Neural Network Based Filter Modeling and Optimization for 5G and Beyond Applications

Capstone Report

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Abstract:

Designing high-performance microwave and millimeter-wave filters is difficult because small changes in geometric dimensions and electrical sizes can significantly affect the filter's characteristic. Typically, in filter design, the initial values of design variables are optimized to achieve the desired performance. In the field of high-frequency RF device modeling, the use of machine learning (ML) through artificial neural networks (ANN) has gained popularity in recent years. Unlike other RF modeling techniques, ANN-based models require training with sufficient datasets to achieve the desired accuracy level. The input data could be the device's dimensions, while the output could be the S-parameters. Once trained, the ANN-based model can provide EM-level accuracy and equivalent-circuit-level speed. Additionally, it is highly scalable, allowing for the introduction of more input parameters to make the model more versatile and complex. Therefore, the ANN-based model is an excellent option for high-frequency RF modeling compared to other techniques. The main objective of this research project is to develop an AAN that can be used in design of RF Filters.

Contents

Preface

RF design is of utmost importance in the field of electrical and computer engineering as it enables efficient wireless communication. However, designing RF filters involves complex optimization processes which can be time-consuming and intricate. The integration of Artificial Neural Networks (ANN) in this domain has opened up new possibilities for improving filter performance and reducing design iterations.With the advent of better design and optimization techniques, new technologies such as 5G are more reachable to humanity, that will further make developments such as autonomous cars, smart cities and fast internet available to consumers.

I would like to express sincere gratitude to my supervisor professor Mohammad Hashmi. With his help. I was able to open a whole new world of RF engineering for myself. Exploring state-of-the-art works and employ new methods and ideas were extremely pleasurable. Also, I would like to express my gratitude to NU for providing with library services, along with a lab that has access to high end simulation software.

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Chapter 1

Introduction

RF devices and circuits constitute essential electronic elements across a wide range of electronic devices. Beyond the consumer electronics sector, the integrated circuit (IC) industry is facing increasing pressure due to the substantial demand in areas such as medical, communication, automotive, and security electronics, in which, analog/RF components make up over half of the annual total IC shipments [1]. Despite its importance, the design process of RF devices is still a challenging task in spite of powerful CAD tools.

Microwave and millimeter-wave filters are crucial components in wireless communication systems, both presently and in the future. They are necessary for rejecting interference signals or combining multiband signals. However, creating these filters is an incredibly difficult task, particularly when designing narrowband filters with high out-of-band rejection at millimeter-wave and sub-THz frequencies. Even a slight variation in a single resonator's dimensions can result in a significant shift in resonant frequency, significantly impacting the filter's inband reflection characteristics. Therefore, precise adjustments to geometrical parameters are required during filter design [2].

The conventional approach of using Kirchhoff's laws and lumped elements in circuit formulation is insufficient to accurately predict the behavior of a design in high-frequency signal applications. Instead, it is necessary to use Maxwell's equations. Filter design involves numerous parameters, making it challenging to identify which ones require adjustments based on poor simulated transfer and reflection characteristics. To address this issue, filter practitioners commonly use circuit models represented by coupling matrices for narrowband filters with high performance. Analytical techniques can diagnose the coupling matrix from measured or simulated S-parameters [3]. By identifying the relationship between coupling matrix entries and physical tuning elements, one can determine how to adjust the design parameters. Another common approach is filter optimization using initial values of design parameters [4]. Optimization algorithms, such as sequential nonlinear programming and evolutionary algorithms, are incorporated into most commercial electromagnetic software [5].

Two essential challenges are linked to direct electromagnetic (EM)-based optimization. Firstly, if the initial design parameters are not sufficiently near the optimal solution, the optimization process may not yield satisfactory results. Secondly, the optimization process typically consumes an impractically long time as it explores various combinations of design variables in full-wave EM simulations, especially when dealing with high-dimensional optimization variables [2]. Therefore, new methods are required to propose better solutions for these challenges.

In modern times, there is an ever-growing demand for complex and intelligent algorithms to effectively process and extract valuable information from large datasets. This need arises in various fields, including healthcare, transportation, and radio frequency systems, where it is crucial for design, improvement, and optimization purposes. Neural networks are considered as advanced tools for achieving high accuracy in the design and optimization of numerous RF devices [6], including antennas,active and passive filters, and resonators.

These modules are capable of learning the behavior of various components and circuits, including both passive and active ones. Once trained, a neural network can be used for high-level design tasks, providing quick and precise answers based on its learned behavior. Neural networks offer a more appealing option compared to traditional methods like numerical modeling, which can be computationally expensive, analytical methods, which can be challenging to obtain for new devices, or empirical modeling solutions that may have limitations in terms of accuracy and range [7].

By using the capabilities of neural networks, in pair with an effective optimization technique, both problems faced by the designers related to optimization can be solved. The main objective of this research project is to overcome the difficulties related to the design and optimization of RF filters by utilizing artificial neural networks (ANNs) combined with a suitable optimization technique.

Chapter 2

Background

2.1 State-of-the-art and related works

Artificial neural networks (ANNs), are systems for processing information designed with inspiration from the human brain's capacity to learn from observations and generalize through abstraction [7]. The ability of neural networks to be trained for learning arbitrary nonlinear input-output relationships from provided data has led to their application in various fields, including pattern recognition, speech processing, control systems, biomedical engineering, and more. Notably, there has been a recent application of ANNs to address RF and microwave computer-aided design (CAD) challenges.

Neural network techniques have found application in a diverse range of microwave scenarios, including embedded passives, transmission-line components, vias, bends, coplanar waveguide (CPW) components, spiral inductors, field-effect transistors (FETs), amplifiers, and more. Additionally, neural networks have been employed in tasks such as impedance matching, inverse modeling, measurements, and synthesis [2], [8], [9], [10], [11], [12].

Filter design optimization involves seeking an optimal 3D design, defined by geometric parameter values, within a given filter structure and initial design. The challenge lies in the highly multimodal nature of filter design landscapes, which contain numerous local optima and prove difficult for many optimization algorithms. Consequently, research on filter 3D design optimization concentrates on two key aspects: methods for obtaining a high-quality initial design (such as the coupling matrix method) and methods for optimizing from the initial design.

Recent years have seen the introduction of successful intelligent filter design optimization approaches. Space mapping methods utilize low-fidelity models, such as equivalent circuits, to reduce the need for computationally expensive high-fidelity electromagnetic simulations [13]. Cognition-driven optimization methods incorporate designers' intuition by first optimizing frequency features and then optimizing ripple heights. The homotopy method formulates a series of intermediate optimization problems from the initial design to the optimal design, proving effective when the initial design lacks high quality [2].

These methods leverage machine learning techniques to enhance speed. In comparison to off-the-shelf local optimizers, they achieve more efficient and higher-quality optimal filter designs. There exist significant opportunities for additional innovations and applications of ANNs in microwave modeling and design. These opportunities span from the development of advanced microwave-specific ANN structures and training algorithms to exploring novel applications. Future methods should focus on creating ANN models capable of handling broader input ranges and higher input dimensions while simultaneously requiring less extensive training data [14]. Given that the effectiveness of ANNs relies on the quality and appropriateness of the training data, and considering the typically high cost of data generation in microwave problems, ongoing progress in microwave-oriented ANN structures, data sampling, and training methods will continue to be crucial.

2.2 RF Filter design using ANNs

In filter design, the presence of numerous design parameters makes it challenging to discern which specific parameters should be adjusted based solely on observing suboptimal simulated transfer and reflection characteristics [5]. To address this issue, practitioners in filter design often turn to circuit models described by coupling matrices, particularly for high-performance narrowband filters. Analytical techniques exist for diagnosing the coupling matrix using either measured or simulated S-parameters. By determining the disparity between the realized coupling matrix and the design target-coupling matrix and establishing a direct correspondence between coupling matrix entries and the physical tuning elements, one can readily discern how to adjust the design parameters [8].

Furthermore, the optimization process typically requires an impractically lengthy duration to explore various combinations of design variables in full-wave electromagnetic (EM) simulations, particularly in instances where the dimension of optimization variables is high. To address this challenge, a surrogate model-based optimization [14], have been extensively employed in existing literature. In this context, the electromagnetic (EM)-based artificial neural network (ANN) is adopted as the surrogate model in this project. The key benefit of utilizing the ANN model lies in its capacity to be trained for comprehending intricate nonlinear relationships involving multiple inputs and outputs. Once the ANN is trained to accurately represent the input-output relationship, it can rapidly provide precise solutions to the learned problem [2].

Chapter 3

Methodology

3.1 ANN model

The training of a neural network involves utilizing a dataset to guide the adjustment of weights and biases. Typically, training data for passive components is derived from high-fidelity full-wave electromagnetic (EM) simulations. Once trained, the artificial neural network (ANN) model can substitute the computationally intensive EM model, offering a balance between circuit-level simulation speed and EM-level accuracy. The primary computational demand in ANN modeling is associated with generating training data through extensive EM simulations. However, this process can be expedited by leveraging parallel computation technology [2].

3.1.1 ANN Structure and Training

A neural network comprises numerous neurons and a corresponding network of connections linking them together. Varied neuron types or diverse configurations of neuron connections can give rise to distinct neural network structures.

Various types of artificial neural network (ANN) structures are selected based on the specific applications. For modeling uncomplicated relationships and when data generation is cost-effective, the Feedforward Neural Network (FFNN) stands out as the simplest and most efficient structure. The quality of neural network training and the accuracy of the trained model hinge on having a sufficient amount of training data [14].

In cases where data generation is computationally intensive, the Knowledge Based Neural Network (KBNN) is a more suitable choice. Its advantage lies in leveraging prior knowledge to reduce the required amount of training data while preserving modeling accuracy. For situations where an equivalent circuit or empirical model is impractical, and the input-output response exhibits highly nonlinear behavior with sharp ripples concerning frequency, the Neuro-Transfer Function (neuro-TF) can be applied. It can be trained with a smaller dataset compared to conventional ANN structures[14].

In scenarios where the model inputs have high dimensionality or a large amount of training data is available, deep neural networks (DNN) often prove to be superior choices. Particularly when the neural network outputs represent time-domain responses, especially those with memory effects, structures like Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), or Time-Delay Neural Networks (TDNN) become necessary[14].

3.1.2 Data Preprocessing

The artificial neural network (ANN) models take the geometrical dimensions and frequency variable of the filter as input. Given that the values of these geometric and physical frequency variables can vary significantly across orders of magnitude, there is a concern with sigmoid neurons experiencing saturation when presented with large inputs. Saturation occurs when the derivative of the sigmoid function approaches zero, impeding the learning process of the ANN model. To address this issue, all input variables undergo preprocessing. Suppose an input variable, x, falls within the range [xmin, xmax]. In that case, its values are linearly scaled to fit within the range of [-1, 1] using the following:

$$\overline{x} = 2\frac{x - x_{min}}{x_{max} - x_{min}} - 1 \tag{3.1}$$

[2]

The inverse mapping is used to retrieve the corresponding physical value, based on the optimized input value for the ANN model:

$$x = \frac{x_{max} - x_{min}}{2} - (\overline{x} + 1) + x_{min} \tag{3.2}$$

[2]

3.1.3 Parameter Initialization And Training

To ensure diverse derivatives and updates in the subsequent training process, the initial weights are randomly generated, making the neurons distinct components of the artificial neural network (ANN) model. Small numbers are used to initialize the weights, particularly to prevent saturation of sigmoid neurons. This is crucial because a higher number of connections to the neurons in the previous layer increases the likelihood of the weighted sum having a large absolute value [2].

3.1.4 High-Dimensional Filter Applications

In general, the volume of training data increases exponentially with the input dimension of the model. Developing a single artificial neural network (ANN) model for an entire filter with numerous geometric variables is impractical. To address this issue, a filter can be broken down into simpler building blocks. A low-dimensional ANN model is created for each block independently. Subsequently, the overall surrogate model of the filter is formed by integrating the ANN models of these smaller building blocks [2].

Once the model for the entire filter is constructed, and the values of the design variables are provided, the S-parameters of the filter can be rapidly computed. The electromagnetic-based ANN model proves to be a valuable tool in filter optimization. However, optimal solutions often lie within very narrow valleys in the landscape of design variables. Additionally, numerous local minima exist that fail to meet design specifications. The success of filter optimization through local search relies on having excellent initial values, which must be sufficiently close to the final solutions.

After choosing a compatible ANN mode depending on the design parameters, an optimization method should be considered as the next step.

3.2 Optimization Technique

Filter optimization techniques can generally be divided into 3 categories - supervised, unsupervised and semi-supervised.

The term "unsupervised" encompasses two key aspects:

1) It has the capability to meet stringent design specifications with a single button press, eliminating the need for designer interaction, and 2) It possesses a general applicability, not confined to specific filter structures. The advantages of unsupervised methods include: 1) Considerable savings in designers' time and cost as their efforts are translated into computing time without requiring interaction. This is particularly beneficial given the current widespread availability and reduced financial cost of computing resources. 2) As unsupervised design optimization is independent of designers' experience, it is well-suited for average engineers with limited design expertise [13]. While unsupervised design optimization has been successfully implemented for antennas, achieving the same for filters remains highly challenging due to their unique landscape characteristics.

When it comes to semi-supervised, local optimizers are employed, and in many cases, designers' interaction is still necessary to jump out of local optima.

An optimization technique must be chosen and adjusted according to the ANN so that it can:

- Take the geometrical or physical parameters as input and generate the EM responses as output.
- Find the geometrical or physical parameters from the given EM responses.

A homotopy optimization technique is designed to achieve the design goal. The cost function is written as:

$$K = max(db(S_{11})passband, -r) + w * max(db(S_{21})stopband, -40) \tag{3.3}$$

Series of homotopy optimizatios are carried out to minimize the cost functions defined by the parameters related to λ as

$$P = (1 - \lambda)P_{initial} + \lambda P_{target} \tag{3.4}$$

where λ = 0, 0.1, 0.2,...,1.

Chapter 4

Results and Discussions

Throughout the course of this project, extensive literature analysis was conducted alongside the simulation of two distinct waveguide filters: a five-pole direct-coupled rectangular waveguide filter, and a variation featuring one frequency-dependent coupling. The core of this methodology involved extracting relevant data sets from the S-parameters of these waveguide filters, subsequently employing advanced Artificial Neural Network (ANN) models for analysis. Notably, the project also encompassed a steep learning curve, introducing us to sophisticated simulation tools such as CST Studio and ANSYS HFSS for 3D electromagnetic simulation, alongside Keysight ADS and MATLAB for constructing ANN models.

To facilitate the training of the ANN models, firstly, filter underwent a decomposition into six manageable components. Using CST, an electromagnetic model was meticulously crafted, followed by simulation and extraction of S-parameters, which were then exported to a touchstone file. Preprocessing of this data was performed using equation 3.1, followed by its division into distinct training and validation sets. Subsequently, six distinct ANN models were trained employing the Levenberg–Marquardt Algorithm, configured with a 3-10-10-4 neuron architecture, chosen for its optimal performance demonstrated through minimal error rates. The process continued with the insertion of initial values, culminating in the plotting of S-parameter outputs post cascading of all six networks, utilizing consistent frequency values.

4.1 Five-Pole Direct-Coupled Filter

Figure 4.1 shows the structure of a five-pole direct-coupled rectangular waveguide filter which is symmetric about its center. H-plane irises realize an all-pole Chebyshev response. This type of structure is selected due to its ability to be deconstructed into six separate blocks, which can be used to develop six different ANN model building blocks using filter decomposition [2]. The ANN model ideally has

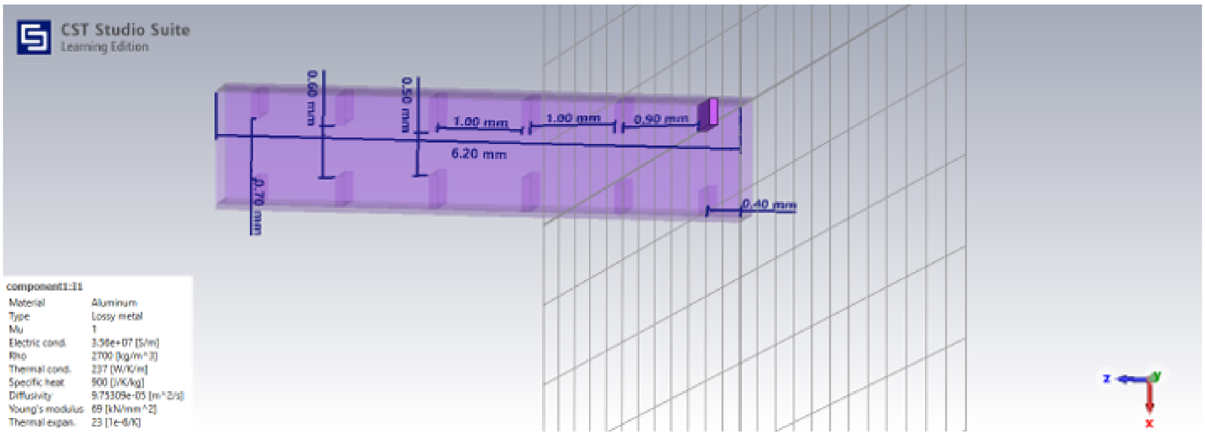


Figure 4.1: Five-pole rectangular waveguide filter. w is the width-distance between iris over the X-axis, L is the length

w, L and frequency as input and complex value S_{11} and S_{21} as output. As an example, the standard WR5 waveguide serves as a basis for designing filters within the frequency range of 140–220 GHz. The dimensions of the WR5 waveguide are a width of 1.2954 mm and a height of 0.6477 mm, with the thickness of the H-plane irises fixed at 0.1 mm. For generating training data for the ANN submodel of the fundamental building block, the design variable w ranges from 0.3 to 0.9 mm in increments of 0.1 mm, and the design variable L ranges from 0.2 to 0.8 mm with a step size of 0.1 mm. This range of design variables allows for the construction of filters operating across a broad range of frequencies [2].

To illustrate, we consider the target design passband for the five-pole filter, which spans 159.5–164.5 GHz. The required in-band return loss (RL) level is set at 22 dB. The initial design variables, determined solely to bring the poles close to each other, are w1 = 0.7 mm, w2 = 0.6 mm, w3 = 0.5 mm, L1 = 0.4 mm, L2 = 0.5 mm, and L3 = 0.5 mm.From looking at the S-parameters in Figure 4.2 the passband extends from 162 to 182 GHz, and the worst in-band RL level is a mere 1 dB. If a direct optimization of the six geometrical variables is attempted using their initial values, it would prove unsuccessful in finding any solution.

Therefore, an optimization method should be considered that can tackle this issue. After normalizing the data, building the ANN submodels is the next step. Zhao and Wu in [2] demonstrated successful design, using homotopy optimization with ANN surrogate model of the same WR5 waveguide

After the parametric simulation of the building block described above, architecture of the neural network was to be decided. Code was written in MATLAb. First, only one network was tested, by dividing the dataset of 49 thousand points into training and validation sets in the ratio of 70/30. Among one and two hidden layers, network was tested to receive the least error, and the least error among them

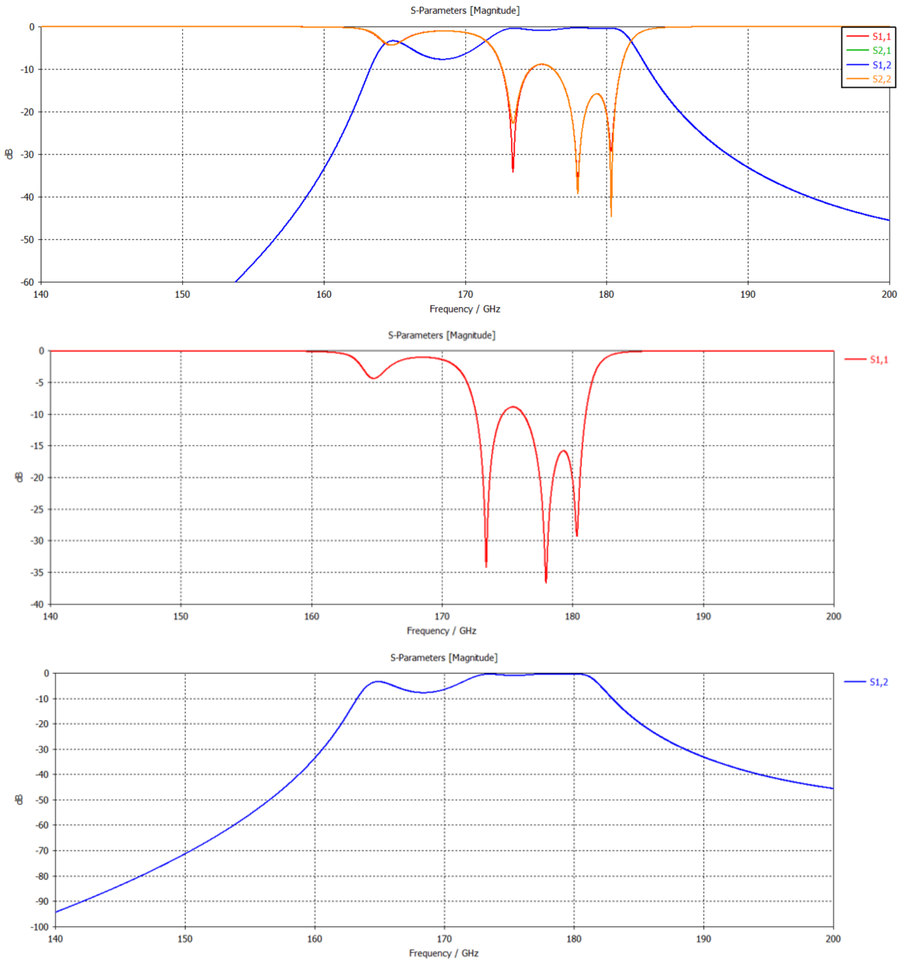


Figure 4.2: S-parameters of the filter in Figure 4.1

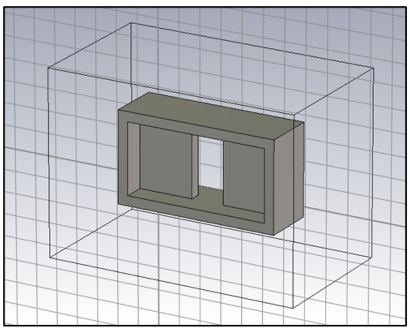
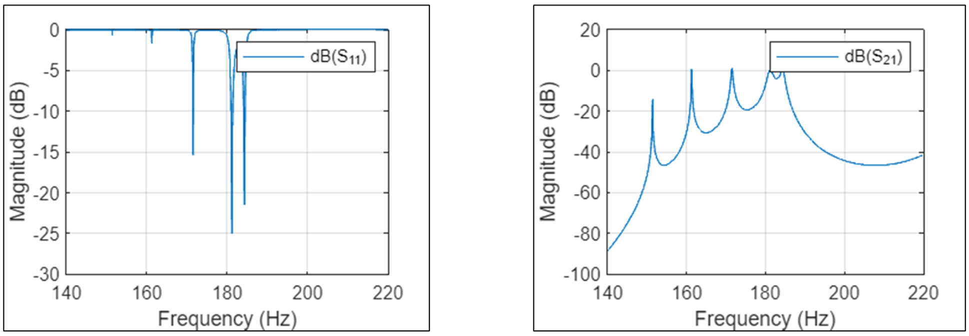


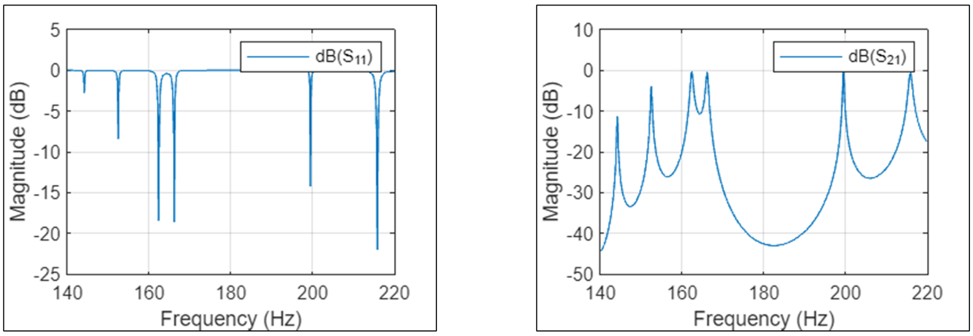
Figure 4.3: Filter decomposition - building block

was received with 3-10-10-4 model, which had an average error of 2.5e-3. However, in the future, the number of hidden layers could be increased to get a more



(a) db S_{11} **(b)** db S_{21}

Figure 4.4: S-parameters of the filter with initial variables – ANN model



(a) db S_{11} **(b)** db S_{21}

Figure 4.5: S-parameters of the filter with optimized variables – ANN model

accurate model. In literature [2] the error was reduced to 4.2e-6. After minimizing the error, five other networks were trained.Then, the S-parameters were cascades in MATLAB to get the combined result.

Finally, the S-parameters from the network were extracted, using the initial parameters and final parameters which were calculated after homotopy optimization.

It can be seen from the figures above that unfortunately the target design parameters were not achieved. The S-parameters do not show the desired response. This may be due to low number of training datasets, different materials and environment used in the simulation software, and different architecture of ANN. We can observe that this method could yield meaningful results and with more fine-tuning, the target design parameters can be achieved.

4.2 Five-Pole Filter With One Frequency-Dependent Coupling

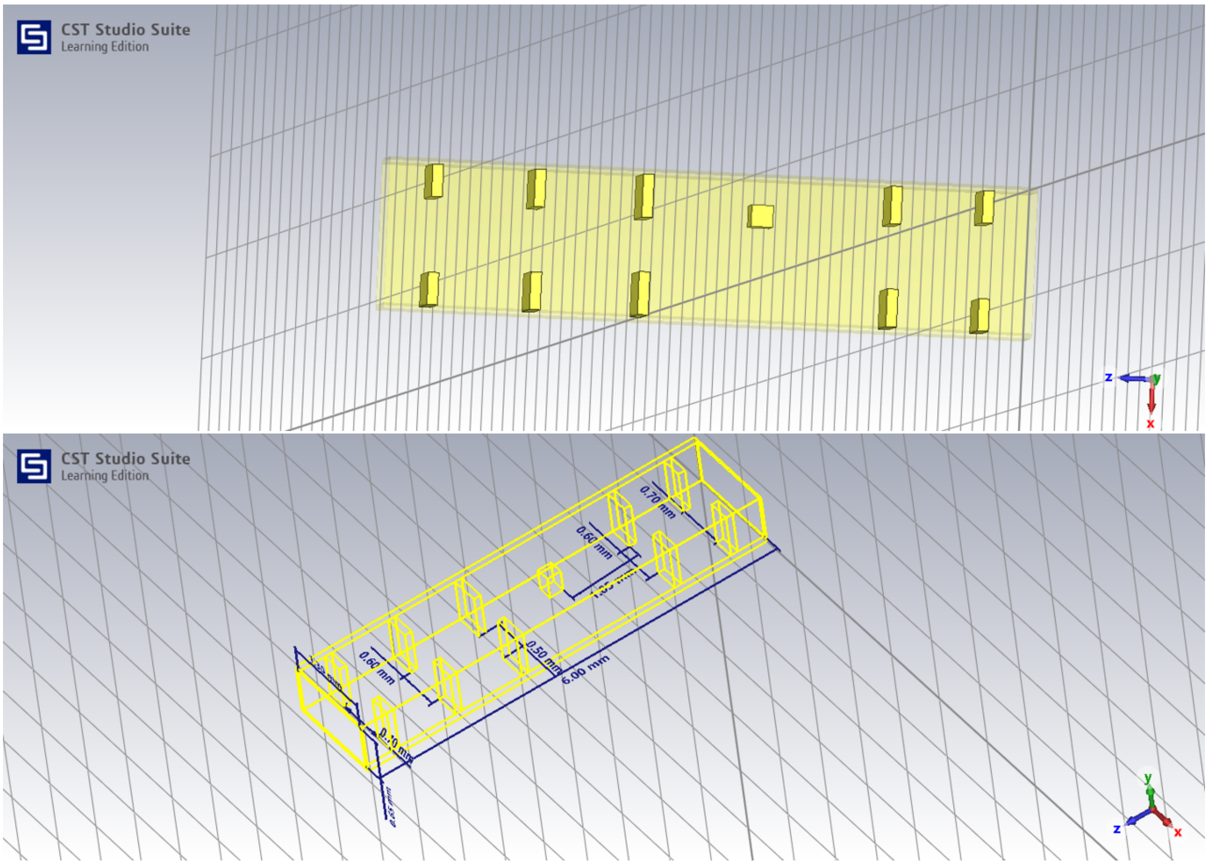


Figure 4.6: Five-pole rectangular waveguide filter. w is the width-distance between iris over the X-axis, L is the length, s is the length of the square shaped post, d is the distance to the side wall while h is the height of the post

The incorporation of inline frequency-dependent coupling (FDC) is a straightforward method to introduce a single transmission zero (TZ) on the imaginary axis, enhancing the near-skirt selectivity of a filter. In the context of waveguide filters, a partial-height metal post can serve as an FDC . As a second example, the design of a five-pole bandpass filter with one FDC generating a TZ on the upper side of the passband is presented. The filter structure is depicted in Figure 4.6, and, like the previous example, it is designed using WR5 waveguide. Similar to the earlier case, this filter is deconstructed into six building blocks. Five of these blocks consist of inductive irises, whose ANN model was developed in the preceding example. The partial-height metal post has a length s of 0.2 mm, and the lengths of connecting waveguides at both ends are fixed at L0 = 0.5 mm.

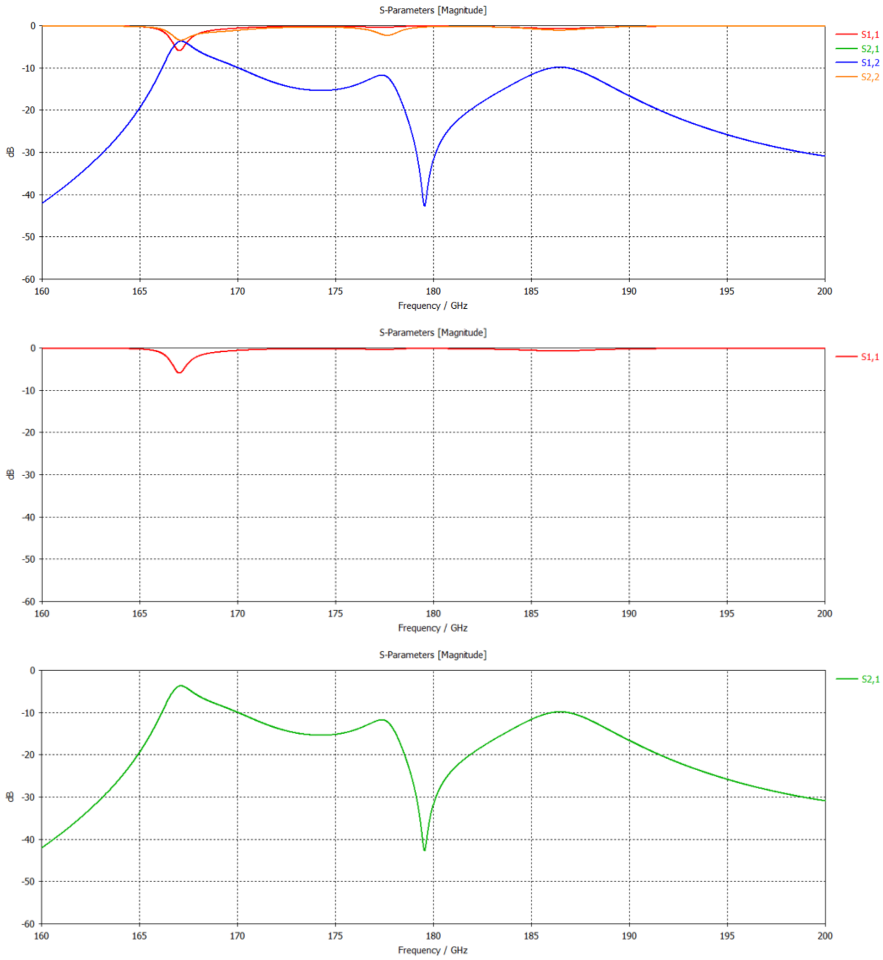


Figure 4.7: S-parameters of the filter in Figure 4.6

Optimization of filter of the FDC is more challenging, when compared to the previous example, because of its asymmetrical structure, there are 12 design variables that need optimization, encompassing five iris widths, five connecting waveguide lengths, and the parameters d and h for the partial-height post. The intended filter passband spans 176–187 GHz, and it features a single transmission zero on the upper side of the passband. After looking at the related literature [2], regarding this, the initial parameter values are set as follows: w1 = 0.7 mm, w2 = 0.6 mm, w3 = 0.5 mm, w4 = 0.6 mm, w5 = 0.7 mm, L1 = 0.4 mm, L2 = 0.45 mm, L3 = 0.45 mm, L4 = 0.45 mm, L5 = 0.4 mm, d = 0.22 mm, and h = 0.32 mm. The S-parameters of the filter is shown in Figure 4.7, from which we can see that initial parameters are poor, which will not converge in case of direct optimization.

Again, Zhao and Wu were able to develop a good-performing filter using the homotopy optimization method, however, it is believed that more effective mehods should be researched and considered for this type of design process, which will be a part of our future tasks.

Chapter 5

Conclusion

Development of innovative tools in the sphere of Microwave and millimeter-wave design is a cruicial task, which has an immense potential for growth. This project intends to develop on prior knowledge pertaining to using ANN models in pair with a robust optimization technique, which has been an emerging concept in the field of RF Filter design, over the last couple of years. At the completion of Capstone II, an extensive literature review, investigation of the methodology, learning and gaining a toolbox for these kind of tasks, along with the development of two waveguides in simulation environment were reported. From the building blocks of one of the waveguides, six different ANN models were trained, optimized and shown to be giving results, however, it needs more fine tuning. After getting less error in ANN, the model in combination with homotopy optimization can be a solid alternative to current design techniques.
This report provided with background information and state-of-the-art related works, and the importance along with the place of this methodology in RF design. There has been works shown in this paper that proved that using initial design values, fine-tuning filter design parameters can be achieved with the current technique and which areas can still be developed. The two main problems faced by RF filter designers can be solved using those steps.

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