Generic Modeling of Differential Striplines Using Machine Learning Based Regression Analysis

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***Abstract*— In this paper, a generic model for a differential stripline is created using machine learning (ML) based regression analysis. A recursive approach of creating various inputs is adapted instead of traditional design of experiments (DoE) approach. This leads to reduction of number of simulations as well as control the data points required for performing simulations. The generic model is developed using 48 simulations. It is comparable to the linear regression model, which is obtained using 1152 simulations. Additionally, a tabular W-element model of a differential stripline is used to take into consideration the frequency-dependent dielectric loss. In order to demonstrate the expandability of this approach, the methodology was applied to two differential pairs of striplines in the frequency range of 10 MHz to 20 GHz.**

Keywords—linear regression, generic model, machine learning, tensorflow, ANN, design of experiments

I. Introduction

As the appetite for fast data transmission rates keeps increasing, the engineers are faced with a task of designing and optimizing complex interconnects up to several tens of GHz. To reduce the simulation times, a ML based regression analysis methodology is used to create generic models (i.e. "black-box") of differential striplines. Generic models enable engineers with little electromagnetic knowledge to develop PCB structures.

Traditionally, Monte Carlo analysis [1] was used for building the input dataset required for simulations. From the obtained dataset, regression-based fitting was performed to generate generic models and perform statistical analysis. The drawback of using Monte Carlo method is that for the cases with large number of parameters, an even larger number of data points is required. Further, the regression analysis is unsuitable for mapping linear input parameter space to nonlinear outputs [5]. Considering these disadvantages, ML provides a solution for solving complex nonlinear output problems.

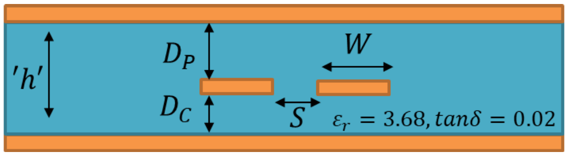
In the past, several research papers have introduced the use of ML and regression-based fitting methods to develop generic models. [2] uses an artificial neural network (ANN) to create a generic model of three differential pairs with an input dataset generated using DoE. The resulting generic model uses per-unit-length resistance (R), inductance (L), conductance (G) and capacitance (C) values obtained using W-element model. The RLGC values are a function of multi-dimensional space of input design parameters, such as: width (W), spacing/pitch (S), spacing between pairs (S_P), pre-preg height (H_P) and core height (H_C). It was shown in [2] that the input parameter *'W'* is the most dominant factor. This is because since the self and mutual RLGC values are functions of *'W'*. An input dataset for *'W'* is expanded outside the required range to obtain a uniform distribution in [2]. Including values outside the required range is a drawback of the proposed method. [3] and [4] use a similar approach for creating a library of interconnects and then use it for optimizing interconnect design. Both [3] and [4] use Latin hypercube and orthogonal arrays, respectively, for creating input dataset for training of the ML models. [6] performs simulations based on orthogonal Taguchi arrays. [7] uses 1500 simulations for optimizing and obtaining time domain reflectometry (TDR) profile for differential vias. Hence, DoE-based input dataset generation limits the control on number of simulations as well as input values used for simulations.

Section II of this paper provides a comparison of ML-based regression analysis to traditional linear regression analysis without DoE. This leads to a decrease in the number of simulations needed for building the generic model. In Section III, the ML algorithm is extended to create a generic model for two pairs of differential striplines. Once the generic model is created, it is verified by using the geometrical dimensions not present in the training dataset. The verification was performed by comparing the S-parameters obtained using Ansys Q2D to the generic model S-parameters. Unlike [3], frequency dependent RLGC values are used instead of per-unit-length parameters. This allows to take into account frequency dependent dielectric loss.

II. Comparison of Fitting Methods for a Differential Stripline

A cross-section of a differential stripline used for creating the generic model is shown in Fig. 1. The inputs to the generic model are geometrical variations like pre-preg and core height (D_P/D_C), width of the conductor (W), pitch between the differential pair (W). The height of the dielectric $('h')$ and the thickness of the conductor $('T_t')$ are kept constant.

After the design space of the parameters is defined (see Table I), simulations are performed in Ansys Q2D. Tabulated and frequency dependent RLGC values are extracted from the results. The RLGC values are used as output dataset.



(a)

Fig. 1. Stripline model used for creating the generic model with variations in parameters shown in Table I. The material characterstics of the dielectric is $\varepsilon_r = 3.68$, $tan\delta = 0.02$ with Djordjevic-Sarakar model. The length of the stripline is 2 inches.

TABLE I. DIFFERENT GEOMETRICAL PARAMETERS AND THEIR RANGES

Parameter	Description	Range [mil]	Simulation Levels [Linear Regression]	Simulation Levels [ML]
D_P/D_C	Pre-preg and core height	3~8	8	3
S	Pitch of Differential pair	3~12	24	8
W	Width of conductor	3~4	6	2
'h'	Dielectric thickness	15	Fixed	Fixed
'T_t'	Conductor thickness	0.65	Fixed	Fixed

A. Linear Regression Fitting

Fig. 2 depicts the flow diagram of the generic model creation process. Linear regression cannot map non-linear outputs to linear inputs accurately [4]. Since the RLGC parameters are non-linear w.r.t frequency before performing the fit they are divided into two different groups: a) 'group-1' contains parameters from 10 MHz to 1 GHz, and b) 'group-2' from 1 GHz to 20 GHz. The data is split because, for performing the linear regression fitting, 50 frequency points are chosen with 30 frequency points in group-1 and 20 frequency points in group-2. This would allow the non-linear region below 1 GHz to be captured accurately. As an example, the parameter R_{11} is plotted in Fig. 3 contains non-linear region below 1 GHz and a linear region above 1 GHz. This is the true for other RLGC parameters of the model. 1152 simulations were performed for obtaining a linear regression fitted equation for each of the RLGC values. This is another drawback of the linear regression model. JMP tool [9] was used to perform linear regression modeling.

B. Machine Learning (ANN) Based Fitting

Before performing a ML based fitting, it should be observed whether the targets (RLGC values) follow a certain pattern that could be related to the input features (stripline cross-section dimensions). As observed from Fig. 3, the R_{11} values can be mapped to the input geometrical structure. Fig. 4 describes the flow diagram for creating a generic model of the differential stripline with ML based fitting. Prior to creating and tuning the ML network, all the parameters values are normalized between 0 and 1, as expressed in (1).

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

$$X = X_{norm} * (\max(X) - \min(X)) + \min(X) \tag{2}$$

where, X is the quantity to be normalized. (2) represents the re-scaling factor for obtaining the original value of X.

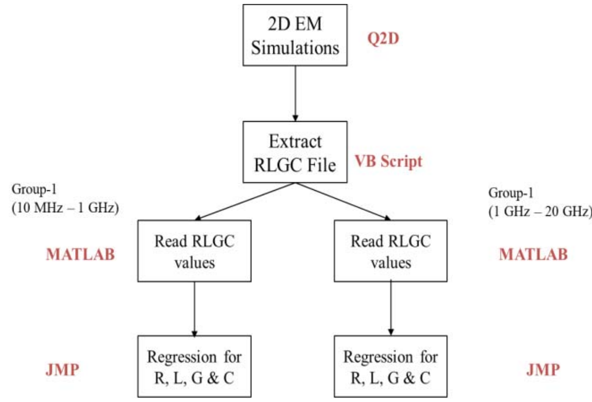


Fig. 2. Flow chart showing the division RLGC values into group – 1 and group – 2 followed for linear regression analysis.

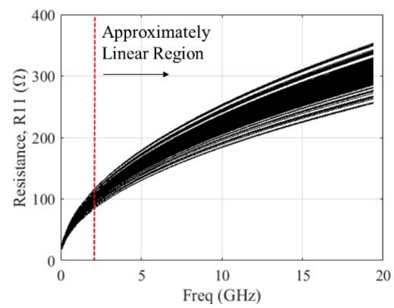


Fig. 3. Example of non-linearity below 1 GHz in R_{11}

Unlike the linear regression modeling, only 48 simulations were used for training and testing. A recursive approach was chosen for selecting the number of simulations and levels for each of the input parameters. This means, at every step, the accuracy of the created generic model is checked. Additional simulations are added to the training dataset until the criteria for accuracy is met. The criteria in this case is the insertional loss to match be matched with 2D simulations within 1 dB. The levels of each input parameter are listed in Table I. While it was observed that a better fit can be obtained using a larger number of simulations, the same effect can be achieved by carefully tuning the number of hidden layers, the input polynomial, the regularization factor, as well as the optimizer. Tensorflow [8] is used for creating the ML model for the 12 parameters(R_{11}, R_{12}, R_{22}, L_{11}, L_{12}, L_{22}, G_{11}, G_{12}, G_{22}, C_{11}, C_{12}, C_{22}) . Tuning the ML parameters individually rather than as a batch (as performed in [2], [3]) also improved the accuracy of the generic model. The training is performed with the ML hyperparameters shown in Table II.

TABLE II. HYPER PARAMETERS FOR SELF & MUTUAL TERMS

Parameter	Self Term	Mutual Term
Hidden Layers	2	5
Optimizer	Adam	Adam
Training : Validation	80:20 %	90:10 %
Epochs/Training Iterations	300	700
Loss Function	Mean Square Error	Mean Square Error
Learning Rate	0.01	0.01

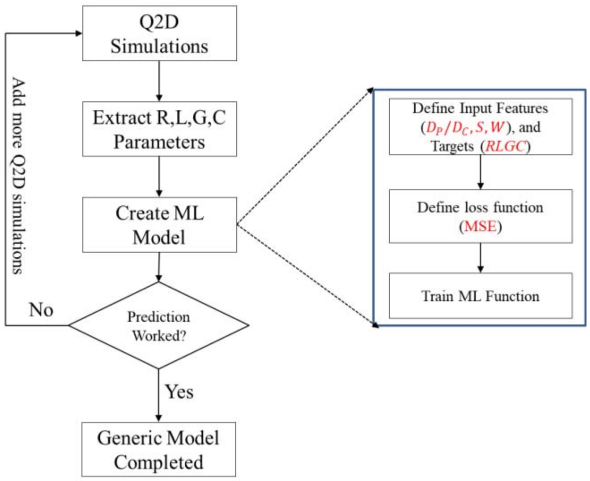


Fig. 4. Flow chart implemented for creating generic model of the Stripline described in Fig. 1. The ML paarameters are tuned for obtaining the generic model is explained in Table II.

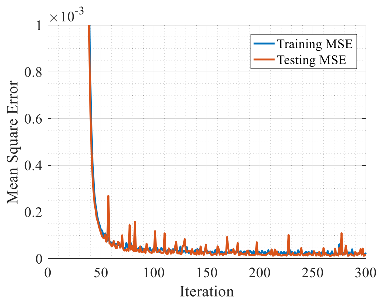


Fig. 5. MSE of training and test cases of R_{11} showing that both MSEs are close to each other, meaning there is no over fitting or under fitting problem.

C. Comparison of Different Fits with 2D Simulations

The created generic model is then tested on the data which is not used in the training process. Fig. 5 shows a comparison of training and testing mean square error (MSE) loss function for R_{11}. Fig. 5 shows no significant difference between the training and testing loss, which indicates that neither under- nor over-fitting occur in the ML model. This is true for the other targets as well. A comparison of the linear regression, ML based generic model and actual RLGC values are shown in Fig. 6. The RLGC values match within 10 % for both ML as well as regression analysis when compared to actual RLGC values. Further, the comparison between S-parameters obtained using predicted RLGC model and S- parameters from Ansys Q2D simulations is done in Fig. 7. The geometrical parameters used for verification are $D_P = 4\,mils$, $W = 3\,mils$, $S = 7\,mils$, $h = 15\,mils$, $T_t = 0.65\,mils$.

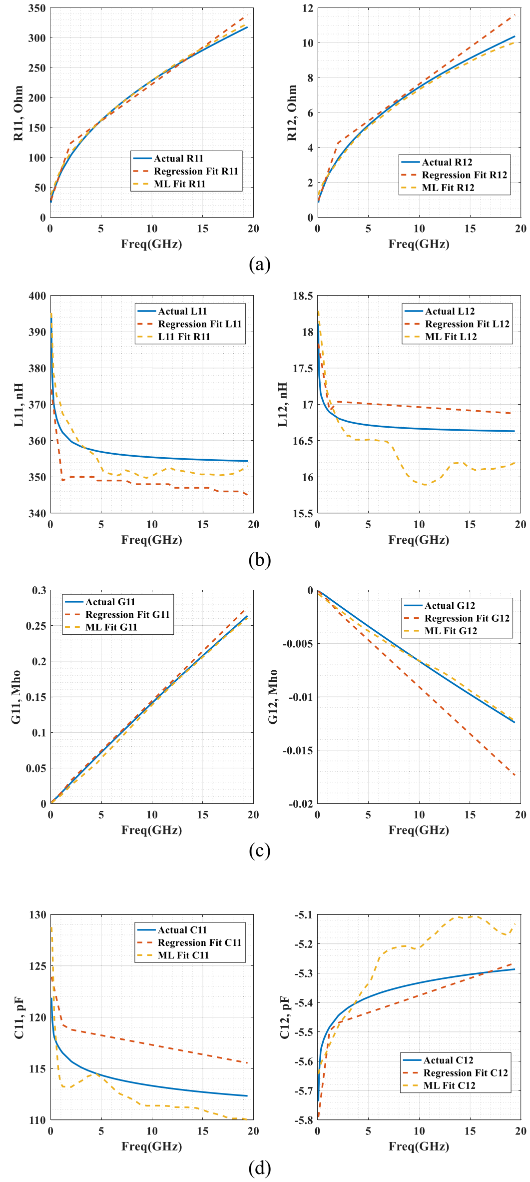


Fig. 6. A comparasion of the self and mutual RLGC values between actual, regression based fitting and ML based fitting model : (a) Resistance, (b) Inductance, (c) Conductance, and (d) Capacitance

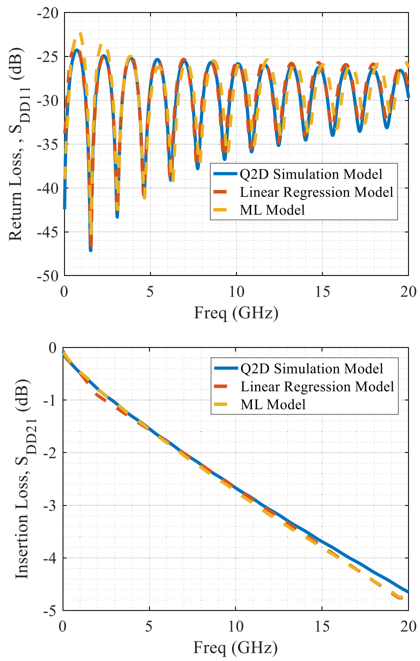


Fig. 7. A comparison of S – parameters between Q2D simulaion, linear regression mode and ML model for $D_P = 4\,mils,\ W = 3\,mils,\ S = 7\,mils,\ h = 15\,mils,\ T_t = 0.65\,mils.$

III. Extending the Proposed ML Model to Two Differential Pairs

The proposed ML model from Section II is extended to two differential pairs (see Fig. 8). The ML training parameters developed for self and mutual terms from Section II are re-applied for the case with two differential pairs. For the mutual terms between conductors $1 \rightarrow 3, 1 \rightarrow 4, 2 \rightarrow 4$, the ML model hyperparameters are listed in Table III.

The inputs to the generic model are the geometrical parameters similar to one differential pair with the addition of the spacing between the differential pairs (S_P). Individual ranges of each of the parameters are shown in Table IV. Similar to the single pair case, the number of levels and total number of simulations are determined by a recursive process described by the flow chart in Fig. 4.

A total of 48 simulations are performed using Ansys Q2D and the frequency dependent RLGC parameter are extracted. Each of the output parameters ($R_{11}, R_{12}, R_{13}, R_{14}, R_{23}, R_{24}, R_{34}$ etc.) is fit with an individual ML model. Fig. 9 shows the comparison between S-parameters obtained using predicted RLGC values and S-parameters extracted using Q2D simulations. The insertion loss matches within 1 dB when compared to 2D simulations. The return loss for ML model matches close to 2D simulations, this could be because the L and C matches with 5 % error which is lower than for single pair differential from Section II. The differential-to-differential near end crosstalk matches within 5 dB. Two possible reason for larger error, they are: 1) the mutual terms are small, specially the L and C, to obtain a better fit, 2) the cross talk is very low in the range of -60 dB. As there are 40 RLGC values for the case of two differential stripline pairs, a comparison between actual RLGC values and predicted RLGC values obtained using ML model are not shown here.

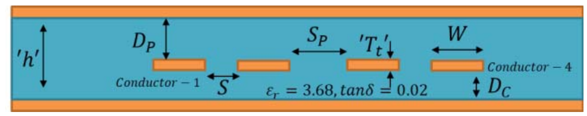


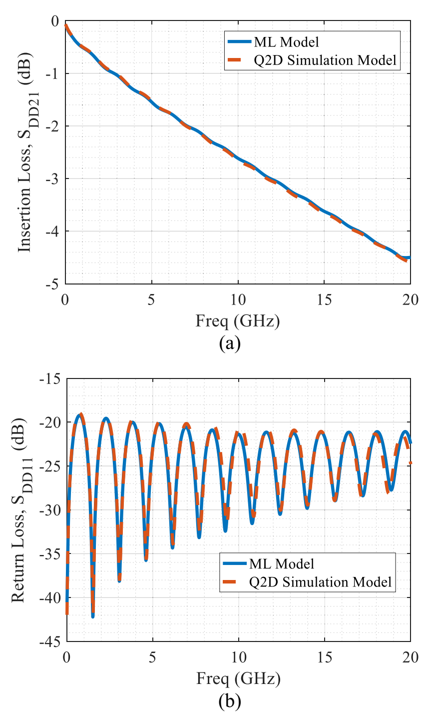
Fig. 8. Two differential stripline model with which the ML technique used in Section II is extended. The material characteristics of the dielectric is $\varepsilon_r = 3.68$, $tan\delta = 0.02$ with Djordjevic-Sarakar model. The length of the stripline is 2 inches.

TABLE III. Hyper parameters Used For conductors $1 \rightarrow 3, 1 \rightarrow 4, 2 \rightarrow 4$

Parameter	*Far Away Mutual Term*
Hidden Layers	8
Optimizer	Adam
Training : Validation	80:20 %
Epochs/Training Iterations	750
Loss Function	Mean Square Error

TABLE IV. Variations and Ranges of Two Differential Pairs

Parameter	*Description*	*Range [mil]*	*Variations Used for Training*
D_P/D_C	Pre-preg and core height	3~8	[3, 9]
S	Pitch of Differential pair	3~12	[3, 6, 12]
S_P	Spacing between Differential pairs	5~25	[5, 10, 20, 25]
W	Width of conductor	3~4	[3, 4]
$'h'$	Dielectric thickness	15	*Fixed*
$'T_t'$	Conductor thickness	0.65	*Fixed*



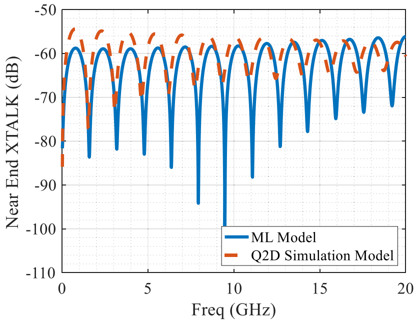


Fig. 9. Comparison between ML model S – parameters and Q2D S – parameters for $D_P = 6\,mils,\ W = 3\,mils,\ S = 9\,mils,\ h = 15\,mils,\ T_t = 0.65\,mils\ and\ S_P = 15\,mils$: (a) Differential Insertion loss for conductors 1,2 , (b) Differential Return Loss for conductor 1,2

IV. Conclusion

A generic model for a differential pairs of stripline is created for a frequency range of 10 MHz – 20 GHz using machine learning based regression fitting. It was observed that while 1152 simulations are required for creating the generic model using linear regression method only 48 simulations were enough when ML based fitting was used. This reduced the time required to create the generic model by 95 %. The accuracy of insertion loss is within 1 dB in both the cases. The reduction in the number of simulations is achieved by avoiding DoE-based Latin hypercube or orthogonal arrays and adapting a recursive process of increasing training data till the required accuracy in prediction is used. The ML technique was then extended to two differential pairs and verified by a 2D solver.

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