An Automatic Parameter Extraction and Scalable Modeling Method for Transformers in RF Circuit

Jian Yao, Zuochang Ye and Yan Wang
Institute of Microelectronics, Tsinghua University, Beijing 100084, China

***Abstract*—In this paper, an automatic parameter extraction and scalable modeling method for transformer with 2π-based equivalent circuit-topology is established for the first time. In contrast to traditional optimization extraction, the adaptive boundary compression technique, combining a new correlated parameter extraction method with the neighboring geometry parameters, is introduced. The method is validated by 42 industry transformers and both accuracy and scalability have been achieved.**

***Index Terms*—Scalable compact model, transformer, optimization, parameter extraction.**

I. Introduction

Transformers are widely used in RF circuit design, e.g., inter-stage impedance matching, power combining and impedance matching with DC bias simultaneously. In contrast to the extensive research on inductors, establishing equivalent circuit model of transformers is perplexed by multiple coupling effects. During the past decades, researchers have devoted considerable efforts for building models for passive elements; however, equivalent circuit for transformers usually contains more than 40 lumped-elements and optimization extraction has to be adopted, which makes scalable modeling extremely difficult.

Existing methods are mainly physical and manual based methods [1]–[3], which usually require deep physical insight and extensive human intervention. In this paper, an automatic parameter extraction and scalable modeling method for transformer with 2π-based equivalent circuit-topology is established for the first time. We integrate the optimization parameter extraction and mapping functions establishment into a unified procedure by iterating inner-loop optimization and outer-loop optimization. The method is validated by the transformer modeling with 41 lumped elements. Results show that both accuracy and scalability have achieved by the proposed method with an acceptable computational cost.

II. The Transformer Model

As shown in Fig. 1 (a), transformers are usually composed of two metal spirals with no DC path. Each metal spiral is considered as an inductor and can be modeled by a well developed inductor model, then they are combined by mutual inductances and coupling capacitances to describe the major desired inductive coupling and undesired parasitic capacitive coupling [4].

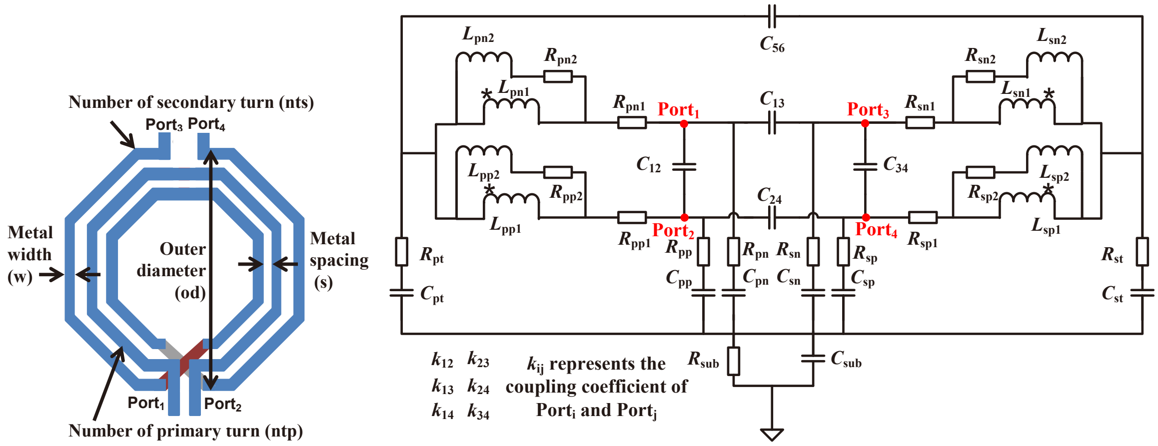
The topology of transformer model developed in this work is shown in Fig. 1 (b). Each inductor coil is modeled by a 2π-based equivalent circuit-topology. Series metal inductance and skin effect are modeled by L_{i1}, R_{i1}, L_{i2} and R_{i2} $(i = pn, pp, sn, sp)$. Dielectric isolation capacitances are modeled by C_i and R_i $(i = pp, pn, pt, sp, sn, st)$. Substrate effects are modeled by C_{sub} and R_{sub}. $C_{12}, C_{34}, C_{13}, C_{24}, C_{56}$ are used to describe distributed capacitive coupling from the primary port to secondary one. The inductive coupling between coils is represented by $k_{12}, k_{13}, k_{14}, k_{23}, k_{24}, k_{34}$.

Totally, there are 41 lumped-elements in the proposed model. To build the compact model, lumped-elements $R/L/C/k$ should be defined as functions of geometry dimensions, such as metal width (w), metal spacing (s) shown in Fig. 1 (a). It is difficult to establish relationship between lumped-elements and geometry dimensions manually. In the following section, we will propose an automatic parameter extraction and scalable modeling method for transformers.

III. Automatic Scalable Modeling

The framework of the proposed method is described in Fig. 2. The core is an inner-loop parameter extraction. In contrast to traditional optimization-based extraction, in which each device is extracted independently, here a special treatment, the so-called **correlated parameter extraction**, is performed to improve the local smoothness of extracted parameters with respect to geometry parameters. In addition, the outer-loop optimization with **adaptive boundary compression** is performed to ensure the global smoothness of parameters.

Assuming that the equivalent-circuit has M model parameters (lumped-elements such as L_{pn1},R_{pn1},k_{12}), defined as $Y = [y_1, y_2, ..., y_M]^T$, and K geometry parameters (e.g., w, s, od), defined as $X = [x_1, x_2, ...x_K]^T$. There are N tested devices with different geometry dimensions $\{X_1, X_2, ..., X_N\}$ and measured S-parameters $\{S_{m1}(j\omega_i), S_{m2}(j\omega_i), ..., S_{mN}(j\omega_i)\}$, where $S_m(j\omega_i) \in \mathcal{C}^{4\times 4}$ and $i \in (1, n_s)$ is the sampling frequency point.



(a) The layout of transformer. (b) The circuit topology.

Fig. 1. The transformer layout and corresponding circuit topology.

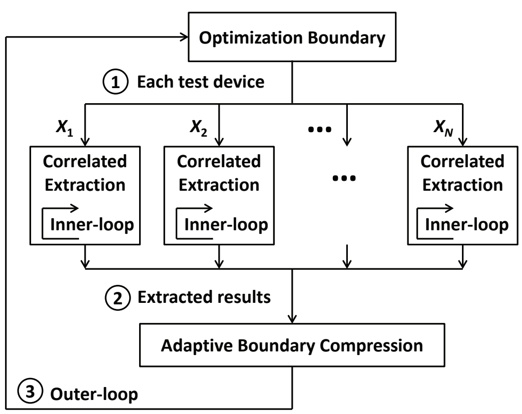


Fig. 2. The framework of automatic scalable modeling method.

A. Correlated Parameter Extraction

In this work, the parameter extraction is diverted to an optimization problem, i.e., for each device $\{X, S_m\}$,

$$\begin{array}{l} \min \quad \mathrm{err}(S_s(Y), S_m) \\ \text{subject to}: \;\; Y^- < Y < Y^+ \end{array} \tag{1}$$

where $S_s(\cdot)$ is the S-parameter of the port network, $Y^- = [y_1^-, y_2^-, ..., y_M^-]^T$ is the lower optimization boundary and $Y^+ = [y_1^+, y_2^+, ..., y_M^+]^T$ is the upper optimization boundary. The err$(\cdot)$ is the Root Mean Square (RMS) Error over the whole sample frequency set $(1, n_s)$.

We adopt the differential evolution algorithm as the core optimizer to realize the optimization extraction [5], [6]. In the experimental section (Section IV), we will show that the extracted results by the differential evolution algorithm are accurate enough. However, a key problem of optimization extraction is that the extracted parameters usually possess considerable fluctuation for different devices, as shown in Fig. 3 (a). This is a general phenomenon for all optimization extraction methods as the optimization extraction is intrinsically not physical and has multiple solutions.

To ensure the local smoothness requirement, the devices with close geometry parameter values should have the close extracted values. Thus a better approach is to consider not only the current device, but also other neighboring devices, during the extraction. To implement such purpose, the optimization population and search direction are shared for differential devices in this work, which is called the correlation parameter extraction.

Based on the above improvements, correlation among neighboring devices is considered during the extraction. To show the effect of the correlated parameter extraction, the extracted results from both traditional extraction and the correlated extraction have been shown in Fig 3. The accuracy of both extraction methods is satisfied, while the smoothness of the results from correlated method is significantly improved compared with the results from basic extraction method without considering correlation.

B. Adaptive Boundary Compression

To achieve a global smoothness while still preserving the accuracy, the fitting technique [7] is combined with the parameter extraction in a iteration procedure (outer-loop in Fig. 2), during which the optimization boundary is adaptively compressed. Six devices with different geometry parameters X are used to illustrate the outer-loop adaptive boundary compression procedure in an one-dimensional example, as shown in Fig. 4. First, all devices are extracted while the optimization boundaries are initially identical for each device as shown in Fig. 4 (a). In a second step, fitting technique is used to find the potential

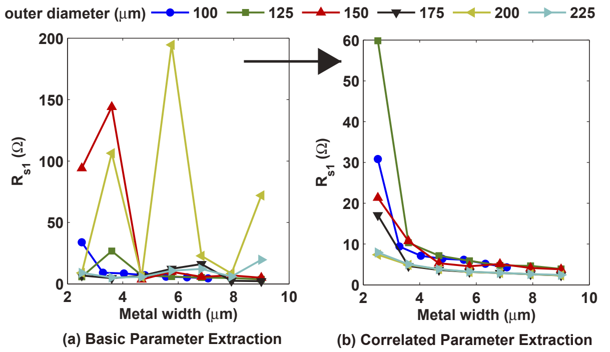


Fig. 3. The comparison of extracted results for R_{s1}. The extracted results are accurate enough and the correlated parameter extraction shows a high enhancement in smoothness.

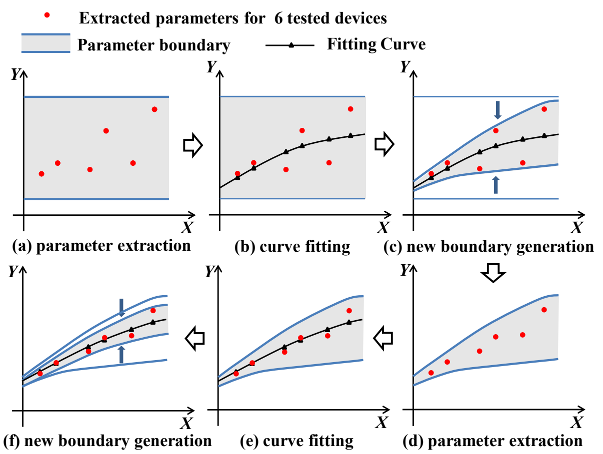


Fig. 4. A 1-d example of the adaptive boundary compression.

mapping function between the extracted parameter and the geometry parameter, as shown in Fig. 4 (b). Next, the new optimization boundaries are defined for each device based on this mapping function and extraction results, as shown in Fig. 4 (c). In the following outer-loop iterations, similar procedure is done until the optimization boundary is tight enough, as shown Fig. 4 (d)-(f).

For those lumped-elements without direct physical explanations, the form of mapping function is difficult to be determined a prior. To tackle this problem, a set of predefined mapping functions (linear, second-order, reciprocal, exponent, etc) are enumerated and fitted, and the best fit function is selected, i.e, for each model parameter y_i,

$$\begin{aligned} y_i &= f_i^{(j)}(x_1, x_2, .., x_K; A_i^{(j)}, B_i^{(j)}, C_i^{(j)}, ...) \\ (i &= 1, 2, ..., M;\ j = 1, 2, ..., T) \end{aligned} \tag{2}$$

where K, M and T are the number of geometry parameters, model parameters and mapping functions respectively. $\{A_i^{(j)}, B_i^{(j)}, C_i^{(j)}, ...\}$ are coefficients, which are determined by the Least Squares Fitting [7] based on the extracted results $\{X_1, y_{i,1}\}$, $\{X_2, y_{i,2}\}$, ..., $\{X_N, y_{i,N}\}$, where N is the number of devices. The function with the minimum fitting error is selected as the current optimized mapping function, which is used for the new boundary generation.

IV. Experimental Validation

In this section, the proposed method is validated for scalable modeling of the transformers fabricated in a commercial 65 nm CMOS process. Totally, 42 transformers with different geometry parameters are fabricated and characterized with S-parameters. The number of primary turn (ntp), metal width (w) and metal spacing (s) are fixed 1, $5.2\mu m$ and $2\mu m$ respectively. The number of the secondary turn (nts) is from 2 to 7 and outer diameter (od) is from $230\mu m$ to $290\mu m$. The measure frequency is up to 10 GHz. Totally, 39 devices are used to build the scalable model and 3 devices are used for verification. The dimensions of the devices to be predicted are {nts=3,od=280μm}, {nts=4,od=260μm} and {nts=6,od=240μm} respectively. The experiments run on a PC with Intel 2.8GHz Core i5.

After applying the proposed method, the parameters for each device have been extracted and the scalable model has been built. To simplify the discussion without losing the generality based on the symmetry of the layout, we only show the port characteristic of Port_1 and Port_3.

To evaluate the accuracy of the scalable model, the prediction results of the self-inductance (L_{11} and L_{33}), mutual-inductance (L_{13}) and quality factor (Q_{11}) for the tested transformers have been plotted in Fig. 5. It can be seen that the predicted inductance and quality factor are accurate for whole sampling frequency compared with measured value.

To show the scalability, we plot the relations between model parameters and geometry parameters. As shown in Fig. 6, the relations are smooth functions, indicating a good scalability between model parameters and geometry parameters.

The time cost of the proposed method is summarized in Fig. 7. The outer-iteration used in the transformer modeling is 23. The optimization boundary determines the search space, and as the search space is compressed, the time required for optimization is also reduced in each iteration, as shown in Fig. 7. Totally, the time spent on the transformer modeling is 192 minutes. Meanwhile, considering model development only needs to be done once for different circuit design applications, such cost is usually worthwhile.

V. Conclusion

In this paper, an automatic parameter extraction and scalable modeling method for transformer is proposed for

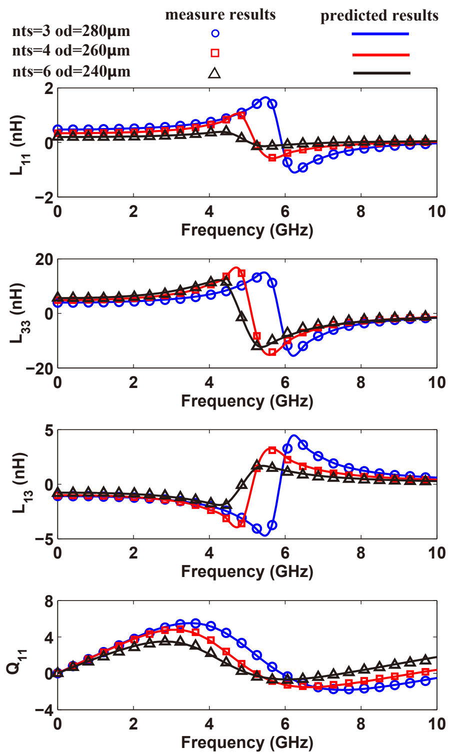


Fig. 5. The prediction results compared with the measured S-parameters for three tested transformers in the form of self-inductance (L_{11} and L_{33}), mutual-inductance (L_{13}) and quality factor (Q_{11}).

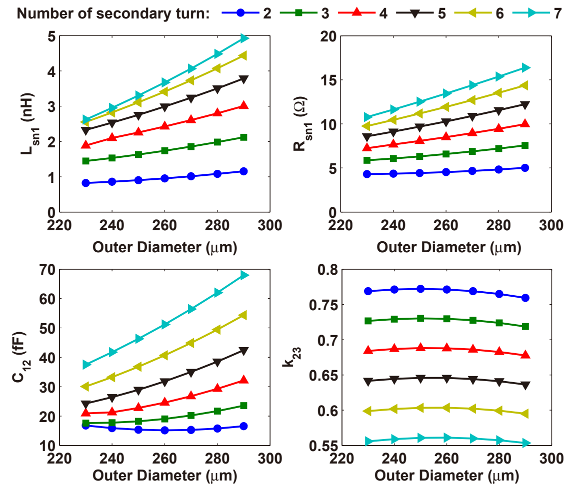


Fig. 6. The generated scalable transformer model by the proposed method. As there are 41 elements, only 4 typical model parameters have been presented and other model parameters have the similar scalability.

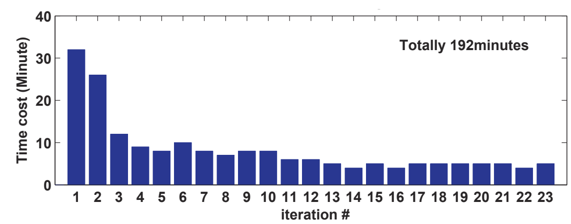


Fig. 7. The time cost of the proposed method.

the first time. The proposed scalable modeling scheme integrates the optimization parameter extraction and mapping functions establishment into a unified procedure by iterating inner-loop optimization and outer-loop optimization. Compared with the traditional optimization extraction method only aiming at the accuracy of the extraction for each single device, the proposed correlated extraction is performed in the inner-loop optimization to ensure the local-smoothness. In the outer-loop optimization, the boundary is adaptively compressed to obtain a simple mapping between model parameters and geometry parameters. The method is validated by the transformer modeling with 41 lumped-elements. Results show that both accuracy and scalability have achieved by the proposed method with an acceptable computational cost.

ACKNOWLEDGMENT

This work was supported in part by the Major State Basic Research Development Program of China (973 Program) under Grants 2010CB327403 and 2011CBA00604, the National Natural Science Foundation of China under Grants 61176034 and 61106031, and Applications and Core Technology University Research of the Agilent Technologies, Inc under Grant ID 2858. The authors wish to acknowledge the assistance and support of the Agilent Technologies, Inc.

REFERENCES

[1] H. Wang, L. Sun, J. Liu, H. Zou, Z. Yu, and J. Gao, "Transfer function analysis and broadband scalable model for on-chip spiral inductors," *IEEE Transactions on Microwave Theory and Techniques*, vol. 59, no. 7, pp. 1696 –1708, Jul. 2011.

[2] Y. Cao, R. Groves, X. Huang, N. Zamdmer, J.-O. Plouchart, R. Wachnik, T.-J. King, and C. Hu, "Frequency-independent equivalent-circuit model for on-chip spiral inductors," *Solid-State Circuits, IEEE Journal of*, vol. 38, no. 3, pp. 419 – 426, Mar. 2003.

[3] C. Yue and S. Wong, "Physical modeling of spiral inductors on silicon," *IEEE Transactions on Electron Devices*, vol. 47, no. 3, pp. 560 –568, Mar. 2000.

[4] Y. Tang, Z. Ye, and Y. Wang, "Broadband compact model for on-chip mm-wave transformers and baluns with emphasis on capacitive coupling effects," in *IEEE Custom Integrated Circuits Conference*, Sept. 2011, pp. 1 –4.

[5] B. Liu, J. lu, Y. Wang, and Y. Tang, "An effective parameter extraction method based on memetic differential evolution algorithm," *Microelectronics Journal*, vol. 39, no. 12, pp. 1761 – 1769, Dec. 2008.

[6] K. Price, R. M. Storn, and J. A. Lampinen, *Differential Evolution. A Practical Approach to Global Optimization*. Berlin, Germany: Springer, 2005.

[7] T. Veerarajan and T. Ramachandran, *Numerical methods with programs in C*. Tata McGraw-Hill, 2006.