Efficient Modeling of Distributed Electromagnetic Coupling in RF/Microwave Integrated Circuits

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Abstract: - Because of ever-higher operating frequencies and circuit integration, distributed electromagnetic (EM) coupling effects are becoming increasingly important in RF/microwave integrated circuits. Although existing EM-based models for passives are accurate, they do not adequately include distributed EM coupling between adjacent components. In this paper, the authors introduce the concept of automatic generation of accurate and fast neural models for passives that can efficiently integrate distributed EM coupling effects between adjacent elements. Examples of passive device modeling and use of these models in commercial circuit simulators demonstrate that the proposed approach is a generic method which can allow to extend the present capabilities to a large variety of RF/microwave circuit design and optimization.

Key-Words: - Passive Modeling, Electromagnetic Effects, Neural Network, Coupling Effects.

1 Introduction

The 21st century will be the information age characterized by ever-increasing need for communication systems. 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 mass production 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 become increasingly important. This trend leads to massive and highly repetitive computational tasks during simulation, optimization and statistical analyses, requiring that the component models be not only fast but also accurate so that the design 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]-[3]. For this aim, several approaches to device modeling are being continuously proposed, especially for passives that are widely used in RF/microwave integrated circuits such as multichip modules [4]-[10] (Fig. 1).

Conventional modeling techniques for passive elements can be grouped into three main classes. The first represents a passive component by an equivalent electrical circuit.

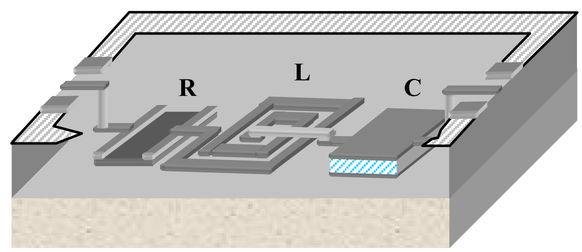


Fig. 1. Passives in RF/Microwave integrated circuit.

Such models exhibit a relatively narrow bandwidth and the circuit parameter extraction procedure is still perfectible, strongly dependent on the device geometry, and relatively complex to achieve [7]-[9]. Similarly, table look-up models can also be fast, but suffer from the disadvantages of large memory requirements and limitation on the number of parameter [11]. The third class uses Maxwell's equations and/or physics-based equations to quantify the electromagnetic (EM) field in a given structure. Such EM numerical methods have demonstrated their efficiency in terms of accuracy, but still require a huge computing time and memory space [7], [12]-[14]. As such, development of full EM representations with physical/geometrical parameter information, and including high-order EM effects, such as coupling, become necessary.

Furthermore, to enable efficient circuit optimization, the model outputs must be directly function of the geometrical and electrical parameters of passives. Therefore, 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 is valid only for a given combination of physical/geometrical parameters. In addition to the above limitations, existing models suffer on an important lack at circuit level. In fact, even if EM-based device models are accurate, they are developed separately, i.e., excluding any external circuit environment effects such as mutual and distributed couplings.

Coupling research has mostly been brought forward from the antenna/microwave community. This includes coupling between transmission lines, interconnects, through apertures, and in printed circuit boards to name a few. Recently there has been activity in bringing this coupling research forward into the circuit design space [12], [15]. Since distributed coupling between elements introduces a major effect at higher frequencies, any efficient modeling technique should include these EM effects.

In the recent years, a CAD approach based on neural networks (NN) has been introduced for microwave circuit modeling, simulation, and optimization. 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 design. Neural models are much faster than original detailed physical/EM models, more accurate than polynomial and empirical models, allow more dimensions than table lookup models, and are easier to develop when a new device/technology is introduced [3], [16]-[18].

This paper introduces a new concept of accurate and fast neural models for passives that efficiently integrate higher-order EM mutual device coupling. In this original approach, EM-based neural models of passives were first trained by varying their geometrical/electrical parameters. This was achieved by an automatic driving of data generation, avoiding any human error. Second, mutual device couplings present in microwave integrated circuits were computed and modeled (Fig. 2). Third, neural models were plugged into commercial simulators to automatically predict not only the optimum geometry of structures but also their optimum placement in the circuit layout taking into account these couplings. Applications in commercial simulators are presented.

2 Proposed Modeling Approach

Neural networks can learn multi-parameter nonlinear relationships and can generalize from complex EM data. They are also easier to update as technology changes and the generated neural function allows a continuous variation of input parameters versus outputs. However, neural model development involves several sub-tasks, such as data generation. This assignment becomes highly tedious and human error prone when extensive data are required for model training. Therefore, there are several advantages of making the process of data generation automatic; we reduce manual labor thereby reducing the time for data generation and any possible chances of human error [8].

In absence of an expensive experimental plant, selecting a full 3D-EM simulator like Anfoft-*HFSS* [19] would provide the desired accurate data. As shown in Fig. 2, once a passive structure is defined, a code is created to drive the EM-simulator. In practice, the code calls the EM simulator, creates a macro for each given structure, runs the simulation and saves the results in desired files. This process is repeated for each new set of input geometrical and/or electrical parameters.

All the process is done automatically without any human intervention. Then, the trained neural models are implemented into a circuit simulator, i.e., *Agilent-ADS* [20] using the internal SDD configuration (for Symbolically-Defined Devices) in order to achieve a circuit layout design taking into account possible EM coupling between adjacent passives.

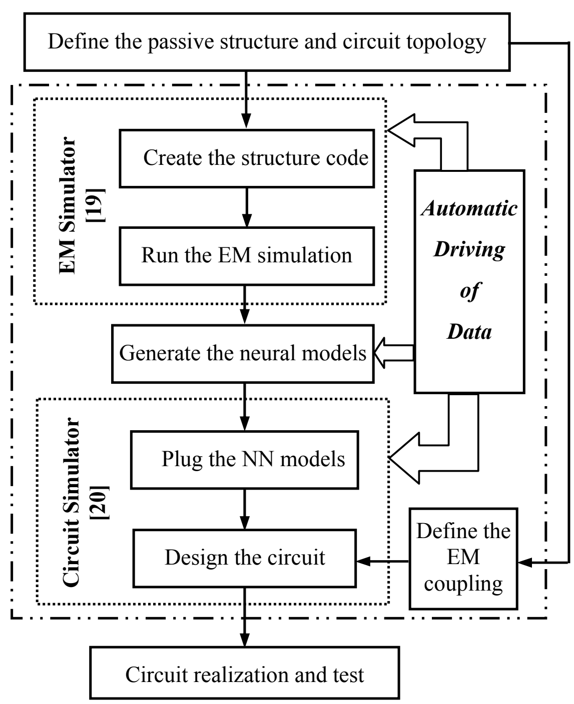
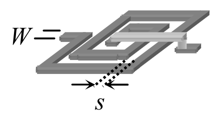


Fig. 2. Algorithm of the technique for circuit design.

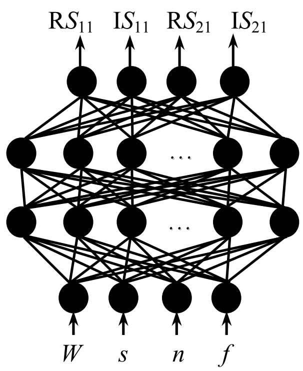
3 From Component to Circuit Level

3.1 Component Modeling Level

All neural models were generated using the *NeuroModeler* tool [21]. The trained neural models have been first validated. For instance, by varying the number n of turns, the width W, the space s between lines, and the frequency f, of a square spiral inductor (Fig. 3-a), Fig. 4 shows a good agreement between original EM data and those obtained by our model. The final training error was 1.65% with a neural network structure of two hidden layers (Fig. 3-b) and the test error was 2.27% with data never shown during training. Similar work was achieved for resistors, capacitors and interconnects [9].



(a)



(b)

Fig. 3. (a) Square spiral inductance, and (b) equivalent neural network structure. The R and I Symbols refer to Real and Imaginary parts of S-parameters, respectively.

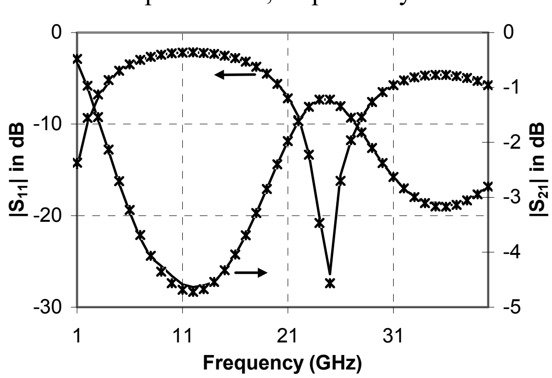
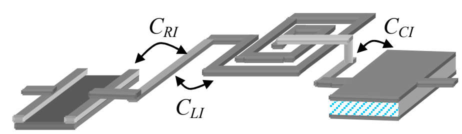


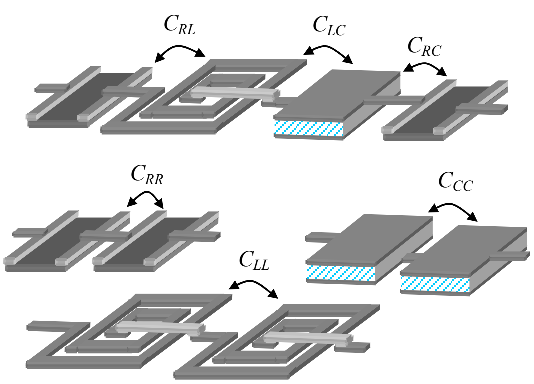
Fig. 4. S-parameters of a square spiral inductor. Our values (—) are successfully compared to those given by the 3D-EM simulator [19] (*).
The parameters are $n = 4.5$, $w = 10$ µm, $s = 2$ µm.

3.2 Circuit Simulation Level

In order to achieve an accurate circuit design, the trained neural models of passives have to been enhanced, at the circuit simulation level, by including distributed EM couplings between adjacent components. In fact, the above models are based on EM simulations generated with the assumption of a “perfect shielded” passive structure. In other words, the structure environment is assumed to be perfect, without any perturbations or field radiations from other structures. Therefore, distributed EM coupling between adjacent elements have to be computed and included. As shown in Fig. 5, distributed EM coupling between adjacent elements can be defined accordingly to the element in the circuit layout and its location in relation to the other passive elements.



(a)



(b)

Fig. 5. Different EM distributed couplings: (a) between interconnect and component, (b) between components. Subscripts R, L, C and I refer to resistors, inductors, capacitors, and interconnects respectively.

4 Examples of Circuit Design

In order to highlight our approach, we designed and built various widely used circuits, such as filters and RLC circuits. Therefore, we compared our EM data and simulated results with measurements and showed the significant effect of distributed coupling between adjacent components, even at the lower side of the RF/microwave frequency range.

4.1 Without Distributed Coupling Effects

The first designed circuit is a 4-6 GHz 4th-ordrer band-pass filter. First, we simulated the circuit in the EM-simulator. Then, we implemented it in the circuit simulator, i.e., *ADS*, replacing all passives by their equivalent neural models. Finally, we realized and tested the circuit. Fig. 6 shows a close agreement between the two simulated responses and an acceptable agreement with measurements when considering all possible errors due to fabrication tolerances, measurements, and coupling.

The simulation in *HFSS* required more than 5h while the one in *ADS* was achieved in 14s. The computing time gain was significant. This was more highlighted by optimizing the filter response using the inductor parameters W, s, and n, as variables. The optimization was achieved in 24mn in *ADS* while a less acceptable response was obtained after more than 9h in *HFSS* (Fig. 7). Moreover, the number n of turns cannot be varied in *HFSS* while it is part of the optimized variables in *ADS*.

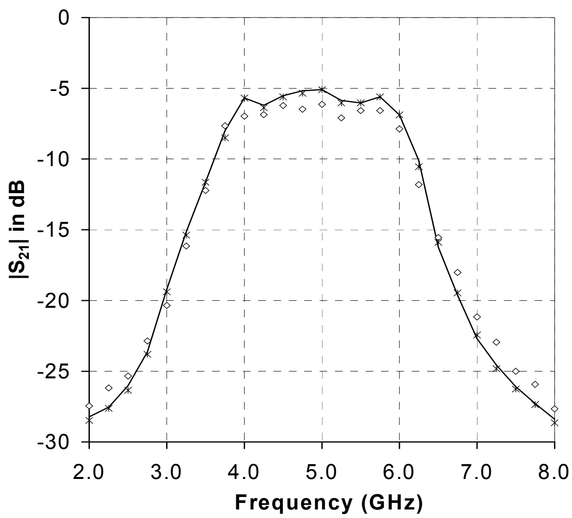


Fig. 6. 4-6 GHz band-pass filter: Comparison between measurements (◊) and simulated values Given by the EM simulator [19](*) and the circuit simulator [20] (—).

4.2 Including the Distributed Couplings

Then, we took into account the different mutual device coupling in order to minimize the errors between measured and computed values. Fig. 8 shows a closer agreement with measurements, demonstrating the soundness of our approach even at the lower side of the RF/microwave frequency range.

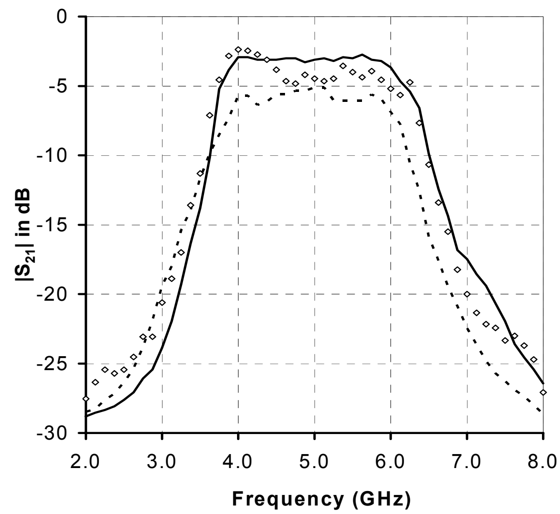


Fig. 7. 4-6 GHz band-pass filter: comparison between the response before (---) and after optimization in the circuit simulator (—) and the EM simulator (◊).

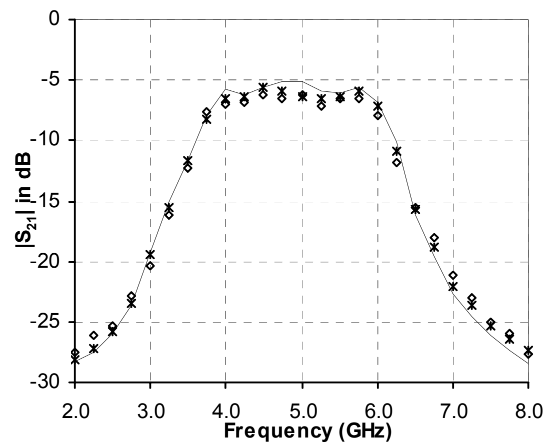


Fig. 8. 4-6 GHz band-pass filter: comparison between measurements (◊) and simulated values given by *ADS* [20] with (*) and without including couplings (—).

At the same time, a circuit layout could be easily optimized in terms of circuit topology layout by varying the geometrical interconnect dimensions [15]. In fact, we optimized the output filter response $|S_{21}|$ of a 2.5-5 GHz frequency doubler, taking as optimized variables the interconnect dimensions $\{(x_i, y_i),\ i = 1, \ldots, 3\}$, as shown in Fig. 9. The optimized function and constraints were defined as

$-3\text{ dB} \le \lvert S_{21}\rvert \le 0\text{ dB}$	for	$4\text{ GHz} \le f \le 6\text{ GHz}$
$\lvert S_{21}\rvert \le -15\text{ dB}$	for	$3.5\text{ GHz} \le f$

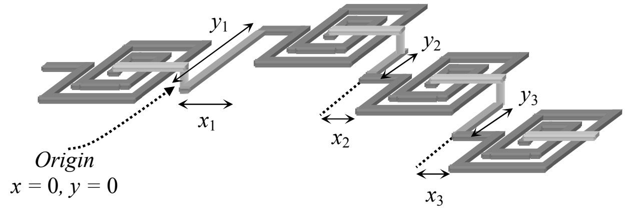


Fig. 9. 4th order output filter: Localization of the four inductances. The capacitors are omitted for clarity.

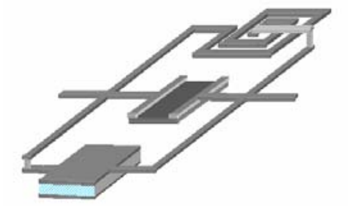


Fig. 10. Parallel RLC Circuit.

Since the (x, y) set values depend directly on the length/width of the interconnects, this optimization was achieved by plugging the neural models of the interconnects in the circuit simulator and setting their geometrical dimensions as optimized variables. After less than 3 minutes, an optimization routine gave the optimized values as shown in Table I.

Now, based on the distributed coupling effects we already computed, we simulated another passive circuit, i.e., an RLC circuit (Fig. 10) both in *HFSS* and *ADS*, including this time all possible distributed couplings. As expected, the results given by the circuit simulator were very close to those given by the full EM simulator (Fig. 11), both in terms of magnitude and phase.

To furthermore investigate the coupling effects in the circuit level, a third circuit, i.e. a 55 GHz tee junction was also designed. As expected, the simulated results showed the significant contribution of such distributed effects in a higher frequency range (Fig. 12).

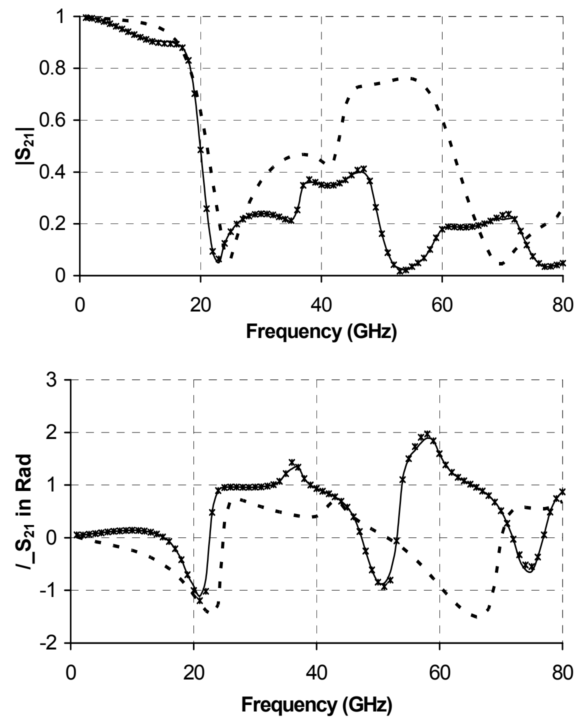


Fig. 11. S-Parameters for the parallel RLC circuit: comparison of results given by the EM simulator *HFSS* (*), and by the circuit simulator *ADS* including (—) or not the distributed coupling (---).

Table I. 4th order output filter: Dimensions of the interconnects 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

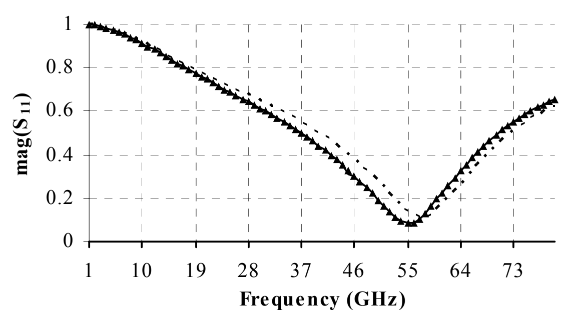


Fig. 2: Magnitude of the S_{11} tee junction parameter: The measured values (Δ) are compared with our computed values (—) and with simulated values obtained by classical approaches that not include the distributed coupling effects (---).

5 Conclusion

An efficient neural network approach for automatic modeling of embedded passives in microwave integrated circuits have been presented. The technique takes into account the self- and mutual-couplings present in such high-frequency systems. It helps making the design of microwave circuits faster, more accurate and efficient, contributing to overall reductions in design cycles.

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