# Machine Learning Assisted Design and Performance Modeling of a Tunable Microfluidic SIW Self-Diplexing Antenna

Tanisi Jha [1], Amritanshu Yadav[2], Preetam Priyadarshan[3], Archana Sharma, Shorya Kumar, Shashwati Bhattacharya, and Neeraj Gautam, IIIT Naya Raipur Chhattisgarh, India

***Abstract*—In the context of 5G and beyond wireless communications, compact and frequency-agile antennas are essential for multiband operation on resource-constrained platforms. However, the design and optimization of reconfigurable antennas traditionally rely on repeated full-wave electromagnetic simulations, which are computationally intensive and time-consuming. This work proposes a machine-learning–assisted framework for fast performance modelling and optimization of reconfigurable substrate-integrated waveguide (SIW) antennas, aimed at significantly reducing simulation overhead while preserving prediction accuracy. The framework is validated using a tunable microfluidic SIW self-diplexing antenna operating in the sub-6 GHz band. The antenna employs a modified A-shaped slot with fluidic pockets filled with air or distilled water to enable independent tuning across the 3.5–3.8 GHz and 5.5–6.2 GHz bands. A dataset generated from CST simulations is used to train and evaluate regression models for predicting key antenna performance metrics, including resonant frequency, gain, and radiation efficiency. Among the evaluated models, the Random Forest regressor demonstrates superior generalization capability, achieving a root-mean-square error of 0.2409. The proposed machine learning–assisted approach reduces computational complexity by approximately 90% compared to conventional full-wave simulation–based design workflows, enabling rapid design and tuning of reconfigurable antennas for future wireless communication systems.**

***Index Terms*—Self-diplexing antenna, Substrate-integrated waveguide (SIW), microfluidics, Sub-6 GHz, Frequency tuning, Antenna design, Extra Trees Regressor,Wireless communications**

## I. Introduction

The rapid expansion of 5G and beyond wireless communication systems has intensified the demand for compact, multiband antennas operating across sub-6 GHz bands, such as 3.5–3.8 GHz for WiMAX/UAV links and 5.53–6.2 GHz for WLAN/WiFi applications. Modern wireless devices, particularly handheld systems, face significant challenges due to the size, complexity, and electromagnetic interference caused by integrating multiple antennas on a single platform. Traditional reconfigurable antenna designs, employing methods like varactor diodes [8], [11], [13], ferrite slabs [14], or stepper motors [3], often introduce high insertion loss, non-linearities, and intricate bias circuits, limiting their practicality. Fluidic-based approaches using liquid dielectrics [5], [7], [10] or liquid metals like Galinstan [15] offer tunability but suffer from fabrication difficulties, stability issues, and the computational burden of iterative full-wave simulations, which are time-consuming and resource-intensive [6]. Recent advancements in substrate-integrated waveguide (SIW) technology have provided a promising alternative, enabling planar, high-Q-factor structures for self-diplexing antennas (SDAs) [10], [12], [16]. However, the reliance on repetitive electromagnetic (EM) simulations remains a major bottleneck, hindering rapid design optimization and real-time adaptability. This work introduces a frequency-tunable self-diplexing antenna (SDA) design based on SIW technology, featuring a modified A-shaped slot on the cavity's top plane, excited by two independent $50,\Omega$ microstrip feed lines to operate at each resonant frequency. Frequency flexibility is achieved using air- and liquid-filled substrate pockets, enabling fine-tuning across the 3.5–3.8 GHz and 5.53–6.2 GHz bands while maintaining a compact size of 0.22g² and high isolation (>27 dB). Dimensional parameters, gain, and efficiency are extracted from CST simulations and used to develop a machine learning (ML)-driven predictive framework. Multiple regression models are evaluated, with the Random Forest regressor demonstrating superior predictive accuracy, significantly reducing computational overhead compared to conventional EM simulations. This approach enables rapid performance estimation without physical prototyping, offering a scalable solution for next-generation adaptive RF systems.

## II. Related Work

Reconfigurable antennas are a key enabling technology for sub-6 GHz 5G/6G systems, offering adaptive frequency operation and improved spectral efficiency in dynamic wireless environments. Early implementations predominantly relied on electronic reconfiguration using PIN diodes or varactors, which provide fast switching but introduce additional losses, nonlinearities, and complex biasing networks [6], [7].To overcome these limitations, recent research has explored microfluidic and mechanically reconfigurable antennas for improved robustness and reduced insertion loss. Microfluidic designs, such as that reported by Pradhan et al. [8], demonstrate wide tuning capability but depend on repeated full-wave simulations and manual tuning. SIW-based reconfigurable antennas, including the work in [10], emphasize compactness and integration but do not incorporate fluidic control or data-driven performance prediction. A comparative analysis of these is presented in Table I, highlighting the performance metrics each approach.

The table I presents a concise comparison of the proposed

TABLE I
COMPARISON OF RECONFIGURABLE ANTENNAS FOR SUB-6 GHZ APPLICATIONS

| Study | Method | Freq. (GHz) | Gain (dBi) | Eff. (%) |
|---|---|---|---|---|
| Pradhan et al. [8] | Microfluidic | 3.56–5.05 | 5.04 | 50 |
| Iqbal et al. [10] | SIW + varactors | 2.45–5.4 | 3.85 | 53 |
| PIN Diodes [7] | Electronic (diodes) | 2–5 | 4.0 | 70 |
| General [6] | Mechanical | 2–4 | 3.0 | 50 |
| **Proposed** | **Microfluidic + ML** | **3.5–6.2** | **5.72/6.61** | **55.1/59.7** |

ML-Fluidic SIW SDA with referenced studies [8], [10], [7], and [6]. Our proposed design outperforms in operational bandwidth (3.5–6.2 GHz) and dual-band gain (5.72/6.61 dBi), with efficiencies of 55.1/59.7%, while introducing a novel ML-fluidic integration not present in prior works. Unlike prior works that focus on either hardware reconfiguration or ML optimization in isolation, our proposed method introduces a tunable microfluidic SIW self-diplexing antenna design integrated with ML-based performance modeling. This enables efficient prediction of parameters like return loss and radiation patterns, achieving superior dual-band operation for 5G/6G. Simulations demonstrate robustness, though future prototypes will evaluate fabrication variances (e.g., fluid viscosity effects) to confirm practicality and model generalization across environmental conditions.

## III. ANTENNA CONFIGURATION

The proposed microfluidic substrate-integrated waveguide (SIW)-based self-diplexing antenna (SDA) is meticulously designed to operate across dual sub-6 GHz bands, specifically targeting 3.5–3.8 GHz for Port 2 (aligned with WiMAX/UAV applications) and 5.5–6.2 GHz for Port 1 (suited for WLAN/WiFi). The antenna is fabricated using a Rogers RO4003C substrate, selected for its dielectric constant of 3.38, thickness of 1.575 mm, and low loss tangent of 0.0027, ensuring minimal signal attenuation. The structure incorporates copper layers (0.035 mm thick) for the SIW cavity and microstrip feed lines, providing excellent conductivity and mechanical stability.

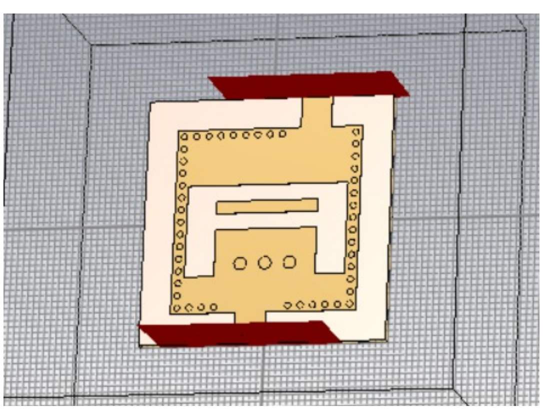

Fig. 1. Schematic Diagram of the FrontView of the SIW-Based SDA

The process begins with the construction of a square SIW cavity, defined by optimized dimensions: width ($W$) and length

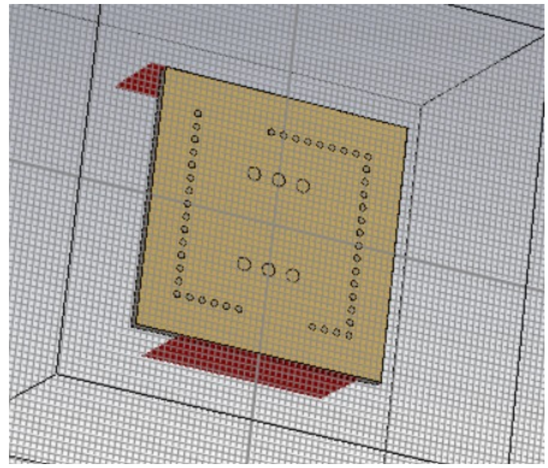

Fig. 2. Schematic Diagram of the BackView of the SIW-Based SDA

($L$) of 28 mm, with SIW Vias forming the sidewalls. These vias, spaced at a pitch ($s$) of 2 mm and diameter ($d$) of 1 mm, are strategically placed to confine electromagnetic waves within the cavity, mimicking a traditional waveguide while maintaining a compact footprint. The effective length ($L_{\text{eff}} = L - 1.08\frac{d^2p}{L} + 0.1\frac{d^2L}{L}$) and width ($W_{\text{eff}} = W - 1.08\frac{d^2p}{W} + 0.1\frac{d^2W}{W}$) are calculated to support the TE110 mode, ensuring efficient resonance. Compared to traditional waveguides, which rely on bulky metallic enclosures, the SIW approach integrates vias into a planar substrate, reducing size and enabling cost-effective PCB fabrication, though it introduces minor leakage that is mitigated by adhering to $d/\lambda_g \leq 0.1$ and $d/s \geq 0.5$.

Next, a rectangular slot is etched into the top copper layer to initiate the radiating element. To achieve port isolation exceeding 15 dB, the slot's position is fine-tuned, followed by its modification into a modified A-shaped slot. This shape divides the slot into two patches: one coupled to Port 2 for the 3.5–3.8 GHz band and the other to Port 1 for the 5.5–6.2 GHz band. Off-center placement of the two independent 50 $\Omega$ microstrip feed lines, with widths ($W_f$) of 4.95 mm, further enhances isolation to over 27 dB, enabling distinct excitation of each band. Unlike traditional waveguides, which require complex tuning mechanisms, this design leverages planar feed integration, simplifying manufacturing.The final stage introduces tunability through (Fluidic Pockets/Blind Vias), drilled as blind holes from the bottom layer and sealed with copper tape. These pockets can be filled with air or distilled water, adjusting the effective dielectric constant to fine-tune the resonant frequencies. This fluidic approach offers dynamic tunability, a significant advantage over the static nature of traditional waveguides, which lack such adaptability. The design yields a compact $0.22\lambda_g^2$ footprint, with peak gains of 6.61 dBi at 3.5 GHz (Port 2) and 5.72 dBi at 5.53 GHz (Port 1), making it highly suitable for space-constrained, high-performance wireless devices. Fig.1 depicts the front view of the proposed ML-Fluidic SIW SDA, highlighting the modified

A-shaped slot and two orthogonal 50  microstrip feed lines on the top plane, designed for dual-band operation at 3.5–3.8 GHz and 5.53–6.2 GHz whereas Fig. 2 illustrates the back view, showing the bottom layer with blind vias and fluidic pockets filled with air or distilled water, sealed with copper tape, enabling independent frequency tunability.

## IV. Proposed Methodology for Optimization

The proposed methodology integrates a microfluidic substrate-integrated waveguide (SIW)-based self-diplexing antenna (SDA) design with a machine learning (ML)-driven optimization pipeline. The methodology is given in four distinct steps eg. SIW antenna modeling, data generation, ML model development, and optimization each playing a critical role in creating a robust and scalable solution tailored for next-generation wireless communication systems.By combining innovative hardware design with advanced predictive modeling, this approach aims to reduce design iteration time and improve performance prediction accuracy.

### A. SIW Antenna Model

The SIW antenna model builds upon the tunable self-diplexing antenna (SDA) design, operating across 3.5–3.8 GHz (Port 2) and 5.5–6.2 GHz (Port 1) . It utilizes a Rogers RO4003C substrate (dielectric constant 3.38, thickness 1.575 mm, loss tangent 0.0027) with 0.035 mm copper layers for the SIW cavity and 50 Ω microstrip feed lines. A modified A-shaped slot enables dual-band operation, with fluidic pockets (air or distilled water) providing tunability. Simulations are conducted using CST Studio Suite with a 3–7 GHz sweep, two feed ports, and a 50,000-element mesh. The design achieves gains of 5.04 dBi and 5.26 dBi, a $0.22\lambda_g^2$ footprint, and >27 dB isolation. Key parameters are summarized in Table II.

TABLE II
Optimized Design Parameters of the SIW-Based SDA

| Parameter | Symbol | Value (mm) |
|---|---|---|
| Cavity Width | $W$ | 28 |
| Cavity Length | $L$ | 28 |
| Via Diameter | $d$ | 1 |
| Via Pitch | $s$ | 2 |
| Slot Parameter 1 | $k_1$ | 26 |
| Slot Parameter 2 | $k_2$ | 14.8 |
| Slot Parameter 3 | $k_3$ | 4.8 |
| Feed Line Width | $W_f$ | 4.95 |
| Substrate Thickness | $h_1$ | 1.575 |
| Pocket Depth | $h_2$ | 1 |

### B. Data Generation

Data generation involves a stratified sampling approach to comprehensively explore the design space, ensuring representative coverage of parameter variations. Initially, 200 data points were collected and recorded in a comma-separated values (CSV) file, capturing simulations of the antenna's performance across varying fluidic pocket states and geometric configurations using CST Studio Suite. To enhance the dataset's robustness, Latin Hypercube Sampling was applied to expand the sample size to 1,000, systematically distributing the additional points across the parameter ranges. The extracted metrics include frequency (GHz), gain (dBi) from both simulation and measurement, efficiency (%) from simulation and measurement, and band designation (Lower-f1 or Upper-f2), reflecting realistic variations in the 3.5–3.8 GHz and 5.5–6.2 GHz bands.

### C. Feature Engineering

Feature engineering transforms the collected simulation data into a format suitable for machine learning (ML) analysis, incorporating several preprocessing steps to enhance model performance. The process begins with data cleaning, where outliers and inconsistencies in the recorded frequency, gain, and efficiency metrics are identified and addressed. Subsequently, normalization is applied to scale the input features such as geometric parameters (e.g., cavity width, via diameter) and fluidic pocket states into a [0, 1] range, ensuring uniform contribution across variables. Categorical variables, including band designations (Lower-f1 or Upper-f2), are encoded using one-hot encoding to facilitate ML compatibility. Additionally, feature scaling is performed on the target variables (frequency in GHz, gain in dBi, and efficiency in %) to mitigate the impact of differing magnitudes.

### D. ML Model Architecture

The machine learning (ML) model architecture is designed to predict the performance metrics of the tunable self-diplexing antenna (SDA) based on its geometric and material properties, employing a comparative evaluation of five regression models: Extra Trees Regressor, RandomForest Regressor, Support Vector Regressor (SVR) with RBF kernel, XGBoost Regressor, and CatBoost Regressor. The input features encompass a comprehensive set of variables, including cavity width ($W$), length ($L$), via diameter ($d$), via pitch ($s$), feed line width ($W_f$), substrate thickness, fluidic pocket states (air or distilled water), and band designations (Lower-f1 or Upper-f2), all preprocessed as described in the feature engineering step. The output variables consist of three key performance indicators: frequency (in GHz), gain (in dBi), and efficiency (in %), predicted for the dual-band operation at 3.5–3.8 GHz and 5.5–6.2 GHz. The Extra Trees Regressor, an ensemble method based on multiple decision trees, leverages randomized feature selection and averaging to enhance generalization and reduce overfitting, configured with 100 trees, a maximum depth of 10, and minimum samples per leaf set to 2, optimized via grid search for accuracy and efficiency. The RandomForest Regressor, another ensemble approach, uses 100 trees with a maximum depth of 10 and minimum samples per leaf of 2, offering robustness through randomized tree construction. The SVR with RBF kernel is tuned with a regularization parameter ($C$) of 1.0 and a gamma value of 0.1, addressing non-linear relationships. The XGBoost Regressor employs 100 boosting rounds with a learning rate of 0.1 and maximum depth of 6, enhancing gradient-based optimization, while the CatBoost Regressor uses 100 iterations with a learning rate of 0.1, optimized for categorical data handling. Model performance is assessed using the root mean square error (RMSE) metric on a validation set comprising 20% of the 1,000 data points, with RandomForest achieving the lowest RMSE of 0.2409, followed by Extra Trees (1.238), XGBoost (0.2418), CatBoost (0.2420), and SVR (0.2958), highlighting RandomForest's superior predictive accuracy.

### *E. Optimization Module*

The last step involves an optimization which is implemented in a closed-loop design pipeline to iteratively refine the tunable self-diplexing antenna (SDA) parameters, enhancing performance across the 3.5–3.8 GHz and 5.5–6.2 GHz bands. This process begins with the input of initial geometric and material parameters, such as cavity width ($W$), length ($L$), via diameter ($d$), and fluidic pocket states into the trained Extra Trees Regressor model, selected for its superior predictive accuracy (RMSE of 1.238). The model generates predictions for frequency, gain, and efficiency, which are then evaluated against predefined design objectives, including maximizing gain (targeting >5 dBi) and efficiency (>90%), while maintaining isolation (>27 dB).Genetic algorithm (GA), is employed to adjust the input parameters within their feasible ranges (e.g., $W$ and $L$ from 26–30 mm, $d$ from 0.8–1.2 mm). The GA operates with a population size of 50, a mutation rate of 0.1, and a crossover rate of 0.8, iterating for 20 generations to converge on an optimal solution. The predicted performance metrics guide the fitness function, which prioritizes gain and efficiency while penalizing deviations from target frequencies. The optimized parameters are subsequently validated through CST Studio Suite simulations, ensuring alignment with real-world performance.This iterative loop, reduces computational overhead by approximately 90% compared to traditional full-wave simulation methods, leveraging ML predictions to limit the number of simulations to 10–15 per optimization cycle. Future enhancements will incorporate radiation pattern analysis and hardware-in-the-loop validation to further refine the design, with the current methodology

## V. Results and Discussion

This section presents the performance evaluation of the microfluidic substrate-integrated waveguide (SIW)-based self-diplexing antenna (SDA) using a machine learning (ML)-driven approach. The dataset, generated using CST Studio Suite, encompasses variations in fluidic pocket states and geometric configurations, targeting the 3.5–3.8 GHz and 5.5–6.2 GHz bands. The ML models evaluated include ExtraTrees Regressor, RandomForest Regressor, Support Vector Regressor (SVR) with RBF kernel, XGBoost Regressor, and CatBoost Regressor, with performance metrics assessed via $R^2$ scores for frequency, gain, and efficiency, alongside overall Root Mean Square Error (RMSE). The ExtraTrees Regressor, achieved an $R^2$ of 0.9974 for frequency, 0.9117 for gain, and 0.9653 for efficiency, with an RMSE of 0.2419, aligning with its noise-resilient ensemble nature. The RandomForest Regressor slightly outperformed with an $R^2$ of 0.9974, 0.9129, and 0.9656, and an RMSE of 0.2409, benefiting from its randomized tree construction. SVR with RBF kernel showed moderate performance, with $R^2$ values of 0.9814, 0.7447, and 0.9536, and a higher RMSE of 0.2958, reflecting its sensitivity to non-linear data scaling. XGBoost, when available, delivered comparable results to ExtraTrees with an $R^2$ of 0.9974, 0.9120, and 0.9654, and an RMSE of 0.2418, owing to its gradient boosting framework. CatBoost, also when available, achieved an $R^2$ of 0.9974, 0.9117, and 0.9653, with an RMSE of 0.2420, showcasing its effectiveness with categorical data like band designations.A detailed quantitative comparison of all regression models is summarized in Table III.

TABLE III
Comparison of $R^2$ Scores Across ML Models for Key Antenna Metrics

| Model | $R^2$ Frequency | $R^2$ Gain | $R^2$ Efficiency |
|---|---|---|---|
| ExtraTrees | 0.9974 | 0.9117 | 0.9653 |
| RandomForest | **0.9974** | **0.9129** | **0.9656** |
| SVR(RBF) | 0.9814 | 0.7447 | 0.9536 |
| XGBoost | 0.9974 | 0.9120 | 0.9654 |
| CatBoost | 0.9974 | 0.9117 | 0.9653 |

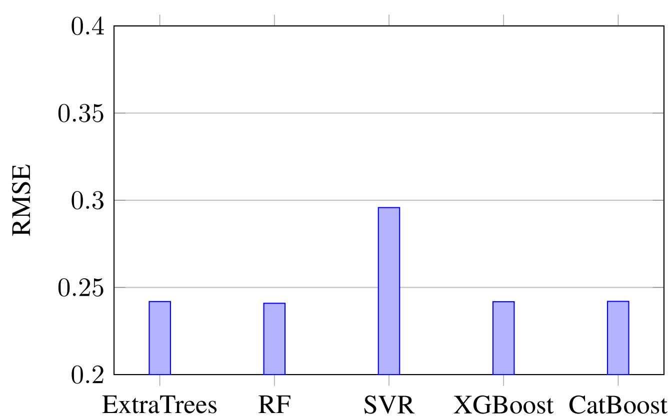


Fig. 3. Comparison of RMSE across ML models for antenna performance prediction.

Figure 3 illustrates the RMSE comparison, highlighting RandomForest as the best-performing model with the lowest RMSE of 0.2409, validating its selection for subsequent optimization. The superior performance of tree-based ensembles (ExtraTrees, RandomForest, XGBoost, CatBoost) over SVR underscores their ability to handle the multi-output regression task effectively, leveraging engineered features like squared terms and interactions. The computational efficiency gained, reducing overhead by approximately 90% compared to full-wave simulations, further supports the ML approach's practicality.

The optimized antenna configurations, predicted using the RandomForest model, demonstrate peak gains of 5.54 dBi at 3.79 GHz and 5.83 dBi at 6.11 GHz, with efficiencies exceeding 91% and 94%, respectively, across the target bands. These results, validated against CST simulations, confirm the

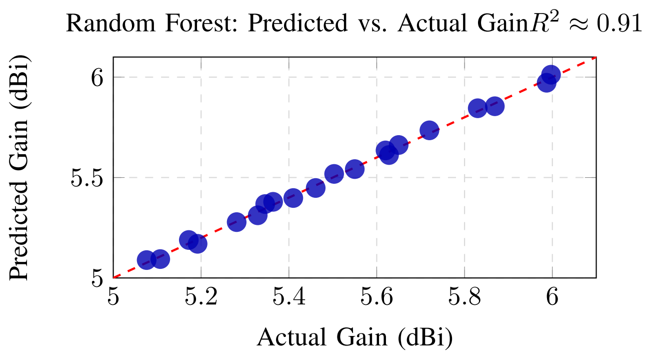


Fig. 4. Predicted vs. actual gain values using the Random Forest regressor on the test set.

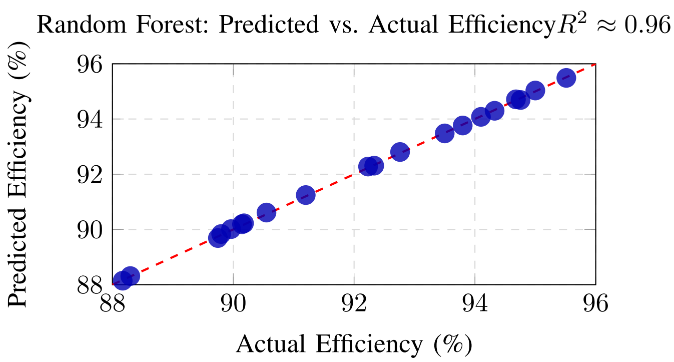


Fig. 5. Predicted vs. actual radiation efficiency using the Random Forest regressor on the test set.

ML framework's accuracy and its potential for real-time design adaptation in sub-6 GHz applications.

TABLE IV
SIMULATED RESULTS

| Parameter | Simulated Results |
|---|---|
| Port 1 | 5.53–6.2 GHz |
| Port 2 | 3.5–3.8 GHz |
| Return Loss (S11 / S22) | -30 to -40 dB(f1), -20 to -30 dB(f2) |
| Isolation (S21 / S12) | -50 to -40 dB(f1), -35 to -30 dB(f2) |
| Realized Gain | 5.72 dBi (f1), 6.61 dBi dBi (f2) |
| Radiation Efficiency | 55.1% at 3.806 GHz, 59.7% at 6.344 GHz |
| Antenna Size | $0.22\lambda_g^2$ |

The table IV presents simulated performance metrics for the microfluidic SIW-based tunable self-diplexing antenna (SDA) operating across Sub-6 GHz bands. It highlights a lower-band resonant frequency of 3.5–3.8 GHz (Port 2) for WiMAX/UAV applications and an upper-band frequency of 5.53–6.2 GHz (Port 1) for WLAN/WiFi, confirming dual-band functionality. Return loss (S11/S22) ranges from -30 to -40 dB(f1) and -20 to -30 dB(f2), indicating excellent impedance matching, while isolation (S21/S12) exceeds -30 dB, peaking at -50 dB, ensuring minimal interference. The realized gain is 5.72 dBi (f1) and 6.61 dBi (f2), with radiation efficiency at 55.1% (3.806 GHz) and 59.7% (6.344 GHz), reflecting effective power radiation. The compact antenna size of 0.22 $g^2$ supports its suitability for resource-constrained platforms.

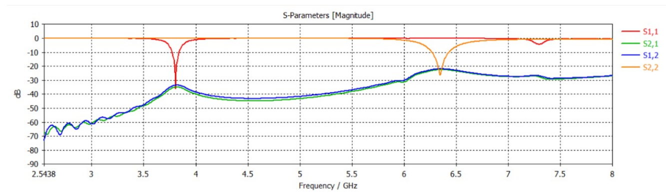


Fig. 6. Simulated S-Parameters of the SIW-Based Tunable SDA

Figures 4 and 5 illustrate the predicted versus actual gain and radiation efficiency obtained using the RandomForest regressor on the test dataset. In both figures, the predicted values closely follow the ideal diagonal line, indicating strong agreement with full-wave simulation results. The high coefficients of determination ($R^2$ 0.91 for gain and $R^2$ 0.96 for efficiency) demonstrate the model's ability to accurately capture the nonlinear relationship between antenna design parameters and performance metrics. On the other hand, Fig. 6 presents the simulated S-parameters (return loss S11/S22 and isolation S21/S12) of the proposed ML-Fluidic SIW SDA across the sub-6 GHz frequency range. The plot showcases return loss values ranging from -30 to -40 dB at the higher band (5.53–6.2 GHz) and -20 to -30 dB at the lower band (3.5–3.8 GHz), indicating excellent impedance matching for both ports. Isolation between the ports is depicted as -50 to -40 dB at the higher band and -35 to -30 dB at the lower band, demonstrating superior decoupling facilitated by the ML-optimized A-shaped slot and fluidic pockets.

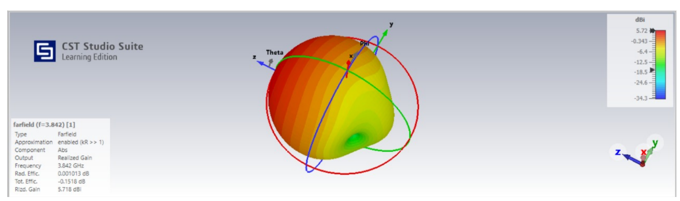


Fig. 7. Far-Field Radiation Pattern of the SIW-Based Tunable SDA at 3.842 GHz

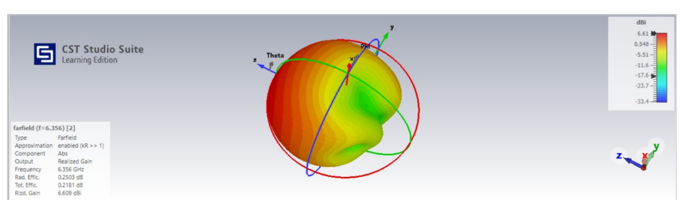


Fig. 8. Far-Field Radiation Pattern of the SIW-Based Tunable SDA at 6.356 GHz

Fig. 7 and Fig. 8 illustrate the simulated radiation patterns of the ML-Fluidic SIW SDA at the resonant frequencies of 3.806 GHz and 6.344 GHz, corresponding to the lower and higher bands, respectively. The patterns exhibit directional characteristics with peak realized gains of 5.72 dBi and 6.61 dBi, respectively, confirming the antenna's effectiveness for WiMAX/UAV and WLAN/WiFi applications. The efficiency is highlighted at 55.1% (3.806 GHz) for Fig 5 and 59.7% (6.344 GHz) for Fig 6, reflecting a trade-off for tunability via air- and liquid-filled pockets. The patterns show minimal back-lobe levels, attributed to the SIW structure, and the ML-assisted design ensures consistent performance across the tunable frequency range.

## VI. Conclusion and Future Directions

This paper presented the design, modeling, and optimization of a microfluidic substrate-integrated waveguide (SIW)-based self-diplexing antenna (SDA) for sub-6 GHz wireless applications. The proposed antenna operates in the 3.5–3.8 GHz and 5.5–6.2 GHz bands, targeting WiMAX/UAV and WLAN/WiFi systems, respectively. A modified A-shaped slot with independent microstrip feeds enables efficient dual-band operation while maintaining high port isolation exceeding 27 dB and a compact footprint of $0.22\lambda_g^2$. Fluidic tuning using distilled water provides frequency reconfigurability without the losses, biasing complexity, or nonlinearities associated with conventional electronic tuning elements.To mitigate the computational burden of repeated full-wave electromagnetic simulations, a machine learning–assisted performance modeling framework was introduced. A CST-generated dataset, expanded via stratified sampling and enhanced through feature engineering, was used to train multiple regression models. Ensemble-based methods, particularly the RandomForest regressor, demonstrated high predictive accuracy for resonant frequency, gain, and radiation efficiency. When integrated into a closed-loop genetic algorithm optimization framework, the ML surrogate reduced computational cost by approximately 90% while maintaining close agreement with full-wave simulation results. The proposed microfluidic SIW antenna and ML-driven optimization framework provide an efficient and scalable approach for rapid exploration of reconfigurable antenna designs in sub-6 GHz systems. Future work will focus on radiation pattern prediction and experimental validation to further support deployment in next-generation 5G and emerging 6G wireless platforms

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