L-Bot: A Physically Motivated Deep Learning Based Inductor Modeling Tool

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***Abstract*—In this paper, we present L-BOT, a physically motivated automatic inductor modeling tool based on deep learning algorithm. This tool uses the physical topology of inductor models representing the winding resistance, core losses, and capacitive effects in the inductor. The parameters of physical topology are automatically extracted using L-BOT after training the deep learning based engine. We show excellent accuracy of the inductor models generated from L-BOT for six different commercial radio-frequency (RF) inductors.**

Keywords—Machine Learning, Deep Learning, Inductor, Coilcraft, Neural Network, LSTM, s-parameters, parameter prediction.

I. Introduction

Machine Learning (ML) and Deep Learning (DL) models have given promising results for many real-life problems in the past decade. Advancing ML researchers came up with new Deep Neural Networks (DNN) and new Deep Learning models for even profound processing of data. Recently DNN have been applied towards semiconductor manufacturing [1] and the development of power electronics [2]. A lot of research work is currently going on in bringing new ML algorithms and models to find new applications in the domain of electronic devices.

Many researchers have utilized different ML models in semiconductor fabrication procedures for processes like tool anomaly detection [3][4], optical proximity correction [5], and Semiconductor defect analysis [6]. Compact models or SPICE models are a very crucial part of the overall circuit design flow. These models enable accurate simulations so that an optimal circuit can be designed in time and cost-effective manner. A few recent works show the application of ML and DL algorithms towards active [7] and passive compact modelling [8]. Among compact models, there are approaches which use empirical or mathematic models for devices, and there are ones which consider the physics of the devices and derive model formulations considering the fundamental device physics. Physics-based models have been shown to have advantages related to better scaling of model to different device geometry, ambient conditions, and better circuit convergence [9].

The application of DL and ML towards compact modelling is extremely promising. DL and ML can cut down the development time of compact models from weeks to a few clicks once the engine is trained. However, DL and ML are mainly mathematical approaches and as a result the works so far have focussed on empirical or mathematical compact models [7], [8] without considering device physics. In this paper, we present an inductor modelling tool which uses DL algorithms but preserves the physical topology of inductor compact models. This physically motivated inductor modelling tool thus produces accurate and scalable compact models. To the best of the authors' knowledge this is the first time DL is applied to physically motivated automated inductor modelling.

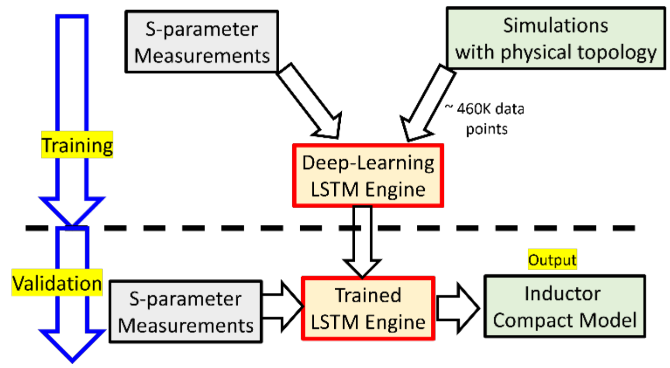

Fig. 1: Block diagram showing the methodology of development and validation of L-Bot.

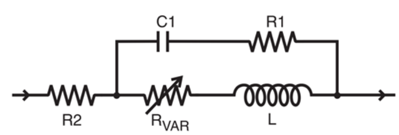

Fig. 2: Physical topology of Coilcraft inductor model representing the skin effects, core losses, and capacitive effects in the inductor.

II. Deep Learning Model Development

L-bot development starts with a training phase and then the trained model can readily generate new inductor models as summarized in Fig. 1. For training data, we used 464 thousand data points. The training data is generated by simulating a physics-based model of inductor shown in Fig. 2. The inductor model included key effects such as skin effect (R2), frequency dependent core loss (R_{VAR}), and elements (C1 and R1) to model the impedance at resonance. These effects are modeled with model parameters. As part of training data, we simulated this physical model with variation in parameters and generated 464 thousand simulation points across frequency, and variation of physical effects.

The training data is fed to the DL algorithm as shown in Fig. 1. Training error is minimized by using the measured S-parameter data for one sample inductor. There are numerous choices of DL algorithms which can be explored. After exploring different choices for the problem of inductor modeling, we focused on to using the **Long short-term memory** (**LSTM**) neural networks. For training, the input and output data were normalized to make the model more efficient. For LSTM algorithm, there are several choices for algorithmic parameters. To look for the most efficient model, we created many models with different number of layers, dimension of the layers, and learning rate. From our analysis we found that the most efficient model was build using an extension to the LSTM layer known as 'Bidirectional'. The bidirectional LSTM layers present in the model along with the dimension of the first layer to be 256 is found to be most optimal. The optimum solution is obtained by simulating models with various dimensions from 256 to 2048 layers as shown in Fig. 3. The lowest Mean Squared Error (MSE) for both model parameter 'R2' and 'C' were obtained for 256 layers. This completes the training phase of L-Bot. Next, L-Bot is used to generate electrical models for inductors other than the one used in training phase.

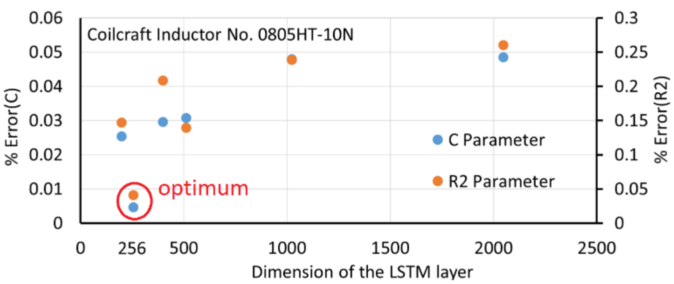

Fig. 3: Comparison plot showing the % error against the dimension of the first LSTM layer. Least error at 256 dimensions

The measured S-parameter data for six new RF inductors is then fed to the L-Bot, and it can automatically predict the values of all the physical parameters of the inductor model. This is a significant enhancement over existing approaches where it can take up-to a week to generate such model for only one inductor. The results showing accuracy of the predicted model as compared to measurements are shown in the next section.

III. Results And Discussions

After the training phase L-Bot is used to generate compact models for commercial RF inductors from Coilcraft. For inductors, Coilcraft (and other companies) give the measured device characteristics in form of S-parameters. This measured data is fed into the trained L-Bot as shown in Fig. 1 in the validation phase. The trained engine generates compact models for these inductors automatically. L-Bot generates the model instantly which is significantly faster than usual model development time of a week or so for each inductor.

The accuracy of the model generated by L-Bot is shown in Fig. 4 for Coilcraft inductor numbers 026011C-11N and 026011C-10N. 026011C-11N and 026011C-10N are ceramic chip inductors which are popularly used in 5G communication systems. Fig. 4 shows a comparison of measured S-parameters with model simulations performed by simulating L-Bot predicted model in a circuit simulator. Fig. 4 and Fig. 5 shows magnitude and phase of S_{11}/S_{22} (for inductors $S_{11} = S_{22}$ and $S_{12} = S_{21}$) demonstrating excellent agreement between model and measurements for both the inductors. A good model accuracy for S_{12}/S_{21} magnitude and phase for inductor 026011C-11N and 026011C-11N can also be seen from Fig. 4 and Fig. 5. This demonstrates excellent model accuracy for two different inductors of the same type (ceramic chip).

Next, we model another type of inductor with L-Bot. The next inductor we model is 0805HT-10N. 0805HT-10N is a surface mount wire wound inductor used in applications needing a very high-quality factor. Excellent model accuracy for magnitude and phase of S_{11}/S_{22} and S_{12}/S_{21} can be seen from Fig. 5. The frequency behaviour for the whole frequency range from 1 to 55 GHz is very well modelled with the model generated by L-Bot. The physically motivated topology thus has helped to make L-Bot generated models scalable as it can work for different kinds and values of inductors as shown in Figs. 4 – 6.

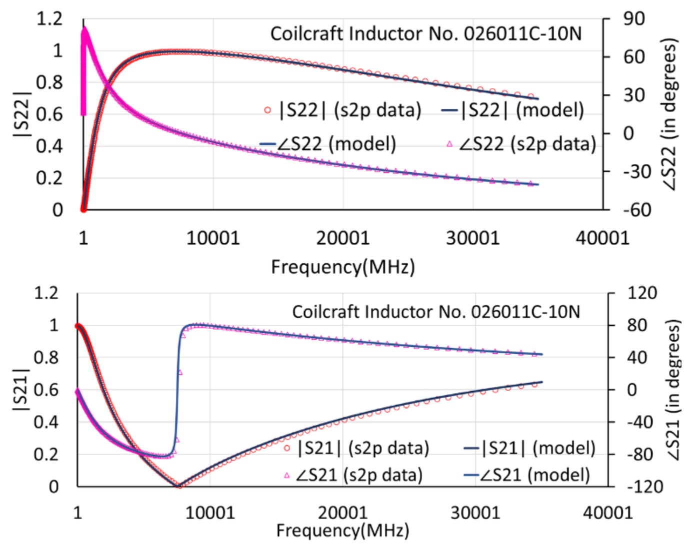

Fig. 4: Magnitude and phase versus frequency for $S_{11/22}$ and $S_{21/12}$ showing a good agreement between model and measured data for Coilcraft Inductor No. 026011C-11N

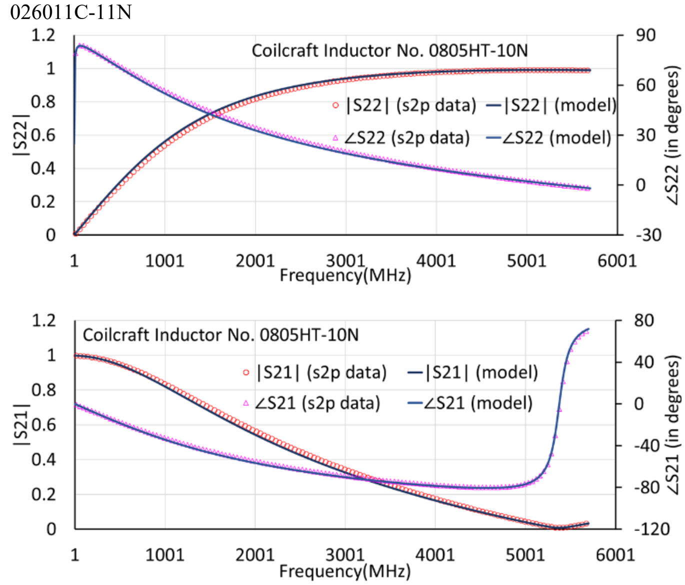

Fig. 5: Magnitude and phase versus frequency for $S_{11/22}$ and $S_{21/12}$ showing a good agreement between model and measured data for Coilcraft Inductor No. 0805HT-10N.

To show the accuracy of the model clearly, we plot histogram of error to quantify the 90th percentile error. The error in S_{11} (Err_{S11}) and error in S_{12} (Err_{S12}) are defined as,

$$Err_{S11} = 100.\frac{|S_{11,model} - S_{11,data}|}{1} \quad (1)$$

$$Err_{S12} = 100.\frac{|S_{12,model} - S_{12,data}|}{|S_{12,\max}|} \quad (2)$$

where $S_{11,model}$ and $S_{12,model}$ are simulations and $S_{11,data}$ and $S_{12,data}$ data are measurements. $S_{12,max}$ is the maximum value of S_{12} in the measurements. The histogram for error in S_{11} and S_{12} for inductor 0302CS-10N are shown in Fig. 7 and Fig. 8. 90th percentile errors for S_{11} and S12 is ~ 1%. This quantifies the excellent accuracy of the models generated by L-Bot.

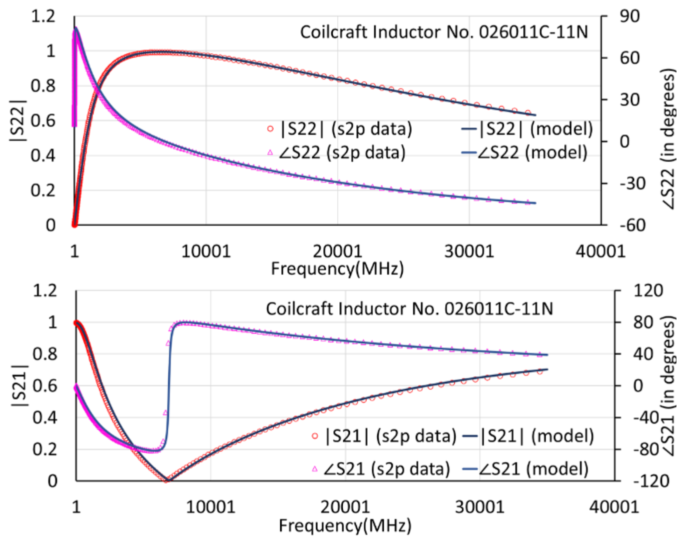

Fig. 6: Magnitude and phase versus frequency for $S_{11/22}$ and $S_{21/12}$ showing a good agreement between model and measured data for Coilcraft Inductor No. 026011C-11N.

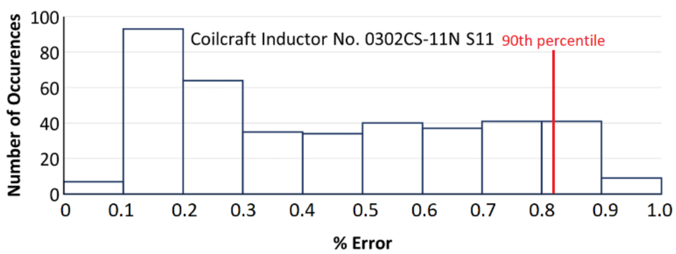

Fig. 7: Histogram of Err_{S11} for 403 points. 90th percentile of the % error is highlighted.

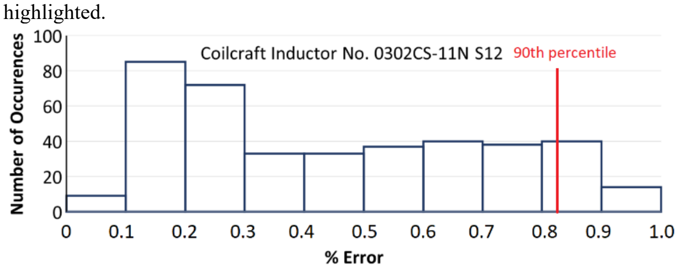

Fig. 8: Histogram of Err_{S12} for 403 points. 90th percentile of the % error is highlighted.

The accuracy of the L-Bot generated models for all six inductors is shown in Table I. A quite reasonable model accuracy can be seen from the table for S-parameters for all six inductors. The maximum 90th percentile error is ~ 5% for S_{12} for inductor 0302CS-11N. Nevertheless, the 90th percentile errors show a very good model accuracy of the automatically generated models.

TABLE I

Inductor	**S_{11} 90th percentile error**	**S_{12} 90th percentile error**
0302CS-11N	4.75	4.77
0302CS-10N	0.88	0.82
026011C-11N	3.50	3.51
0805HT-10N	2.79	2.80
0402CT-10N	0.96	0.99
026011C-10N	0.92	0.92

Table I: Represents 90th percentile error of every s-parameter for all six inductors modelled with L-Bot.

IV. Conclusions

A physically motivated deep learning-based tool L-Bot for automatic inductor modelling is presented. The physically motivated topology combined with deep learning LSTM algorithm is used to develop the tool. Physically motivated tool helps scalability of the tool, and accurate model for different values and types of inductors are shown. L-Bot can be used to generate accurate and scalable inductor models significantly cutting the model development time for inductors.

References

[1] D.-Y. Liao, C.-Y. Chen, W.-P. Tsai, H.-T. Chen, Y.-T. Wu, and S.-C. Chang, ''Anomaly detection for semiconductor tools using stacked autoencoder learning,'' in Proc. Int. Symp. Semiconductor Manuf. (ISSM), Dec. 2018, pp. 1–4.

[2] G. A. Susto, M. Terzi, and A. Beghi, ''Anomaly detection approaches for semiconductor manufacturing,'' Procedia Manuf., vol. 11, pp. 2018–2024, Jan. 2017, doi: 10.1016/j.promfg.2017.07.353.

[3] R. Luo, ''Optical proximity correction using a multilayer perceptron neural network,'' J. Opt., vol. 15, no. 7, Jul. 2013, Art. no. 075708, doi: 10.1088/ 2040-8978/15/7/075708.

[4] K. Irani, et. al., "Applying Machine Learning to Semiconductor Manufacturing," IEEE Expert, Volume: 8, Issue: 1, Feb. 1993.

[5] B. K. Bose, ''Neural network applications in power electronics and motor drives—An introduction and perspective,'' IEEE Trans. Ind. Electron., vol. 54, no. 1, pp. 14–33, Feb. 2007.

[6] Y. Yuan-Fu, ''A deep learning model for identification of defect patterns in semiconductor wafer map,'' in Proc. 30th Annu. SEMI Adv. Semiconductor Manuf. Conf. (ASMC), May 2019, pp. 1–6.

[7] J. Wang, Y. H. Kim, J. Ryu, C. Jeong, W. Choi, & D. Kim (2021). Artificial Neural Network-Based Compact Modeling Methodology for Advanced Transistors. IEEE Transactions on Electron Devices, 68(3), 1318-1325.

[8] T. Guillod, P. Papamanolis, & J. W. Kolar, (2020). Artificial neural network (ANN) based fast and accurate inductor modeling and design. IEEE Open Journal of Power Electronics, 1, 284-299.

[9] S. Khandelwal (2019, April). Physics-based compact models: An emerging trend in simulation-based GaN HEMT power amplifier design. In 2019 IEEE 20th Wireless and Microwave Technology Conference (WAMICON) (pp. 1-4). IEEE.