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► **To cite this version:**

Alexandre Plot, Benoit Goral, Philippe Besnier. Machine Learning Techniques for Defining Routing Rules for PCB Design. 2023 IEEE 27th Workshop on Signal and Power Integrity (SPI), May 2023, Aveiro, Portugal. pp.1-4, 10.1109/SPI57109.2023.10145545 . hal-04131946

**HAL Id: hal-04131946**

**<https://hal.science/hal-04131946>**

Submitted on 17 Jun 2023

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# Machine Learning Techniques for Defining Routing Rules for PCB Design

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**Abstract**—This article presents a methodology using machine learning techniques for defining printed circuit board (PCB) design rules in order to reduce signal integrity (SI) or electromagnetic interference (EMI) issues. The scenario illustrating the situation for which these rules must be defined is modelled with a 3D EM solver available on the market and simulations are run with varying parameters in order to obtain a representative sample of the design space. This data set is then used to train a surrogate model (i.e. a metamodel) of the scenario based on kriging algorithm. Using this surrogate model, more than ten thousands of simulations are computed in a decent time. The surrogate model estimations allow to estimate the sensitivity of the varying parameters with respect to some specifications (crosstalk level and insertion loss). Finally, an analysis of output values for which some requirements (crosstalk level, insertion) loss are not fulfilled provide some insights about possible adjustment of guidelines in terms of parameter ranges. Finally, a practical design example is given to illustrate the methodology.

**Index Terms**—PCB Design, Design Rules, Machine learning, Kriging, EMC, Signal Integrity

## I. INTRODUCTION

Today's market for electronic devices is extremely competitive. To keep or earn market shares, electronic companies have to release new products, in an always shorter time-to-market, and including either innovations in their products; new technologies or new services, or with the same functional perimeter but in a smaller form factor. This trend to offer always more capabilities in smaller devices lead engineers to design new products within a SWAP-C (Size, Weight and Power - Cost) optimized design methodology.

The SWAP-C constraints lead to smaller, denser, and more complex PCBs. Moreover, it is pushed by the higher integration of functionalities associated to the development of system on chip (SoC) or system in package (SiP) components. Power density inside PCB increases. Rising data rates and working frequencies lead to an increase of SI, PI and EMI issues. To cope with these challenges, design rules for board routing must be strictly respected. These rules are automatically checked by CAD tools called design rule check (DRC) applications. However, these rules may be inherited from past experiences, rule of thumb, or generalized for the whole board when they

can be tuned for different interfaces given, for instance, their data rates. This stringent design methodology can thus lead to overdesign. As a result unnecessary vias or decoupling capacitors are added and routing complexity is increased due to over-stressing.

In recent literature, the use of machine learning techniques in engineering has widely emerged, including surrogate modeling (SM) [1]. Surrogate models are a set of mathematical tools which can interpolate the output of the initial (but complex) model using known experiments in a very quick time. These models make possible the realization of parametric analyses, consisting in the evaluation of a large number of configurations of the design, which is normally very time-consuming in terms of computation when using classical physical based simulations. However, a large variety of algorithms exists when it comes to metamodeling. In EMC/SI/PI domain some methods have shown great performances like Kriging [2] [3] [4], support vector machines [5] or polynomial chaos [6] [7] to name a part of them. For this study, we choose to use Kriging due to its overall good performance.

This article presents a methodology using surrogate model to precisely and quickly define routing rules for a given routing scenario in PCB Design. The methodology used for defining these rules is presented in the second section of this article. The third section of this article consists in applying the methodology to a case study in order to deduce adequate routing rules according to some specifications. Finally, conclusions are presented in the fourth section.

## II. DESCRIPTION OF THE METHODOLOGY

This section describes the methodology developed for defining the routing rules. In PCB design, CAD tools make possible to check design rules of objects such as pads, pins, via, traces. These rules deal with sizes of these objects or spacing between them. In order to define a rule, an electromagnetic simulation can be run to study the impact of these parameters and define their appropriate range of values for which a given requirement is fulfilled, like a maximum coupling level or a maximum return loss. However, if the number of parameters is high and

over large ranges, running an important number of simulations becomes time consuming. That is why the use of a surrogate model is proposed to make it possible.

#### A. Case study definition

The first step of the methodology is the definition of a relevant scenario. This is often performed by analyzing potentially critical situations of PCB design impacting the functionalities of the system. Then, the parameters of interest and their acceptable value ranges are defined. The scenario is modeled using an appropriate software tool (CST microwave studio for the test case considered in this article). One or more outputs of interest are selected such as radiated power, voltages, currents or S-parameters for example, according to the considered risk analysis of the design.

#### B. Simulation and training of the surrogate model

The construction of a metamodel requires obtaining a dataset first. A design of experiment (DOE) is defined using the latin hypercube sampling (LHS) method. Each variable is then sampled following a uniform distribution, thereby uniformly covering the parameter space. This experimental design is then computed by physical based simulations, which require a certain amount of time depending on the complexity of the simulated design, the available computing resources, and the size of the DOE. Moreover, the size of the training sample is an open question in the literature since it is not known in advance and has a large impact on the accuracy of the metamodel. It is chosen as a function of the number of parameters and is generally a compromise between simulation time and its desired accuracy. Some authors [8] [9] [4] tried to tackle this problem by proposing an iterative learning of the metamodel and gradually increasing the sample size.

For this study, the strategy adopted is to choose a training sample size by rule of thumb and with past experiences. More realizations can still be added to the initial design of experiment if the metamodel precision is insufficient.

As explained in the introduction, Kriging method is selected for the training. The Kriging method consists in approaching the response of a model with a Gaussian process of random variables which is determined by optimizing hyperparameters of a kernel function from a limited set of observations according to the DOE. Exponential kernel is selected among other possibilities in this paper.

The accuracy of the surrogate model needs to be quantified to estimate the degree of confidence of predictions. The validation method used is based on the so-called  $k$ -fold cross validation. It consists in splitting the dataset into  $k$  groups of samples of equal size. Training is done using  $k - 1$  folds, the remaining fold being used for test. The prediction error is calculated as:

$$\epsilon_i^k = \frac{|\max(\hat{Y}_i, Y_i) - \min(\hat{Y}_i, Y_i)|}{\min(\hat{Y}_i, Y_i)} \quad (1)$$

where  $Y_i$  is the physical model output to be predicted and  $\hat{Y}_i$  is the predicted output of the surrogate model.  $\epsilon_i^k$  is a

relative error. The median relative error of  $\epsilon_i^k$  is computed for all the samples of each fold and for all the folds. For a reliable metamodel, we consider that a median error less than 20% is sufficient to perform parametric and risk analyses.

#### C. Parametric analysis and definition of the routing rule

The surrogate model allows to run ten or hundred thousands of predictions in a very short computing time. Running a very important number of predictions gives then a statistical distribution of the outputs of interest allowing to analyse the sensitivity of geometrical parameters over the observed output. The contribution of each parameter to the output variance is calculated thanks to a Sobol sensitivity analysis [10].

To define the routing rules, the following process is used: A Monte Carlo sample of size 100,000 is built and evaluated with the two metamodels. Then, a selection is made among all the configurations of the sample that meet the requirements defined through appropriate tolerance limits for  $S_{21}$  and  $S_{41}$ . Thus, a smaller sample size is obtained. The probability densities of each parameter of this restricted sample are then examined and routing rules are defined given certain criteria discussed later in the article.

### III. CASE STUDY ANALYSIS

#### A. Description

The studied scenario, illustrated in Fig. 1, is composed of two microstrip lines parameterized by their length and two centered openings in the ground plane described by their width and length.

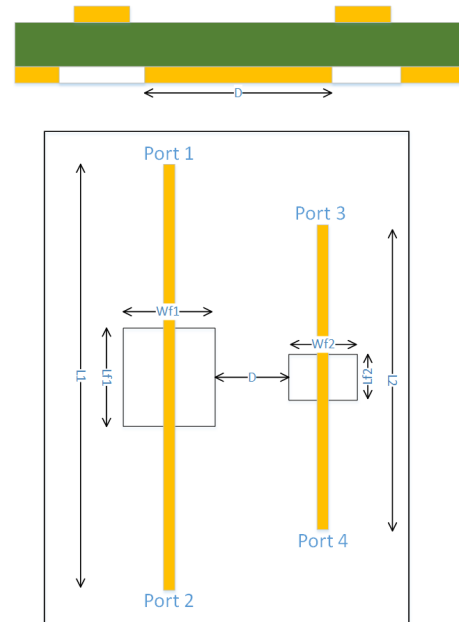


Fig. 1. Overview of the case study

The dataset consists of an input vector  $X$  containing all design configurations, and two output parameters  $Y_{S_{21}}$  and  $Y_{S_{41}}$  corresponding to insertion loss and crosstalk, respectively.

In total 7 parameters are studied and their range are given in the following table. I. Therefore  $X = (L_1, L_2, L_{f1}, L_{f2}, W_{f1}, W_{f2}, d)$ .

TABLE I  
PARAMETERS DEFINITION

Parameter	Description	Range (mm)
$L_1, L_2$	Length of traces	20 - 100
$L_{f1}, L_{f2}$	Length of openings	0.1 - 5
$W_{f1}, W_{f2}$	Width of openings	0.1 - 5
$d$	Distance between traces	0.5 - 5

### B. Training and validation of the surrogate model

A DOE of 650 realizations is constructed using LHS over the parametric space. For each of this 650 configurations, simulation is performed using the time domain solver of CST microwave studio and two outputs are monitored:  $S_{21}$  which is the transmission parameter of the first line and  $S_{41}$  which is the crosstalk (FEXT) factor between line 1 and 2. This study focuses on a frequency band ranging from 2 GHz to 20 GHz uniformly sampled with 1000 points. It is therefore necessary to train a metamodel for each frequency point considered. Thus, 1000 Kriging surrogate models are trained. In the rest of the article, we group all these metamodels under the label  $SM$ .

Two surrogate models are trained independently and are named  $SM_{S_{21}}$  and  $SM_{S_{41}}$ . Their prediction errors are computed using k-fold strategy with  $k = 5$ . Median relative errors of the two  $SM$  are shown in Fig. 2

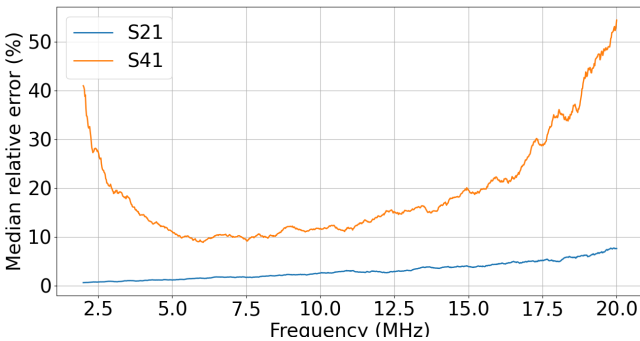


Fig. 2. Median relative error over the 5 test folds of  $SM_{S_{21}}$  and  $SM_{S_{41}}$

For  $SM_{S_{21}}$  the error criteria is respected. For  $SM_{S_{41}}$ , the error is more significant, particularly in the 2-5 GHz and 17-20 GHz intervals which can also be observed in Fig. 5. This is due to weak crosstalk levels, which make the relative error significant as soon as there is a small difference between prediction and simulation. The criteria of an error less than 20% is however respected for a frequency bandwidth ranging from 2.5 to 17 GHz.

Despite the fact that the  $SM_{S_{41}}$  metamodel does not meet the error criterion across the entire frequency band, it will be

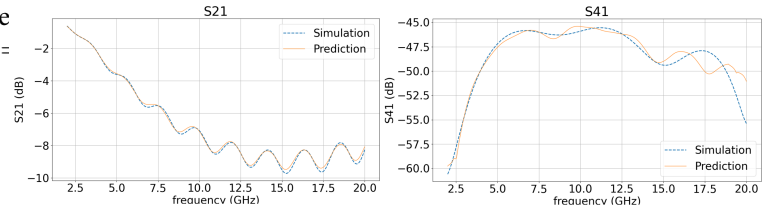


Fig. 3. Examples of predictions for both  $SM_{S_{21}}$  on the left, and  $SM_{S_{41}}$  on the right

retained for the rest of the study. To decrease the error, it is possible to add realizations to the initial DOE.

An example of a response for a random set of parameters is provided in Fig. 5.

### C. Exploitation of the SM: Sensitivity analysis and routing rules extraction

Once the two surrogate models were validated, they can be exploited to extract information like parametric sensitivity or design rules.

Sobol sensitivity analysis is performed using 7168 evaluations of the surrogate model and the results are given in Fig. 4

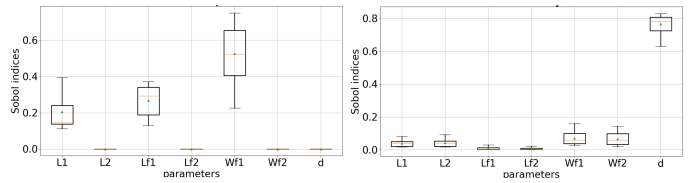


Fig. 4. Sobol sensitivity analysis for both  $SM_{S_{21}}$  (left) and  $SM_{S_{41}}$  (right).

The box-plot representation is adopted in order to observe the dispersion of Sobol indices over frequencies. For  $S_{21}$ , only  $W_{f1}$ ,  $L_{f1}$  and  $L_1$  are relevant parameters. For  $S_{41}$ , the distance  $d$  between the lines is the most sensitive parameter influencing the crosstalk. This sensitivity analysis tells us which parameters of the scenario are important in order to apply design rules to meet the requirements.

The rest of the article is dedicated to routing rules extraction. Thus, a large DOE (100,000) is constructed and estimated by the two metamodels. Two criteria are set on the outputs, based on the following hypothetical requirements for this case study:

- $S_{21} > -5dB$
- $S_{41} < -30dB$

The PCB configurations that meet these 2 criteria are extracted from the 100,000 samples and the distribution of 4 of the parameters identified in the Sobol analysis are plotted in Fig. 5.

Fig. 5 only represents the distribution of the four most influential parameters. The blue distribution represents the distribution of the complete sample which is uniform. The orange distribution corresponds to the only set of realizations among the initial sample which satisfies both  $S_{41}$  and  $S_{21}$  criteria.

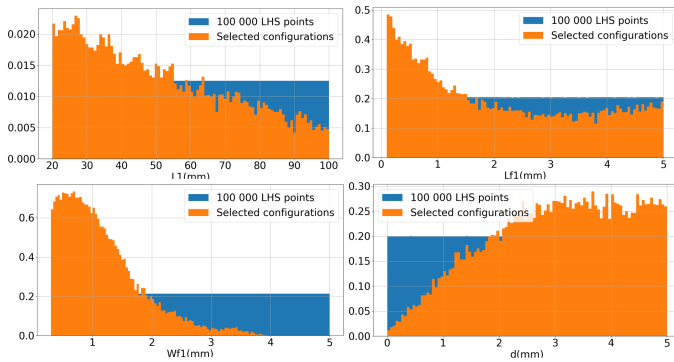


Fig. 5. Distribution of  $L1$  (top left),  $Lf1$  (top right),  $Wf1$  (bottom left) and  $d$  (bottom right)

Here, the upper bound for  $L1$  corresponds to the intersection of the orange and blue densities. From these plots, routing rules can easily be defined and are summed up in the table II.

TABLE II  
ROUTING RULES

Parameters	Routing rules
$L1$	$<55$ mm
$Lf1$	$<1.4$ mm
$Wf1$	$<1.9$ mm
$d$	$>1.8$ mm

The distributions of  $S_{41}$  and  $S_{21}$ , computed from Monte Carlo sample are plotted in Fig. 6 in both cases of unrestricted and constrained parameter space. According to these results, the rules of the table II are validated.

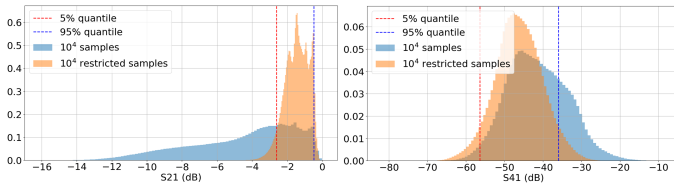


Fig. 6. Compared distribution when restricting parameters. On the left,  $S_{21}$  distribution, on the right  $S_{41}$  distribution

The results show that for  $S_{21}$ , all the configurations for which routing rules are applied meet the  $-5$  dB threshold. For  $S_{41}$ , more than 95% of the configurations achieve the  $-30$  dB goal, which is sufficient.

#### IV. CONCLUSION

Routing rules for PCB design must be followed in order to avoid SI, PI and EMC issues and meet the requirements of the system. However, these rules are not always available or can be too conservative, leading to overdesign in the system or over constraining the routing and generate additional design and recurrent costs. Based on a surrogate model, the proposed method allows to find routing rules with estimated design margin and with limited computing resources with respect to parametric physical-based simulations.

As a benefit, this methodology pave the way for building a library of surrogate models for each critical situation encountered recurrently in the design process. Such surrogate models could be tuned according the specific requirements of the project.

Finally, this methodology could be easily extended to other physics like thermal or mechanical problem.

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