International Journal of Engineering, Management, Humanities and Social Sciences Paradigms (IJEMHS)
Volume 37, Issue 01 and Publication Date: 4th January, 2025
An Indexed, Referred and Peer Reviewed Journal ISSN (Online): 2347-601X
www.ijemhs.com

Role of Artificial Intelligence & Machine Learning in Novel Antenna Designs

Manas Ranjan Jena[1], Amiya Bhusan Sahoo[2], Saumendra Behera[3], Monalisa samal[4]

[1, 2]Silicon Institute of Technology, Sambalpur, Odisha, India

[3,4]GIFT Autonomous, Bhubaneswar, Odisha, India

Email: [1]manas.synergy@gmail.com,[2] amiybhusana@gmail.com

Abstract- This paper emphasizes the role of Artificial Intelligence (AI) in antenna design, particularly through machine learning (ML) techniques. With the increasing availability of diverse data, advanced processing capabilities, and cost-effective data storage, ML has gained significant attention for optimizing solutions across various domains. ML algorithms are central to contemporary research and are expected to play a pivotal role in modern technologies. The paper explores fundamental ML concepts, distinguishes between AI, ML, and deep learning, discusses various learning algorithms, and highlights their extensive applications, with a primary focus on antenna design.

Key Terms*-ML, AI, DL, Antenna design, NN, NLP, DNN, IOT.*

INTRODUCTION

Artificial Intelligence (AI) involves developing machines capable of performing tasks that typically require human intelligence, such as learning, decision-making, and problem-solving. Recent advancements in big data analytics, software engineering, and affordable high-performance computing have positioned AI as a pivotal element in contemporary research. Its influence permeates various aspects of daily life, driving significant transformations in science, engineering, and societal structures. AI's capacity to innovate, transform, and optimize diverse applications continues to reshape our world.

Implementing Artificial Intelligence (AI) necessitates equipping machines with various capabilities to emulate human intelligence. Key components include:

- **Natural Language Processing (NLP):** Enables machines to comprehend and interact using human language.
- **Knowledge Representation:** Involves structuring information for efficient storage and retrieval, facilitating reasoning and decision-making processes.
- **Automated Reasoning:** Allows machines to draw conclusions and make decisions based on stored knowledge, utilizing logical inference methods.
- **Machine Learning (ML):** Empowers systems to learn from data, identify patterns, and adapt to new situations without explicit programming.
- **Computer Vision:** Enables machines to interpret and understand visual information from the environment, such as images and videos.
- **Robotics:** Involves designing machines capable of performing physical tasks, integrating perception, planning, and action.
- Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are interconnected yet distinct fields, each contributing uniquely to the development of intelligent systems.
- **Artificial Intelligence (AI):** AI encompasses the broader concept of machines exhibiting human-like intelligence, enabling them to perform tasks such as reasoning, problem-solving, and understanding natural language.
- **Machine Learning (ML):** ML is a subset of AI that focuses on algorithms allowing systems to learn from and make decisions based on data. Unlike traditional AI, which may rely on rule-based programming, ML enables systems to improve their performance over time through experience.
- **Deep Learning (DL):** DL, in turn, is a subset of ML that utilizes neural networks with multiple layers to model complex patterns in data. This approach is particularly effective in handling unstructured data such as images, audio, and text.

- The relationship among these fields can be visualized as a hierarchy: AI encompasses ML, and ML encompasses DL.
- Understanding these distinctions is crucial for developing and implementing AI applications effectively, as each level offers unique methods and capabilities for processing information and learning from data.
  The Block diagram of AI-ML applications is shown in Fig 1.

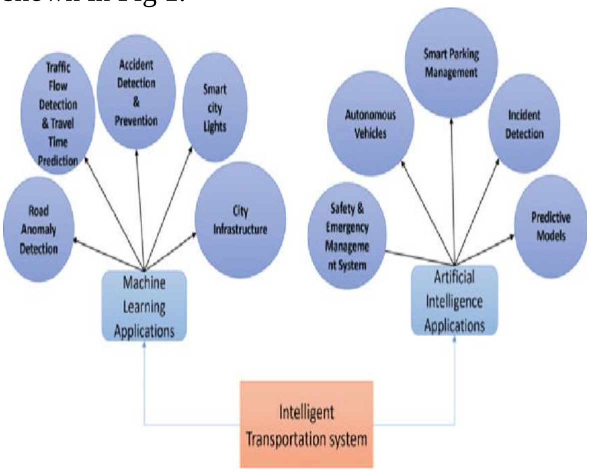

Fig 1: Block diagram of AI-ML applications

Machine Learning (ML) involves extracting valuable insights from data by developing reliable predictive algorithms. The effectiveness of these algorithms heavily depends on the quality and quantity of the collected data. Consequently, machine learning is closely associated with statistics and data analysis .

Neural Networks are a category of machine learning algorithms inspired by the human brain's architecture. They consist of interconnected layers of nodes, each performing nonlinear transformations on its inputs. When these networks contain multiple hidden layers, they are referred to as Deep Neural Networks (DNNs), a concept central to Deep Learning .

Understanding the distinctions between machine learning, neural networks, and deep learning is essential, as each represents a different approach to processing data and learning from it.

In multi-band antenna design, machine learning (ML) techniques often encounter significant challenges due to the complexity of optimizing multiple resonant frequencies simultaneously. This complexity arises from the intricate non-linear relationships between antenna structures and their multi-band responses, making it difficult for ML models to accurately capture these interactions. Traditional ML models typically rely on fixed functional forms, which may not effectively represent the dynamic and multi-dimensional nature of antenna performance across various frequencies.

To address these challenges, researchers are exploring advanced ML approaches tailored for antenna design. For instance, Gupta et al. introduced a deep neural network-based framework that rapidly generates desired antenna structures by effectively searching a vast design space, eliminating the need for extensive domain-specific knowledge. Their method utilizes tandem neural networks and a novel "smooth thresholding" activation function to design non-intuitive structures, achieving compactness and efficiency in antenna design.

Similarly, Al-Zawqari et al. proposed the use of Uniform Cross-Entropy optimization as a Monte-Carlo sampling technique to optimize patch antenna geometries. This approach demonstrated improved performance over traditional methods, converging in approximately 16 minutes, and highlighted the potential of combining ML techniques with optimization algorithms in antenna design.

Moreover, Bessant explored the application of Auxiliary Classifier Wasserstein Generative Adversarial Networks (ACWGAN) to generate synthetic data representing electromagnetic field distributions and antenna characteristics across various frequencies. This method aids in designing multiband antennas suitable for Internet of Things (IoT) applications, showcasing the effectiveness of generative models in antenna design.

Despite these advancements, challenges persist in automating the design process and improving the learning efficiency of ML models, especially when prior knowledge is limited. Addressing these issues requires ongoing research into high-quality training data generation, reduction of solution space complexity, and the development of hybrid learning approaches that combine imitation learning with reinforcement learning. Such efforts aim to enhance the practicality and effectiveness of ML-assisted antenna design in real-world applications.

II. ML-BASED ANTENNA DESIGN

Integrating machine learning (ML) into antenna design involves a structured workflow aimed at enhancing performance and productivity. This process encompasses several key stages:

1. **Data Generation:** Utilize electromagnetic simulation tools such as CST Studio Suite®, HFSS, IE3D, Altair FEKO, and Antenna Magus to model and simulate various antenna designs. These simulations produce datasets that capture the complex relationships between antenna structures and their performance metrics.
2. **Model Development:** Employ machine learning algorithms to analyze the generated datasets, identifying patterns and correlations that inform the development of predictive models.
3. **Training and Validation:** Divide the dataset into training and testing subsets. Use the training data to teach the ML models, and the testing data to evaluate their accuracy and generalization capabilities.
4. **Optimization:** Apply the trained models to optimize antenna designs, exploring a vast design space efficiently to achieve desired performance characteristics.
5. **Deployment and Tuning:** Implement the optimized designs and, if necessary, fine-tune model parameters based on real-world performance feedback to further enhance efficiency.

Tools like Antenna Magus facilitate the exploration of a comprehensive database of over 350 antennas, aiding in the selection and initial design phases. Designed antennas can be exported to simulation platforms like CST Studio Suite® for detailed analysis.

Altair FEKO offers a range of solution methods suitable for various antenna types, including wire, microstrip, horn, and phased array antennas. Its integration with ML techniques enables efficient optimization and performance enhancement.

By systematically combining these simulation and machine learning tools, antenna designers can achieve more efficient, innovative, and performance-optimized designs.

In antenna design, simulation tools like CST, HFSS, IE3D, Altair FEKO, and Antenna Magus are instrumental in generating datasets for optimizing antenna performance. These tools facilitate the modeling, simulation, and analysis of various antenna structures.

FEKO Simulation Process:

1. **Designing Antennas in CADFEKO:**
   - Use CADFEKO to create detailed geometric models of antennas. This tool provides a user-friendly interface for designing complex structures.
2. **Simulating and Analyzing in POSTFEKO:**
   - After designing, simulate the antenna's electromagnetic performance using FEKO's solver. POSTFEKO is then employed to visualize and analyze simulation results, including radiation patterns, impedance, and gain.
3. **Integration with Antenna Magus:**
   - Antenna Magus complements FEKO by offering a comprehensive database of antenna designs. Users can explore, design, and export antenna models directly to FEKO for further simulation and optimization.

Additional Simulation Tools:

- **CST Microwave Studio:**
  Utilizes the Finite Integration Technique (FIT) for simulating the electromagnetic behaviour of antennas, aiding in the analysis of various antenna designs.

- **HFSS (High-Frequency Structure Simulator):**
  Employs the Finite Element Method (FEM) to solve complex electromagnetic problems, providing accurate results for antenna performance evaluations.

By leveraging these simulation tools, designers can efficiently model, analyze, and optimize antenna structures, leading to enhanced performance and innovation in antenna design. The antenna design steps are shown in Fig 2.

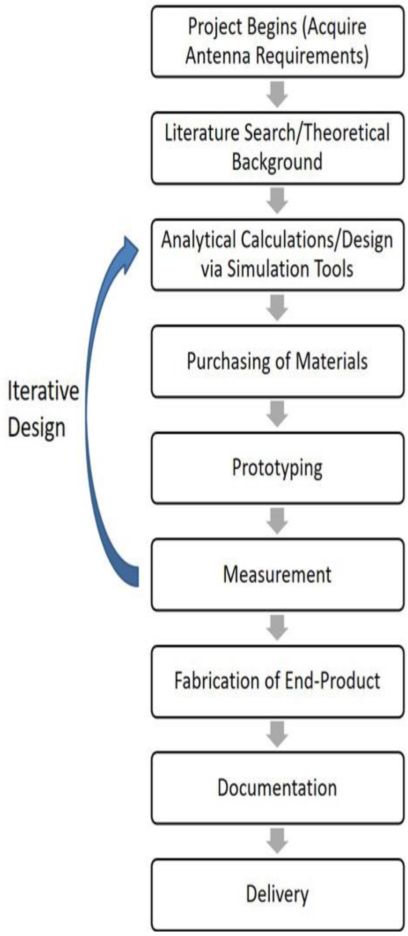

Fig 2: Antenna design steps

Integrating Machine Learning (ML) algorithms into antenna design significantly enhances efficiency by reducing reliance on exhaustive trial-and-error simulations. Traditional design methods, which involve manually adjusting antenna dimensions through numerous electromagnetic (EM) simulations, are time-consuming and may not consistently achieve desired accuracy levels. ML techniques address these challenges by predicting antenna performance, thereby streamlining the design process.

Commonly Used ML Algorithms in Antenna Design:

- **Multistage Collaborative Machine Learning (MS-CoML):** This approach combines multiple ML models to collaboratively optimize antenna designs, effectively capturing complex design-performance relationships.
- **Support Vector Regression (SVR) and Support Vector Machines (SVM):** SVR is utilized for regression tasks, while SVM is employed for classification problems in antenna design, aiding in performance prediction and classification of design parameters.
- **Artificial Neural Networks (ANN):** ANNs model intricate non-linear relationships between design parameters and performance metrics, facilitating accurate predictions and optimization.
- **K-Nearest Neighbors (KNN):** KNN is used for classification and regression tasks, assisting in identifying optimal design configurations based on proximity in the feature space.
- **Decision Tree Regression (DTR) and Random Forest Regression (RFR):** These algorithms are employed to model and predict antenna performance, aiding in identifying optimal design parameters.

Benefits of ML in Antenna Design:

1. **Enhanced Efficiency:** ML models expedite the design process by predicting performance outcomes, reducing the need for extensive simulations.
2. **Improved Accuracy:** By capturing complex relationships, ML algorithms provide precise performance predictions, aiding in achieving desired design specifications.
3. **Reduced Computational Load:** ML-assisted designs minimize the computational resources and time required for simulation-based optimization.

Case Study: Optimization of Multiband Antennas Using ML

In the design of multiband antennas, Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms have been integrated with ML techniques to enhance efficiency. For instance, PSO has been applied to design multiband patch antennas, while DE has been used for E-shaped antennas. These hybrid approaches effectively reduce the number of simulations needed, accelerating the design process without compromising accuracy.

Incorporating ML into antenna design represents a significant advancement, offering a systematic approach to optimize designs efficiently while maintaining high accuracy. This integration not only streamlines the design process but also fosters innovation in developing antennas with superior performance characteristics.

In the study referenced as [21], a beam-shaped reflect array antenna design employs Support Vector Machines (SVM) to model the reflection coefficient matrix. This design utilizes two sets of four parallel dipoles, with SVM effectively characterizing the reflection coefficients, leading to accurate predictions of antenna performance. However, discrepancies in the cross-polarization patterns at lower levels were observed, attributed to manufacturing and measurement tolerances.

This approach aligns with broader research efforts aiming to enhance reflect array antenna designs through machine learning techniques. For instance, a study titled "Efficient Shaped-Beam Reflect array Design Using Machine Learning Techniques" demonstrates how SVMs can accelerate the design process by accurately characterizing the reflection coefficient matrix, reducing reliance on full-wave analysis tools. The research highlights that while SVMs offer high accuracy, some discrepancies in cross-polar patterns at low levels may arise due to manufacturing and measurement tolerances.

Additionally, the paper "Wideband Shaped-Beam Reflect array Design Using Support Vector Regression Analysis" explores the application of Support Vector Regression (SVR) in designing wideband shaped-beam reflect arrays. The study underscores the potential of SVR to optimize antenna performance efficiently, though it also notes that certain performance variations can occur due to practical implementation factors.

These studies collectively illustrate the efficacy of machine learning, particularly SVM and SVR, in modelling and optimizing reflect array antennas. While achieving high accuracy, it's essential to account for potential discrepancies arising from manufacturing and measurement tolerances, emphasizing the need for meticulous design and fabrication processes. Antenna Design and Optimization Using Machine Learning is shown in Fig 3.

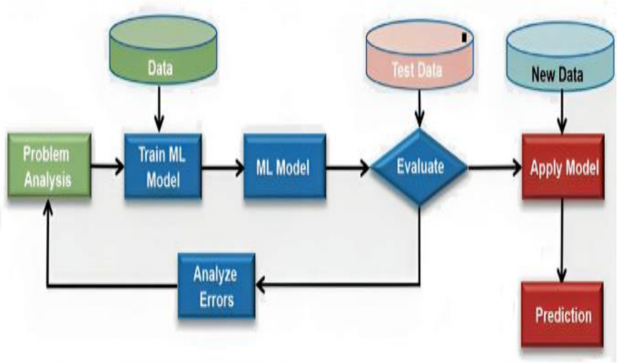

Fig 3: Antenna Design and Optimization Using Machine Learning

Integrating Machine Learning (ML) techniques into antenna design has proven effective in optimizing performance and streamlining the design process. Several studies have demonstrated the application of various ML methods in designing different types of antennas.

1. Planar Inverted-F Antenna (PIFA) Design Using Bayesian Regularization Neural Networks:
In the study referenced as [22], Bayesian regularization was employed during the neural network learning process to design a Planar Inverted-F Antenna (PIFA). The research involved developing an ML model to determine the complex permittivity and permeability based on varying particle radius and volume fraction. Additionally, a modified magneto-dielectric material was introduced for the antenna substrate. This artificial substrate contributed to the PIFA's acceptable performance, as detailed in the study.

2. Multiband Patch Antenna Design Using ANN with PSO-Based Learning:
Reference [23] describes the use of an Artificial Neural Network (ANN) combined with a Particle Swarm Optimization (PSO)-based learning model to design a multiband patch antenna with enhanced bandwidth. The study presents a user-friendly Computer-Aided Design (CAD) tool for designing stacked patch antennas operating in the X-Ku band. However, it's important to note that the study primarily focuses on estimating resonant frequencies and bandwidth, without addressing other performance metrics such as gain, directivity, efficiency, and radiation patterns.

3. Double T-Shaped Monopole Antenna Analysis Using ANN and Optimization Algorithms:
The analysis of a double T-shaped monopole antenna was conducted using an ANN-based Multilayer Perceptron (MLP). To train the ANN, optimization algorithms such as the Sine-Cosine Algorithm (SCA) and Grey Wolf Optimizer (GWO) were utilized. These

methods aimed to enhance the antenna's performance by effectively determining optimal design parameters.

These studies highlight the efficacy of ML techniques, including Bayesian regularization, ANN, PSO, SCA, and GWO, in advancing antenna design. By integrating these methods, designers can achieve improved performance metrics and more efficient design processes across various antenna types.

Integrating Machine Learning (ML) techniques into antenna design has significantly enhanced optimization processes, leading to improved performance and efficiency. Recent studies have demonstrated the effectiveness of various ML models and algorithms in designing and optimizing different antenna structures.

1. SCGWO-MLP Model for Double T-Shaped Monopole Antenna:
A study combined the Sine Cosine Algorithm (SCA) with the Grey Wolf Optimizer (GWO) to create the SCGWO model, which was used to train a Multilayer Perceptron (MLP) neural network for designing a double T-shaped monopole antenna. This hybrid approach outperformed traditional K-Nearest Neighbors (KNN) and MLP models, achieving precise optimization of design parameters with a minimal computation time of 272.13 seconds.

2. SADEA Surrogate Model for Antenna Design Optimization:
A novel surrogate model integrating the Sparrow Search Algorithm (SA) with Differential Evolution Algorithm (DEA) (SADEA) was proposed for antenna design and optimization. Compared to commonly used DE and PSO, the SADEA model demonstrated enhanced antenna efficiency and accelerated the design process, highlighting the potential of combining metaheuristic algorithms for complex optimization tasks.

3. Levenberg–Marquardt Algorithm with ANN for Elliptical Printed Dipole Antenna:
The Levenberg–Marquardt Algorithm was applied in conjunction with an Artificial Neural Network (ANN) to design an elliptical printed dipole antenna. However, the study was limited by a small dataset, utilizing only 24 data samples generated through Electromagnetic (EM) simulations, which may affect the generalizability of the model.

4. SVR, ANN, and Random Forest for Microstrip Patch Antenna Dimension Prediction:
Support Vector Regression (SVR), ANN, and Random Forest algorithms were employed to predict the optimized dimensions of rectangular microstrip patch antennas. These ML approaches aimed to enhance the accuracy and efficiency of antenna design by accurately forecasting critical dimensional parameters.

5. Multi-Objective Genetic Learning Algorithm for Dual Antenna Systems:
A multi-objective genetic learning algorithm was utilized to design and optimize dual antenna systems comprising a four-element patch antenna array and a log-periodic dual-dipole antenna. This approach effectively minimized side lobe levels and improved directionality by optimizing multiple performance metrics simultaneously, as depicted in the proposed dual antenna system with dimensions of 500×143.66×8.175 mm³.

6. EM-Driven and ML-Based Multiband Rectangular Spiral-Shaped Microstrip Antenna:
An Electromagnetic-driven and ML-based approach was introduced for designing a multiband rectangular spiral-shaped microstrip antenna. Models such as Decision Tree Regression (DTR), Differential Evolutionary Forest (DFR), and ANN were employed for modeling and optimization, with DTR demonstrating superior performance in predicting antenna characteristics.

These advancements underscore the pivotal role of ML in modern antenna design, offering enhanced optimization capabilities, improved performance metrics, and efficient design processes across various antenna configurations. AI enabled 6G network is shown in Fig 4.

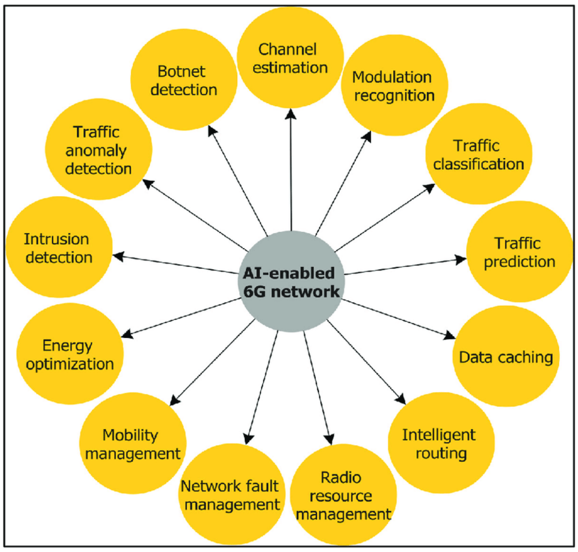

Fig 4: AI enabled 6G network

TABLE II: Comparison of the different machine learning techniques used in the investigated papers

Paper	Antenna Type	Learning Algorithm	Compared To	Results

International Journal of Engineering, Management, Humanities and Social Sciences Paradigms (IJEMHS)
Volume 37, Issue 01 and Publication Date: 4th January, 2025
An Indexed, Referred and Peer Reviewed Journal ISSN (Online): 2347-601X
www.ijemhs.com

		Used		
[26]	Reflectarrays	SVM	MoM & ANN	Accelerated design process while maintaining high accuracy levels
[14]	Planar Inverted F-antenna (PIFA)	Bayesian Regularization		Minimization of error and acceleration of cycle time for new materials synthetization
[15]	Reflectarrays	Kriging		Time saving can reach 99.9% while maintaining a prediction error below 5%
[29]	Planar Inverted F-Antenna (PIFA)	ANN	Conventional Simulations	Possible prediction of antenna behavior without extensive electromagnetic simulations
[28]	Rectangular Microstrip Antenna	SVM	ANN	Better computation efficiency with a faster convergence rate
[30]	Slotted Waveguide Antenna	ANN	Conventional Simulations	Computation of several antenna parameters with good agreement with the simulated and fabricated results
[35]	Antenna (SWA)	ANN	Conventional Simulations	Design process can be sped up by eliminating the need for time-consuming simulations
[36]	Stacked Patch Antenna	Kriging	Conventional Simulations	Similar results of other optimization techniques can be obtained while reducing the number of necessary simulations by 80%
[39]	E-Shaped Antenna	Linear Regression	Conventional Simulations	The optimum results were found without any necessary simulations
[40]	Microstrip Antenna	Gaussian Process ML	Differential Evolution	The speed of the design and optimization procedure by more than four times compared with differential evolution

CHALLENGES IN MACHINE LEARNING:

While machine learning offers significant advantages, it also presents several challenges. Some of the most common challenges include:

1. **Choice of Learning Algorithm**: Selecting the appropriate algorithm can be difficult due to the vast number available. The choice depends largely on the type of prediction being made and the nature of the acquired data. A good practice is to visualize the data before deciding on the algorithm.
2. **Problem Formulation**: Starting with incorrect assumptions can lead to unproductive results, wasting both time and resources. It is crucial to identify the most relevant area of the problem to focus on to ensure efficient use of time and effort.
3. **Acquiring Sufficient Data**: Gathering enough data can be a significant challenge, as certain datasets are difficult to obtain. In antenna design, for example, numerous simulations are required to generate a comprehensive training set.
4. **Data Pre-processing**: Ensuring that the learning algorithm functions properly requires several pre-processing steps, such as data cleaning, normalization, and feature selection. These tasks can be time-consuming, especially when dealing with large datasets.
5. **Debugging the Algorithm**: Troubleshooting the algorithm can also be difficult. When issues like high bias or high variance arise, knowing how to proceed is essential. Effective diagnosis techniques, such as plotting learning curves, can help identify and resolve problems.

CONCLUSION

This paper provides an overview of machine learning, exploring its core concepts, distinctions from artificial intelligence and deep learning, and its various algorithms and techniques. A thorough investigation is also conducted on the application of machine learning in antenna design, highlighting its advantages over traditional design and computational methods. It was found that machine learning can significantly accelerate the antenna design process, achieving high levels of accuracy, reducing errors and time, predicting antenna behavior, improving computational efficiency, and minimizing the need for extensive simulations.

This paper explores the application of artificial intelligence (AI) in antenna engineering. It thoroughly examines various learning algorithms used for antenna design, optimization, and selection. The review covers machine learning (ML) based antenna design processes with electromagnetic (EM) simulators such as CST, HFSS, and FEKO. Additionally, the article discusses several antenna design optimization techniques, including parallel optimization, single and multi-objective optimization, variable fidelity optimization, and multilayer ML-assisted optimization.

The paper also highlights the use of ML in intelligent antenna selection for wireless applications. To automate the antenna engineering process, generating adequate datasets is crucial. The findings suggest that ML can accelerate the antenna design process while maintaining high accuracy, reducing errors, and saving time. Additionally, these technologies can predict antenna behavior, enhance computational efficiency, and reduce the number of required simulations. This paper will be a valuable resource for readers looking to explore further research on the application of ML in the design, optimization, and selection of antennas for wireless communications.

REFERENCES

[1] S. J. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, 3rd Edition. Pearson Education, 2016.
[2] M. Mohri, A. Rostamizadeh and A. Talwalkar, Foundations of Machine Learning. The MIT Press, 2012.
[3] P, Harrington, Machine Learning in Action. Manning Publications, 2012.
[4] R. Jiang, X. Wang, S. Cao, J. Zhao and X. Li, "Deep Neural Networks for Channel Estimation in Underwater Acoustic OFDM Systems," IEEE Access, vol. 7, pp. 23579–23594, 2019.
[5] D. Pyle and C. S. Jose, "An executive's guide to machine learning," tech. rep., McKinsey & Company, June 2015.
[6] M. Chen, U. Challita, W. Saad , C. Yin and M. Debbah, "Machine learning for wireless networks with artificial intelligence: A tutorial on neural networks," CoRR, vol. abs/1710.02913, 2017.
[7] S. Marsland, Machine Learning: An Algorithmic Perspective, Second Edition. Chapman and Hall/CRC, 2014.
[8] A. Burkov, The Hundred-Page Machine Learning Book. Andriy Burkov, 2019.
[9] S. Shalev-Shwartz and S. Ben-David, Understanding Machine Learning: From Theory to Algorithms. Cambridge University Press, 2014.
[10] S. O. Haykin, Neural Networks and Learning Machines. Prentice Hall, 2008.
[11] K. Crammer and Y. Singer, "On the algorithmic implementation of multiclass kernel-based vector machines," Journal of Machine Learning Research, vol. 2, p. 265–292, 2001.
[12] L. Hyafil and R. L. Rivest, "Constructing optimal binary decision trees is NP-complete," Information Processing Letters, vol. 5, no. 1, p. 15–17, 1976.
[13] Y. Freund and R. Schapire, "A decision-theoretic generalization of online learning and an application to boosting," European Conference on Computational Learning Theory (EuroCOLT), p. 23–37, 1995.
[14] C. Gianfagna, M. Swaminathan, P. M. Raj, R. Tummala and G. Antonini, "Enabling antenna design with nano-magnetic materials using machine learning," 2015 IEEE Nanotechnology Materials and Devices Conference (NMDC), pp. 1–5, Anchorage, AK, 2015.
[15] L. Tenuti, G. Oliveri, D. Bresciani and A. Massa, "Advanced learningbased approaches for reflectarrays design," 2017 11th European Conference on Antennas and Propagation (EUCAP), pp. 84–87, Paris, 2017.
[16] X. Wang, P. Wang and X. Wang, "Adaptive Sparse Array Reconfiguration based on Machine Learning Algorithms," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1159–1163, Calgary, AB, 2018.
[17] J. Joung, "Machine Learning-Based Antenna Selection in Wireless Communications," IEEE Communications Letters, vol. 20, no. 11, pp. 2241– 2244, Nov. 2016.
[18] Z. M. Fadlullah and M. M. Fouda and N. Kato and X. Shen and Y. Nozaki, "An early warning system against malicious activities for smart grid communications," IEEE Network, vol. 25, no. 5, pp. 50–55, 2011.
[19] B. A. Sonkamble and D. D. Doye, "Use of Support Vector Machines through Linear-Polynomial (LP) Kernel for Speech Recognition," International Conference on Advances in Mobile Network, Communication and Its Applications, pp. 46–49, 2012.
[20] C. Perera and A. Zaslavsky and P. Christen and D. Georgakopoulos, "Context Aware Computing for The Internet of Things: A Survey," IEEE Communications Surveys Tutorials, vol. 16, no. 1, pp. 414–454, 2014.
[21] S. S. W. Samek and T. Wiegand, "The convergence of machine learning and communications," CoRR, vol. abs/1708.08299, 2017.
[22] J. Huang and J. Antonio Encinar, Reflectarray Antennas. Wiley-IEEE Press, 2007.
[23] D. R. Prado, M. Arrebola, M. R. Pino, R. Florencio, R. R. Boix, J. A. Encinar and F. Las-Heras, "Efficient Crosspolar Optimization of Shaped-Beam Dual-Polarized Reflectarrays Using Full- Wave Analysis for the Antenna Element Characterization," IEEE Transactions on Antennas and Propagation, vol. 65, no. 2, pp. 623–635, 2017.
[24] P. Robustillo, J. Zapata, J. A. Encinar and J. Rubio, "ANN Characterization of Multi-Layer Reflectarray Elements for Contoured-Beam
Space Antennas in the Ku-Band," IEEE Transactions on Antennas and Propagation, vol. 60, no. 7, pp. 3205–3214, 2012.
[25] V. Richard R., Loison, R. Gillard, H. Legay and M. Romier, "Loss analysis of a reflectarray cell using ANNs with accurate magnitude prediction," 2017 11th European Conference on Antennas and Propagation (EUCAP), pp. 2396–2399, 2017.
[26] D. R. Prado, J. A. L´opez-Fern´andez, M. Arrebola and G. Goussetis, "Efficient Shaped-Beam Reflectarray Design Using Machine Learning Techniques," 2018 15th European Radar Conference (EuRAD), pp. 525–528, Madrid, 2018.
[27] R. Florencio, R. R. Boix and J. A. Encinar, "Enhanced MoM Analysis of the Scattering by Periodic Strip Gratings in Multilayered Substrates," IEEE Transactions on Antennas and Propagation, vol. 61, no. 10, pp. 5088–5099, 2013.
[28] N. T. Tokan and F. Gune, "Support Vector Characterization of the Microstrip Antennas Based on Measurements," Progress In Electromagnetics Research B, vol. 5, pp. 49–61, 2008.
[29] C. Gianfagna, H. Yu, M. Swaminathan, R. Pulugurtha, R. Tummala, and G. Antonini, "Machine-Learning Approach for Design
of Nanomagnetic-Based Antennas," Journal of Electronic Materials, vol. 46, no. 8, pp. 4963–4975, 2017.
[30] J. Tak, A. Kantemur, Y. Sharma and H. Xin, "A 3-D-PrintedW-Band Slotted Waveguide Array Antenna Optimized Using Machine Learning," IEEE Antennas and Wireless Propagation Letters, vol. 17, no. 11, pp. 2008–2012, Nov. 2018.
[31] A. Hoorfar, "Evolutionary Programming in Electromagnetic Optimization: A Review," IEEE Transactions on Antennas and Propagation, vol. 55, no. 3, pp. 523–537, March 2007.
[32] J. M. Johnson and Y. Rahmat-Samii, "Genetic algorithms and method of moments (GA/MOM) for the design of integrated antennas," IEEE Transactions on Antennas and Propagation, vol. 47, no. 10, pp. 1606– 1614, Oct. 1999.
[33] M. D. Gregory, Z. Bayraktar and D. H. Werner, "Fast Optimization of Electromagnetic Design Problems Using the Covariance Matrix
Adaptation Evolutionary Strategy," IEEE Transactions on Antennas and Propagation, vol. 59, no. 4, pp. 1275–1285, April 2011.
[34] J. Zhang, Z. Zhan, Y. Lin, N. Chen, Y. Gong, J. Zhong, H. S. H. Chung, Y. Li and Y. Shi, "Evolutionary Computation Meets Machine Learning: A Survey," IEEE Computational Intelligence Magazine, vol. 6, no. 4, pp. 68–75, Nov. 2011.

International Journal of Engineering, Management, Humanities and Social Sciences Paradigms (IJEMHS)
Volume 37, Issue 01 and Publication Date: 4th January, 2025
An Indexed, Referred and Peer Reviewed Journal ISSN (Online): 2347-601X
www.ijemhs.com

[35] S. K. Jain, "Bandwidth Enhancement Of Patch Antennas Using Neural Network Dependent Modified Optimizer," International Journal of Microwave and Wireless Technologies, vol. 8, no. 7, pp. 1111–1119, 2016.
[36] X. H. Chen, X. X. Guo, J. M. Pei and W. Y. Man, "A hybrid algorithm of differential evolution and machine learning for electromagnetic structure optimization," 2017 32nd Youth Academic Annual Conference of Chinese Association of Automation (YAC), pp. 755–759, Hefei, 2017.
[37] M. D. Gregory and Z. Bayraktar and D. H. Werner, "Fast Optimization of Electromagnetic Design Problems Using the Covariance Matrix Adaptation Evolutionary Strategy," IEEE Transactions on Antennas and Propagation, vol. 59, no. 4, pp. 1275–1285, 2011.
[38] Z. Bayraktar and M. Komurcu and J. A. Bossard and D. H. Werner, "The Wind Driven Optimization Technique and its Application in Electromagnetics," IEEE Transactions on Antennas and Propagation, vol. 61, no. 5, pp. 2745–2757, 2013.
[39] C. R. Silva and S. R. Martins, "An Adaptive Evolutionary Algorithm for UWB Microstrip Antennas Optimization Using a Machine Learning Technique.," Microw. Opt. Technol. Lett., vol. 55, no. 8, pp. 1864–1868, 2013.
[40] B. Liu, H. Aliakbarian, Z. Ma, G. A. E. Vandenbosch, G. Gielen and P. Excell, "An Efficient Method for Antenna Design Optimization Based on Evolutionary Computation and Machine Learning Techniques," IEEE Transactions on A
ntennas and Propagation, vol. 62, no. 1, pp. 7–18, Jan. 2014.