

A Review of the Design and Al-Driven Optimization Techniques on Patch Antennas for 5G Applications

¹Marcus Ibekwe, ²Frederick Alapa, ³Shamsuddeen Mikail, ⁴Stanislaus Ogbuokebe

^{1&3}Department of Electronics and Telecommunications Engineering

Ahmadu Bello University Zaria, Nigeria,

^{2&4}Department of Satellite Mission and Data Communication

National Space Research and Development Agency Abuja, Nigeria

ABSTRACT

The rapid demand for faster data rates, ultra-low latency, and energy efficiency has accelerated the shift from LTE to 5G networks. A major challenge in 5G communication is multipath fading, which reduces signal strength due to wave propagation around obstacles. To counter this, advanced antenna designs are needed that can enhance coverage, mitigate fading, and meet strict 5G requirements. Modern antenna design must address multiple factors such as gain, bandwidth, radiation patterns, coupling suppression, compactness, fabrication, and cost. Traditional trial-and-error methods are inadequate for these complex optimization needs. Artificial intelligence (AI) and machine learning (ML) now play a crucial role in antenna development by enabling adaptive optimization, accurate prediction, and reduced dependency on costly simulations. This review highlights the challenges of multilayer patch antenna design for millimetre-wave 5G applications and emphasizes how Al-driven techniques are transforming antenna engineering into more adaptive, reliable, and high-performance systems for next-generation wireless communication.

ARTICLE INFO

Article History
Received: March, 2025
Received in revised form: June, 2025
Accepted: August, 2025
Published online: September, 2025

KEYWORDS

Artificial Intelligence, Machine learning, Optimization, MPAs

INTRODUCTION

Information and communication technology has advanced rapidly, with global mobile data traffic expected to grow by 45%. translating to a tenfold increase between 2016 and 2023 (Dateki et al., 2016). This surge is largely attributed to the shift from wired, voice-centric systems to wireless multimedia applications. To meet the growing demands of digital wireless networks and internet convergence, modern systems require higher data rates, lower latency, and greater energy efficiency (AL-Saif et al., 2018). This has driven the transition from LTE to 5G, with studies focusing on moving from conventional UHF bands (300 MHz-3 GHz) to higher frequency ranges such as 6.0-7.9 GHz, 27.5-28.35 GHz, and 37.6-40 GHz (Matinmikko et al., 2018). However, high-frequency operation

poses challenges, including multipath propagation and fading effects (AL-Saif et al., 2018).

Overcoming these issues requires innovative antenna designs with wide bandwidth, high gain, low envelope correlation, minimal power loss, and strong isolation. With increasing data demand and disruptive technologies, 5G networks depend on advanced antennas to support applications in Industry 5.0, Society 5.0, and the IoT (Farasat et al., 2021; Koziel et al., 2019). Currently, 5G operates across two key frequency ranges: FR1 (450 MHz-6 GHz) and FR2 (24-100 GHz). FR1 dominates traditional mobile use due to better coverage and penetration, while FR2—particularly the 26-40 GHz band—supports emerging technologies like beamforming, spatial multiplexing, and massive MIMO (Alsaif & Eleiwa, 2021; Hwang et al., 2022).

Corresponding author: Marcus Ibekwe

<u>ibekwemarcus@gmail.com</u>





The ITU has identified 28 GHz, 38 GHz, 60 GHz, and 73 GHz as critical FR2 bands (Alsaif & Eleiwa, 2021), with the 28/38 GHz ranges gaining traction for their lower absorption rates (Hwang et al., 2022).

Antenna design is central to achieving 5G requirements of ultra-low latency, high reliability, energy efficiency, and extreme data throughput (Zhang et al., 2021). Microstrip patch antennas (MPAs) are widely used due to their compactness, ease of integration, and reliable performance (Koziel et al., 2019; Matin, 2016). Despite these benefits, MPAs face challenges such as destructive interference, mutual coupling, and design complexity (Mchbal et al., 2018). Thus, efficient 5G patch antennas must address issues related to radiation pattern control, miniaturization, isolation, and bandwidth enhancement (Sagar et al., 2021).

Traditionally, antenna design relied on iterative geometric adjustments derived from prior models and parametric studies (Roshani et al., 2023). While effective to some degree, such methods are time-consuming and limit design alternatives. Techniques like multilayer dielectric stacking, beamforming, and phased arrays (Sagar et al., 2021; El Misilmani et al., 2020; Bellekhiri et al., 2023) improve performance, but heavy dependence on numerical approaches such as FEM and MoM prolongs the design cycle and hinders scalability (Tang et al., 2017; Cheng et al., 2022). To overcome these inefficiencies. advanced optimization methods—including gradient-based and global EM models-have been adopted for more accurate, multi-objective performance improvements (Tang et al., 2017; Cheng et al., 2022; Cao et al., 2017; Shao et al., 2020; An et al., 2023).

Nonetheless, conventional synthesis methods remain constrained by computational overhead, high costs, and long processing times (Abdul et al., 2019). As a result, recent research emphasizes Al-driven frameworks that enhance reconfigurability, fault detection, pattern recognition, and optimization of antenna arrays (Sabah & Jasim, 2020). With machine learning integration, Al methods have proven effective in improving multilayer patch antennas, offering

faster, more efficient, and reliable design processes for 5G (Kilani et al., 2019).

This review therefore, discusses design and optimization strategies for 5G patch antennas, highlighting key challenges and solutions. It also underscores the pivotal role of AI in reducing computational demands and accelerating antenna development while achieving optimal performance for next-generation wireless networks.

Contemporary Optimization-Driven MPA Design

Contemporary optimization-driven MPA increasingly employs advanced design computational algorithms and innovative material platforms to achieve superior electromagnetic performance in compact, high-frequency, and multifunctional wireless systems. Hwang et al., (2022) introduced a vertically stacked dual-band dipole antenna operating at 28/38 GHz, specifically engineered for seamless device integration. The design utilized a flexible liquid crystal polymer (LCP) substrate and supported both single-ended and differential feed structures to ensure impedance consistency across different RF front ends. A 4-element array achieved gains of 10.3 dBi at 38.5 GHz and 9.0 dBi at 28 GHz. Similarly, Bellekhiri et al., (2023) developed a multilayer microstrip antenna optimized through meshing density and electromagnetic solvers. vielding an enhanced bandwidth of 2.9 GHz centered at 28 GHz and improved radiation efficiency (lyobhebhe et al., 2025).

For 5G wearable and IoT applications, Tang et al., (2017) proposed a planar multilayered electrically small Huygens source antenna with broadside radiation at 28 GHz. Simulations using ANSYS HFSS demonstrated that linear and circular polarization configurations enable versatility for cloud computing, RFID, and mobile connectivity. Chen et al., (2022) further applied design of experiments (DOE) and response surface methodology to optimize an E-shaped antenna, highlighting performance improvements in gain and return loss. However, the study also emphasized the limitations of DOE, particularly its susceptibility to local optima in higher-dimensional design spaces.





To address beamforming requirements, Lima de Paula *et al.*, (2021) presented a compact 38 GHz antenna integrating an 8 × 10 patch array with a multi-folded Butler matrix based on substrate-integrated waveguide technology. This design achieved four highly directive beams with peak gains of 19.8 dBi and 21 dBi. Shao et al. (2021) introduced a differentially fed multilayer stacked patch antenna optimized via the bat algorithm, which effectively suppressed crosspolarization and delivered gains of 6.4 dBi and 6.5 dBi.

An et al., (2023) incorporated metasurface structures in a dual-polarized antenna to minimize polarization mismatch and enhance port isolation (>31 dB), ensuring robust performance in 5G and Wi-Fi applications. Sparse array synthesis has also gained attention. Buttazzoni et al., (2020) applied compressive sensing algorithms to optimize sparse antenna arrays, reducing radiating elements while preserving main-lobe radiation patterns suitable for 5G IoT.

Despite the success of conventional electromagnetic solvers such as the method of moments (MoM), finite element method (FEM), and finite difference time-domain (FDTD), their application remains limited by challenges including boundary reflections, dispersion errors, excessive computation times, and inefficiencies for inhomogeneous or composite materials (Francavilla *et al.*, 2012; Guan *et al.*, 2014).

To overcome these limitations, artificial intelligence (AI) and machine learning (ML) techniques are increasingly integrated into antenna design frameworks. As demonstrated by Cao et al., (2017), ML algorithms can accelerate optimization. FEM-based reduce functions, and deliver scalable solutions for largeelectromagnetic problems, scale while simultaneously complementing MoM-based methods. Collectively, these advancements underscore the transformative role of Al-driven optimization in developing efficient, compact, and high-performance MPAs for next-generation 5G and beyond.

MPA Design Challenges

The design of MPA is inherently complex due to several evolving demands in modern wireless communication systems. The increasing need for higher capacity in mobile networks, the advent of disruptive technologies such as 5G New Radio (NR), the influence of multipath propagation, and the practical requirements of specific applications all impose significant design constraints. Four critical challenges in the development of MPAs are outlined below.

Bandwidth Enhancement

One of the fundamental limitations of MPAs is their inherently narrow bandwidth, attributed to their compact and planar structure (Alsaif & Eleiwa, 2021). Wide bandwidth, however, is indispensable in 5G systems, as it supports high data rates and enables operation across multiple frequency bands (Al-Saif et al., 2018). To address this, various enhancement techniques have been proposed, including the use of metamaterial structures, defected ground structures, etching slots on the radiating patch, and advanced feeding mechanisms (Sabah & Jasim, 2020; Abdul et al., 2019; Kilani et al., 2019; Gharbi et al., 2017). Each of these approaches involves trade-offs with respect to antenna size, radiation efficiency, and gain, necessitating careful optimization.

Mutual Coupling

Mutual coupling, an inherent issue in MPAs, alters the impedance and radiation characteristics of individual elements, leading to pattern distortion and reduced overall efficiency (Roshani & Shahveisi, 2022). Various techniques have been developed to mitigate this effect, such as the integration of frequency-selective surfaces (Mandal & Ghosh, 2022), metamaterials (Alibakhshikenari *et al.*, 2020), and microstrip resonators (Roshani & Shahveisi, 2022). Despite their effectiveness, these solutions often introduce additional complexity, bandwidth constraints, and alterations to the radiation pattern, which must be balanced against performance gains.





Radiation Pattern Control

Radiation pattern control plays a pivotal role in enhancing 5G performance by enabling efficient MIMO operations (Singh et al., 2021), facilitating advanced beamforming (Cao et al., 2014), minimizing interference (Tang et al., 2017), and ensuring reliable high-speed connectivity (Parchin et al., 2023). However, achieving precise radiation pattern control in MPAs remains highly challenging. Techniques such as defected ground structures, multilayer dielectric stacking, phased arrays, metamaterial surfaces, and Al-driven optimization strategies have been employed to generate directional, sectorial, or omnidirectional radiation profiles (Alibakhshikenari et al., 2020). These methods, while promising, require significant design sophistication to balance flexibility and efficiency.

Cost and Manufacturing

The exponential growth of user devices. sensors, and actuators in the 5G ecosystem (Comisso et al., 2019; Mao et al., 2019) presents additional challenges for antenna design and manufacturing. Producing high-performance, compact, and scalable patch antennas that can meet the demands of emerging technologies requires cost-effective yet advanced fabrication processes. Innovative manufacturing approaches such as flexible substrate integration, additive manufacturing, polymer-based fabrication, and roll-to-roll printing techniques offer significant potential for reducing cost while maintaining high design flexibility (Rouf et al., 2022). Nonetheless, the widespread implementation of these methods requires overcoming barriers related to precision, material limitations, and scalability.

Artificial Intelligence in MPA Design

Artificial Intelligence (AI) has emerged as a transformative approach to overcoming the intrinsic limitations of MPA design by enabling data-driven optimization and predictive modeling of complex, nonlinear design trade-offs. Leveraging machine learning algorithms, deep neural networks, and evolutionary strategies, AI can enhance bandwidth through optimal geometrical configurations, predict and mitigate

mutual coupling effects, and refine radiation patterns to achieve advanced beamforming, interference suppression, and MIMO performance (Goudos, 2021). Simultaneously, Al streamlines design-to-manufacturing pipeline identifying cost-effective materials and fabrication techniques, thereby accelerating development cycles while ensuring scalability and adaptability for next-generation wireless systems (Gaibhive et al., 2025). Central to this paradigm is the use of predictive and generative models that map input parameters such as geometry, substrates, and feeding methods to performance metrics like return bandwidth, loss. and radiation characteristics. functioning as intelligent surrogates of highly nonlinear behaviors (Wu et al., 2020).

To this end, antenna engineers have adopted diverse Al techniques, including multistage collaborative machine learning (MS-CoML), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Artificial Neural Networks (ANNs), clustering algorithms, and advanced generative methods such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Deep Q-Networks (DQNs) (Wu et al., 2020; Akinsolu et al., 2020; Singh et al., 2022), all of which collectively provide intelligent decision-making capabilities that significantly improve efficiency, adaptability, and innovation in antenna design.

To accelerate antenna design, hybrid models that integrate Support Vector Machines (SVMs) with Evolutionary Algorithms (EAs) such as Genetic Algorithms (GAs), Differential Evolution (DE), and Particle Swarm Optimization (PSO) have been applied to automate the development of beam-shaped reflect arrays, multiband patch antennas, and E-shaped antennas (Prado et al., 2018; Goudos, 2021). While EAs efficiently explore the design space for near-optimal solutions. thev computationally intensive due to reliance on fullwave electromagnetic (EM) simulations (Grout et al., 2019).

To address compactness and coupling challenges, Roshani *et al.* (2023) introduced an Al-powered framework that combines GAs with





split-ring resonators. enabling dual-band metamaterial antennas suitable for sub-6 GHz applications. wearable More recently, reinforcement learning (RL), augmented with imitation learning (IL), has been employed for automated antenna design and adaptive beamforming, domain where knowledge enhances convergence beyond standard RL techniques (Wei et al., 2023). Collectively, these Al-driven strategies enable novel antenna structures, strengthen predictive modeling, support comprehensive parametric exploration. prototyping, accelerate effectively overcoming key limitations of conventional design approaches.

Al-Based MPA Optimization

The optimization of microstrip patch antennas (MPAs) centers on selecting design parameters that maximize or minimize key performance metrics. Artificial intelligence (AI), particularly through machine learning (ML), enhances this process by employing predictive models and surrogate approximations to reduce reliance on costly full-wave electromagnetic (EM) simulations, enabling efficient exploration of highdimensional design spaces (Akinsolu et al., 2019; Koziel Pietrenko-Dabrowska, 2023; Papathanasopoulos et al., 2023). Several Aldriven frameworks have been developed to improve MPA optimization.

Machine Learning-assisted Single/Multi-Objective Optimization

Antenna design strategies can be divided into single-objective and multi-objective approaches. Single-objective MPA optimization (SMPAO) refines one metric at a time, such as gain, bandwidth, efficiency, size, or return loss (Kadlec & Capek, 2023; Zhang et al., 2023). While computationally efficient, SMPAO suffers from narrow solution spaces, local minima, and limited adaptability (Kadlec & Capek, 2023). Advanced SMPAO methods have been introduced, including trust-region, gradient-based algorithms with sparse Jacobian updates, which improve convergence and reduce complexity (Koziel & Pietrenko-Dabrowska, 2019). Other refinements

are reported in (Koziel et al., 2010; Liu et al., 2014; Bekasiewicz & Koziel, 2019).

In contrast, multi-objective optimization (MMPAO) balances several metrics simultaneously, offering richer trade-offs. Studies such as Easum et al. (2018) and Dong et al. (2019) demonstrate the integration of ML-based surrogate models, including neural networks and back-propagation neural networks (BPNNs), to accelerate the generation of Pareto fronts, enabling more efficient trade-off analysis.

Machine Learning-assisted Parallel Optimization

High-dimensional and computationally intensive antenna design tasks have led to the development of Machine Learning-assisted Parallel Optimization (MLPO). This approach integrates surrogate modeling with evolutionary algorithms to improve convergence and solution accuracy (Akinsolu et al., 2019; Liu et al., 2019, 2021). An example is the Parallel Surrogate-Differential Assisted Evolution Algorithm (PSAEDA), which uses Gaussian Process Regression (GPR) alongside multiple differential **PSAEDA** evolution streams. achieves performance up to 20× faster than conventional global optimization while maintaining accuracy (Akinsolu et al., 2019). Similarly, the Training-cost-Reduced Surrogate Model-Assisted Hybrid Differential Evolution (TR-SADEA) reduces training overhead by 90% and iterations by 20%. delivering efficient antenna designs in terms of gain, bandwidth, and efficiency (Liu et al., 2019).

Machine Learning-assisted Variable-Fidelity Optimization

Variable-Fidelity Optimization (ML-VFO) addresses the trade-off between computational cost and accuracy by combining low-fidelity (LF) and high-fidelity (HF) EM simulations. LF models provide inexpensive initial exploration, while HF models refine solutions for accuracy (Koziel & Pietrenko-Dąbrowska, 2019; Koziel et al., 2018). Techniques such as co-kriging and two-stage Gaussian Process Regression (GPR) enable effective knowledge transfer between LF and HF models, improving both speed





and reliability (Jacobs & Koziel, 2020). Advanced frameworks like multi-fidelity Bayesian optimization (MFBO) and modified-MFBO (M-MFBO) merge LF and HF data through multioutput GPR, selectively resampling promising LFderived candidates with HF models. These methods consistently outperform conventional HF-only optimization in efficiency and accuracy (Song et al., 2019; Jacobs & Koziel, 2019). Collectively, ML-VFO frameworks balance efficiency and precision, leveraging hierarchical fidelity modeling and surrogate-based optimization to reduce simulation costs while enhancing reliability. As EM simulations grow increasingly complex, ML-VFO offers a scalable solution for advanced antenna design (Jacobs & Koziel, 2020; Jacobs & Koziel, 2019).

CONCLUSION

Al-enhanced optimization techniques mark a fundamental shift in the design of 5G microstrip patch antennas, metamorphosing a traditionally laborious, resource-intensive process into a dynamic, data-driven ecosystem. The review highlights how Al-driven approaches are not isolated innovations, but foundational to the optimization of complex, high-dimensional, and multi-objective designs characteristic of 5G patch antennas. By enabling adaptive tuning, predictive modeling, and intelligent exploration of complex design spaces, these methodologies significantly elevate design efficiency, performance, and reliability.

Looking ahead, the integration of advanced Al innovations, such as generative modeling, transfer learning, and reinforcement learning, paired with adaptive materials, rapid prototyping technologies, and scalable computational platforms, will undoubtedly accelerate the evolution of high-performance, intelligent antenna systems. As wireless landscapes progress toward 6G and beyond, Aldriven antenna design will serve as a cornerstone of next-generation connectivity.

REFERENCES

Abdul Aziz, M. A., Seman, N., & Chua, T. H. (2019). Microstrip antenna design with

partial ground at frequencies above 20 GHz for 5G telecommunication systems. *Indonesian Journal of Electrical Engineering and Computer Science*, 15(3), 1466–1473. https://doi.org/10.11591/ijeecs.v15.i3.p p1466-1473

Akinsolu, M. O., Liu, B., Grout, V., Lazaridis, P. I., Mognaschi, M. E., & Barba, P. D. (2019). A parallel surrogate model assisted evolutionary algorithm for electromagnetic design optimization.

IEEE Transactions on Emerging Topics in Computational Intelligence, 3(2), 93–105.

https://doi.org/10.1109/TETCI.2018.28 64747

Akinsolu, M. O., Mistry, K. K., Liu, B., Lazaridis, P. I., & Excell, P. (2020, March). Machine learning-assisted antenna design optimization: A review and the state-of-the-art. In *Proceedings of the 14th European Conference on Antennas and Propagation (EuCAP)* (pp. 1–5).

Alibakhshikenari, M., Virdee, B. S., Shukla, P., See, C. H., Abd-Alhameed, R. A., & Limiti, E. (2020). Isolation enhancement of densely packed array antennas with periodic MTM-photonic bandgap for SAR and MIMO systems. *IET Microwaves, Antennas & Propagation, 14*(3), 183–188. https://doi.org/10.1049/ietmap.2019.0362

Alsaif, H., & Eleiwa, M. A. H. (2021). Compact design of 2 × 2 MIMO antenna with super-wide bandwidth for millimetres wavelength systems. *Symmetry*, 13(2), 233.

https://doi.org/10.3390/sym13020233 AL-Saif, H., Usman, M., Chughtai, M., & Nasir, J. (2018). Compact Ultra-Wide Band MIMO Antenna System for Lower 5G Bands. Wireless Communications and Mobile Computing, 2018, 1–6. https://doi.org/10.1155/2018/2396873





- An, W., Tian, X., Wang, J., & Wang, S. (2023). Low-profile dual-polarized double-layer microstrip antenna for 5G and 5G Wi-Fi. *Micromachines*, *14*(5), 942. https://doi.org/10.3390/mi14050942
- Bekasiewicz, A., & Koziel, S. (2019). Reliable multistage optimization of antennas for multiple performance figures in highly dimensional parameter spaces. *IEEE Antennas and Wireless Propagation Letters*, 18(7), 1522–1526. https://doi.org/10.1109/LAWP.2019.292 1610
- Bellekhiri, A., Chahboun, N., Zbitou, J., Laaziz, Y., & El Oualkadi, A. (2023). A new design of 5G multilayer planar antenna with the enhancement of bandwidth and gain. *Indonesian Journal of Electrical Engineering and Computer Science*, 29(3), 1502–1510. https://doi.org/10.11591/ijeecs.v29.i3.p p1502-1510
- Buttazzoni, G., Babich, F., Vatta, F., & Comisso, M. (2020). Geometrical synthesis of sparse antenna arrays using compressive sensing for 5G IoT applications. *Sensors*, 20(2), 350. https://doi.org/10.3390/s20020350
- Cao, Y., Chin, K.-S., Che, W., Yang, W., & Li, E. S. (2017). A compact 38 GHz multibeam antenna array with multifolded Butler matrix for 5G applications. *IEEE Antennas and Wireless Propagation Letters*, 16, 2996–2999. https://doi.org/10.1109/LAWP.2017.275 7045
- Chen, J.-H., Cheng, C.-Y., Chien, C.-M., Yuangyai, C., Chen, T.-H., & Chen, S.-T. (2022). Multiple performance optimization for microstrip patch antenna improvement. *Electronics*, 11(9), 1–15. https://doi.org/10.3390/electronics1109 1448
- Comisso, M., Palese, G., Babich, F., Vatta, F., & Buttazzoni, G. (2019). 3D multi-beam and null synthesis by phase-only

- control for 5G antenna arrays. *Electronics*, *8*(6), 656. https://doi.org/10.3390/electronics8060656
- Dateki, T., Seki, H., & Minowa, M. (2016). From LTE-Advanced to 5G: Mobile Access System in Progress. *Fujitsu Scientific & Technical Journal*, 52, 97–102.
- Dong, J., Qin, W., & Wang, M. (2019). Fast multiobjective optimization of multiparameter antenna structures based on improved BPNN surrogate model. *IEEE Access*, 7, 77692–77701. https://doi.org/10.1109/ACCESS.2019. 2920945
- Easum, J. A., Nagar, J., Werner, P. L., & Werner, D. H. (2018). Efficient multiobjective antenna optimization with tolerance analysis through the use of surrogate models. *IEEE Transactions on Antennas and Propagation, 66*(12), 6706–6715. https://doi.org/10.1109/TAP.2018.2870 338
- El Misilmani, H., Naous, T., & Al Khatib, S. (2020). A review on the design and optimization of antennas using machine learning algorithms and techniques. *International Journal of RF and Microwave Computer-Aided Engineering*, 30(7), e22356. https://doi.org/10.1002/mmce.22356
- Farasat, M., Thalakotuna, D., Hu, Z., & Yang, Y. (2021). A review on 5G sub-6 GHz base station antenna design challenges. *Electronics*, 10(16), 2000. https://doi.org/10.3390/electronics1016 2000
- Francavilla, M., Vipiana, F., Vecchi, G., & Wilton, D. (2012). Hierarchical fast MoM solver for the modeling of large multiscale wire-surface structures. *IEEE Antennas and Wireless Propagation Letters*, *11*, 1378–1381. https://doi.org/10.1109/LAWP.2012.222 7927
- Gajbhiye, P. A., Singh, S. P., & Sharma, M. K. (2025). *A comprehensive review of AI*





- and machine learning techniques in antenna design optimization and measurement. Electronics, 2, Article 46. https://doi.org/10.1007/s44291-025-00084-9
- Gharbi, I., Barrak, R., Menif, M., & Ragad, H. (2017, December). Design of patch array antennas for future 5G applications. In 2017 18th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA) (pp. 674–678). IEEE. https://doi.org/10.1109/STA.2017.8314 954
- Goudos, S. K. (2021). Emerging Evolutionary Algorithms for Antennas and Wireless Communications. SciTech Publishing, The IET.
- Guan, J., Yan, S., & Jin, J.-M. (2014). An accurate and efficient finite element-boundary integral method with GPU acceleration for 3-D electromagnetic analysis. *IEEE Transactions on Antennas and Propagation*, 62(10), 6325–6336. https://doi.org/10.1109/TAP.2014.2361 896
- Grout, V., Santos, C. M., Kourdi, Z., Tsimenidis, C., Hussain, A., & Ghavami, N. (2019). Software solutions for antenna design exploration: A comparison of packages, tools, techniques, and algorithms for various design challenges. *IEEE Antennas and Propagation Magazine*, 61(3), 48–59. https://doi.org/10.1109/MAP.2019.2900 196
- Hwang, I.-J., Oh, J.-I., Jo, H.-W., Kim, K.-S., Yu, J.-W., & Lee, D.-J. (2022). 28 GHz and 38 GHz dual-band vertically stacked dipole antennas on flexible liquid crystal polymer substrates for millimetre-wave 5G cellular handsets. *IEEE Transactions on Antennas and Propagation*, 70(5), 3223–3236. https://doi.org/10.1109/TAP.2021.3137 234

- Iyobhebhe, M., Tekanyi, A. M. S., Abubilal, K., Usman, A. D., Abdulkareem, H., Isiaka, Y., et al. (2025). A Review on Battery Life and Energy Management in HWSNs using Adaptive Energy Harvesting Techniques. Vokasi Unesa Bulletin of Engineering, Technology Applied Science, 2(2), 322-335.
- Jacobs, J. P., & Koziel, S. (2020). Variable-fidelity modeling of antenna input characteristics using domain confinement and two-stage Gaussian process regression surrogates.

 International Journal for Numerical Modelling: Electronic Networks,

 Devices and Fields, 33(6), Article e2758.
- https://doi.org/10.1002/jnm.2758
 Kadlec, P., & Capek, M. (2023). Multi-objective memetic algorithm with adaptive weights for inverse antenna design.

 IEEE Transactions on Antennas and Propagation.

 https://doi.org/10.1109/TAP.2023.3267884
- Kilani, S., El Abdellaoui, L., Zbitou, J., Ahmed, E., & Latrach, M. (2019). A compact dualband PIFA antenna for GPS and ISM band applications. *Indonesian Journal of Electrical Engineering and Computer Science*, 14(3), 1266–1271. https://doi.org/10.11591/ijeecs.v14.i3.p p1266-1271
- Koziel, S., Bekasiewicz, A., & Pietrenko-Dąbrowska, A. (2018). Multi-fidelity surrogate modelling for antenna design problems. *IET Microwaves, Antennas & Propagation, 12*(13), 2088–2094. https://doi.org/10.1049/ietmap.2018.5193
- Koziel, S., Bandler, J. W., & Cheng, Q. S. (2010).
 Robust trust-region space mapping algorithms for microwave design optimization. *IEEE Transactions on Microwave Theory and Techniques*, 58(8), 2166–2174.
 https://doi.org/10.1109/TMTT.2010.205 2666





- Koziel, S., & Pietrenko-Dabrowska, A. (2019).

 Reduced-cost electromagnetic driven optimisation of antenna structures by means of trust-region gradient-search with sparse Jacobian updates. *IET Microwaves, Antennas & Propagation,* 13(10), 1646–1652.

 https://doi.org/10.1049/ietmap.2018.5879
- Koziel, S., & Pietrenko-Dabrowska, A. (2019). Variable-fidelity simulation models and sparse gradient updates for costefficient optimization of compact antenna input characteristics. Sensors, 19(8), 1806. https://doi.org/10.3390/s19081806
- Koziel, S., & Pietrenko-Dabrowska, A. (2023). On nature-inspired design optimization of antenna structures using variableresolution EM models. *Scientific Reports*, 13(1), 8373. https://doi.org/10.1038/s41598-023-35470-4
- Koziel, S., & Sigurosson, A. T. (2018). Multifidelity EM simulations and constrained surrogate modelling for low-cost multiobjective design optimisation of antennas. *IET Microwaves, Antennas & Propagation, 12*(13), 2025–2029. https://doi.org/10.1049/ietmap.2018.5184
- Lima De Paula, I., Morcelles, K. F., De Melo, M. T., De Salles, A. A., Campos, A. L. P. S., & De Souza, R. M. S. (2021). Costeffective high-performance air-filled SIW antenna array for the global 5G 26 GHz and 28 GHz bands. *IEEE Antennas and Wireless Propagation Letters*, 20(2), 194–198. https://doi.org/10.1109/LAWP.2020.304 4114
- Liu, B., Aliakbarian, H., Ma, Z., Vandenbosch, G. A. E., Gielen, G., & Excell, P. (2014). An efficient method for antenna design optimization based on evolutionary computation and machine learning techniques. *IEEE Transactions on Antennas and Propagation*, 62(1), 7–

- 18. https://doi.org/10.1109/TAP.2013.2283 605
- Liu, B., Akinsolu, M. O., Ali, N., & Abd Alhameed, R. A. (2019). Efficient global optimisation of microwave antennas based on a parallel surrogate model assisted evolutionary algorithm. IET Microwaves, Antennas & Propagation, 13(2), 149–155. https://doi.org/10.1049/ietmap.2018.5009
- Liu, B., Akinsolu, M. O., Song, C., Hua, Q., Excell, P., Xu, Q., Huang, Y., & Imran, M. A. (2021). An efficient method for complex antenna design based on a self-adaptive surrogate model-assisted optimization technique. IEEE Transactions on Antennas and Propagation, 69(4), 2302–2315. https://doi.org/10.1109/TAP.2021.3051 034
- Mandal, S., & Ghosh, C. K. (2022). Mutual coupling reduction in a patch antenna array based on planar frequency selective surface structure. *Radio Science*, 57(2), e2021RS007392. https://doi.org/10.1029/2021RS007392
- Mao, C., Khalily, M., Xiao, P., Brown, T., & Gao, S. (2019). Planar sub-millimeter-wave array antenna with enhanced gain and reduced sidelobes for 5G broadcast applications. *IEEE Transactions on Antennas and Propagation*, 67(1), 160–168. https://doi.org/10.1109/TAP.2018.2874796
- Matin, M. A. (2016). Review on Millimeter Wave Antennas- Potential Candidate for 5G Enabled Applications. *Advanced Electromagnetics*, 5(3), 98. https://doi.org/10.7716/aem.v5i3.448
- Matinmikko, M., Latva-aho, M., Ahokangas, P., & Seppänen, V. (2018). On regulations for 5G: Micro licensing for locally operated networks.

 Telecommunications Policy, 42(8), 622–635.





- https://doi.org/10.1016/j.telpol.2017.09.
- Mchbal, A., Touhami, N. A., Elftouh, H., & Dkiouak, A. (2018). Mutual Coupling Reduction Using a Protruded Ground Branch Structure in a Compact UWB Owl-Shaped MIMO Antenna.

 International Journal of Antennas and Propagation, 2018,
- Papathanasopoulos, A., Apostolopoulos, P. A., & Rahmat-Samii, Y. (2023). Optimization assisted by neural network-based machine learning in electromagnetic applications. *IEEE Transactions on Antennas and Propagation*. Advance online publication. https://doi.org/10.1109/TAP.2023.3269 883
- Parchin, N. O., Al-Yasir, Y. I. A., Abd-Alhameed, R. A., Noras, J. M., Hussein, H. A., Ojaroudi Parchin, N., Ullah, A., & Hu, Y. (2023). An efficient antenna system with improved radiation for multistandard/multi-mode 5G cellular communications. *Scientific Reports*, 13(1), Article 31407. https://doi.org/10.1038/s41598-023-31407
- Prado, D. R., Lopez-Fernandez, J. A., Arrebola, M., & Goussetis, G. (2018, September). Efficient shaped-beam reflectarray design using machine learning techniques. In *Proceedings of the 15th European Radar Conference (EuRAD)* (pp. 1545–1548). IEEE. https://doi.org/10.23919/EuRAD.2018.8 546527
- Roshani, S., Roshani, S., Forouzeshfard, M. R., Parvizi, H., Alibakhshikenari, M., & Limiti, E. (2023). Mutual coupling reduction in antenna arrays using artificial intelligence approach and inverse neural network surrogates. *Sensors*, 23(16), 7089. https://doi.org/10.3390/s23167089
- Roshani, S., & Shahveisi, H. (2022). Mutual coupling reduction in microstrip patch antenna arrays using simple microstrip

- resonator. Wireless Personal Communications, 126(2), 1665–1677. https://doi.org/10.1007/s11277-022-09815-7
- Rouf, S., Rahman, A., Hossain, M. S., Alsharif, M. H., Chowdhury, M. S., Akhtaruzzaman, M., & ... (2022). Additive manufacturing technologies: Industrial and medical applications. Sustainable Operations and Computers, 3, 258–274. https://doi.org/10.1016/j.susoc.2022.05.001
- Sabah, A., & Jasim, M. (2020). A new patch antenna for ultra wide band communication applications. Indonesian Journal of Electrical Engineering and Computer Science, 18(2), 848–855. https://doi.org/10.11591/ijeecs.v18.i2.p p848-855
- Sagar, M. S. I., Hasan, M. R., Hossain, M. I., Rahman, M. M., & Islam, M. T. (2021). Application of machine learning in electromagnetics: Mini-review. *Electronics*, 10(22), 2752. https://doi.org/10.3390/electronics1022 2752
- Salucci, M., Poli, L., Rocca, P., & Massa, A. (2022). Learned global optimization for inverse scattering problems: Matching global search with computational efficiency. *IEEE Transactions on Antennas and Propagation, 70*(8), 6240–6255. https://doi.org/10.1109/TAP.2021.3139 627
- Shao, Z., Qiu, L.-F., & Zhang, Y. P. (2020).

 Design of wideband differentially fed multilayer stacked patch antennas based on bat algorithm. *IEEE Antennas and Wireless Propagation Letters*, 19(7), 1172–1176.

 https://doi.org/10.1109/LAWP.2020.299 4158
- Singh, O., Bharamagoudra, M. R., Gupta, H., Dwivedi, A. K., Ranjan, P., & Sharma, A. (2022). Microstrip line fed dielectric





- resonator antenna optimization using machine learning algorithms. *Sādhanā*, 47(4), 226. https://doi.org/10.1007/s12046-022-01989-x
- Singh, S., Singh, A. K., Karunesh, Pandey, A., & Singh, R. (2021, February). A novel MIMO microstrip patch antenna for 5G applications. In 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS) (pp. 828–833). IEEE. https://doi.org/10.1109/ICCCIS51004.2 021.9397137
- Song, Y., Cheng, Q. S., & Koziel, S. (2019).

 Multi-fidelity local surrogate model for computationally efficient microwave component design optimization.

 Sensors, 19(13), 3023.

 https://doi.org/10.3390/s19133023
- Tang, M.-C., Shi, T., & Ziolkowski, R. W. (2017).
 A study of 28 GHz, planar,
 multilayered, electrically small,
 broadside radiating, Huygens source
 antennas. *IEEE Transactions on Antennas and Propagation*, 65(12),
 6345–6354.
 https://doi.org/10.1109/TAP.2017.2700
 888
- Wei, Z., Zhou, Z., Wang, P., Ren, J., Yin, Y., Pedersen, G. F., & Shen, M. (2023). Automated antenna design via domain

- knowledge informed reinforcement learning and imitation learning. *IEEE Transactions on Antennas and Propagation*, 71(7), 5549–5557. https://doi.org/10.1109/TAP.2023.3266 051
- Wu, Q., Wang, H., & Hong, W. (2020). Multistage collaborative machine learning and its application to antenna modeling and optimization. *IEEE Transactions on Antennas and Propagation*, 68(5), 3397–3409. https://doi.org/10.1109/TAP.2019.2963 570
- Zhang, J., Akinsolu, M. O., Liu, B., & Vandenbosch, G. A. E. (2021). Automatic Al-driven design of mutual coupling reducing topologies for frequency reconfigurable antenna arrays. *IEEE Transactions on Antennas and Propagation*, 69(3), 1831–1836. https://doi.org/10.1109/TAP.2020.3012 792
- Zhang, J., Xu, J., Chen, Q., & Li, H. (2023).

 Machine-learning-assisted antenna optimization with data augmentation.

 IEEE Antennas and Wireless

 Propagation Letters, 22(8), 1932–1936.

 https://doi.org/10.1109/LAWP.2023.328 0269.