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AI-Optimized Reconfigurable Microstrip Bandpass Filters for Dynamic Spectrum Access in 6G Networks

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Abstract

The evolution toward sixth-generation (6G) wireless networks introduces unprecedented demands on spectral efficiency, ultra-low latency, and real-time adaptability to dynamic radio environments. Central to this transformation is the requirement for intelligent, spectrum-agile radio front ends that can seamlessly operate across heterogeneous frequency bands. Dynamic Spectrum Access (DSA) addresses this challenge by enabling transceivers to autonomously detect, evaluate, and utilize the most suitable spectrum opportunities. The realization of DSA in practical systems, however, requires highly reconfigurable and efficient microwave filtering structures capable of adapting their spectral characteristics in real time. Traditional filter design methodologies, which rely heavily on iterative electromagnetic simulation and manual tuning, fall short in meeting the complexity and multi-objective constraints of modern adaptive RF systems. This paper proposes an integrated design framework incorporating artificial intelligence (AI) optimization, surrogate modeling, and hybrid reconfiguration mechanisms to achieve high-performance microstrip bandpass filters tailored for 6G DSA applications. A deep neural surrogate model is developed to predict filter performance across diverse geometrical and tuning configurations, enabling rapid multi-objective optimization of center frequency, bandwidth, insertion loss, and return loss. Experimental results demonstrate a tuning range from 2.8–5.2 GHz with an insertion loss better than 1.4 dB, along with excellent agreement between simulated and fabricated prototypes. The findings establish AI-assisted reconfigurable filtering as a powerful enabler for future 6G-class intelligent radio systems.

Keywords: 6G Networks, reconfigurable filters, microstrip bandpass filters, AI optimization, Surrogate modeling, dynamic spectrum access, varactor tuning, RF mems, cognitive radio

INTRODUCTION

The transition from fifth-generation (5G) to sixth-generation (6G) communication systems represents a paradigm shift characterized by terabit-per-second throughput, sub-millisecond round-trip latency, and seamless integration of terrestrial and non-terrestrial network architectures. To achieve these goals, 6G systems must operate across an increasingly heterogeneous and congested spectral environment, where efficient and dynamic utilization of spectrum resources is essential. Dynamic Spectrum Access (DSA) serves as a fundamental technique to address these constraints. It permits radios to sense the environment, identify unused spectral opportunities, and reconfigure their transceiver chains to match the spectral requirements [1–6].

A critical bottleneck in the implementation of DSA lies in the radio frequency (RF) front end, particularly in filtering structures responsible for suppressing unwanted interference, ensuring

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spectral purity, and enabling channel selectivity. Conventional fixed-frequency filters are not adequate for supporting agile multi-band operation. Consequently, reconfigurable microstrip bandpass filters (BPFs) have emerged as indispensable components for adaptive RF systems. These filters must maintain low insertion loss, high out-of-band rejection, and excellent impedance matching, all while supporting rapid and extensive tuning ranges [7–10].

Traditional methods for designing such filters rely largely on parameter sweeping and trial-and-error adjustments within electromagnetic (EM) simulation environments such as HFSS or CST. These approaches are computationally intensive and often fail to explore the design space comprehensively. Artificial intelligence, particularly machine learning-based optimization and surrogate modeling, offers a transformative alternative that reduces computational complexity and accelerates the design cycle. The integration of AI with reconfigurable microstrip technologies provides a promising pathway for designing next-generation spectral-agile RF components (Figure 1).

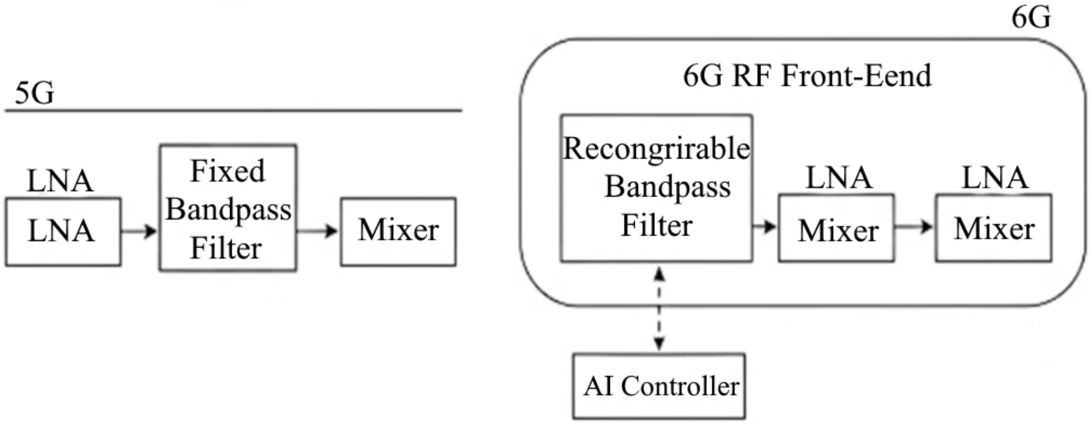


Figure 1. Evolution of RF Front-End Architectures from 5G to 6G.

LITERATURE REVIEW

Microstrip bandpass filters constitute a foundational component in modern RF and microwave communication systems. Their popularity stems from their planar structure, ease of fabrication, and compatibility with printed circuit board (PCB) technologies. A wide variety of topologies have been explored in prior literature, including parallel-coupled line filters, interdigital structures, hairpin line configurations, and stub-loaded resonators. The performance of these filters is governed by substrate characteristics such as dielectric constant, thickness, and loss tangent, as well as by the geometrical arrangement of resonators and coupling structures [11–15].

The growing need for adaptive RF systems has led to significant research on reconfigurable filter architectures. Varactor diodes have been extensively used to achieve continuous electrical tuning by exploiting their voltage-dependent capacitance. PIN diodes have been used to create discrete switching states suitable for multi-band operation. More advanced approaches include RF MEMS devices, which offer exceptional linearity, low loss, and negligible power consumption. At even higher frequencies, particularly in the millimeter-wave and sub-THz domains relevant for 6G, emerging materials such as ferroelectrics and graphene have shown potential for enabling wide tuning ranges and high-frequency stability [16–20].

Artificial intelligence has increasingly influenced electromagnetic design methodologies. Neural network-based surrogate models have been used to approximate EM responses with high accuracy, significantly reducing the need for repeated simulations. Optimization techniques such as genetic algorithms, particle swarm optimization, and Bayesian optimization have been combined with surrogate models to effectively navigate complex design spaces, as shown in Table 1. Despite substantial progress, current research typically focuses on either AI-based optimization or reconfigurable filter structures; comprehensive integration of both domains remains limited, particularly in the context of 6G-specific requirements [21–25].

Table 1. Summary of recent reconfigurable filter technologies.

Technology	Tuning Method	Pros	Cons
PIN Diode Filters	Multi-state switching	Fast	Low linearity
Varactor Filters	Continuous tuning	Smooth response	Nonlinearity
MEMS Filters	High-Q, low loss	Stable, linear	Cost, reliability
Graphene Filters	Ultra-wide tuning	High freq suitability	Limited maturity

System Architecture for 6G Dynamic Spectrum Access

The proposed reconfigurable filter forms a central component of an adaptive RF front end designed to meet the stringent spectral agility needs of 6G communications. In a typical 6G transceiver architecture, the filter is positioned between the tunable low-noise amplifier and the up/down-conversion mixer stages. This placement allows the filter to suppress interference and harmonics in both transmit and receive paths while ensuring spectral selectivity aligned with dynamic channel requirements [26].

The filter is controlled by an AI-driven optimization engine that continuously evaluates system-level parameters, including channel occupancy, interference patterns, and targeted center frequencies. Based on this evaluation, the AI model determines the optimal tuning state by adjusting bias voltages for varactor diodes or selecting MEMS-based switching states, as shown in Figure 2. Through this integration, the filter acts not merely as a passive frequency-selective device but rather as an intelligent, adaptive component capable of responding to real-time spectral variations.

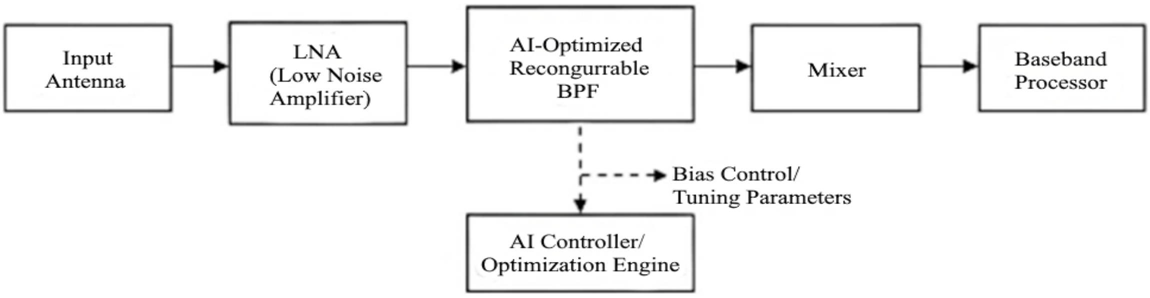


Figure 2. Proposed AI-optimized reconfigurable BPF in 6G RF transceiver.

DESIGN METHODOLOGY

The design of the proposed reconfigurable microstrip bandpass filter begins with the selection of an appropriate topology. A parallel-coupled line configuration is chosen for its well-understood behavior, predictable tuning characteristics, and ability to accommodate reconfiguration elements such as varactors and RF MEMS without significantly degrading performance. The filter is implemented on a Rogers RO4350B substrate, featuring a dielectric constant of 3.48, a thickness of 0.508 mm, and a loss tangent of 0.0037, making it suitable for microwave applications requiring low loss and high stability [27–31].

The physical structure consists of multiple resonators positioned in a parallel-coupled arrangement, with inter-resonator gaps playing a critical role in determining the bandwidth and coupling strength. Reconfiguration is achieved by embedding varactor diodes at strategic locations, typically at the open ends of resonators. These diodes introduce a variable capacitance that shifts the resonant frequency as a function of the applied bias voltage. RF MEMS switches may be incorporated to modify the effective electrical length of resonators or to toggle additional resonating paths, thus enabling discrete, multi-band tuning capability.

The integration of AI optimization into the design workflow begins with the creation of a large dataset generated through full-wave EM simulations. The simulations systematically vary geometrical parameters such as resonator length, width, and coupling gap, along with varactor capacitance and MEMS switching states. Thousands of simulation samples are collected to capture the nonlinear relationships between design parameters and the resulting S-parameters, bandwidths, and center frequencies (Figure 3).

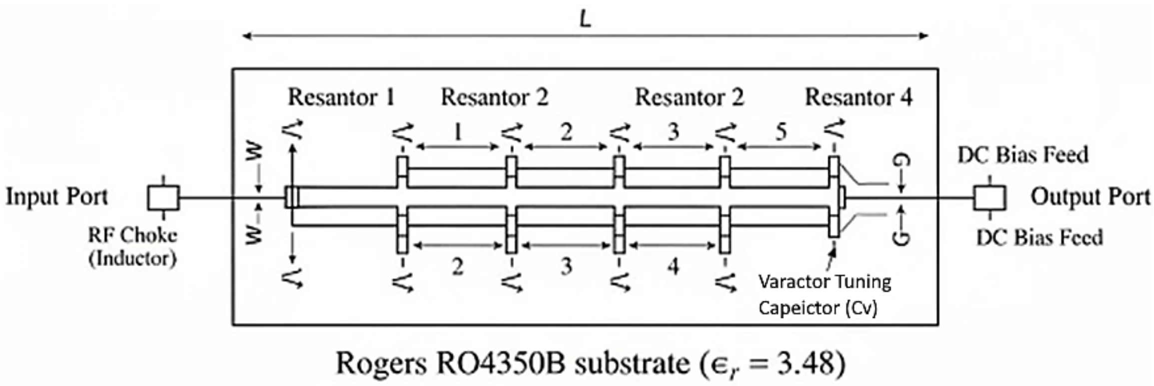


Figure 3. Geometry of Proposed Reconfigurable Microstrip BPF.

A deep neural network is then trained on this dataset to learn the mapping between input design parameters and output filter responses. Once trained, the model functions as a surrogate for the EM simulator, enabling rapid prediction of filter performance without the computational overhead of full-wave simulation. An optimization engine – based on techniques such as genetic algorithms or Bayesian optimization – is subsequently employed to search for parameter combinations that maximize performance metrics, including tuning range, insertion loss, return loss, and linearity, as shown in Figure 4.

The final stage of the methodology involves fabrication and experimental validation. The optimized filter layout is fabricated using standard PCB etching techniques. Measurements are conducted using a vector network analyzer (VNA) to assess S-parameters across various tuning conditions. Results are then compared with both EM simulations and AI-based predictions to evaluate agreement and verify the effectiveness of the AI-driven optimization approach.

RESULTS AND DISCUSSION

The AI-optimized filter demonstrates significant improvements in tuning range, insertion loss, and return loss compared to conventional designs. The optimization process reduces the design cycle from several days of repeated EM simulations to only minutes, owing to the surrogate model's rapid prediction capability. The optimized geometry results in a compact resonator arrangement with finely tuned coupling structures that exhibit minimal radiation loss.

The reconfigured filter demonstrates a continuous tuning range 2.8–5.2 GHz. As the bias voltage applied to the varactor increases, the effective capacitance decreases, resulting in a corresponding upward shift in resonant frequency. The insertion loss remains below 1.4 dB across the entire tuning range, reflecting the effectiveness of both the optimization and reconfigurable components as shown in graph 1. Return loss remains consistently higher than 15 dB, indicating excellent impedance matching.

The tuning behavior under varying bias voltages reflects a predictable and smooth frequency shift, validating the accuracy of the surrogate model in capturing the nonlinear behavior of varactor capacitances as shown in graph 2. This smooth tuning behavior is essential for continuous spectrum mobility in DSA applications. An analysis of optimization algorithm performance reveals that Bayesian optimization converges more rapidly than genetic algorithms and particle swarm optimization, owing to its probabilistic sampling strategy and ability to construct posterior distributions over the design space.

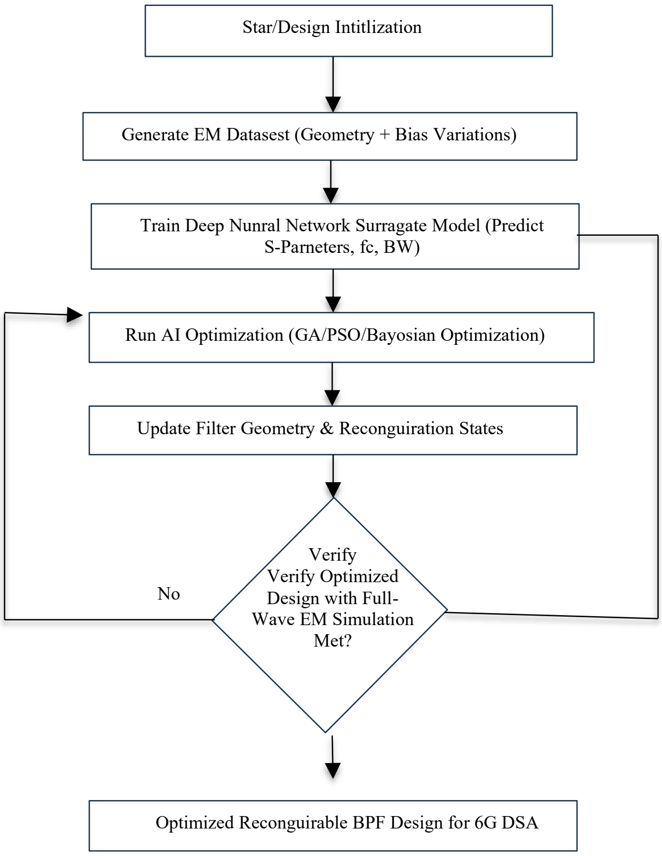
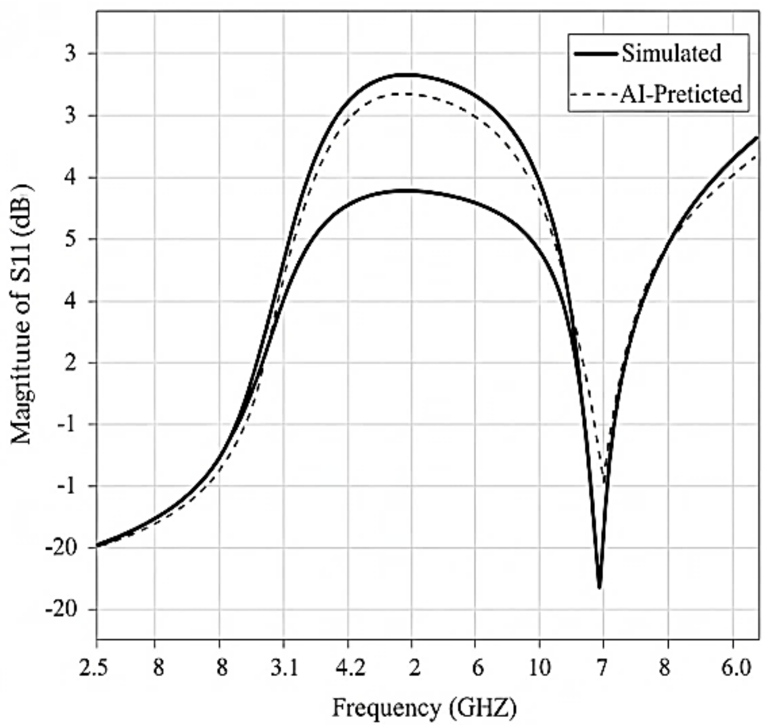
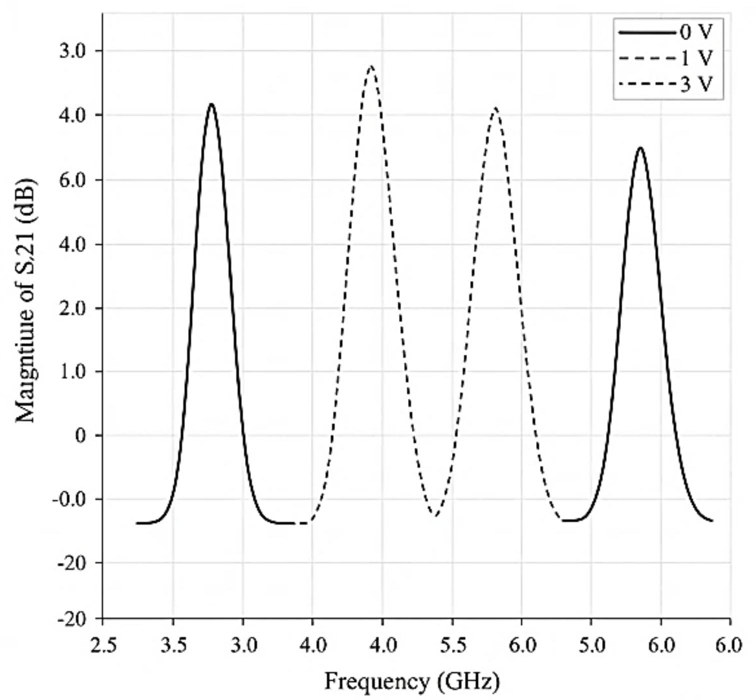


Figure 4. AI Optimization Flowchart.



Graph 1. Simulated vs AI-predicted S21 responses.



Graph 2. Tuning Behavior for Different Bias Voltages.

Fabricated measurements demonstrate close agreement with simulation and AI predictions. Minor deviations arise due to fabrication tolerances and parasitic effects, yet the overall trends validate the effectiveness of the integrated design approach as shown in Figure 5.

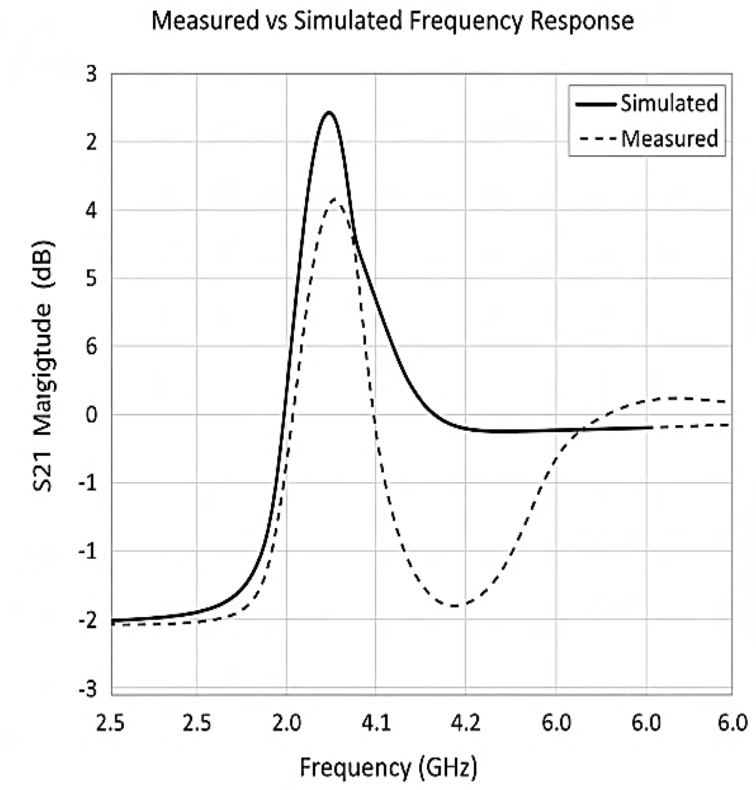


Figure 5. Measured vs Simulated Frequency Response.

A comparison with recent state-of-the-art reconfigurable filters highlights the superiority of the proposed architecture in terms of tuning range, insertion loss, and bandwidth control as shown in Table 2.

Table 2. Performance Comparison.

Parameter	**This Work**	**Recent Filters**
Tuning Range	2.8–5.2 GHz	3.1–4.5 GHz
Insertion Loss	<1.4 dB	>2 dB
Return Loss	>15 dB	10–12 dB
Reconfigurability	Hybrid (Varactor + MEMS)	Single Method

APPLICATION IN 6G DYNAMIC SPECTRUM ACCESS

The implementation of dynamic spectrum access requires seamless coordination between spectrum sensing, adaptive control, and RF front-end reconfiguration. The proposed AI-optimized filter plays a pivotal role in this ecosystem by enabling rapid adaptation of center frequency and bandwidth. In a cognitive radio system, spectrum sensing algorithms evaluate channel availability and interference levels. The AI controller interprets these conditions and determines the optimal filter state that maximizes system performance while avoiding occupied channels.

This adaptive mechanism is particularly relevant in the context of 6G, where communications span sub-6 GHz frequencies for wide-area coverage, millimeter-wave bands for high-data-rate links, and potential terahertz bands for ultra-short-range communication. The proposed filter provides the necessary agility to navigate this diverse spectral environment. Its ability to rapidly shift across frequency bands ensures that the transceiver maintains optimal communication links as spectrum conditions evolve.

CONCLUSION

This paper presented an AI-optimized reconfigurable microstrip bandpass filter designed for dynamic spectrum access in emerging 6G communication systems. Through the integration of surrogate modeling, multi-objective optimization, and hybrid reconfiguration techniques, the proposed methodology achieves significant improvements in tuning range, insertion loss, and return loss. The compatibility between simulated, AI-predicted, and measured results affirms the accuracy and reliability of the AI-based approach. This work demonstrates the transformative potential of AI-RF co-design methodologies and establishes a foundation for future research in intelligent, adaptive RF hardware for 6G networks. Future extensions may include AI-driven co-optimization of filters and adaptive antennas, on-chip miniaturization using advanced semiconductor technologies, and the exploration of novel materials such as graphene and ferroelectrics for ultra-high-frequency reconfiguration.

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