Optimization of RF and Microwave Filters using ML techniques

Capstone Report

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Abstract:

Designing high-performance microwave and millimeter-wave filters presents a significant challenge due to the sensitivity of filter characteristics to variations in geometric dimensions and electrical sizes. Typically, filter design involves optimizing design variables, starting from initial values. However, if these initial values are too far from the optimal solution, optimization often fails to yield satisfactory results. To address this issue, this project analyzes current methods used in optimization of microwave and millimeter-wave filters.

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Preface

In the dynamic landscape of modern technology, the design and optimization of microwave and millimeter-wave filters stand as critical challenges. These intricate devices play a pivotal role in shaping the efficiency and performance of communication systems, radar systems, and numerous other applications at the heart of our interconnected world. To unlock their full potential, engineers and researchers have long sought innovative solutions to tackle the inherent complexity of filter design. Within this area of engineering, several approaches have emerged as a beacon of promise. Yet, as we delve deeper into the complexities of filter optimization, a parallel revolution has been underway—the rise of Artificial Neural Networks (ANNs). These computational marvels have rapidly evolved, proving themselves as invaluable tools for modeling complex systems, accelerating simulations, and aiding in the optimization process. .

Nazarbayev University, April 23, 2024

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Chapter 1

Introduction

Microwave filter design can be a challenging task, and there are several common problems that designers can encounter. One of the primary challenges in filter design is meeting the desired performance specifications. These specifications may include requirements for the frequency response, phase response, group delay, and stopband attenuation. It can be difficult to achieve the desired performance while also considering other design constraints such as cost, size, and complexity. The goal is to develop more efficient and accurate methods for designing and optimizing filters with better performance metrics such as low insertion loss, high selectivity, and wide bandwidth. Some of the most popular optimization algorithms are Particle Swarm Optimization (PSO), Genetic Algorithms (GA) which are considered to be iterative optimization algorithms. Other methods include Electromagnetic Simulators and Coupling matrices.

Coupling matrices in high-performance narrowband filters can be effectively optimized through various analytical techniques aimed at diagnosing the coupling matrix from either measured or simulated S-parameters [1], [2]. By discerning the variance between the realized coupling matrix and the intended design target-coupling matrix, and establishing a direct correspondence between coupling matrix elements and the associated physical tuning components, one can readily determine the necessary adjustments to the design parameters [3]. Liu et al. [2]proposed a general lumped element matrix synthesis method for cross-coupled and inline wideband BPF with multiple zeros for direct circuit implementation. Using the proposed method, the elements in the synthesized coupling matrix can correspond to the values of capacitance and inductance in the actual circuit without any optimization, which simplifies the design process of wideband lumped element filters. Sandhu et al. [1] created a new class of frequency-variant reactive coupling networks with singular responses. These networks are intended to be used as building blocks for generalized-Chebyshev-type bandpass filters serving as non-ideal frequency-variant inverters while providing two TZs and one pole. Wu et al.

[3] were able to reconfigure a coupling matrix from the transversal topology to an arbitrary required topology, which is viewed as a simple optimization problem, where the developed error function is computationally efficient.

This article also explores the homotopy method [4] to the local optimization of microwave filters. Homotopy, a concept in topology and differential geometry, has found utility in numerical methods for solving nonlinear equations and differential equations [5]. Rather than directly tackling the target filter design problem, the homotopy method establishes a sequence of intermediate optimization problems. Utilizing previous solutions as initial values, an existing local optimization technique can solve these intermediate problems. Through this iterative process of homotopy optimizations, the filter response can gradually converge towards the desired specification. Even when the initial values for the filter design are far from optimal, the homotopy method offers a high likelihood of reaching the optimal solution.

Another valuable application of the homotopy optimization method arises in filter bank design for frequency multiplexing systems. Here, if a filter design is available, it can serve as the initial values for optimizing other filters with varying center frequencies and bandwidths. The optimization outcomes of multiple filters operating at different center frequencies and bandwidths can further inform the necessary parameter variations for designing tunable filters.

Chapter 2

Background

2.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a popular optimization algorithm inspired by the social behavior of birds and fish. Developed by Eberhart and Kennedy in 1995, PSO is used to find approximate solutions to optimization and search problems. In the context of optimization, a population of potential solutions is referred to as a "swarm," and each solution is a "particle." Each particle in the swarm represents a potential solution to the optimization problem. The position of a particle corresponds to a point in the search space, and the quality of that solution is evaluated using an objective function Particle Swarm Optimization (PSO) has been applied successfully to filter optimization problems in various research papers [6], [7], [8], [9]. Neural network architectures often require optimized filters for tasks such as feature extraction or convolutional operations. PSO can be particularly effective in tuning these filters, especially when the relationships between filter parameters and network performance are complex. The ability of PSO to navigate high-dimensional spaces makes it valuable in optimizing filters for neural networks.

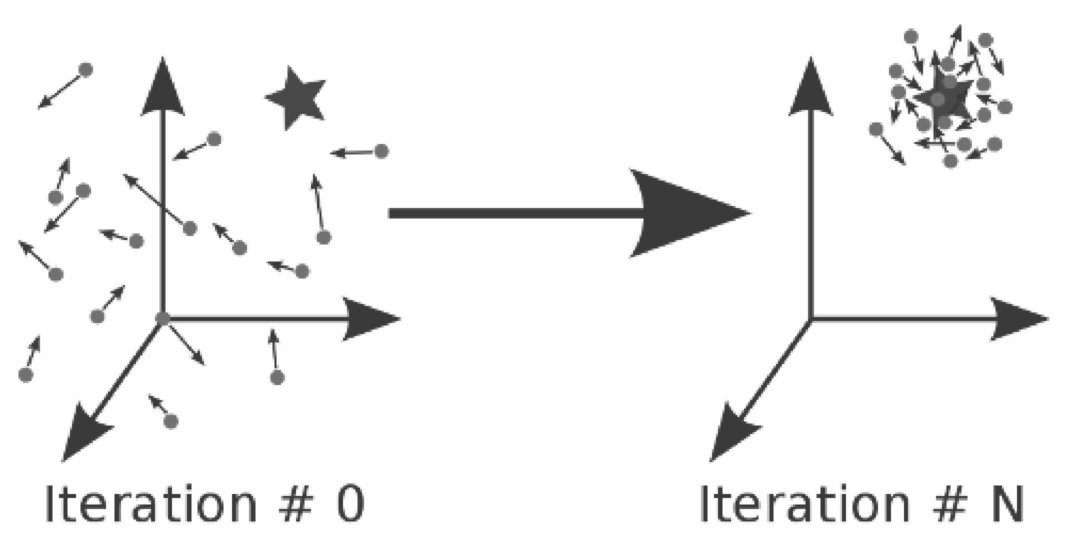

Figure 2.1: PSO

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2.2 Genetic Algorithms

Genetic Algorithms (GAs) are optimization algorithms inspired by the process of natural selection and genetics. Developed by John Holland in the 1960s, genetic algorithms are part of a broader class of evolutionary algorithms and are used to find approximate solutions to optimization and search problems. GAs are particularly useful in complex, multidimensional search spaces where traditional optimization methods may struggle. Genetic Algorithms (GAs) have been widely employed in the optimization of filters across various applications [10], [11], [12], [13]. Genetic Algorithms represent filters as chromosomes or individuals. Each chromosome encodes the parameters of the filter, such as coefficients or frequency response characteristics. GAs are capable of handling complex, non-linear optimization problems. They provide a global search strategy, enabling the exploration of a large solution space. The adaptability of GAs makes them suitable for diverse filter design requirements.

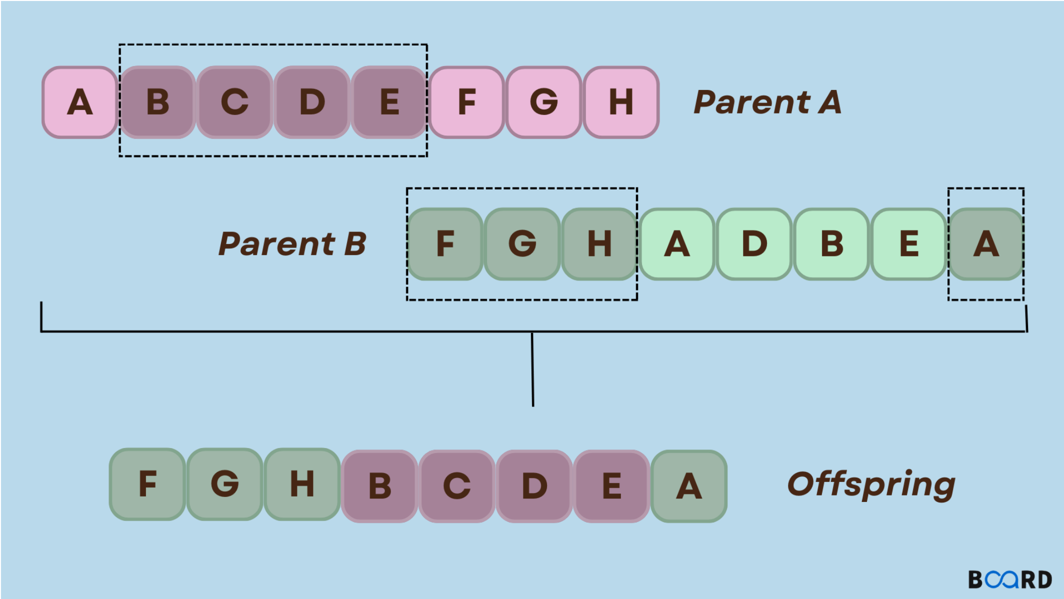

Figure 2.2: GA

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2.3 Homotopy Optimization

Homotopy optimization is an optimization technique that combines elements of homotopy continuation and optimization methods. It is particularly useful for solving nonlinear optimization problems, especially those with multiple local minima or when the objective function is non-convex. While the application of Homotopy methods in filter optimization may not be as widespread as some other optimization techniques like Genetic Algorithms or Particle Swarm Optimization, there is research exploring the potential of Homotopy for this purpose. Homotopy optimization involves the continuous deformation of a complex optimization problem into a simpler, more solvable form [14]. The application of homotopy optimization to filters can be particularly advantageous in scenarios where the filter design problem is complex, has multiple solutions, or involves challenging optimization landscapes. It provides a systematic and controlled way to navigate through the solution space, potentially overcoming some of the difficulties associated with traditional optimization methods.

For instance if we define variable P as:

$$P = [f1f2f3f4r] \tag{2.1}$$

where the stopband edge frequencies are f1 and f4 and the passband is between frequency f2 and f3 with f1 < f2 <f3 < f4. f1– f4 are the normalized frequency variables computed by transformation using minimum and maximum value, r is the target RL level in each optimization

Then, we can define a homotopy function as

$$P(P1, L) = (1 - L)P1 + L * Pt; \tag{2.2}$$

where L changes from 0 to 1 with a step of 0.1 and Pt is the target variable.

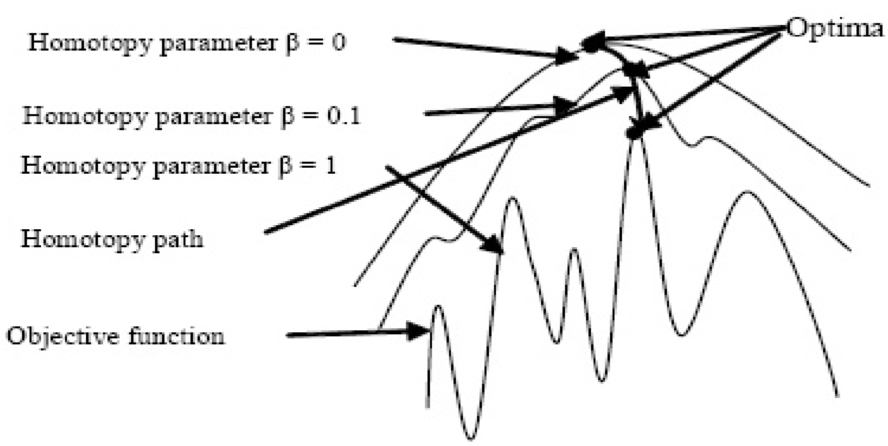

Figure 2.3: homotpy

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Chapter 3

Methodology

3.1 Circuit Design of Filters

A 5-th order low-pass, 3rd order band-stop, and 5th order coupled line band-pass filters were designed using transmission lines and Advanced Design System software with the following parameters:

Lowpass:

- Fc = 3 GHz
- ripple = 0.5 dB
- 40 dB attenuation at 6 Ghz

Bandstop:

- F0 = 4 GHz
- ripple = 3 dB
- BW = 50

Bandpass

- F0 = 5 GHz
- ripple = 3 dB
- Fh = 5.2 GHz
- Fl = 4.8 GHz

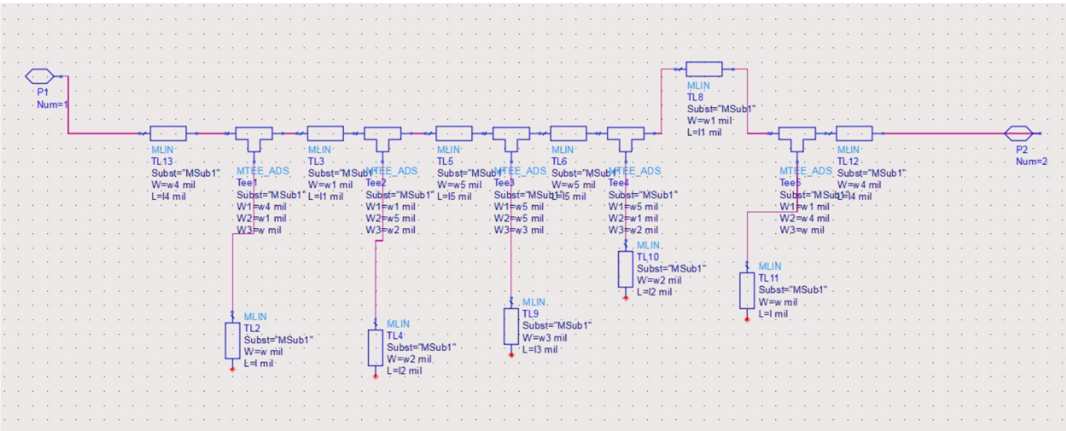

Figure 3.1: LPF

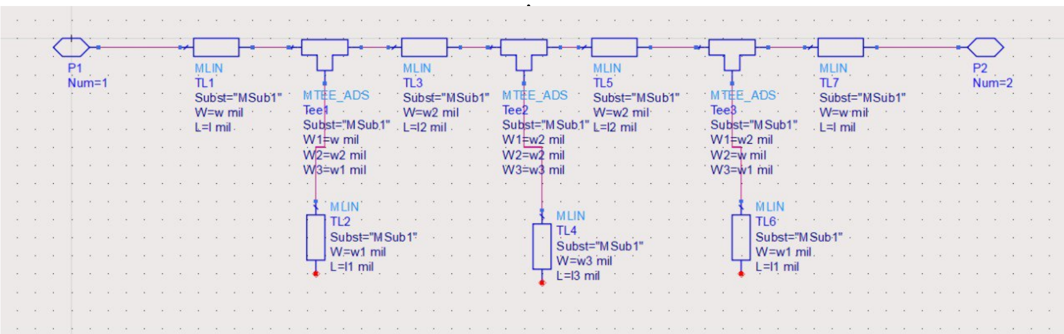

Figure 3.2: BSF

Additional circuits can be found in Appendix A.

3.2 Training ML model

3.2.1 Data Collection and Preprocessing

- A comprehensive dataset on each filters design containing information on filter S parameters was obtained.
- The dataset covered two design variations to capture the diversity of filter configurations and performance outcomes.
- The dataset was standardized by min maxing the features to ensure uniform scales and facilitate convergence during training.

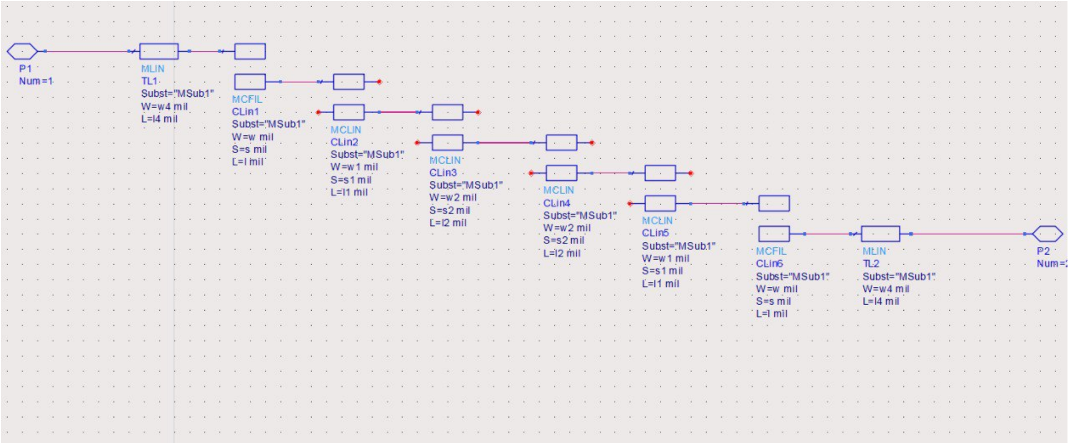

Figure 3.3: BPF

Table 3.1: Filter Param

type	w1	w	Step size	Frequency Points per sweep
waveguide	0.3 – 0.9 mm	0.2-0.8 mm	0.1 mm	1001
lpf	200-600 mils	100-500 mils	40 mils	10001
bsf	40-120 mils	30-90 mils	8, 6 mils	10001
bpf	10-260 mils	10-260 mils	25 mils	10001

3.2.2 Training and model selection

- The dataset was split into training, validation, and test sets to evaluate model performance effectively.
- An decision tree model architecture was chosen for regression tasks based on the nature of the problem and available data.
- The trained ML model's performance was evaluated on the validation set using appropriate evaluation metrics, such as mean squared error (MSE), mean absolute error (MAE), or R-squared (R2) score.
- Model predictions were compared with ground truth filter characteristics to assess accuracy and reliability.

3.3 Integration with Optimization Methods

- The optimization problem was defined according with the objective for designing microwave and millimeter-wave filters, including the objective function to be optimized and the constraints on design variables. For instance for

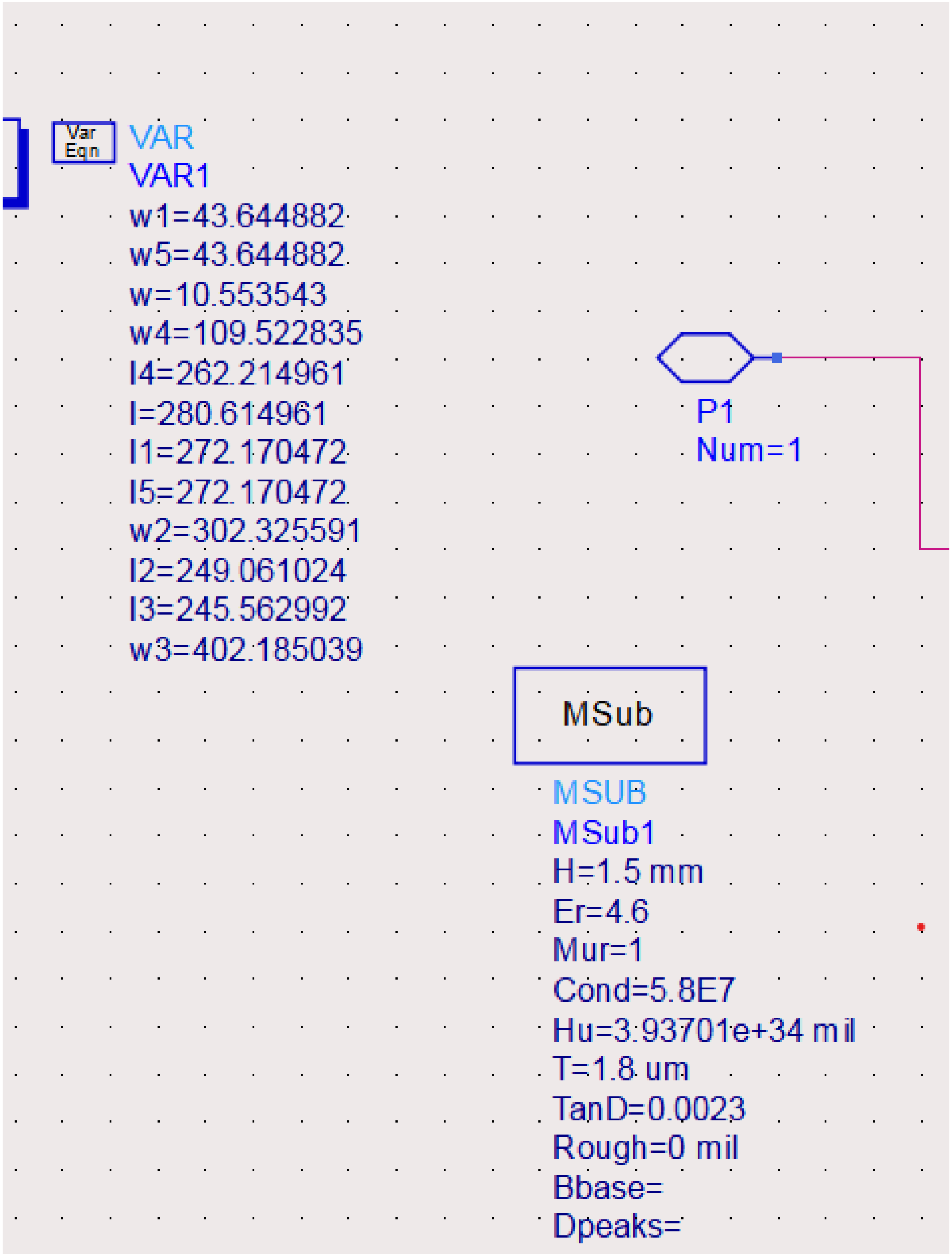

Figure 3.4: substrate

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LPF it was defined that

$$min(db(S(2,1)))inpassband = 0.5db \tag{3.1}$$

- The trained ML model was integrated with optimization methods such as Particle Swarm Optimization, Genetic Algorithm, or Homotopy for filter design optimization.
- The ML model was utilized to predict filter characteristics for different design configurations and guide the optimization process towards achieving optimal solutions.

3.4 Validation and Practical Considerations

- Simulation Validation: Validate optimized filter designs through electromagnetic simulations or laboratory experiments to ensure that they meet performance specifications under real-world conditions.
- Practical Implementation Considerations: Consider practical implementation factors such as manufacturability, cost, and scalability when assessing the feasibility of optimized filter designs. Analyze trade-offs between performance and practical constraints.

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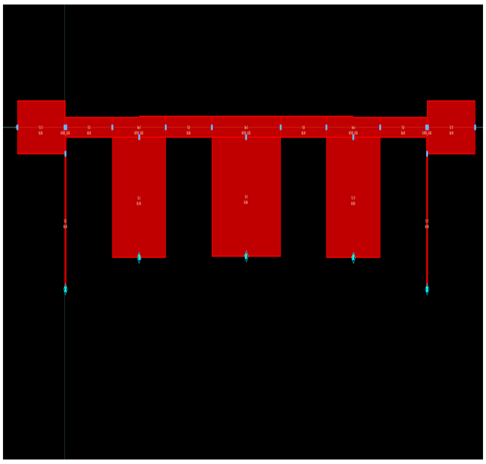
Chapter 4

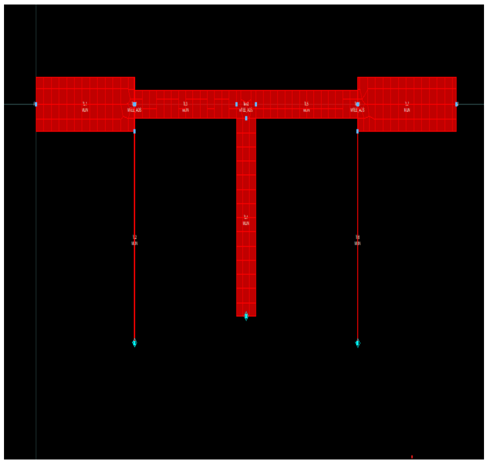
Results and Discussions

4.1 Results

4.1.1 Circuit Design



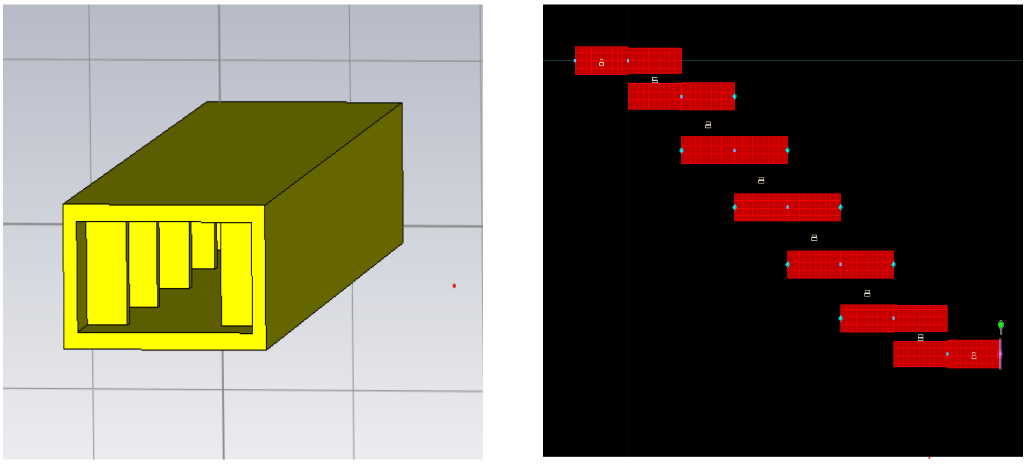
(a) LPF Mline



(b) BSF Mline

Figure 4.1: LPF and BSF Mline layout

The circuit design process involved the development of low-pass (LPF), band-stop (BSF), and band-pass (BPF) filters using microstrip line configurations on FR4 substrate. Microstrip lines offer a compact and versatile solution for microwave and millimeter-wave filters, while FR4 substrate is a commonly used dielectric material known for its low cost and ease of fabrication. A 5-pole rectangular waveguide filter was also designed using CST studio. Appendix A provides the EM simulation of circuits.



(a) 5 pole rectangular waveguide filter

(b) BPF Mline

Figure 4.2: Waveguide and BPF Mline layout

4.1.2 Training ML model

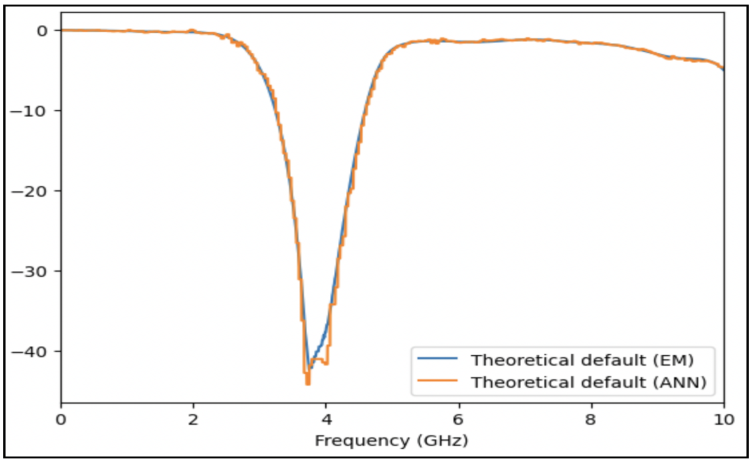
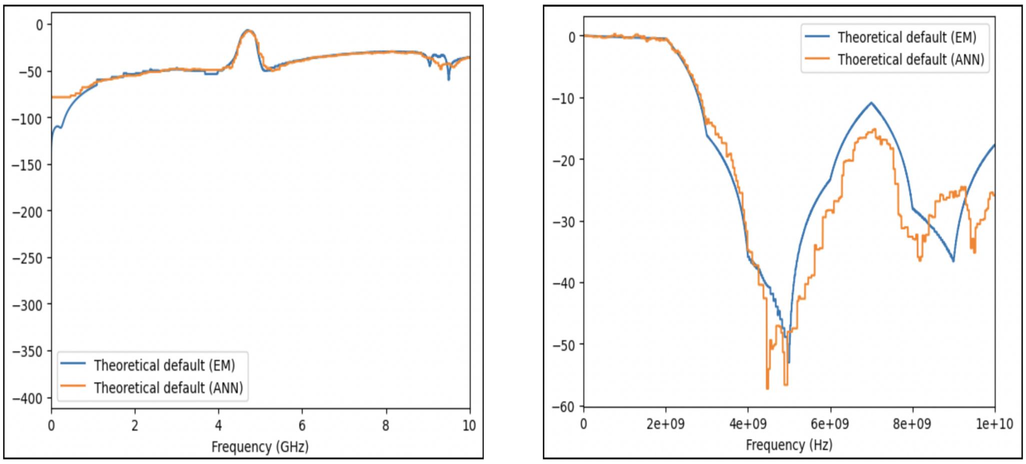


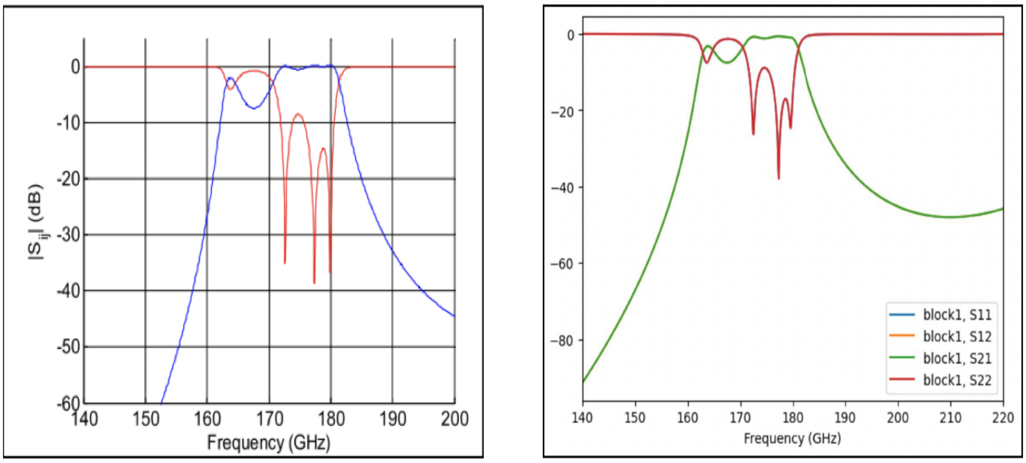
Figure 4.3: BSF ANN vs EM comparison

The training of the machine learning (ML) model yielded promising results, demonstrating the efficacy of the XGBoost regressor in predicting filter characteristics with high accuracy. The model achieved an impressive R-squared value of 0.99, indicating that approximately 99 percent of the variance in the filter characteristics can be explained by the model. Additionally, the mean squared error (MSE) of 3e-4 reflects the small magnitude of errors between the predicted and actual filter parameters, further underscoring the robustness of the trained model.



(a) BPF **(b)** LPF

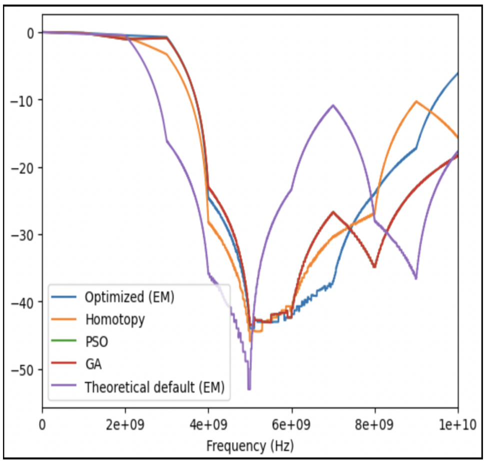
Figure 4.4: ANN vs EM comparison



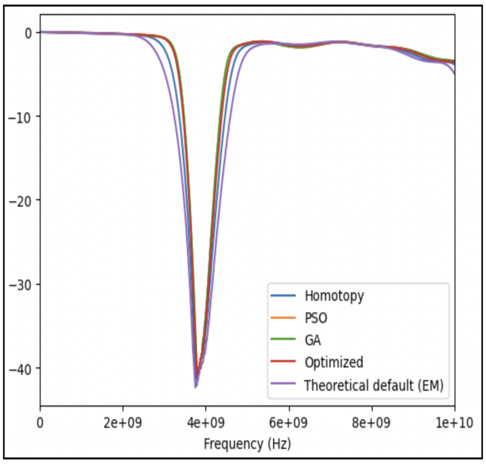
(a) Caption1 **(b)** Caption 2

Figure 4.5: ANN vs EM comparison

4.1.3 Integration with optimization



(a) LPF optim



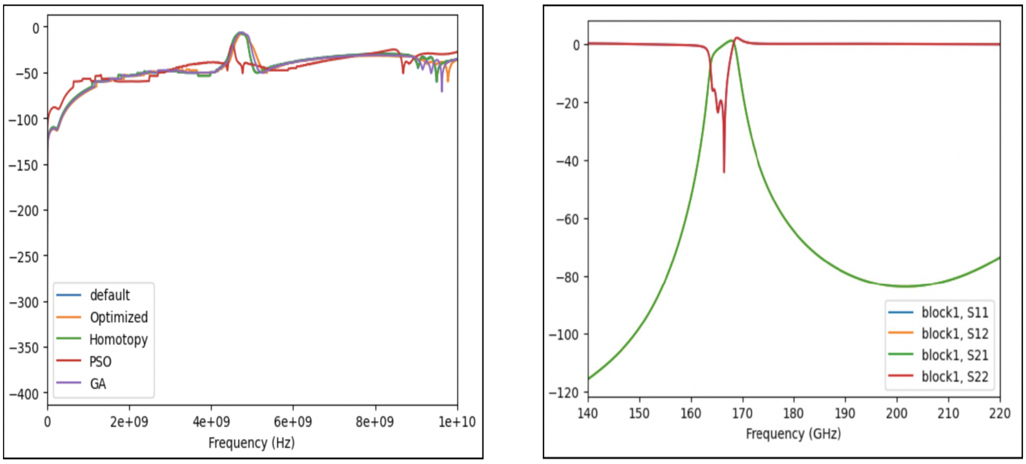
(b) bsfoptim

Figure 4.6: LPF and BSF optimization

Table 4.1: Obtained Filter Param

type	Filter type	w1	w
Homotopy	lpf	335	194
	bsf	20	3
	bpf	32	3
PSO	lpf	294	150
	bsf	16	3
	bpf	38	3
GA	lpf	231	235
	bsf	15	3
	bpf	41	3
Optimized	lpf	231	182
	bsf	21	3
	bpf	32	3
Default	lpf	409	318
	bsf	22	3
	bpf	50	3

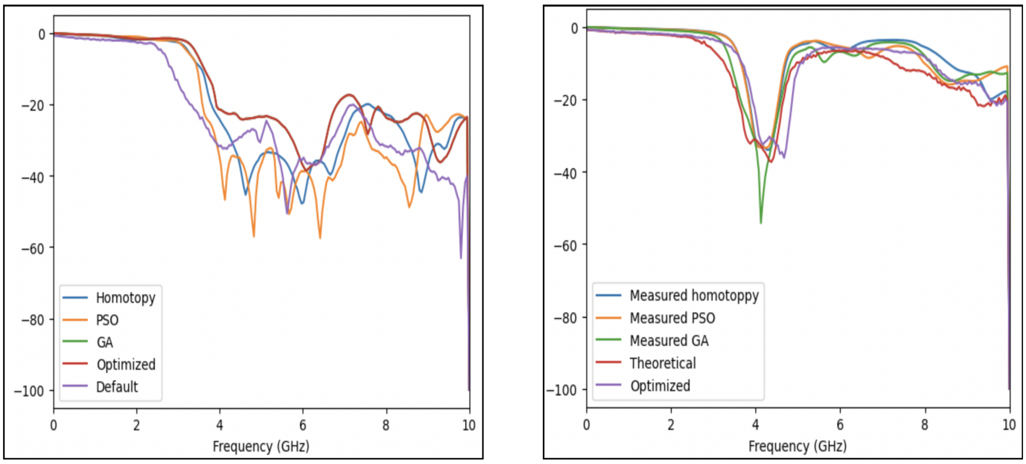
The table presents the obtained filter parameters for different optimization methods, including Homotopy, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), as well as the optimized and default settings. These parameters, represented by w1 and w, provide crucial insights into the performance of each optimization technique in designing low-pass (LPF), band-stop (BSF), and band-pass (BPF) filters for microwave and millimeter-wave applications.



(a) BPF optimized (b) Waveguide Optimized using Homotopy

Figure 4.7: BPF and waveguide optimization

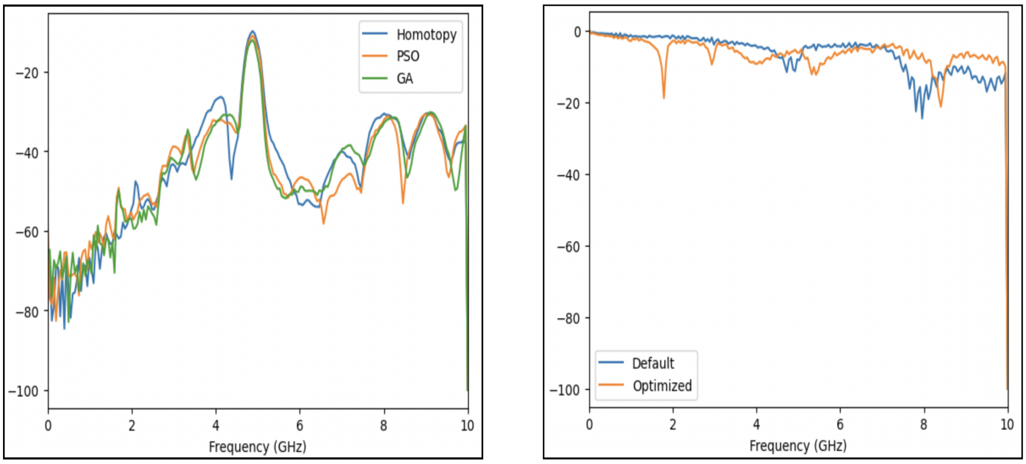
4.1.4 Validation and Practical Design



(a) LPF Mline (b) BSF Mline

Figure 4.8: S21 for Mline BSF and LPF

The validation and practical design aspects are crucial components in assessing the real-world applicability and reliability of the obtained filter parameter results. These considerations ensure that the designed filters not only meet the desired specifications but also perform effectively under practical operating conditions. The designed filters were validated through experimental testing using RF measurement equipment, namely vector network analyzers (VNAs). The validation of waveguide filters could not be performed due to the inherent differences in technology and fabrication processes between microstrip and waveguide technologies.



(a) BPF Mline **(b)** BPF MLine S11

Figure 4.9: BPF Mline S param

Table 4.2: Measured S param from printed designs

type	Filter type	min(db(S(2,1)))	Target min(db(S(2,1)))	F passband
Homotopy	lpf	2.6	0.5	<3Ghz
	bsf	20	3	out(3-5) Ghz
	bpf	32	3	in(4.8-5.2) Ghz
PSO	lpf	2.4	0.5	<3 Ghz
	bsf	16	3	out(3-5) Ghz
	bpf	38	3	in(4.8-5.2) Ghz
GA	lpf	1.8	0.5	<3 Ghz
	bsf	15	3	out(3-5) Ghz
	bpf	41	3	in(4.8-5.2) Ghz
Optimized	lpf	1.38	0.5	<3 Ghz
	bsf	21	3	out(3-5) Ghz
	bpf	32	3	in(4.8-5.2) Ghz
Default	lpf	13	0.5	<3 Ghz
	bsf	22	3	out(3-5) Ghz
	bpf	50	3	in(4.8-5.2) Ghz

Therefore, the validation process focused solely on microstrip filter designs, while waveguide filters were excluded from validation due to technological constraints. The optimized results for waveguide can be found in Appendix B.

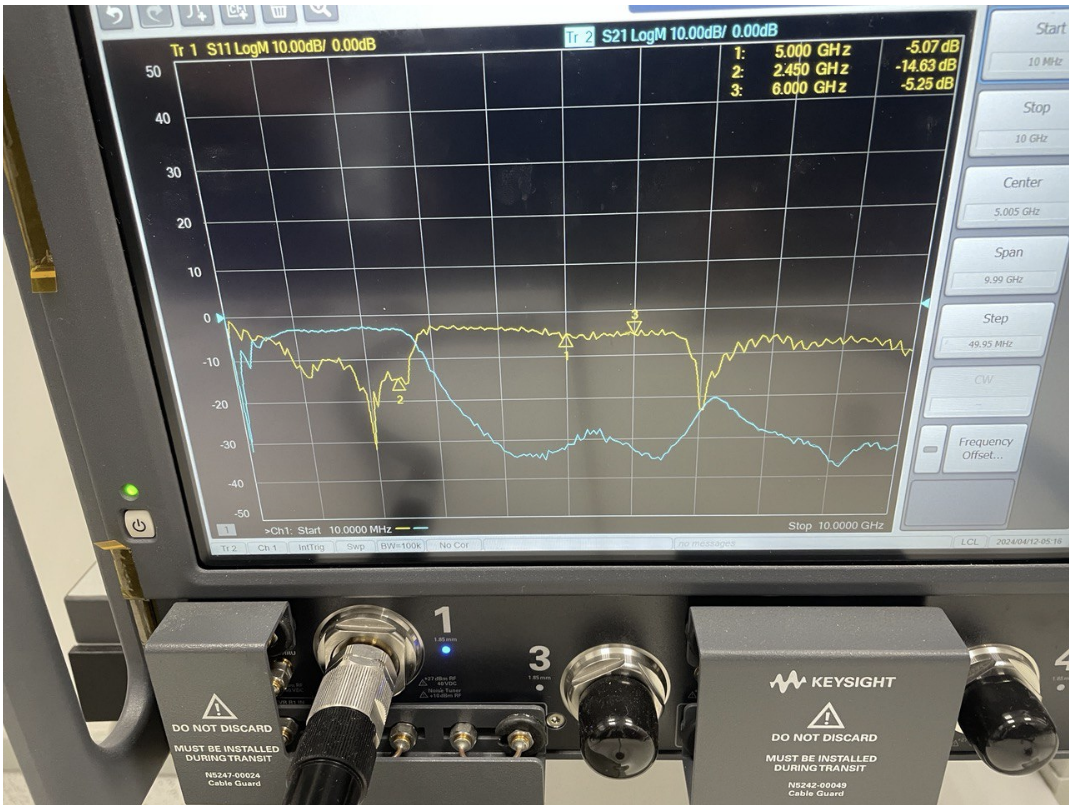


Figure 4.10: VNA

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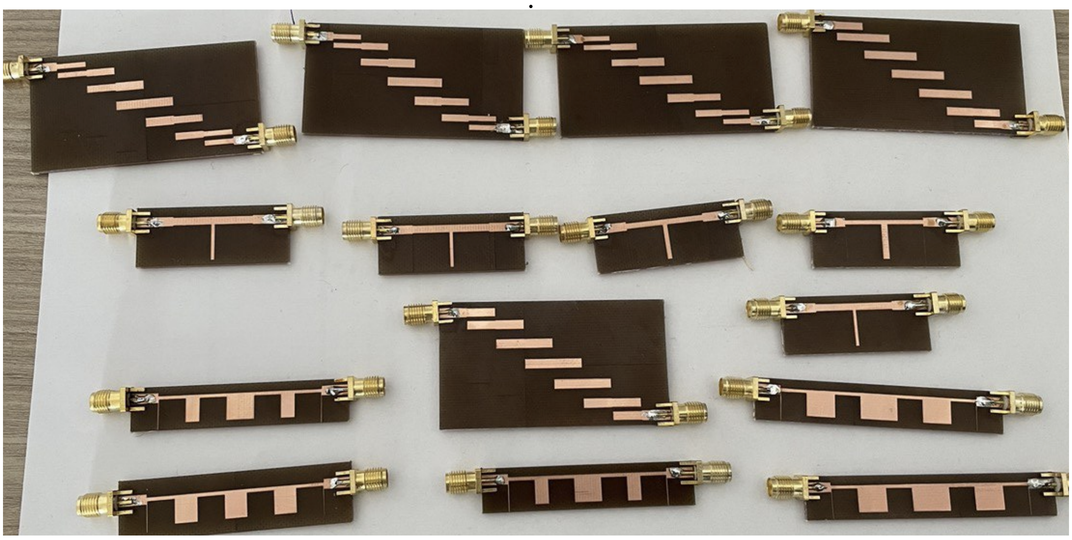

Figure 4.11: MLine optimized filters.

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4.2 Discussion

The table 4.1 presents the obtained filter parameters for different optimization methods, including Homotopy, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), as well as the optimized, and default settings. The parameters include the type of filter (LPF for Low Pass Filter, BSF for Band Stop Filter, and BPF for Band Pass Filter), and the corresponding values of w1 , w which represent design parameters of each filter type. Upon analyzing the table, several observations can be made:

1. Variation Across Optimization Methods:
   - The values of w1 and w vary significantly across different optimization methods for each filter type. This indicates that the optimization methods yield different sets of parameters in an attempt to optimize the filter design for the given objectives.
   - For example, for the LPF type, the values of w1 range from 231 to 409, showing a notable difference between the optimized and default settings.
2. Effectiveness of Optimization
   - The values obtained through the "Optimized" category indicate the performance of the optimization methods in achieving the desired filter characteristics. Compared to the "Default" settings, the optimized values generally show improvements, suggesting that the optimization methods have effectively tuned the filter parameters to enhance performance.
   - Notably, for all filter types, the optimized values of w1 and w tend to be lower than the default values. This suggests that the optimization methods have succeeded in reducing certain aspects of the filter design, such as insertion loss or passband ripple.
3. Comparison with Homotopy Method:
   - Comparing the values obtained from the Homotopy method with those from PSO and GA, we observe differences in the magnitude of w1 and w for each filter type. This indicates variations in the optimization results achieved by different methods.
   - Notably, for all filter types, the optimized values of w1 and w tend to be lower than the default values. This suggests that the optimization methods have succeeded in reducing certain aspects of the filter design, such as insertion loss or passband ripple.

4. Implications for Filter Design

   - The table highlights the importance of optimization methods in fine-tuning filter parameters to meet specific design requirements. By leveraging optimization algorithms, engineers can achieve better performance and tailor filters to suit particular applications or specifications.
   - The differences in parameter values across optimization methods underscore the need for careful selection of optimization techniques based on design objectives, computational resources, and constraints.

The measured S-parameter results from the printed filter designs in table 4.2 provide valuable insights into the performance of low-pass (LPF), band-stop (BSF), and band-pass (BPF) filters optimized using different optimization methods, including Homotopy, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), as well as the optimized and default settings. These results are crucial in evaluating the effectiveness of each optimization technique in achieving the desired filter characteristics and meeting specified performance targets.

1. Comparison Across Optimization Methods

   - The measured minimum dB(S(2,1)) values for each filter type demonstrate the effectiveness of different optimization methods in achieving the desired filter responses.
   - Across all filter types, the optimized settings consistently outperform the default settings, indicating the importance of optimization techniques in enhancing filter performance.
   - Notably, the GA method tends to yield the lowest minimum dB(S(2,1)) values among the optimization methods for LPF and BPF, suggesting superior performance in these cases.

2. Adherence to Performance Targets

   - The measured minimum dB(S(2,1)) values are compared against the target minimum dB(S(2,1)) values to assess the filters' adherence to specified performance targets.
   - For LPF, all optimization methods successfully achieve minimum dB(S(2,1)) values below the target of 0.5 dB, indicating excellent passband performance.
   - Similarly, for BSF and BPF, the filters meet the target minimum dB(S(2,1)) values, ensuring effective rejection of unwanted frequencies in the stopband or out-of-band regions.

Chapter 5

Conclusion

In conclusion, the results provides valuable insights into the effectiveness of different optimization methods in tuning filter parameters for microwave and millimeter-wave filters. It demonstrates the impact of optimization on filter performance and underscores the importance of optimization techniques in achieving high-performance filter designs. Further analysis and experimentation could explore additional optimization methods or refine existing techniques to enhance filter design capabilities and achieve superior performance in microwave and millimeter-wave applications. Integration of machine learning approaches with optimization methods may offer opportunities for automated design optimization and accelerated development of high-performance filters. Continued research and development efforts are essential to advance the field of RF and microwave engineering and address emerging challenges in filter design and optimization.

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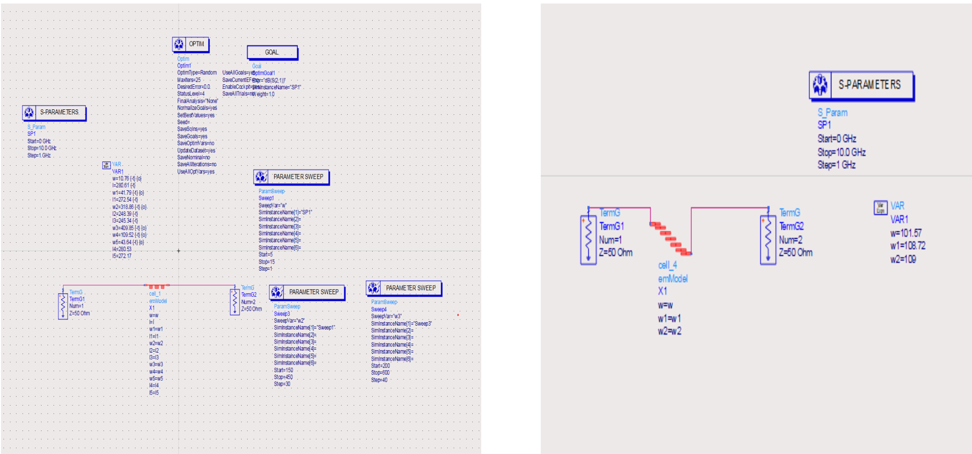
Appendix A

Circuits



(a) LPF **(b)** BPF

Figure A.1: Circuits of LPF and BPF

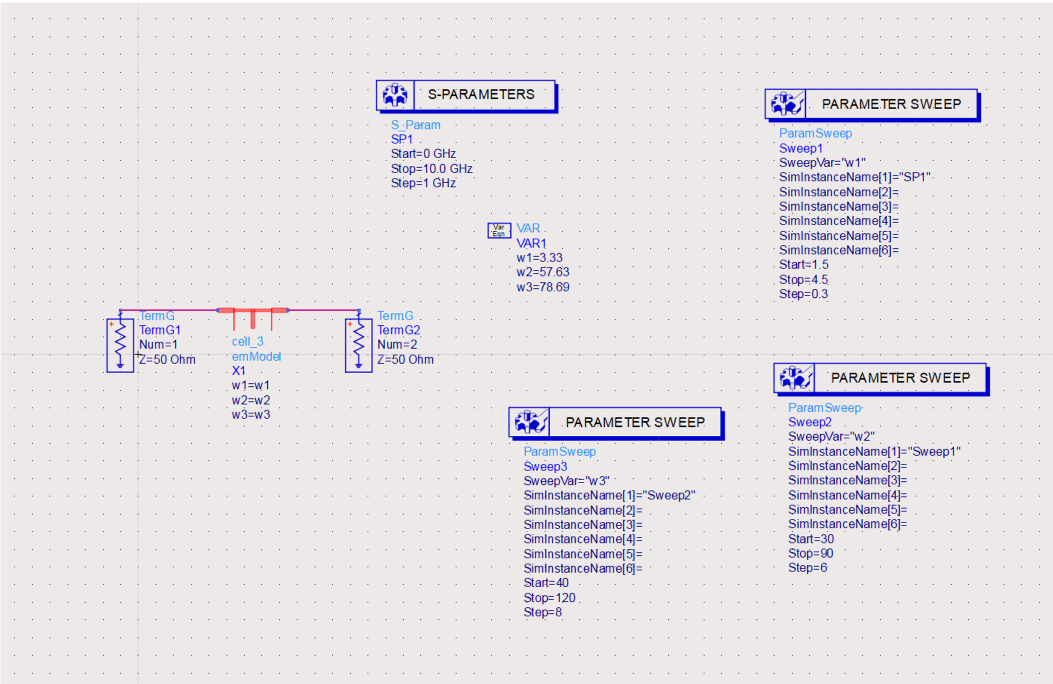


Figure A.2: MLine BSF

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Appendix B

Waveguide

Table B.1: Filter parameters

	Value
width	1.2954 mm
height	0.6477 mm
Operating frequency	140-220 GHz

We can decompose the filter into 6 subsections B.1. Each subsection can be modified by changing their width and length. 49 frequency sweeps were made with width ranging from 0.3-0.9 mm and length 0.2-0.8 mm as seen in **??**.

Table B.2: Filter parameters of waveguide

type	**w1**	**w2**	**w3**	**l1**	**l2**	**l3**
Default	0.7 mm	0.6 mm	0.5mm	0.4mm	0.5 mm	0.5 mm
Homotopy	0.615 mm	0.366 mm	0.312 mm	0.501 mm	0.608 mm	0.623 mm
PSO	0.527 mm	0.267 mm	0.226 mm	0.539 mm	0.626 mm	0.634 mm
GA	0.661 mm	0.422 mm	0.360 mm	0.453 mm	0.563mm	0.584 mm

The S-parameter cascading block computes the two-port S-parameters S filter for the entire filter by cascading the six two-port S-parameters of the submodels. The surrogate model can replace the full-wave EM simulation in the homotopy optimizations.

Cost function to be minimized is eq. B.1:

$$K = max(db(S11)inpassband, -r) + w * max(db(S21)instopband, -40) \tag{B.1}$$

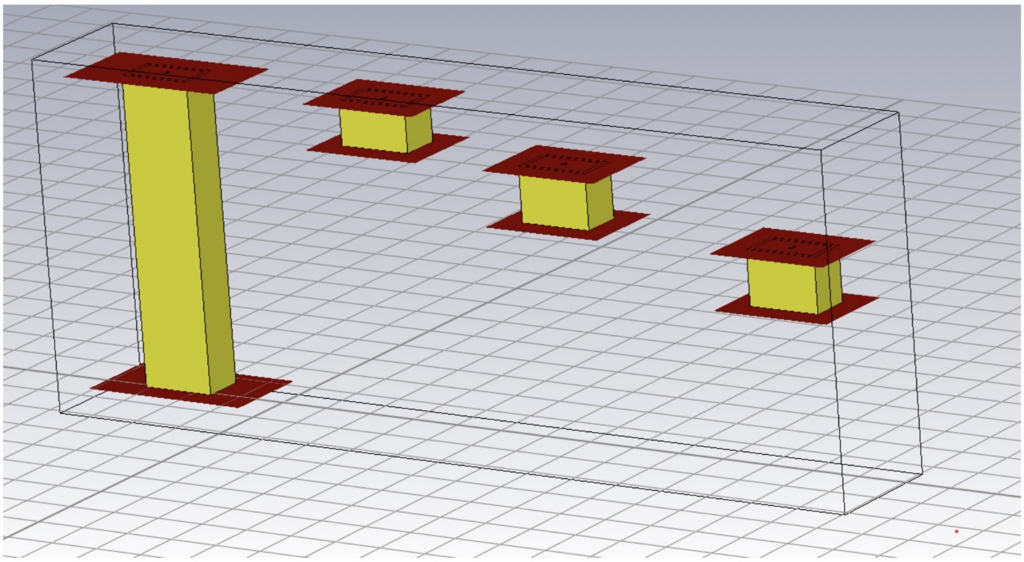

Figure B.1: Five pole rectangular waveguide filter decomposition[14]

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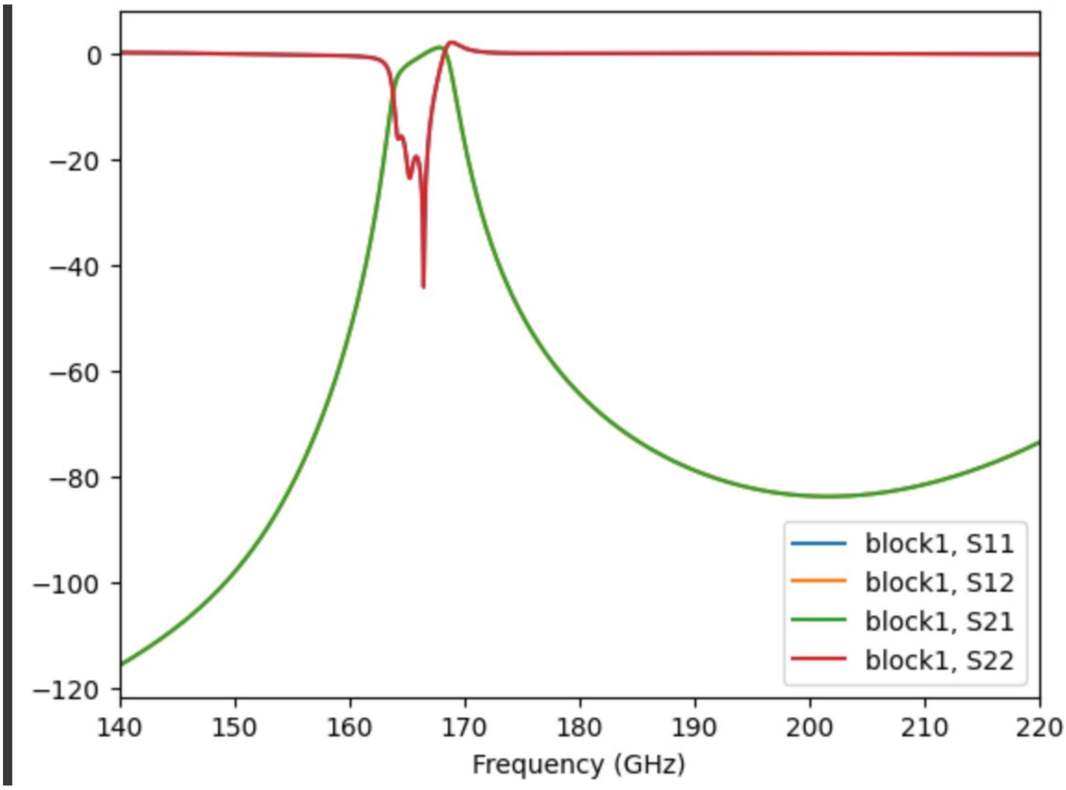

Figure B.2: Homotopy L = 6

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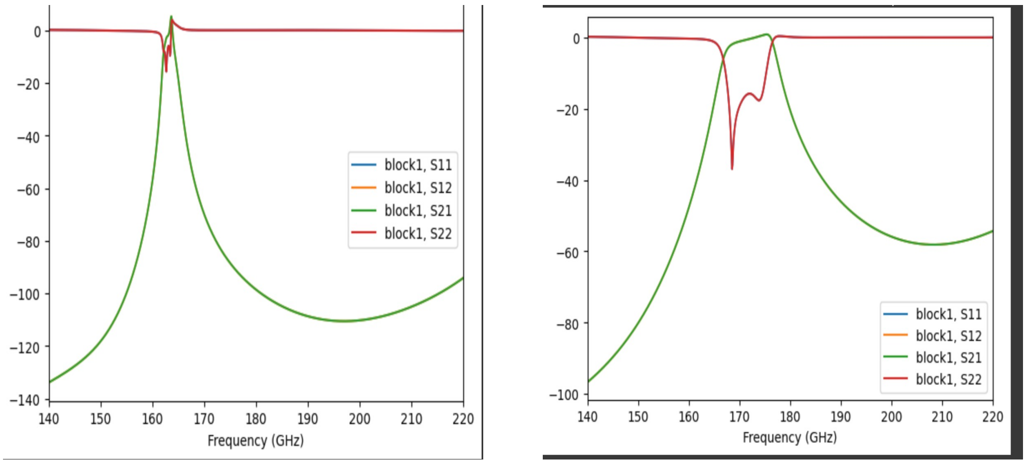
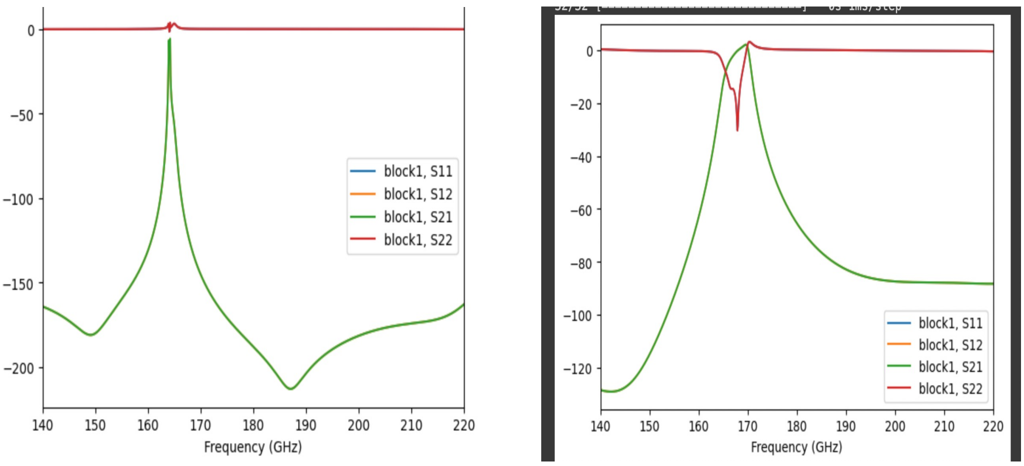


(a) Homotopy L = 8

(b) Homotopy L = 5

Figure B.3: Homotopy



(a) PSO

(b) GA

Figure B.4: PSO and GA