Computationally Efficient Surrogate Modeling Applied to Transmission Lines

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Abstract: In this paper, we present a methodology that allows the efficient automatic generation of surrogate models for arbitrary transmission lines. The technique is based upon a transmission line model that is used to map the electromagnetic simulation results on to equivalent circuit parameters (ECPs). Sampling techniques are then employed on the ECPs rather than the S-parameters, contributing to a simplified model structure and reduced training data samples. The technique is demonstrated through the generation and testing of a transmission line on a conductive silicon substrate. Only 18 training data points were required to create the model, which is shown to be accurate over a large range of widths, oxide thickness, and lengths. The model formulation allows extrapolation and we show that our model is capable of accurately predicting the S-parameters at frequencies over two times greater than the highest frequency in the training data.

keywords: Surrogate modeling, transmission lines, electromagnetic simulation, automatic model generation

1. Introduction

In the past decade there has been tremendous research directed towards automatic model generation techniques as the time taken to generate models still remains a major bottleneck for CAD-based design processes. For a semiconductor device manufacturer this is especially prominent as many changes to the substrates are made while optimizing the performance of the transistor and passive matching components. Models are necessary to understand the effects of the technology optimization on the multi-stage power-amplifier performance, and repeated extraction is often required for all of the planar components witin the MMIC including: transmission lines, spiral inductors, capacitors, interconnects, discontinuities, as illustrated in Fig. 1.

There exists a large variety of extraction techniques and compact models that can be used for microwave circuit design. Many of these models are physics-based analytical expressions and have inherent limiting assumptions about the device physics. Measurement-based models are also frequently employed but they require significant characterization time, which also cannot be performed until structures have been built. Thus, an established trend is to create models based on electromagnetic simulation (EM) results [1]. From the simulation of a parameterized circuit geometry, the generation of efficient and accurate models suitable for the implementation within standard

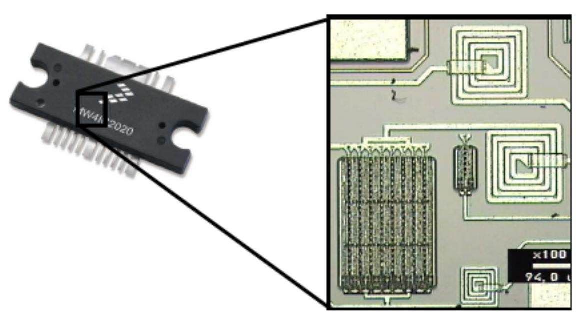


Figure 1. A photograph of an RFIC with a zoomed view of the internal transistor and matching circuits.

circuit-based simulation packages has been demonstrated with several commercially available software packages [2]–[4]. The goal of an EM-based model is to provide the same level of accuracy as an electromagnetic simulator but be as computationally efficient as lumped-element models implemented within a circuit-based simulator [1].

While generating models automatically from electromagnetic simulations is very attractive, there are two key issues that have to be addressed. First, the computational cost associated with repeatedly performing electromagnetic simulations is high. Second, a function approximation method must be selected that not only accurately approximates the simulation data but does so in a manner which minimizes the amount of required data. The function approximation methods can range from data-based look-up tables with interpolation, polynomial curve fits, complex rational function approximation schemes [5], and artificial neural networks [1].

In this paper we leverage a novel form of space-mapping knowledge-based artificial neural networks (ANNs), and a physical-based model to develop a generalized model of a transmission line. We demonstrate a significant reduction in the number of electromagnetic simulations required over that by conventional approaches. This technique also permits accurate extrapolation far outside of the training region. In the Sections that follow we shall present the background formulation of the transmission line model using the space-mapping concept and demonstrate its applicability, efficiency, and extrapolation capabilities for a transmission line on a semiconductor substrate.

2. Background

Researchers have long used equivalent circuits to transform the terminal-parameters (Z/Y/S-parameters) into equivalent circuit parameters (ECPs) [6], [7], noting that the ECPs were smoother functions of the input variables than were the terminal parameters. The transformation from terminal-parameters to ECPs can be viewed as a mapping from one space to another. By mapping, it is meant that a function is used to modify the domain of one function to that of another. The purpose of the mapping is to modify the existing domain so that the problem in the new domain becomes easier to solve. The value of space-mapping is well documented for optimizing complex electromagnetic structures and modeling microwave circuits and systems [8], [9].

To concisely summarize, the operation of space mapping can be explained by considering two models, a coarse model and a fine model [8]. As an example, the coarse model could be an equivalent-circuit and the fine model could be the output of an electromagnetic simulator. Let $f(x)$ represent the fine model response and let $R_c(x_c)$ represent the coarse model response. The objective of space-mapping is to find a mapping M from the fine model input-space x to the coarse model space x_c

$$x_c = M(x) \tag{1}$$

such that,

$$R_c(M(x)) \approx f(x) \tag{2}$$

The mapping of the fine to coarse input space can be accomplished through standard function approximation. Once the mapping has been found, the coarse model can be used in combination with the mapping to provide results with comparable accuracy to that of the electromagnetic simulator used to generate the fine model space. While using the space-mapped model during an optimization process the algorithm controlling the EM simulator operates through the established mapping. A dramatic reduction in the number of iterations occurs as compared to a gradient-based optimization performed directly on the fine-model response [8].

Building on the concept and nomenclature of space-mapping, we propose the following method using inverse coarse models as outlined in Fig. 2. The fine model response $R_f(x_f)$ is operated on by the inverse coarse model R_c^{-1}. It is desired to find a mapping such that,

$$M(x_f) \approx R_c^{-1}(R_f(x_f)) \tag{3}$$

then the response of the fine model can be expressed as,

$$R_f(x_f) \approx R_c(M(x_f)) \tag{4}$$

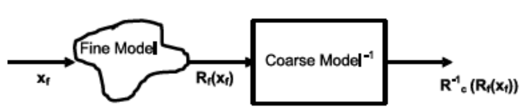


Figure 2. A flow-chart illustrating how the results of the EM simulation are mapped through the inverse coarse model to equivalent circuit parameters.

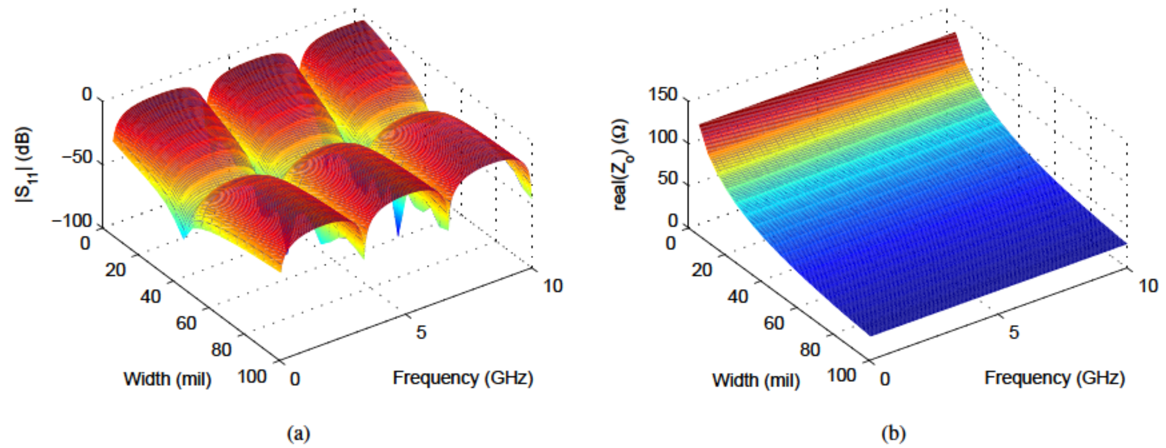


Figure 3. Simulated magnitude of S_{11} and the real part of Z_o vs. frequency and line width

Mathematically, we are using the physics contained within the mapping, or knowledge, to transform the circuit response.

Ideally, the mapping R_c^{-1} should be a one-to-one mapping, perform a transformation into a space with reduced complexity, and have favorable error performance. That is, when small errors in the function approximation occur, the map should be selected such that these errors are minimized during the inverse mapping. The ideal map is one that provides all of these benefits and is the simplest to implement. Once the transformation from terminal-parameters to equivalent-circuit parameters is viewed as a mapping, it becomes possible to compare different circuits, or maps, and determine which one is the best suited to approximate a function. The implicit assumption is that the smoother a function becomes the less samples are required to approximate it [10].

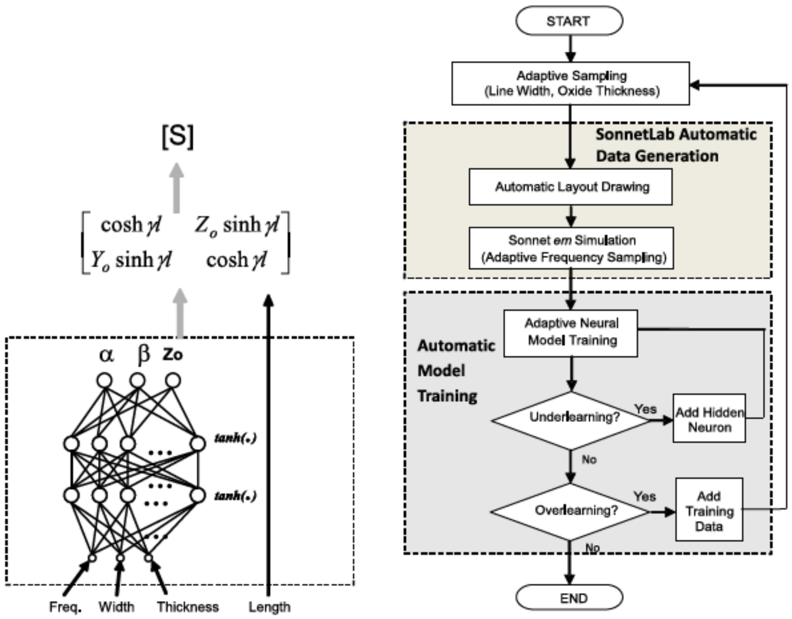
Minimizing the number of samples is essential since the sample points are generated through the use of a time-consuming electromagnetic simulator. The transformation of the output space through a set of equations, or mappings, can be very advantageous if the resulting functional-behavior is more linear in the transformed space. In the general case, determining a set of equations to perform this transformation can be very difficult, unless some prior knowledge about the system is assumed. In the case of planar microwave circuit elements, the prior knowledge takes the form of existing equivalent circuits. So it is possible to transform the S-parameters which are a function of the geometry and frequency to equivalent-circuit parameters. If the correct equivalent circuit is selected, the resulting function in ECP-space will be much more linear than the original function. Function approximation is then performed in ECP-space and the S-parameters can be regenerated.

To demonstrate this we consider the behaviour of a transmission line over frequency for a range of line widths. In Fig. 3(a) we have simulated a 1 inch long transmission line, on a 20 mil thick R04350 substrate for widths varying from 5 to 100 mil. Although not evident in the surface plots the frequency of the nulls and the peaks vary with changing widths. Using the inverse coarse model, we transform the S-parameters via the ABCD model of a transmission line into the characteristic impedance, Z_o and the propagation constant γ. In Fig. 3(b) the real part of the characteristic impedance is plotted and it is significantly smoother than the S-parameters. In addition the ABCD-representation of the transmission line removes length as an explicit input to the model thus collapsing the number of dimensions that need to be sampled in the model generation process.

3. General Transmission Line Model Development

Within this subsection, the generalized framework for a transmission line model is presented and it is applied to a transmission line constructed on top of an oxide of varying thickness, grown on $75\mu m$ conductive silicon substrate. We continue with the development of the transmission line model based on the $ABCD$-parameters, where the characteristic impedance, Z_o, and propagation constant, γ, specify its performance. The equivalent circuit parameters can be directly extracted, i.e. no optimization, from the simulated S-parameters using the $ABCD$ parameters of a transmission line. The characteristic impedance is directly extracted using,

$$Zo = \sqrt{\frac{B}{C}} \tag{5}$$



(a) (b)

Figure 4. A diagram of the transmission line model (a) and the model development flow-chart in (b)

and the complex propagation constant is extracted using,

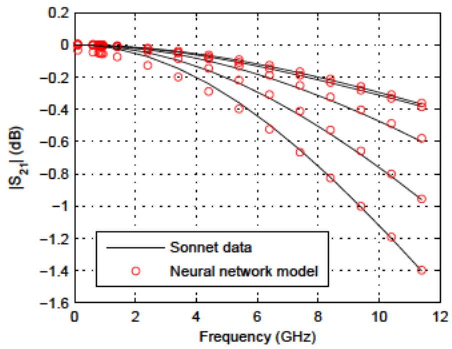
$$\gamma = \frac{\cosh^{-1}(A)}{l} = \alpha + j\beta \tag{6}$$

where A, B and C are from the $ABCD$-matrix and l is the length of the transmission line.

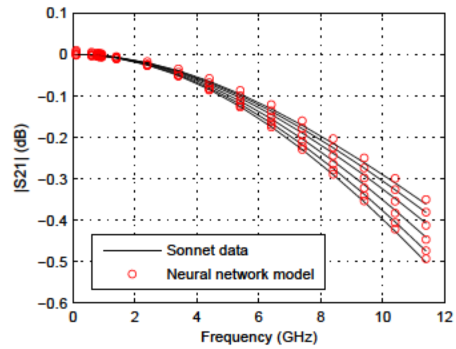
A diagram representing the transmission line model is shown in Fig. 4(a) [11]. Artificial neural networks are used to approximate the characteristic impedance and the propagation constant as a function of the frequency, width of the line and oxide thickness. The outputs of the neural network and the line length are then assembled into the $ABCD$ matrix and converted to S-parameters.

To minimize interactive trial-and-error efforts in model development, we adapted an automatic model generation flow [12]. A university developed neural network based modeling tool, NeuroAMG [2], is used to interface with SonnetLab for automatic modeling. SonnetLab is a MATLAB toolbox that enables scripting the layout drawing and control of Sonnet's 3D planar electromagnetic simulator. We developed the drawing script for a transmission line over a specified substrate in SonnetLab, with the length and width of the line and the oxide thickness as input parameters. This script is then fed into NeuroAMG, where the inputs are adaptively sampled within a given input range. NeuroAMG then drives the Sonnet EM simulator to generate EM data at the sampled geometries, and start training neural network to capture the data behavior. Such modeling process from data sampling, layout drawing, EM simulation, and model training are fully automated, and only the initial setup of input range, desired model accuracy, and sampling algorithm is needed at the beginning of the model development. Adaptive sampling also allows accurate model development with the minimum number of training samples and simplest neural network structure possible. The automatic model generation flow is illustrated in Fig. 4(b).

The neural network is built upon the physics-based structure as shown in Fig. 4(a), where the line width, oxide thickness, and frequency are considered inputs to the neural network. The range of the line width is 5–80μm, the oxide thickness is 0.25–2μm, and the frequency range is from 50 MHz to 12 GHz. The outputs of the neural network are the real and imaginary parts of the characteristic impedance Z_o, and the complex propagation constant γ. We request the automatic model generation to reach the raining error of 1%. The adaptive sampling used 18 training samples, i.e., 18 EM simulations of different transmission lines in Sonnet, and the resulting neural network is a simple 3-layer MLP with 8 hidden neurons. The overall model development time, including EM data generation and adaptive model training is 45 minutes. To verify our model accuracy, we picked a different geometry not included in our training and generated S-parameter data from EM simulation. This set of test data are then compared with the S-parameters predicted by the neural model. The comparison result for a line with length of 500μm, oxide



(a)



(b)

Figure 5. A comparison of the magnitude the reflection coefficient for varying line widths (a) and for varying oxide thickness (b).

Table I

COMPARISON BETWEEN CONVENTIONAL AND PHYSICS-BASED MODELING TECHNIQUES FOR TRANSMISSION LINE MODELING

	Automatic Model Generation				Final Neural Model Structure	Valid Physical Range of Model Usage		
	No. of Training Samples	No. of Validation Samples	Overall Modeling Time (hours)	Training/ Validation Error (%)		Length (um)	Width (um)	Oxide thickness (um)
Physics-Based Modeling Approach	18	14	0.75	0.84/0.92	3-8-4	Any physical length	5~80	0.25~2
Conventional Modeling Approach	52	106	8.388	0.96/0.99	4-16-4	100~1500	5~80	0.25~2

thickness of $1.86\mu m$, and different width from 10–$90\mu m$ is shown in Fig. 5, and very good agreement between the Sonnet data and model solution is observed. Note that in Fig. 5, we used a width of 90 μm, which is outside of the training range. Also shown is the comparison of results in Fig. 5(b) where the oxide thickness was varied between $0.3\mu m$ and $2\mu m$. Again the model matches with EM data very well.

4. Analysis of results

To further demonstrate the efficiency of the physics-based inverse mapping approach, another model is developed through conventional modeling approach where the line length, line width, oxide thickness, and frequency are model inputs, and S-parameters are model outputs. Compared to the physics-based model, the conventional model has one extra input which is the line length. The number of the outputs of the conventional model remains the same as that of the physics-based model. But instead of being real and imaginary parts of Z_o and γ, the outputs are defined as real and imaginary parts of S_{11} and S_{12} which are more complicated in as compared to with the smooth Z_o and γ as shown in Fig. 3(b).

Table I shows efficiency comparison between the conventional and the physics-based modeling approaches. Both conventionally developed model and the physics-based model are developed through automatic model generation by NeuroAMG. It is demonstrated that the physics-based modeling approach is more accurate, requires much less data samples, and uses much shorter modeling time. The final neural model structure of the physics-based model is more compact than the neural model obtained from conventional method. The physics-based model is more general than the conventional model and is valid for any given line length due to its embedded physics formulation. Due the knowledge embedded within the model, it has the ability to extrapolate well outside of its training region. We demonstrate this by using the model to predict S-parameters up to 40 GHz, although only trained up to 12 GHz. All of the S-parameters agree well past 25 GHz, over twice the highest frequency used in the training data, as shown in Figs. 6(a) and 6(b).

5. Conclusions

We have demonstrated a general modeling methodology applicable to transmission lines that enables very efficient generation of compact neural network models. The transmission line model we developed only contained 8 hidden neurons and was completed in less than 45 minutes of simulation. The model was shown to extrapolate well over two times the frequency range of data upon which it was trained.

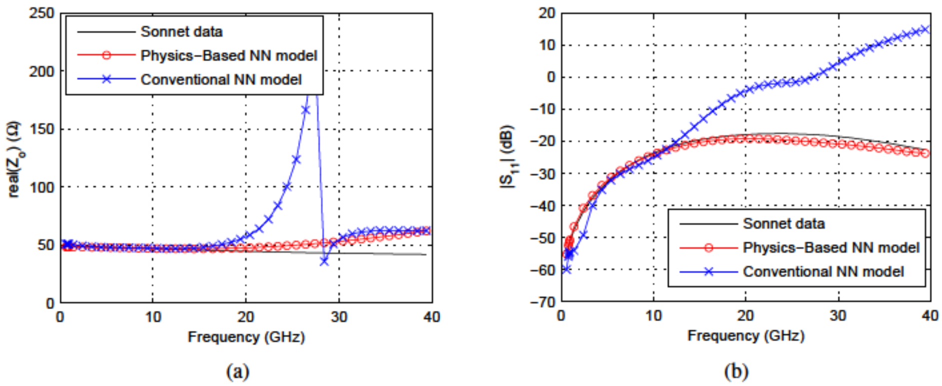


Figure 6. Plots of the characteristic impedance (a) and the magnitude of the reflection coefficient (b) showing the good agreement between the neural network model and EM simulations. The extrapolation capabilities of the model are demonstrated as it was based on simulation data up to 12 GHz

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