Machine Learning Approaches for Transformer Modeling

F. Passos[1], N. Lourenço[1], R. Martins[1], E. Roca[2], R. Castro-López[2], N. Horta[1] and F. V. Fernández[2]
[1]Instituto de Telecomunicações, Lisbon, Portugal
[2]Instituto de Microelectrónica de Sevilla, CSIC and Universidad de Sevilla, Seville, Spain
fabio.passos@lx.it.pt

***Abstract*— In this paper, several machine learning modeling methodologies are applied to accurately and efficiently model transformers, which are still a bottleneck in millimeter-wave circuit design. In order to compare the models, a statistical validation is performed against electromagnetic simulations using hundreds of passive structures. The presented models using machine learning techniques have proven to be accurate, efficient, and useful for a wide range of frequencies from (around) DC up to the millimeter-wave range (around 100GHz). As an application example, the models are used as a performance evaluator in a synthesis procedure to optimize a transformer and a balun.**

Keywords—Integrated circuits, Machine learning, Millimeter-wave, Transformers

I. Introduction

Nowadays, there is a massive demand for high data rate communications. Therefore, the need for millimeter-wave (mm-Wave) circuits operating in the high gigahertz range increases [1]. However, the design of transformers, used in mm-Wave circuits for many applications, is still a significant bottleneck [2]-[4]. Most foundries do not provide a transformer model in their process design kits (PDKs), and therefore the design of such passive components is still highly dependent on electromagnetic (EM) simulators. This lack of readily available models is highly inefficient because the designers must usually perform a considerable number of iterative EM simulations to reach a satisfactory design. In order to overcome the costly EM simulations, lumped-element analytical models were proposed [5]-[10]. However, most of these models are based on analytical equations, which fail to accurately model the transformer behavior in the mm-Wave range (i.e., more than ~20GHz).

In the past few years, machine learning approaches have been proposed to model passive structures that were historically difficult to model and costly to simulate [11][12]. In this work, different machine learning techniques for modeling transformers are studied, in order to evaluate which modeling approach presents the best trade-offs between accuracy and model creation time. The objective is to model the transformer's S-parameters instead of the transformer parameters (e.g., inductance and quality factor). Therefore, the transformer can be used in any configuration (i.e., single-ended or differential). Furthermore, the S-parameters can be easily incorporated in electrical simulators using adequate SPICE devices (e.g., *nport* in Cadence SpectreRF).

The remainder of this paper is organized as follows. Section II briefly presents the main transformer design parameters and performances. Section III presents the basics of the machine learning approaches used and compares their accuracy for a 65-nm CMOS technology test case. In Section IV, the model's suitability to the design of transformers and baluns is demonstrated, and, finally, in Section V, conclusions are drawn.

II. Transformer Design Parameters and Performances

Transformers are devices composed of a primary and a secondary coil. In the mm-Wave range, these components are usually formed using one-turn coils built with the two uppermost metal layers with an intermediate dielectric layer.

A. Design Parameters

Fig. 1 shows an octagonal symmetrical transformer. Six geometric parameters define the geometry of this transformer: the number of turns of the primary (N_P) and secondary (N_S) coils, their inner diameters (D_{inP} and D_{inS}), and their turn widths (w_P and w_S).

B. Performances

Some of the most relevant transformer performances are the inductance of the primary and secondary coils, L_P and L_S, respectively, and the quality factor of the primary and secondary coils, Q_P and Q_S, respectively. Also, a critical performance of the transformer is the mutual inductance (M) and the coupling factor (k). In this work, the transformers are modeled via the S-parameters, but the previously discussed performances can be calculated applying an S- to Z-parameter transformation [13] and applying the formulas as follows:

$$L_P = \frac{Im(Z_{11})}{2\pi f} \tag{1}$$

$$Q_P = \frac{Im(Z_{11})}{Re(Z_{11})} \tag{2}$$

$$L_S = \frac{Im(Z_{22})}{2\pi f} \tag{3}$$

$$Q_S = \frac{Im(Z_{22})}{Re(Z_{22})} \tag{4}$$

$$M = \frac{Im(Z_{21})}{2\pi f} \tag{5}$$

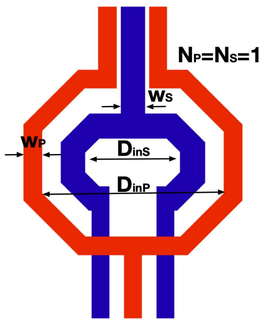


Fig. 1. Example of transformer with center taps (top-view of the layout).

This research is funded by the European Union's Horizon 2020 research and innovation program under the MSCA grant agreement No. 892431 and also by the Instituto de Telecomunicações internal research projects LAY(RF)^2 (X-0002-LX-20) and HAICAS (X-0009-LX-20). This work was supported by AEI under Project PID2019-103869RB-C31/AEI/10.13039/501100011033

$$k = \frac{M}{\sqrt{Im(Z_{11})Im(Z_{22})}} \quad (6)$$

where Z_{11} is the input impedance of the transformer (viewed from the primary), Z_{22} is the output impedance of the secondary, and f is the frequency.

III. Machine Learning Approaches

This section introduces how machine learning models are created and briefly presents the different techniques used to model the transformer. In the end, accuracies and efficiencies of approaches are compared.

A. *Modeling using Machine Learning Approaches*

The objective of a machine learning model is to mimic the output response of a given system based on some inputs [14]. In our case, the inputs are the geometric parameters of the transformer, and the outputs are its S-parameters. To create the model, it must first learn how the system behaves from a set of input samples (known as the training samples or training set); then, it will be able to predict the behavior of new samples. Thus, in order to create a machine learning model, three steps must be performed: design of experiments, model creation, and model validation.

First, in the design of experiments, the design space is sampled using effective techniques to create the training set from which the model is going to learn. Ideally, machine learning models should learn from the most accurate evaluation possible. In our work, these accurate evaluations are EM simulations performed with ADS Momentum. Second, the model is created with a given approach (i.e., Gaussian process, Radial Basis Function, etc.) and, in the end, in the third step, we validate the model using a test set (different samples from the ones used for its training).

To perform the design of experiments, the range for each input variable must be defined. In this work, the design space for the model creation was D_{inP}, $D_{inS} \in [20, 200]$ µm, w_P, $w_S \in [3, 15]$ µm and only transformers with one turn were considered (nevertheless, the technique can be extended to any N_P:N_S transformer topology). This design space was sampled using a Quasi-Monte-Carlo technique [15] and is considered sufficiently large to cover design applications above 20GHz. Although transformers and baluns have similar layouts, their behavior is extremely different because baluns are stacked transformers with much higher magnetic interaction between primary and secondary. Therefore, in this work, transformers and baluns are considered as two different topologies, and two different models will be created.

In order to create these models, 1500 training samples are used to build the transformer model, and 200 training samples are used to build the balun model. Fewer samples are used to train the balun model because these structures are stacked transformers and, therefore, $D_{inP} = D_{inS}$ and $w_P = w_S$, a fact that considerably decreases the diversity of their design space. For the statistical validation of the models, a test set was generated with new samples of the same design space: 100 samples for the transformers and 50 samples for the baluns.

Regarding the outputs of the models, independent models will be created for each S-parameter's real and imaginary part at each frequency point. However, in order to ease the model comparison, the models will be compared in inductance, quality factor and coupling factor instead of S-Parameters. The translation between S-Parameter and inductance, quality factor and coupling factor will be performed as discussed in Section II.

B. *Gaussian Process Regression (GPR)*

GPR has been successfully applied to modeling transformers in [12]. GPR is a near parameterless tool that takes a Bayesian approach to fit a distribution of functions using the data to reduce uncertainty. A detailed description can be found in [16]. The results shown in this work were obtained considering the radial kernel shown in Eq. (7), where a and b are scale factors, α is scale mixture, and l is the length scale.

$$\mathrm{k}(x, y) = a\left(1 + \frac{\|x-y\|^2}{2\alpha l^2}\right)^{-\alpha} + b \times exp\left(\frac{\|x-y\|^2}{2l^2}\right) \quad (7)$$

C. *Radial Basis Function (RBF) interpolation*

Interpolation with RBFs is done by the weighted sum of RBFs of (8), where the weights and the reference points are computed from the data [17]:

$$f(x) = \sum_{i=1}^{M} w_i \varphi(\|x - r_i\|) \quad (8)$$

Any radial Basis Function φ, i.e., a function whose value depends only on the distance between the x and a reference point r_i, can be used. For this model, we considered the linear RBF in the form of $\varphi(\|x - r_i\|) = \|x - r_i\|$ and added a polynomial of degree 4 on x leading to the overall interpolator in (9), where $\boldsymbol{w_P}$ is a column vector of the coefficients of the polynomial regression, and $\boldsymbol{p}(x)$ is a row vector with the monomials of x that span the polynomial of degree 4.

$$rbf(x) = f(x) + \boldsymbol{w_P}\boldsymbol{p}(x) \quad (9)$$

D. *Nearest Neighbors (NN) interpolation*

The NN interpolation uses only the value of the nearest data point for each prediction, resulting in a piecewise-constant interpolation. NN interpolation is the simplest way to use the sample point to estimate a new transformer's performance and provide a baseline for comparing the other two approaches.

E. *Accuracy and Efficiency Comparison of the Modeling Approaches*

All models were created using the exact same training set, with the same conditions, and validated with the same test set. The accuracy in the test set of all previously discussed approaches for the transformers and baluns are reported in Tables I and II, respectively. The time reported in such Tables refers to model creation time. The results are shown for the

TABLE I
STATISTICAL STUDY FOR THE DIFFERENT MODELING APPROACHES AT 28GHZ FOR 100 TRANSFORMERS (TEST SET)

Model Approach	*Mean Square Error (%)*					*Time (s)*
	L_P	Q_P	L_S	Q_S	*k*	
GPR	**0.14**	**1.54**	**0.11**	**1.93**	**0.17**	**217**
RBF	**0.15**	**2.09**	**0.12**	**1.57**	**0.26**	**0.3**
NN	**2.85**	**4.18**	**4.58**	**8.95**	**7.76**	**0.7**

TABLE II
STATISTICAL STUDY FOR THE DIFFERENT MODELING APPROACHES AT 28GHZ FOR 50 BALUNS (TEST SET)

Model Approach	*Mean Square Error (%)*					*Time (s)*
	L_P	Q_P	L_S	Q_S	*k*	
GPR	**0.24**	**1.87**	**0.26**	**1.62**	**0.07**	**0.9**
RBF	**0.17**	**2.89**	**0.20**	**2.06**	**0.08**	**0.2**
NN	**3.74**	**3.99**	**3.54**	**5.05**	**1.43**	**0.5**

central frequency point of the 5G 26.5-30.5GHz band (28GHz), however, any other value may have been chosen. It is possible to conclude that in terms of accuracy results the GPR and the RBF achieve very similar results, with most of the mean square errors (MSE) below 2% for both transformers and baluns. However, the RBF accuracy is slightly lower when compared to GPR for the baluns. This indicates that for smaller training sets (as it is the case for baluns) RBF has lower accuracy than GPR models. When the number of training samples is higher (i.e., transformers) the accuracy is similar. In both cases (baluns and transformers), as expected, the NN behaves the worst of all approaches.

Regarding efficiency, GPR is the worst approach. GPR fitting optimizes the kernel hyperparameters, significantly reducing the need for hyperparameter tuning, but that comes with an execution cost. This internal optimization time exponentially increases with the number of training samples, which can be observable if we compare the execution time between transformers and baluns (i.e., 217 versus 0.9 seconds). However, since the model is only created once, the model creation times of a couple of minutes are perfectly acceptable for our application.

IV. Transformer and Balun Synthesis

Transformers/baluns are typically very difficult to design because they have multiple design parameters that influence their performance. In transformers, the designer is usually interested in a given L_P, L_S and k, with the maximum Q possible. However, optimizing the transformer (i.e., obtaining a high Q) is usually exceptionally difficult given the design space and amount of different sizing possibilities. Therefore, in this work, the developed GPR transformer model was integrated into a single objective optimization algorithm (Selection-Based Differential Evolution algorithm [18]) as the performance evaluator, allowing for the possibility of designing transformers/baluns with optimal performances. The choice of the GPR model over the others is related to the fact that it was the one achieving best accuracy for both the transformers and the baluns.

A. Transformer

The first optimization was formulated as:

$$\begin{aligned} &\quad Maximize\ Q_p\ and\ Q_S\ @28GHz \\ &Such\ that \begin{cases} L_P = 300pH \pm 10pH\ @\ 28GHz \\ L_S = 200pH \pm 10pH\ @\ 28GHz \\ \quad k = -0.3 \pm 0.1\ @\ 28GHz \\ \quad SRF_P \text{ and } SRF_S > 38GHz \end{cases} \end{aligned} \tag{10}$$

where SRFP and SRFS are the self resonance frequency of the primary and secondary coil respectively. The optimization was performed with 50 individuals and 200 generations and took approximately 274 seconds, and the obtained transformer had the following design parameters: D_{inP}=110µm, D_{inP}=68µm, w_S=3µm and w_S=7µm. The layout of the transformer can be seen in Fig. 2, and the comparisons between the model and the EM simulation of the same transformer are shown in Fig. 3 for all the performances of interest (inductance, quality factor, and coupling factor). The shaded region marks frequencies above 38GHz (the limit for the SRF objectives in the synthesis procedure).

B. Balun

The second optimization, to achieve an optimal balun, was formulated as:

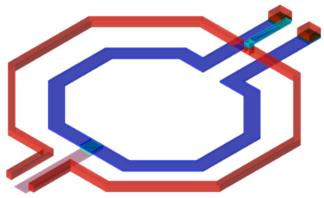
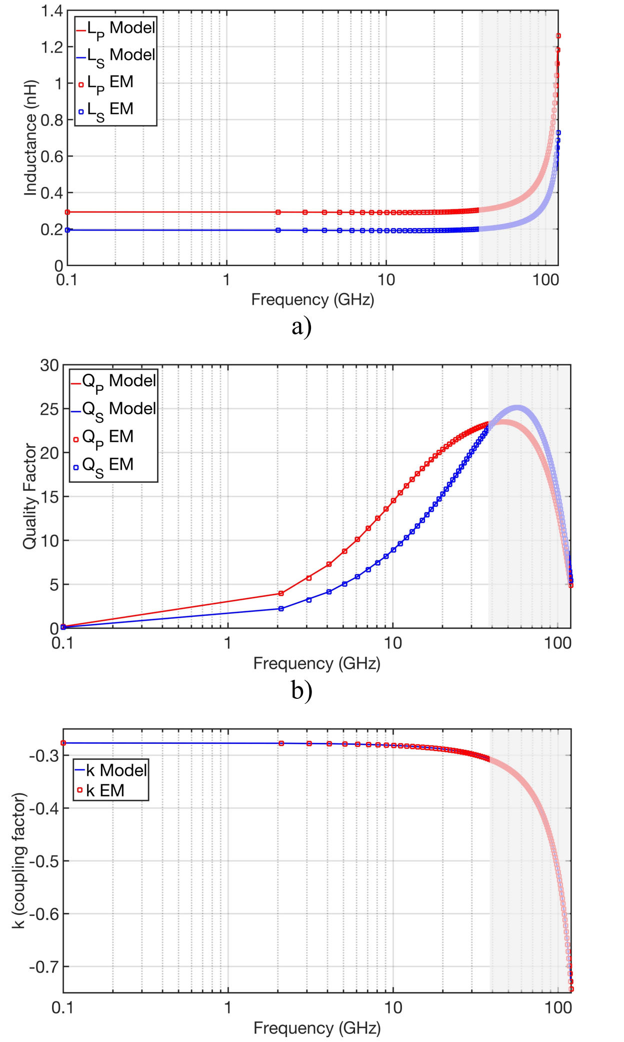


Fig. 2. Layout of the transformer with D_{inP}=110µm, D_{inP}=68µm, w_S=3µm and w_S=7µm.



c)

Fig. 3. Performance comparison between the model and EM simulation of the transformer with D_{inP}=110µm, D_{inP}=68µm, w_S=3µm and w_S=7µm. a) Primary and secondary coil inductance. b) Primary and secondary coil quality factor. c) k-factor.

$$\begin{aligned} &\quad Maximize\ Q_p\ and\ Q_S\ @28GHz \\ &Such\ that \begin{cases} L_P = 330pH \pm 20pH\ @\ 28GHz \\ L_S = 330pH \pm 10pH\ @\ 28GHz \\ \quad k = -0.8 \pm 0.1\ @\ 28GHz \\ \quad SRF_P \text{ and } SRF_S > 38GHz \end{cases} \end{aligned} \tag{11}$$

This optimization aims not only at maximizing the quality factor of both the primary and secondary coils but also at minimizing the insertion loss of the balun. The optimization

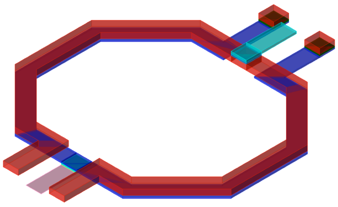
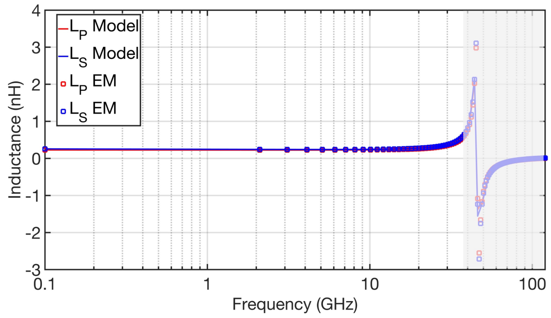


Fig. 4. Layout of the balun with D_{inP}=D_{inP}=97 µm, w_S= w_S=9.5.

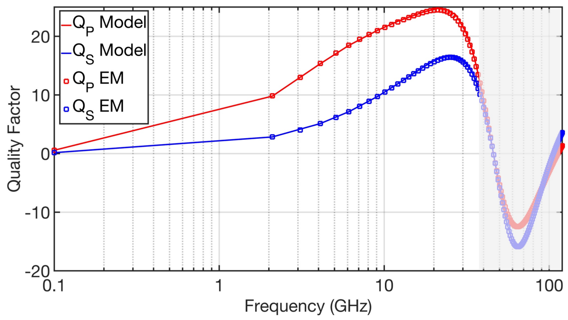
was performed with 50 individuals and 200 generations and took approximately 260 seconds, and the obtained balun had the following design parameters: D_{inP}= D_{inS} =97µm, and w_P =w_S=9.5µm. The layout of the balun can be seen in Fig. 4, and the comparisons between the model and the EM simulation of the same balun can be seen in Fig. 5 for all the performances of interest (inductance, quality factor, and coupling factor).

V. CONCLUSIONS

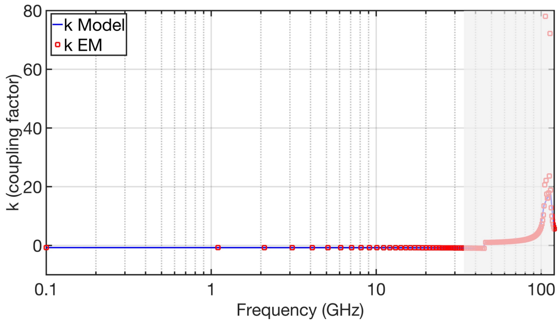
This paper presents a comparison between different machine learning approaches for the modeling of transformers up to mm-Wave frequencies. It was shown that GPR models present the best accuracy to model both baluns and transformers, at the cost of some training time. The GPR model was integrated into a single-objective optimization algorithm to perform both balun and transformer synthesis to design optimal structures, which were then compared to EM simulations to show the validity of the model.



a)



b)



c)

Fig. 5. Performances comparison between the model and EM simulation of the balun with D_{inP}=97µm, D_{inP}=97µm, w_S=9.5µm and w_S=9.5µm a) Primary and secondary coil inductance. b) Primary and secondary coil quality factor. c) k-factor.

REFERENCES

[1] C. Doan, S. Emami, A. Niknejad, and R. Brodersen, “Millimeter-wave CMOS design,” IEEE J. Solid-State Circuits, vol. 40, no. 1, pp. 144-155, 2005.

[2] H. Yeh, Z. Liao and H. Wang, “Analysis and design of millimeter-wave low-power CMOS LNA with transformer multicascode topology,” IEEE Trans. Microw. Theory Techn., vol. 59, no. 12, pp. 3441–3454, 2011.

[3] B. Venumadhav and J. Rudell, “Analysis and design of a transformer-feedback-based wideband receiver,” IEEE Trans. Microw. Theory Techn., vol. 61, no. 3, pp. 702–713, 2013.

[4] D. Chowdhury, P. Reynaert and A. Nijknejad, “Design considerations for 60 GHz transformer-coupled CMOS power amplifiers,” IEEE J.Solid-State Circuits, vol. 44, no. 10, pp. 2733–2744, Oct. 2009.

[5] F. Rorella, C. Cismaru, Y. Tkachenko, Y. Cheng and P. Zampardi, “Characterization, design, modeling, and model validation of silicon on-wafer M:N balun components under matched and unmatched conditions,” IEEE J. Solid-State Circuits, vol. 41, no. 5, pp. 1201–1209, 2006.

[6] O. El-Gharniti, E. Kerherve and J. Begueret, “Modeling and characterization of on-chip transformers for silicon RFIC,” IEEE Trans. Microw. Theory Techn., vol. 55, no. 4, pp. 607-615, 2007.

[7] C. Wang, H. Liao, Y. Xiong, C. Li, R. Huang and Y. Wang, “A physics-based equivalent-circuit model for on-chip symmetric transformers with accurate substrate modeling,” IEEE Trans. Microw. Theory Techn., vol. 57, no. 4, pp. 980-990, 2009

[8] J. Brinkhoff, D. Pham, K. Kang and F. Lin, “A new six-port transformer modeling methodology applied to 10-dBm 60-GHz CMOS ASK modulator designs,” IEEE Trans. Microw. Theory Techn., vol. 58, no. 2, pp. 297-309, 2010.

[9] D. Hou et al., “Distributed modeling of six-port transformer for millimeter-wave SiGe BiCMOS circuits design,” IEEE Trans. Microw. Theory Techn., vol. 60, no. 12, pp. 3728-3738, 2012.

[10] Z. Gao et al., “A broadband and equivalent-circuit model for millimeter-wave on-chip M:N six-port transformers and baluns,” IEEE Trans. Microw. Theory Techn., vol. 63, no. 10, pp. 3109-3121, 2015.

[11] F. Passos, E. Roca, R. Castro-López, and F. V. Fernández, “Radio-frequency inductor synthesis using evolutionary computation and Gaussian-process surrogate modeling,” Appl. Soft Comput., vol. 60, pp. 495-507, 2017.

[12] F. Passos, E. Roca, J. Sieiro, R. Castro-Lopez, F. V. Fernandez, “An efficient transformer modeling approach for mm-wave circuit design”, AEU – Inter. J. of Elect. and Comm., Vol.128, 2021.

[13] D. A. Frickey, "Conversions between S, Z, Y, H, ABCD, and T parameters which are valid for complex source and load impedances," in IEEE Transactions on Microwave Theory and Techniques, vol. 42, no. 2, pp. 205-211, 1994

[14] M. B. Yelten, T. Zhu, S. Koziel, P. D. Franzon and M. B. Steer, “Demystifying surrogate modeling for circuits and systems,” in IEEE Circuits and Systems Magazine, vol. 12, no. 1, pp. 45-63, Firstquarter 2012.

[15] A. I. J. Forrester, A. Sobester, and A. J. Keane, Engineering Design via Surrogate Modelling - A Practical Guide. Wiley, 2008.

[16] Rasmussen, C. E., & Williams, C. K. I., Gaussian processes for machine learning (2016), The MIT Press.

[17] Buhmann, M., 2003. Radial basis functions: theory and implementations 5th ed., Cambridge University Press.

[18] K. Zielinski and R. Laur, “Constrained single-objective optimization using differential evolution,” in IEEE congress on Evolutionary Computation, pp. 223-230, 2006.