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FACULTÉ DES ÉTUDES SUPÉRIEURES
ET POSTDOCTORALES

FACULTY OF GRADUATE AND
POSTDOCTORAL STUDIES

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GRADE - DEGREE

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FACULTÉ, ÉCOLE, DÉPARTEMENT - FACULTY, SCHOOL, DEPARTMENT

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EM-BASED MODELING OF PASSIVES FOR RF/MICROWAVE INTEGRATED CIRCUITS

Prasun Sharma, B. Eng.,

A thesis submitted to the Faculty of Graduate and Postdoctoral Studies in partial
fulfillment of the requirements for the degree of Master of Applied Science,
Electrical Engineering

July 2004

Ottawa-Carleton Institute for Electrical and Computer Engineering
School of Information Technology and Engineering (SITE)
University of Ottawa, Ottawa, Ontario, Canada

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ABSTRACT

The 21st century will be the information age characterized by an ever-increasing need for advanced communication systems. To reach such target, the demand for more complexity and higher performance leads to new generations of fast and accurate passive models. This thesis addresses an important aspect of high-frequency Computer Aided Design (CAD), i.e., the modeling of passive devices and interconnects in the RF/microwave frequency range where high-order electromagnetic (EM) effects are quite significant.

The main objective of this thesis is the EM circuit optimization and design based on neural models. To achieve this goal efficiently, different external codes for automated data generation for neural model training of passive components and interconnects has been developed. A CAD tool for circuit topology optimization using neural models of interconnects and passives have been also introduced. It allows automatic adjustment of component and connection geometry and then provides fast estimation of overall circuit performance.

A technique for including mutual coupling effects between passives in circuit design has also been proposed. It allows the usage of individual neural models in a circuit level design and optimization, providing fast estimation of the EM effects with respect to the different connecting positions.

ACKNOWLEDGMENTS

Many thanks to Dr. Mustapha Yagoub for giving me inspiration and instruction when I was writing this thesis. I really appreciate his help, advice and guide. During these years I have known Dr. Yagoub as a sympathetic and principle-centered person. His overly enthusiasm and integral view on research and his mission for providing 'only high-quality work and not less', has made a deep impression on me. I owe him lots of gratitude for having me shown this way of research. He could not even realize how much I have learned from him. Besides of being an excellent supervisor, Dr. Yagoub was as close as a relative and a good friend to me. I am really glad that I have come to get know Dr. Yagoub in my life. I give a sincere gratitude to the people who do science with pure and honest passion, as they are the people who made me grow and appreciate the world in the way I see.

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GLOSSARY

f	Frequency
∇	Gradient operator
E	Electric field intensity (V/m)
D	Electric flux density (C/m ²)
H	Magnetic field intensity (A/m)
B	Magnetic flux density (T)
J	Current density per unit area
σ	Conductivity
ϵ	Electrical permittivity (F/m)
μ	Magnetic permeability (H/m)

ACRONYMS

CAD	Computer-aided design
MCM	Multichip Modules
RF	Radio Frequency
EM	Electromagnetic
S	Scattering
CPU	Central Processing Unit
CPW	Coplanar waveguide
FET	Field Effect Transistor
HBT	Heterojunction Bipolar Transistor
HEMT	High electron-mobility transistor
CPW	Coplanar waveguide
VLSI	Very Large Scale Integration
DE	Differential Equation
IE	Integral Equation
FEM	Finite Element Methods
FEEC	Finite element equivalent circuits
MoM	Method of Moments
ASITIC	Analysis and Simulation of Spiral Inductors and Transformers for Ics
PEEC	Partial Element Equivalent Circuit

HFSS	High-frequency Structure Simulator
ANN	Artificial Neural Networks
MLP	Multi Layer Perceptrons
RBF	Radial-basis-function
KBNN	Knowledge-based neural networks
CAP	Circuit Analysis Program
PBM	Physics-based models
TL	Transmission lines
ADS	Agilent Design Systems

CHAPTER I

INTRODUCTION

1.1 Background and Motivations

The 21st century will be the information age characterized by an ever-increasing need for communication. There are several constraints on the nature of the communicating terminal,

- (i) it must be wireless and portable,
- (ii) should include several advanced and complex functions,
- (iii) be able to work properly under severe conditions,
- (iv) cost-effective production in large numbers must be possible, and
- (v) the communication device must be suitable for broadband operation.

To reach such targets, the needs for concurrent and multi-disciplinary design with simultaneous consideration of electrical and reliability criteria becomes increasingly important. This trend leads to massive and highly repetitive computational tasks during simulation, optimization and statistical design [1]-[4].

Furthermore, the need for statistical analysis and yield optimization, taking into account process variations and manufacturing tolerances in the components, requires that the component models be not only fast but also accurate so that the design solutions can be achieved accurately and reliably. In fact, the demand for more complexity and higher performance leads to new generations of passive models where first-order approximations and/or semi-empirical equations are no longer sufficient to achieve proper design [1]-[4]. In the past, it was common for engineers to build prototypes to verify their design expectations. Today, with increasing costs, shrinking design margins, and expanding system complexities, engineers prefer to avoid prototyping and expect simulation to yield the same information. However, difficulties in modeling have limited the use of Computer Aided Design (CAD) techniques at high frequencies. It is for this reason several approaches to device modeling are being continuously proposed in technical literature, especially for a large class of components, namely passive elements, which are widely used in RF/microwave integrated circuits such as multichip modules (MCM) [5]-[10].

This thesis addresses an important aspect of high-frequency CAD, i.e., modeling of passive devices in MCMs in both the radio frequency (RF) and microwave ranges where high-order electromagnetic (EM) effects are quite significant. RF/microwave passive components are subject to intensive research for efficient modeling and design. Usual simulation approaches for passives can be grouped into three main classes. The first represents a passive component by an equivalent electrical circuit. There are many drawbacks from using such models: they have a relatively narrow frequency bandwidth, and methods for extracting circuit parameters can still be perfectible, strongly dependent on the device geometry, and relatively complex to determine [11] - [22].

Similarly, table look-up models can be also relatively fast, but suffer from the disadvantages of large memory requirements and limits on the number of parameters [5]. The third approach attempts to quantify the electromagnetic field in a given structure by using an integro-differential form of Maxwell's equations and/or physics-based equations. Such EM numerical methods, e.g., finite elements, finite difference or variational techniques, have demonstrated their effectiveness in terms of accuracy, but still require a huge computing time and memory space [23] - [31]. As such, development of full nonlinear EM representations of circuit components becomes an important task both in time and frequency domains. Furthermore, to enable efficient optimization of circuit parameters, the model outputs must be continuously varied both with frequency and geometrical and/or electrical parameters. So modeling techniques that can provide such continuous variations are essential while almost all-existing passive models are "frozen" once implemented in commercial circuit simulators. In other words, the set of S-parameters that characterize any passive device are valid *only* for a given combination of physical/geometrical parameters. Thus, in order to avoid the unrealistic "return loop" shown in Figure I-1, a designer has only two alternatives when an optimization process is required. First, one can optimize the S-parameters and then synthesize the structure (deduce the new topology based on optimized S-parameters). This is not realistic. Therefore, the alternative is to provide the model of the passive structure with a huge S-parameters data file based on large combinations of electrical/physical/geometrical parameters.

This option implies a huge cost human-time work hours (repetitive geometry changes), and could generate human errors in building such data file. The development of an automatic data generation code for model training would be the first step of the present work.

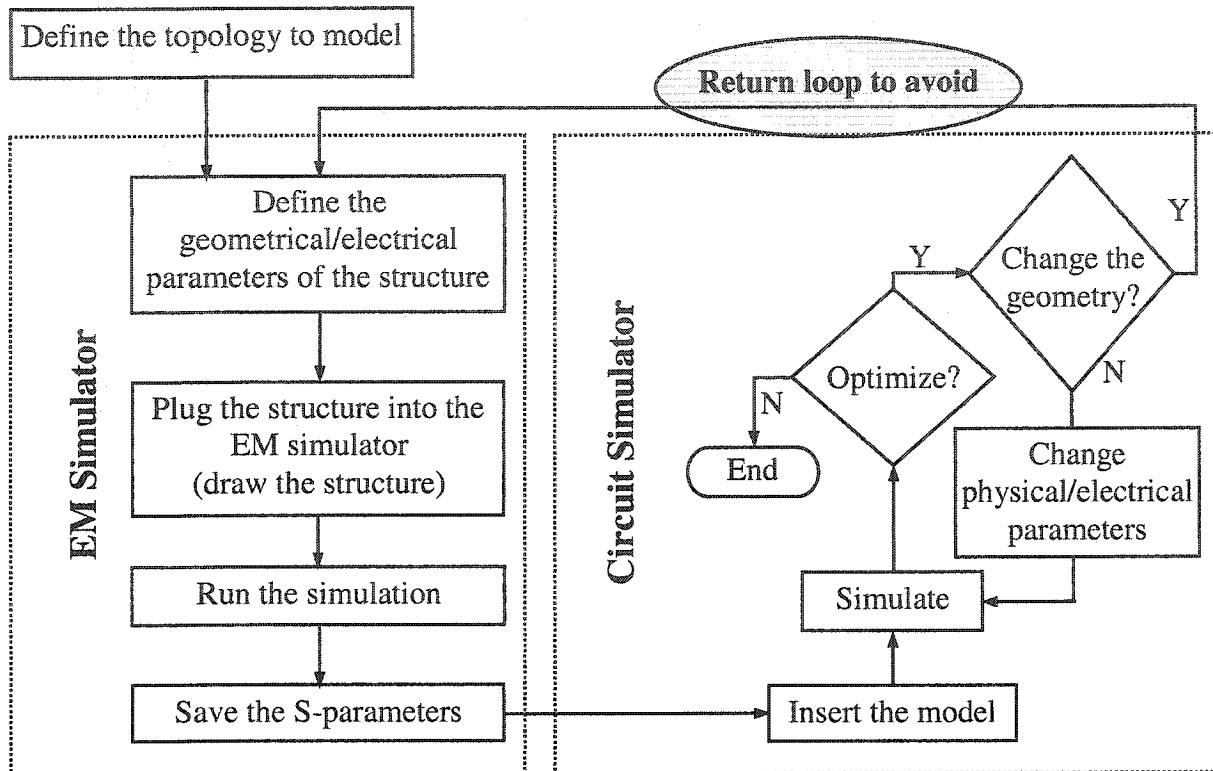


Figure I-1. Algorithm of the classical optimization procedure for a passive component. In practice, only optimization of physical/electrical parameters is possible in circuit simulator.

By varying the geometrical dimensions of passive components or interconnects directly in a circuit simulator a fast optimization of the circuit performance could be efficiently achieved as reported in [16], [19], [32], and [33]. How to apply this concept to the optimization of a circuit layout would be *the first contribution* of the present work.

In addition to the above difficulties, existing models suffer on a quite important lack at circuit level. In fact, even if such EM models are accurate, they are developed one by one, i.e., isolated from the others in terms of mutual-device coupling and interconnect effects. How to include these mutual-device coupling effects would be *the second contribution* to the present work.

However, computing the mutual-device couplings will require the manipulation of the S matrices of all individual components present in the circuit layout. A code that helps to compute the overall S matrix of a general circuit would be developed.

In the recent years, a CAD approach based on neural networks has been introduced for circuit modeling, simulation, and optimization [32] - [57]. Fast, accurate, and reliable neural models can be trained from measured or simulated data. Once developed, these neural models can be used in place of computationally intensive device models to speed up circuit/system design. Neural models are much faster than original detailed physical/EM models [36], and more accurate than polynomial and empirical models [41], allow more dimensions than table lookup models [22], and are easier to develop when a new device/technology is introduced [32]. Once developed, these neural network models can be used in place of computationally intensive physical/EM models of active and passive components [32] [33] [36] to speed up microwave circuit design.

Recent work by microwave researchers demonstrated the ability of neural networks to accurately model a variety of microwave components, such as microstrip interconnects [37] [42] [51], vias [43], spiral inductors [45], FET devices [44], HBT devices [45], HEMT devices [46], filters [47], amplifiers [48], coplanar waveguide (CPW) circuit components [49], mixers [48], antennas [50], embedded resistors [33], packaging and interconnects [37] [43] [51], etc. Neural networks have also been used in circuit simulation and optimization [51], signal integrity analysis and optimization of VLSI interconnects [51] [53], microstrip circuit design [54], process design [55], synthesis [56], and microwave impedance matching [57].

These pioneering works have established the framework of neural modeling technique in both device and circuit level of microwave applications. To efficiently overcome this challenge and address the difficulties encountered in device modeling and circuit modeling, are the strong motivations for this thesis work.

1.2 Thesis Overview

In chapter 2 we give an overview of different EM modeling approaches. We start with differential equation-based methods and cover integral equation-based method. We also cover in brief various CAD tools using these methods and select the ones we will use. In chapter 3 we discuss our approach for modeling the integrated passive components using neural networks. Some software codes will be discussed and our approach will be described in detail. Chapter 4 discusses the results and finally Chapter 5 presents future work based on current work.

1.3 Publications

- M.C.E. Yagoub, P. Sharma, "Characterization of EM effects in RF/microwave integrated circuits," *IEEE Trans. Microwave Theory Tech.*, to be submitted as extended paper of the *34th European Microwave Conf.*.
- M.C.E. Yagoub, P. Sharma, "Characterization of EM effects in RF/microwave integrated circuits," *34th European Microwave Conf.*, Oct. 12-14, 2004, Amsterdam, Netherlands.
- M.C.E. Yagoub, P. Sharma, "Optimization of RF/Microwave multichip module performance based on neural models of passives and interconnects," *54rd Electronic*

Components and Technology Conf., Las Vegas, Nevada, June 1-4, 2004.

- M.C.E. Yagoub, P. Sharma, "Caractérisation des effets de couplage dans les circuits intégrés micro-ondes," *Canadian Conf. on Electrical and Computer Engineering*, Niagara Falls, Ontario, Canada, May 2-5, 2004.
- M.C.E. Yagoub, P. Sharma, M. Abdeen, S. Gaoua, "Génération de modèles efficaces pour une détermination optimale des performances de circuits et systèmes micro-ondes non linéaires," *2nd Conf. Int. sur le génie Électrique (CGE'02)*, Algiers, Algeria, Dec. 17-18, 2002, pp. 601-606.

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CHAPTER II

EM TECHNIQUES FOR PASSIVE DEVICE MODELING

The key word in this work is *modeling*. This term is used to describe the development of methodologies and associated tools for the modeling of passive element problems at various levels of complexity. Two objectives, namely, *performance prediction* and *design optimization* are also challenging and of instrumental importance to the ultimate objective of computer modeling. The first concerns the methodologies and associated tools used for the prediction of the response of the model to a specific excitation. Model complexity translates directly to analysis complexity. Consequently, a variety of approaches have been devised to affect analysis of acceptable engineering accuracy at the level of sophistication required by the model. The second objective is the effective usage and interpretation of the results of analysis so that performance assessment of the passives design can be accomplished in an efficient and accurate manner. Therefore, conclusions must be reached about ways in which the design can be optimized. This last objective will be referred to with the descriptive term of *design optimization*.

When microwave designers like to predict circuit performance, electromagnetic effects of passives have to be considered. Usual simulation approaches for passives can be grouped into three main classes [1] - [13]. The first represents a passive component by an equivalent electrical circuit. Such models have a relatively narrow frequency bandwidth and the circuit parameter extraction procedure is still perfectible, strongly dependent on the device geometry, and relatively complex to achieve. Moreover, in high frequency circuits, they are not as accurate as EM models because they do not adequately include the high frequency nonlinear effects such as discontinuities, radiation losses, coupling, etc. Similarly, table look-up models can be relatively fast, but suffer from the disadvantages of large memory requirements and limitations on the number of parameters. The third uses an integro-differential form of Maxwell's equations and/or physics-based equations to quantify the electromagnetic field in a given structure.

All EM modeling approaches of interest to modeling can be classified as either *differential equation* (DE) or *integral equation* (IE) based. This classification refers to the fundamental way Maxwell's equations are solved in their differential

$$\nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t} \quad (\text{II-1})$$

$$\nabla \times \mathbf{B} = \mu \left(\mathbf{J} + \frac{\partial \mathbf{D}}{\partial t} \right) \quad (\text{II-2})$$

$$\nabla \cdot \mathbf{D} = \rho_v \quad (\text{II-3})$$

$$\nabla \cdot \mathbf{B} = 0 \quad (\text{II-4})$$

or integral form

$$\oint_C \mathbf{E} \cdot d\mathbf{l} = - \iint_S \frac{\partial \mathbf{B}}{\partial t} \cdot d\mathbf{S} \quad (\text{II-5})$$

$$\oint_C \mathbf{B} \cdot d\mathbf{l} = \iint_S \mu \left(\mathbf{J} + \frac{\partial \mathbf{D}}{\partial t} \right) \cdot d\mathbf{S} \quad (\text{II-6})$$

$$\iint_S \mathbf{D} \cdot d\mathbf{S} = \iiint_V \rho_v dV \quad (\text{II-7})$$

$$\iint_S \mathbf{B} \cdot d\mathbf{S} = 0 \quad (\text{II-8})$$

Here, \mathbf{E} , \mathbf{H} , \mathbf{D} , and \mathbf{B} are the four fundamental field vectors defined in Table II-1, S is the surface with the bounding contour C of line element $d\mathbf{l}$, ϵ and μ are the permittivity and permeability of the medium respectively, ρ_v is the volume charge density of free charges (C/m^3), and \mathbf{J} is the current density vector (A/m^2), which may comprise both convection current due to the motion of the free charge distribution ($\rho_v \mathbf{u}$) as well as conduction current caused by the presence of an electric field in a conducting medium ($\sigma \mathbf{E}$); \mathbf{u} is the charge velocity and σ the conductivity [14] – [16].

Table II-1. EM fields.

Symbol	Quantity	Unit
\mathbf{E}	Electric field intensity	V / m
$\mathbf{D} = \epsilon \mathbf{E}$	Electric flux density or Electric induction	C / m^2
\mathbf{H}	Magnetic field intensity	A / m
$\mathbf{B} = \mu \mathbf{H}$	Magnetic flux density or Magnetic induction	T (Tesla)

2.1 Differential Equation-Based Methods

Two of the most prevalent groups of techniques in the DE class are the *finite difference* and the *finite element* techniques [17], [18]. We will refer to these methods as *finite methods* which are based on the direct discretization of Maxwell's equations. With regard to the spatial discretization, the discrete approximation of the curl operators results in a strongly localized coupling of interactions of the electromagnetic fields, involving only a few nodes or a few elements in the numerical grid used for the discretization of the volume of interest. While in the case of finite difference methods Maxwell's equations are enforced at each node of the grid, in the case of finite element methods (FEM) a functional is introduced, the minimization of which over the volume of interest solves Maxwell's equations. We use the term *finite element equivalent circuits* (FEEC) to describe these DE-based methodologies, where the discrete forms of Maxwell's curl equations over the elements used to discretize the geometry can be described in terms of circuit element relationships.

2.2 Integral Equation-Based Methods

Integral equation (IE) based methods are also very effective for EM modeling [19]. The first step in the integral equation solution of the electromagnetic problem is the development of the integral equation statement of the system of Maxwell's equations that is the most adequate for the specific problem.

One of the most appropriate integral equation statements is where the electric field at some point in the structure is expressed as a superposition integral of the fields due to all currents and charges in the system.

The development of the discrete form of the integral equation is the second important step toward the numerical solution of the problem. The most popular method for the discretization of integral equations was called by Harrington the *method of moments* (MoM) [19]. Since MoM is used in the applied mathematics literature to describe the discretization process of both DE and IE statements of a given boundary value problem, it may be more appropriate to use the term IE-MoM when referring to its application to integral equations.

Compared to DE-based methods, the matrices that result from IE-MoM solutions are smaller in size but more dense. The smaller size is a direct consequence of the fact that the unknowns in the integral equation statement of the electromagnetic problem are only the electric currents and charges in or on the conducting parts of the structure. For the IE-MoM, the conducting structures are wires and conducting surfaces. In spite of their smaller size, IE-MoM solutions were, until recently, computationally more expensive than their DE-based counterparts. As already stated, the reason for this is that IE-MoM matrices are dense.

2.3 EM commercial solvers

In the absence of efficient experimental equipment, the use of commercial EM software is required.

2.3.1 ASITIC

This is a program that is freely available from the University of California, Berkeley [20]. In the words of the author, “ASITIC is a CAD tool that aids RF/microwave engineers to analyze, model, and optimize passive metal structures residing on a lossy conductive substrate”. ASITIC is a tool for the analysis of passive elements fabricated on the Si substrate. Maxwell’s equations are solved under the quasi-static assumption and a modified Partial Element Equivalent Circuit (PEEC) technique is used to derive n-port parameters for the device. The program relatively fast and simple gives a good first cut for the designer.

2.3.2 Momentum

Momentum is a complete suit from Agilent, which uses a “method-of-moments” based engine to run electromagnetic simulations of 2D structures [21]. This saves a lot of time when testing different geometries under a single process but it is not as accurate as 3D solvers.

2.3.3 Sonnet

SONNET is a suite that provides high-frequency planar electromagnetic analysis for different products using the MoM [22]. It uses a modified method of moments analysis based on Maxwell's equations to perform a quasi-true three-dimensional current analysis of predominantly planar structures. For this reason, such software is also referred as a 2.5D solver.

2.3.4 ANSYS

ANSYS Emag simulates low-frequency electric currents and electric fields in conductive and capacitive systems, as well as magnetic fields resulting from currents or permanent magnets [23]. It contains a comprehensive tool set for static, transient and harmonic low-frequency EM studies, while it is not so accurate in the microwave frequency range.

2.3.5 Ansoft-HFSS

HFSS (High-frequency Structure Simulator) is one of the most widely used 3D-EM solvers in the microwave area [24]. It can provide accurate results using finite element method. The wave equation is derived from the differential form of Maxwell's equations. Boundary conditions define the field behavior across discontinuous boundaries.

2.4 Conclusions

In practice, the 2.5D *Sonnet-Lite* EM-simulator is much faster than the full 3D-EM solver *Ansoft-HFSS* and exhibits quite similar responses in the low microwave frequency range. Thus, we will generate EM-based data for neural modeling of embedded passives using these two commercial EM solvers: *Sonnet-Lite* up to 10 GHz and *Ansoft-HFSS* starting from 10 GHz.

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CHAPTER III

AUTOMATED DATA GENERATION FOR NEURAL MODELING

As pointed out in the previous sections, accurate and efficient modeling of passive devices is a critical step in the CAD process. Use of artificial neural networks (ANN) provides a powerful approach for developing such models.

3.1 What is an artificial neural network?

When the theoretical model is not available, too complicated to implement or too expensive to build, a neural network model can efficiently overcome such numerical and/or theoretical constraints. An ANN is a mathematical model typically consisting of a number of smooth switch functions and has the ability to learn and generalize arbitrary continuous multi-dimensional nonlinear input-output relationships. ANN can be trained from measured or simulated data (samples) and subsequently used during circuit analysis and design. The models are fast and can represent the task behaviors it learnt which otherwise are computationally expensive [1].

Once developed, these neural models can be used in place of computationally intensive physics/EM models of active/passive devices to speed up microwave design [1]-[3]. Neural network techniques have been used to model a wide variety of microwave devices/circuits such as transmission line components [4]-[18], bends [19][20], vias [21]-[25], CPW components [24][26][27], spiral inductors [28][29], FETs [5][6][11][13][17][30]-[40], HBTs [32][41][42], HEMTs [38][43][44], waveguides [24][45], laser diodes [46], filters [18][26][32][47]-[53], amplifiers [13][31][33][54]-[56], mixers [56], antennas [27][57]-[68] and embedded resistors [53]. Neural networks have also been used in object recognition [66][69][70], wave propagation [71][72], impedance matching [73]-[75], electronic packaging [12], inverse modeling [35][45][70][76]-[78], circuit design and optimization [9][10][12][16][18][20], synthesis [18][54][79] and yield prediction [35][40]. Neural models are much faster than original detailed physics/EM models [37], more accurate than polynomial and empirical models [80], allow more dimensions than table lookup models [81] and are easier to develop when a new device/technology is introduced [9].

3.1.1 Neural network structure

Let \mathbf{x} be an n -vector $\{x_i, i = 1, \dots, n\}$ containing the external inputs and \mathbf{y} be an m -vector $\{y_k, k = 1, \dots, m\}$ containing the outputs from the output neurons. The original problem can be

$$\mathbf{y} = \mathbf{f}(\mathbf{x}) \quad (\text{III-1})$$

while the neural network model for the problem is

$$\tilde{\mathbf{y}} = \tilde{\mathbf{y}}(\mathbf{x}, \mathbf{w}), \quad (\text{III-2})$$

where w is a N_w -vector $\{w_i, i = 1, \dots, N_w\}$ containing all the weight parameters representing the connections in the neural network. The definition of w and the way in which y is computed from x and w determines the structure of the neural network.

The most commonly used neural network configuration is the Multi Layer Perceptrons (MLP) [1], [82]. It belongs to the most popular class of structures called feedforward neural networks. In the MLP structure, the neurons are grouped into layers as shown in Figure III-1.

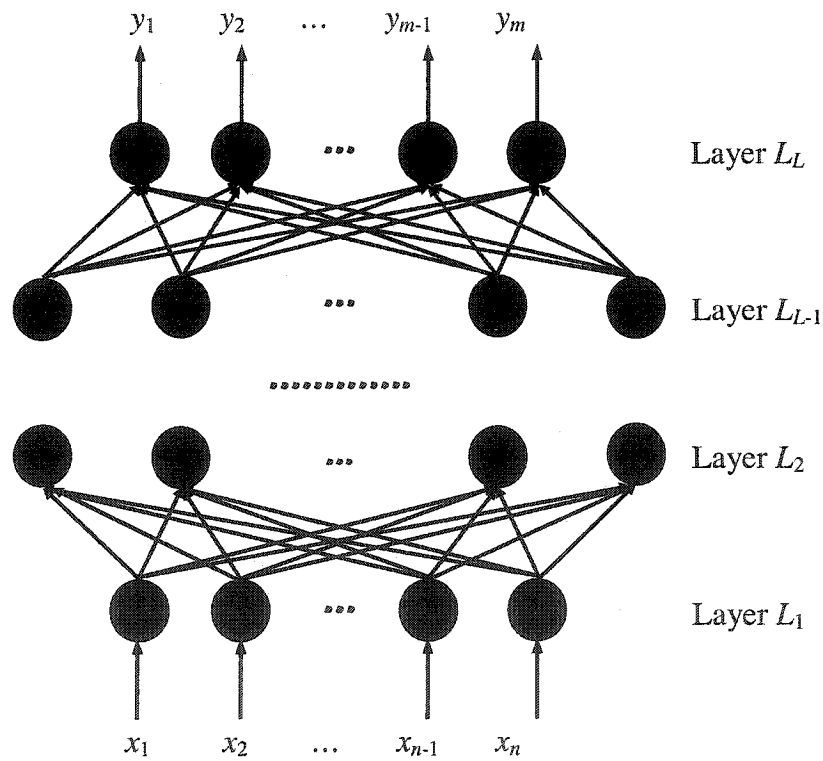


Figure III-1. Neural network multilayer perceptrons (MLP) structure.

Typically, the neural network contains L layers.

The layers L_2 to L_{L-1} are called hidden layers, while the last layer L_L , called the output layer, contains the response of the device to be modeled, for example the S parameters. The various layers are placed end to end with neuron connections between them, as shown in Figure III-1. For such a network of neurons, the function given by relation (III-1) is calculated on the basis of the layer of entry while using [1]

$$z_i^1 = x_i, \quad i = 1, \dots, N_1, \quad n = N_1 \quad (\text{III-3})$$

z_i^1 is the output of the i^{th} neuron of layer 1 (i.e., input layer), and while proceeding layer by layer following this relation, the output at the end of the layer L_L is given by

$$z_j^l = \sigma \left(\sum_{k=0}^{N_{l-1}} w_{jk}^l z_k^{l-1} + w_{j0}^l \right), \quad i = 1, \dots, N_l, \quad l = 1, \dots, L \quad (\text{III-4})$$

to reach the output layer which gives

$$y_k = z_k^L, \quad k = 1, \dots, N_L, \quad m = N_L \quad (\text{III-5})$$

In these relations, N_l is the number of neurons in the layer L_l , w_{jk} represents the weight of the connection between the k^{th} neuron of the layer L_{l-1} and the j^{th} neuron of the layer L_l . In equation (III-4), the function σ is known as the activation function of the neuron. It is usually equivalent to a sigmoid function for the hidden layers

$$\sigma(t) = \frac{1}{(1+e^{-t})} \quad (\text{III-6})$$

with

$$\sigma(t) \longrightarrow \begin{cases} 1 & \text{as } t \rightarrow +\infty \\ 0 & \text{as } t \rightarrow -\infty \end{cases} \quad (\text{III-7})$$

Other possible candidates for σ are the arctangent function given by,

$$\sigma(t) = \left(\frac{2}{\pi}\right) * \arctan(t) \quad (\text{III-8})$$

and the hyperbolic tangent function given by,

$$\sigma(t) = \frac{(e^t - e^{-t})}{(e^t + e^{-t})} \quad (\text{III-9})$$

All these functions are bounded, continuous, monotonic and continuously differentiable.

3.1.2 Other Structures

3.1.2.1 Radial-basis-function (RBF)

A typical radial-basis-function neural network has an input layer, a radial basis hidden layer, and an output layer. Commonly used radial basis activation functions are Gaussian and multiquadratic. The Gaussian function is given by

$$\sigma(\gamma) = \exp(-\gamma^2) \quad (\text{III-10})$$

and the multiquadratic function is given by

$$\sigma(\gamma) = \frac{1}{(c^2 + \gamma^2)^\alpha}, \quad \alpha > 0 \quad (\text{III-11})$$

where c is a constant. The output value of the i^{th} hidden neuron is $z_i = \sigma(\lambda_i)$, where $\sigma(\gamma)$ is a radial basis function. The activation function of each hidden neuron in an RBF network processes the Euclidean norm between the input vector and the center of that neuron. RBF networks use exponentially decaying localized nonlinearities to construct local approximations to non-linear input-output mapping. In RBF, a hidden neuron influences the network output only for those inputs that are near to its center, thus requiring an exponential number of hidden neurons to cover the entire input space. Hence, RBF is only suited for problems with small number of inputs [1].

3.1.2.2 Knowledge-based neural networks (KBNN)

In knowledge-based neural networks, the knowledge is embedded into the neural structure in the form of empirical functions or analytical approximations. Usually empirical functions are valid only in a certain region in space. So, to represent the entire space several empirical equations are needed and a mechanism to switch between them must be devised. The Knowledge Based Neural Network (KBNN) structure is a non-fully connected structure as shown in Figure III-2 [1], [15].

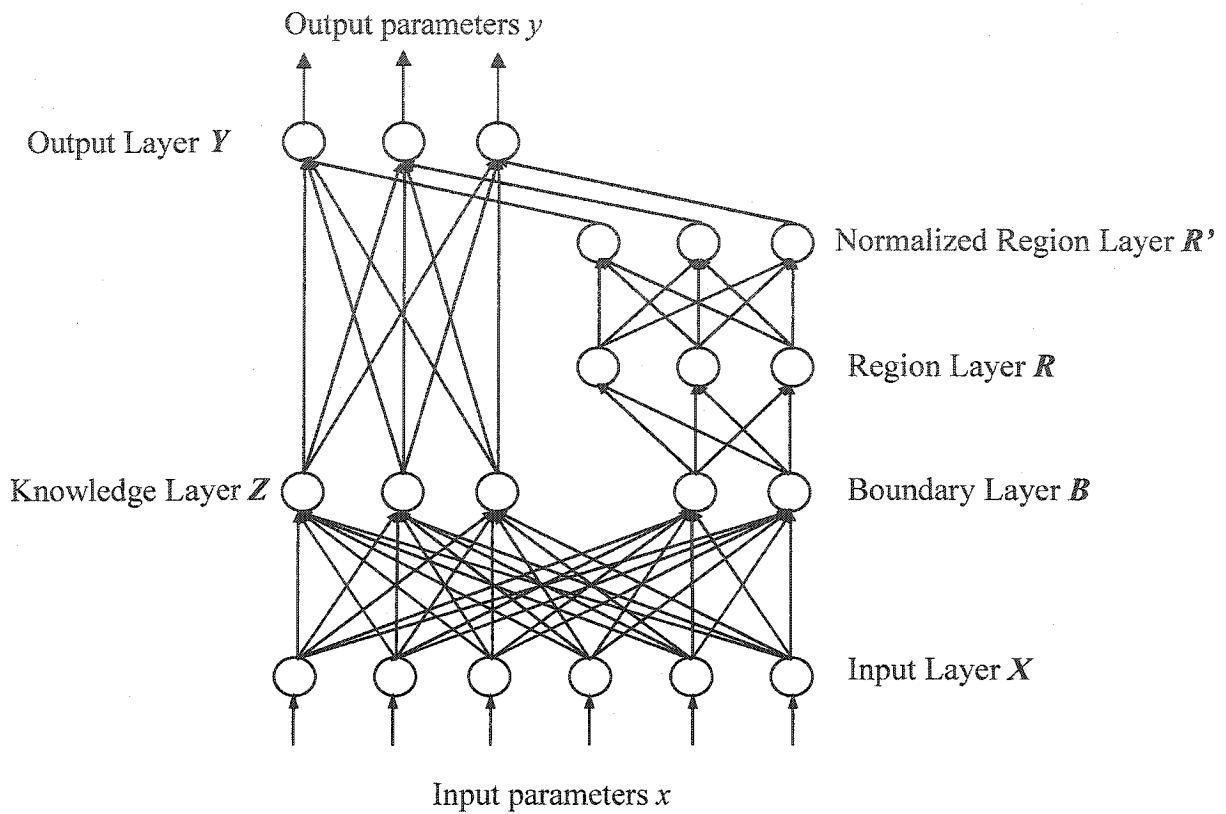


Figure III-2. Knowledge based neural network (KBNN) structure.

Typically, the neural network contains 6 layers.

There are 6 layers in the structure, namely input layer X , knowledge layer Z , boundary layer B , region layer R , normalized region layer R' and output layer Y . The input layer X accepts parameters x from outside the model. The knowledge layer Z contains the knowledge function $\psi()$. The output of the i^{th} knowledge neuron is given by,

$$z_i = \psi_i(x, w_i), \quad i=1,2,\dots,N_z \quad (\text{III-12})$$

where x is a vector including neural network inputs and w_i a vector of parameters in the knowledge formula. The boundary layer B can incorporate knowledge in the form of problem dependent boundary functions $B(*)$ or in the absence of boundary knowledge just as linear boundaries. Output of the i^{th} neuron is calculated by,

$$b_i = B_i(x, v_i), \quad i=1,2,\dots,N_b \quad (\text{III-13})$$

where v_i is a vector of parameters in B_i defining an open or closed boundary in the input space x . The region layer R contains neurons to construct regions from boundary neurons,

$$r_i = \prod_{j=1}^{N_b} \sigma(\alpha_{ij} b_j + \theta_{ij}), \quad i=1,2,\dots,N_r \quad (\text{III-14})$$

where α_{ij} and θ_{ij} are the scaling and bias parameters, respectively. The normalized region layer R' contains rational function based neurons to normalize the outputs of R

$$r'_i = \frac{r_i}{\sum_{j=1}^{N_r} r_j}, \quad i=1,2,\dots,N_{r'}, \quad N_{r'}=N_r \quad (\text{III-15})$$

This technique enhances neural model accuracy, especially for the data not seen during training (generalization capability), and reduces the need for a large amount of training data. However, even if such structures have been already applied to model passive components [87], we did not notice significant improvement vs MLP structures for our specific work. Hence, they will be not considered in the present work.

3.2 Training the Neural Model

Neural network training is an optimization process in the weight space using optimization-based training algorithms such as Back-propagation [43][52], Conjugate gradient [53], quasi-Newton [54], Levenberg-Marquardt [55], Genetic algorithm [31], Huber-quasi-Newton [8], Sparse Training algorithm [8] etc. Training is done to determine neural network internal weights \mathbf{w} such that the neural model output best matches the training data (a bias weight w_0 can be added to the vector \mathbf{w}). Training data are set of $\{(\mathbf{x}_p, \mathbf{d}_p), p \in T_A\}$ data, where \mathbf{d}_p represents the \mathbf{y} vector obtained by measurements or simulations of the input vector \mathbf{x}_p and where T_A is the index set of training data. The vector solution \mathbf{w}^* is the one which minimize the training error $E(\mathbf{w})$ defined as

$$E(\mathbf{w}) = \frac{1}{2} \sum_{p \in T_A} \sum_{k=1}^m (\tilde{y}_k(\mathbf{x}_p, \mathbf{w}) - d_{kp})^2 \quad (\text{III-16})$$

where d_{kp} is the k^{th} element of the vector \mathbf{d}_p and \tilde{y}_k is the k^{th} output of the neural network for the input sample \mathbf{x}_p .

3.3 Testing the Neural Model

This is the final step of the model generation. Actually this step is performed after the models are generated. This step ensures the quality of the model produced. Depending upon the quality, the model needs to be re-trained if the testing error is too high. An independent set of data known, as the test data is required for this purpose.

A quantity δ_{pk} is defined as

$$\delta_{pk} = \frac{\tilde{y}_k(x_p, w) - d_{pk}}{d_{k, \max} - d_{k, \min}}, \quad k = 1, \dots, N, \quad p \in T_E \quad (\text{III-17})$$

A quality criterion based on the q^{th} norm is then defined as

$$M_q = \left[\sum_{p \in T_E} \sum_{k=1}^{N_y} |\delta_{pk}|^q \right]^{\frac{1}{q}} \quad (\text{III-18})$$

When $q = 1$, the average test error can be calculated directly from M_1 as

$$\text{Average Test Error} = \frac{M_1}{N_{T_E} N_y} \quad (\text{III-19})$$

where N_{T_E} is the number of samples in test data set and N_y is the number of neural model outputs. When $q = 2$, the q^{th} norm is the Euclidean distance between neural model prediction and test data. When $q = \text{infinite}$, the q^{th} norm measure is the maximum test error, which is also called as the worst-case error among entire test data and all model outputs.

3.4 Data Generation

A complete process of generation of an accurate neural model requires three sets of data: training data, validation data and test data.

Training Data – These sets of data generally come from EM simulations. As the name suggests this set of data is used to train the neural models by updating the neural network training weights.

Validation Data – These sets of data are generally required to monitor the training quality of the neural network model. This will give an indication to terminate the training.

Test Data – The models generated with the training data are tested with this set of data. These data actually determine the final quality of the models generated.

Every modeling approach requires data and so does the neural modeling approach. The data can come either from detailed simulation software (simulator) or measurements. Typical examples include EM-simulators such as *Sonnet-Lite* [88] and *Ansoft-HFSS* [86].

3.5 Data Distribution

Properly selecting data samples are very important for the accuracy of neural network function structure [1]. Validation data and test data should be generated in the range of input space over which the neural model would be used. Training data could be generated in the same range as the input space. However, it is a good idea to have training data sampled slightly beyond the model utilization range. This ensures good performance of the neural model at the boundaries of the input space. There are various strategies for sampling like the

- **Uniform Grid Distribution:** which generally leads to a large number of samples but it is the most convenient when no prior knowledge is available regarding the behavior of the structure to model. We will use this distribution for our work.
- **Nonuniform grid distribution:** This strategy is for sampling highly non-linear region. The samples are taken unequal intervals. This scheme suits the highly non-linear sub region of the input space. Dense samples are chosen from the corresponding sub regions.

The total number of data samples can be reduced in this way. However, the samples have to be selected manually which can be a tedious process and care should be taken for accurate representation of the input space.

- **Star Distribution:** Star Distribution is used in situations where data generation is very expensive, and the model behavior is assumed to vary smoothly within the input parameter space which is not the case in the present work.
- **Random Distribution:** Random distribution is used in input parameter space is of high dimension (i.e. n is very large). The total number of samples of P is dictated by user applications.

3.6 Data Scaling

For efficient training of a neural network, scaling is very important because the orders of magnitude of input/output parameters values in microwave applications can be very different from one another. Scaling of data samples can be performed on the input parameter values, output parameter values or both. Let x , x_{min} , and x_{max} represent a generic element in the vectors \mathbf{x} , \mathbf{x}_{min} , and \mathbf{x}_{max} of the original data, respectively. Let \tilde{x} , \tilde{x}_{min} , and \tilde{x}_{max} represent a generic element in the vectors $\tilde{\mathbf{x}}$, $\tilde{\mathbf{x}}_{min}$, and $\tilde{\mathbf{x}}_{max}$ of scaled data, respectively, where $[\tilde{x}_{min}, \tilde{x}_{max}]$ represent the input parameter range after scaling [1].

- **Linear Scaling:** Linear scaling of inputs improves the condition of the trainable parameters (weights), and the balance between different inputs. Linear scaling of outputs can balance different outputs whose magnitudes are very different.

The linear scaling is given by

$$\tilde{x} = \tilde{x}_{\min} + \frac{x - x_{\min}}{x_{\max} - x_{\min}} (\tilde{x}_{\max} - \tilde{x}_{\min}) \quad (\text{III-20})$$

The corresponding descaling is given by

$$\tilde{x} = x_{\min} + \frac{\tilde{x} - \tilde{x}_{\min}}{\tilde{x}_{\max} - \tilde{x}_{\min}} (x_{\max} - x_{\min}) \quad (\text{III-21})$$

- **Log-Arithmetic Scaling:** Applying log-arithmetic scaling to outputs with large variations provides a balance between large and small magnitudes of the same output in different regions of the model. A simple form of log arithmetic scaling is given by

$$\tilde{x} = \ln (x - x_{\min}) \quad (\text{III-22})$$

The corresponding descaling is given by

$$x = x_{\min} + \exp (\tilde{x}) \quad (\text{III-23})$$

- **Two-Sided Log-Arithmetic Scaling:** This scaling provides a balance between large and small magnitudes of the same output in different region of model and avoids the overshadowing of mid-range values of the response by greatly decreasing trends.

3.7 Algorithm

Figure III-3 summarizes the required steps for the development of a neural model.

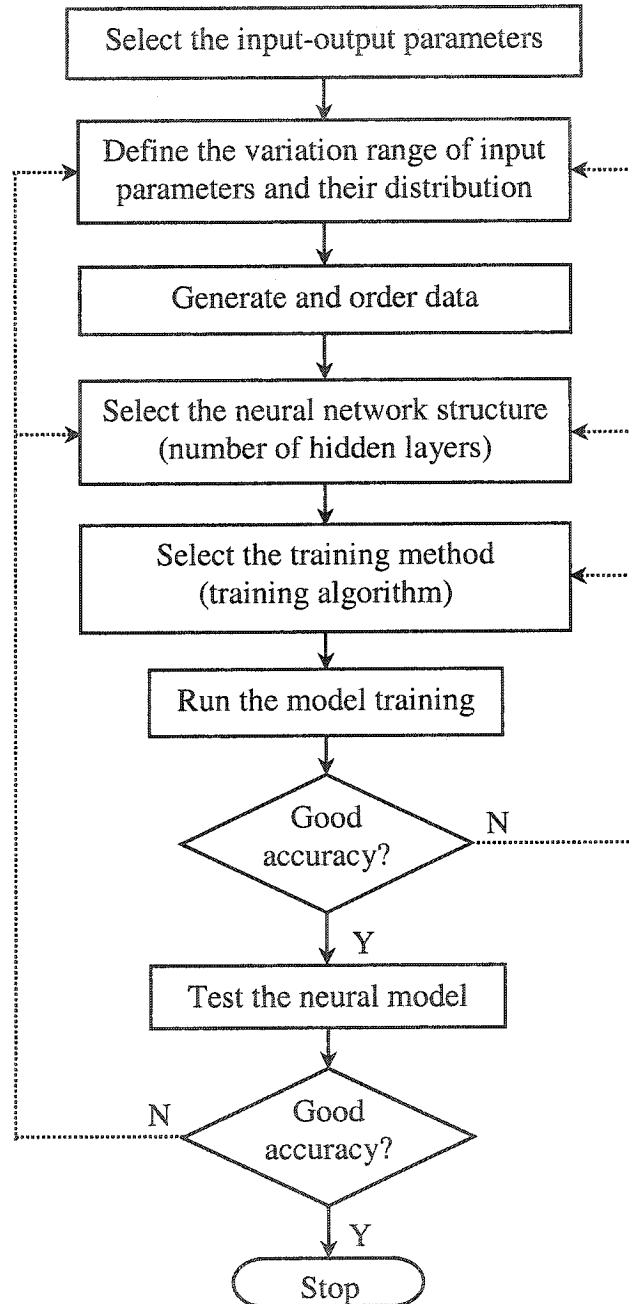


Figure III-3. Algorithm showing the required steps for the development of a neural network model.

3.8 Process Automation

As detailed in the above sections, neural model development involves several sub-tasks, which are usually carried out manually in a sequential manner. Such an approach, referred to as the step-by-step neural modeling approach, requires intensive human effort. There is a definite need for automation of neural model development process. However, a successful automation technique needs to address multiple complicated and inter-dependent challenges. One of the most critical steps to make the entire process of model generation automated is the automatic generation of data by the EM-simulators [87]. In this section we will discuss about the automatic driving of such simulators.

There are several advantages of making the entire process of data generation automatic; the most important is to reduce manual labor thereby reducing the time for data generation and any possible chances of human error [87].

As shown in Figure III-4, in the conventional method of model generation, the physical/geometrical or the electrical parameters should be changed manually after every simulation. Then the simulation is restarted again to obtain output for the new set of changes. This assignment becomes highly tedious and error prone when extensive data are generated. But in the proposed method once data generation begins no human effort is necessary to change any parameters.

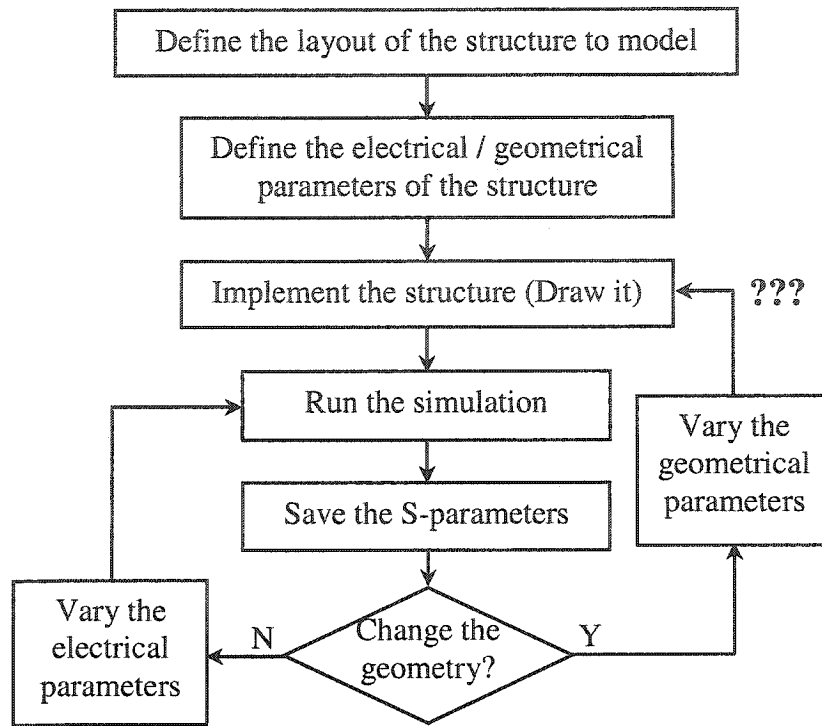


Figure III-4. Algorithm of conventional data generation using an EM simulator.

Figure III-5 summarizes the algorithm used for automation of EM simulator [89], which is similar to the work presented in [87]. Once the structure of neural network has been determined, the first stage is to define the input space, i.e., the range and distribution of the input parameters. Then, a macro is created to drive the EM-simulator. In practice, a C++ code generates the macro for each set of input geometrical and electrical parameters. The code calls the simulator, generates the macro for the simulator to use, runs the simulation for the macro and saves the results in desired files. This process is repeated for each new set of input geometrical and electrical parameters. All this process is done automatically without any human intervention.

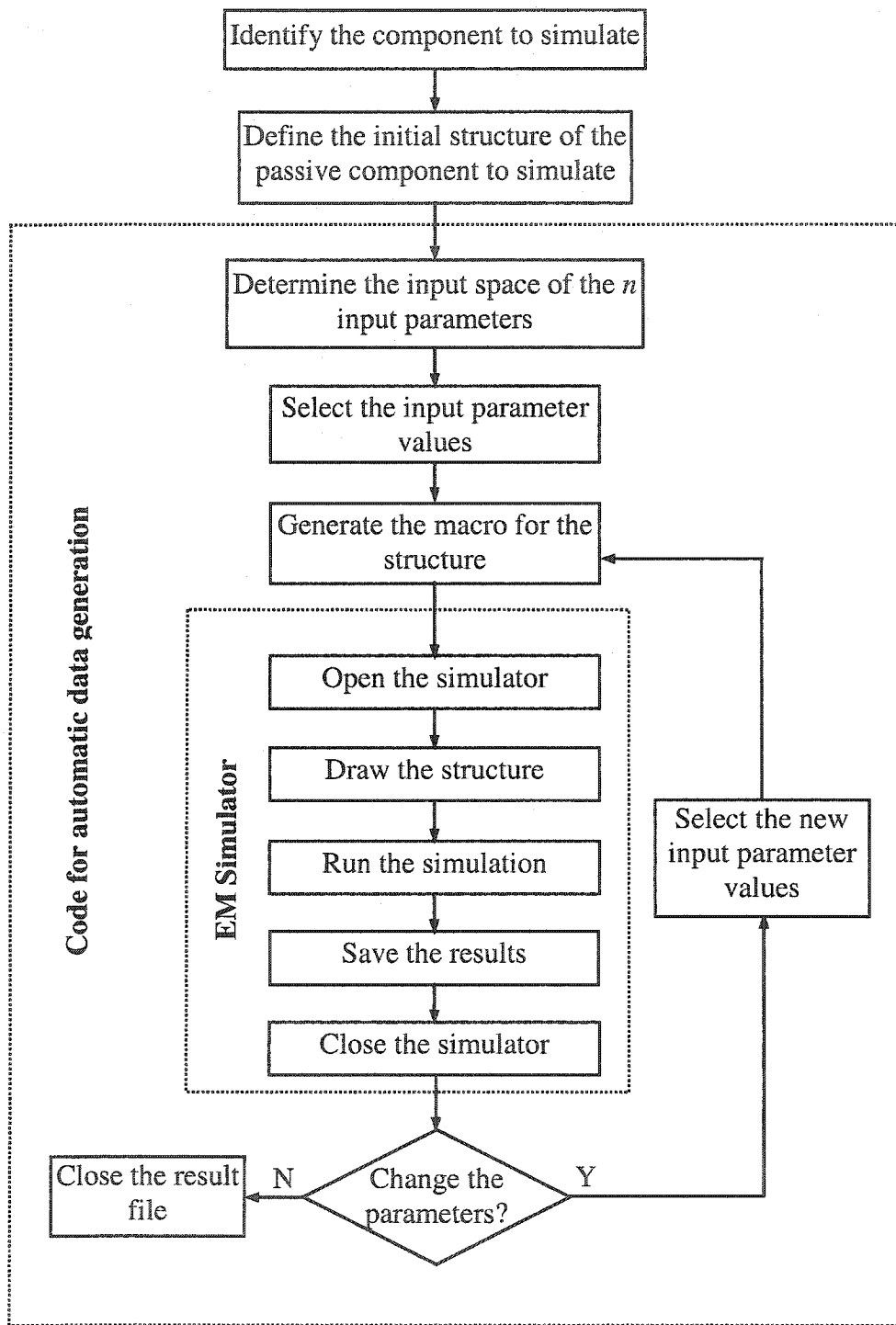


Figure III-5. Automated process of data generation using an EM simulator.

The data for similar structures are gathered together according to the interval of variation of their respective input parameters. This will prevent simulation of the same component with the same data file.

Here, it is necessary to make the distinction between the development of the model and the use of the model. Our target is to provide the user of the model (thus the designer of the circuit) a fast and precise tool, integrated effectively in a loop, for optimization of the performance of a given circuit. The neural network models are well adapted for the purpose. The generation of model is independent of user and even if the generation time of the data is relatively long (from few hours to few days depending on the number of data to be simulated), the time-to-market of such models is definitely lower than the time required by the traditional methods of development of electromagnetic models satisfying same criteria of functionality, precision and adaptability. Having a slotted measuring section would make the process free from the time constraint of calculation; nevertheless, for maximum development of such models we chose a parallel simulation dependent on the number of data to simulate (we used several terminals to split the computing time for data generation). The time-to-market of neural model is definitely lower than those other modeling approaches such as deriving semi-empirical formulas [90] or equivalent electrical circuit representation of passives [91].

Figure III-6 shows that our complete algorithm breaks up into six main parts:

- Definition of the structure to simulate and identification of all passive components and interconnects to model. Figure III-7 gives an illustration of such a structure with three inductors (Model # 1), one “Z” interconnection (Model # 2), three “L” interconnections (Model # 3), a resistor (Model # 4) and a capacitor (Model # 5).
- Generation of the data and training of neural networks by using the process of automation described in Figure III-5.
- Implementation of the models in the circuit simulator *Agilent-ADS*. The option SDD (for Symbolically-Defined Devices) in *Agilent-ADS* makes it relatively easy to insert such neural models.
- Identification of the P variables $\{ x_i, i = 1, \dots, P \}$ to vary in order to optimize the circuit performance (in general the S_{21} parameter). In our case, the variables to be varied could be any input parameter of the neural models (length and width of lines, permittivity of substrate, etc.) except for the frequency.
- Simulation and/or optimization of circuit performance according to the parameter of the circuit to be varied and save new values of the variables.
- Realization and test of the final circuit.

In the optimization process of a circuit performance, it is to be noticed that it is possible to vary not only the parameters of a passive component such as the width of an inductor or the thickness of a capacitor, but also its optimal placement in the circuit layout through the geometrical parameters of the related interconnects. Thus, our approach allows not only optimizing the performance of a circuit, but also determining the optimal position of the passives, thus making it possible to obtain the optimal layout of the overall structure.

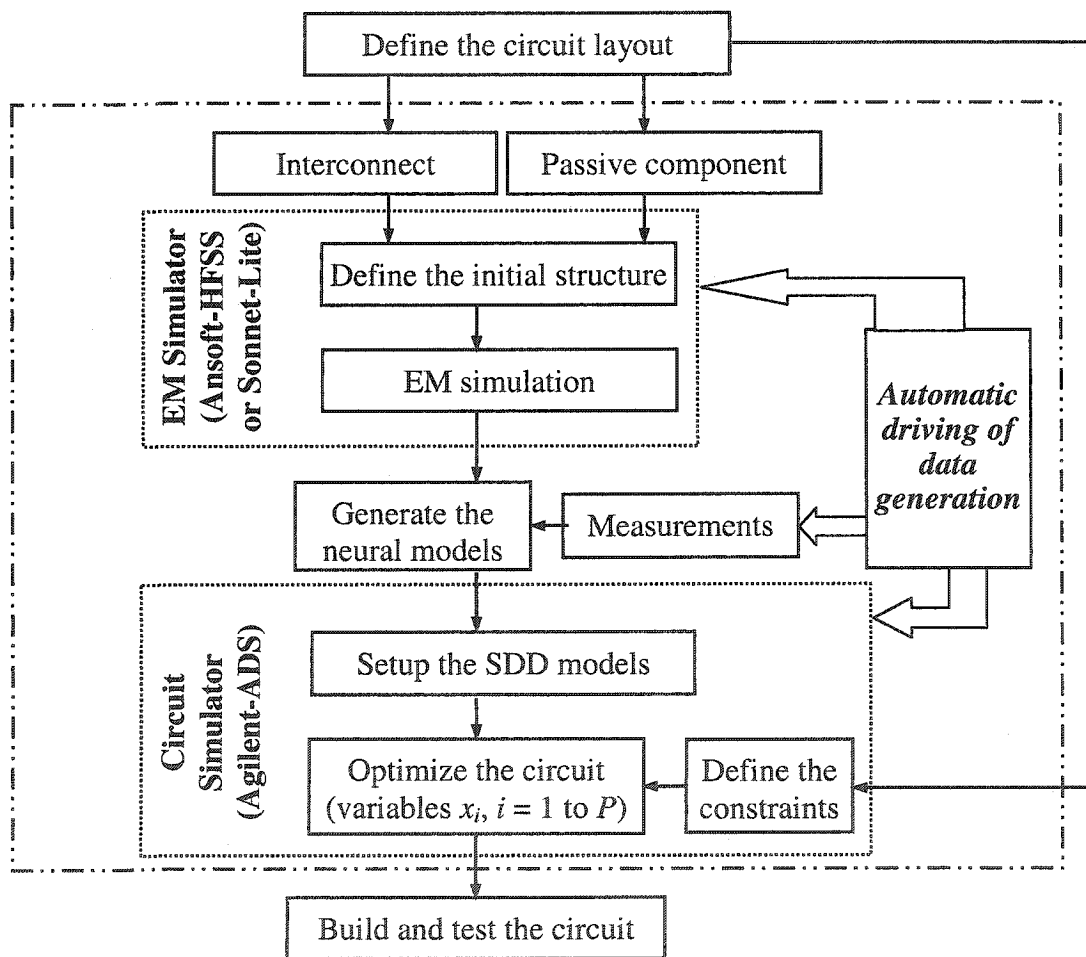


Figure III-6. Complete algorithm for the optimization of the circuit performance.

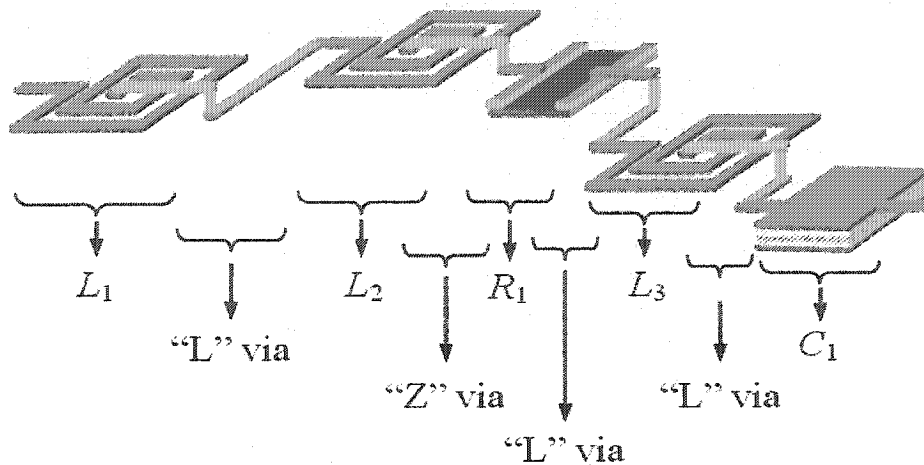


Figure III-7. Circuit: Illustration of a structure to optimize.

3.9 EM mutual-device coupling effects

At device level, neural modeling is efficient [1] [2] [7] [10] [16] [18] [21] [25] [87]. However, is it enough to guarantee an accurate circuit response? In other words, for an efficient prediction of circuit performance, is it *enough* to plug and connect together different individual neural models?

To our current knowledge, all research about neural modeling for passives used data based on individual device simulation and/or measurement setup. The device to be modeled is simulated/measured inside an isolated environment without any link to other components involved in the layout and final real circuit environment. Therefore, such models do not include the impact of the EM device environment in a real circuit.

In an integrated circuit, the layout is dense and elements would be very close in terms of distance between them. In these conditions, electromagnetic coupling between passives (either R-L-C elements or interconnects) would be more significant as the frequency increases.

In fact, electromagnetic effects (both desirable and parasitic) are much more significant as operating frequencies rise. Inductive coupling is now significant on chip, while packages and boards are larger today (relative to the wavelength of operation) than ever before, requiring fullwave electromagnetic simulation. Integrated passives (on chips and packages) have significantly reduced integration costs, but require accurate high frequency models that can be incorporated into analog simulators. Finally, hierarchical, block based, mixed signal design methodologies are very complicated and not currently well integrated into EM-CAD tools. The models for interaction between blocks are often too simplistic and the coupling between analog and digital components on a chip is often ignored. The result can be resignation to designing in silicon, which keeps design cycle time and the cost of advanced RF chips high [92] – [95].

When RF/microwave devices are in close proximity there are two types of coupling, namely the substrate coupling and the power delivery- and interconnect- induced coupling.

3.9.1 Substrate Coupling

Substrate coupling refers to induction of currents in the substrate due to presence of electromagnetic waves in lines (passives or transmission lines) in close proximity.

3.9.2 Interconnect induced coupling

The impact of retardation effects on coupling becomes evident when the dimensions of the transmission lines (strip lines from interconnects or passive components) are of the order of the wavelength λ . Interconnect resistor is due to ohmic loss in the conductor. The return path of the resistor is important. Ohmic loss is frequency dependent since the current tends to crowd along the perimeter of the conductor as the frequency increases (skin effect). Frequency dependence of the field penetration inside the wire results in a frequency-dependent inductor also. The line coupling leads to dispersion and losses (ohmic and dielectric).

We have then to take into account these coupling effects. Since they are more significant in high frequencies, we have to model passives accordingly to evaluate such effects. Based on the internal technical literature provided by the EM softwares, we selected the point 80 GHz as the maximum frequency value to simulate in order to capture the coupling effects, without scarifying to the response accuracy.

3.10 Circuit analysis

In order to build a circuit, we have to connect components in series and/or in parallel. This process leads to the manipulation of several S matrices in order to evaluate the total S-parameters of the overall circuit. Of course, this step could be easily achieved in a circuit simulator. However, since our target is to include the EM mutual coupling effects into consideration during the design, we want to have our own source code. The evaluation of

circuit parameters depends on the individual characterization of each component of the circuit. There are several methods to analyze a circuit such as the Connection-Scattering Matrix method, the Multiport Connection method and the Sub-network Growth method [96] - [105].

3.10.1 Analysis using Connection-Scattering Matrix

This method is applicable when the network contains arbitrarily interconnected multiports and independent generators. Let us consider a network with M components. The S matrix of this circuit (Figure III-8) could be expressed as

$$[\mathbf{b}] = [\mathbf{S}][\mathbf{a}] + [\mathbf{c}] \quad (\text{III-24})$$

$[\mathbf{a}]$ and $[\mathbf{b}]$ are the vectors of incident and reflected waves respectively. The extended form

$$\begin{bmatrix} [\mathbf{b}_1] \\ \vdots \\ [\mathbf{b}_M] \end{bmatrix} = \begin{bmatrix} [\mathbf{S}_1] & [\mathbf{0}] & \cdots & [\mathbf{0}] \\ [\mathbf{0}] & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & [\mathbf{0}] \\ [\mathbf{0}] & \cdots & [\mathbf{0}] & [\mathbf{S}_M] \end{bmatrix} \begin{bmatrix} [\mathbf{a}_1] \\ \vdots \\ [\mathbf{a}_M] \end{bmatrix} + \begin{bmatrix} [\mathbf{c}_1] \\ \vdots \\ [\mathbf{c}_M] \end{bmatrix} \quad (\text{III-25})$$

shows that the S matrix is a block diagonal matrix whose submatrices along the diagonal are the scattering matrices of various components and 0's represent null matrices. In this equation, the $[\mathbf{c}_k]$, $k = 1, \dots, M$, are the scattering matrices of independent generators. Equation (III-25) contains the characterizations of individual components but does not take into account the constraints imposed by interconnections.

For a pair of connected ports, the outgoing wave variable at one port must equal the incoming wave variable at the other. For example, if port j of one component is connected to port k of another component, the incoming and outgoing waves must satisfy

$$a_j = b_k \quad \text{and} \quad a_k = b_j \quad (\text{III-26})$$

or

$$\begin{bmatrix} b_k \\ b_j \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} a_k \\ a_j \end{bmatrix} \quad (\text{III-27})$$

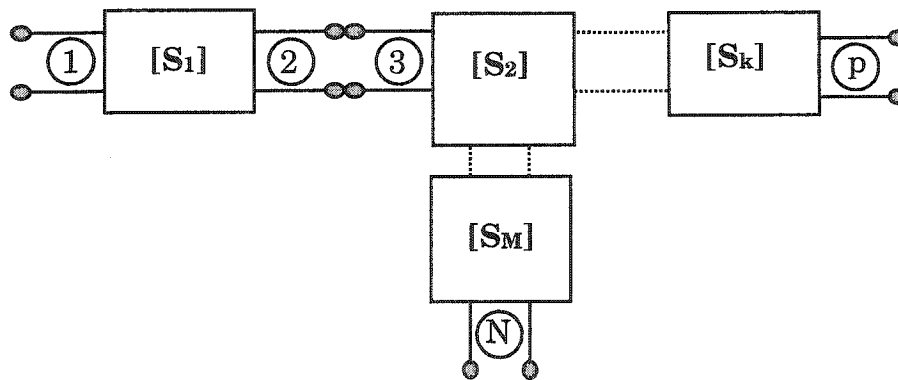


Figure III-8. An N -port network containing M components.

The matrix on the right-hand side can be recognized as the inverse of the S-matrix of the interconnection. The elements of this matrix are 1's and 0's because the normalizing impedances for the two ports are taken to be equal. In the case of unequal normalization at ports j and k , the elements of the matrix are obtained as inverse of the corresponding S-matrix of the junction.

The relations given by (III-27) are written together for all the interconnected ports in the network and put in the form

$$[\mathbf{b}] = [\Gamma][\mathbf{a}] \quad (\text{III-28})$$

where $[\Gamma]$ is a connection matrix describing the topology. In each row of $[\Gamma]$ all elements are zero except an entry 1 in the column indicating the interconnection. If the element (j, k) of $[\Gamma]$ is "1", it implies that the port j is connected to the port k . By substitution of $[\mathbf{b}]$ from (III-28) to (III-24), we obtain

$$[\Gamma][\mathbf{a}] = [\mathbf{S}][\mathbf{a}] + [\mathbf{c}] \quad (\text{III-29})$$

then

$$\{[\Gamma] - [\mathbf{S}]\}[\mathbf{a}] = [\mathbf{W}][\mathbf{a}] = [\mathbf{c}] \quad \Leftrightarrow \quad [\mathbf{a}] = [\mathbf{W}]^{-1}[\mathbf{c}] \quad (\text{III-30})$$

In the above equation $[\mathbf{W}]$ is called the connection scattering matrix. All other elements are zero except those corresponding to the two ports connected together (the $[\Gamma]$ matrix elements).

The zero nonzero patterns in $[\mathbf{W}]$ depend only on the topology and do not change with component characterization or frequency. When the dimension of $[\mathbf{W}]$ is large, the computing time is large too. In spite of that, this method has advantage of giving waves at each port, which is very useful in sensitivity analysis.

3.10.2 Multiport Connection Method

This method is applicable when the network contains arbitrarily interconnected multiport components without independent generators. When one or more independent generators are present, these can be treated as existing outside the remaining N -port network. If the principal network has c ports internal (which are connected) and p external ports, the relations between the variables of the incidental and reflected waves are given by

$$[\mathbf{b}] = [\mathbf{S}][\mathbf{a}] \quad (\text{III-31})$$

The rows and columns can be reordered so that the wave variables are separated into two groups; the first corresponding to the p external ports, and the second to c internally connected ports

$$\begin{bmatrix} [\mathbf{b}_p] \\ [\mathbf{b}_c] \end{bmatrix} = \begin{bmatrix} [\mathbf{S}_{pp}] & [\mathbf{S}_{pc}] \\ [\mathbf{S}_{cp}] & [\mathbf{S}_{cc}] \end{bmatrix} \begin{bmatrix} [\mathbf{a}_p] \\ [\mathbf{a}_c] \end{bmatrix} \quad (\text{III-32})$$

where $[\mathbf{S}_{pp}]$, $[\mathbf{S}_{pc}]$, $[\mathbf{S}_{cp}]$ and $[\mathbf{S}_{cc}]$ are vectors of incident waves obtained after separation of the ports; their dimensions are respectively (p, p) , (p, c) , (c, p) and (c, c) . The interconnection constraints for the c internal ports can be written as

$$[\mathbf{b}_c] = [\Gamma][\mathbf{a}_c] = [\mathbf{S}_{cp}][\mathbf{a}_p] + [\mathbf{S}_{cc}][\mathbf{a}_c] \quad (\text{III-33})$$

⇓

$$[\mathbf{a}_c] = \{[\Gamma] - [\mathbf{S}_{cc}]\}^{-1} [\mathbf{S}_{cp}][\mathbf{a}_p] \quad (\text{III-34})$$

This leads to

$$[b_p] = [S_{pp}][a_p] + [S_{pc}][a_c] = \{ [S_{pp}] + [S_{pc}]([\Gamma] - [S_{cc}])^{-1} [S_{cp}] \} [a_p] \quad (\text{III-35})$$

where $[\Gamma]$ is the connection matrix. Therefore,

$$[a_c] = \{ [\Gamma] - [S_{cc}] \}^{-1} [S_{cp}] [a_p] \quad (\text{III-36})$$

and we obtain finally

$$[b_p] = [S_{pp}][a_p] + [S_{pc}][a_c] = \{ [S_{pp}] + [S_{pc}]([\Gamma] - [S_{cc}])^{-1} [S_{cp}] \} [a_p] \quad (\text{III-37})$$

where the matrix $\{ ([\Gamma] - [S_{cc}])^{-1} \}$ has similar characteristics with that of the matrix $[W]$ described previously. Then,

$$[S_g] = [S_{pp}] + [S_{pc}]([\Gamma] - [S_{cc}])^{-1} [S_{cp}] \quad (\text{III-38})$$

However this method is not efficient if the circuit has a large number of internal ports (like in integrated circuits) and does not include independent generators [99].

3.10.3 Analysis by Subnetwork Growth Method

When a network has many internal ports, the computing time is rather high. It can be reduced if the principal network is broken up into sub-networks. Thus the matrices of the sub-networks are separately calculated then their combination makes it possible to obtain the matrix of the network. This method uses less memory but the decomposition into sub-blocks is

not evident. To have a very fast analysis program, a Circuit Analysis Program (CAP) was written in C++ language based on the Connection-Scattering Matrix method. This program evaluates the overall scattering matrix of a multiport circuit from the known S-matrices of the constituent components of the circuit.

3.11 Conclusion

In this chapter, we demonstrated the need for automated data generation for neural model training of passive components and interconnects. We showed the principle of determining the optimal layout of a circuit by varying the geometrical parameters of interconnects. Finally, we highlighted the importance of mutual coupling between components. The next chapter will show the validation of our proposed approach.

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CHAPTER IV

RESULTS

For neural network modeling of passives (Figure IV-1), we have to generate EM-based data using our automated EM-simulator drivers, i.e., *EM-DA* for *Ansoft-HFSS* [1] and *EM-DS* for *Sonnet-Lite* [2]. The first step is to select the input parameter space for each passive structure. Once a circuit is designed, the input parameter ranges of every neural network to train are selected accordingly to the passive element this network has to model, except for the frequency. Since our target is to highlight the coupling effects, very high frequencies are required. In practice, the 2.5D *Sonnet-Lite* EM-simulator is used up to 10 GHz while the 3D-EM simulator *Ansoft-HFSS* is used to generate data from 10 to 80 GHz.

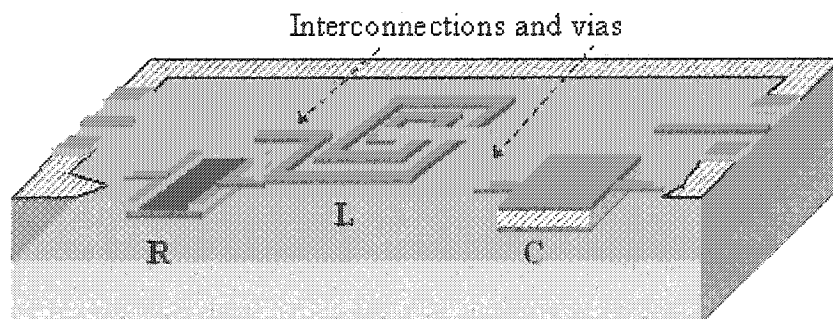


Figure IV-1. Embedded passives in a microwave integrated circuit.

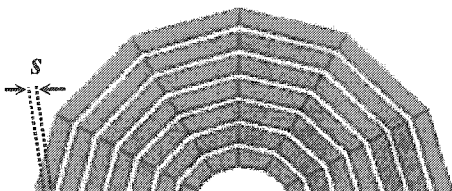
4.1 Component Level

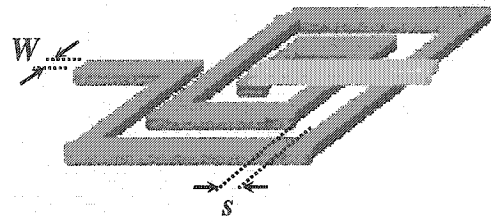
In the component level, we used MLP neural structures. The input layer that contains as many neurons as input variables uses relay functions. The output layer uses linear functions [3]. Since we utilize EM simulators, the neural model output parameters are the real and imaginary parts of the S-parameters S_{11} and S_{21} , i.e., $\{RS_{11}, IS_{11}, RS_{21}, IS_{21}\}$. All data files are split into two files: a training data file containing 75% of the data and a test file with the rest of the data. All neural models have been trained using the *NeuroModeler* software [4].

4.1.1 Inductors

We have considered spiral and square spiral inductors (Figure IV-2). By varying the number n of turns, the width W , the space s between lines, and the operating frequency, we obtained the neural structure shown in Figure IV-3. Tables IV-1 and IV-2 summarize the effective range of those input variables for the spiral and the square spiral inductor respectively.

For data generation, spiral inductors were simulated from 1 to 10 GHz using *Sonnet-Lite*, while square spiral inductors were simulated in *Ansoft-HFSS* in the frequency range of 1-80 GHz. The difference is due to the fact that the topology of spiral inductors is quite difficult to implement in *Ansoft-HFSS*.





(a)

(b)

Figure IV-2. Structures of the inductors:

(a) Spiral form, (b) Square spiral form.

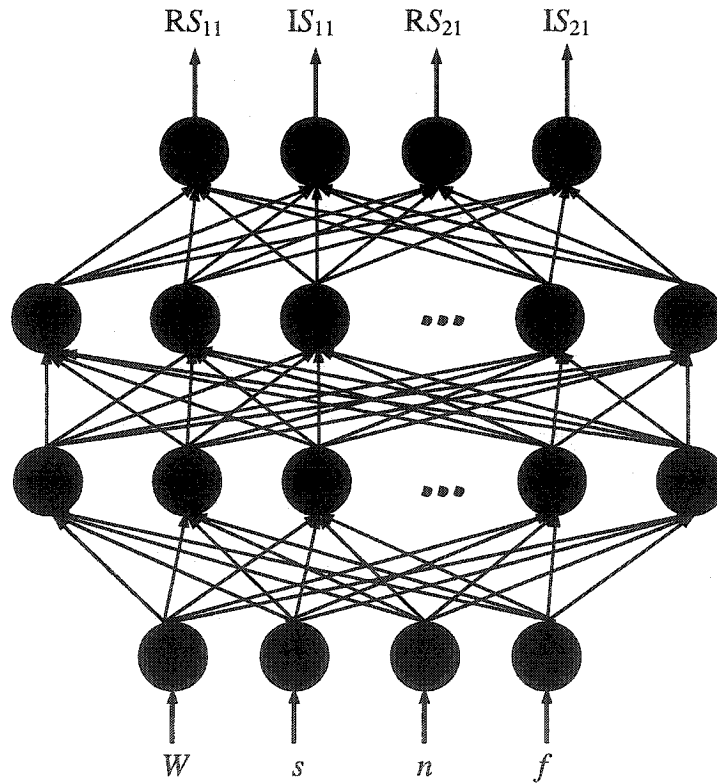


Figure IV-3. Inductors: Corresponding neural network. Input variables are the number n of turns, the width W , the space s between lines, and the operating frequency.

Table IV-1. Spiral inductor: data range of input parameters.

Parameters	Symbol	Range
Number of turns	n	1 - 5
Width (μm)	W	4 - 10
Space (μm)	s	1 - 3
Frequency (GHz)	f	1 - 10

Table IV-2. Square spiral inductor: data range of input parameters.

Parameters	Symbol	Range
Number of turns	n	1 - 5
Width (μm)	W	4 - 10
Space (μm)	s	1 - 3
Frequency (GHz)	f	1 - 80

For spiral inductors, the final training error $E(w)$ is 0.98% with 29 neurons in the first and 18 in the second hidden layer. The test error is 1.63% with data never shown during training. For square spiral inductors, the final training error $E(w)$ is 1.38% with 32 neurons in the first and 19 in the second hidden layer. The test error is 1.93% with data never used during training. Figure IV-4 shows a very good agreement between the original EM data and the results obtained by the neural model.

Moreover, we have compared our results with those published by Mohan *et al.* [5] who used empirical formulas to model inductors and with those given by Niknejad *et al.* [6] using

an equivalent electrical circuit (Figure IV-5). The aim of this comparison is to highlight the limitations of these two other approaches to efficiently model inductors, namely, semi-empirical formulas and equivalent electrical circuit representation.

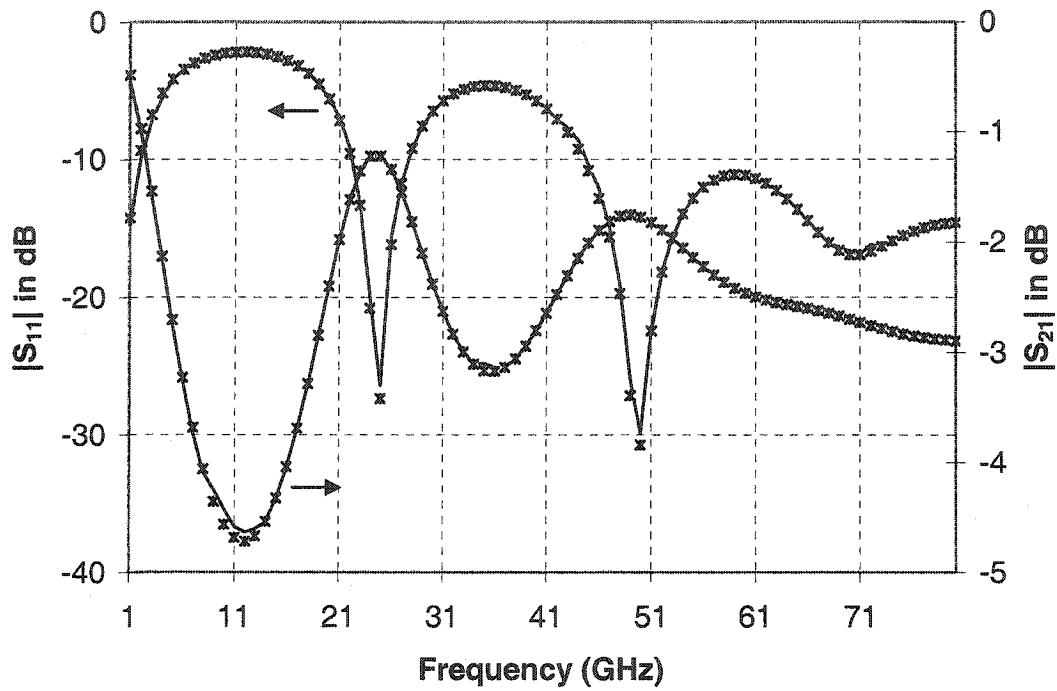


Figure IV-4. S_{11} and S_{21} parameters of a square spiral inductor.

Our values (—) have been successfully compared to those given by the EM-simulator (*).

The input parameters are $n = 4.5$, $W = 10 \mu\text{m}$, and $s = 2 \mu\text{m}$.

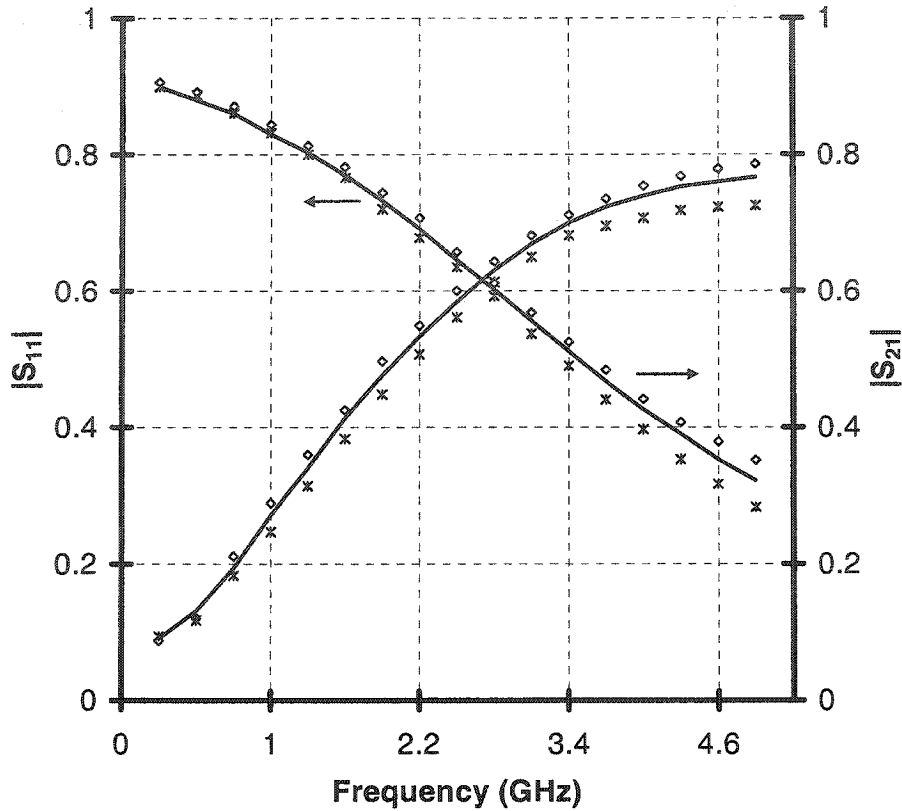


Figure IV-5. S_{11} and S_{21} parameters of a spiral inductor of 5.45nH. Our values (—) have been compared to those given by [5] (*) and by using the equivalent circuit given by [6] (◊).

The input parameters are $n = 5$, $W = 5\mu\text{m}$, and $s = 2\mu\text{m}$.

4.1.2 Resistors

A similar work has been done for resistors (Figure IV.6). Table IV-3 summarizes the effective range of the input variables, namely, the length L , the width W , the resistivity R per surface unit, and the operating frequency (Figure IV-7). The final training error $E(w)$ is 0.09% with 18 neurons in the hidden layer and the test error is 0.27% with data never shown during training.

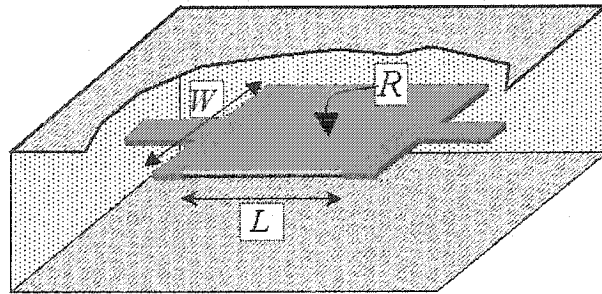


Figure IV-6. Resistor: Physical structure.

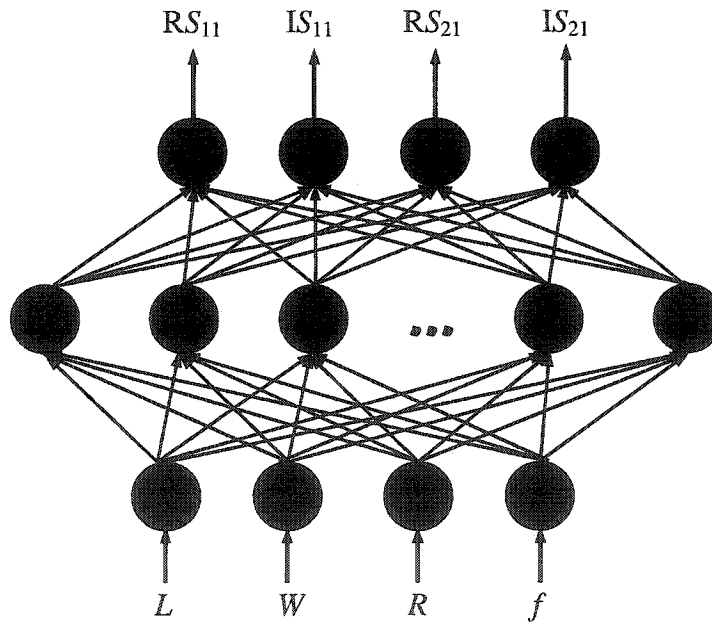


Figure IV-7. Resistor: Corresponding neural network. Input variables are the length L , the width W , the resistivity R per surface unit, and the operating frequency.

For validation, Figure IV-8 shows a successful comparison between the neural model outputs and data given by the EM simulator.

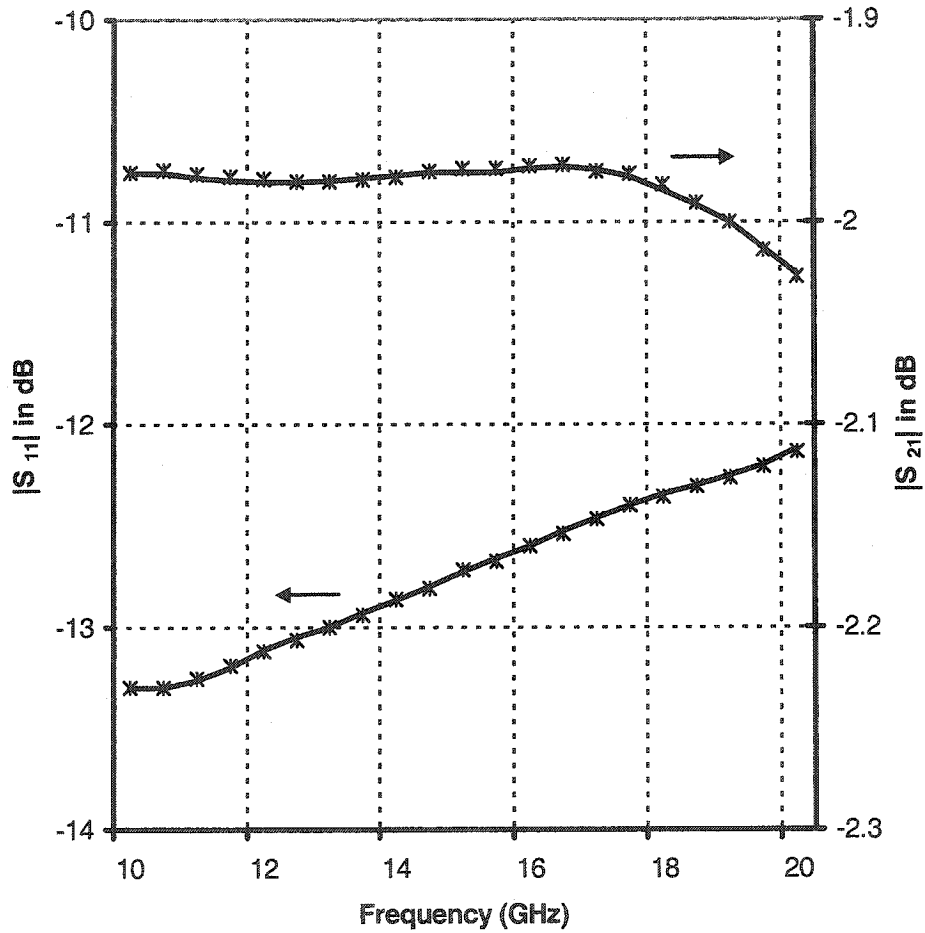


Figure IV-8. S_{11} and S_{21} parameters of a square resistor of 100Ω per square unit.

Our values (—) have been successfully compared to those given by the EM-simulator (*).

The input parameters are $L / W = 0.25$, $R = 100\Omega$.

Table IV-3. Resistor: data range of input parameters.

Parameters	Symbol	Range
Length (μm)	L	100 - 500
Width (μm)	W	100 - 500
Resistivity ($\Omega / \mu\text{m}^2$)	R	10 - 100
Frequency (GHz)	f	1 - 80

4.1.3 Capacitors

By varying the side length L , the thickness T between plates, the relative permittivity ϵ_{rc} and the frequency f , EM-data for square capacitors have been generated (Figure IV-9). Table IV-4 shows the effective range of the input parameters. The final training error $E(\mathbf{w})$ of the corresponding neural network shown in Figure IV-10 is 0.29% with 12 neurons in the hidden layer and the test error is 0.84%.

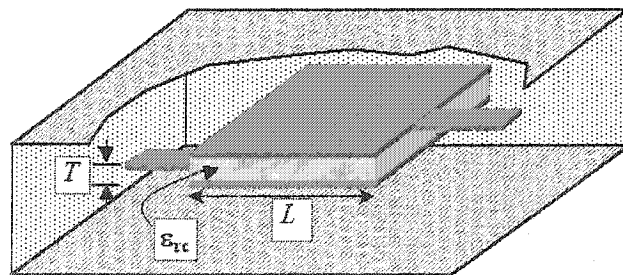


Figure IV-9. Square capacitor: Physical structure.

Table IV-4: Square capacitor: data range of input parameters.

Parameters	Symbol	Range
Side (μm)	L	100 – 500
Thickness (μm)	T	0.5 - 3
Relative Permittivity	ϵ_{rc}	100 - 500
Frequency (GHz)	f	1 - 80

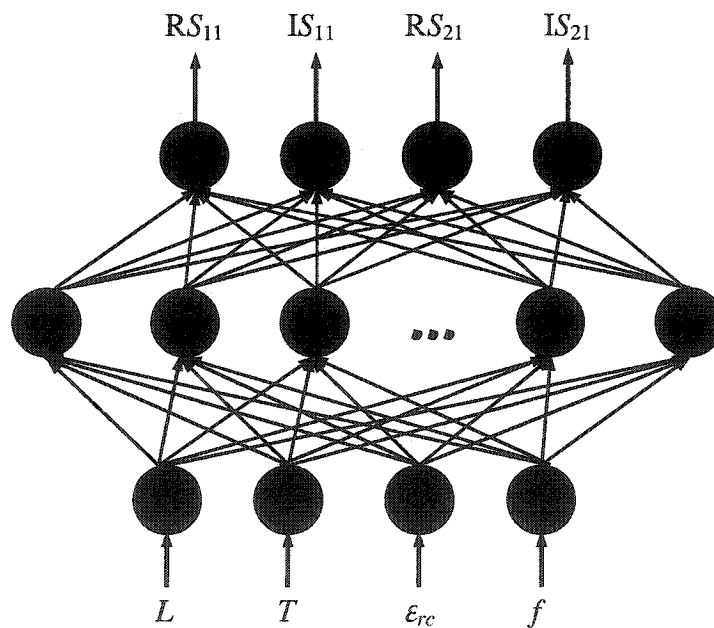


Figure IV-10. Square capacitor: Corresponding neural network. Input variables are the side L , the thickness T , the relative permittivity ϵ_{rc} , and the operating frequency.

For validation, Figure IV-11 shows a successful comparison between the neural model outputs and data given by the EM simulator.

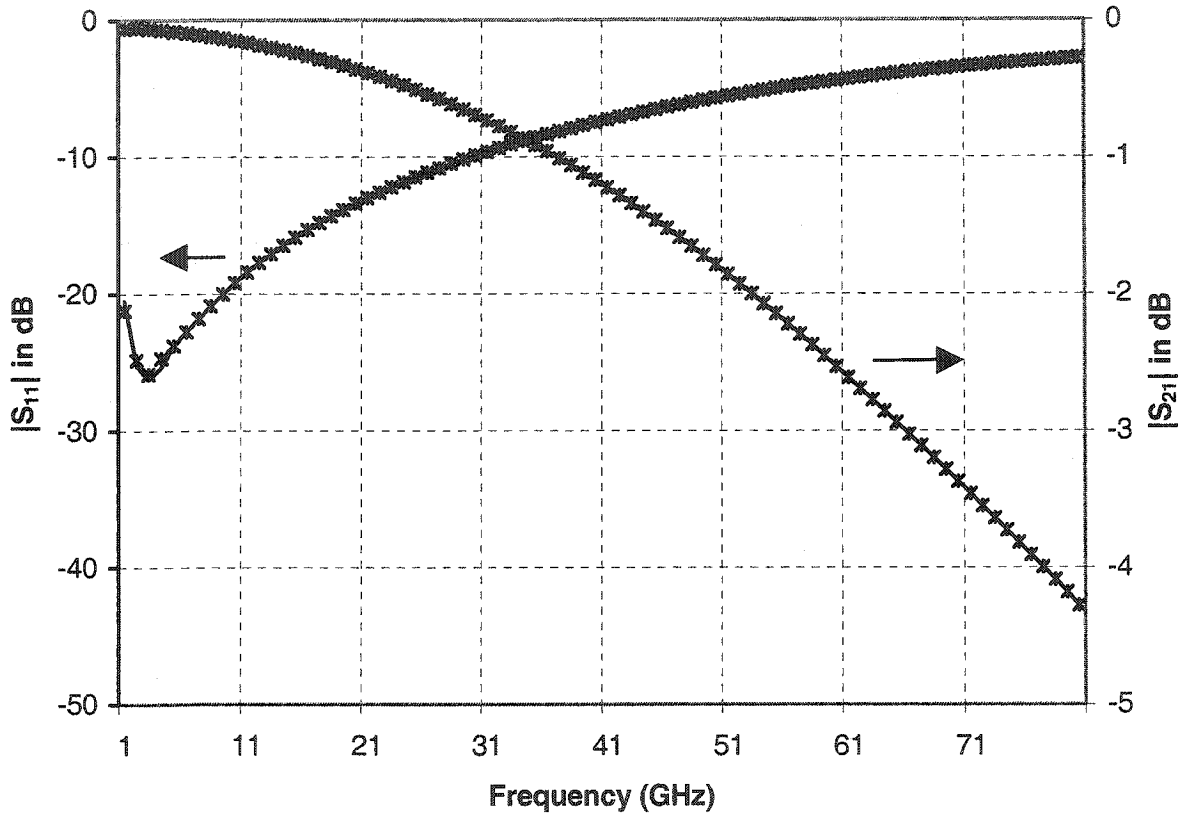


Figure IV-11. S_{11} and S_{21} parameters of a square capacitor.

Our values (—) have been successfully compared to those given by the EM-simulator (*).

Input parameters are $L = 150 \mu\text{m}$, $T = 1 \mu\text{m}$, and $\epsilon_{rc} = 100$.

4.1.4 Interconnections: Vias

As for the other components, neural models of different types of vias shown in Figure IV-12 have been generated (Figure IV-13). The input variables are the length of the upper and the lower line, respectively L_1 and L_2 , the line widths, respectively W_1 and W_2 , and the height H of the via connecting them (Table IV-5). The final training error $E(w)$ is 0.07% with 8 neurons in the hidden layer and the test error is 0.11%.

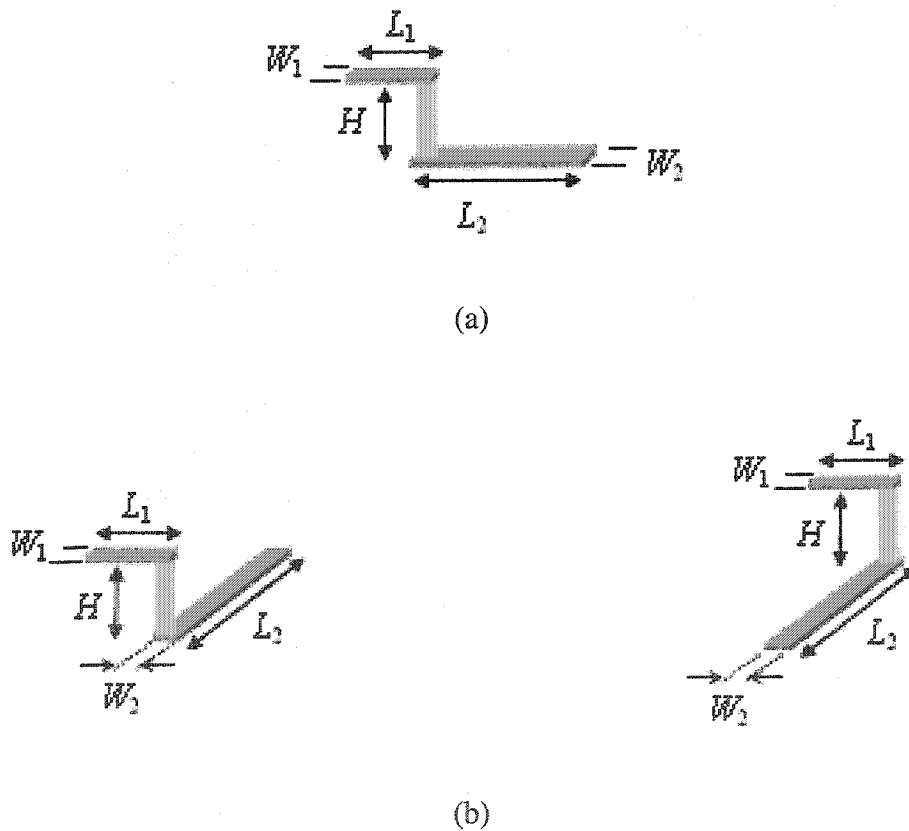


Figure IV-12. Different type of interconnects to be modeled:

(a) "Z" vias, (b) "L" vias.

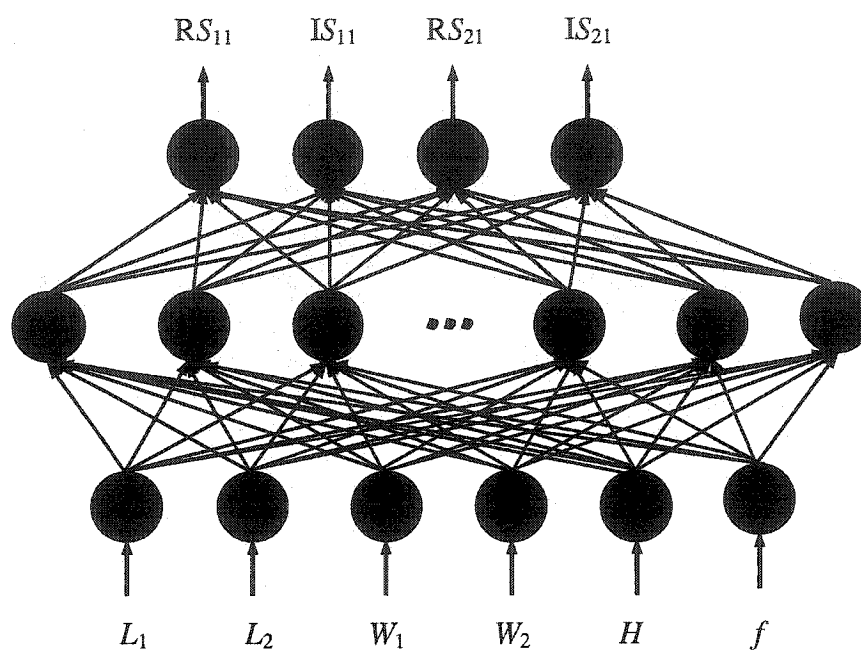


Figure IV-13. Vias: Corresponding neural network.

Table IV-5. Vias: data range of input parameters.

Parameters	Symbol	Range
Length of the upper line (μm)	L_1	0.5 – 20
Length of the lower line (μm)	L_2	0.5 – 20
Width of the upper line (μm)	W_1	4 – 10
Width of the lower line (μm)	W_2	4 – 10
Height of the via (μm)	H	0.5 – 5
Frequency (GHz)	f	1 - 80

For validation, Figure IV-14 shows a successful comparison between the neural model outputs and data given by the EM simulator.

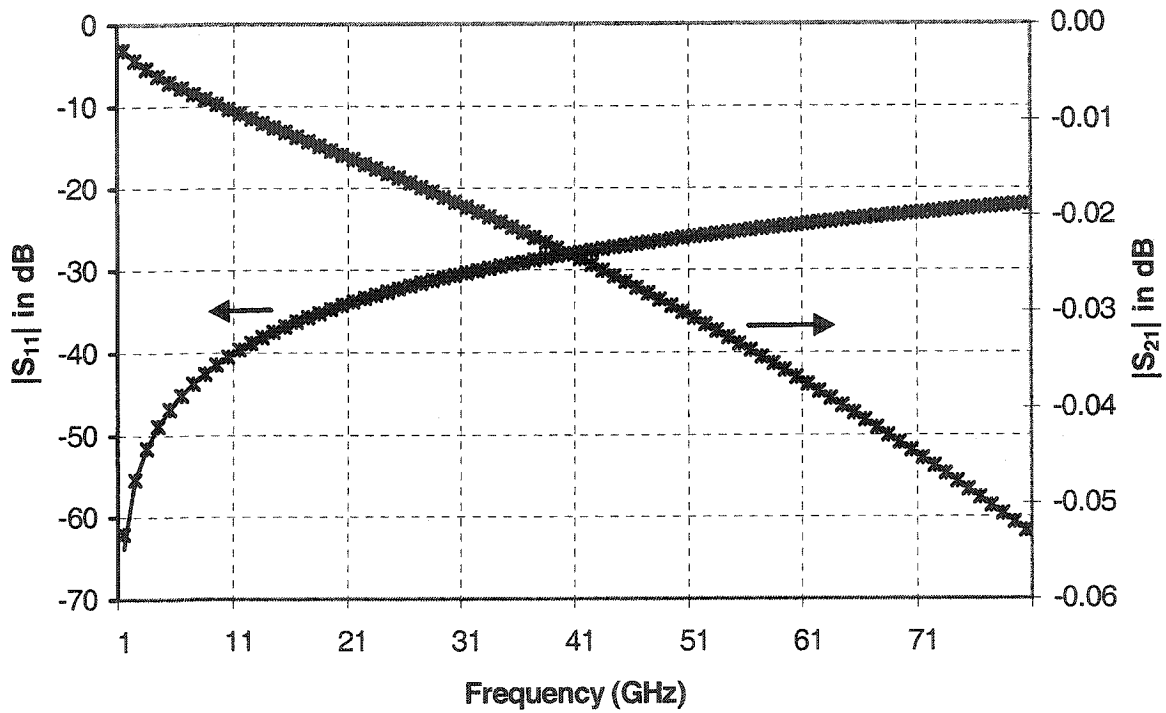


Figure IV-14. S_{11} and S_{21} parameters of a "Z" via.

Our values (—) have been successfully compared to those given by the EM-simulator (*).

Input parameters are $L_1 = L_2 = 10 \mu\text{m}$, $W_1 = W_2 = 4 \mu\text{m}$, and $H = 1 \mu\text{m}$.

4.1.5 Interconnections: transmission lines

Another type of interconnects, transmission lines, has been also modeled (Figure IV-15) by the neural structure shown in Figure IV-16. The input variables are the width W and the plane coordinates x and y (Table IV-6). With a final training error $E(w)$ of 0.008% with 7 neurons in the hidden layer and a test error of 0.011%, the neural model fits closely with original EM-data (Figure IV-17).

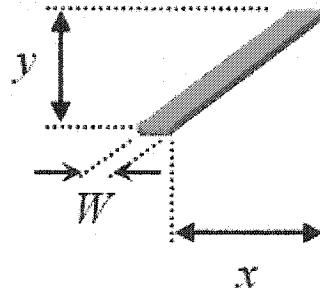


Figure IV-15. Different type of interconnects to be modeled: Transmission lines.

Table IV-6: Transmission lines: data range of input parameters.

Parameters	Symbol	Range
Width (μm)	W	4 – 10
Length on the x axis (μm)	x	0 – 20
Length on the y axis (μm)	y	0 – 20
Frequency (GHz)	f	1 - 80

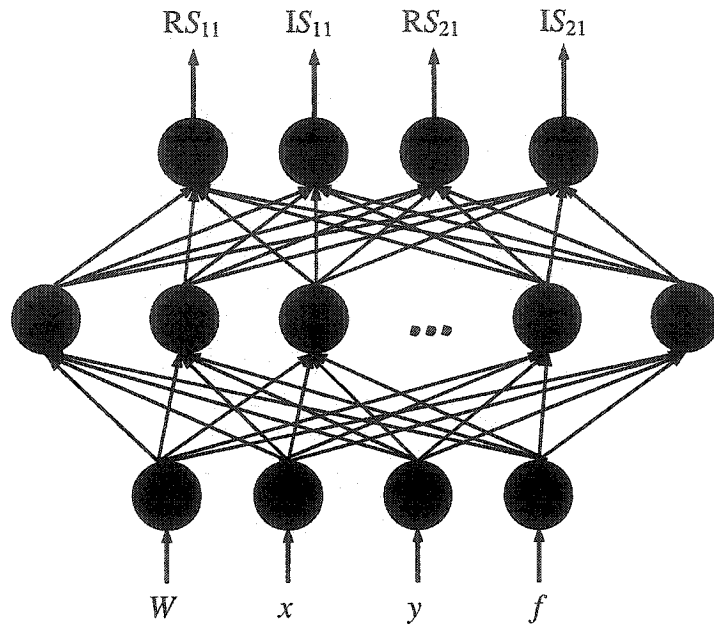


Figure IV-16. Transmission lines: Corresponding neural network.

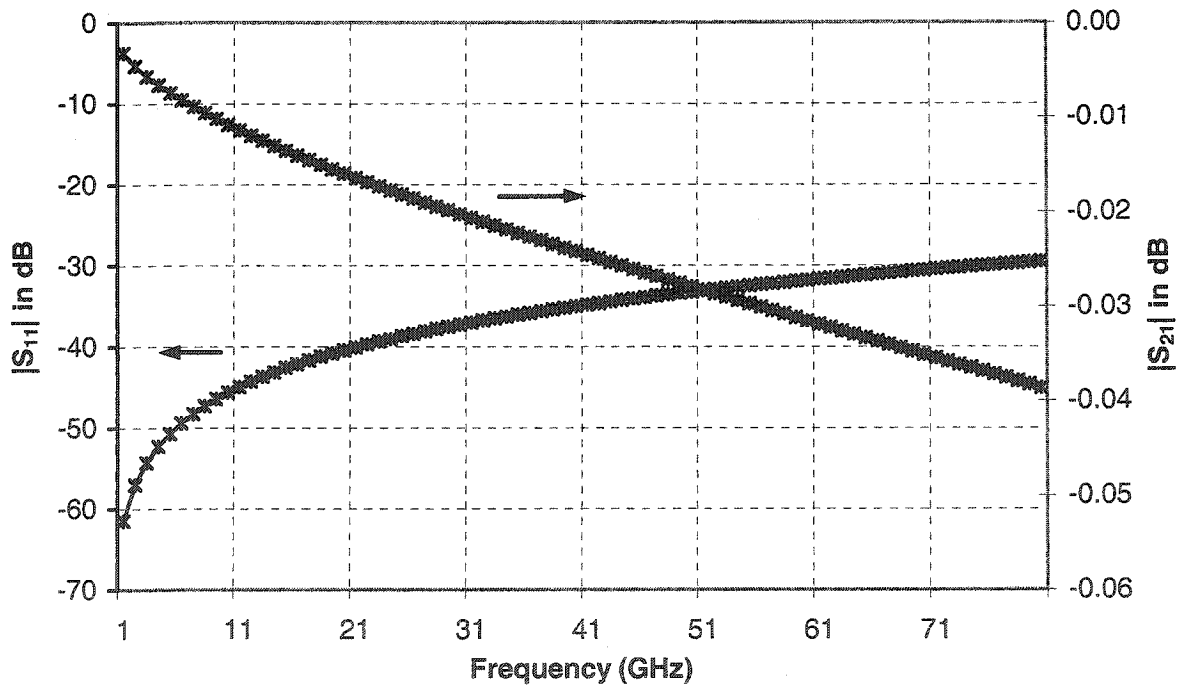


Figure IV-17. S_{11} and S_{21} parameters of a transmission line.

Our values (—) have been successfully compared to those given by the EM-simulator (*).

The input parameters are $W = 4 \mu\text{m}$, $x = 11 \mu\text{m}$, $y = 17 \mu\text{m}$.

4.1.6 Conclusion

Through the above examples, we have demonstrated the accuracy of our neural models of passives. Then we implemented them in the circuit simulator *Agilent-ADS* [7] in order to achieve efficient design and optimization of practical RF/microwave circuits.

4.2 Circuit Level

4.2.1 Band-pass filter

The first circuit we considered is a 4-6 GHz band-pass filter of order 4 (i.e., 4 *L-C* cells). All geometrical dimensions of interconnects are fixed for this example. We first simulated the circuit in the EM-simulator *Ansoft-HFSS*. Then, we implemented the filter in the circuit simulator *Agilent-ADS* [7] and replaced all passives by their equivalent neural models using the SDD modules (for Symbolically Defined Devices) available in *Agilent-ADS*. Finally, we realized and tested the circuit. Figure IV-18 shows a close agreement between the two simulated responses and an acceptable agreement with the measurements when considering all possible errors due to fabrication tolerances and measurements. In parallel, we should notice that the simulation in *Ansoft-HFSS* was achieved in more than 5 hours while the same simulation in *Agilent-ADS* was done in 14 seconds. The gain in terms of computing time is obvious and demonstrates the efficiency of our technique.

This gain could be more evident if an optimization is run. Therefore, we started an optimization with the magnitude of the S_{21} parameter as the objective function.

The optimized variables are the inductor parameters $\{(W_k, s_k, n_k), k = 1, \dots, 4\}$ and with the following constraints

$$\left. \begin{aligned} -4 \text{ dB} \leq |S_{21}| \leq 0 \text{ dB} \\ 4 \text{ GHz} \leq f \leq 6 \text{ GHz} \\ W_1 = W_2 = W_3 = W_4 \end{aligned} \right\} \quad (\text{IV-1})$$

The optimization process was achieved in 24 minutes in the circuit simulator while a less acceptable optimized response was obtained after more than 9 hours in the 3D-EM simulator (Figure IV-19). Moreover, the number n of turns cannot be varied in *Ansoft-HFSS* while it is part of the optimized variables in *Agilent-ADS*.

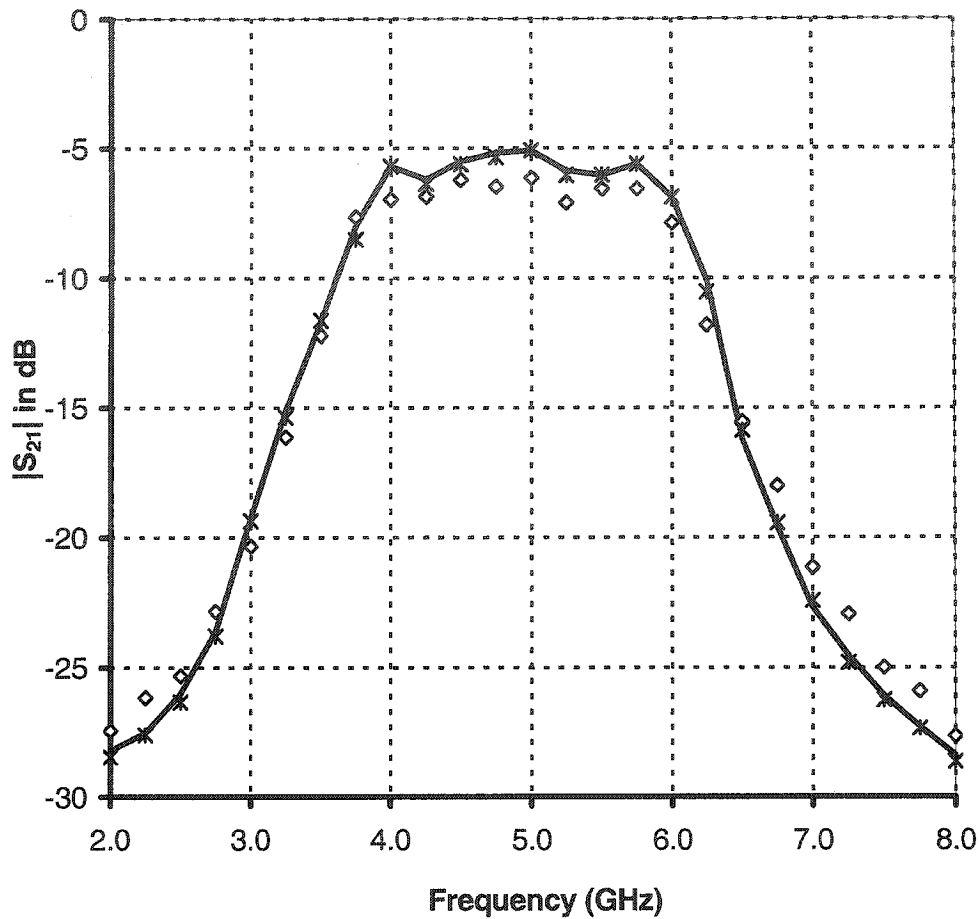


Figure IV-18. 4-6 GHz Band-pass filter: Comparison between measurements (◇) and simulated values given by the EM simulator (*) and the circuit simulator (—).

4.2.2 Amplifier

Once the neural models have been successfully tested in a passive circuit, we considered an active circuit, i.e., a transistor amplifier (Figure IV-20). We first simulated the circuit with all passives, i.e., resistors R_1 , R_2 , R_3 , and R_L plus capacitors C_{cc} modeled by ideal lumped elements (independent of frequency).

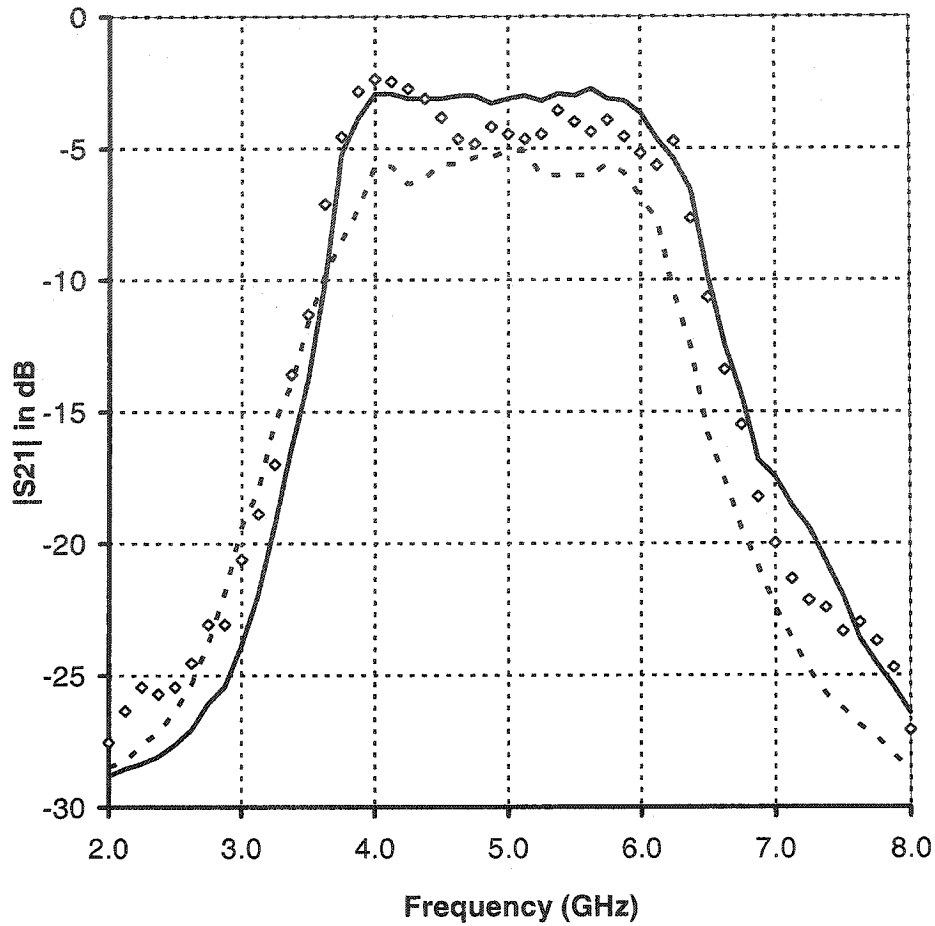


Figure IV-19. 4-6 GHz Band-pass filter: Comparison between the response before (---) and after optimization in the circuit simulator (-) and the EM simulator (◊).

Next, we replaced all passives by their equivalent neural models and simulated again the amplifier. Figure IV-21 shows the difference between ideal models and EM models, highlighting the importance of EM effects in high frequencies even in the lower part of the RF/microwave spectrum.

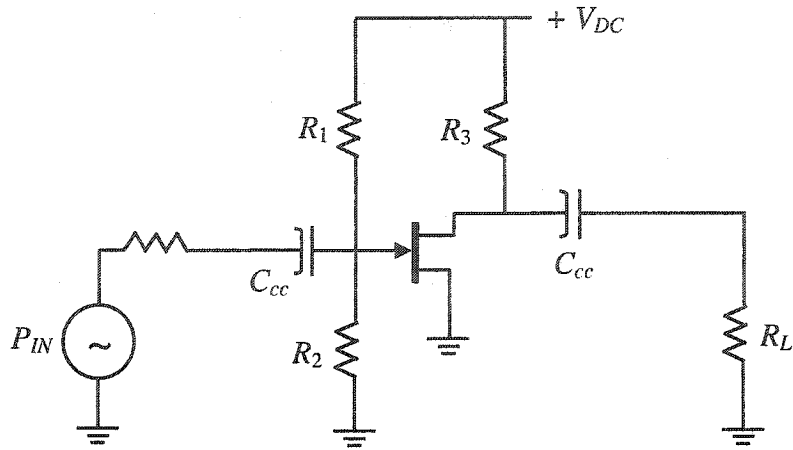


Figure IV-20. Amplifier: All passives have been replaced by their equivalent neural models.

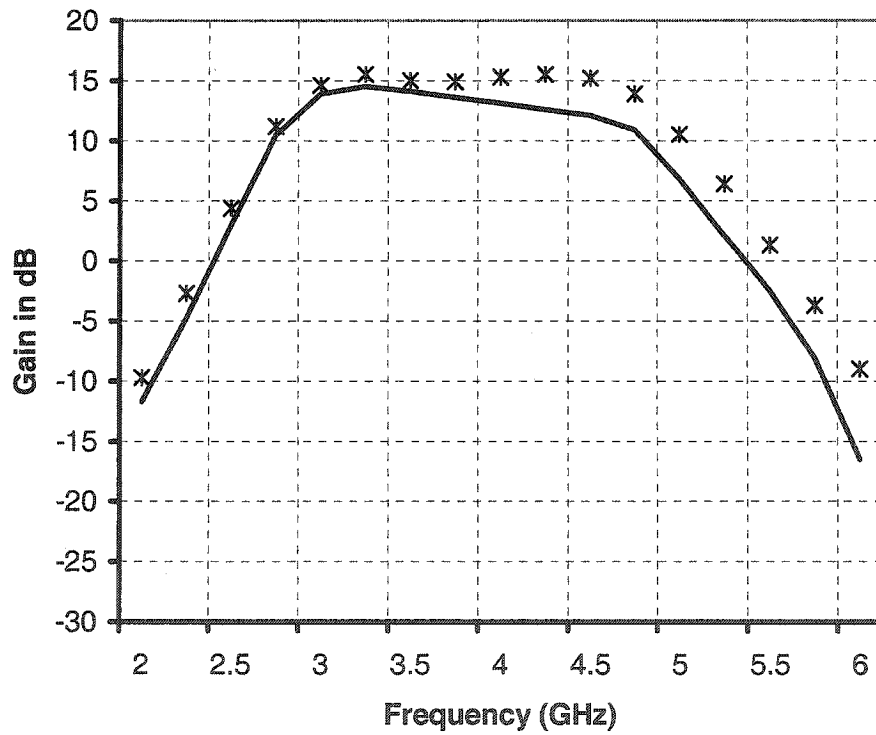


Figure IV-21. Amplifier: Comparison between the response of the ideal circuit (using ideal passive models) (*) with that obtained when the same passives include the electromagnetic effects present at the operating frequencies (-).

4.2.3 Frequency Doubler

With the filter, we demonstrated that our neural models are much more efficient in terms of computing time than the original EM models, with quite close responses. With the amplifier, we showed the importance of the EM effects we would like to capture.

The purpose of this third circuit example is to include the interconnects in the optimization process in order to determine the optimum location of a passive device in a circuit layout. A similar work was achieved for the power plane of an amplifier [8], but not for a circuit layout. Hence, we designed a 3-6 GHz frequency doubler in *Agilent-ADS* (Figure IV-22)

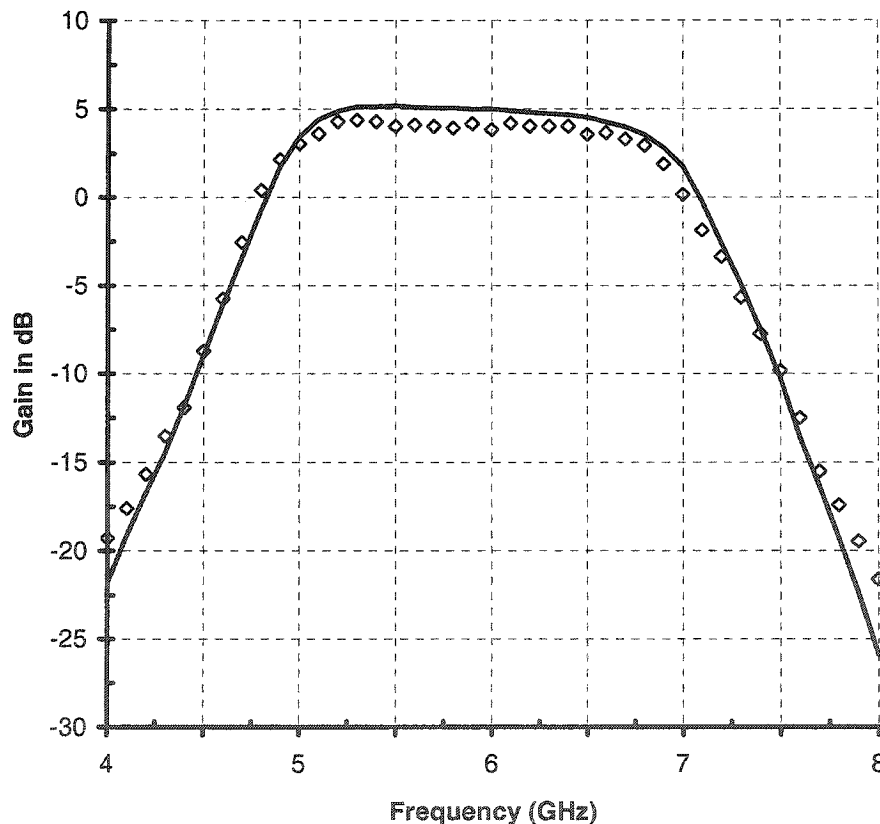


Figure IV-22. Frequency doubler: Comparison between measurements (\diamond) and simulated values obtained with our neural models ($-$).

4.2.4 Optimization of the device placement in the circuit layout

In the filter example, we have optimized the circuit response with fixed interconnects. In this stage, we will integrate it as the output filter of a 2.5-5 GHz frequency doubler. We will start with the optimized values of inductors and keep them fixed. The variables to vary would be now the parameters of the three lines connecting the inductors $\{(x_i, y_i), i = 1, \dots, 3\}$.

As shown in Figure IV-23, the output of the first inductor will be chosen as reference in order to easily formulate the (x, y) couples in terms of distance to the origin. A simple optimization in the circuit simulator was done in less than 3 minutes (Table IV-6) with the following constraints on the filter

$$-3 \text{ dB} \leq |S_{21}| \leq 0 \text{ dB} \quad \text{for} \quad 4 \text{ GHz} \leq f \leq 6 \text{ GHz} \quad (\text{IV-2-a})$$

$$|S_{21}| \leq -15 \text{ dB} \quad \text{for} \quad 3.5 \text{ GHz} \leq f \quad (\text{IV-2-b})$$

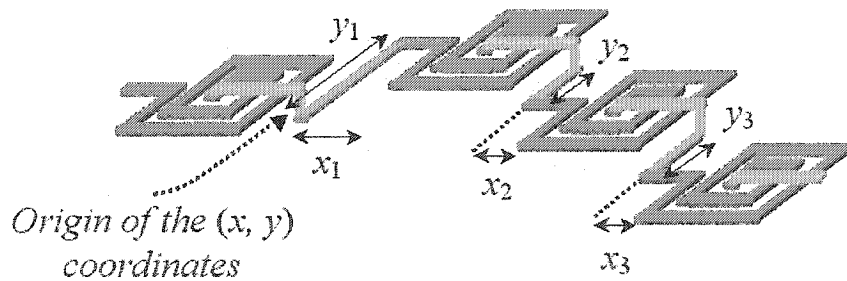


Figure IV-23. Frequency doubler output filter: Localization of the inductors.

Even if we started from an already optimized response, we were able to reach a more restrictive optimization criterion (3dB instead of 4dB) only by varying the geometrical dimensions of the interconnects. So, we were able to determine a new placement of the passives in the circuit layout after optimizing the circuit performance. We recognized that this work is still perfectible. A more complete and significant contribution would be to use this concept on a complicated circuit containing more passive elements. We have also to take into account non-ideal power plane [8], etc.. However, we demonstrated that it is possible to optimize the layout of a circuit using the dimensions of interconnects. Such optimization for a complicated circuit is impossible in an EM solver.

Table IV-7. Dimensions of the interconnections before and after optimization.

	Before optimization	After optimization
x_1 (mils)	2	1.3
x_2 (mils)	2	2.7
x_3 (mils)	2	1.8
y_1 (mils)	2	3.7
y_2 (mils)	2	0.5
y_3 (mils)	2	0.8

4.3 Including coupling effects between components

After this round of device/ circuit modeling and optimization, a question could be raised:

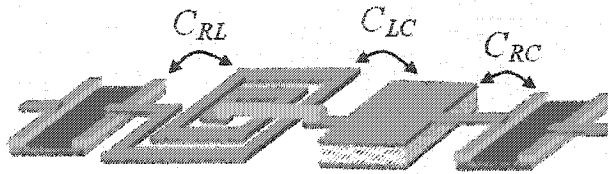
Why generating data up to 80 GHz while using the corresponding trained models
only in the range of 1-8 GHz?

To answer to that question, we simulated circuits in a higher frequency range. However measurements showed some significant differences with simulations. Therefore, we decided to investigate the difference between plugging single models together in a layout and including EM coupling effects between them when combined in a circuit topology (Figure IV-24).

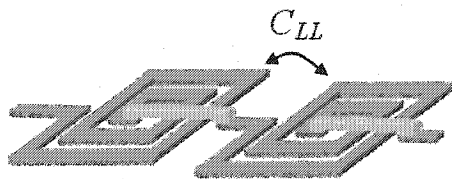
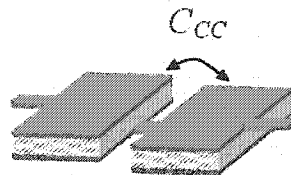
Using a combination of the device models includes the effect of environment in the simulations. This is useful in high frequency circuits involving long transmissions lines and several components.

4.3.1 Circuit code

First, we have to validate our circuit program that computes the overall S matrix of a circuit. Therefore, we successfully tested several circuits based on individual S matrices of passives or their equivalent in microstrip lines. As an illustration, Figure IV-25 shows a microstrip rat-race coupler (3 dB coupler) proposed by Gupta *et al.* [9].



(a)



(b)



(c)

Figure IV-24. Types of mutual coupling: (a) between components of different types, (b) between components of same types, (c) between interconnects and components. The subscripts R , L , C and I refer respectively to resistors, inductors, capacitors and interconnects.

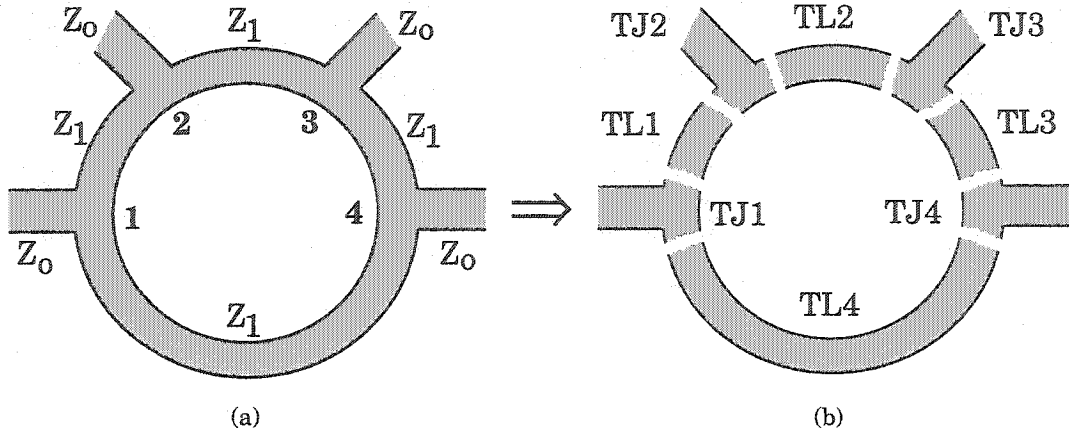


Figure IV-25: (a) rat-race coupler, (b) its decomposition into elementary components.

Its decomposition gives eight elementary components: 4 Tee junctions (TJ1 to TJ4) and 4 transmission lines (TL1 to TL4); three of $\lambda/4$ and one of $3\lambda/4$. The input reflection coefficient was successfully compared to the one obtained by [9] (Figure IV-26 where the 3 GHz center frequency is normalized).

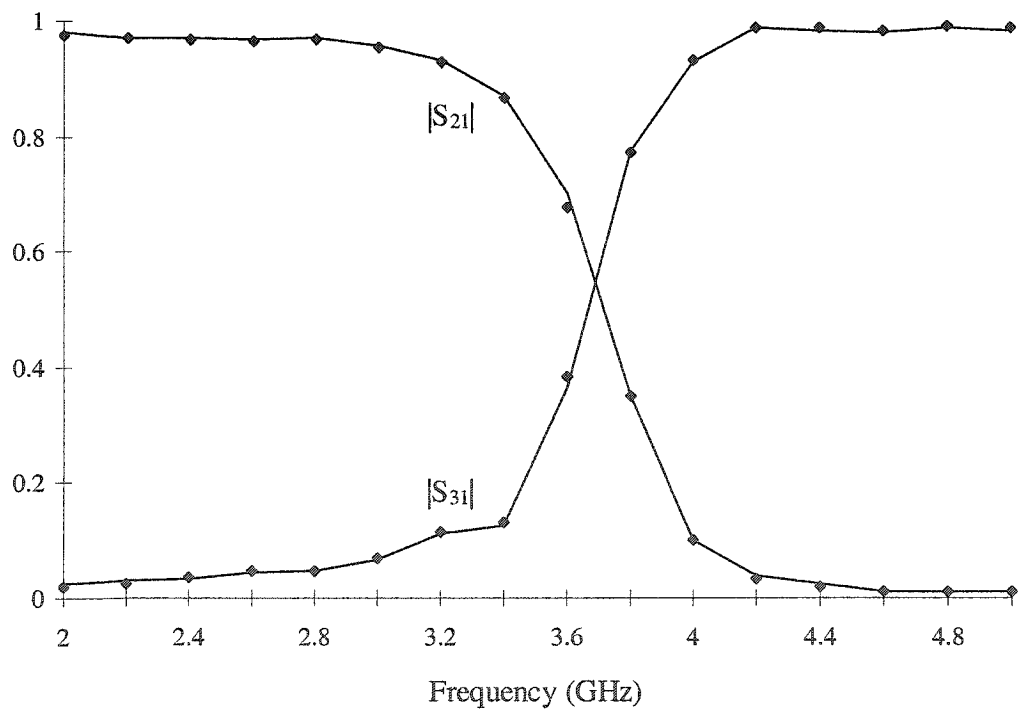
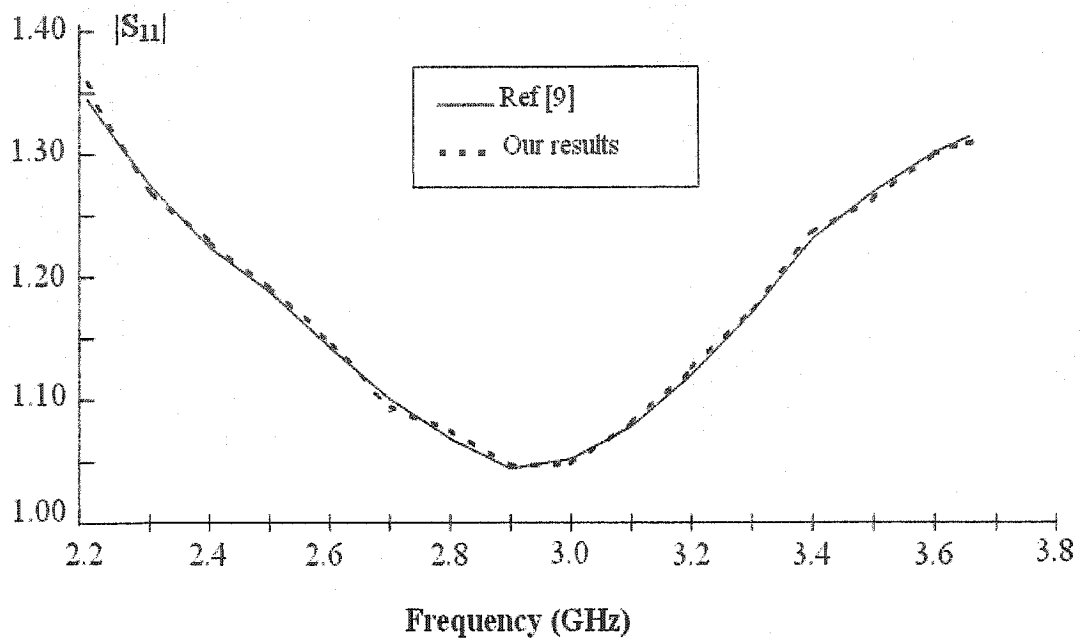


Figure IV-26: Coupler: Comparison of S_{11} , S_{21} and S_{31} parameters obtained by our program (—) and those published by [9] (*).

4.3.2 Effect of mutual coupling - Resistors in series

To explore the effects of the EM environment on our individual neural models in terms of coupling, we simulated a set of three identical resistors in series as shown in Figure IV-27. First, we ran the simulation in *Ansoft-HFSS* up to 40 GHz in order to capture the EM mutual coupling effects between the different passives involved in the layout. Second, we used our circuit code to get the overall S matrix based on individual S matrices generated by our neural models. Third, we simulated the circuit in *Agilent-ADS* based on our individual neural models. Fourth, we simulated the same circuit in *Agilent-ADS* based on ideal lumped elements.

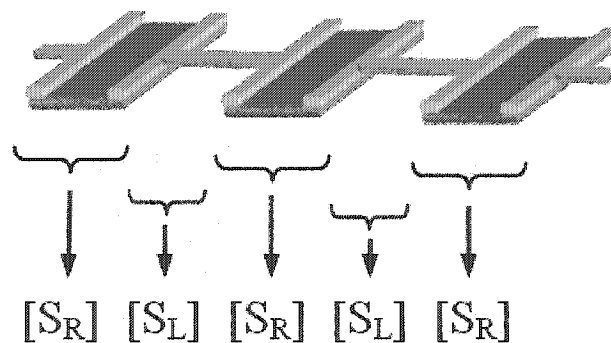


Figure IV-27. Three resistors: Combination of the individual S matrices. $[S_R]$ and $[S_L]$ are the S matrices of respectively the resistor and the interconnect (line).

As shown in Figure IV-28, and as expected, both responses using individual models are between the "ideal" one using lumped elements and the full EM one using the EM simulator. This simulation confirms the non negligible effects of device coupling in circuit performance.

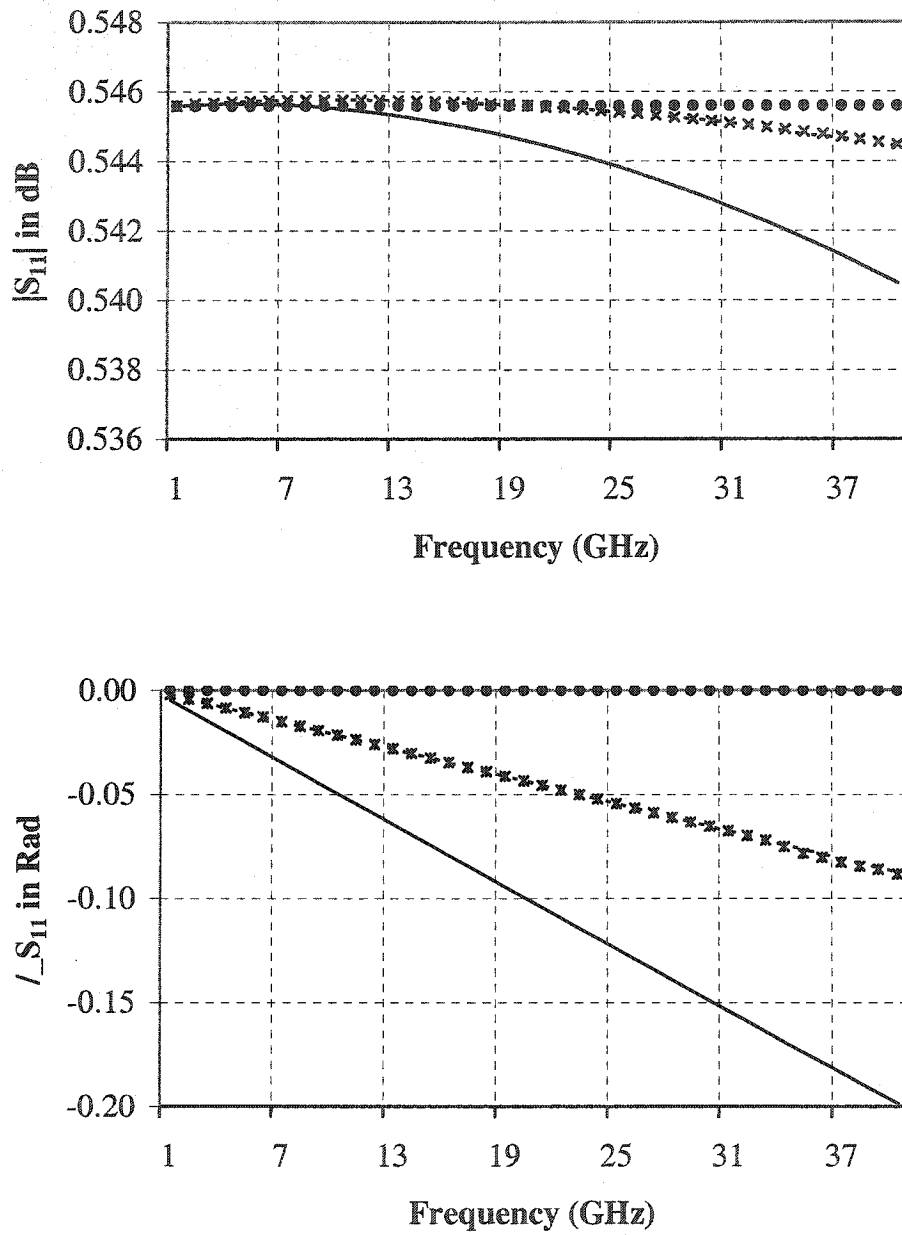


Figure IV-28. S_{11} parameter for a set of three resistors in series: Comparison of results given by the EM simulator (—), by the circuit simulator using ideal lumped elements (•), by the circuit simulator using individual neural models (*), and by our circuit code using individual neural models (---).

4.3.3 Effect of mutual-device coupling – RLC circuit

Furthermore, we developed a code to compute the S matrix of the mutual coupling based on the difference between the EM simulator response and the one obtained by our circuit program using individual S matrices. We ran the simulation up to 80 GHz for a parallel RLC circuit shown in Figure IV-29. In this simulation, we highlighted the importance of mutual coupling between components and demonstrated, *for the first time*, the possibility, not only to compute efficiently these effects using neural network techniques (Figures IV-30 and IV-31), but also to achieve such simulations much faster. In fact, the simulation in the EM simulator required 2.4 hours while the same was achieved in the circuit simulator in less than 1 minute.

4.4 Conclusion

In this chapter, we first validated our passive neural network models using automated data generation. Second, we showed the efficiency of neural modeling on circuit design and optimization. Third, we highlighted the non-negligible effects of mutual coupling even for simple circuits, opening the research for more advanced design including statistical analyses.

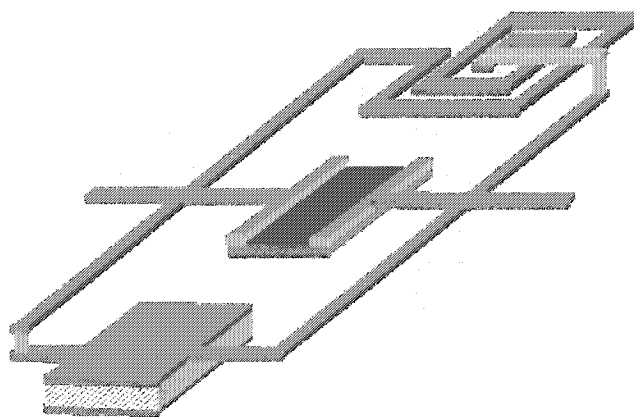


Figure IV-29. Parallel RLC circuit.

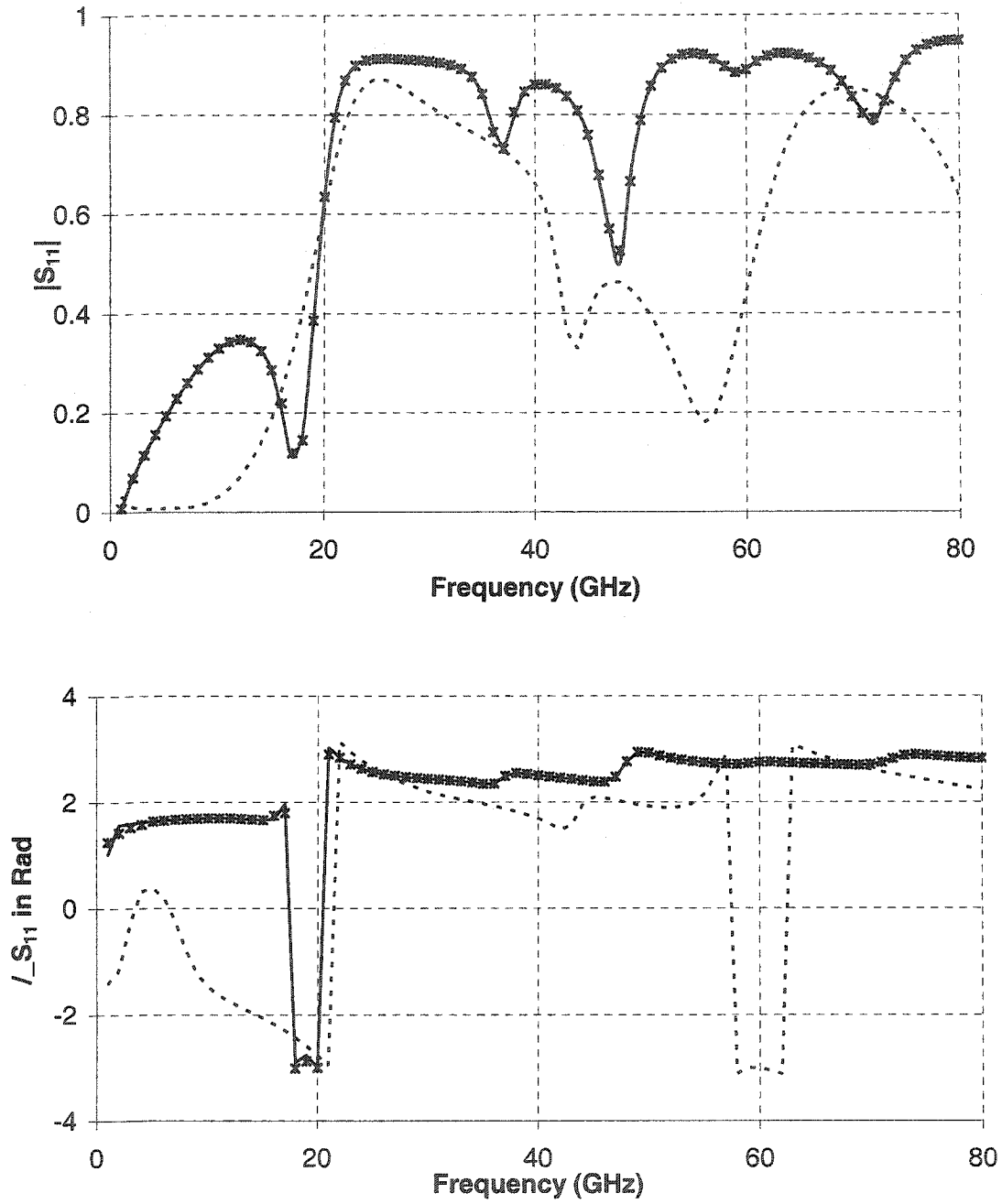


Figure IV-30. S_{11} parameter for the parallel RLC circuit: Comparison of results given by the EM simulator (x), and by the circuit simulator including (—) or not the coupling between components (---).

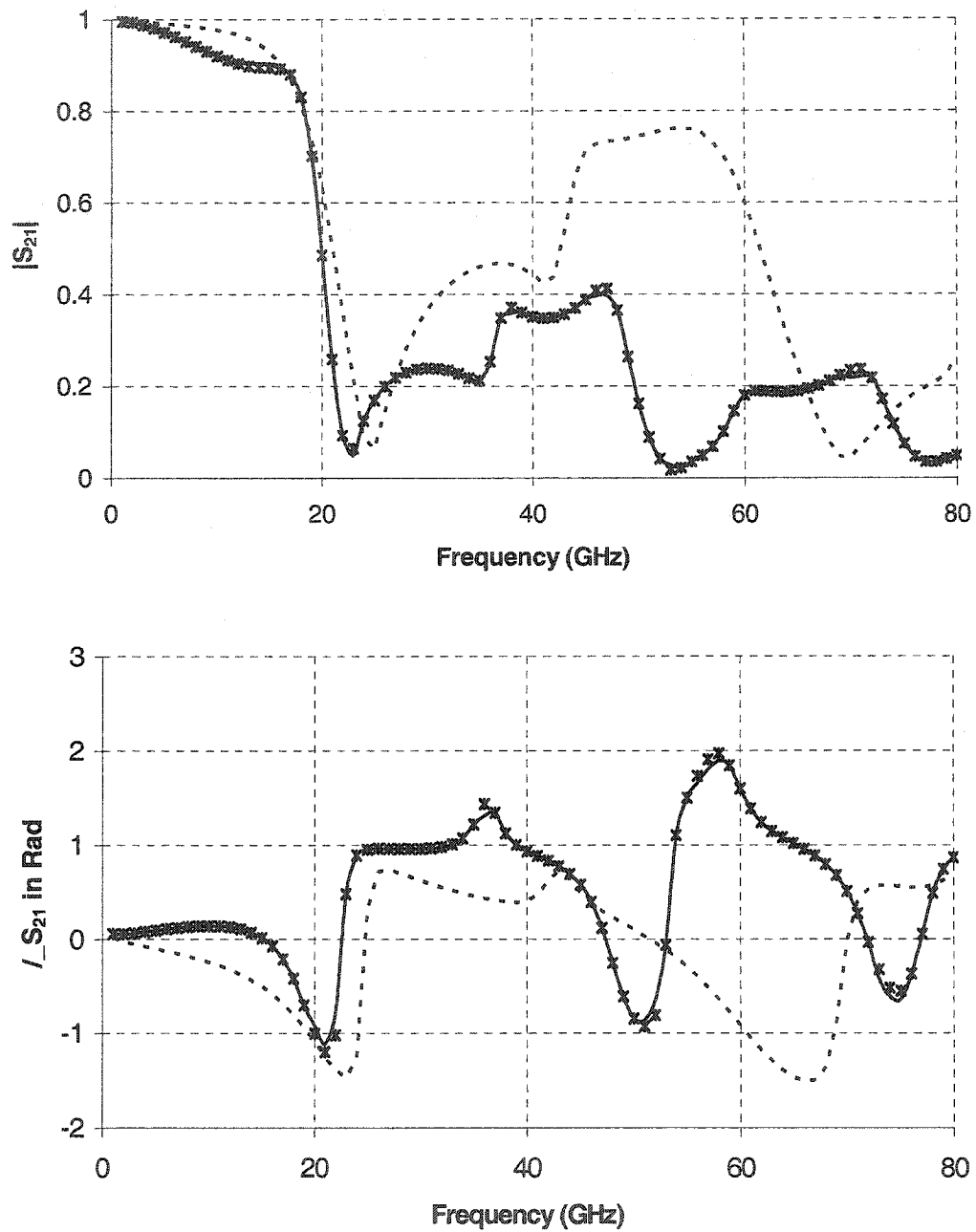


Figure IV-31. S_{21} parameter for the parallel RLC circuit: Comparison of results given by the EM simulator (x), and by the circuit simulator including (—) or not the coupling between components (---).

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CHAPTER V

CONCLUSIONS AND FUTURE WORK

5.1 Conclusion

Because of a potential need for accurate and fast RF/microwave models of passives and interconnects, we proposed different approaches for an efficient use of EM-based neural network models in circuit design and optimization. This choice was motivated by the fact that neural networks has gained an unprecedented popularity in the field of RF/microwave modeling and design mainly because of their ability to learn component/circuit behaviors nearly as accurate as those obtained from full-wave EM simulations. Moreover, the proposed models allow dynamic geometric parameter based design and optimization. However, data generation for neural model training could be very costly in terms of human involvement. To avoid such limitations, we developed a successful automation technique that makes the entire process of data generation fully automated using external drivers for commercial EM-simulators.

There are several advantages of making the entire process of data generation automatic; the most important is to reduce manual labor thereby reducing the time for data generation and any possible chances of human error.

Based on the circuit performance, an original approach that predicts the placement of the components in the circuit layout has been presented. It permits to obtain a better layout of the circuit based on optimized geometrical/electrical parameters of passives and interconnects.

A simple technique to take into account mutual device coupling effects while performing design tasks has been proposed, providing thereby a useful enhancement to the existing design criterion such as layout optimization.

5.2 Suggestions for Future Research

Neural network is emerging as one of the most powerful tools for modeling of microwave devices and systems. Modeling still remains a major bottleneck for CAD of certain classes of RF/microwave circuits.

From the viewpoint of future research, complicated circuit modeling and more improvement in model generation algorithms will benefit the application of combined neural networks in all level of microwave design from modeling and simulation to optimization and statistical design.

An interesting topic in this regard is the application of advanced neural structures, such as Prior Knowledge Inputs (PKI) neural network structures, for modeling from individual passive components to integrated circuits, which can be applied to include EM coupling between components.

Our methodology acts as a bridge that connects EM simulation with circuit design, thus contributing to advancement in microwave CAD.

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