A Neural Network Based Method for Predicting PCB Glass Weave Induced Skew

Jose A. Hejase*, Pavel Roy Paladhi, Roger S. Krabbenhoft, Zhaoqing Chen, Junyan Tang and Dylan J. Boday
Systems Group – POWER Series Hardware Development
IBM Corporation
Austin, TX, USA
*jahejase@us.ibm.com

***Abstract*—This paper proposes the use of a neural network based tool to predict the skew factor of PCB laminate differential channel designs. A multitude of differential stripline design scenarios are 3D modelled, each with a different expected within differential pair skew factor. The modelled data is used to train a neural network. The neural network is tested using an unseen set of design data in order to evaluate the goodness of its predictions. Preliminary results show this machine learned technique to be a viable way to predict PCB glass weave skew without the need to resort to intensive 3D modelling. This method has potential to shorten design cycles and simplify analysis while still achieving good simulation accuracy.**

Keywords—Printed Circuit Board (PCB); Glass Weave; Differential Pair; Skew; Stripline; Artificial Neural Network (ANN); Machine Learning

I. Introduction

High speed communications exist in many different technologies at present. Of interest are the high speed communication channels (or buses) which exist in computer systems interconnecting CPUs to each other or to other peripheries such as storage systems or network switches. Realizing these high speed channels can happen in many different forms constrained by cost, reliability, available manufacturing options and technological limitations. Such choices can include: differential or single ended wiring, wiring density, PCB design characteristics (such as thickness, layer quantity & material properties), types of connectors, via types and properties, etc. No matter what form the high speed channel design takes, it is always required to achieve good signal integrity.

Striplines wired in a differential fashion have been used for many years in high speed channel design as they are more robust to signal distortion and external interference than tradition single ended lines when designed appropriately [1]. A key implementation challenge of differential-pair striplines though is maintaining uniform stripline impedance throughout the length of the pair of striplines. Any uneven change in dimensions or dielectric constant of the surrounding leads to differential impedance changes and differential to common mode conversion. The total signal delay seen by each stripline within the pair must be the same. Any difference in the delay leads to common mode conversion thus degrading the quality of the differential signal. The difference in delay between the two striplines within the differential pair is called skew. Ideally for best signal integrity, within differential pair skew should be zero.

Within differential pair skew can be caused by a variety of factors, most importantly: copper etch length difference of both striplines of the differential pair and dielectric surrounding heterogeneity caused by glass weaves in PCB laminates [2]. While the copper length difference of the striplines composing a differential pair can be mitigated by matching lengths on the board, the glass weave effects must be treated more carefully.

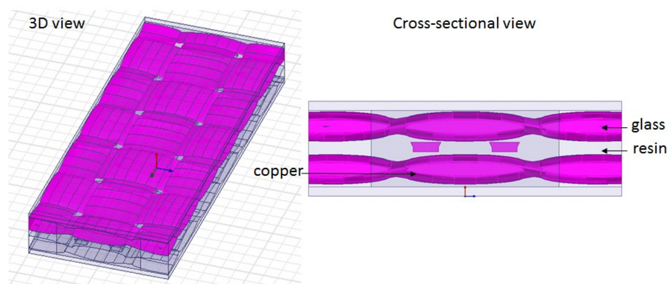

Fig. 1. PCB laminate showing a differential stripline and the glass weaves within the glass-epoxy resin dielectric surrrounding.

Commonly, PCB laminate layers are made of glass -epoxy resin composites. The glass weaves are bound together, surrounded and impregnated by resins to compose the dielectric filling between copper layers of multilayer PCB laminates. Fig. 1 shows a differential stripline pair embedded between two ground layers and surrounded by dielectric. The glass weaves within the dielectric is clearly seen in Fig. 1.

The dielectric constants of the glass and resin are usually different. Moreover, the space occupied by glass in the vertical direction can change relative to the planar position. Looking at these facts in relation to the differential stripline pair, it can be concluded that depending on the position of the traces relative to the weave, the dimensions of the weave, the dielectric properties of the resin and glass and the dimensions of the PCB laminate layers; different propagation delays may be seen on each of the traces leading to skew.

In practice, glass weave skew has been mitigated in several ways during board design. Most commonly used is trace rotation relative to glass weave orthogonal grid [3]. In this method, each stripline of the differential pair would pass over low density and high density glass regions thus balancing out the total propagation delay seen by each trace for a long enough section of wiring. Fig. 2 shows an illustration of the method. The green areas on the two strips will result in matching propagation delays as well as the red areas. The total skew then within the differential pair will balance out for a long enough differential pair, when wired diagonally as opposed to being wired orthogonally.

It would be very beneficial to know the amount of skew mitigation by rotation needed for board physical design. This would help for planning reasons especially if many design constraints are placed on the design, to conserve space, or not incur additional costs. In order to quantify the need, the anticipated worst case skew factor which is a function of PCB physical dimensions and material properties, glass weave type and differential pair dimensions must be known. The worst case skew factor is a number in time per distance units (typically ps/inch) describing the worst case skew which a differential pair may have. Using 3D EM solvers to model PCB configurations and calculate the skew factor is highly accurate but also a time consuming and effort intensive process.

This paper proposes employing artificial neural networks (ANNs) to estimate/predict the worst case skew for a given set of board and stripline dimensional and material parameters. In the proceeding sections of the paper, the ANN based predictive methodology and setup is described and the method is applied on a dataset for which results are obtained and discussed.

II. Predictive ANN Tool SetUP, Test and Results

A. *Artifcial Neural Network Setup for Skew Prediction*

ANNs are machine learning models which mimic biological nervous systems. They are characterized by being highly adaptable to different types of applications and data, are self-organizing and once trained sufficiently with representative data can be good predictors of outputs given certain inputs. [4]

For this study, the MATLAB neural network toolbox was utilized. In particular the neural network fitting tool was used. The neural network implements a two layer feedforward network with a Bayesian regularization training algorithm. The network consists of one input, one hidden and one output layer with a 45-12-1 topology. At the hidden node the sigmoid function is used to relate the input to the output. The input to the neural network are parameters describing the differential pair dimensions and surrounding material and glass weave properties around it adding up to a total of 45 parameters. The output is a number, a skew factor, describing the skew associated with the particular PCB and differential pair build in time (ps) per distance (inch).

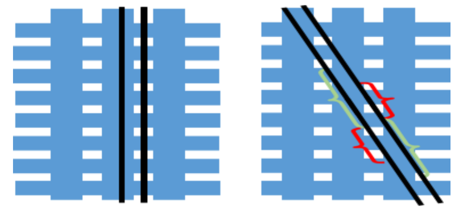

Fig. 2. Diagonal wiring for within differential pair skew mitigation.

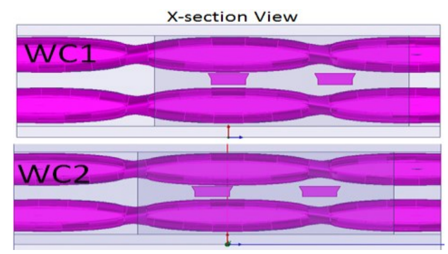

Fig. 3. Two worst case positions for skew for othogonally routed differential pairs within a PCB dielectric layer having 1ply in the core and prepreg.

B. *Obtaining the ANN Training, Validation and Test Dataset*

For this paper, more than 120 data points were obtained through 3D EM modelling using ANSYS HFSS. Every modelled structure represented a differential stripline pair within a dielectric PCB layer placed in an orthogonally routed worst case position relative to the glass weave bundles. In principle, there are two different worst case scenarios for an orthogonally routed differential pair in an internal PCB layer relative to a glass weave. These are: when one of its lines is routed over the glass richest region or when one of its lines is routed over the glass poorest region. These are referred to as WC1 and WC2 respectively in the remainder of this paper. Fig. 3 shows an illustration of the two worst case scenarios described above.

TABLE I. Summary of Properties of Modelled Data Points

Case	# of plys	PCB Material Type	Glass Weaves Used (Core; Prepreg)	Differential Pair Cases	Min-Max Differential Pair Dimensions (mils)	Stripline Copper Thickness	Core-Prepreg Thickness (mil)	WC1 & WC2?
1	1ply	Standard Loss	1x2116; 1x2116	8	(W=3.1; S=4.1) – (W=4.1; S=8.5)	1.2mil	4-4.4	Yes
2-0deg	2ply	Low Loss	2x106;2x1037	7	(W=3.1; S=4.1) – (W=4.4; S=10)	1.2mil	4.2-3.6	Yes
2-90deg	2ply	Low Loss	2x106;2x1037	7	(W=3.1; S=4.1) – (W=4.4; S=10)	1.2mil	4.2-3.6	Yes
3-0deg	2ply	Very Low Loss	2x1067;2x1067	7	(W=3.1; S=4.1) – (W=4.8; S=10)	1.2mil	4-3.8	Yes
3-90deg	2ply	Very Low Loss	2x1067;2x1067	7	(W=3.1; S=4.1) – (W=4.8; S=10)	1.2mil	4-3.8	Yes
4-0deg	2ply	Standard Loss	2x106; 1x106 1x1078	8	(W=3.1; S=4.1) – (W=4.6; S=12.4)	1.2mil	4-4.6	Yes
4-90deg	2ply	Standard Loss	2x106;1x106 1x1078	8	(W=3.1; S=4.1) – (W=4.6; S=12.4)	1.2mil	4-4.6	Yes
5-0deg	2ply	Standard Loss	2x1067; 1x106 71x1078	6	(W=3.3; S=4.1) – (W=4.3; S=9.3)	1.2mil	4-4.5	Yes
5-90deg	2ply	Standard Loss	2x1067; 1x1067 1x1078	6	(W=3.3; S=4.1) – (W=4.3; S=9.3)	1.2mil	4-4.5	Yes

In total 5 different PCB builds were utilized, with each build having different stack up thicknesses, glass weave combinations and material family type. For each PCB build, multiple 85Ohm differential impedance stripline dimensions were modelled (ie different line widths and in-pair spacing combinations leading to the same 85Ohm impedance). Many glass weaves do not have a square grid and as a result routing orthogonally in one direction can lead to different worst case skews than the other perpendicular direction. These two directions are known as the glass weave warp and weft directions. In case the PCB build had any non-square grid glass weaves both directions were considered in modelling and are referred to as 0deg and 90deg in the rest of this paper. Table I. summarizes the properties of the modelled data points. For every modelled data point, the skew factor was calculated using differential time domain transmissometry (TDT). Table II shows a minimum and maximum summary of the calculated skew factor for every individual PCB build. The wide range of skews is clearly noticeable. Note that the minimum and maximum skews for a particular worst case build corresponds to the minimum and maximum obtained amongst the different 85Ohm impedance pair dimensions that were modelled.

TABLE II. SUMMARY OF SKEW FACTORS OBTAINED AS A RESULT OF MODELLING EXERCISES

Skew (ps/in)				
Case	Worst Case - 1		Worst Case - 2	
	Least	Highest	Least	Highest
1	4.36	9.26	5.49	9.46
2-0deg	0.96	4.89	0.1	4.79
2-90deg	0.1	2.24	0.1	2.35
3-0deg	0.1	2.63	0.1	1.83
3-90deg	0.33	6.06	0.12	5.36
4-0deg	~0	6.89	0.18	6.99
4-90deg	0.27	1.61	0.09	1.70
5-0deg	1.52	6.36	1.52	6.36
5-90deg	0.09	3.76	0.72	3.76

C. *Neural Network Method Application and Testing*

After the full modelled dataset was obtained with each data point characterized by having 45 input characteristics describing the structure and one output skew factor, the data was divided into a neural network training dataset and a neural network blind testing dataset. For testing the neural network, two data points from each of the structure cases were selected in addition to all of case 5-90deg's data points. The rest of the data points were used for training the neural network.

Fig. 4 shows the result of testing the trained neural network with the training data. Comparing the skew factors obtained from simulations versus the ones obtained through the neural network, it can be seen that for most data points the neural network prediction was very close to what was obtained in simulation from a practical point of view. Comparing the results seen for case 5-90deg (points 15→26) from which no points were used for training, the difference looks small again from a practical point of view. The reason for the large difference seen on data point 4 is to be investigated in future work. As goes with many machine learning methods, it is expected as well for this neural network tool that more training data points which are well distributed leads to a better predicting model. It is also worthy to note that the neural network prediction was obtained in a matter of seconds which is negligible in comparison to the hours or days sometimes required to obtain the glass weave skew factor as a result of modelling and simulation.

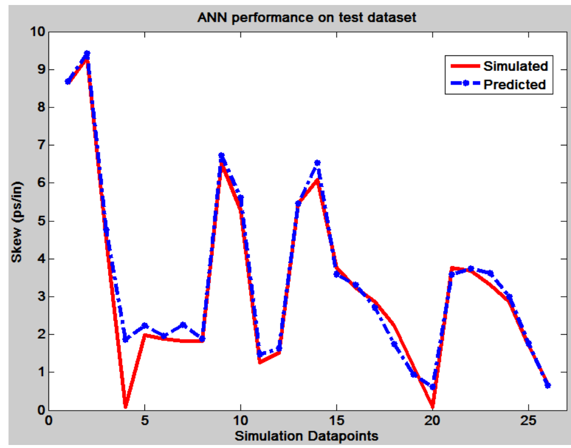

Fig. 4. Simulated versus neural network predicted results.

III. CONCLUSION

This work addressed the issue of glass weave skew. In particular the cause of the skew was defined and its consideration was motivated. Glass weave mitigation by rotation was explained. Most importantly, the need for quickly figuring out the worst case expected glass weave skew factor was motivated. A neural network based method to predict the worst case glass weave skew given particular PCB structure dimensions and material properties and differential pair dimensions and locations was presented. As an exercise, a neural network was setup. The datasets used to train and test it were explained. Finally, the results obtained from testing it were presented. The results were favorable giving promise to this method to be used in future high speed bus design exercises and improve design efficiency and turn-around time.

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