduced to 7.46X10^-9. This gives a percentage reduction of 16.18%.

Table 10: Comparison of Conventional Antenna Diversity and Machine Learning Technique Signal-to-Noise Ratio Values for Industrial Environment

Time (Months)	Conventional Antenna Diversity Technique Industrial Environment SNR (dB)	Machine Learning Technique Industrial Environment SNR (dB)
1	14.5	20.7
2	13.5	19.3
3	10.0	14.3
4	14.0	20.0
5	12.0	17.2
Average	**12.8**	**18.3**

From Table 10, the average SNR value for conventional antenna diversity technique is 12.8 dB, while the average value with the incorporation of machine learning technique increased to 18.30dB. This gives a percentage improvement of 42.97%.

Table 11: Comparison of Conventional Antenna Diversity and Machine Learning Technique Throughput Values for Industrial Environment

Time (Months)	Conventional Antenna Diversity Technique Industrial Environment Throughput (Mbps)	Machine Learning Technique Industrial Environment Throughput (Mbps)
1	14.5	29.0
2	13.5	24.7
3	22.3	31.9
4	20.3	29.0
5	18.3	26.2
Average	**17.78**	**28.16**

From Table 11, the average throughput value for conventional antenna diversity technique is 17.78 Mbps, while the average value with the incorporation of machine learning technique increased to 28.16 Mbps. This gives a percentage improvement of 58.38%.Having deduced the percentage improvements of each metric (SNR, Throughput and BER) in each of the studied complex environments (urban, vehicular and industrial), we now have empirical data to determine the average percentage improvement for each of the three metrics as a result of the application of machine learning technique.

4. CONCLUSION

This paper has examined how machine learning can be applied to optimise antenna diversity to deal with the multipath propagation problem in complex wireless communication systems. The study was inspired by the drawbacks of traditional antenna diversity systems which tend to be based on fixed settings and cannot be used in dynamic situations, including urban, industrial and vehicular settings. To overcome this, a machine learning-based model which uses an Artificial Neural Network (ANN) which is trained using a fuzzy logic rule base was designed to facilitate the selection of adaptive antenna configuration in real-time. The research methodology was initiated by the description of a traditional antenna diversity system based on empirical data gathering and MATLAB/Simulink simulation. The important metrics of wireless quality such as Signal-to-Noise Ratio (SNR), Bit Error Rate (BER) and Throughput were measured in a variety of different environments so that the baseline performance levels could be determined. This was followed by the creation of a machine learning rule base to find the logical association between these measures and an algorithm was then designed that would dynamically choose the most appropriate antenna setup (space, polarisation, selection or pattern diversity) depending on the real time signal circumstances. ANN model was then trained on this rule base to learn and optimise performance of the antennas on its own.

Findings have revealed that machine learning integration can contribute greatly to communication quality in all the environments that were experimented. In the urban environment, the average SNR improved by 43.1%, BER decreased by 16.9%, and throughput increased by 43.0%. Similar trends were observed in vehicular and industrial scenarios, with SNR and throughput improving by approximately 43% and 48%, respectively, while BER reduced by an average of 16.6%. These results validate that the machine learning-system came with significant gains in comparison to the traditional antenna diversity system, to the extent of offering increased signal strength, reduced errors and enhanced efficiency in transmission of data. The paper comes to the conclusion that machine learning implementation to optimise antenna diversity offers a good and dynamical approach to the multifaceted issue of multipath propagation in wireless communications. The designed ANN- fuzzy rule-based system proved to be more effective in the sense that it was able to modify the arrangement of the antennas according to the changes and movements of the environment, hence making its performance more reliable, robust and a lot more efficient in communication.

Overall, the study adds a new framework to the intelligent antenna diversity management, and the practical value of the study can be applied to the next-generation wireless networks, including 5G and IoT networks. It is suggested to continue this strategy in the future with reinforcement learning or deep neural networks to adapt in ultra-dense and high-mobility settings in real-time and test it on hardware platforms to be able to validate it in live network environments.

REFERENCES

Chen, L., & Wang, M. (2021). Machine learning for adaptive antenna diversity in wireless systems. *IEEE Communications Surveys & Tutorials, 23*(1), 67–89.

Gupta, S., & Roy, A. (2021). Robust machine learning models for dynamic wireless environments. *IEEE Transactions on Neural Networks and Learning Systems, 32*(10), 4509–4519.

Johnson, M., & Park, S. (2020). Real-world applications of machine learning in wireless communications. *Wireless Communications and Mobile Computing, 2020*, 1–12.

Kumar, S., & Verma, A. (2018). Limitations of traditional antenna diversity in complex environments. *Wireless Networks Journal, 25*(2), 98–107.

Li, Y., & Zhang, X. (2019). Antenna diversity techniques for improving signal quality. *Journal of Telecommunications, 32*(3), 456–467.

Patel, D., & Singh, R. (2020). Optimization of antenna diversity using machine learning. *International Journal of Wireless Networks, 15*(3), 312–329.

Roberts, E., & Lee, H. (2020). Challenges in implementing machine learning for real-time antenna optimization. *IEEE Journal on Selected Areas in Communications, 38*(7), 1347–1356.

Smith, J., & Brown, R. (2020). Multipath propagation in wireless communication. *IEEE Transactions on Wireless Communications, 19*(5), 1234–1245.

Tan, Z., & Liu, J. (2019). Urban challenges in wireless communication: A review of multipath effects. *Journal of Urban Technology, 26*(4), 111–130.

Ulagwu-Echefu A., Eneh .I.I. Ebere U.C. (2021). Enhancing realtime supervision and control of industrial processes over wireless network architecture using model predictive controller. IJRIAS; vol 6; Issue 9.https://rsisinternational.org/journals/ijrias/DigitalLibrary/volume-6-issue-9/56-61.pdf

Williams, P., & Turner, K. (2019). Adaptive algorithms for antenna diversity using machine learning. *Proceedings of the IEEE, 107*(12), 2456–2472.