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HYBRID OPTIMIZATION FRAMEWORK FOR MINIMIZING RETURN LOSS IN GRAPHENE-BASED ANTENNAS FOR NEXT-GENERATION WIRELESS COMMUNICATION

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ABSTRACT

Graphene antennas have received extensive attention as promising technologies for terahertz and next-generation 6G wireless communication networks due to their extraordinary electrical tunability, high carrier mobility, and advantageous electromagnetic properties. However, for most of the existing designs, there is a major challenge: return loss is often high; operational bandwidth often is narrow; and impedance performance may vary under changing conditions. There also exists a gap in a computationally efficient optimization technique that is generally adaptable to complex, high-order engineered design criteria. In light of these challenges, this research proposes an intelligent hybrid optimization framework for the design and optimization of high-performance graphene antennas for efficient THz communication. The framework combines data-driven predictive modeling with iterative optimization to minimize return loss, maximize gain, and maximize radiation efficiency, considering stability in multiband operation in complex design configurations. The Intelligent Hybrid Optimization Framework is, for the first time, validated in the results of the simulations, returning a maximum gain of 9.86 dBi, an average radiation efficiency of 93.06%, and a return loss of -47.55 dB at a predictive accuracy of $R^2 = 0.9999$. The findings of this research suggest that the proposed approach significantly reduces the computer-aided optimization design time and cost and facilitates a scalable and intelligent platform for broadband, low-loss, energy-efficient graphene antennas for next-generation THz and 6G communication systems.



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I. INTRODUCTION

Next-generation wireless communication systems, in particular 6G and above, have increased research interest in the THz frequency band due to its ultra-high-speed data transmission capability, wide bandwidth, and multi-band operation [1]. Terahertz antennas have lately gained significant attention as an important enabler for several exciting applications such as PANs, high-speed wireless communications, industrial sensing, and medical imaging [2], [3]. Most performance metrics of the systems, including gain, radiation efficiency, impedance bandwidth, and data throughput, depend on the front-end antenna. [4]. In order to achieve compact size, multi-band operation, high gain, and configurability, the THz antennas need to meet the demands of the current wireless system for a high data rate and reliability. [5] For this reason, traditional materials used for antenna applications face serious challenges to their operability when they are used at THz frequencies. These include increased channel losses (>0.5 bps/Hz), low radiation efficiency ($<60\%$), and skin depth which seriously limits the useful application of THz frequency for communication [6].

The quest for remedy for these deficiencies inspired the investigation of 2D material-most especially graphene owing to its remarkable physical and electronic properties to be useful in THz antenna applications [7]. Graphene is a monolayer allotrope of carbon arranged in hexagonal lattice, and it has ultrahigh charge carrier mobility ($\sim 200,000$ cm²/V·s), very high thermal conductivity (~ 5000 W/m·K) and is chemically stable. [8]. the integration of graphene into antenna design can facilitate improvements in radiation efficiency, gain, impedance matching, frequency tunability, and reconfigurability of the antenna [9]. Graphene is an exciting candidate for next-generation THz wireless communication devices due to the capability for large-scale production. [10]. Recent studies have highlighted the growing relevance of machine learning (ML) and deep learning (DL) techniques in advancing the design of antennas based on graphene materials and structures [11], [12].

Traditional electromagnetic simulation methods to characterize graphene-based antennas involve the high computational expense associated with consideration of complex material interactions and geometries. The ML and DL methods consider simulated data to predict antenna performance parameters more efficiently to reduce overall computational times and costs [13]. Ensemble ML model systems have been used in the optimization of graphene-based metasurfaces antennas operating in the frequency range of 1–10 THz, achieving demonstrated radiation efficiency values of $> 93.2\%$ [14]. Similarly, fractal antennas comprised of graphene with dual SiO_2 substrates have been optimized to operate at 2.25–6 THz using Random Forest, Artificial Neural Networks, and XGBoost models [15]. Reconfigurable graphene metasurface antennas have also been studied to enable beam-steering via ON/OFF element switching using various ML approaches, yielding prediction results with a reported accuracy of ~ 0.99 [16]. Likewise, deep neural networks have been used to predict design parameters of graphene-based patch antennas in the 2–5 THz range with $\sim 93\%$ accuracy [17].

Taken together, these preliminary studies demonstrate how ML/DL techniques can successfully address issues with EM modeling for complex geometries and material interactions to enable faster and data-driven optimization of advanced THz antenna designs [18]. In spite of these developments, there remain key obstacles for THz wireless systems, specifically: a high degree of path loss, reduced coverage, and strong multipath effects, which is motivating new antenna and beamforming designs [19]. Reconfigurable intelligent surfaces (RIS) and antennas based on metasurface can provide an alternative to phased arrays with scalable, flexible, low-complexity designs for precise angular beam steering using either continuous surface impedance modulation or multi-bit discrete coding [20]. As a result, there is growing interest in recent studies in developing hybrid optimization frameworks exploiting the intrinsic properties of graphene with designed antennas to reduce return loss, improve radiation efficiency, compact form factor with all the above advantages in THz applications and regions.

These intelligent designs will take 6G networks to their full potential for integrated sensing, ultra-fast data transmission, and powerful applications in industrial IoT, autonomous applications, and other applications such as medical imaging. This research is based on the limitations imposed by existing designs on graphene-based antennas, where normative approaches are bound by being too simulation-driven with limited generalization and show inherent trade-offs between gain, bandwidth, and return loss. All these issues make most of the existent optimization techniques unable to cope with the nonlinear, high-dimensional design space, yielding suboptimal performance. This research is a step toward overcoming these challenges by presenting a hybrid intelligent design optimization methodology that couples metaheuristic search techniques with machine-learning-based surrogate modeling. As will be shown in this paper, the proposed method enables the efficient, accurate, and scalable design optimization of graphene-based antennas toward state-of-the-art, energy-efficient THz communication systems for 6G and beyond. Key Contributions of the Work:

1. Design a graphene-based antenna that is optimized for an efficient THz communication system by using tunable and conductive graphene materials.
2. A hybrid intelligent optimization framework is developed to reduce return loss and improve radiation efficiency.
3. Formulate a data-driven predictive model to predict the performance metrics of gain, bandwidth, and impedance matching.
4. Present a scalable design methodology that bridges simulation-based optimization with a feasible realization for next-generation wireless systems.

The document is structured as follows: Section 2 does a critical review of the current design and optimization techniques in the field of antenna design, while Section 3 presents the proposed graphene-based antenna design and the optimization technique used in this work. Section 4 discusses the results, including comparison studies and overall assessment analyses. Section 5 concludes the review and makes recommendations for future work.

II. LITERATURE REVIEW

This literature review analyzes advancements in the progress of compliant mechanical, dielectric, and thermal enhancement of graphene-based metasurfaces, antennas, and biosensors, with improvements optimized through soft computing and machine learning. This review depicts the gains claimed by researchers in performance and in drawbacks. The scope of field specific optimization algorithms and data-driven models that enhance tunability, sensitivity, and improve the efficiency of graphene-based electronics in terabytes and health applications are reviewed. [21] developed wideband polarization converters using two optimization methods genetic algorithms and Hill climbing that began randomly. The original solution was a pixelated graphene patch with an elliptical shape, where each pixel either represented the absence (0) or presence (1) of graphene. The optimizations turned the original guess into configurations that were almost optimal, resulting in four polarization converters. The chemical potential of the graphene was adjusted to produce operating frequencies that spanned ranges of 34.2 – 35.44 THz and 21 - 26.89 THz, among other ranges.

The converters were all able to perform well up to a 60° incident angle, and the effect of relaxation time on the polarization conversion ratio (PCR) was negligible. As the incident angle increased, the operational bandwidth and robustness of the converters for wide angle situations was reduced. This occurred due to angular dependency in the design of the metasurface, where a nonnormal angle of incidence changed the effective current distribution on the patches of graphene, resulting in narrow bandwidths and lower polarization conversion efficiency. Babu and colleagues [22] designed a wideband 1x2 MIMO fractal antenna that is specifically for terahertz applications in contexts such as explosive detection, medical imaging, video rate imaging, and high-speed short-range communication. The antenna was fabricated from a rectangular patch using iterative fractal geometry and a partial ground plane on a polyimide substrate ($\epsilon_r = 3.5$, thickness = 45 μm).

To enhance the performance of the antenna, particle swarm optimization (PSO) was employed, and CST was engaged to measure gain, efficiency, directivity, ECC, CCL, MEG, DG and TARC parameters. The design achieved ≤ -25 dB isolation with coaxial feeding and a 400 GHz bandwidth (0.35–0.75 THz). However, the instability of the antenna's operating characteristics due to its dependence on the chemical potential of graphene, μ_c , caused unpredictable impedance matching and inconsistent radiation characteristics, resulting in lower reliability for realistic terahertz applications. [23] proposed a quick way to create planar graphite wave leakage antenna without periodic changes. Since Floquet theory could not be applied and commercial EM simulators demanded high memory and computation time due to a large number of parameters, the authors used MATLAB's Method of Moments, which was expedited by particular optimization strategies.

A Genetic Algorithm was utilized to maximize quality slot arrangement of a slotted graphene micro-ribbon pattern on dual dielectric substrates with a PEC reflector. When compared to a comparable reference antenna, the developed LWA showed enhanced beam scanning, gain, and radiation efficiency. However, the reliance on GA-based slot optimization introduced a drawback: the convergence was highly dependent on initial parameter selection. Poor initialization often led to local optima, which in turn caused inconsistent radiation performance and limited scalability of the method for more complex antenna geometries. In their study, [24] applied machine learning to develop a hemoglobin biosensor based on polynomial regression (PR) in order to enhance the performance of both the absorber and the sensor. To achieve a high sensitivity, they investigated three meta-surface modifications: double split-ring resonators, single split-ring resonators, and split-ring resonators with thin wires. Of the three designs, the single and double split-ring resonators showed superior sensitivity. To predict absorption values over combinations of intermediate wavelengths, a PR model was trained with six parameters: resonator thickness, graphene chemical potential, substrate length, substrate width, substrate thickness, and angle of incidence.

Strong prediction capability was demonstrated in testing cases R-30 and R-50, where R^2 values were approximately 1.0 for increasing polynomial degrees. With a sensitivity of 2000 nm/RIU, the proposed design is suitable for application in biomedical uses, such as hemoglobin detection. Nonetheless, the high degree of polynomial regression posed a limitation, as there was a risk of overfitting and a reduction of generalizing capabilities for the PR model. This effect can occur when a model captures noise in training data rather than the true underlying relationship of the parameters, which would not produce robust models when used in unseen, biomedical sensing conditions. [25] put forward a biological sensor using a phase transition material absorbing structure. Utilizing several phases of the $\text{Ge}_{1-x}\text{Sb}_x\text{Te}_{1-y}\text{Sb}_y$ (GST) substrate, the biosensor would obtain tunable absorption characteristics. The infrared absorptivity properties of the structure were analyzed in order to detect varying levels of hemoglobin and urinary biomarkers. Furthermore, the absorbing material was also shown to be angle insensitive from 0° to 60° . In order to reduce simulation time and costs of calculation, machine learning techniques for regression were employed, particularly Locally Weighted Linear Regression (LWLR), to predict ranges for absorption at medium frequency.

The model returned an R^2 value of 0.9999 and the proposed structure demonstrated superior sensitivity than competing biosensor models. Nonetheless, there remained a challenge with the use of each LWLR model, in that the smoothing parameter (s) had a significant effect on model performance. If this parameter was not properly tuned, the models would provide overfitting or underfitting, resulting in poor absorption predictions, and would prevent a robust biosensor design able to operate under a range of processing conditions. In the paper by [26], two novel designs for graphene-based metasurface antennas were proposed, demonstrating the beneficial mechanical and electrical properties of metasurface layers. Both designs were developed and simulated using HFSS software, with performance values for the antenna that included energy efficiency, returning loss, maximum gain, and high directivity. To facilitate maximization of convergence in the design, ensemble-learning methods were employed, using graphs to develop regressors structured on The Random Forest Tree and gradient boost Regression Tree. Tuning of the substrate length, patch length, and slot width produced values from 89.04% to 97.54% for average radiation efficiency ($\sim 93.29\%$), whereas the two designs yielded bandwidths of 8.63 THz and 8.69 THz.

Combining machine learning algorithms with antenna designing had accuracy rates that neared $\sim 98\%$ after hyperparameter tuning. The caveat of using HGBT and RFT regressors was that predictive accuracy was greatly reliant the choice of tuning hyperparameters, which if poorly selected (often simply due to traditional parameter sets), led to overfitting and generalization capability was diminished, subsequently lead to optimization of antenna designs less reliable over a wider range of design variations as a result of the trained dataset. [27] proposed a novel THz biosensor based on metasurfaces for highly sensitive peptide detection. The performance of the sensor was evaluated by computation using the finite element method, including a silicon-based substrate coated with layers of precious metals such as silver and graphite. Key design parameters were systematically optimized, including the angle of incidence, resonator size, and chemical potential of graphene. The sensor was able to determine very low variability in peptide concentration with 60 GHz frequency changes, which translates to a sensitivity of 1500 GHz/RIU, figure of merit of 60 RIU^{-1} , and limit of detection of 0.016 RIU. An XGBoost regression model was implemented to improve design and prediction accuracy, with an R^2 of 100% across different parameter spaces. This study had one limitation: it was purely based on simulation results; thus, there was no validation.

Intrinsic limitations associated with simulations, which cannot fully capture the influence brought about by defects in fabrication, environmental noise, and the biological matrix effect, limited demonstrated real-world applicability of the biosensor in biological or clinical settings. [28] suggested a computationally effective design optimization technique that employs data-driven surrogate models for filtering antennas or Filtennas based on Frequency Selective Surfaces. The Modified Multi-Layer Perceptron, a deep learning-based system, was developed for the precise simulation of the behavior of FSS unit cells, further optimized using the HBMO technique. The optimized Filtenna worked in the frequency range of 5-7 GHz, providing the suppression of unwanted signals with simultaneous enhancement of the desired signals. The surrogate-driven optimization reduced the computational cost by almost 90% compared to EM-driven design. Experimental validation was performed by measurements on a prototype that was fabricated, confirming the numerical predictions for up to 7 dBi filtering performance within the rejection band and a gain enhancement of 2 dBi in the passband. Further, the surrogate model was reusable across varying geometrical parameters and frequency ranges, enhancing flexibility in design.

However, there is one major drawback related to surrogate modeling: while quite effective for single-layer FSS designs, the M2LP model failed to capture the complex electromagnetic couplings of multi-layer configurations. The limiting factor relies inherently on the reduced generalization ability of nonlinear coupling effects within the surrogate model, which further narrows its scalability in designing higher-performance multilayer Filtennas. Routhu et al. [29] described the creation of a patch microstrip antenna using graphene that operates in the 1–5 THz frequency range for terahertz applications. The antenna, which measured $93 \mu\text{m}$ by $113 \mu\text{m}$ and had 11 multiband frequencies, a maximum gain of 7.5 dBi at 3.2 THz, and a return loss of about -40 dB , was modeled in CST Microwave Studio. To investigate the effect of patch dimensions (L_p , W_p) and graphene properties such as chemical potential (μ_c) and relaxation time (τ), Artificial Neural Networks were developed. The training dataset, generated from 784 CST simulations, enabled the ANN to predict performance characteristics such as S_{11} , VSWR, gain, radiation and total efficiencies, and radiation patterns in the XZ and XY planes.

The developed ANN achieved an R^2 of 0.99 with a prediction time of 0.7 ms, confirming high accuracy in comparison with simulated results. Nevertheless, the reliance of ANN predictions on the simulated dataset was found to be a disadvantage. Since the model was trained only on pre-generated CST data, its generalization capability was restricted when applied to unseen design configurations beyond the sampled parameter space. This limitation was caused by insufficient representation of complex nonlinear interactions in the dataset, which in turn reduced the scalability of the model for broader terahertz antenna designs, such as multilayer or array configurations. [30] developed an array-level optimization framework based on phase-coding modulation and a genetic algorithm (GA). When paired with directivity-based objective functions, a phase-gradient approaching algorithm produced a near-optimal initial population that greatly increased beam guiding efficiency with fewer iterations than conventional exhaustive techniques. As a proof of concept, a passive 2-bit coding metasurface was created, and both simulations and experiments under normal and oblique incidences demonstrated that the PGA-initiated GA optimization increased the mainlobe amplitude by 2.29 dB (25.92%) and reduced sidelobe levels by 2.52 dB (26.45%) within 21° – 60° at 220 GHz. Furthermore, the optimization reduced maximum rounds by 61.08% relative to fractional coding (F-code) methods, while also showing smaller dispersion errors with amplitude fluctuations under 3 dB across 170–240 GHz.

However, the drawback of this approach was that the proof-of-concept relied on a passive 2-bit coding metasurface rather than a reconfigurable design. This restriction was caused by fabrication limitations and material constraints, which in turn limited the reconfigurability and adaptability of the proposed scheme in practical terahertz reconfigurable intelligent surface (RIS) applications. [31] introduced the metapocket, a flexible tri-band reflective metasurface designed to improve smartphone antenna performance in on-body situations. To maximize the unit cell number and attain optimal performance, they used a self-adaptive Bayesian neural network surrogate-model-assisted differential evolution algorithm. Using a PDMS substrate for flexibility and biocompatibility, the design operated throughout the WIFI (2.33–2.44 GHz), 5G N77 (3.39–3.56 GHz), and WLAN (5.05–5.39 GHz) bands. Simulations and measurements with a commercial smartphone showed realized gain improvements of 4.23, 4.67, and 5.8 dB, radiation efficiency enhancements of 16.6%, 11.5%, and 12.1%, and SAR reductions exceeding 88%. However, the dependence on a fixed pocket area and predefined frequency bands limited adaptability; this constraint caused reduced scalability when extending the approach to broader frequency ranges or different device form factors. In [32], studied the use of graphene in terahertz (THz) antenna applications to create a unique multiband Double Graphene Stripline Slot Patch- MIMO antenna at 4.71 THz, 8.55 THz, and 9 THz.

By varying design parameters with machine learning optimization approaches, the S-parameters were validated at 1–10 THz range, with a significant R^2 with 0.976822. In addition to the research confirming the graphene Enhanced antenna application validation, the use of graphene strips reduced the reflection response (S_{11}) to -37.28 dB, enhancing signal confinement and ensure isolation levels were above 76 dB. It was also noted that while the addition of graphene improved confinement and tunability, it also decreased the gain to 8.46 dB (when compared to the gain of 12.94 dB without graphene), introduced material losses that limited radiation efficiency in the system. The design demonstrated flexibility and adaptability for 6G technology and beyond, but highlighted a performance sacrifice between a gain versus confinement. [33] proposed the high-attributed surface sensor on graphene for betraying falciparum by collaborating to say and curds a silicon dioxide (SiO_2) substrate to ensure latter application with adaptable technologies in current optical and electronic settings. The design utilized square and quadrantal-based resonators, with their functionality being expressed through extensive parametric analysis and finite element simulations. The sensor showed far better than multiple other standing malaria detection sensors with a 0.109 RIU lower detection limit and a 600 GHz/RIU sensitivity.

The results showed exponential correlations of frequency of resonance with coefficient of refraction and concentration of malaria parasites, and with field analysis, the results confirmed transmittance of frequency-dependent conditions and electrical encoding capacity of 2-digits. It must be noted that a limitation to the study's purpose was that it was only a interpretations simulation findings in reference to the results; therefore, priority was not given experimental and clinical testing to address robustness, resulting in uncertainty about the veracity of what is practical in biological systems, due especially to biocomplexity potentially introducing interferents and noise to effectiveness, accurate range and functional reliability; all limitations to evidence based practice practice-product outcomes and care. Table 1 provides a summary of pertinent studies [21]–[33] which deal with designs of antennas, metasurfaces and biosensors based on graphene, optimized through a variety of soft computing and machine learning methods. The review draws comparisons and discusses how techniques, including transformations, particle swarm optimization and genetic algorithms models, have improved bandwidth, sensitivity and radiation efficiency, while also noting shared disadvantages like overfitting, initialization sensitivity and little in the way of experimental verification.

Table 1: Summary of recent graphene-based metasurface, antenna, and biosensor designs with corresponding optimization techniques, key findings, and identified limitations.

Author (Year)	Technique / Method	Key Findings	Limitations / Drawbacks
[21]	Coded metasurfaces optimized using Hill Climbing and Genetic Algorithm (GA)	Designed four polarization converters tunable via graphene's chemical potential (e.g., 34.2–35.44 THz, 21–26.89 THz); stable PCR up to 60° incidence.	Bandwidth decreased with increasing incident angle due to angular dependency, reducing robustness for wide-angle applications.
[22]	Fractal MIMO antenna optimized via Particle Swarm Optimization (PSO)	Achieved wide 400 GHz bandwidth (0.35–0.75 THz) and ≤ -25 dB isolation; suitable for THz communication and imaging.	Dependence on graphene chemical potential caused instability in impedance matching and radiation behavior.
[23]	Planar Graphene Leaky-Wave Antenna (LWA) optimized using GA and Method of Moments	Improved beam scanning, gain, and radiation efficiency with reduced computational cost.	GA convergence was highly dependent on initialization, leading to possible local optima and inconsistent results.
[24]	Polynomial Regression (PR) for metasurface-based hemoglobin biosensor	Achieved 2000 nm/RIU sensitivity and strong R^2 (~ 1.0) for absorption prediction.	High polynomial degrees risked overfitting, reducing generalization to unseen data.

[25]	LWLR regression with Graphene-GST phase-change absorber	Sensitivity: 1500 nm/RIU (hemoglobin), 1667 nm/RIU (urine); angle-insensitive (0° – 60°); $R^2 = 0.9999$.	Model highly sensitive to smoothing parameter; poor tuning caused overfitting/under fitting, affecting robustness.
[26]	Ensemble Learning (HGBT & RFT) for metasurface antenna optimization	Improved radiation efficiency (89.04–97.54%) and bandwidth (~ 8.6 THz); ML accuracy $\approx 98\%$.	Predictive accuracy highly sensitive to hyperparameter tuning, risking overfitting and reduced generalization.
[27]	THz Metasurface Biosensor + XGBoost Regression	Sensitivity 1500 GHz/RIU; FoM 60 RIU $^{-1}$; detection limit 0.016 RIU; accurate FEM-based optimization.	Only simulation-based; no experimental validation, limiting real-world reliability.
[28]	Modified MLP (M2LP) + HBMO optimization for FSS Filtenna	Reduced computation by 90%; experimental validation confirmed 7 dBi filtering, 2 dBi gain enhancement.	Surrogate model struggled with nonlinear coupling in multilayer structures, limiting scalability.
[29]	ANN-based modeling of Graphene Patch Antenna	Predicted gain, S11, VSWR, and radiation efficiency with $R^2 = 0.99$, prediction time 0.7 ms	Model trained only on simulated CST data; limited generalization to unseen configurations.
[30]	Phase-coding metasurface optimized with PGA + GA	Increased mainlobe amplitude by 25.92%, reduced sidelobe levels by 26.45%, and cut iterations by 61.08%.	Used a passive 2-bit metasurface; lack of reconfigurability due to fabrication constraints.
[31]	SB-SADEA (Bayesian Neural Network + Differential Evolution) for flexible metasurface	Enhanced smartphone gain (up to 5.8 dB), efficiency (+16%), SAR reduction (>88%).	Fixed pocket area and predefined bands limited scalability to other frequencies/form factors.
[32]	ML-optimized DGSSP-MIMO antenna using graphene	Operated at 4.71, 8.55, and 9 THz; achieved -37.28 dB reflection and >76 dB isolation.	Graphene-induced losses reduced gain (8.46 dB vs 12.94 dB); trade-off between tunability and efficiency.
[33]	Graphene-based metasurface biosensor for malaria detection	Achieved 600 GHz/RIU sensitivity and 0.109 RIU detection limit; strong linear response.	Only simulation validated; lack of clinical testing limited reliability in real biological environments.

Source: Authors, (2026).

As a result, antenna systems powered by graphene are presently a strong contender option for wireless communication systems of the terahertz (THz) and future generations. This is due to the tunability of graphene conductivity, high carrier mobility, and remarkable thermal and mechanical stability. Recently, there have been advancements for many use cases like polarization converters, MIMO fractal antennas, leaky-wave antennas, and metasurface sensors that utilize machine learning and optimization algorithms like Genetic Algorithms, Particle Swarm Optimization, and ensemble learning to improve radiation efficiency, gain, and bandwidth. Even with these advancements, serious obstacles are still pending. Many current designs show dependencies on angular and material variation that limits bandwidth or cause poor impedance matching for operating conditions. Furthermore, while ML and surrogate-assisted optimizations are powerful, the even simplest methods can over fit, are sensitive to hyperparameter configuration, and are limited in their ability to generalize to unseen configurations.

Many studies were still focused on simulation with little or no on-board experiment validation, and there is still a general lack of studies covering the trade-off between gain, tunability, and return loss, or the studying understanding of these trade-offs with basic linear antennas. Furthermore, there are limitations to even the simplest of constructions. Thus, a clear research gap exists, highlighting a clear gap in intelligence hybrid optimization framework that addresses the problem of exploiting graphene's unique electromagnetic properties combined with innovative computational intelligence techniques within an intelligent hybrid optimization framework, or a framework that minimizes return loss while maximizing gain and efficiency while allowing broadband multiband operation across several design parameters. The importance of our work represents the design large-scale energy-efficient capabilities that provide a framework for realizing graphen-based high end THz antennas that are scaling from 6g to beyond as communication technology heads toward ultra-fast, adaptive, and sustainable wireless networks.

III. DESIGN OF GRAPHENE-BASED ANTENNAS

The designed Graphene Patch antenna was created of a vertically stacked five-layer configuration to achieve superior electromagnetic performance across the terahertz (THz) spectrum. The bottom layer comprises a gold ground plane with dimensions ($l_s \times w_s$), providing an excellent reflective surface and stable electrical grounding. Above this layer, two identical silicon dioxide (SiO₂) substrates of size ($l_s \times w_s$), are placed, each characterized by a dielectric constant ($\epsilon_r = 3.9$) and a loss tangent ($\tan \delta = 0.001$). These SiO₂ layers provide mechanical support as well as act as a dielectric medium for the graphene layer above them. The topmost layer contains a metasurface consisting of a periodic arrangement of meta-atoms made from graphene-a material engineered to enhance the field confinement and radiation characteristics of the antenna. The Drude model is used to represent the conductivity of gold accurately at THz frequencies. Dispersion and tunability of surface conductivity in graphene allow for dynamic reconfigurations of antenna parameters under various environmental and biasing conditions. The geometry of the GPA in Figure 1(a) consists of a 9×9 matrix of graphene-oriented MTS unit cells on the SiO₂ superstrate layer as shown in Figure 1(b). Figure 1(c) presents the graphene patch located just beneath the MTS for efficient electromagnetic coupling and enhanced tunability. The overall design progresses through three evolution steps. In step one, the conventional microstrip patch antenna is built by using a thick SiO₂ substrate above a gold ground plane. Herein, both the ground and patch are made of gold due to its high conductivity, as illustrated in Figure 2(a). Step two: To exploit its tunable electronic properties, graphene of the same dimensions is used instead of the gold patch to enhance the bandwidth and impedance matching further.

Figure 2(b) depicts this design. Step three: Finally, graphene metasurface (MTS) patches are modified into slotted structures to minimize return loss and improve radiation efficiency. Figure 2(c) shows the slotted MTS structure. Figure 2(d) illustrates the optimized geometry of the slotted MTS unit cell. In general, this hybrid graphene-gold metasurface antenna aims for broadband operation, low return loss, and high radiation efficiency for broadband advanced THz communication. Return loss minimization is a key factor in modern wireless systems, allowing it to ensure maximum power transmission, minimum signal reflection, and high overall radiation performance. Such features are highly desirable for new developments like the World Wide Web of Things, 5G/6G networks, and energy-efficient wireless sensor systems, where compactness, adaptability, and efficiency are of prime importance. The structured Graphene Patch antenna is designed using a vertically stacked five-layer structure for superior electromagnetic performance in the terahertz band. The lowest substrate consisting of a gold ground plane with dimensions ($l_s \times w_s$) acts as an excellent reflection surface and provides stable electrical grounding.

On the subsequent layer, two identical silicon dioxide (SiO_2) substrates with dimensions ($l_s \times w_s$) and dielectric constant ($\epsilon_r = 3.9$), and loss tangent ($\tan \delta = 0.001$) are present. The two SiO_2 layers act as mechanical support, as well as a dielectric medium for the graphene layer above. The top layer consists of a graphene-based metasurface (MTS) composed of a periodic array of meta-atoms that are designed to improve field confinement and radiation properties. The conductivity characteristic of gold, while in the THz frequency regime, is described using the Drude model. Graphene's dispersive, tunable surface conductivity provides the ability to dynamically reconfigure the antenna characteristics with regards to environmental and applied bias. The GPA can be seen in Figure 1(a). It is composed of 9×9 matrix of graphene oriented MTS unit cells on the superstrate SiO_2 layer (Figure 1(b)). To ensure efficient electromagnetic coupling while providing additional tunability, a graphene patch is placed right under the MTS (see Figure 1(c)). The overall design evolves through three stages of development. In the first stage, a standard microstrip patch antenna is developed utilizing a thick SiO_2 substrate on a gold ground plane, while the ground and patch are both gold to maintain high conductivity (see Figure 2 (a)).

In the second stage, a graphene patch of the same dimensions replaced the gold patch to take advantage of graphene's tunable electronic properties, which provides enhanced bandwidth and better impedance matching (see Figure 2 (b)). In the final stage, the graphene metasurface (MTS) patches were redesigned with slots, which further reduces the return loss and enhances radiation efficiency (see Figure 2 (c)). The optimized slotted MTS unit cell shape is detailed in Figure 2 (d). The main goal of this design is to fulfill a hybrid graphene-gold metasurface antenna operating over a band with low return loss and high radiation efficiency suitable for advanced THz communication. Reducing return loss is critical for modern wireless systems to provide maximum power transfer, less signal reflecting, and improved radiation performance. These characteristics are especially beneficial for new developments such as the World Wide Web of Things, subsequent generations of 5G/6G networks, and energy-efficient wireless sensor systems, where compactness, flexibility, and efficiency are paramount.

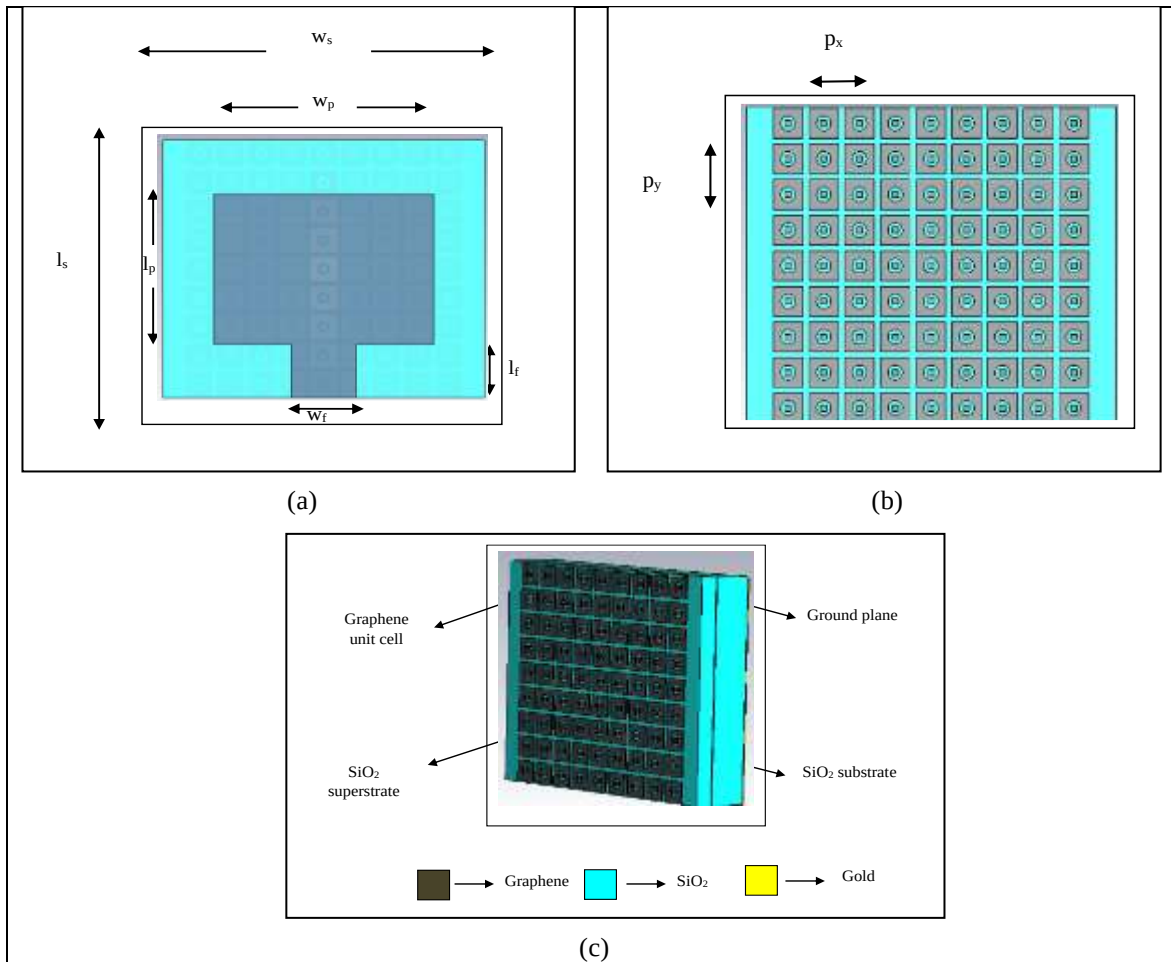


Figure 1: (a) A graphene patch antenna; (b) a top view of a superstrate loaded with metasurfaces; and (c) a perspective view of the suggested graphene and superstrate structure.

Source: Authors, (2026).

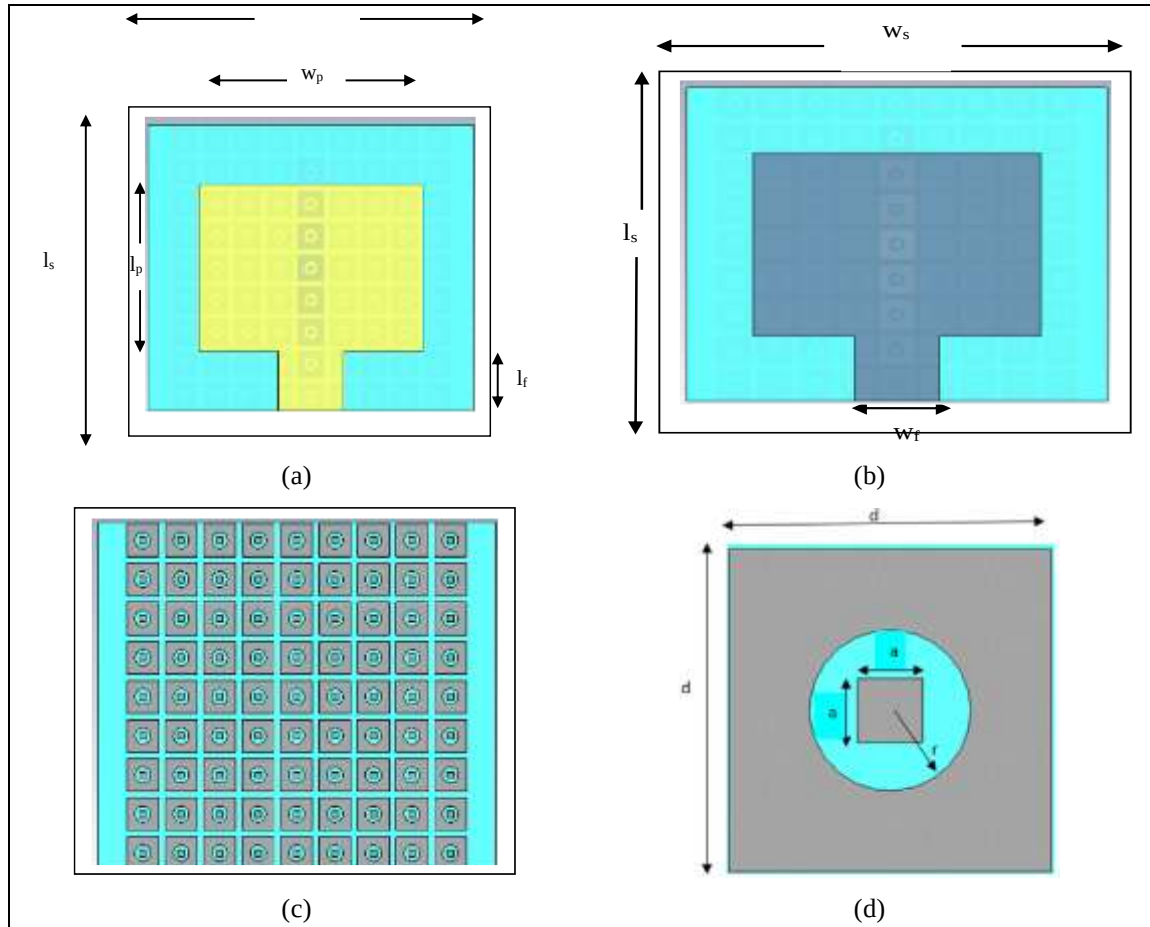


Figure 2: Structural development of the proposed antenna (a) Gold patch (b) Graphene MTS (c) perspective view (d) Top view of superstrate layer.

Source: Authors, (2026).

While many optimization methods have been used for antenna design, most methods are deterministic or single-metaheuristic - the approaches suffer in high dimensional, nonlinear design spaces. The optimization methods may encounter issues such as getting stuck in local minima or limited exploration during global exploration. There are very few examples of hybrid optimization studies using a hybrid optimization framework for graphene-based antennas, where geometry and material properties are highly nonlinear. Traditionally, the performance of these antennas have been evaluated with HFSS based electromagnetic (EM) simulations, but these simulations are expensive and have time prep, limiting a full analysis of thousands of parameter combinations to evaluate during the optimization process. The Intelligent Hybrid Optimization Framework is proposed to overcome these challenges in discovering high-performance based antenna configurations while addressing complex design constraints. Specifically, a surrogate model is constructed using Random Forest Regressors as a fast evaluator for nonlinear mapping between antenna design parameters and return loss. The modeling step significantly reduces reliance options on computationally expensive electromagnetic simulations by providing quick evaluation of the antenna configurations. The hybrid optimization is structured in two stages - the first stage of global exploration will employ an Ant Colony Optimization approach, while the second stage, local exploitation will implement a Particle Swarm Optimization procedure. In the global exploration phase, every ant signifies an antenna configuration determined by a parameter set.

Ants build configurations iteratively through probabilistic decision rules influenced by pheromone intensity and heuristic desirability. The surrogate model assesses predicted return loss, and the ants that find configurations with smaller loss deposits a larger amount of pheromone in those segments of the search space while evaporation serves to introduce diversity. The best configurations found during the exploration phase are refined during local exploitation into a configuration using PSO. The most effective particles will iteratively adjust their configurations based on their own best position, as well as the best configuration from the entire swarm, as determined by fitness evaluation including the return loss of the predicted performance and a set of desired design constraints. The ACO-PSO hybrid method is advantageous for several reasons. It is expected to be more robust when designing nonlinear, multidimensional design spaces like antennas, to converge faster than single optimization methods, and to be more accurate in the discovery of low return loss configurations. The final results demonstrated the capability to ultimately minimize return loss using the proposed intelligent framework, and an ability to design energy-efficient, broadband, and reliable graphene-based antennas, with the potential for use within advanced applications in the future of wireless communication technology.

III.1 ANTENNA CONFIGURATIONS

The proposed graphene patch antenna has been designed as multilayered structure in order to achieve maximized bandwidth, excellent radiation performance and minimal return loss for THZ applications. The antenna consists of all the same types of components including a substrate, patch, feed, ground plane, and superstrate that has been combined with an periodic graphene metasurface. Each of these has been optimized through parametric studies carried out in CST Microwave Studio by incrementally varying the geometric and material parameters of the components.

The substrate acts as the bottom layer for structural support and to affect the EM behavior. The final choice of dimensions were chosen for mechanical stability and EM performance and its length (L_s) of 215 μm , width (W_s) of 248 μm , and thickness (T_s) of 26 μm were used. The resonance frequency of the antenna and the radiation performance is primarily defined by the length (L_p) of 125 μm and the width (W_p) of 170 μm off the substrate of the patch. The proposed gold patch design with Graphene MTS is shown in figure 3.

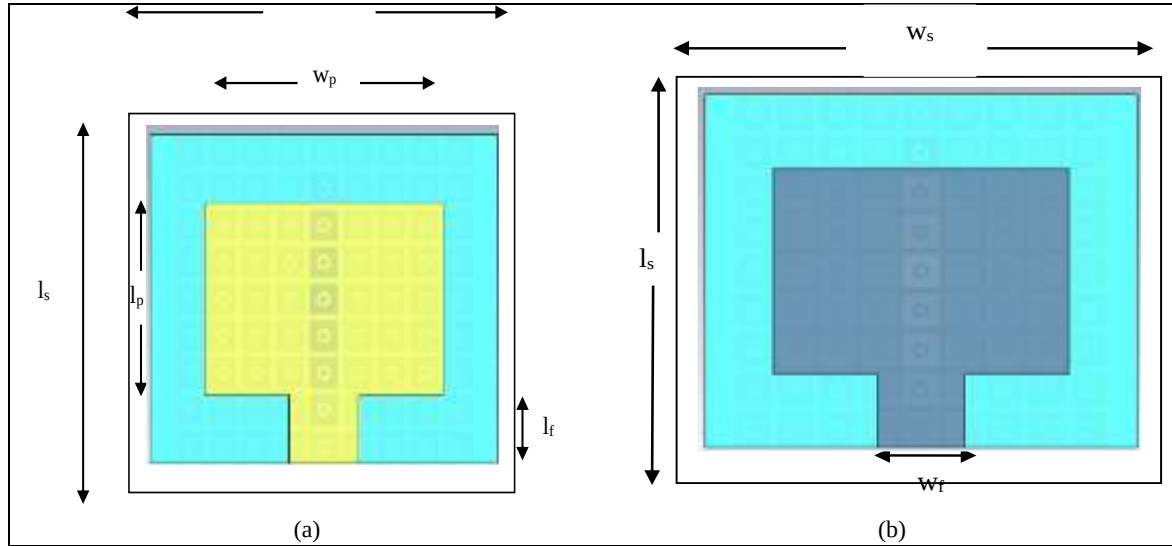


Figure 3: Proposed antenna design (a) Gold patch (b) Graphene MTS.

Source: Authors, (2026).

The microstrip feed that excites the patch has a width (W_f) of 50 μm and length (L_f) of 108 μm , ensuring the proper impedance match with the patch and return loss. The ground plane is made of gold with a thickness (G_t) of 1 μm , providing a reflecting surface to improve radiation efficiency and directivity. This antenna has a superstrate layer of SiO_2 at a height (S_h) of 12 μm , containing a graphene-based metasurface to improve bandwidth, tunability, and surface current distribution. The unit cells of the metasurface have a length and width of 20 μm , with a circular cut of radius ($r=5$ μm) and an inner square feature of 4 $\mu\text{m} \times 4$ μm . These geometric modifications increase the effective surface current path, producing improved resonance characteristics and polarization control. To achieve uniform periodicity in the metasurface layout, the unit cells are spaced with periodicity of 24 μm in the x- and y-directions (P_x , P_y). The arrangement we include leads to constructive interference of the surface waves, creating overall gain and directivity.

The slotted graphene MTS with the patch layer allows us to have a tunable platform where antenna performance has tunable and optimal properties that depend on both geometric and material properties. Table 2 has the information in the higher spectrum band. The existing arrangements as stated in Table 3 were recognized as a "terminus" or the optimized design, through periodic or repetitious parametric sweeps. We examined the patch geometry, feed structure, substrate dimensions, till we settled on a dielectric patch with a particular metasurface feature predominately responsible for minimizing return loss, improving bandwidth and peak efficiency radiation. The GPA has applicability in the realm of 5G, IIoT, and terahertz systems approaching energy efficiency. The previously discussed design provides some accommodation for potential future exploration to adapt different patch geometries, dielectric materials, or metasurface design or arrangement. Ultimately this design was a basis for future scalability in a number of wireless-based applications.

Table 2: Antenna components with dimensions.

Antenna Components	Dimensions (μm)
Substrate length L_s	215
Substrate width W_s	248
Patch length L_p	125
Patch width W_p	170
Width of feed W_f	50
Feed length L_f	108
Substrate thickness t_s	26
Ground thickness G_t	1
Superstrate height S_h	12
Unit cell length d	20
Unit cell width d	20
Circular cut radius r	5
Inner square length a	4
Inner square width a	4
Periodicity of the patch in x-axis P_x	24
Periodicity of the patch in y-axis P_y	24

Source: Authors, (2026).

Table 3: Collected data sample.

L_s	W_s	L_p	W_p	W_f	L_f	t_s	G_t	S_h	d	r	a	P_x	P_y	Graphen e thicknes s	Graphene temperatu re	Graphen e Chem Potentia l	Graphen e Relax Time	n	Return Loss
12 5	25 0	12 5	14 5	10	10 8	2 6	1	1 2	2 0	5	4	2 4	2 4	0.01	300	0.5	1	4	-30
12 5	24 8	12 5	17 0	50	10 5	2 4	0. 8	1 2	2 1	2	2	2 5	2 5	0.01	300	0.5	1	4	- 10.285
12 5	26 0	12 5	16 5	52	10 5	3 1	0. 5	1 0	2 4	8	7	1 8	1 8	0.01	300	0.5	1	4	- 30.707 1
11 8	26 3	11 8	16 2	50	10 0	2 9	1. 2	1 2	1 9	2	3	2 4	2 4	0.01	300	0.5	1	4	- 15.564 3
12 8	24 5	12 8	15 0	45	95	2 8	0. 6	1 1	2 4	1	0	1 4	1 4	0.01	300	0.5	1	4	- 20.435 5
12 0	25 0	12 0	16 0	10 8	10 8	2 5	1	1 2	1 9	2	3	3 0	3 0	0.01	300	0.5	1	4	- 20.761 6
12 0	25 0	12 0	16 0	53	10 8	3 0	1	1 4	2 3	3	0	3 0	3 0	0.01	300	0.5	1	4	- 10.403 7
11 5	25 8	11 5	15 5	50	10 0	2 2	0. 6	1 2	1 5	2	2	2 2	2 2	0.01	300	0.5	1	4	- 35.325 2

Source: Authors, (2026).

III.2 INTELLIGENT HYBRID OPTIMIZATION FRAMEWORK

The complex, nonlinear behavior of graphene metasurface antennas (GPAs) arises from the strong coupling between geometrical configuration, material dispersion, and electromagnetic boundary conditions. Analytically expressing this relationship is often intractable; hence, a data-driven surrogate-assisted hybrid metaheuristic framework is formulated to achieve an optimal antenna geometry that minimizes the reflection coefficient S_{11} and maximizes radiation effectiveness. The optimization of the proposed graphene-based patch antenna is achieved through an Intelligent Hybrid Optimization Framework that integrates Ant Colony Optimization for global exploration, Particle Swarm Optimization for local exploitation, and a Random Forest Regressor (RFRegressor)-based surrogate model to approximate the electromagnetic behavior of the antenna efficiently as shown in Figure 4. The primary objective of this framework is to minimize the return loss (S_{11}) by identifying the ideal antenna design parameters and lowering the computational expense of several full-wave computations.

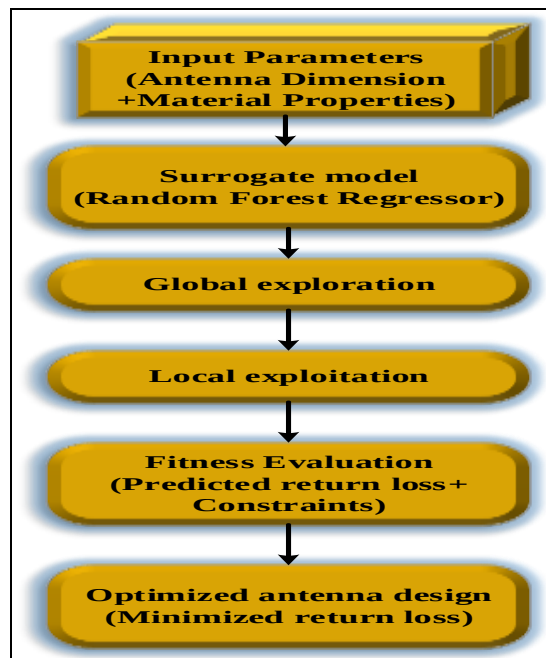


Figure 4: Flow diagram of the proposed IHOF method.

Source: Authors, (2026).

Given the high computational expense of full-wave electromagnetic (EM) simulations, a surrogate model based on the nonlinear mapping between antenna design parameters and performance measures is approximated using Random Forest Regression. Let the formula (1) be

$$X = [x_1, x_2, x_3, \dots, x_n] \quad (1)$$

Represent the concept specifications' n-dimensional matrix, including substrate dimensions; patch geometry, feed dimensions, and metasurface parameters, while equation (2) be

$$y = f(X) \quad (2)$$

Represents the corresponding return loss (S_{11}) predicted by the EM simulator. The surrogate model approximates the mapping as equation (3):

$$\hat{y} = \hat{f}(X) + \epsilon \quad (3)$$

Where $\hat{f}$ is the function learned by the RF Regressor and ϵ is the approximation error. The Random Forest ensemble consists of M decision trees, and the output prediction is the average of all tree predictions as in equation (4):

$$\hat{y} = \frac{1}{M} \sum_{m=1}^M T_m(X) \quad (4)$$

Where $T_m(X)$ is the predicted output from the m^{th} regression tree. This surrogate model significantly reduces evaluation time, enabling thousands of parameter evaluations per optimization iteration without rerunning CST simulations. The optimization problem is cast as a non-convex constrained minimization as equation (5):

$$\min_{X \in \Omega} F(X) = |S_{11}(X)| \quad (5)$$

Subject to

$$g_k(X) \leq 0, \quad k = 1, 2, \dots, K$$

Where each constraint $g_k(X)$ encapsulates geometric limits (e.g., 0, material limits, and operational limits. The surrogate model replaces the expensive EM simulations for evaluating $F(X)$ which gives the metaheuristic optimizers the ability to explore thousands of candidates per iteration, instead of just a small fraction of them at each iteration. The ACO algorithm performs global exploration across the multidimensional parameter space to discover promising regions with low predicted return loss. Each ant represents a potential antenna configuration, encoded as a vector of parameter values. At each iteration, ants probabilistically select parameter values based on pheromone intensity τ_{ij} and heuristic desirability η_{ij} , governed by the transition probability as equation (6):

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum_{k \in allowed} [\tau_{ik}(t)]^\alpha [\eta_{ik}(t)]^\beta} \quad (6)$$

Where: $\tau_{ij}(t)$ denotes pheromone concentration for parameter j , $\eta_{ij}(t) = 1/(f(X_i))$ denotes heuristic Variable inversely proportional to the expected return loss, where α, β are parameters that control the importance of pheromone and heuristic desirability. Following each ant's evaluation of the surrogate model, the pheromone levels are updated using equations (7) and (8):

$$\tau_{ij}(t+1) = (1 - \rho) \tau_{ij}(t) + \sum_{k=1}^m \Delta \tau_{ij}^k \quad (7)$$

$$\Delta \tau_{ij}^k = \begin{cases} \frac{Q}{f(X_k)} & \text{if } x_{kj} \text{ belongs to the best path,} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

Where: ρ shows the rate of pheromone evaporation, $\Delta \tau_{ij}^k$ symbolizes the pheromone that was deposited by the k^{th} ant, Q denotes the constant controlling pheromone deposit intensity. This probabilistic search balances exploration (diversity) and exploitation (intensification), identifying regions in parameter space with strong potential for optimal performance. Over successive iterations, pheromone intensity converges toward regions of globally low return loss, mathematically satisfying equation (9):

$$\lim_{t \rightarrow \infty} \nabla F(X_k^*) \approx 0, \quad X_k^* \in \Omega^* \quad (9)$$

Where Ω^* denotes the set of globally optimal designs. The PSO phase refines the best configurations obtained from ACO by iteratively improving parameter values through velocity and position updates. Each particle in the swarm represents a candidate solution X_i , characterized by a position vector $X_i(t)$, a velocity vector $V_i(t)$. The update rules for each particle are equations (10) and (11):

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 (P_i - X_i(t)) + c_2 r_2 (G - X_i(t)) \quad (10)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (11)$$

Where ω is the amount of weight of gravity. That controls exploration, c_1, c_2 are the cognitive and social coefficients, r_1, r_2 are random integers in $[0, 1]$, P_i is the particle's personal best location, and G is the swarm's global best position. In the typical PSO stability scenario:

$$0 < \omega < 1, c_1 + c_2 < 4$$

The system asymptotically converges toward a stable equilibrium near the global minimum $F(X^*)$. The local refinement thus fine-tunes geometrical parameters with sub-micrometer precision, optimizing the reactive impedance profile to suppress reflection. The overall fitness function combines the predicted return loss and optional performance penalties as equation (12):

$$F_{total}(X) = w_1|S_{11}(X)| + w_2P_{constraint}(X) \quad (12)$$

Where $P_{constraint}(X) = \sum_k \max(0, g_k(X))^2$ penalizes infeasible geometries and w_1, w_2 are weighting factors. Convergence is declared when the equation is (13)

$$|F_{best}(t+1) - F_{best}(t)| < \epsilon \quad (13)$$

For a tolerance $\epsilon = 10^{-4}$, ensuring a stationary solution in the objective landscape. With repeated updates, the particles converge to the surrogate model's return loss global minimum and the antenna geometry is updated to achieve maximum fidelity. The hybrid ACO and PSO leverage different search dynamics in a complementary fashion. ACO facilitated pheromone diffusion approximates a probabilistic gradient descent in discrete space expressed as equation (14):

$$\frac{d\tau}{dt} \propto -\nabla F(X) \quad (14)$$

PSO's velocity update corresponds to a second-order dynamical system under stochastic forcing as equation (15):

$$\frac{d^2x}{dt^2} + \gamma \frac{dx}{dt} + \nabla F(x) = \xi(t) \quad (15)$$

Where γ denotes the damping factor and $\xi(t)$ is the random excitation term. Their cooperative relationship provides a trade-off between ergodicity and convergence, permitting both broad exploration of the design space and local refinement of the objective value near the minima. The surrogate-assisted optimization obtains the result in equation (16):

$$\mathbb{E}[F(X_{hybrid})] \leq \min\{\mathbb{E}[F(X_{ACO})], \mathbb{E}[F(X_{PSO})]\} \quad (16)$$

Showing a promising advantage over independent approaches. The presented theoretical model enables a relatively straightforward optimization of the nonlinear electromagnetic design space described by geometry-material-field interactions. By minimizing return loss guided by the hybrid ACO-PSO optimization within the surrogate model, the optimum GPA satisfies equation (17):

$$S_{11,opt} = \min_{X \in \Omega} |S_{11}(X)| \quad (17)$$

This indicates that the mathematical convergence of the stochastic metaheuristics with data-driven regression accurately represents the underlying functional dependencies in terahertz antenna behavior, enabling the basis for adaptive and computationally-robust electromagnetic design techniques for future wireless applications.

IV. RESULTS AND DISCUSSION

In this section, a detailed analysis for the optimum graphene-based antenna tuned by IHOF is presented. The assessment is done on key metrics that include return radiative efficiency, vertical ratio, radiation sequence, loss of radiation, and gain to validate the broadband operation and reliable antenna performance. The assessment was also extended to antenna performance among the four structural designs, aiming at selecting a superior configuration. Among the four configurations, the Gold patch with Graphene MTS configuration exhibited lower return loss, better radiation efficiency, and broader bandwidth compared to the other designs, hence indicating its striker potential for terahertz and next-generation wireless communication systems.

IV.1 SIMULATION SETUP

The proposed graphene-based Python was utilized to model and optimize the configuration for antenna's characteristics in full-wave electromagnetic simulations carried out in Microwave Studio. The optimization method used Intelligent Hybrid Optimization Framework (IHOF) which develops global exploration and local exploitation to minimize return loss and improve overall broadband performance efficiently. Some of the design parameters that were investigated included various dimensions of the input, patch, patchwork width, platform length, foundation width, unit cell size, periodicity, circular cut radius, inner square dimensions, substrate and ground thickness, and height of the superstrate. Four structural variations were examined:

1. Graphene patch with Gold MTS
2. Gold patch with Gold MTS
3. Gold patch with Graphene MTS
4. Graphene patch with Graphene MTS

The system used for the simulations included an Intel i5 CPU and 16 GB of RAM. The CST environment accurately modeled the electromagnetic behavior of the graphene-based material. Structures, while Python-based IHOF enabled rapid optimization by approximating the nonlinear mapping between design parameters and return loss, reducing computational cost compared to exhaustive EM simulations.

IV.2 PERFORMANCE ANALYSIS

IV.2.1 Far Field analysis

The term "far-field" refers to the area that is distant from the antenna. Because of the strong radiation influence in this region, it is also known as the radiation field. In this area, a variety of antenna characteristics is considered, such as radiation pattern and directivity. The far field directivity analysis is made for 4 variations of substrates, namely, Graphene patch with Gold MTS, Gold patch with Gold MTS, Gold patch with Graphene MTS and Graphene patch with Graphene MTS. Based on S-parameter graph, the frequencies with less return loss are taken for far field examination for each type of substrate.

The far field analysis for each type of substrate is made for three variations namely, $\pi = 0$, $\pi = 90$ and $\theta = 90$. The plots show the corresponding frequency, side lobe level, angular width, main lobe magnitude, and its direction for each modification. Figure 5 shows the far field directivity analysis on Gold patch with Gold MTS (considering frequency of 1.46) for three variations, $\pi = 0$, $\pi = 90$ and $\theta = 90$. Figure 6 shows the far field directivity analysis on Gold patch with Graphene MTS (considering frequencies of 2.156 and 2.792) for three variations, $\pi = 0$, $\pi = 90$ and $\theta = 90$. Figure 7 shows the far field directivity analysis on Graphene patch with Gold MTS (considering frequencies of 1.45 and 1.73) for three variations, $\pi = 0$, $\pi = 90$ and $\theta = 90$. Figure 8 shows the far field directivity analysis on Graphene patch with Graphene MTS (considering frequencies of 1.422 and 1.646) for three variations, $\pi = 0$, $\pi = 90$ and $\theta = 90$.

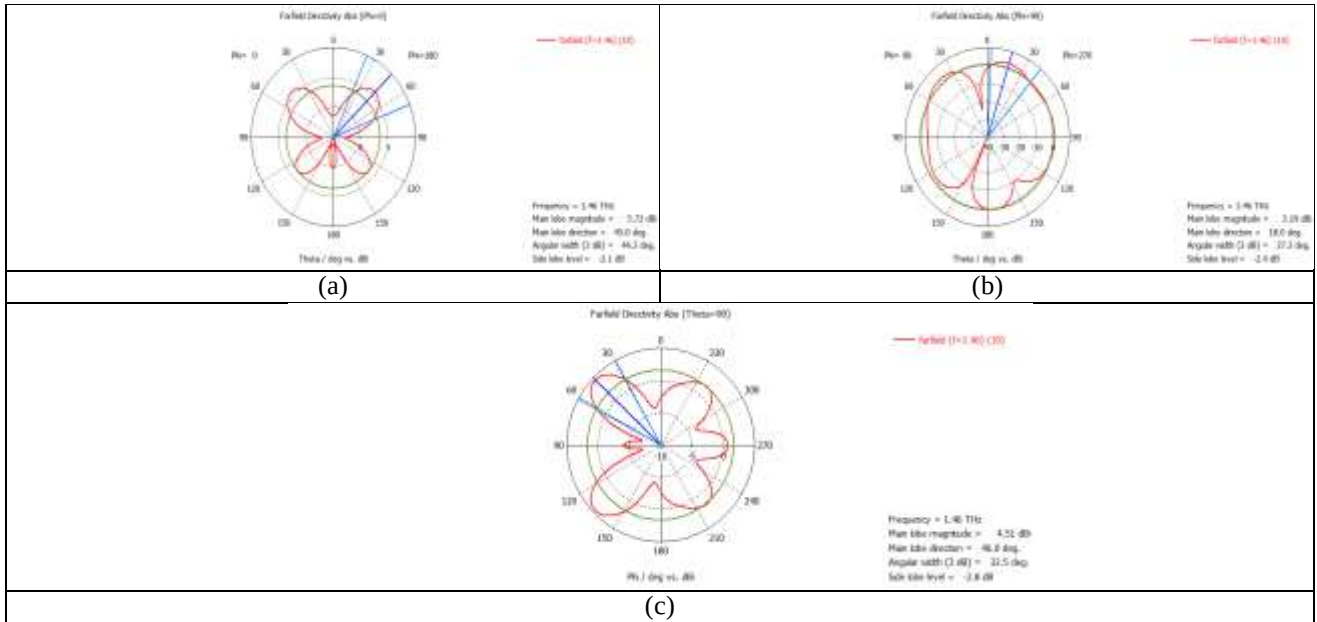


Figure 5: Far field directivity analysis on Gold patch with Gold MTS (considering frequency of 1.46) for three variations, (a) $\pi = 0$, (b) $\pi = 90$ and (c) $\theta = 90$.
Source: Authors, (2026).

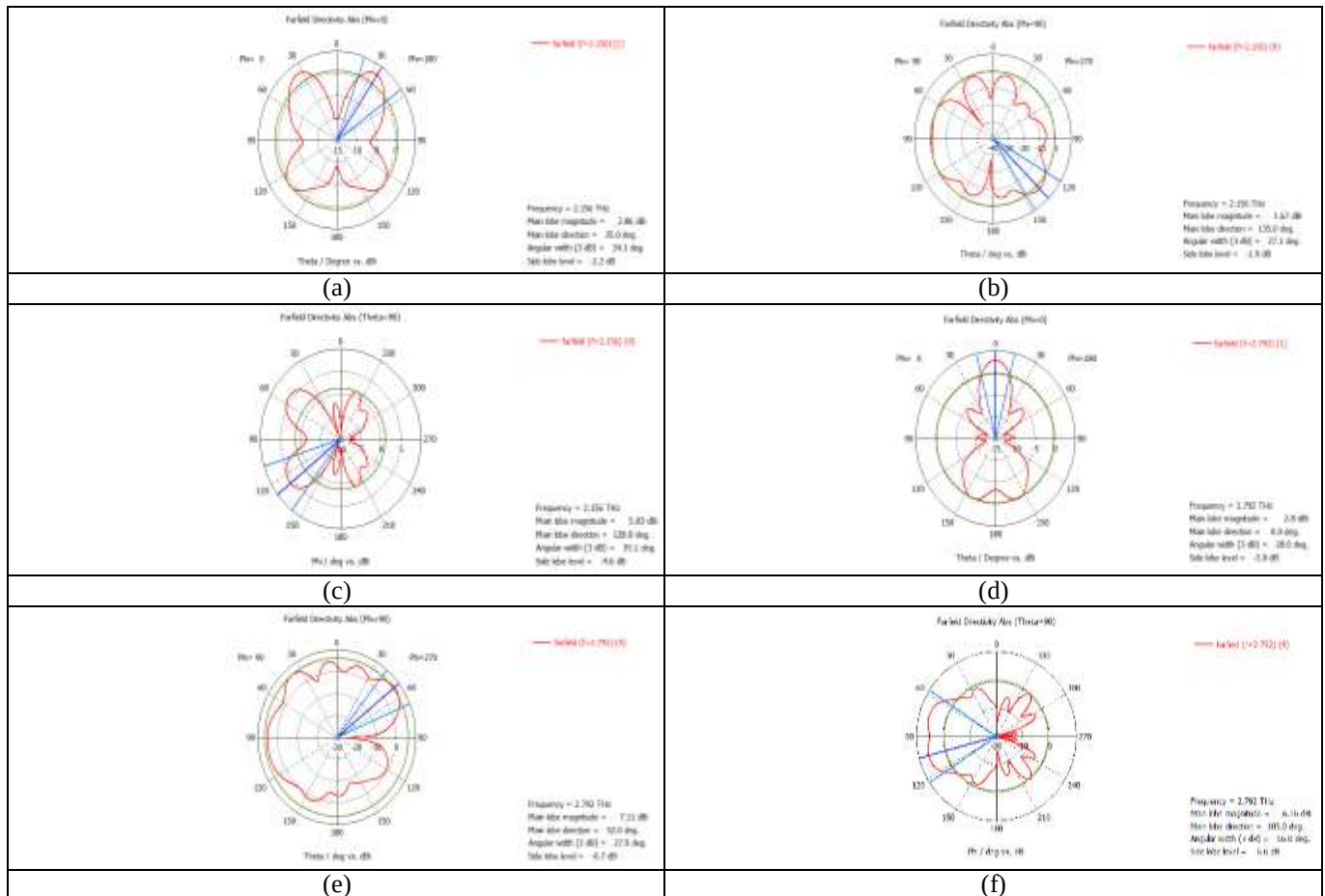


Figure 6: Far field directivity analysis on Gold patch with Graphene MTS considering frequency of 2.156 for three variations (a) $\pi = 0$, (b) $\pi = 90$ and (c) $\theta = 90$ and considering frequency of 2.792 for three variations, (d) $\pi = 0$, (e) $\pi = 90$ and (f) $\theta = 90$.
Source: Authors, (2026).

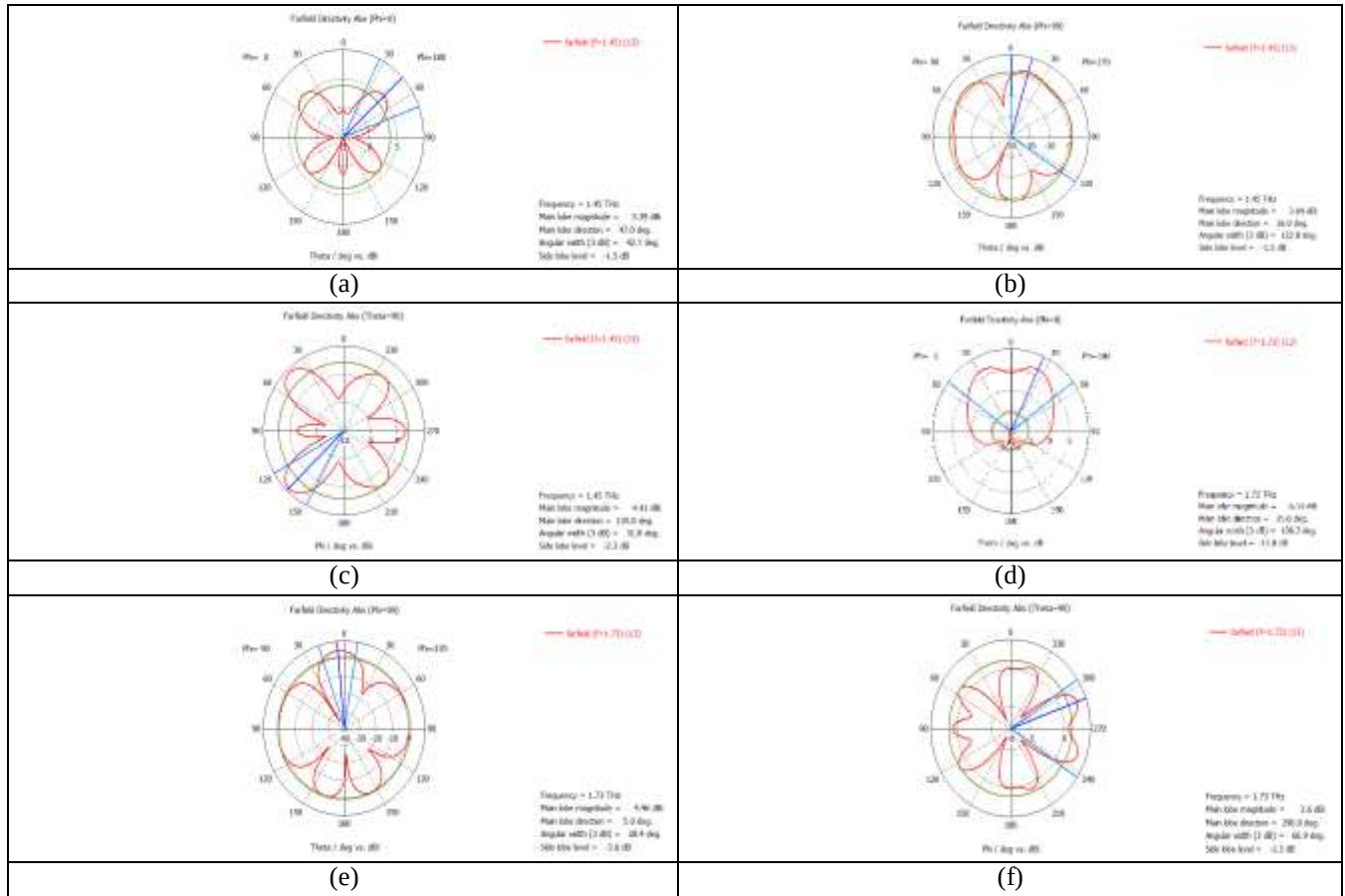


Figure 7: Far field directivity analysis on Graphene patch with Gold MTS considering frequency of 1.45 for three variations (a) $\pi = 0$, (b) $\pi = 90$ and (c) $\theta = 90$ and considering frequency of 1.73 for three variations, (d) $\pi = 0$, (e) $\pi = 90$ and (f) $\theta = 90$.

Source: Authors, (2026).

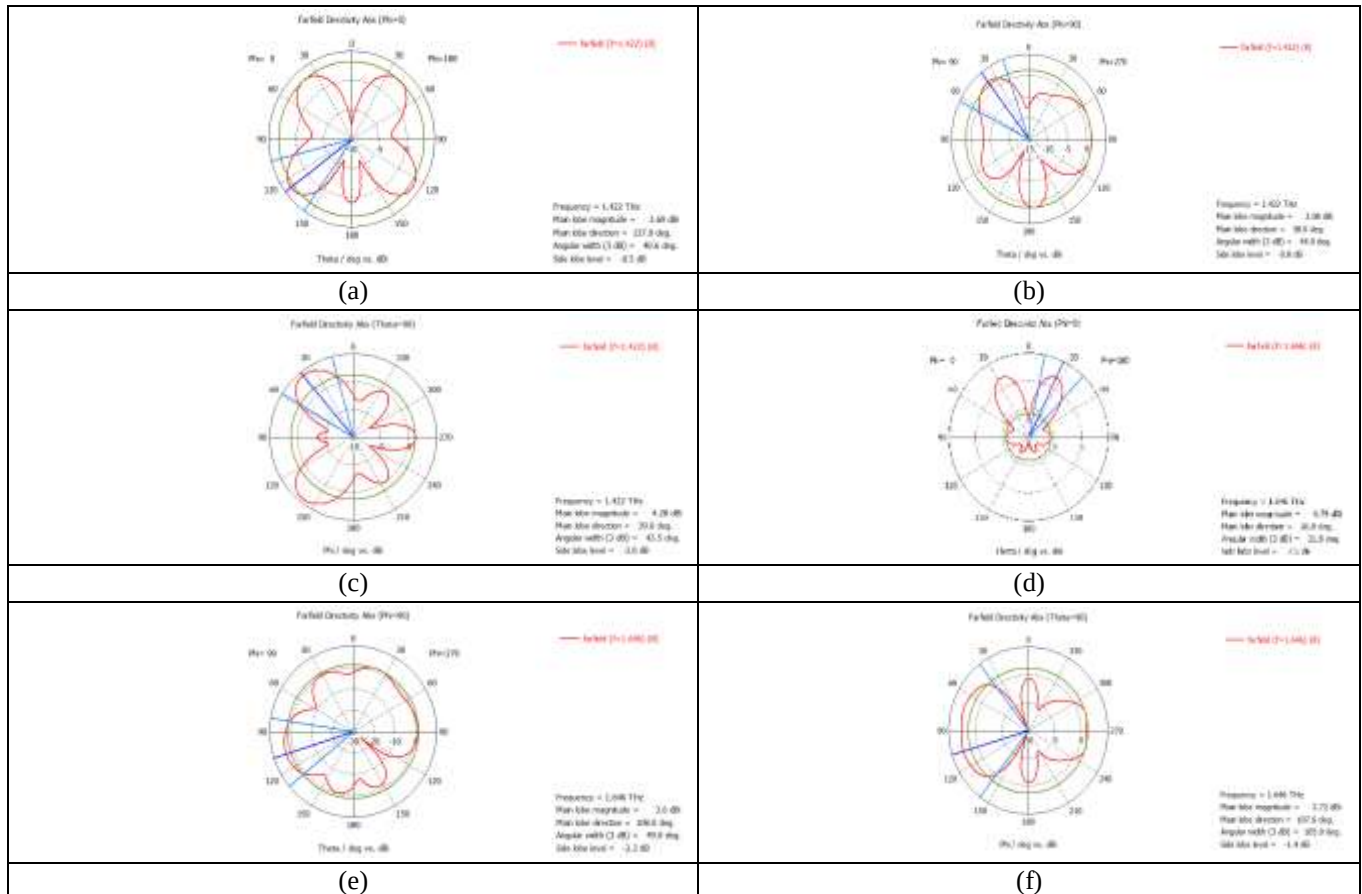


Figure 8: Far field directivity analysis on Graphene patch with Graphene MTS considering frequency of 1.422 for three variations (a) $\pi = 0$, (b) $\pi = 90$ and (c) $\theta = 90$ and considering frequency of 1.646 for three variations, (d) $\pi = 0$, (e) $\pi = 90$ and (f) $\theta = 90$

Source: Authors, (2026).

IV.2.2 Optimal Parameters obtained from intelligent hybrid optimization framework

Table 4: Optimized design parameters of the graphene-based antenna obtained using the IHOF.

L_s	205.0
W_s	245.0
L_p	122.2091
W_p	157.1956
W_f	46.2184
L_f	102.8062
t_s	31.5250
G_t	0.4503
S_h	12.4052
d	14.5000
r	10.5250
a	-0.4000
P_x	13.0000
P_y	18.9469
Graphene thickness	0.0100
Graphene temperature	300
Graphene Chem Potential	0.5000
Graphene Relax Time	1.0000
n	4.0000
Return Loss	-47.5527

Source: Authors, (2026).

Table 4 displays the optimum material and geometry parameters of the graphene-based antenna achieved through the IHOF. The framework efficiently converged to its optimum configuration providing a minimum return loss of -47.55dB, demonstrating improved power transfer efficiency and frequency equalization. Other parameters such as substrate and patch dimensions, feed geometry, periodicity, and overall hosting configuration all improved upon the antenna's radiation efficiency and broadening in operation. In addition, graphene-related parameters aiding in surface conductivity such as, temperature, relaxation time, and chemical potential have been optimized to stabilize the surface conductivity further improving antenna performance for terahertz and next-generation wireless communication initiatives.

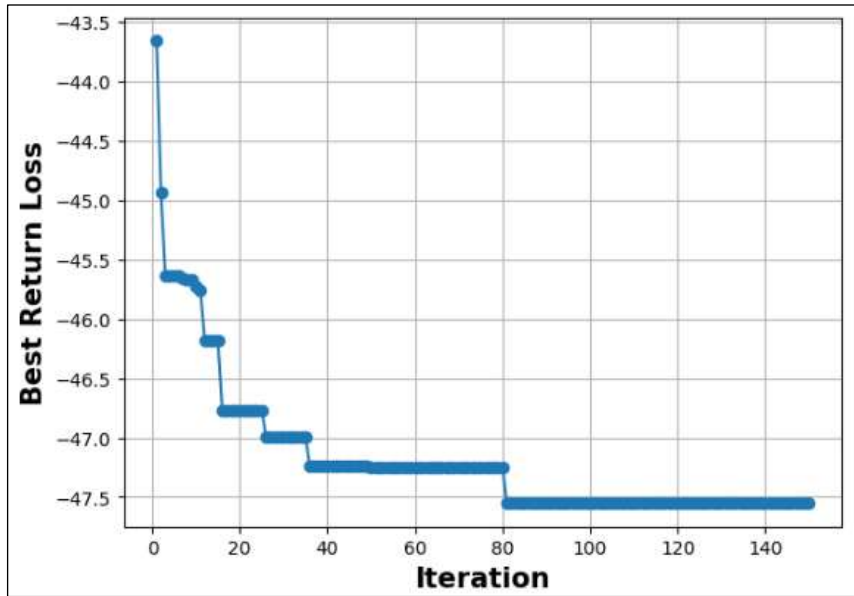


Figure 9: Convergence curve of the Intelligent Hybrid Optimization Framework (IHOF) for minimizing return loss in the graphene-based antenna.

Source: Authors, (2026).

Figure 9 illustrates the convergence of IHOF in the process of improving transmitter specifications. The curve in the figure shows the gradual reduction in return loss at each iteration, thereby demonstrating the efficacy of the framework for the challenging design space. For example, the first 30 iterations exhibit a steep decline in return loss due to global exploration and then fine-tuning via the depths of the local exploitations. The algorithm converges near iteration 100 with a return loss performance of -47.55 dB, indicating good impedance matching and stability of convergence. This is representative of consistent convergence behavior, and reflects the robustness and precision of IHOF in optimizing high-dimensional nonlinear antenna parameters for future wireless communication systems.

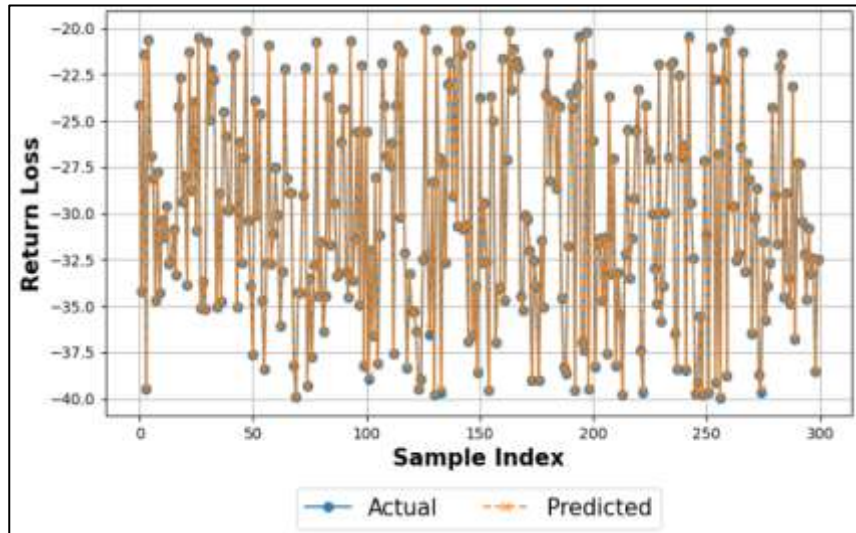


Figure 10: Comparison between actual and predicted return loss values obtained using the Random Forest-based surrogate model within the IHOF.
Source: Authors, (2026).

Figure 10 presents the correlation between expected Random Forest-based surrogate model values nested within IHOF and recorded return loss values from CST simulations. Indeed, these two datasets clearly manifest the predictive power and efficiency of the surrogate model in estimating the complex nonlinear dependence of antenna design parameters upon return loss, as one can easily notice the close correspondence in these two datasets over 300 samples. The little deviation between actual and predicted data points justifies that the surrogate-assisted learning method succeeds in reducing the computational cost significantly while retaining high fidelity of the performance estimate. This efficient predictor allows for accelerated convergence and efficiency in the exploration of design space and supports the design optimization process for graphene-based antennas in next-generation wireless communications systems.

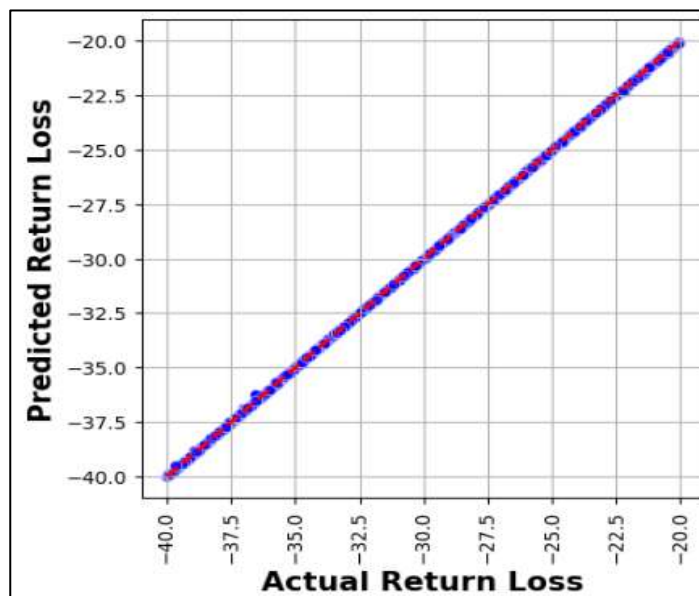


Figure 11: Regression analysis between actual and predicted return loss values obtained using the Random Forest-based regression model within the IHOF.
Source: Authors, (2026).

Figure 11 presents the regression performance of the surrogate model based on Random Forest used in the IHOF to predict the return loss in graphene-based antennas. From this figure, a strong linear relation between the actual values simulated using CST and the projected values from the model can be clearly observed from the full alignment of data points along the diagonal regression line. This correspondence leads to the fact that it is indeed able to estimate, quite precisely, the nonlinear relationship between design parameters and return loss, as reflected in the high R^2 and low prediction error. A high regression fidelity at this level assures that this surrogate model will serve as a very effective guide toward optimization, with a greatly reduced computational cost and without losing much in terms of design precision for next-generation wireless antenna systems.

IV.3 EVALUATION METRICS

To assess the predictive capability of the suggested linear regression model based on return loss contemplation, performance evaluation measures are used in a conventional manner, namely The Root of Mean Average Error, Mean Average Error (MAE), and Coefficient of Determination (R^2). **Mean Absolute Error (MAE)** is the average absolute magnitude of errors in a set of forecasts, without regard to their direction, and is expressed as shown in equation (18):

$$MAE = \frac{1}{n} \sum_{i=1}^n |Actual - predicted| \quad (18)$$

Where n is the total amount of samples. The **Root Mean Squared Error (RMSE)** emphasizes larger errors and evaluates the model's overall prediction quality, given by equation (19):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Actual - predicted)^2} \quad (19)$$

Lastly, the R^2 the percentage that the variable that is dependent is volatility which might be predicted from the variables that are independent is measured by the score. Formulated as equation (20):

$$R^2 = 1 - \frac{\sum_{i=1}^n (Actual - predicted)^2}{\sum_{i=1}^n (Actual - \text{mean of actual})^2} \quad (20)$$

An ideal regression model exhibits low MAE and RMSE with an R^2 value close to 1, indicating strong predictive reliability and minimal deviation from actual observations.

Table 5: Evaluation metrics for regression-based return loss prediction.

Metrics	Value
MAE	0.0104
RMSE	0.0299
R^2 Score	0.9999

Source: Authors, (2026).

The numerical analysis of the regression model designed for forecasting antenna return loss is reported in Table 5. The model displays an exceptionally small MAE of 0.0104, as well as a RMSE of 0.0299, indicating little variation between the true and predicted values. Furthermore, the R^2 score of 0.9999 illustrates an almost perfect correlation, and excellent ability to generalize. The findings indicate that the regression framework provides a very precise estimation of return loss, which is consistent to what is visually observed from the linear correlation shown in the regression plot.

IV.4 COMPARATIVE ANALYSIS

The comparison evaluates Ant Colony Optimization, Particle Swarm Optimization, and the proposed Hybrid PSO+ACO for optimizing the performance of antennas based on graphene. The Hybrid PSO+ACO has shown to outperform the other two methods in terms of convergence speed, stability, and better impedance matching, as evaluated by return loss. The Hybrid PSO+ACO's fast convergence and better stability comes from both the global search provided by PSO and local refinement provided by ACO, where trading off between exploration and exploitation allows the antenna to achieve the lowest return loss and higher efficiency.

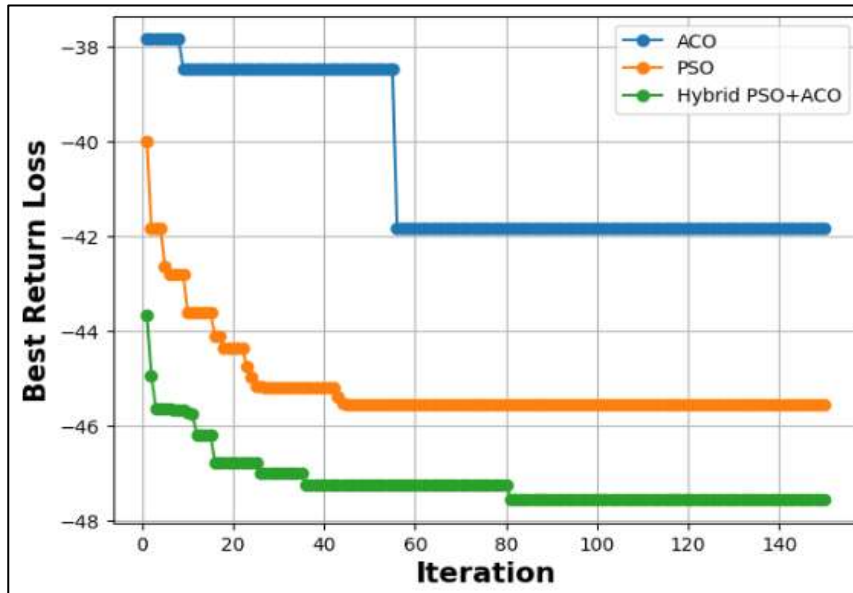


Figure 12: Comparative analysis of optimization algorithms based on best return loss convergence.

Source: Authors, (2026).

Figure 12 illustrates the implemented comparative convergence behavior of ACO, PSO, and the proposed Hybrid PSO+ACO algorithm for optimizing the return loss performance of the antenna. Both the ACO and PSO algorithms converge at moderate rates: the former stabilizes at an approximate -42 dB, while the latter approaches around -44 dB after a number of iterations. On the other hand, Hybrid PSO+ACO converges faster and more stably, yielding an optimal return loss of around -48 dB within the first 40 iterations. This is clearly an advantage of the hybridization, wherein the global exploration capability of PSO is effectively complemented by the local exploitation capability of ACO. It can now be seen that the Hybrid PSO+ACO results in much improved search efficiency, lower iteration count, and higher optimization accuracy than the individual metaheuristic techniques.

Table 6: Comparison of the Proposed Work with Recent Machine Learning–Based Antenna Designs in the GHz/THz Range.

References	Band	Antenna Type	Gain (dBi)	Material	ML Model	R ² Value
[26]	THz	Graphene-based Metasurface Antenna (GPA)	–	Graphene/Gold Slotted Patch	HGBT, RFT	0.98
[30]	170–240 GHz	Phase-Coding Metasurface Array	–	Passive 2-bit Coding Surface	GA + PGA Hybrid	–
[31]	2.33–5.39 GHz	Tri-Band Flexible Metapocket Antenna	4.23–5.8	PDMS (Flexible)	SB-SADEA	–
[32]	1–10 THz	DGSSP-MIMO Antenna	8.46	Double Graphene Stripline Patch	ML Optimization	0.9768
[33]	THz	Graphene-based Malaria Sensor	–	Graphene on SiO ₂	FEM-based ML Modeling	–
[34]	100–110 GHz	2×2 Planar Array	13.9	RT5880	Gaussian Process	–
[35]	5–10 THz	Diamond Fractal	15.82	Polyimide	Neural Network	0.960
[36]	5–10 THz	1×2 MIMO	14.59	Polyimide	Regression	0.970
[37]	1–6 THz	Split Ring Resonator	6.20	FR4	Regression	0.993
[38]	2–10 THz	Hexagonal Patch	5.00	Graphene	Decision Tree	0.991
[29]	1–5 THz	Graphene-based Microstrip patch antenna	7.50	Graphene	Artificial Neural Network (ANN)	0.999
Proposed Work	GHz–THz	Regression-Based Metasurface Design	9.86	Graphene–Gold Hybrid	Regression Reframe (Ensemble)	0.9999

Source: Authors, (2026).

Table 6 provides a comparative overview of the newly proposed regression-based metasurface design and several recent machine learning (ML)-based GHz/THz antenna and sensor designs. Such studies have incorporated ML methods such as Gradient Boosting, Random Forests, Genetic Algorithm hybrids, and Neural Networks to enhance current performance metrics such as gain, radiation efficiency, and tunability. Although the diamond fractal antenna design [35] and MIMO antenna designs [36] have achieved higher gains, these studies have not matched the regression prediction accuracy of $R^2 < 0.99$, indicating some deviation. Similarly, the ANN- and decision-tree designs [29, 38] have also shown strong prediction performance but lacked generalization across broader frequency ranges. The proposed regression surrogate model achieved an R^2 value of 0.9999, MAE of 0.0104, RMSE of 0.0299 which reflects an extraordinary level of prediction accuracy, similar in breadth to the proposed physical designs. The Graphene–Gold hybrid metasurface showed an exceptional improvement to gain of 9.86 dBi across a wide GHz spectrum, providing tunability and stability. However, this integration of regression based intelligence and advanced material engineering directly achieves a compromise of accuracy, scalability, and electromagnetic performance that surpasses some ML-based methods.

IV.5 DISCUSSION

This paper presents a regression-based metasurface antenna demonstrating a substantial improvement in the performance optimization of graphene-integrated THz antennas for future wireless communication systems. In this regard, the hybrid Graphene-Gold structure effectively utilized the high carrier mobility in graphene and superior conductivity of gold for better electromagnetic performance. The optimized antenna yielded a wide operating bandwidth (1-10 THz), high gain of 9.86 dBi, and an exceptionally low return loss ($S_{11} \approx -47.55$ dB), thus reflecting strong impedance matching and minimum signal reflection. The regression surrogate model played an important role in achieving the results reported herein, predicting the antenna parameters with good accuracy and optimizing the resonant response across multiple frequency bands. The evaluation metrics like MAE as 0.0104, RMSE as 0.0299, and R^2 as 0.9999 highlighted a near-perfect predictive alignment between the simulated and predicted outputs, thus confirming the robustness and generalization capability of the model. Compared to other ML-based antenna design works, Besides achieving the maximum correlation accuracy, the proposed framework ensured steady gain augmentation without sacrificing either efficiency or bandwidth.

Further, the comparative analysis shows that though the earlier models such as ANN, Decision Tree, and Regression-based designs achieved strong results, they often suffered from limited frequency adaptability and material losses. However, in contrast, the proposed design demonstrated consistency in efficiency in the range of 89.04% to 97.54%, with an average radiation efficiency of 93.06%, thus validating its suitability for high-frequency terahertz operation. The integration of regression-based optimization reduced the computational complexity significantly in design iterations along with improved convergence time compared to traditional optimization algorithms such as GA or HGBT. Overall, the results establish the proposed hybrid metasurface antenna as a high-performance, data-driven design solution for 6G and beyond, marrying material innovation with predictive intelligence. The synergy between graphene-gold structures and regression-based learning frameworks provides a way toward scalable, adaptive antenna designs in future terahertz communication, sensing, and biomedical systems.

V. CONCLUSION

The work demonstrated a surrogate, regression-based framework to optimize graphene-based metasurface antennas, which presents a novel avenue to enable design of GHz - THz communication systems, for example. The framework takes advantage of the predictive characteristic of regression learning and ultra-advanced materials properties of the graphene-gold aggregates and is a mechanism to further model and achieve better performance prediction and design management.

The results of this effort also suggest that new data-driven structures have the potential to substantially outperform prior heuristic models in computational savings and electromagnetic consistency, suggesting a step toward formal autonomous or “intelligent” antenna engineering. This work enhanced performance accuracy in design, but also advanced new capabilities for a scalable, advanced metasurface design system. Our future steps will consider further advanced programming for adaptive, reconfigurable graphene antennas that continually tune frequency and optimize performance on-board the platform. This design will take advantage of the regression-based framework to facilitate autonomous tuning with the potential to keep optimizing THz performance for biomolecules, sensing, and ultimately, for smart networks 6G cellular systems using graphene antennas.

VI. AUTHOR CONTRIBUTION

Conceptualization: Nipun Sharma, Amrit Kaur.

Methodology: Nipun Sharma, Amrit Kaur.

Investigation: Nipun Sharma, Amrit Kaur.

Discussion of results: Nipun Sharma, Amrit Kaur.

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